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Infrared moving point target detection based on an anisotropic spatial-temporal fourth-order diffusion filter☆

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ABSTRACT

Infrared moving point target detection is a challenging task in infrared tracking systems. In this paper, an anisotropic spatial-temporal fourth-order diffusion filter (ASTFDF) is proposed for background prediction from infrared frame images. Using it, we can detect infrared point targets by subtracting the predicted background from the original image. Experiments in detecting targets from several different infrared image frame sequences indicated that the proposed ASTFDF can predict the background effectively and that the target can be detected precisely while achieving a higher background suppression factor (BSF) and signal-to-clutter ratio gain (SCRG) compared with state-of-the-art methods.

1. Introduction

Infrared target detection as a key technology has been widely used in surveillance and military applications [1]. In many situations, targets are embedded in complicated backgrounds and appear as points or speckles in infrared images. Detecting infrared point targets is a challenging task because there are no available structural features [2]. To detect these kinds of targets, many different methods have been proposed [3,4]. Generally, there are two kinds of detection methods: spatial filters based on single images, and spatial-temporal filters based on multi-frame images.

One of the classical spatial filter methods used for detecting small targets is the two-dimensional least mean square (TDLMS) filter proposed by Hadhoud et al. [5]. Some modified filters based on TDLMS have been proposed, such as a TDLMS filter based on neighborhood analysis [6], a TDLMS filter based on block statistics [7], and a bilateral TDLMS filter [8]. In [9], Deshpande et al. proposed a max-mean filter and a max-median filter for detecting moving targets, but they cannot achieve good performance in small target detection. In [10], a human visual system was used in infrared small target detection. In [11], a directional saliency-based method was proposed to detect infrared small targets. In [12], an adaptive Butterworth high-pass filter (BHPF) was proposed by viewing a point target as a high-frequency component of an image. Then, in [13], Wang et al. proposed a directional high-pass template filter based on a least-squares support vector machine (LS-SVM) for detecting infrared small targets. In [14], point targets were detected using a background prediction algorithm based on drifting and evolving clutter. In [15], a background suppressing method based on harmonic and sparse matrix decomposition (HSMD) was proposed for infrared small target detection, in which the decomposed harmonics and a sparse component are viewed as the background and the small target, respectively. In [16], methods

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based on the Top-Hat morphological filter were proposed for infrared small target detection. However, the premise of using a spatial filter method mostly involves the assumption that the target intensity is higher than that of the background, which cannot ever be satisfied in real applications.

Some spatial-temporal filters were proposed on the basis of a mixed spatial and temporal process. Some of these methods process spatial followed by temporal information, and some others process image sequences simultaneously by viewing multiple image frames as an integration. In [17], a small target detection method based on a temporal profile was proposed, which operates on the temporal profile only in 1-D space so that it incurs a lower computational cost. In [18], a directional matched filter based on spatial-temporal information was proposed for clutter suppression. In [19], a bilateral filter and temporal cross product were combined to detect infrared small targets. In [20], Sun et al. proposed a spatial-temporal 3-D anisotropic diffusion filter based on a traditional anisotropic diffusion filter for suppressing clutter and further detecting infrared moving point targets. The methods based on binary patterns were proposed for background suppression and infrared point target detection, such as a clutter suppression method based on bidirectional local binary patterns [21] and based on spatial-temporal local increment coding (STLIC) [22]. Recently, some other infrared moving point target methods have also been proposed, such as the spatio-temporal saliency approach [23] and spatial temporal local contrast filter [24].

Considering that any information of a point target cannot be known a priori, a method based on background suppression is an effective method. In this paper, we propose an anisotropic spatial-temporal fourth-order diffusion filter (ASTFDF) for detecting infrared point targets by suppressing background. The main contributions of this study are as follows. First, ASTFDF is proposed by extending the traditional fourth-order diffusion filter. Second, considering that fourth-order diffusion filters have achieved superior performance in image denoising, ASTFDF is used to predict background by viewing an infrared point target as a kind of noise point. Then, targets are detected by subtracting the predicted background from the original observed image. The outline of this paper is as follows. The theory and method of ASTFDF are discussed in Section 2. In Section 3, experiments in detecting moving point targets from different infrared frame sequences are described for verifying the performance of the proposed ASTFDF. Section 4 draws the final conclusions.

2. Theory and method

2.1. Classical diffusion filter model

In [25], Perona and Malik proposed a fundamental diffusion model:

$$\frac{\partial G}{\partial t} = \mathrm{div}(c(\|\nabla G\|)\nabla G) \tag{1}$$

where G is the gray level of the image and t represents the evolution time. The diffusion coefficient $c(\|\nabla G\|)$ is defined as

$$c(\|\nabla G\|) = \frac{\gamma^2}{\gamma^2 + \|\nabla G\|^2} \tag{2}$$

where γ is a parameter and $\|\cdot\|$ represents the Euclidean norm. Then, in [26], You and Kaveh proposed a fourth-order diffusion filter model:

$$\frac{\partial G}{\partial t} = -\nabla^2(c(|\nabla^2 G|)\nabla^2 G) \tag{3}$$

where $\nabla^2 G$ represents the Laplacian of image G. Then, in [27], another fourth-order diffusion filter model was proposed:

$$\frac{\partial G}{\partial t} = -\nabla^2(c(\|\nabla G\|)|)\nabla^2 G) \tag{4}$$

Compared with Eq. (3), the model of Eq. (4) has better performance in edge preservation and convergence rate.

From the application of the diffusion model to image denoising, the diffusion model can also be used for background prediction during the target detection process. Then, the original image can be seen as the sum of the target map and the predicted background map.

2.2. Anisotropic spatial-temporal fourth-order diffusion filter for target detection

Background prediction, as one kind of target detection method, has been widely used. In this method, the result of background prediction has great influence on target detection performance.

During infrared target detection, we can not only use spatial information for preserving the spatial details such as ramp edges, but also make the most of temporal information for obtaining better prediction. For this purpose, a spatial-temporal 3-D Laplacian of image G is used, which is written simply as

$$\nabla^2 G = G_{xx} + G_{yy} + G_{kk} \tag{5}$$

where G_{xx}, G_{yy} and G_{kk} are the second-order derivatives of G with respect to x, y, and temporal frame sequence direction k.

According to [28], it also can be rewritten as

$$\nabla^2 G = G_{\eta\eta} + G_{\xi\xi} + G_{kk} \tag{6}$$

where $G_{\eta\eta}$ and $G_{\xi\xi}$ are the second-order derivatives of G with respect to η and ξ;

$$G_{\eta\eta} = \frac{G_{xx}G_x^2 + 2G_xG_yG_{xy} + G_{yy}G_y^2}{G_x^2 + G_y^2} \tag{7}$$

$$G_{\xi\xi} = \frac{G_{xx}G_y^2 + 2G_xG_yG_{xy} + G_{yy}G_x^2}{G_x^2 + G_y^2} \tag{8}$$

where η and ξ represent the direction of gradient and level, which are given as

$$\eta = \frac{[G_x, G_y]}{\sqrt{G_x^2 + G_y^2}} \qquad \xi = \frac{[-G_y, G_x]}{\sqrt{G_x^2 + G_y^2}} \tag{9}$$

In order to obtain better background prediction performance, we propose an anisotropic spatial-temporal fourth-order diffusion filter (ASTFDF) as

$$\frac{\partial G}{\partial t} = -\nabla^2(c_1G_{\eta\eta} + c_2G_{\xi\xi} + c_3G_{kk}) \tag{10}$$

The coefficients c_1, c_2, and c_3 control the diffusion rate along their corresponding directions. In this paper, c_1, c_2 and c_3 are defined as

$$c_1 = c(\|\nabla G\|)^2 \tag{11}$$

$$c_2 = c(\|\nabla G\|) \tag{12}$$

$$c_3 = 1 \tag{13}$$

Let ...,G_{k-1}, G_k, G_{k+1}, ... be an infrared image sequence, and $G(x, y, k)$ represent the intensity at pixel (x, y) of the kth frame. The discretization of the first and second derivatives of image G are given as follows:

$$\begin{aligned}
G_x &\approx D_xG(x, y, k) = \frac{G(x-1, y, k) - G(x+1, y, k)}{2}\\
G_y &\approx D_yG(x, y, k) = \frac{G(x, y-1, k) - G(x, y+1, k)}{2}\\
G_k &\approx D_tG(x, y, k) = \frac{G(x, y, k-1) - G(x, y, k+1)}{2}\\
G_{xx} &\approx D_{xx}G(x, y, k) = G(x-1, y, k) + G(x+1, y, k) - 2G(x, y, k)\\
G_{yy} &\approx D_{yy}G(x, y, k) = G(x, y-1, k) + G(x, y+1, k) - 2G(x, y, k)\\
G_{kk} &\approx D_{kk}G(x, y, k) = G(x, y, k-1) + G(x, y, k+1) - 2G(x, y, k)
\end{aligned}$$

Supposing that B represents the result of background prediction using the ASTFDF model, we can obtain the target map T by subtracting B from the original image G.

$$T = G - B \tag{14}$$

Algorithm 1 is the implementation of the proposed method for infrared point target detection.

3. Experimental results

To verify the performance of the proposed ASTFDF method, we compared the target detection results obtained by the proposed ASTFDF with state-of-the-art methods such as STLIC [22], BF-TCP [19], BHPF [12], and the max-mean and max-median methods [9]. In the test, we provided four groups of infrared frame sequences as background, and added moving point targets to the background sequences. For simplicity, only one target was added in each sequence. The simulated frame images are shown as Fig. 1 (A0)–(D0),

1. **Input:** Image sequence $\{\cdots, G_{k-1}, G_k, G_{k+1}, \cdots\}$.
2. **Output:** Target detection map.
3. Initialize: parameter γ and evolution time t.
4. **while** not converged **do**
5. Compute spatial-temporal 3D Laplacian of image G using Eq. (6).
6. Update image sequence.
7. **end while**
8. Compute target image using Eq. (14).

Algorithm 1. ASTFDF for detecting an infrared point target.

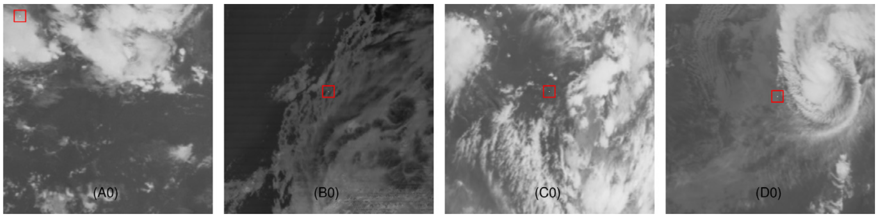

Fig. 1. Original infrared images (one frame selected from the corresponding infrared frame sequence.

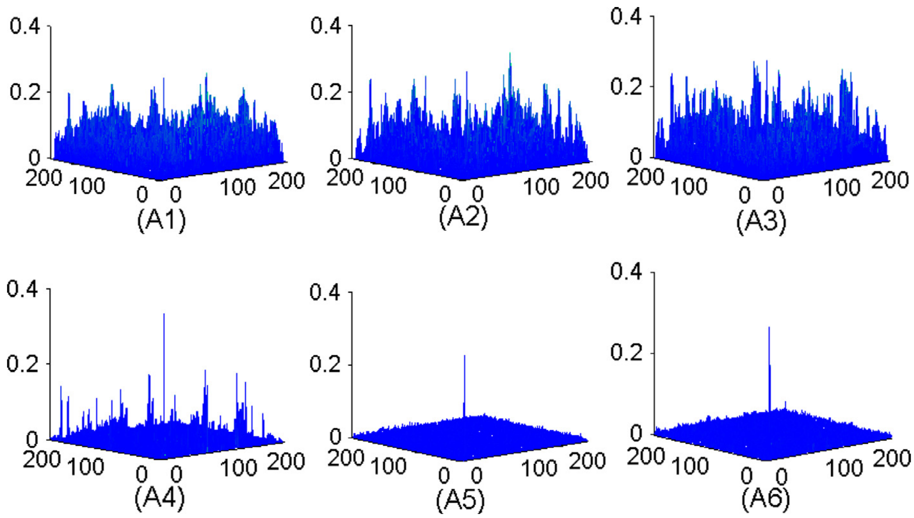

Fig. 2. Target detection map of the image in Fig. 1 (A0). (A1)–(A6) are detection results using the max-mean, max-median, BHPF, BF-TCP, STLIC, and proposed ASTFDF methods.

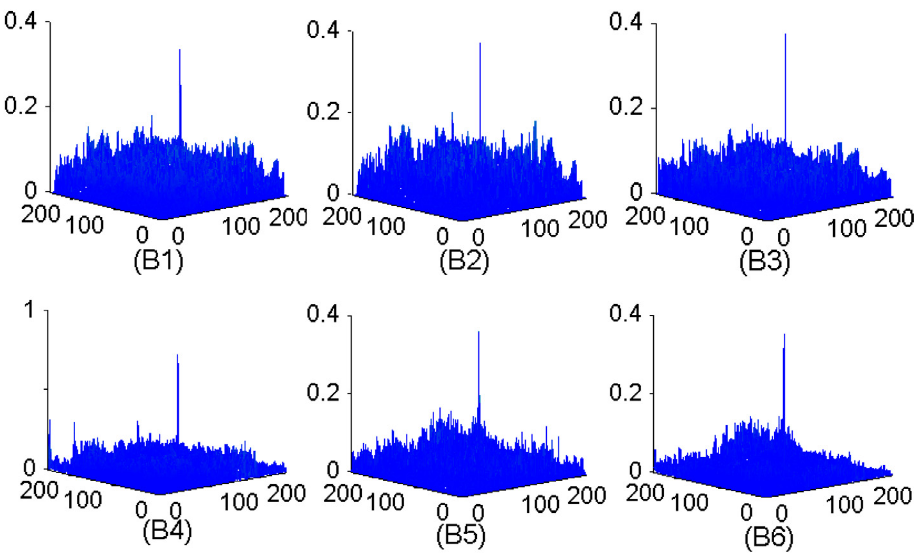

Fig. 3. Target detection map of the image in Fig. 1 (B0). (B1)–(B6) are detection results using the max-mean, max-median, BHPF, BF-TCP, STLIC, and proposed ASTFDF methods.

which were selected from the corresponding sequences; the targets are marked with red borders.

Targets were detected from every frame, and only one frame of the detection results was selected for the figures. The target maps of the detections from Fig. 1 (A0)–(D0) using the abovementioned methods are shown in Figs. 2–5. From Figs. 2–5, it can be found that the proposed ASTFDF method can detect the targets more reliably than the other methods. The running time is related to the image size. For an image of size 256 × 256 pixels, the average running time using the proposed ASTFDF method to detect a target

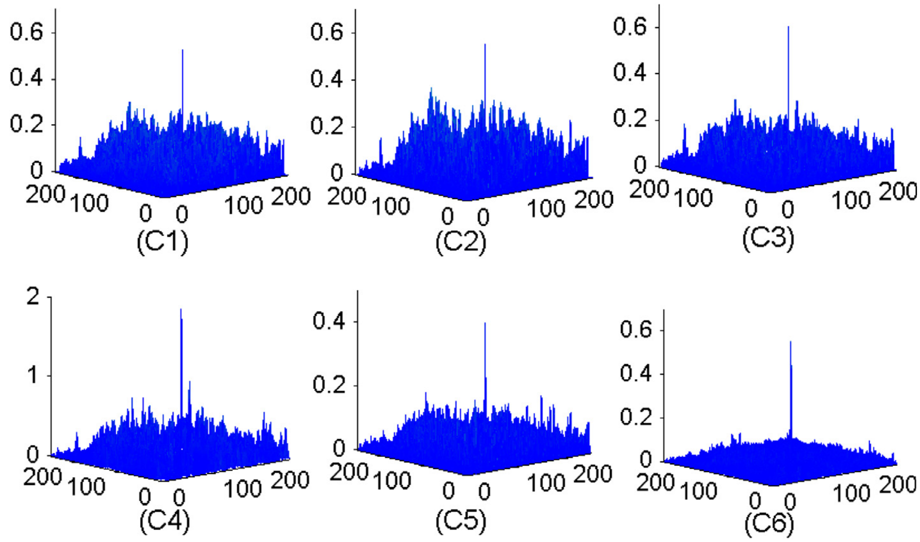

Fig. 4. Target detection map of the image in Fig. 1 (C0). (C1)–(C6) are detection results using the max-mean, max-median, BHPF, BF-TCP, STLIC, and proposed ASTFDF methods.

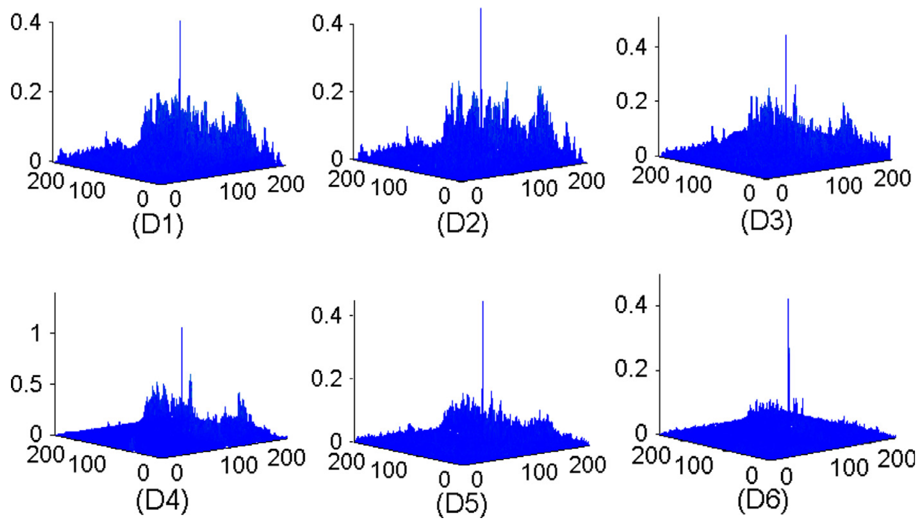

Fig. 5. Target detection map of the image in Fig. 1 (D0). (D1)–(D6) are detection results using the max-mean, max-median, BHPF, BF-TCP, STLIC, and proposed ASTFDF methods.

Table 1
Quantitative performance comparison of BSF and SCRG.

Methods		(A0)	(B0)	(C0)	(D0)
ASTFDF	BSF	53.6776	10.9721	22.3229	35.4153
	SCRG	17.4410	5.7829	12.5234	17.6762
STLIC	BSF	56.5475	7.8113	11.2314	19.1926
	SCRG	15.9353	4.2128	4.5550	10.0693
BF-TCP	BSF	37.0998	3.9670	2.6611	5.5697
	SCRG	14.0905	4.3025	5.0056	6.9488
BHPF	BSF	7.0526	4.6155	5.4810	8.8528
	SCRG	2.3447	2.5911	3.3705	4.6389
Max-median	BSF	7.7353	3.9831	4.7055	8.6468
	SCRG	2.4668	2.2103	2.6388	4.5199
Max-mean	BSF	6.5928	4.1894	4.9770	8.1219
	SCRG	1.9750	2.1134	2.6437	3.8596

from one frame was approximately 5 s.

In order to conduct a quantitative performance comparison, the background suppression factor (BSF) and signal-to-clutter ratio gain (SCRG) [24,29] of the target detection results were evaluated. According to the definitions of BSF and SCRG, greater values mean better target detection performance. Corresponding to Figs. 2–5, the values of BSF and SCRG were evaluated as shown in Table 1. We found that the proposed ASTFDF method can achieve greater values than the other methods. That is, under the same circumstances, the ASTFDF method can achieve better performance than the other methods on detecting infrared moving point targets.

4. Conclusion and discussion

In this paper, an anisotropic spatial-temporal fourth-order diffusion filter is proposed by introducing the second-order derivatives of an image with respect to its gradient and level directions. We used the proposed filter to predict the background and then to detect infrared moving point targets by subtracting the predicted background from the original image. During background prediction, the setting of the parameter γ and evolution time t affects the background prediction performance. A larger γ value results in edge blurring. If t is set too small, much time is needed for convergence; if it is too large, the background cannot be predicted because the noise cannot be diffused. Unfortunately, there is no algorithm that can determine the best values for γ and t. In this study, γ and t were set experimentally. The experimental results for detecting infrared moving point targets from different background images demonstrate that the proposed ASTFDF model can achieve better target detection performance in complicated situations.

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