Postprint: A Low-Orbit Light-Varying Target Tracking Method Based on Kalman Filter and Camshift

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Abstract

To address the difficulty in accurately acquiring position information of low-orbit space variable-light targets characterized by frequent changes in target image morphology and high-velocity motion during tracking, a target tracking method combining Kalman filtering with Camshift is proposed. Based on the difficult-to-acquire characteristics of the target, Kalman filter extrapolation is introduced for position prediction, and an improved Camshift algorithm is employed to track the target—specifically, a target tracking method based on white extraction from single-channel grayscale images—thereby achieving robust tracking of low-orbit variable-light targets and improved target capture rates. When transient mutual occlusion occurs between the target and stars, an improved occluded target prediction method is utilized for position prediction, while the predicted position from the Kalman filter replaces the target position calculated by Camshift as the observation position to update the Kalman filter, thus achieving robust tracking of occluded targets and improving target capture rates. Experimental results demonstrate that the variable tracking gate adaptively adjusts according to target size, enabling not only stable tracking of medium-high orbit targets but also robust tracking performance for low-orbit variable-light targets. When the target and stars experience transient mutual occlusion, the target can be tracked robustly, thereby improving the effective tracking data rate. This method features fast computational speed, high sensitivity, strong applicability, and good real-time performance, possessing significant practical value and broad application prospects.

Full Text

Preamble

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Low-orbit Space Dimming Target Tracking Method Based on Kalman Filter and Camshift

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Abstract

Tracking low-orbit space targets with variable brightness presents significant challenges due to their rapidly changing morphology and high angular velocities, making accurate position capture difficult. To address this, we propose a novel tracking method that integrates Kalman filtering with Camshift. Leveraging the predictive capabilities of Kalman filter extrapolation, we employ an improved Camshift algorithm—specifically a single-channel white extraction method based on grayscale imagery—to achieve robust tracking of low-orbit variable-brightness targets and improve capture rates. For scenarios involving instantaneous mutual occlusion between targets and background stars, we introduce an improved occlusion prediction method for position estimation. During occlusion events, the predicted position from the Kalman filter replaces the target position computed by Camshift, serving as the observation to update the filter. This approach enables robust tracking through occlusions while maintaining high capture rates. Experimental results demonstrate that the adaptive tracking gate adjusts according to target size, enabling stable tracking of both medium/high-orbit targets and robust performance for low-orbit variable-brightness targets. The method exhibits fast execution, high sensitivity, strong applicability, and excellent real-time performance, offering substantial practical value and broad application prospects.

Keywords: Kalman filtering; Camshift; dimming target; tracking

1 Introduction

Space target tracking is a critical means of obtaining orbital information, and its robustness directly impacts automatic target identification, localization, cataloging, and telescope operational efficiency. As international research on moving object detection advances, tracking methods have evolved from manual to automatic operation, and from single-target to multi-target tracking paradigms. Furthermore, tracking platforms are transitioning from ground-based to space-based systems, opening broader development directions and application scenarios for space situational awareness.

Despite continuous improvements in space target tracking methodologies, stable tracking of low-orbit variable-brightness targets remains a formidable challenge. First, the high angular velocity of low-orbit targets causes tracking gates to lag behind target motion, frequently resulting in target loss. Second, instantaneous mutual occlusion between targets and background stars—where occlusion occurs only in the current frame but not in adjacent frames—causes the target and star images to merge into a larger irregular object, leading to excessive tracking errors or complete position capture failure. Third, while fixed-aperture (gate) methods are widely used for centroid calculation, variable-brightness targets exhibit frequent morphological changes and poor circularity, making accurate centroid determination within the gate difficult. Conventional fixed-gate tracking cannot adapt to these star image variations and captures limited positional information, reducing target acquisition rates.

These issues are illustrated in [Figure 1: see original paper], where red boxes represent tracking gates, near-white dots denote space targets, and elongated white objects are stars. Figure 1a shows gate lag causing target loss; Figure 1b demonstrates target-star occlusion preventing position capture or yielding large errors; and Figure 1c illustrates a target larger than the gate, hindering accurate position determination.

Current research predominantly employs Kalman filtering for space target tracking, with scientists proposing various methods based on Kalman filtering, Camshift, and deep learning. Chai et al. and Ren Nan developed Kalman filter and deep learning approaches to reduce tracking errors. Ping Yiding proposed methods for separating target and star images during mutual occlusion. Wang Xin, Xu Zhanwei, Li et al., and He Pengcheng focused on enhancing tracking robustness and applicability. Xu Zhanwei and Wang Xin proposed contour-based tracking specifically for low-orbit variable-brightness targets, though the algorithm is relatively complex and does not address occlusion handling. While these methods offer certain applicability, none simultaneously solves the three aforementioned challenges in low-orbit variable-brightness target tracking.

Given that Kalman filtering provides optimal position prediction and Camshift offers adaptive adjustment of window center and size with fast execution and real-time performance—commonly using window centroid as target centroid—

we combine these approaches to address the three key challenges. Although Kalman-Camshift integration has been applied to vehicles, ships, and pedestrians, this represents its first application to space variable-brightness targets. Moreover, unlike conventional Kalman-Camshift combinations, we propose an improved Camshift tailored for low-orbit variable-brightness targets, along with novel occlusion prediction and tracking methods to achieve robust performance.

2 Hybrid Algorithm of Kalman Filter and Camshift

As shown in [Figure 2: see original paper], the Kalman-Camshift hybrid algorithm operates in three stages: background subtraction for target detection, Kalman filter-based position prediction, and Camshift tracking using the prediction. During Camshift tracking, three scenarios are handled separately: low-orbit variable-brightness targets, medium/high-orbit targets, and occluded targets. For non-occluded variable-brightness and medium/high-orbit targets, improved Camshift tracks the target and captures positions. For target-star occlusion, an occlusion-specific tracking method is employed. Finally, the Kalman filter is updated to predict the next frame's position, and the cycle repeats.

2.1 Kalman Filter for Position Prediction

Let the state vector $X_k = [x_k; y_k; v_{xk}; v_{yk}]^T$ represent the target's position and velocity in x and y directions, and the observation vector $Z_k = [x_k; y_k]^T$ denote the observed position obtained during Camshift tracking. The state and observation equations are:

$$X_k = A_{kX_{k-1}} + B_{kW}k$$
$$Z_k = H_{kX}k + V_k$$

where X_k and X_{k-1} are state vectors at times k and k-1, A_k is the state transition matrix, B_k is the input matrix, and H_k is the observation matrix. W_k and V_k represent state and observation noise with covariance matrices Q and R, respectively. The derivation formulas are:

$$\tilde{X}_k = A_k\tilde{X}_{k-1} + B_{kW_{k-1}}$$
$$\tilde{P}_k = A_{kP_{k-1}}A^T + Q$$
$$K_k = \tilde{P}_{kH}k^T(H_k\tilde{P}_{kH}k^T + R)^{-1}$$
$$X_k = \tilde{X}_k + K_k(Z_k - H_k\tilde{X}_k)$$
$$P_k = (I - K_{kH}k)\tilde{P}_k$$

Here, $\tilde{X}_k$ is the predicted state, $\tilde{P}_k$ is the predicted covariance matrix, K_k is the Kalman gain, X_k is the corrected state estimate, and P_k is its covariance matrix. The predicted positions from equations (3) and (4) are not optimal as they neglect current observations from Camshift. Equations (5), (6), and (7) update these predictions using current observations to yield optimal estimates.

2.2 Camshift Target Tracking

Camshift tracks space targets based on Kalman filter predictions. In the Camshift algorithm, let $I(x_k, y_k)$ be the pixel value at coordinate (x_k, y_k). The zeroth moment M_{00} and first moments M_{10}, M_{01} of the search window are used to compute the centroid (x_{kc}, y_{kc}) and updated window size S:

$$x_{kc} = \frac{M_{10}}{M_{00}}$$

$$y_{kc} = \frac{M_{01}}{M_{00}}$$

$$S = 2\sqrt{M_{00}}$$

The search window size is adjusted based on M_{00}, and its center progressively moves toward the centroid. When the movement distance exceeds a preset threshold, the centroid is recalculated for the adjusted window. Convergence is achieved when the center-to-centroid distance falls below the threshold or maximum iterations are reached, proceeding to the next frame.

2.3 Improved Camshift

Camshift operates efficiently and performs well on CCD images with black backgrounds and white targets. Traditional Camshift converts RGB to HSV color space for tracking, where hue H ranges from 0°–360°, saturation S from 0–1, and value V from 0–1, requiring extraction across three color channels. This complex process is prone to tracking errors under noise, complex backgrounds, or low contrast. We improve the HSV model for space target tracking.

Since space target images are single-channel grayscale, we modify multi-channel color extraction to single-channel white extraction on grayscale images, significantly simplifying the process. The principle is as follows: In RGB color space, white is represented by $R = G = B$. In HSV extraction, optimal white values are $H = 0$, $S = 0$, $V = 1$. However, space target white is rarely pure white. We set maximum saturation $S_{max} = P$ and minimum value $V_{min} = Q$, modifying the extraction algorithm accordingly. Appropriate values are $P = 0.25$ and $Q = 0.75$.

2.4 Improved Occlusion Prediction and Tracking

Instantaneous target-star occlusion is common in low-orbit variable-brightness target tracking. While Kalman-Camshift integration offers adaptive gate adjustment and accurate position prediction, occlusion causes the target and star to be tracked as a single larger object, increasing errors and compromising tracking value. We propose solutions specifically for low-orbit variable-brightness targets.

2.4.1 Occlusion Prediction **(1) Finding nearby stars around the target:** Nearby star prediction is crucial. Large-scale distance calculation between target and star centroids across the entire frame increases computational load and reduces efficiency, while small-scale prediction may miss occlusions. We employ a specific rectangular area for distance prediction, using the tracked target centroid as the rectangle center. With target gate coordinates (x_i, y_i) and expansion factor n, the rectangular area S is:

$$S = |n(\max(x_i) - \min(x_i))| \times |n(\max(y_i) - \min(y_i))|$$

(2) Position prediction for targets and stars: During occlusion, stellar interference prevents accurate centroid calculation. The Kalman filter predicts positions using the target's actual position from the previous frame to estimate the current position. Similarly, star positions are predicted from previous frames, replacing actual positions for occlusion prediction. Multi-frame prediction is required for extended occlusions.

(3) Distance calculation between predicted positions: Using search window centroids as target and nearby star centroids, the Kalman filter predicts their separation. Let the target's predicted centroid be (x_{kc}, y_{kc}) and a nearby star's be (x_{ic}, y_{ic}). The predicted distance D is:

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

(4) Threshold setting: To determine occlusion, we set threshold F:

$$K = \begin{cases} 1, & D < F \\ 0, & D > F \end{cases}$$

When $D > F$, $K = 0$ indicates no occlusion; when $D < F$, $K = 1$ indicates occlusion.

2.4.2 Occluded Target Tracking When occlusion is predicted, the Kalman filter's predicted position replaces the Camshift-computed position as the observation for filter updating. After occlusion ends, tracking switches back to the standard Kalman-Camshift algorithm.

3 Experimental Results

Experiments used multi-frame moving target images captured on multiple days. Implementation was performed on a Dell laptop running Windows 10, using PyCharm 2022 with OpenCV 3.4.17.63 for Python 3.9. Fixed-gate tracking employed conventional Kalman filtering, while adaptive variable-gate tracking used the proposed Kalman-Camshift combination. Tracking accuracy was evaluated using RMS error between estimated and predicted positions.

3.1 Camshift Tracking Performance

In [Figure 3: see original paper], red, green, and blue gates represent measurement, prediction, and state gates, respectively. Figure 3a shows standard Camshift tracking, which is generally stable but occasionally exhibits anomalies. Figure 3b demonstrates improved Camshift tracking, which robustly extracts target color information and converges all three gates to the target centroid. Under identical conditions, the improved version achieves a 1.17× speedup.

summarizes anomalies across multiple tracking passes. Standard Camshift has an average anomaly rate of 4.6%, while the improved version exhibits no anomalies.

3.2 Medium/High-Orbit Target Tracking

[Figure 4: see original paper] compares fixed-gate Kalman filtering (a, b, c) with adaptive Kalman-Camshift (d, e, f) for medium/high-orbit targets. Fixed gates cannot adapt to varying target sizes—sometimes larger (a) or smaller (b, c) than the target—lacking convergence. The adaptive approach converges gates to target centroids effectively.

shows that Kalman-Camshift achieves a 6% higher capture rate than Kalman alone. [Figure 5: see original paper] demonstrates that the combined method improves tracking accuracy by an average factor of 1.21×, yielding superior performance.

3.3 Low-Orbit Variable-Brightness Target Tracking

3.3.1 Occluded Target Tracking [Figure 6: see original paper] compares tracking during occlusion. Fixed-gate Kalman (a, b) tracks both target and star as a single object, with the target 偏离 gate center. Kalman-Camshift with occlusion handling (c) distinguishes target from star, tracking only the target. Figures 6d–f show the same frame processed differently: fixed gate (e) merges target and star, while the occlusion-aware method (f) tracks only the target, eliminating stellar interference.

[Figure 7: see original paper] plots frame counts for 15 target passes. Compared to Kalman alone, the Kalman-Camshift occlusion method captures significantly more occlusion frames and valid frames. Statistics show Kalman achieves 45.7%

occlusion frame capture rate with 30% valid frames, while the proposed method achieves 97.3% capture rate with 97.9% valid frames.

3.3.2 Variable-Brightness Target Tracking [Figure 8: see original paper] shows six frames of a fast low-orbit variable-brightness target. Fixed-gate Kalman (a, b, c) loses the target due to rapid motion and size changes, with the target exceeding gate size in (c). Kalman-Camshift adaptive gating (d, e, f) adjusts to target size, converging on the centroid and achieving robust tracking.

summarizes capture rates for non-trailing low-orbit variable-brightness targets. The combined method improves capture rate by an average of 18.4% compared to Kalman alone.

[Figure 9: see original paper] addresses trailing targets from short exposures. Figures 9d–i show results after probabilistic Hough line detection for trail removal. Fixed gates (d, e, f) lose the fast-moving target when orientation changes (e), while variable gates (g, h, i) adapt to target morphology.

shows that for trailing variable-brightness targets, Kalman-Camshift improves capture rate by an average of 17.82%.

[Figure 10: see original paper] compares tracking accuracy for the targets in Figures 8 and 9. The combined method improves accuracy by an average factor of 1.3×, validating the approach's feasibility.

3.3.3 Factors Affecting Target Tracking Our method is not applicable when thin clouds or target attitude changes cause star image loss, as detection and identification become impossible. While using Kalman predictions as observations may partially address this, it lacks rigor when no trackable object exists, yielding large errors even if data is captured. For thin clouds, image binarization, denoising, and enhancement may enable tracking of partially visible targets but are ineffective for completely lost targets. For targets with changing attitude that appear intermittently, they can be treated as faint targets through image enhancement.

Capture rate is defined as the ratio of captured frames to total frames in a pass. Within fixed exposure times, total frames are constant, but captured frames vary by algorithm. As shown in Tables 2–4, the proposed method increases captured frames per pass, thereby improving capture rate. Image processing time refers to Camshift's execution time. The improved Camshift reduces processing time, improving real-time performance and consequently enhancing capture rate. However, capture rate improvement primarily reflects algorithmic effectiveness rather than processing speed.

When target and star images overlap, they typically merge into a larger object, altering the centroid and producing large position errors. Such cases cannot be treated as variable-brightness targets, as even occasional valid captures are exceptional and unreliable. For precise, stable tracking of variable-brightness targets, our Kalman-Camshift approach uses predicted positions as observations during occlusion.

4 Conclusions and Future Prospects

Space object and debris observation is crucial for tracking, identification, monitoring, and early warning. Low-orbit variable-brightness target tracking is an important component of this field. This paper combines Kalman filtering with Camshift, using Kalman extrapolation for position prediction and Camshift for target tracking. Two key improvements ensure robust tracking: (1) modifying Camshift from color-based to grayscale-based white extraction, reducing complexity, preventing anomalous tracking, and enhancing stability; (2) implementing occlusion prediction to detect target-star overlap, using Kalman predictions as observations during occlusion instead of Camshift outputs.

Experimental results demonstrate that adaptive variable gates, replacing fixed gates, provide robust tracking for challenging variable-brightness targets, ideal occlusion handling, and general applicability to medium/high-orbit targets. The method enhances tracking robustness, accuracy, and capture rates.

The approach is simple, efficient, and applicable to both single- and multi-target tracking, with promising theoretical foundations and strong practicality. It offers a valuable method for domestic and international space target tracking, with broad prospects for application in photoelectric telescope arrays, fence telescope arrays, optical survey telescopes, and large-aperture wide-field optical telescopes.

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