Postprint: A Kalman Filter-Based Target Tracking Method for Strong Interference and Momentary Occlusion

Authors: Wang Enwang, Chen Xiaolin, Wang Enda

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Abstract

To address the difficulty in precisely capturing target positions under close-range strong interference from stars and transient occlusion interference for space targets, we propose utilizing Kalman filtering to predict target positions and track targets, with the tracking gate employing an improved adaptive variable gate. Additionally, a novel prediction and tracking method for targets under strong interference and transient occlusion is designed. When such targets are predicted, the Kalman filter' s predicted values are used as observations for target tracking, and the predicted target centroid is employed to constrain and correct the gate centroid, thereby capturing useful observation data. Experimental results demonstrate that the proposed method can robustly track targets under strong interference and transient occlusion, improve space target tracking accuracy, reduce data error rates, enhance data quality, and provide more useful data for orbital position acquisition. The method exhibits fast program execution speed and possesses certain applicability and scientific value.

Full Text

Preamble

Strong Interference and Momentary Occlusion Target Tracking Method Based on Kalman Filter

Wang Enwang1,2,3†, Chen Xiaolin1,5†, Wang Enda4†

1 School of Information Engineering and Automation, Kunming University of Technology, Kunming, Yunnan 650031
2 Zijinshan Observatory, Chinese Academy of Sciences, Nanjing, Jiangsu 210008
3 Key Laboratory of Space Target and Debris Observation, Chinese Academy of Sciences, Nanjing, Jiangsu 210008

4 School of Mathematics and Computer Science, Chuxiong Normal University, Chuxiong, Yunnan 675099
5 School of Information Science and Technology, Qiongtai Normal University, Haikou 571127

Abstract

Accurately capturing target positions is challenging when space targets experience close-proximity strong interference and momentary occlusion from stars. This paper proposes using Kalman filtering to predict target positions for tracking, employing an improved adaptive variable tracking gate. Simultaneously, a novel prediction and tracking method for strong interference and momentary occlusion targets is designed. When such targets are anticipated, the Kalman filter' s predicted values serve as observation values for target tracking, while the predicted target centroid is used to constrain and correct the gate centroid, thereby capturing useful observation data. Experiments demonstrate that this method enables robust tracking of strong interference and momentarily occluded targets, improves space target tracking accuracy, reduces data error rates, enhances data quality, and provides more valuable data for orbital position determination. The method operates with fast computational speed and offers both applicability and scientific value.

Keywords: strong interference and momentary occlusion; Kalman filter; space targets; tracking

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Space target detection and identification utilize multiple approaches to acquire various features and information reflecting target characteristics, enabling discrimination of space target types, attributes, purposes, and threats. Space target tracking is a critical means of obtaining orbital information, and its robustness directly impacts automatic target recognition, positioning, cataloging, and telescope operational efficiency [**?**]. Currently, both domestic and international research primarily employs universally applicable Kalman filtering and particle filtering for space target tracking, without addressing methods specific to strong interference and momentary occlusion scenarios. While numerous methods exist for handling strong interference and momentary occlusion in non-space moving targets [**?**], these lack application examples for space targets. Consequently, an appropriate method must be developed to address this problem. Strong interference and momentary occlusion between space targets and stars occur frequently. Classical Kalman filtering, widely used in astronomical observations, produces observation data with excessive errors when tracking strong interference and momentary occlusion targets, sometimes failing to obtain any observation data altogether. This occurs because when targets are close to or merged with stars, the conventional fixed tracking gate causes the captured target centroid to deviate from the actual target centroid.

Space target strong interference and momentary occlusion can be categorized into three types: (1) Strong interference targets, where the target and star are close but not merged, affecting normal tracking due to proximity; (2) Partially occluded targets, where space targets and stars momentarily overlap, causing them to be tracked as a single larger target; and (3) Completely occluded targets, where space targets are fully obscured by stars, making target detection and effective tracking impossible. As shown in [Figure 1: see original paper], panel (a) shows a target near a star without merging, creating interference; panel (b) shows a target partially occluded by a star at the center; and panel (c) shows two stars with a target at the upper right of center completely occluded by a star.

This paper proposes solutions for these three problems. Based on Kalman filtering' s ability to accurately predict target positions, the main implementation process for predicting strong interference and momentary occlusion targets is as follows: First, identify nearby stars around the tracking target, then perform position prediction for both the target and nearby stars. Next, calculate the distance between the predicted positions of the target and stars. When this distance falls below a given threshold, a new tracking method for strong interference and momentary occlusion targets is activated: the Kalman filter predicts the position of the interfered or occluded target for tracking at that predicted location, while the tracking gate retains its size from the previous frame. Simultaneously, the predicted target centroid is used to constrain and correct the gate centroid, achieving robust and accurate target tracking. When the predicted distance exceeds the threshold, the target is treated as normal and tracked using Kalman filtering combined with an improved gate. This implementation process is illustrated in [Figure 2: see original paper].

1 Kalman Filter Prediction and Tracking

Let the state vector $\mathbf{X}_k = [x_k, y_k, v_{xk}, v_{yk}]^T$ represent the position and velocity of a space target in the x and y directions, and the observation vector $\mathbf{Z}_k = [x_k, y_k]^T$ represent the observed position obtained during Kalman filter tracking. The state equation and observation equation are respectively:

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

$$\mathbf{Z}_k = \mathbf{H}_k \mathbf{X}_k + \mathbf{V}_k, \tag{2}$$

where $\mathbf{X}_k$ and $\mathbf{X}_{k-1}$ are state vectors at times k and $k-1$, respectively; $\mathbf{A}_k$ is the state transition matrix representing a hypothesized model of target state transformation; $\mathbf{B}_k$ is the input matrix converting inputs to states; $\mathbf{H}_k$ is the observation matrix converting from state to observation space; and $\mathbf{W}_k$ and $\mathbf{V}_k$

are state noise and observation noise matrices with covariance matrices $\mathbf{Q}$ and $\mathbf{R}$, respectively. The derivation formulas are:

$$\mathbf{X}_k^- = \mathbf{A}_k\mathbf{X}_{k-1} + \mathbf{B}_k\mathbf{W}_{k-1}, \tag{5}$$

$$\mathbf{P}_k^- = \mathbf{A}_k\mathbf{P}_{k-1}\mathbf{A}^T + \mathbf{Q}, \tag{6}$$

$$\mathbf{K}_k = \mathbf{P}_k^-\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{R})^{-1}, \tag{7}$$

$$\mathbf{X}_k = \mathbf{X}_k^- + \mathbf{K}_k(\mathbf{Z}_k - \mathbf{H}_k\mathbf{X}_k^-), \tag{8}$$

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_k^-. \tag{9}$$

Here, $\mathbf{X}_k^-$ is the state prediction; $\mathbf{P}_k^-$ is the covariance matrix; $\mathbf{K}_k$ is the Kalman gain matrix; $\mathbf{X}_k$ is the corrected value of $\mathbf{X}_k^-$; and $\mathbf{P}_k$ is the covariance matrix. The predicted position from equations (5) and (6) is not optimal because it does not incorporate the observed position obtained during Camshift tracking. Through updating and correction using equations (7), (8), and (9), the optimal predicted position is output for target tracking [**?**].

2 Improved Tracking Gate Design

Given that space target star images often lack good circularity, the moment method is the most widely used approach for calculating space target centroids. Classical Kalman filtering employs a fixed gate method for tracking space targets, which lacks adaptability to target size changes and frequently produces errors, particularly when tracking strong interference and momentary occlusion targets. Therefore, a variable gate is proposed to adaptively adjust according to target size. Let the target pixel positions be (x_k, y_k). The rectangular center (a_x, a_y) is:

$$a_x = \frac{\max(x_k) + \min(x_k)}{2}, \tag{10}$$

$$a_y = \frac{\max(y_k) + \min(y_k)}{2}. \tag{11}$$

The tracking gate width (w) and height (h) are:

$$w = \max(x_k) - \min(x_k), \tag{12}$$

$$h = \max(y_k) - \min(y_k). \tag{13}$$

3 New Strong Interference and Momentary Occlusion Target Tracking

Kalman filtering achieves space target tracking through continuous prediction, updating, and correction. Strong interference and momentary occlusion targets frequently appear in space moving target observations, causing the error between the theoretical and actual positions of tracked targets to increase substantially, sometimes making position information unobtainable and tracking worthless. Compared with classical Kalman filtering for space target observations, the new method primarily uses the predicted position of interfered targets as the observation value for tracking. Simultaneously, the tracking gate retains the previous frame' s size, and the predicted target centroid is used to constrain and correct the gate centroid, achieving robust tracking. A novel prediction method based on centroid distance between targets and stars is also proposed.

1. **Determining the Prediction Range for Nearby Stars Around the Tracking Target**
   For robust tracking of strong interference and momentary occlusion targets, predicting nearby stars is crucial. Performing centroid distance prediction between targets and stars across the entire frame would significantly increase computational load and time, reducing program efficiency. Conversely, predicting only within a small area around the target may fail to accurately identify strong interference and momentary occlusion issues. Typically, stars predicted within a circle of specific radius R centered at the tracking target centroid are identified as nearby stars, with the prediction area $S = \pi R^2$.

2. **Position Prediction for Targets and Stars**
   When strong interference or momentary occlusion occurs between moving targets and stars, stellar interference prevents accurate calculation of the target's actual centroid position. In such cases, Kalman filtering is required for position prediction. The actual position from the previous frame is used to predict the current frame position for both the tracked target and nearby stars, using predicted positions instead of actual positions for centroid distance calculation. Multi-frame prediction is necessary when targets are occluded across multiple frames.

3. **Distance Calculation Between Predicted Positions of Targets and Stars**
   Let the predicted centroid of the strong interference or momentarily occluded target in the current frame be (x_{ic}, y_{ic}), and the predicted centroid of the corresponding nearby star be (x_{kc}, y_{kc}). The predicted distance between target and star is:

$$D = \sqrt{(x_{ic} - x_{kc})^2 + (y_{ic} - y_{kc})^2}. \tag{14}$$

4. **Threshold Setting and Target Tracking**
   To better determine whether strong interference or momentary occlusion exists between targets and stars, a threshold F is set for the predicted distance:

$$K = \begin{cases} 1, & D < F \\ 0, & D \geq F \end{cases}. \tag{15}$$

   When the predicted distance between star and target centroids exceeds the threshold, $K = 0$, indicating no strong interference or momentary occlusion, and the target is tracked using Kalman filtering combined with the improved gate. When the predicted distance falls below the threshold, $K = 1$, indicating strong interference or momentary occlusion. In this case, the Kalman filter' s predicted position serves as the observation position for target tracking, the gate retains the previous frame' s size, and the predicted target centroid is used to constrain and correct the gate centroid.

5. **Gate Constraint Correction**
   When strong interference or momentary occlusion is predicted, the target' s gate retains the previous frame' s size. To ensure tracking robustness in that frame, given the accuracy of Kalman filter predictions, the difference between the gate centroid and predicted centroid is constrained within a specific range Q. The constraint relationship between the predicted centroid (x_{ic}, y_{ic}) obtained from the previous frame and the gate centroid (a_x, a_y) obtained from the current frame is:

$$|x_{ic} - a_x| < Q, \tag{16}$$

$$|y_{ic} - a_y| < Q. \tag{17}$$

   After tracking of strong interference and momentary occlusion targets concludes, the tracking gate reverts to the variable gate method, switching back to Kalman filtering combined with the improved gate.

4 Experimental Results

Experimental data consisted of multi-frame space moving target images captured by the 500mm aperture LiBa optical telescope at the Yaoan Observatory Station of Zijinshan Observatory, Chinese Academy of Sciences. Experiments were conducted on a Dell laptop running Windows 10, using PyCharm 2022 software with OpenCV 3.4.17.63 for Python 3.9. The proposed method used Kalman filtering combined with the improved variable gate for target tracking, switching to the new strong interference and occlusion target tracking method when encountering such targets. The comparative experiment used classical Kalman filtering from space moving target observation systems with a fixed gate, performing no special processing for strong interference and momentary occlusion targets. In each frame, the white circle within the red gate represents the space target, while other objects are stars.

4.1 Gate Comparison Experiment

[Figure 3: see original paper] shows gate comparison results. Panels (a) and (b) use classical Kalman filtering with a fixed gate, where the target is larger than the gate in (a) and smaller in (b). Panels (c) and (d) use Kalman filtering combined with the improved variable gate, where the gate converges on the target centroid, preventing excessive errors between theoretical and measured centroids.

[Figure 4: see original paper] compares the accuracy of classical Kalman filtering with the proposed method. The proposed method demonstrates overall accuracy improvement, with an average enhancement of 1.14 times, highlighting its applicability and effectiveness.

4.2 Strong Interference Target Tracking

[Figure 5: see original paper] shows strong interference target tracking comparisons for the same target-star configuration. Panel (a) uses classical Kalman filtering, where the target appears at the upper left of the gate, deviating from the gate center, visually indicating relatively large centroid capture errors. Panel (b) uses the proposed strong interference and momentary occlusion processing method, where the gate converges on the target, yielding relatively small centroid capture errors.

[Figure 6: see original paper] analyzes the motion patterns of strong interference frames captured across multiple target revolutions. Frames following consistent motion patterns are considered valid. Compared with the traditional method, the proposed method captures more strong interference frames, with most being valid, whereas the traditional method captures fewer frames, most of which are invalid.

4.3 Occlusion Target Tracking

[Figure 7: see original paper] compares partially occluded target tracking for two groups of the same target moving from upper left to lower right. Panels (a), (b), and (c) use classical Kalman filtering, tracking the target and star as a single larger target, causing errors between gate centroid and target centroid. Panels (d), (e), and (f) use the proposed method, tracking at predicted positions with gates retaining previous frame sizes, preventing stars from being enclosed within gates and achieving ideal tracking results based on predicted positions and corrected gate sizes.

[Figure 8: see original paper] compares fully occluded target tracking for two groups of the same target moving from upper right to lower left, with panels (a) and (d) showing complete occlusion. Panels (a), (b), and (c) use classical Kalman filtering with fixed gates, which enclose targets but produce large centroid errors when targets are fully occluded by stars. Panels (d), (e), and (f) use the proposed method, where gates enclose targets based on predictions while retaining previous frame sizes and applying constrained corrections during complete occlusion, achieving robust tracking and obtaining useful observation data.

[Figure 9: see original paper] statistically analyzes valid frames for partially and fully occluded targets, similar to [Figure 6: see original paper]. The proposed method significantly increases the number of valid frames captured for both partial and complete occlusion scenarios, demonstrating desirable experimental results and further highlighting the method' s feasibility.

4.4 Analysis of Factors Affecting Target Tracking

Error impact statistics are presented in . Smaller telescope tracking errors yield better tracking performance, while increasing errors degrade tracking effectiveness. Excessive errors produce observation data that deviates from the target' s motion trajectory, rendering it meaningless.

When telescope jitter occurs, captured observation data exhibits excessive errors, preventing valid data acquisition. However, when jitter is infrequent and tracking errors are small in non-jitter frames, directly using predicted values to replace observation values for jitter frames can yield valid observation data. Frequent or excessive jitter prevents both tracking data acquisition and replacement of observations with predictions.

External environmental factors and equipment limitations can reduce signal-to-noise ratio and increase dark noise, causing target loss or mis-tracking and capturing invalid observation data. When abnormal tracking conditions are detected and invalid observation data are obtained, predicted values can replace observation values to obtain actual target positions.

Space target and debris observation research constitutes a vital component for acquiring orbital data and maintaining space situational awareness, essential for space science development. Effective tracking of strong interference and momentary occlusion targets is crucial for obtaining more valuable data, reducing error rates, improving data quality, and providing more precise data for orbital position determination. The proposed tracking method builds upon classical Kalman filtering, adapting gate size to target dimensions and introducing new prediction and tracking methods for strong interference and momentary occlusion targets. The method is applicable not only to normal target tracking but also demonstrates ideal performance for strong interference and momentary occlusion scenarios, offering significant applicability.

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Note: Figure translations are in progress. See original paper for figures.