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A Feature Prior Tensor Nuclear Norm with Improved Bilateral Filtering Regularization for Dim and Small Target Detection

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Abstract

In complex infrared scenes containing abundant strong edge contours and high levels of noise, effectively suppressing edges and noise poses a critical challenge for dim and small target detection algorithms. Many state-of-the-art algorithms often suffer from high false alarm rates when dealing with such scenarios. This challenge primarily stems from background clutter. To address this issue, this paper proposes a dim and small target detection model based on a feature prior tensor nuclear norm with improved bilateral filter regularization. The model aims to enhance the suppression of interference from background clutter, thereby improving detection performance. Furthermore, to effectively mitigate the interference caused by strong edge structures and corner points, this paper introduces a novel corner strength function constructed based on the structure tensor. This function is designed to accurately characterize the background characteristics within the

prior model, thus mitigating the negative impact of strong edges and corners on target detection.

Keywords: Dim and small target detection, Improved IPT Structure Tensor, Bilateral Filtering

1 Introduction

Infrared dim and small target detection has remained a popular research topic due to its significant application value in both military and civilian sectors. In military applications, it serves as a core technology for tasks such as long-range drone detection and missile interception [1]. In civilian contexts, it is widely employed in areas including infrared early warning, target tracking, medical image processing, and surveillance systems, all of which require robust target detection and tracking capabilities. [2]- [5] The term "dim and small target" inherently encompasses two key characteristics: "dim" refers to the target's low radiant energy and low contrast against the background, while "small" indicates that the target occupies very few pixels in the image [6] [7]. These inherent traits pose several significant challenges for infrared dim and small target detection, including: The target occupies an extremely small number of pixels in the image, typically ranging from 2 to 6, making it easily obscured by noise [8]. Furthermore, the detection process faces interference from clutter such as edge structures and corner points generated by complex backgrounds. For instance, false alarms are often triggered by spurious signals from clouds [9], forests, and other objects. The targets lack distinguishing features such as texture and color, and their shape can vary significantly depending on the specific target [10]. The issues outlined above represent the most common challenges in current infrared dim and small target detection [11], highlighting that the task remains highly difficult in complex backgrounds.

To address these challenges, this paper proposes a dim and small target detection model based on an improved bilateral filtering-regularized tensor nuclear norm. The innovation of this work lies in two key aspects: First, a novel regularization term, inspired by bilateral filtering, is established to suppress clutter interference in the background, thereby enhancing the robustness of the low-rank background representation. Second, a prior model utilizing a new corner strength function, constructed based on the structure tensor, is introduced to mitigate the interference from edge and corner structures, reduce false alarms, and consequently improve the detection rate.

2 Related work

Current infrared dim and small target detection methods can be categorized into single-frame and multi-frame detection based on the image data processed [12]. Multi-frame detection algorithms rely on the association and verification of suspicious targets across consecutive frames [13]. However, factors such as jitter in the optoelectronic equipment during capture and rapid target movement [14] can adversely affect the performance of multi-frame detection algorithms. Nevertheless, for slowly moving targets,

multi-frame algorithms can leverage the short inter-frame displacement of targets to enhance detection robustness across the image sequence. Classical multi-frame detection algorithms include the three-dimensional matched filter proposed by Zhang et al [15], the projection transformation algorithm introduced by Moyer et al [16], and the multilevel hypothesis testing algorithm developed by Blostein et al [17].

In contrast, single-frame detection algorithms do not depend on inter-frame correlations and utilize information solely from individual images, offering the advantage of rapid detection [18]. However, since they cannot exploit information from multiple frames, the technical challenges are greater. Notable single-frame detection algorithms include an anisotropic infrared dim and small target detection method proposed by Fan et al [19], an adaptive annular structural element based on M-estimation developed by Deng et al [20], which establishes a new local entropy to weight the structural elements, and a two-layer two-dimensional minimum mean square error (TDLMS) filter-based infrared dim and small target detection algorithm introduced by Zhang et al [21]. Based on deep learning frameworks, several methods have been proposed for dim and small target detection. For instance, Ding et al [22] introduced the SSD-ST model, which constructs detection and information layers at different resolutions through a multi-scale feature pyramid structure of SSD. During training, the model classifies image information, suppresses low-resolution layer energy, and enhances high-resolution layer energy to achieve background modeling and target detection. Cai Yunze [23] proposed a dual-channel feature-enhanced integrated attention network for infrared dim and small target detection. This model primarily utilizes dual channels to extract richer feature information, employs a feature enhancement module to further enrich target features, and finally uses a contextual attention module to adaptively enhance target features while suppressing background noise, thereby achieving accurate detection. Ma Yuying [24] developed a dim and small target detection algorithm based on the SSD network. By designing an SSD framework specifically for dim and small targets, the algorithm leverages convolutional features to capture fine-grained image details, enabling effective differentiation between target and background features for detection. Cai Wei [25] proposed a YOLO-FCSP network-based detection method. Building upon the YOLO framework, this algorithm reduces downsampling operations and incorporates Cross-Stage Partial (CSP) modules, Focus structures, and Spatial Pyramid Pooling (SPP) to design a feature extraction network that improves detection accuracy through information reuse.

Addressing the challenges of dim and small target detection, Han et al [26] proposed a knowledge-driven context-aware network model. This model establishes a balanced feature fusion network that integrates high-level and low-level feature maps, preserving high resolution while maintaining rich feature information, thereby avoiding feature loss due to repeated pooling operations and effectively improving detection rates. Kou et al [27] introduced an infrared small target detection and tracking algorithm based on segmentation networks and multi-strategy fusion. The method first uses IRSTNet and pixel clustering strategies to segment and extract candidate targets, then further narrows down candidate regions through threshold adjustment. Finally, it employs large-area search, small-area tracking, and gate tracking strategies to achieve real-time detection and tracking of infrared small targets. Zhang et

al [28]. proposed an attention-guided pyramid context network for dim and small target detection. The method designs an attention-guided context block and integrates multi-scale feature information through a context pyramid module to achieve superior detection performance. Cao et al [29]. introduced a collaborative detection network for targets and false alarms to leverage information from both false alarm sources and the background. The approach first incorporates a false alarm source estimation block to estimate potential interferences in the background, followed by a target segmentation block to precisely segment the targets. Li et al [30]. proposed a difference-enhanced spatiotemporal attention network for dim and small target detection. The method first introduces a difference enhancement module to extract critical features from difference maps for detecting changed regions, then designs a temporal memory module to capture temporal and spatial information. Additionally, four encoding layers are employed to extract semantic information at different levels from multi-temporal images, enabling final target point detection.

3 An Improved IPT Model for Dim and Small Target Detection

3.1 Construct the IPT model

Compared to 2D matrices, 3D tensors can more effectively represent the structural information within images. Therefore, to enhance both the detection capability of infrared dim and small target detection algorithms and their robustness across various complex environments, researchers have extended the IPI model from the 2D matrix domain to the tensor domain. The construction process of the tensor image is illustrated in Figure 1. To better explore the correlations between image patches, Dai et al [31]. proposed an IPT model, which can be formulated as follows:

$$\mathcal{D} = \mathcal{B} + \mathcal{T} + \mathcal{N} \quad (1)$$

Here, $\mathcal{D}, \mathcal{B}, \mathcal{T}, \mathcal{N} \in R^{n_1 \times n_2 \times n_3}$ represent the input tensor image, background tensor image, target tensor image, and noise tensor image, respectively.

3.2 Construction of a High-Order Regularization Model Based on Bilateral Filtering

The conventional approach to constructing a regularization model using bilateral [32] filtering leverages the concept of filtering in both the intensity domain and the spatial domain. A kernel of size $(2L + 1) \times (2L + 1)$ is defined. To illustrate this with a specific case, let $L=1$. When $L=1$, the kernel size is 3, as shown in Figure 2. The eight surrounding pixels are numbered from 1 to 8, and the central pixel is denoted as $0_j (j = 1, 2, \dots)$.

First, the weights in the intensity domain are calculated. The intensity difference between the i -th pixel and the central pixel (pixel 0) is denoted as $G_i (i = 1, 2, \dots, 8)$.

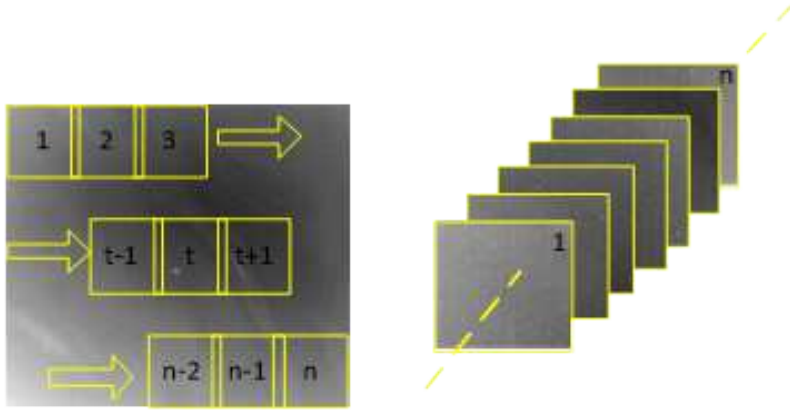


Fig. 1 Construction Process of the Infrared Tensor Image

1	2	3
8	0j	4
7	6	5

Fig. 2 Kernel Diagram

The weight in the intensity domain is then given by the following expression:

$$W_G = \exp[-G_i^2/(2\sigma_r^2)] \quad (2)$$

where σ_r is the standard deviation in the intensity domain. Next, the weights in the spatial domain are calculated. The Euclidean distance between the i -th pixel and the central pixel (pixel 0) is denoted as $R_i (i = 1, 2, \dots, 8)$. The weight in the spatial domain

is then given by the following expression:

$$W_R = \exp[-R_i^2/(2\sigma_s^2)] \quad (3)$$

where σ_s is the spatial domain standard deviation. By combining the weights from the two domains mentioned above, the final weight of the two-dimensional bilateral filtering regularization term at pixel j can be obtained as follows:

$$W_j = W_G \times W_R = \exp[-G_i^2/(2\sigma_r^2)] \times \exp[-R_i^2/(2\sigma_s^2)] \quad (4)$$

The combined weights are then normalized to obtain the final weights as follows:

$$W_j^* = \frac{W_j}{\sum W_j} \quad (5)$$

By applying this process to every pixel, we obtain the two-dimensional regularization plane W_1 . Building upon this 2D regularization, our proposed method further constructs the regularization term as detailed below. Using the method of IPT model in the previous section, the two-dimensional regularization plane W_1 is first partitioned into patches and then constructed into a third-order tensor. The slices of this third-order tensor correspond to image patches 1 n. A residual map is generated by computing the intensity difference between any two distinct image patches. For example, taking image patch i and image patch j ($i \neq j$), the residual image patch Δy_{ij} is obtained. The nuclear norm $\|\Delta y_{ij}\|_*$ of Δy_{ij} is used to characterize the difference between the two patches in the intensity domain, while the Euclidean distance between patch i and patch j is adopted as the representation in the spatial domain. By integrating the patch differences from both the intensity and spatial domains, the regularization term is constructed as follows:

$$TV(\mathcal{B}) = \sum_{i \neq j} W_2(i, j) \|I(i) - I(j)\| \quad (6)$$

Here, $\|\cdot\|$ is the mean intensity of the matrix; $I(\cdot)$ represents the grayscale matrix of the image patch; and $\|\cdot\|_d$ denotes the Euclidean distance between the two image patches. The weighting coefficient is given by:

$$W_2(i, j) = \frac{1}{C} \exp(\|i - j\|_d^2) \exp(-\|I(i) - I(j)\|^2) \quad (7)$$

$$C = \sum_{i \neq j} \exp(\|i - j\|_d^2) \exp(-\|I(i) - I(j)\|^2) \quad (8)$$

Where C is a normalization constant. As can be seen from the weighting coefficient formula, the coefficient depends on both the distance between image patches and their intensity difference.

3.3 Construction of a Novel Corner Strength Function

The structure tensor plays a critical role in image processing tasks such as feature extraction and corner detection. It not only captures gradient orientation information within a specific neighborhood of an image point but also measures the consistency of these orientations. Compared to using gradient information alone, the structure tensor provides more comprehensive local structural features, thereby enabling more effective image structure analysis and orientation estimation. Assuming the original image is D , the classic linear structure tensor is computed [33] as follows:

$$J_\rho = K_\rho * (\nabla D_\sigma \otimes \nabla D_\sigma) = \begin{pmatrix} K_\rho * I_x^2 & K_\rho * I_x I_y \\ K_\rho * I_y I_x & K_\rho * I_y^2 \end{pmatrix} = \begin{pmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{pmatrix} \quad (9)$$

Here, K_ρ denotes a Gaussian kernel function with variance ρ ; the symbol $*$ represents the convolution operation, and D_σ denotes Gaussian smoothing applied to the original image with variance $\sigma > 0$. The symbol $\otimes$ represents the Kronecker product, and ∇ denotes the gradient operator. Specifically, $I_x = \frac{\partial D_\sigma}{\partial x}$ represents the gradient of D_σ along the x-direction; $I_y = \frac{\partial D_\sigma}{\partial y}$ represents the gradient of D_σ along the y-direction. The linear structure tensor constructed in this manner is symmetric positive semi-definite. The structure tensor at each pixel location possesses two non-negative eigenvalues. For J_ρ , its two eigenvalue matrices $\lambda_a = \Delta_1(x, y)$ and $\lambda_b = \Delta_2(x, y)$ are calculated using the following formulas:

$$\lambda_1, \lambda_2 = (J_{11} + J_{22}) \pm \sqrt{(J_{22} - J_{11})^2 + 4J_{12}^2} \quad (10)$$

Let $\lambda_a = \lambda_1(x, y)$ and $\lambda_b = \lambda_2(x, y)$, where $\lambda_a \geq \lambda_b$. Different local structural characteristics can be inferred based on the relative magnitudes of λ_a and λ_b :

When $\lambda_a \approx \lambda_b \approx 0$, it indicates minimal intensity variation around the pixel, corresponding to a flat region.

When $\lambda_a \geq \lambda_b \gg 0$, it reflects rapid intensity changes along two perpendicular directions, which is characteristic of a corner.

When $\lambda_a \gg \lambda_b \approx 0$, the intensity variation along one direction is significantly stronger than that in the orthogonal direction, indicating the presence of an edge.

Therefore, based on the above analysis, a corner strength function $W(\lambda_a, \lambda_b)$ is constructed to suppress both corner and edge structures, defined as follows:

$$W(\lambda_a, \lambda_b) = \frac{\lambda_a}{\lambda_b} \times \exp[-(\lambda_a + \lambda_b)] \quad (11)$$

Based on the above, the corner strength function effectively suppresses both corner and edge structures. To further optimize Equation (11), a small constant $\varepsilon = 0.05$ is added to the denominator to prevent division by zero. The refined corner strength function is thus formulated as follows:

$$W(\lambda_a, \lambda_b) = \frac{\lambda_a}{\lambda_b + \varepsilon} \times \exp[-(\lambda_a + \lambda_b)] \quad (12)$$

Finally, W is normalized using the following formula:

$$W(x, y) = \frac{W(x, y) - W_{min}}{W_{max} - W_{min}} \quad (13)$$

The resulting two-dimensional tensor W is subsequently partitioned into multiple equally-sized patch images using a fixed-size sliding window with a constant stride, traversing from the top-left to the bottom-right of W . These patch images are then stacked in their original order as slices to form a third-order tensor $\mathcal{W}$. This third-order tensor $\mathcal{W}$ constitutes the prior model constructed based on the structure tensor in this work.

3.4 Improved Structure Tensor Decomposition Model for IPT

In infrared image target detection, using the Partial Sum of the Tensor Nuclear Norm [34](PSTNN) to constrain the background component has been demonstrated to be highly effective. The PSTNN is calculated as follows:

$$\|\mathcal{A}\|_{PSTNN} = \sum_{i=1}^{n_3} \|\bar{A}^{(i)}\| \quad (14)$$

Where $\bar{A}^{(i)}$ denotes the i -th frontal slice of tensor $\mathcal{A}$ after Fourier transformation. This paper also adopts the PSTNN to construct an infrared dim and small target detection model as follows:

$$\min_{\mathcal{B}, \mathcal{T}} \|\mathcal{B}\|_{PSTNN} + TV(\mathcal{B}) + \lambda \|\mathcal{W} \odot \mathcal{T}\|, \text{ s.t. } \mathcal{D} = \mathcal{B} + \mathcal{T} \quad (15)$$

In the equation, In the formula, λ is a positive constant whose role is to balance the three items to be optimized mentioned above; $\mathcal{D}, \mathcal{B}, \mathcal{T}$ represent the original tensor block image, the background tensor block image, and the target tensor block image, respectively. The symbol $\odot$ denotes the Hadamard product. A flowchart of the model is shown in Figure 3.

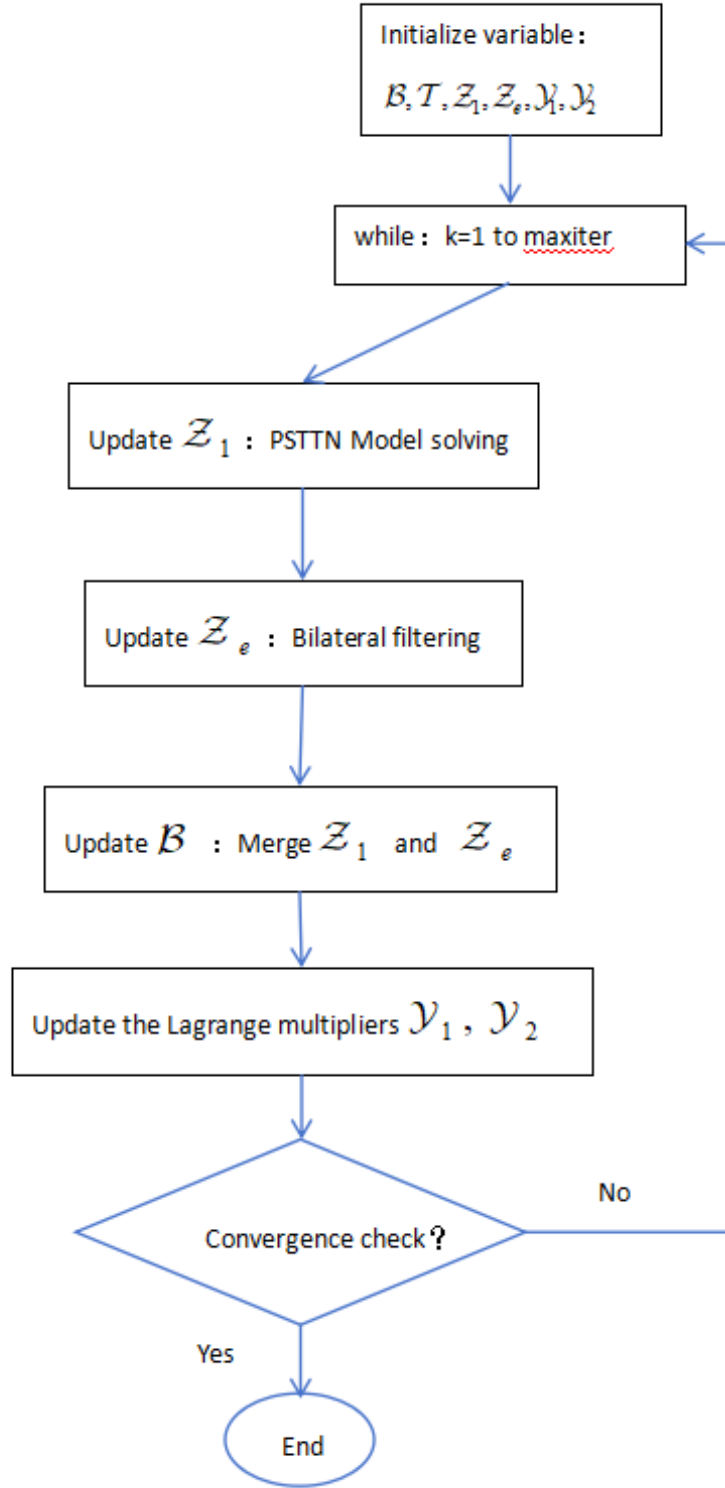


Fig. 3 Algorithm Flowchart

3.5 Optimization Algorithm and Solution

To solve the aforementioned model, this paper adopts the Alternating Direction Method of Multipliers (ADMM) for the solution. For a detailed derivation of the solution process [35], readers are referred to the relevant literature. As can be observed from Equation (15), the target detection model in this work constitutes a constrained optimization problem. To decouple the interdependencies among the variables, auxiliary variables $\mathcal{Z}_1$ and $\mathcal{Z}_e$ are introduced, thereby transforming Equation (16) equivalently into the following model:

$$\min_{\mathcal{B}, \mathcal{T}} \|\mathcal{Z}_1\|_{PSTNN} + TV(\mathcal{Z}_e) + \lambda \|\mathcal{W} \odot \mathcal{T}\|, \text{ s.t. } \mathcal{D} = \mathcal{B} + \mathcal{T}, \mathcal{Z}_e = \mathcal{B}, \mathcal{Z}_1 = \mathcal{B} \quad (16)$$

Thus, the augmented Lagrangian function is formulated as:

$$\begin{aligned} L = & \|\mathcal{Z}_1\|_{PSTNN} + TV(\mathcal{Z}_e) + \lambda \|\mathcal{W} \odot \mathcal{T}\| \\ & + \frac{\beta}{2} \left(\left\| \mathcal{Z}_1 - \mathcal{B} + \frac{\mathcal{Y}_1}{\beta} \right\|_F^2 + \left\| \mathcal{Z}_e - \mathcal{B} + \frac{\mathcal{Y}_2}{\beta} \right\|_F^2 \right. \\ & \left. + \left\| \mathcal{D} - \mathcal{B} - \mathcal{T} + \frac{\mathcal{Y}_3}{\beta} \right\|_F^2 \right) \end{aligned} \quad (17)$$

where $\mathcal{Y}_1, \mathcal{Y}_2, \mathcal{Y}_3$ are the Lagrangian multiplier tensors, and β is the penalty factor. This paper employs the Alternating Direction Method of Multipliers (ADMM), which treats the optimization of each parameter as a subproblem. During the optimization process, other parameters are fixed while one parameter is updated iteratively. By cyclically updating each variable in this manner, the optimal solution to the overall problem is eventually obtained. The pseudocode of the proposed algorithm is summarized in Table 1 below.

4 Experimental Results and Analysis

Through experiments, six different scene datasets were utilized to validate the effectiveness of the proposed algorithm. Three evaluation metrics—Background Suppression Factor (BSF), Signal-to-Noise Ratio (SNR), and Area Under the Curve (AUC)—were employed for quantitative analysis. In addition, 3D Receiver Operating Characteristic (ROC) curves were adopted to assess the detection performance of different algorithms.

4.1 Original Image Information

The original image data used in this chapter are sourced from a publicly available dataset collected by Hui et al [36]. from the National University of Defense Technology (NUDT) between 2017 and 2019. The images were acquired using a mid-wave (wavelength range: 3–5 μm) infrared imaging device, with each infrared image having a fixed resolution of 25656 pixels. This dataset captures various scenarios under both

Table 1 Pseudocode of the Proposed Algorithm

Input: Patch image matrix $\mathcal{D}$, parameters $\lambda_1, \lambda_2, \sigma, \rho$
Initialize: $\mathcal{B}^0 = \mathcal{T}^0 = \mathbf{0}, \mathcal{Z}_1^0 = \mathcal{Z}_e^0 = \mathbf{0}, \mathcal{Y}_i^0 = \mathbf{0} (i = 1, 2, 3, 4), k = 0, \text{max_Iter} = 500, \text{tol} = 5 \times 10^{-10}$
Output: $\mathcal{B}, \mathcal{T}$

1. **while** $k < \text{max_Iter}$ and $\frac{\|\mathcal{D} - \mathcal{T}^k - \mathcal{B}^k - \mathcal{N}^k\|_F}{\|\mathcal{D}\|_F} \geq \text{tol}$ **do**
2. Update $\mathcal{Z}_1^k$: $\mathcal{Z}_1^{k+1} = \arg \min_{\mathcal{Z}_1} \|\mathcal{Z}_1\|_{\text{symN}} + \frac{\beta}{2} \left\| \mathcal{Z}_1 - \mathcal{B}^k + \frac{\mathcal{Y}_1^k}{\beta} \right\|_F^2$
3. Update $\mathcal{Z}_e^k$: $\mathcal{Z}_e^{k+1} = \arg \min_{\mathcal{Z}_e} TV(\mathcal{Z}_e) + \frac{\beta}{2} \left\| \mathcal{Z}_e - \mathcal{B}^k + \frac{\mathcal{Y}_2^k}{\beta} \right\|_F^2$
4. Update $\mathcal{T}^k$:

$$\mathcal{T}^{k+1} = \arg \min_{\mathcal{T}} \lambda \|\mathcal{T} \odot \mathcal{W}\|_1 + \frac{\beta}{2} \left\| \mathcal{D} - \mathcal{B}^k - \mathcal{T} + \frac{\mathcal{Y}_3^k}{\beta} \right\|_F^2$$

This weighted L1-norm minimization problem admits a closed-form solution, namely the soft thresholding operation:

$$\mathcal{T}^{k+1} = S_{\frac{\lambda \mathcal{W}}{\beta}}(\mathcal{D} - \mathcal{B}^k + \frac{\mathcal{Y}_3^k}{\beta})$$

The soft thresholding operator S operates element-wise and is defined as:

$$S_{\kappa}(x) = \text{sign}(x) \cdot \max(|x| - \kappa, 0)$$

5. Update $\mathcal{B}^k$:

$$\mathcal{B}^{k+1} = \arg \min_{\mathcal{B}} \frac{\beta}{2} \left[\left\| \mathcal{Z}_1^{k+1} - \mathcal{B} + \frac{\mathcal{Y}_1^k}{\beta} \right\|_F^2 + \left\| \mathcal{Z}_e^{k+1} - \mathcal{B} + \frac{\mathcal{Y}_2^k}{\beta} \right\|_F^2 + \left\| \mathcal{D} - \mathcal{B} - \mathcal{T}^{k+1} + \frac{\mathcal{Y}_3^k}{\beta} \right\|_F^2 \right]$$

This is a least squares problem, and its solution is given by:

$$\mathcal{B}^{k+1} = \frac{1}{3} \left[\mathcal{Z}_1^{k+1} + \mathcal{Z}_e^{k+1} + (\mathcal{D} - \mathcal{T}^{k+1}) + \frac{\mathcal{Y}_1^k + \mathcal{Y}_2^k - \mathcal{Y}_3^k}{\beta} \right]$$

6. Update the Lagrangian multiplier $\mathcal{Y}_i^k (i = 1, 2, 3)$ via:
 $\mathcal{Y}_1^{k+1} = \mathcal{Y}_1^k + \mu^k (\mathcal{Z}_1^{k+1} - \mathcal{B}^{k+1})$
 $\mathcal{Y}_2^{k+1} = \mathcal{Y}_2^k + \mu^k (\mathcal{Z}_e^{k+1} - \mathcal{B}^{k+1})$
 $\mathcal{Y}_3^{k+1} = \mathcal{Y}_3^k + \mu^k (\mathcal{D} - \mathcal{B}^{k+1} - \mathcal{T}^{k+1})$
7. Update μ^k : $\mu^{k+1} = \min(\rho \mu^k, \mu_{\max})$
8. $k := k + 1$
9. **end while**

sky and terrestrial backgrounds. Six representative scenes were selected for experimental validation. The selected image sequences are shown in Figure 4, and their detailed specifications are summarized in Table 2.



Fig. 4 Five Scenarios of Original Images

Table 2 Scene Information

Series	Frames	Size	Background Description
Scene 1	80	512*512	Target from near to far, single target, ground background
Scene 2	80	512*512	Target from far to near, single target, target maneuvering midway, ground background
Scene 3	80	512*512	Target from far to near, single target, extended target, target maneuvering, ground background
Scene 4	80	512*512	Target from far to near, single target, ground background
Scene 5	80	512*512	Single target, target maneuvering, ground background
Scene 6	80	512*512	Single target, target maneuvering, air-ground background

4.2 Parameter Analysis and Setting

A key parameter in the aforementioned dim and small target detection model based on the feature prior tensor nuclear norm with improved bilateral filtering regularization significantly influences the model's performance. In this section, we thoroughly investigate the impact of this parameter and validate the findings through experiments. During the solution process of our model, the sliding window stride is systematically varied while observing changes in the Signal-to-Noise Ratio (SNR) evaluation metric, thereby identifying the optimal stride value for the model.

During the construction of the patch-image matrix, the entire image is traversed using a sliding window with a fixed stride. The data within each sliding window is then formed into a column vector, and these column vectors are subsequently constructed into the patch-image matrix. Consequently, the window stride significantly affects the matrix construction. In this paper, the relationship between the window stride and the Signal-to-Noise Ratio (SNR) is illustrated in Figure 5.

As shown in Figure 5, with the increase of the window stride, the SNR first rises rapidly. When the window stride reaches a certain size, the SNR begins to decrease slowly within a certain range, accompanied by minor fluctuations. The figure indicates that the best results are achieved when the window stride is 4, 5, and 7. Furthermore, the relationship between different window strides and the algorithm's runtime is illustrated in Figure 6. As shown in Figure 6, the algorithm's runtime decreases as the window stride increases. When the window stride exceeds 4, the runtime stabilizes with no significant further reduction. Taking into account both the SNR performance (Figure 5) and computational efficiency (Figure 6), a stride of 7 is ultimately selected as the optimal value for our method.

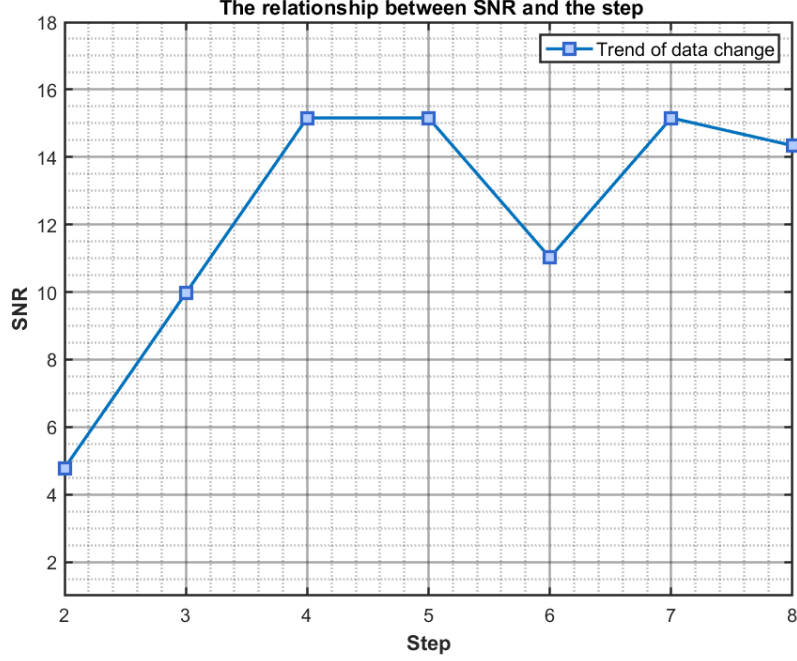


Fig. 5 Relationship Between Window Stride and SNR

4.3 Experimental Results and Analysis

Detecting dim and small targets in complex backgrounds presents significant challenges. To effectively enhance the detection capability for such targets, this chapter proposes a detection method based on a feature prior tensor nuclear norm with improved bilateral filtering regularization. First, leveraging the sparse and low-rank properties of the target and background, a regularization term based on improved bilateral filtering is introduced. Furthermore, to better suppress background interference in target detection, a prior model based on the structure tensor is proposed. Experiments are conducted on sequence images, focusing on evaluating the proposed method's ability to suppress noise in complex aerial and space backgrounds, as well as its accuracy in detecting targets across spatial and temporal dimensions. The experimental results are shown in Figures 7 to 8, where (a) to (f) represent Scenarios 1 to 6, respectively. The first, second, and third columns show the original images, the candidate target images after background modeling, and the signal-to-noise ratio images, respectively. The experimental results above demonstrate that, in terms of background suppression, the background noise is significantly reduced in the target images processed by the proposed prior model with the novel bilateral filtering regularization term. Comparing the original images (first column) with the candidate target images after background modeling (second column), it can be observed that most of the background clutter has been removed, with only some residual weak noise remaining. In summary, the experimental results validate that the proposed method can effectively

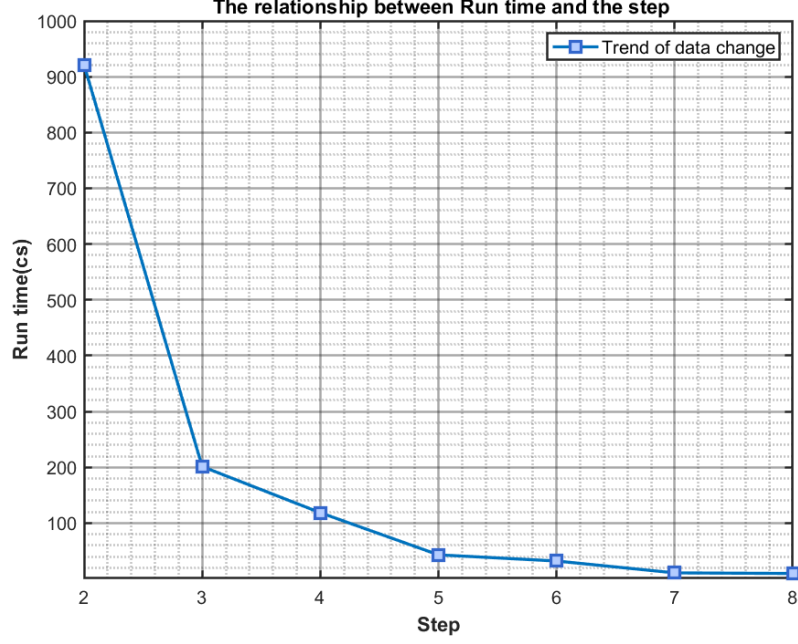


Fig. 6 Relationship Between Window Stride and Runtime

suppress noise in complex aerial and space backgrounds while achieving robust detection of dim and small targets.

To better demonstrate the performance of the proposed algorithm, it is compared with six different target detection methods across six scenarios, including GDR-PCD [37], PSTNN [38], ASTTV-NTLA [39], IPI [40], IPT [41], and STWRT [42]. A visual analysis is conducted focusing on target detection accuracy and the level of residual noise in the detection results. Among them, STWRT is a multi-frame detection algorithm, and its inclusion as a comparative method aims to demonstrate the effectiveness of the proposed algorithm even when compared to multi-frame approaches. The GDR-PCD algorithm employs traditional neighborhood filtering in its regularization term; comparing with it serves to highlight the superiority of the improved regularization term proposed in this paper over conventional neighborhood filtering methods. The comparative results of the seven algorithms (including the proposed one) for Scenarios 1 to 6 are shown in Figures 9 to 15, where (a) to (g) correspond to: (a) the proposed method, (b) GDR-PCD, (c) PSTNN, (d) ASTTV-NTLA, (e) IPI, (f) IPT, and (g) STWRT. The experimental results indicate that all seven methods mentioned above possess certain detection capabilities. Each method can effectively identify the target and demonstrates a degree of background noise suppression. However, there are still noticeable differences in their performance.

Across the six different scenarios, the proposed algorithm demonstrates clear and precise target detection with accurately positioned red bounding boxes. It exhibits excellent noise suppression, leaving almost no noticeable residual noise. Furthermore,

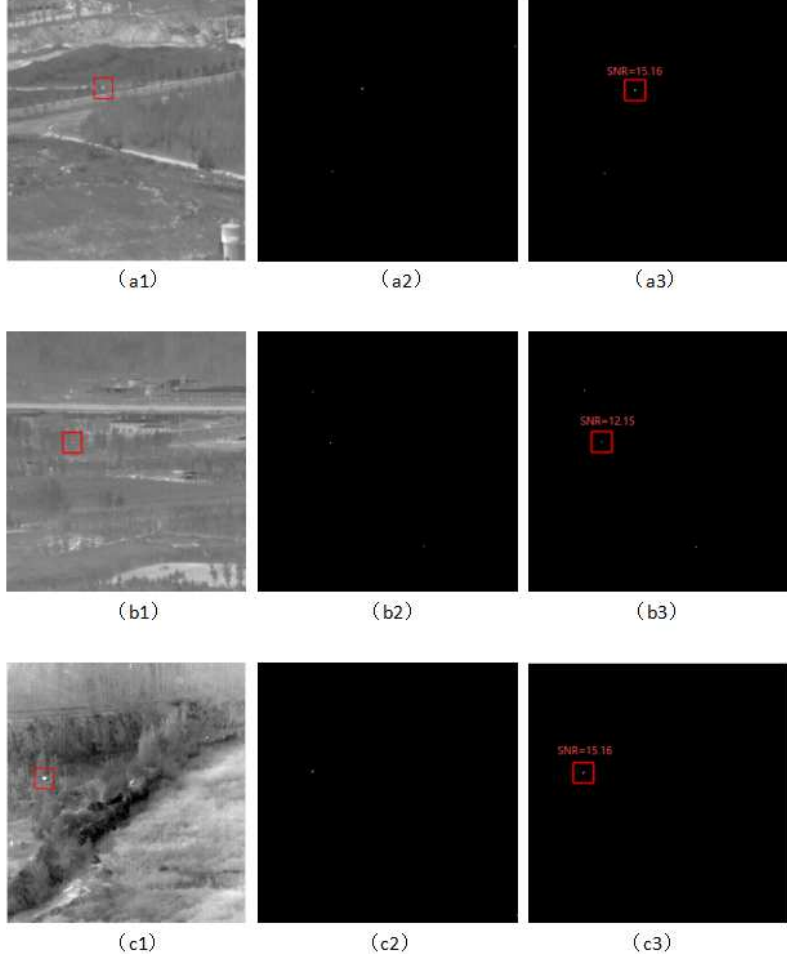


Fig. 7 Result Images for Scenarios 1

in most scenarios, the proposed method achieves significantly superior noise suppression compared to the other benchmark algorithms. Although the other methods are also capable of detecting targets, in most cases, the detected targets are surrounded by noise interference, which could adversely affect subsequent in-depth analysis. Overall, while all the compared algorithms demonstrate certain capabilities in target detection and noise resistance, the proposed method exhibits distinct advantages in both detection accuracy and noise suppression across various scenarios when compared to the other six benchmark algorithms. Particularly in complex environments, our approach enables more precise target identification while effectively minimizing noise interference in the detection results. This provides a more reliable and efficient solution for target detection tasks, as evidenced by the experimental results.

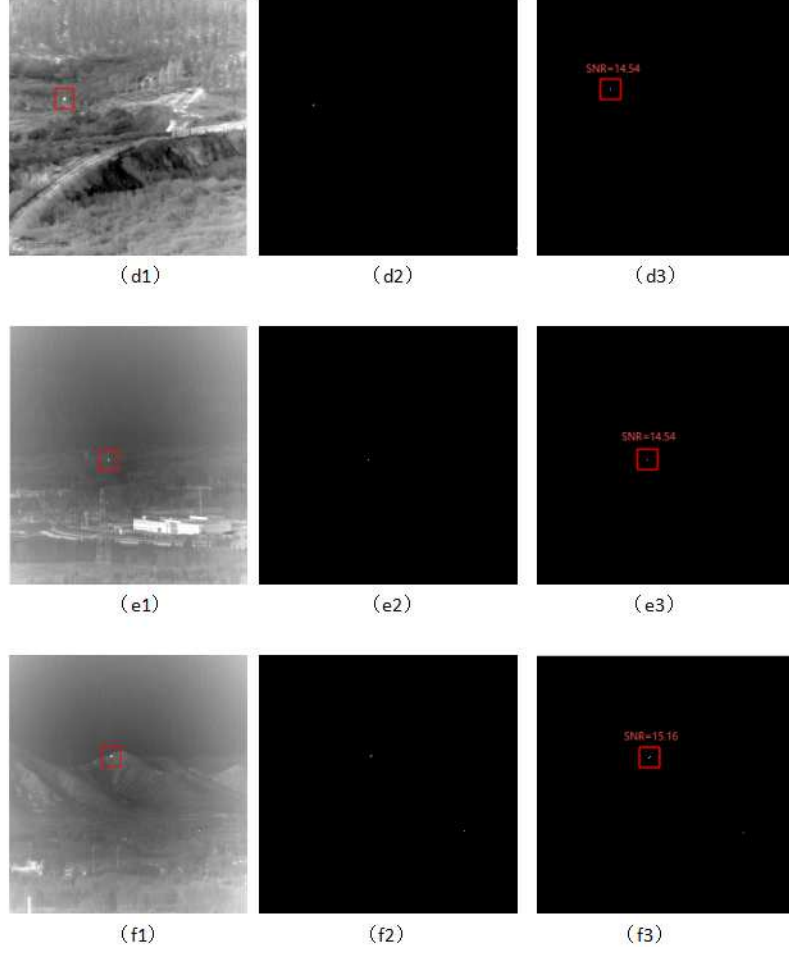


Fig. 8 Result Images for Scenarios 4

4.4 Analysis of Evaluation Metrics

To further compare the performance of the proposed algorithm with other methods, several evaluation metrics are employed to assess its capability in background suppression, target energy enhancement, and noise elimination. This paper introduces two specific metrics: the Background Suppression Factor (BSF) and the Signal-to-Noise Ratio (SNR). The BSF primarily evaluates the effectiveness of the predicted background image by comparing the difference image with the original image. Its calculation formula is as follows:

$$BSF = \frac{\sigma_{in}}{\sigma_{out}} \quad (18)$$

Where σ_{in} and σ_{out} represent the mean squared deviations of the input image and the difference image, respectively. The Signal-to-Noise Ratio (SNR) is used to evaluate the

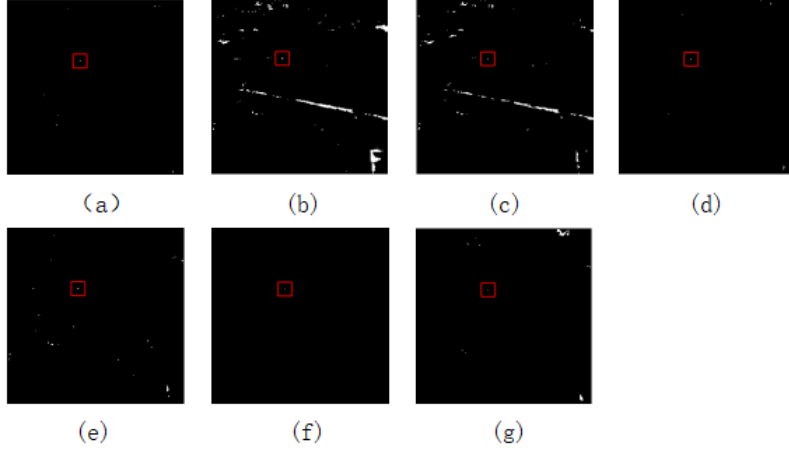


Fig. 9 Comparative Results of the Seven Algorithms for Scenario 1

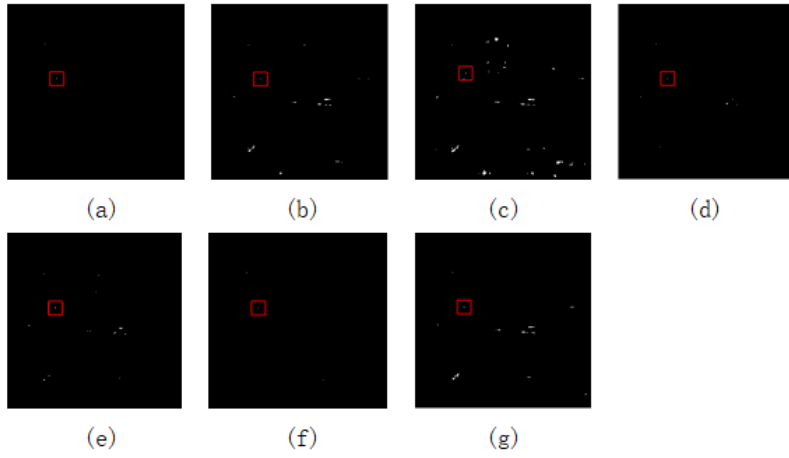


Fig. 10 Comparative Results of the Seven Algorithms for Scenario 2

contrast between the target and noise energy in the algorithm's output, thus validating the detection and background estimation performance. The calculation formula is as follows:

$$SNR = 10 \times \log_{10} \frac{(A_E - A_B)}{\sigma_B} \quad (19)$$

where A_E is the mean grayscale value of the target region; A_B is the mean grayscale value of the background region; σ_B is the standard deviation of the grayscale values in the background region. To provide a more comprehensive and objective comparison of the overall detection performance between the proposed algorithm and other methods, the Area Under the Curve (AUC) is introduced as an evaluation metric. The AUC is derived from the Receiver Operating Characteristic (ROC) curve, which is formed by

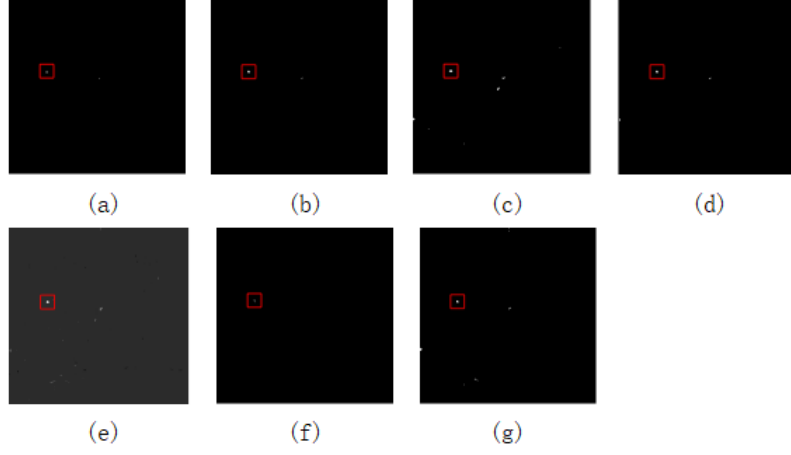


Fig. 11 Comparative Results of the Seven Algorithms for Scenario 3

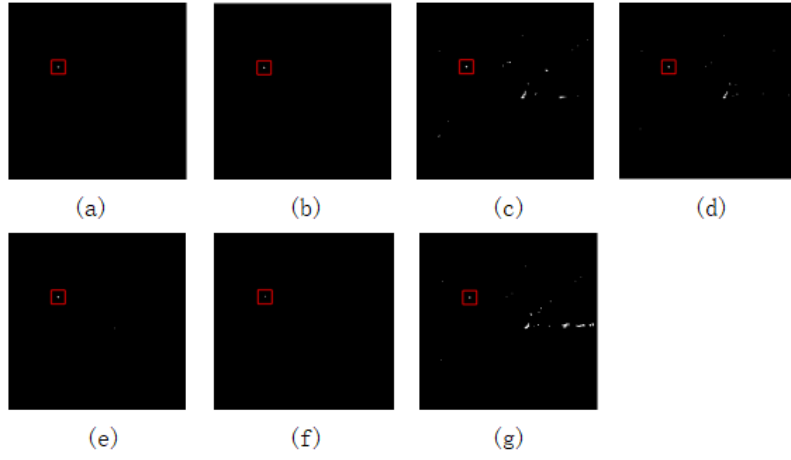


Fig. 12 Comparative Results of the Seven Algorithms for Scenario 4

the Probability of Detection (P_d) and the False Alarm Rate (FAR). It comprehensively evaluates the algorithm's ability to distinguish between targets and background across different decision thresholds. A value closer to 1 indicates superior overall detection performance of the algorithm. The calculation of AUC can be expressed as the integral of the ROC curve, with the formula given as follows:

$$\int_0^1 pd(FAR)d(FAR) \quad (20)$$

Where P_d denotes the Probability of Detection, representing the ratio of correctly detected true targets; and FAR signifies the False Alarm Rate, indicating the probability that background or noise is mistakenly identified as a target.

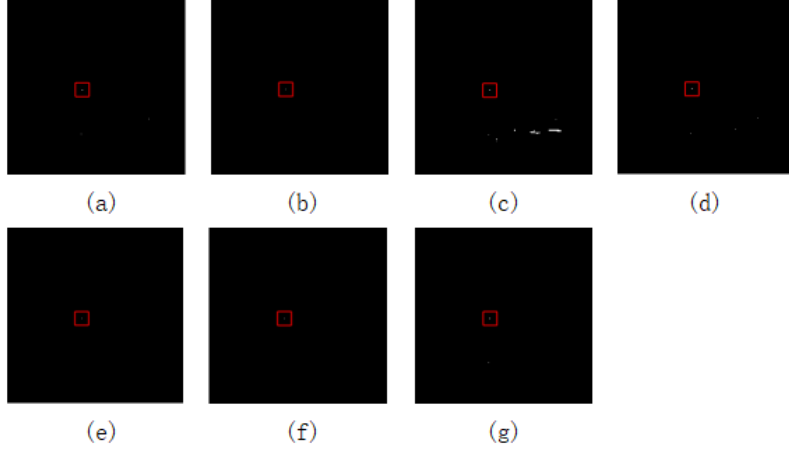


Fig. 13 Comparative Results of the Seven Algorithms for Scenario 5

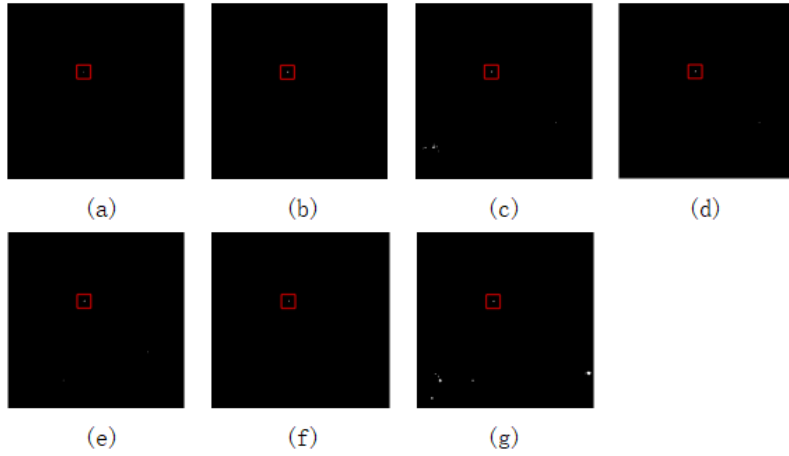


Fig. 14 Comparative Results of the Seven Algorithms for Scenario 6

The quantitative results of the three evaluation metrics for the proposed algorithm and the other six comparison algorithms across the six scenarios are summarized in Table 3, with the maximum value in each metric bolded.

In terms of background suppression capability, the proposed algorithm achieves significantly higher BSF values than all other comparative methods across all scenarios. Taking Scenario 3 as an example, our method attains a BSF value of 43.3627, substantially outperforming top-performing counterparts such as IPT (9.3598) and IPI (9.0574). This notable advantage stems primarily from the improved bilateral filtering strategy adopted in our regularization term. By extending traditional local bilateral filtering of 2D image patches to a global bilateral filtering regularization model constructed from 3D patch tensors, our approach enhances both local and global correlations among patches, thereby effectively suppressing background clutter in target detection.

Table 3 Evaluation Metrics for Detection Methods

Detection Methods	Evaluation Indicators	Seq1	Seq2	Seq3	Seq4	Seq5	Seq6
Proposed method	BSF	3.9884	16.7096	43.3627	24.4731	10.1452	12.1203
	SNR	15.16	12.15	15.16	14.54	14.54	15.16
	AUC	0.92656	0.92813	0.86719	1.00000	0.97656	0.92812
GDR-PCD	BSF	2.9131	4.0313	8.7923	5.7090	4.2069	7.4379
	SNR	5.56	5.18	18.57	18.03	14.54	16.93
	AUC	0.81094	0.73215	0.97501	0.85156	0.70937	0.71233
PSTNN	BSF	2.2687	2.6089	5.6657	4.2072	4.9574	6.3004
	SNR	3.59	5.82	16.36	12.51	8.13	12.80
	AUC	0.85938	0.84844	0.72829	0.82500	0.92500	0.92500
ASTTV-NTLA	BSF	0.9215	1.2455	0.9162	1.1540	3.3857	3.6523
	SNR	10.39	9.53	17.42	13.31	16.30	16.30
	AUC	0.80156	0.79375	0.97344	0.83594	0.74062	0.74412
IPI	BSF	1.5292	1.1810	9.0574	2.2032	2.1120	1.7923
	SNR	10.30	10.31	3.76	17.67	14.54	15.82
	AUC	0.94531	0.70312	0.98712	0.84688	0.92031	0.91121
IPT	BSF	4.3553	3.9002	9.3598	7.0963	3.3857	2.7500
	SNR	14.54	13.03	17.94	16.04	14.54	16.04
	AUC	0.85156	0.92031	0.84531	0.88750	0.91094	0.89762
STWRT	BSF	1.9916	1.9092	4.6778	2.2722	8.6328	5.4726
	SNR	4.17	8.24	16.33	10.97	15.16	10.76
	AUC	0.72813	0.77693	0.80781	0.82423	0.81563	0.83274

Furthermore, the proposed method demonstrates competitive SNR performance across all six scenarios, with values largely comparable to the highest SNR achieved by other algorithms. Notably, in Scenario 1, our algorithm achieves an SNR of 15.16, the highest among all methods compared. This indicates the method’s efficacy in background noise suppression and target enhancement, significantly reducing interference from background clutter during detection. Besides the improved regularization term, this performance also benefits from the structure tensor-based prior model’s noise suppression capability.

When compared to the multi-frame detection algorithm STWRT, our method shows superior performance across all evaluation metrics in every scenario, demonstrating its effectiveness even relative to multi-frame approaches. Similarly, compared to the GDR-PCD algorithm that uses conventional neighborhood filtering in its regularization term, our method achieves higher BSF values in all scenarios, confirming the advantage of our improved regularization strategy over traditional neighborhood filtering methods.

In summary, both from a global image perspective and local regional analysis, the proposed method produces more salient targets with significantly reduced noise interference, particularly achieving unparalleled background suppression effects compared to other algorithms. Considering both evaluation metrics comprehensively, our approach demonstrates clearly superior overall performance against all comparative methods.

4.5 Analysis and Discussion of Algorithmic Limitations

Although the proposed model?based on the feature prior tensor nuclear norm with improved bilateral filtering regularization?demonstrates promising detection performance across multiple complex scenarios, particularly exhibiting significant advantages in background suppression capability (BSF) over comparative algorithms, it still possesses certain limitations. These limitations are observable in specific experimental scenarios and metric comparisons.

First, while the proposed corner strength function effectively suppresses interference from edges and corner structures, its detection performance may be suboptimal in scenarios with dense textures or periodic noise backgrounds (e.g., Scenario 1). In this scenario, the IPI algorithm achieves a higher AUC value (0.94351) than the proposed method (0.92656). This is because when the background contains structured noise with similar size and intensity to the target, the function may struggle to fully distinguish between the target and noise, leading to an increased false alarm rate or partial suppression of target energy.

Furthermore, although the proposed method maintains stable performance in terms of the Signal-to-Noise Ratio (SNR) metric, it does not significantly outperform some comparative algorithms in certain scenarios. For instance, in Scenario 4, the GDR-PCD algorithm achieves a higher SNR (18.03) than the proposed method (14.54). This suggests that in ideal scenarios with extremely clean backgrounds and strong target signals, the strong regularization constraints introduced in this study may cause excessive smoothing, resulting in the loss of target edge details and a consequent reduction in target-background contrast. In summary, although the proposed



Fig. 15 Comparison of Target Images between the Proposed Method and IPI Algorithm in Scenario 1(a) Proposed Method, (b) IPI Algorithm?

algorithm demonstrates excellent performance in background suppression and target detection, there remains room for improvement in computational efficiency, adaptability to extreme scenarios, and parameter robustness. Future research could explore the integration of lightweight network structures, adaptive parameter tuning mechanisms, or multi-scale feature fusion to further enhance the algorithm's performance.



Fig. 16 Comparison of Target Images between the Proposed Method and GDR-PCD Algorithm in Scenario 4?(a) Proposed Method, (b) GDR-PCD Algorithm?

4.6 Ablation Study

To analyze the effectiveness of the key innovations in the proposed algorithm, this section conducts an ablation study comparing the following models in terms of evaluation metrics: the traditional PSTNN model, the PSTNN model with only the regularization term added, the PSTNN model with only the structure tensor-based prior model incorporated, and the full constrained model proposed in this paper. Using Scenario 2 from Figure 4 as the input image, we compare the two evaluation metrics (BSF and SNR) of the above different constrained models, as shown in Table 4 below. The results in Table 4 demonstrate that both the improved regularization term

Table 4 Ablation Study

Model Name	Constraint Term		BSF	SNR
	Regularization Term	Prior Model		
PSTNN			3.4393	5.47
PSTNN+Regularization Term	✓		13.9679	11.13
PSTNN+Prior Model		✓	3.7169	6.93
PSTNN+ Regularization Term + Prior Model	✓	✓	16.7096	12.15

and the structure tensor-based prior model in the proposed algorithm contribute to enhancing the evaluation metrics BSF and SNR. Notably, the improved regularization term plays a crucial role in boosting both metrics. In conclusion, the two innovations introduced in this work are validated as effective and contribute significantly to the algorithm’s performance.

4.7 Analysis of Detection Rate and False Alarm Rate

To comprehensively evaluate the algorithm proposed in this chapter, a three-dimensional Receiver Operating Characteristic (3D-ROC) [43] curve plotting the relationship between Detection Rate (Pd), False Alarm Rate (FAR), and the segmentation threshold τ is utilized. Here, τ denotes the segmentation threshold. The Detection Rate and False Alarm Rate are calculated as shown in Equation (21):

$$\begin{cases} Pd = \frac{\text{The number of real targets detected}}{\text{Number of images to detect}} \\ Pf = \frac{\text{The area occupied by the false alarm target}}{\text{The area of the image}} \end{cases} \quad (21)$$

Here, Pd denotes the Detection Rate, while Pf represents the False Alarm Rate. These two metrics are crucial for assessing the accuracy of a detection method: Pd reflects the proportion of correctly identified true targets, whereas Pf indicates the rate at which non-targets are mistakenly classified as targets. Together, they provide a comprehensive evaluation of the detection performance. The 3D-ROC curves for the six scenarios are shown in Figures 17(a) to 17(f).

As observed in Figure 17, the proposed algorithm achieves high detection rates across

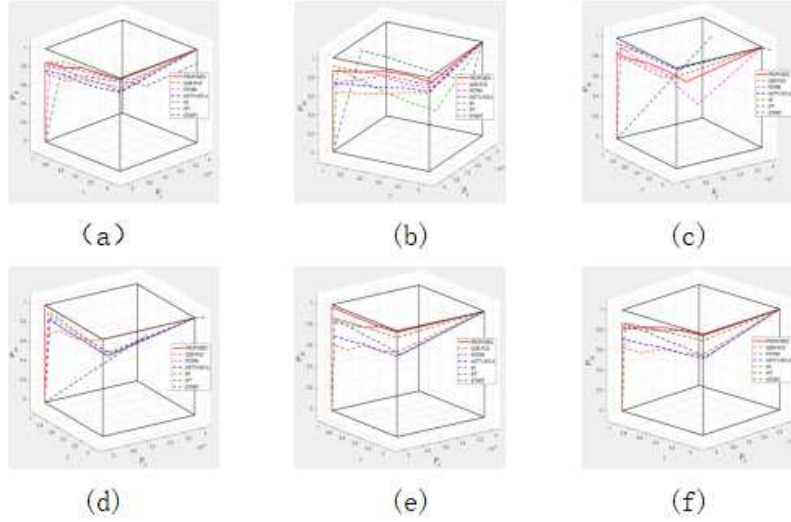


Fig. 17 3D-ROC Curves of Different Algorithms in Six Scenarios

all six scenarios, approaching nearly 100% in most cases. Moreover, its detection performance significantly outperforms that of other comparative algorithms in the vast majority of scenarios. In conclusion, experimental results demonstrate that the proposed method delivers superior detection performance for sequential dim and small target detection compared to other state-of-the-art approaches.

5 Conclusion

For infrared dim and small target detection in complex backgrounds, this paper proposes a detection method based on a feature prior tensor nuclear norm with improved bilateral filtering regularization. First, an improved bilateral filtering-based regularization term is established to enhance the robustness of the low-rank background characteristics. Subsequently, a novel corner strength function based on the structure tensor is constructed to suppress edge and corner structures in the background. Finally, an IPT structure tensor model is developed to achieve accurate dim and small target detection. The main contributions and findings are summarized as follows:

(1) This study employed a total of six different comparative algorithms and two evaluation metrics, SNR and BSF. The specific results are presented in Table 3. As shown in the table, the proposed model based on the feature prior tensor nuclear norm with improved bilateral filtering regularization demonstrates overall superior performance compared to the other algorithms. Notably, it achieves the highest BSF values across all scenarios, with a significant margin over the counterparts. Moreover, the proposed method achieves competitive SNR results, ranking among the top performers in most scenarios and obtaining the highest value in Scenario 1. In summary, the proposed algorithm demonstrates clear superiority.

(2) In terms of target detection, the proposed algorithm achieves a detection rate exceeding 90% in all six scenarios. Regarding the AUC metric for detection performance, the proposed method outperforms most comparative algorithms in the majority of scenarios. However, two main limitations are observed: first, when processing scenes containing structured noise with similar size and intensity to the target, the proposed corner strength function may not fully distinguish between targets and noise, leading to increased false alarm rates or partial suppression of target energy; second, in ideal scenarios with extremely clean backgrounds and strong target signals, the strong regularization constraints introduced in this work may cause excessive smoothing, resulting in loss of target edge details and consequently reduced contrast between targets and background.

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