A Dim Small Infrared Moving Target Detection Algorithm Based on Improved Three-Dimensional Directional Filtering

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Abstract. In this paper, we introduce a new detection method for extremely weak moving target in infrared image sequences based on the novel three-dimensional directional filtering. The main points of the method are, first, we use a dual-diffusion partial differential equation (DFPDE) to pre-whitening an image, which can suppress the constructive texture background effectively and keep the target signal steadily. And second, to match precise target motion characteristic, we propose a Wide-to-Exact search method that can improve the speed of filtering. Experiment results demonstrate that our method can perform good detection results, even at poor signal-to-noise ratio.

Keywords: Weak target detection, Dual-diffusion partial differential equation, Directional filter, Wide-to-Exact search.

1 Introduction

From the 1950s, the technology of infrared detection has been widely used in various fields, especially in the infrared imaging guidance, infrared surveillance and reconnaissance [1]. Due to the factors of natural meteorological conditions, background environment, target structure and so on, dim small target detection in infrared images is a difficulty of imaging target detection.

In recent years, the researches on the background suppression are very active, including image filtering, pixel transform and so on. Anisotropic diffusion methods based on partial differential equations (PDE) have been well used on image de-noising. Perona and Malik [3] introduced nonlinear coefficient distribution function, but it is bad for strong noise, so Catté etc [6] used the gradient after Gaussian smoothing instead of the original gradient, however, it is not applicable for the noise with statistical properties. To overcome the "ladder" effect of P-M model, You and Kaveh [7] proposed a fourth-order partial differential equations (FPDE), but it will introduce the impulse noises. Yu etc [8] introduced Kernel function theory into anisotropic diffusion, which can well express nonlinear mapping relationship of data. For speckle noise of the ultrasound image, Zhang etc [9] proposed a Laplacian pyramid-based nonlinear diffusion, and Yu etc [10] combined SUSAN edge detection

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with anisotropic diffusion. In this paper, we propose a dual-diffusion partial differential equation (DFPDE). The method can control the diffusion more finely, and it is applicable for suppressing the structural clutter even at poor signal-to-noise.

Directional filtering [2] has the ability of selectively enhancing point targets with linear motion characteristics, which are submerged in the Gaussian noises.

2 Local Background Prediction Based on Dual-Diffusion Partial Differential Equations(DFPDE)

We consider $\xi = \nabla u / |\nabla u|$ as a unit vector of the gradient direction, η is also a unit vector, and it is perpendicular to ξ .Formula of DFPDE can be described as follow.

$$\frac{\partial u}{\partial t} = c_1(|\nabla u|)(c_2(|\nabla u|)u_{\eta\eta} + (1 - c_2(|\nabla u|))u_{\xi\xi}) \tag{1}$$

Where, $c_1(|\nabla u|)$ and $c_2(|\nabla u|)$ are two diffusion functions.

$$c_1 = 1/1 + (|\nabla u|/K)^2 \qquad\qquad c_2(|\nabla u|) = K_2 \tan(|\nabla u|)/2\pi \tag{2}$$

For $c_1(|\nabla u|)$, if K is large, the diffusion effect will be stronger when the gradient is small. Conversely, if K is small, the diffusion effect will be weaker when the gradient is large. And $c_2(|\nabla u|)$ has the opposite effect to $c_1(|\nabla u|)$. Constants K and K_2 are respectively equal to the integrations of $c_1\%$ and $c_2\%$ of “noise estimator” of Canny operator, and they also depend on image type and actual application requirements. After background clutter restoration, we get suppression result by eliminating background clutter prediction from original image $u(x,y,t)$.

3 Dim Small Moving Target Detection Method Based on Three-Dimensional Directional Filtering

3.1 Three-Dimensional Directional Filtering Principle

We describe the observed spatial and temporal signal by formula (3).

$$y(\mathbf{r},t) = s(\mathbf{r},t) + b(\mathbf{r},t) \tag{3}$$

Where, s is the signal and b is the background. Three dimensional matched filtering can be expressed as equation (4) in the frequency domain.

$$H(\mathbf{k},\omega) = \frac{S^*(\mathbf{k},\omega)}{B(\mathbf{k},\omega)} \exp(-j(\mathbf{k}\mathbf{r}_0 + \omega t_0)) \tag{4}$$

And $(\mathbf{r}_0, t_0)$ is the starting time-space location and $(\mathbf{k}, \omega)$ is the frequency coordinate. We can get background power spectrum $B(\mathbf{k},\omega)$ by Fourier transform of auto-correlation. Provided that the background is white noise obeyed Gaussian distribution, we assume that $B(\mathbf{k},\omega) = N_0$ (constant).

$$H(\mathbf{k},\omega) = (T\sqrt{v_x^2 + v_y^2 + 1}/N_0)\,\mathrm{sinc}((\omega + \mathbf{kv})T/2)\exp(j(\omega + \mathbf{kv})T/2) \tag{5}$$

Accordingly, the result in the frequency domain is like below form.

$$\hat{S}(\mathbf{k},\omega) = H(\mathbf{k},\omega)\cdot S(\mathbf{k},\omega) = (T\sqrt{v_x^2 + v_y^2 + 1}/N_0)\,\mathrm{sinc}^2((\omega + \mathbf{kv})T/2)\exp(-j(\mathbf{kr}_0 + \omega t_0)) \tag{6}$$

For the target with velocity $\mathbf{v}$, the energy of the target signal will be better cumulated when $(\mathbf{k},\omega)$ of equation $\omega + \mathbf{kv} = 0$ is in the main lobe of the function sinc.

When using 3D directional filtering to process the image sequence, we can get the formula (7).

$$G(\mathbf{k},\omega) = H(\mathbf{k},\omega)S(\mathbf{k},\omega) = (T/N_0)\,\mathrm{sinc}^2\left[(\omega + \mathbf{kv})T/2\right]\exp\left\{-j\mathbf{kr}_0\right\} \tag{7}$$

The time-space domain form of (7) is as follow. $\Lambda(t/T)$ is a triangle function.

$$g(\mathbf{r},t) = h(\mathbf{r},t) * s(\mathbf{r},t) = (T^2/N_0)\partial^2(\mathbf{r} - \mathbf{r}_0 - \mathbf{v}t)\Lambda(t/T) \tag{8}$$

Through analyzing the formula (7), we know that spatial phase part $\exp(-j\mathbf{kr}_0)$ maintains the starting position of the moving targets, and if we don't make the extension operation on the filtering along the time axis, the convolution operation will introduce the aliasing in a cycle time, as shown in the Fig. 1.

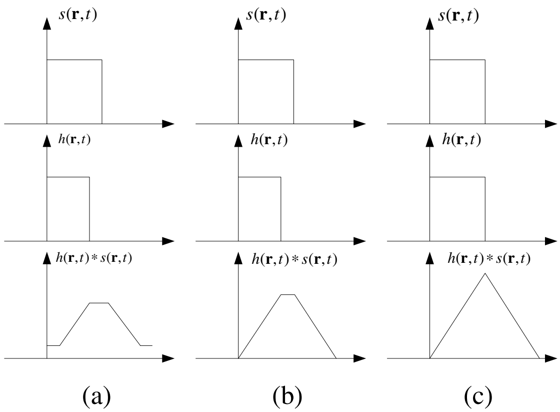


Fig. 1. Matching between the target and filtering (a) Without cycle extension for $h(\mathbf{r},t)$ and $s(\mathbf{r},t)$; (b) Cycle extension for $h(\mathbf{r},t)$ and $s(\mathbf{r},t)$; (c) cycle extension for $h(\mathbf{r},t)$ and $s(\mathbf{r},t)$ and matching perfectly

In order to overcome the need to know the velocity, Boaz, Porat etc. [4] proposed an exhaustive search algorithm, which will search for every possible target directions. Blostein etc. [5] proposed a heuristic search algorithm, which can improve the time-cost problem to some degree. We improve the method to be a three-dimensional Wide-to-Exact search dual-directional filtering, which can get excellent compromise between the performance and the operation cost.

3.2 Three-Dimensional Wide-to-Exact Search Double Directional Filtering.

Three-dimensional Wide-to-Exact search double directional filtering (3DWESDDF) (10) is composed by a set of 3D fan-shaped bi-directional filters, which are formed by a group of 3D bi-directional filters and cover the entire velocity space.

$$\begin{aligned} H_{FD}(\mathbf{k},\omega) &= \frac{1}{N_0}\sum_{i=1}^{k}\left[S^*(\mathbf{k},\omega)\exp\{-j\mathbf{k}\mathbf{r}_0\}\exp(-j\omega j\ ) + S_i(\mathbf{k},\omega)\exp\{j\mathbf{k}\mathbf{r}_0\}\exp(j\omega\omega)\right] \\ &= \frac{T}{N_0}\sum_{i=1}^{k}\left[\exp\{j(\mathbf{kv}-\omega)T/2\} + \exp\{j(\mathbf{kv}-\omega)T/2\}\right]\mathrm{sinc}\left[(\mathbf{kv}+\omega)T/2\right] \end{aligned} \tag{9}$$

We select 3D fan-shaped directional filter with small deviations of velocity direction and velocity magnitude to reduce the influence of interaction of the filters and to determine the approximate direction of the target track on a coarser scale. Furthermore, in order to obtain the precise orientation of the target trajectory, we also need exact searches on the approximate directions.

4 Results

The infrared image sequence we choose has low signal-to-noise ratio and complex background clutter, and the trajectory of dim small moving targets displays uniform linear motion characteristics. The image size is 256x256, and totally 16 frames per sequence. Fig .2 shows the results of DFPDE and 3DWESDDF.

In order to measure performance of the background clutter suppression, we definite an integrated signal-to-clutter ratio (ISCR).

$$ISCR = \frac{u_s}{\sigma_c} \tag{13}$$

Where, u_s is the signal value, and σ_c is the standard deviation of the image.

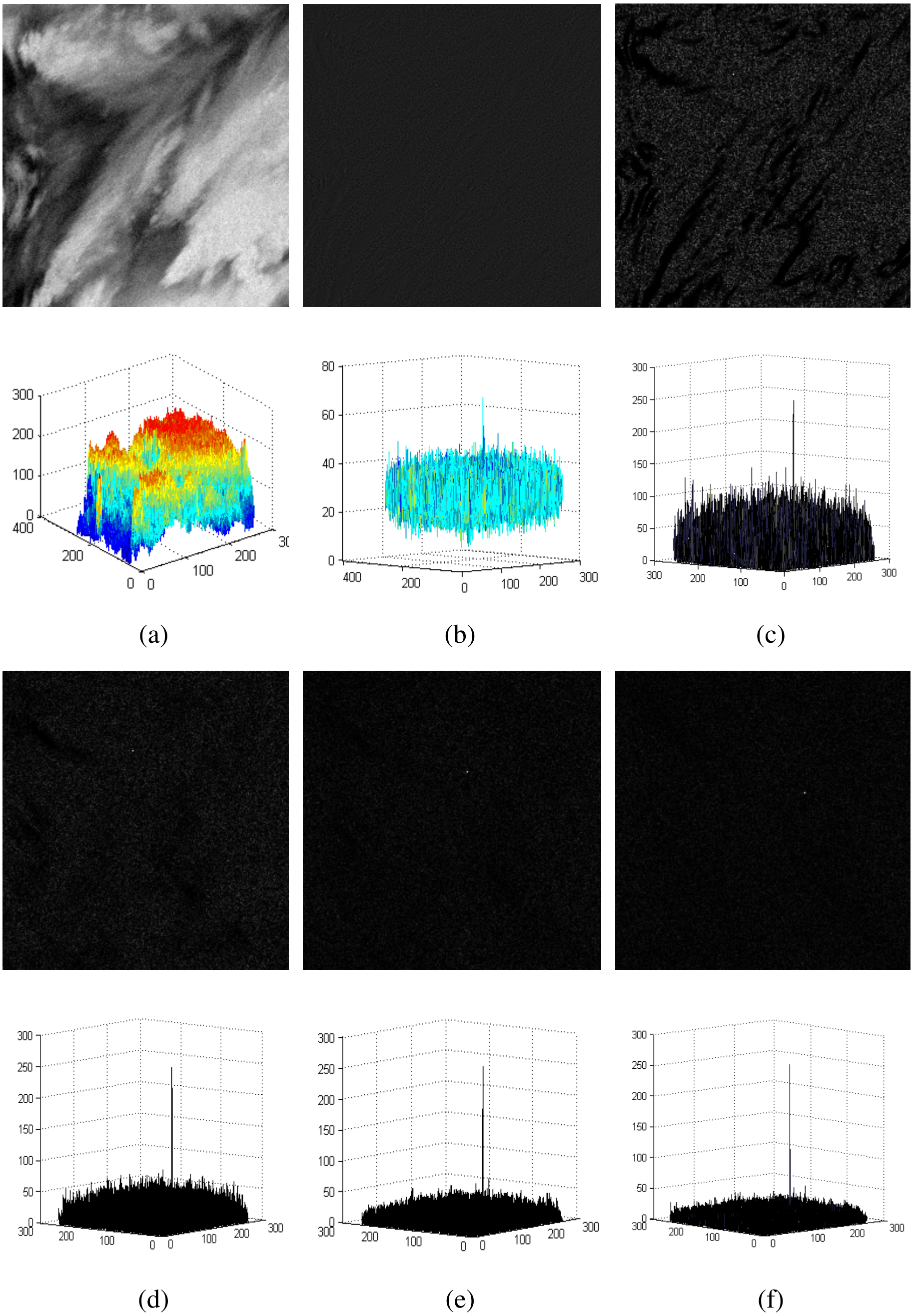
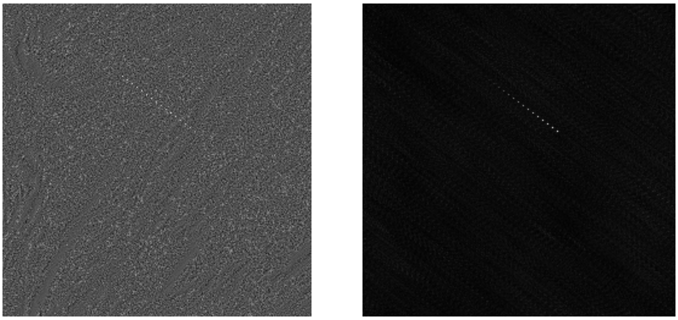


Fig. 2. The results of DFPDE and 3DWESDDF (a) is the first frame original image and its 3D energy result; (b) is the first frame image processed by DFPDE and its 3D energy result; (c),(d),(e),(f) are respectively the first, forth, tenth and last frame images processed by 3DWESDDF and its 3D energy result

Table 1. ISCRs of different algorithems

	Original image	Wiener Filter	Med Filter	PDE	DFPDE
ISCR	1.22	2.5	4.55	6.72	7.78

Through the DFPDE processing, the result as shown in the Fig .2(b) shows that the complex background clutter can be well suppressed, and the targets have been retained and highlighted. Moreover, ISCR value of our method is greater, it can be proved that DFPDE outperforms the traditional methods on the background clutter suppression and signal-to-noise ratio improvement.



(a) (b)

Fig. 3. The projection of the detection result on the time axis. (a) The result of DFPDE; (b) The result of 3DWESDDF.

Under the condition of unknown moving characteristic of the targets, after the processing of 3DWESDDF, even the trajectory of targets has the tailing and diffusion phenomenon, the energy of the targets can be well accumulated as the frame of image increases, as shown Fig. 3(b), thus, the signal-to-noise gets clearly improved.

5 Conclusion

In this paper, in order to suppress the affection of structural clutter texture acting on dim small moving point target detection at the poor signal-to-noise ratio, we propose a new filtering algorithm based on a dual-diffusion anisotropy partial differential equation (DFPDE). After filtering, we can assume that the results only have target points and irrelevant quasi-Gaussian white noises on the gray scale.

We develop a three-dimensional directional filtering, which ensures that the cumulative strength of the target energy is only associated with the length of the integration time. To get excellent compromise between the detection performance and the operation cost, we propose a three-dimensional Wide-to-Exact search double directional filtering (3DWESDDF), which will search for the whole state-space and the corresponding state-subspace in the different accuracy. The experiment results show that our method reduces the operation cost and computation time, meanwhile it can increase target detection capability, and the effect of detection is independent of obtained frequency of image sequence.

However, our method is restricted to the condition that the targets must obey to uniform linear motion characteristics. For irregular moving targets, more work need to be done.

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