

# Point Target Detection in Space-Based Infrared Imaging System Based on Multi-Direction Filtering Fusion

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**Abstract**—Point target detection in space-based infrared (IR) imaging system is an important task in many applications such as IR searching and tracking and remote sensing. Although it has attracted great interest and tremendous efforts during last decades, it remains a challenging problem due to the uncertain heterogeneous background and the limited processing resources on the planet. Aiming at this problem, a novel background suppression method based on multi-direction filtering fusion is proposed in this paper. The process of background prediction for each pixel by this method can be divided into two steps. Firstly, eight predicted values are obtained by using linear filtering methods along eight different directions respectively. Then, Gaussian weighted sum of the eight predicted values is computed to generate the final result. We conduct several groups of experiments on different categories scenes with simulated targets, and the final experimental results demonstrate that our methods can not only obtain state-of-the-art performance on background suppression (especially for heterogeneous backgrounds), but also detect targets accurately with low false alarm rate and high speed in IR point target detection tasks.

## 1. INTRODUCTION

Because of good concealment, high sensitivity, strong anti-interference ability and no limit for service time, IR imaging technique is widely used in many areas, such as IR searching and tracking system and remote sensing. As an important technique of an IR imaging system, IR point target detection has always been a research hotspot during last decades. However, as there are no available features such as shapes, scales, and textures to use for detection, it remains an extremely challenging problem, especially under a heterogeneous background. In order to solve this problem, a variety of background suppression algorithms have been proposed, which can be summarized in two large categories: 1) algorithms based on image sequences and 2) algorithms based on single frame image.

Image sequences based methods, which can utilize both temporal and spatial information simultaneously, have been widely used for small moving targets detection and achieved good performance in experiments [1–3]. However, these methods are greatly limited in real applications due to the following three factors: 1) Most of these methods need to know some prior information like the velocity of targets, the target may be regarded as background if the velocity is too low, moreover some algorithms even need to know the target movement direction, which is always violated in practice. 2) Almost all of these methods need to achieve accurate image registration before any other processes to weaken the influences of vibration between consecutive frames; however, it remains a challenging and time consuming problem due to the motion of both targets and imaging sensors simultaneously. 3) Most of these algorithms are computational complex and require a lot of storage space as they will make use of multi-frame

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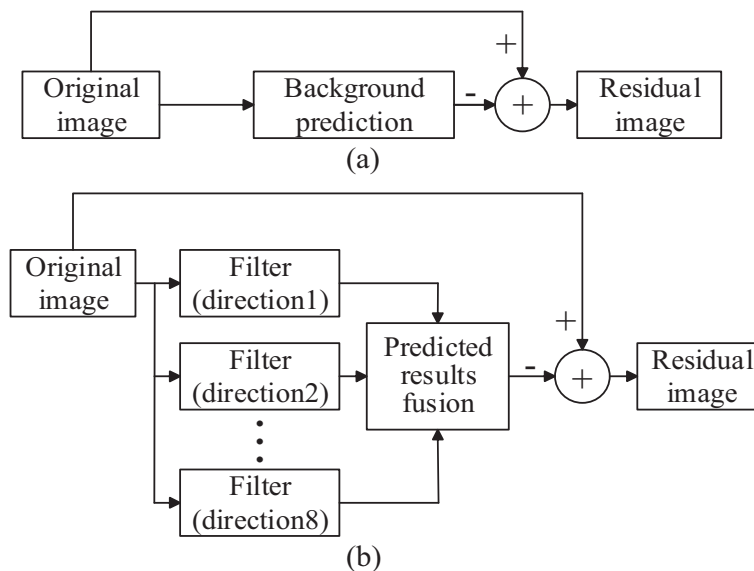
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information, which are not suitable for the real applications, especially for the onboard IR imaging system.

Methods based on single frame image can also be summarized in two categories [4]: 1) based on transformation domain and 2) based on spatial filter. The former methods transform the original image from spatial domain to another domain firstly, e.g., frequency domain, wavelet domain and intrinsic mode function (IMF domain), etc. Then the background clutters are suppressed according to the difference between background and point targets in the transformed domain [3–8]. Because of transformation and inverse transformation, these methods are always time consuming and limited in real applications. By comparison, the later kind of methods, which use spatial filters to predict the background, have become the mainstream methods of background suppression and been successfully used in many practical applications, because they can obtain good performance while maintaining the algorithms computationally simple and suitable for real time processing. The main idea of spatial filter based methods is that the background is spatially correlated and changing slowly in local areas, while the point targets are just the opposite, so the gray value of background can be predicted using its adjacent pixels. Two main steps are always included as follows: 1) predict the background gray value by some spatial filters, and 2) subtract the background from original image to obtain the residual image, as shown in Fig. 1(a). Various spatial based methods such as constant weight, median, max-median [9], high-pass [8], top-hat [10–12], and two-dimensional LMS (TDLMS) [13,14] have been developed and successfully used in many real applications during last decade. However, the performance of prediction is degraded when the background is heavily cluttered.

For the space-based infrared imaging system, there are two factors making point target detection a more challenging problem: 1) limited processing resources on onboard platform; and 2) uncertain clutter background. To solve these problems, a novel background suppression method based on multi-direction filtering fusion (MDFF) is proposed in this paper. Firstly, eight predicted values are obtained by using linear filtering methods along eight different directions respectively. Then, Gaussian weighted sum of the eight values is computed to generate the final result, as shown in Fig. 1(b). Experimental results show that our methods can not only obtain state-of-the-art performance on IR background suppression, especially for the heterogeneous background, but also detect targets accurately with low false alarm rate and high speed in IR point target detection tasks. The remaining part of this paper is organized as follows: In Section 2, we analyze the difficulties of background suppression based on normal spatial filters for the space-based IR imaging system. In Section 3, the proposed method MDFF is described in detail. Experimental results are given in Section 4 and conclusions follow in Sections 5.



**Figure 1.** Architecture comparison of MDFF and normal spatial filter based methods. (a) Normal algorithm. (b) Proposed MDFF algorithm.

## 2. PROBLEM STATEMENT

In this section, we analyze the difficulties of point target detection in space-based IR imaging systems in detail. Generally, an IR image can be modeled as sum of three parts: background, targets and noise, which is described as Eq. (1).

$$F(i, j) = \begin{cases} B(i, j) + T(i, j) + N(i, j) & \text{targets exist} \\ B(i, j) + N(i, j) & \text{no target} \end{cases} \quad (1)$$

where  $(i, j)$  denotes the pixel's coordinates, and  $F, B, T, N$  stand for observed IR image, background image, target image and noise, respectively. In general,  $N$  is often assumed as the Gaussian noise with mean 0 and variance  $\sigma^2$ . The purpose of point target detection is to identify the target  $T$  in the observed image  $F$ , and the foundation for achieving this purpose is the difference of IR radiation characteristics between backgrounds  $B$  and targets  $T$ . Taking the space-based IR missile warning system as an example, a brief description of the difference between  $B$  and  $T$  is presented as follows:

(1) Backgrounds. Space-based IR imaging system achieves star-to-earth observation, so the terrain backgrounds are the principal components of the background image, such as forest, ocean and glaciers. Besides, it may also contain some random clouds, earth edge and orbital background. With the development of IR technology in recent years, the view field of IR sensors is getting larger and larger, and a real IR image always contains many different categories of backgrounds.

(2) Targets. Detecting and tracking missile targets is an important task of space-based IR system. Taking the third generation Defense Support Program (DSP) satellites of the US as an example, its actual resolution for terrestrial targets is  $1.7\text{ km} \times 1.7\text{ km}$ , whereas the missile targets are generally just tens of meters. Therefore, the targets are always represented as single-pixel bright spot. In spite of considering the point spread effect of the targets, the size of targets should not be larger than  $3\text{ pixel} \times 3\text{ pixel}$ .

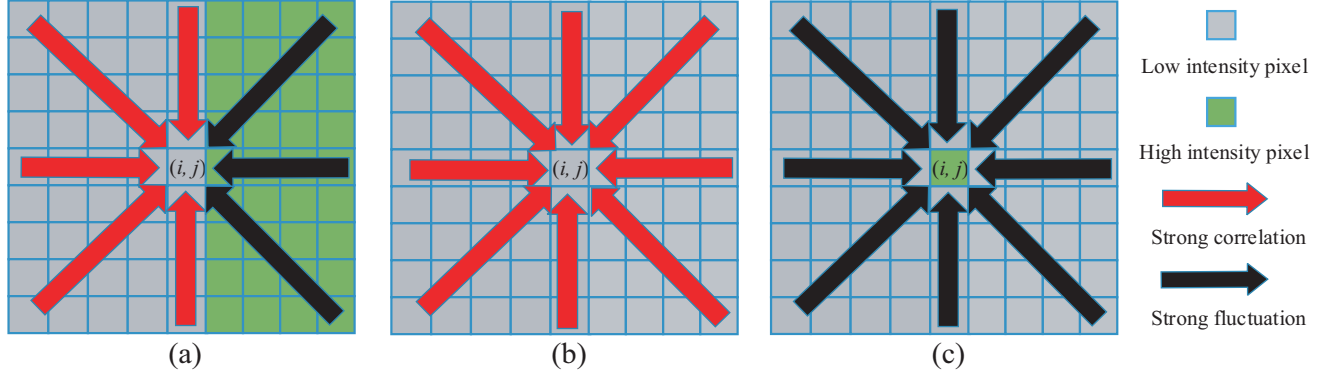
In general, the background is always considered to be slowly changed and strong correlative in spatial domain, so it should be a low frequency signal. On the other hand, the point targets are always represented as separated high intensity pixels, strong fluctuation in spatial domain making them one type of high frequency signal. Therefore, we can achieve point target detection according to the difference. However, a real IR image always contains some heterogeneous backgrounds like aforementioned analyses, e.g., various edges, ragged clouds, and lake with strong reflection. In this case, the backgrounds are also represented as a high frequency signal, which brings us a great challenge for point target detection. In addition, limited processing resources on the planet are another challenge for point target detection in space-based IR system, which require the algorithms to be computationally simple.

## 3. PROPOSED METHODS

According to the analyses in Section 2, the heterogeneous background is the main challenge for point target detection, because it is mostly represented as strong fluctuation in spatial domain, just as the pint targets, so that it hardly distinguishes them by normal spatial filters. However, if observing along different directions, we will find that the heterogeneous background, the homogeneous background and the targets are all different. Fig. 2 shows the different observed results, where gray color represents low intensity pixel; green color represents high intensity pixel; red arrowhead represents strong correlation; black arrowhead represents strong fluctuation. When the reference pixel is located in the heterogeneous area such as cloud edge, it is represented as strong correlation along certain directions and strong fluctuation along others, as shown in Fig. 2(a). When the reference pixel is located in the homogenous region, it is represented as strong correlation along all directions, as shown in Fig. 2(b). And when the reference pixel is located on the point target, it is represented as strong fluctuation along all directions, as shown in Fig. 2(c). Based on above analyses, a more appropriate background suppression method named multi-direction filtering fusion (MDFF) is proposed in this paper.

### 3.1. Linear Prediction along Eight Directions

The first stage of the proposed MDFF method is estimating the background gray value of each pixel along eight different directions ( $0^\circ, 45^\circ, \dots, 315^\circ$ ) respectively. As shown in Fig. 3, an outer window of



**Figure 2.** Different observed results in three different pixels: (a) the reference pixel is located on an edge, (b) the reference pixel is located in homogeneous area, (c) the reference pixel is located on the point target.

size  $N \times N$  (blue block) and an inner window of size  $M \times M$  (green block) are defined around the central pixel  $(i, j)$ . The red color represents the pixels involved in the calculation. Taking the  $0^\circ$  direction as an example, the predicted background gray value can be represented as Eq. (2).

$$B_1(i, j) = f\left(F\left(i - \frac{M-1}{2} - 1, j\right), F\left(i - \frac{M-1}{2} - 2, j\right), \dots, F\left(i - \frac{N-1}{2}, j\right)\right) \quad (2)$$

where  $F$  is the observed IR image,  $B_1$  the predicted result along  $0^\circ$  direction,  $(i, j)$  the pixel's coordinates, and  $f$  a predicted function. To simplify computation and be suitable for real time processing, the strong correlation between adjacent background pixels is simply assumed as linear relationship, and least square rule is used to predict the gray value. Because the vertical ordinates of the active pixels are all the same, and the horizontal ordinates are evenly spaced, we can simply use one-dimensional variable  $x$  to represent their location relationship. The central pixel  $(i, j)$  is assumed as  $x_0 = 0$ , and the active pixels  $(i - \frac{M-1}{2} - 1, j)$ ,  $(i - \frac{M-1}{2} - 2, j)$ ,  $\dots$ ,  $(i - \frac{N-1}{2}, j)$  can be set as  $x_1 = \frac{M-1}{2} + 1$ ,  $x_2 = \frac{M-1}{2} + 2$ ,  $\dots$ ,  $x_{\frac{N-M}{2}} = \frac{N-1}{2}$  respectively. Another variable  $y$  is used to represent pixel's gray value, so  $y_k = F(i - k, j)$  stand for observed gray values, where  $k = \frac{M-1}{2} + 1, \frac{M-1}{2} + 2, \dots, \frac{N-1}{2}$ , and  $y_0 = B_1(i, j)$  is the result we want to obtain. Then a straight line  $y = ax + b$  is used to fit the observed data, the object is to minimize the error function as described in Eq. (3), and the results are given in Eq. (4).

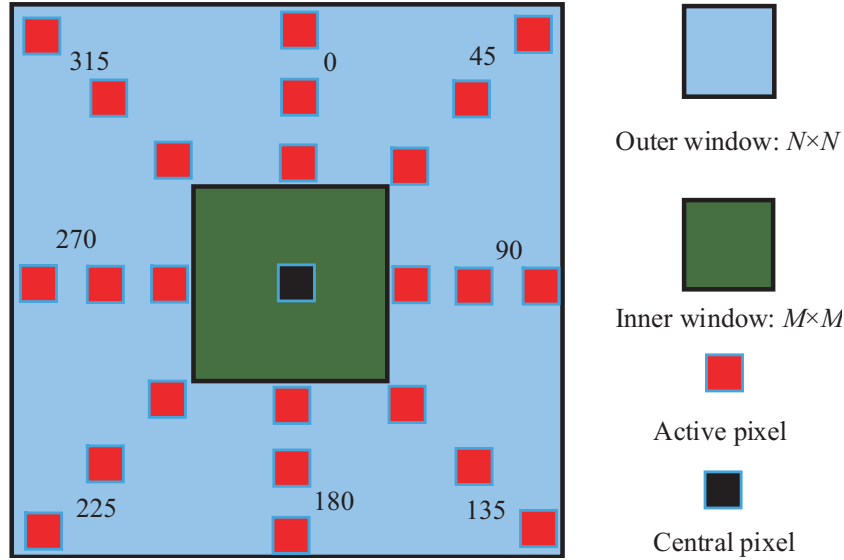
$$E = \sum_i (y_i - ax_i - b)^2 \quad (3)$$

$$\begin{cases} y_0 = b = \frac{\sum y_k - a \sum x_k}{n} \\ a = \frac{n \sum x_k y_k - (\sum x_k)(\sum y_k)}{n \sum x_k^2 - (\sum x_k)^2} \end{cases} \quad (4)$$

### 3.2. Predicted Results Fusion

After obtaining eight predicted values, along different directions for each pixel, the next stage of MDFF is generating the final predicted value by merging the eight values. An image fusion method based on Gaussian weighted sum is proposed in this paper, which is described in Eq. (5).

$$\hat{B}(i, j) = \frac{\sum_{k=1}^8 p_k(i, j) B_k(i, j)}{\sum_{k=1}^8 p_k(i, j)} \quad (5)$$



**Figure 3.** Illustration of background prediction along difference directions.

where  $\hat{B}(i, j)$  is the fusion result,  $B_k(i, j)$  the predicted value along a certain direction, and  $p_k(i, j)$  the fusion weight. It is obvious that the more accurate the predicted value is, the greater the corresponding fusion weight should be. Based on this, the fusion weight is defined as Eq. (6), where  $F(i, j)$  stands for observed gray value.

$$p_k(i, j) = \exp\left(-\frac{(B_k(i, j) - F(i, j))^2}{F(i, j)^2}\right) \quad (6)$$

#### 4. EXPERIMENTS

In this section, the experimental data are firstly described. Then the evaluation and comparison methods are introduced. And next we analyze the influence of parameters on experimental results. Finally, we compare the proposed MDFP algorithm to three methods on several groups of real IR images with six different categories of backgrounds: cirrus cloud, ragged cloud, earth edge, ice, lake and dark background.

##### 4.1. Experimental Data

All the IR background images in the experiments are taken by an onboard IR camera. The image size is normalized to 320 pixels  $\times$  256 pixels, with 8 bit grayscale. Six different categories of backgrounds are chosen as our test data. All the point targets in images are synthesized according to a certain signal-noise ratio (SNR) and a point spread function (PSF). The SNR and the PSF are defined as Eqs. (7) and (8) respectively.

$$\text{SNR} = \frac{I_T - \mu_B}{\sigma} \quad (7)$$

$$h(x, y) = \begin{cases} \frac{1}{2\pi\sigma^2} \int_{x-1/2}^{x+1/2} \int_{y-1/2}^{y+1/2} \exp\left(-\frac{(x-x_0)^2 + (y-y_0)^2}{2\sigma^2}\right) dx dy & (x, y) \in C \\ 0 & \text{others} \end{cases} \quad (8)$$

Equation (7) defines the SNR of one target, where  $I_T$  denotes the target intensity, and  $\mu_B, \sigma$  stand for average intensity and standard deviation of the image. In Eq. (8),  $(x_0, y_0)$  is the target position,

and  $C$  and  $\sigma$  denote the distribution range and concentration degree of the target energy, respectively. SNR of an image is defined as the average SNR of all the targets in the image.

## 4.2. Evaluation and Comparison Methods

To show the advantage of our proposed method in IR background suppression and point target detection (especially under a complex background), we choose two classical methods named Top-hat and Median filter as our baseline methods. In recent years, a new method called accumulated center-surround difference (ACSD) was proposed to improve IR small target detection performance in heavy clutter [15], and it is also chosen as our comparison method.

To compare the background suppression performance of different methods quantitatively, gain of SNR (GSR) and background suppression factor (BSF) are employed and defined as Eq. (9).

$$\begin{cases} \text{GSR} = \frac{\text{SNR}_{OUT}}{\text{SNR}_{IN}} \\ \text{BSF} = \frac{\sigma_{IN}}{\sigma_{OUT}} \end{cases} \quad (9)$$

where  $\text{SNR}_{OUT}$ ,  $\text{SNR}_{IN}$  stand for SNR of residual and original image, respectively, and  $\sigma_{IN}$ ,  $\sigma_{OUT}$  denote the standard deviations of the original and residual images, respectively. It is obvious that the greater the GSR and BSF are, the better the background suppression performance we achieve.

Besides, the receiver operating characteristic (ROC) curves are also employed to evaluate the detection performance of different methods quantitatively. The ROC curve represents the varying relationship of the probability of false alarm and detection, which is defined as Eq. (10).

$$\begin{cases} P_d = \frac{N_{right}}{N_{targets}} \\ P_f = \frac{N_{false}}{N_{total}} \end{cases} \quad (10)$$

where  $N_{right}$  is the number of successfully detected targets,  $N_{targets}$  the number of real targets,  $N_{false}$  the number of false alarms, and  $N_{total}$  the total number of pixels in the image. It is obvious that at the same probability of false alarm, the higher the detection probability is, the better performance we obtain.

## 4.3. Analyses on Effects of Parameters

There are two important parameters of our proposed method which need to be determined in advance: the outer window size  $N$  and inner window size  $M$ . The inner window should be large enough to cover the target which needs to be detected. In this paper, the target size is assumed less than  $3 \text{ pixel} \times 3 \text{ pixels}$  according to aforementioned analyses in Section 2, so  $M$  is fixed at 3. The outer window size should not be less than 7, because at least 2 pixels are needed for background prediction along each direction. A larger outer window size implies that more pixels will be considered for calculation, and the noise effect will be reduced. However, too large an outer window size may lead to false prediction as the correlation between pixels decreases. In this subsection, 4 different window sizes  $7 \times 7$ ,  $9 \times 9$ ,  $11 \times 11$  and  $13 \times 13$  are chosen for experiments on six images with different categories of backgrounds. Ten simulated point targets are randomly added to each image, and GSR and BSF are chosen as objective standard to evaluate the performance of background suppression. We have repeated the experiments for five times, and the average results are recorded as shown in Fig. 4, which suggests that 7 pixel  $\times$  7 pixel is the most reasonable outer window size.

## 4.4. Experimental Results Comparison of Four Methods

In this subsection, we compare our proposed method MDFF to three methods named median filter, top-hat and ACSD on six groups of real IR images with different categories of backgrounds. The parameters of MDFF are set as  $7 \times 7$  for an outer window and  $3 \times 3$  for an inner window, and the parameters of three comparison methods are well set to achieve their best performances. GSR, BSF, and ROC



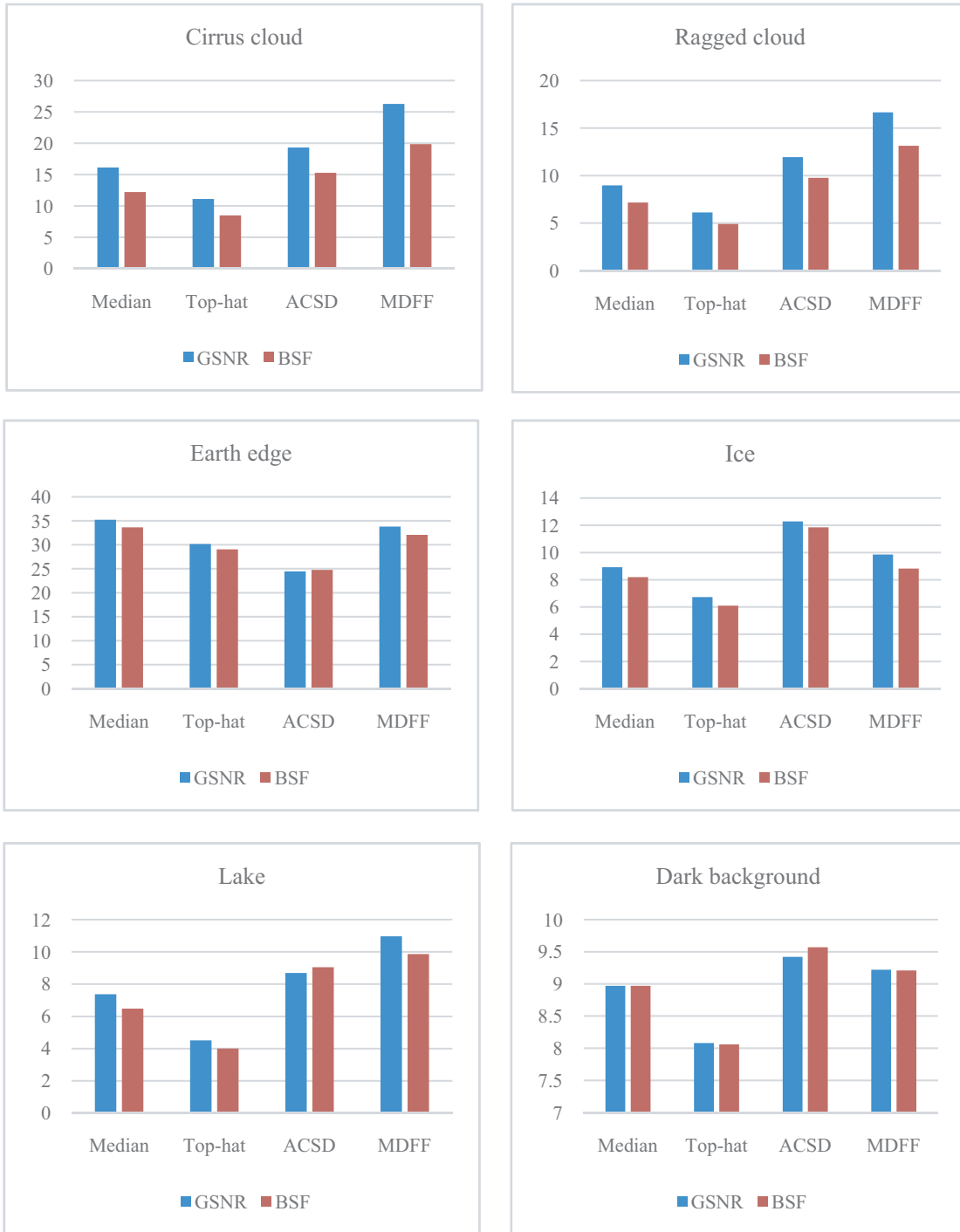
**Figure 4.** Influence of the outer window size on simulation results.

curves are chosen as objective standard to evaluate the performance of background suppression and target detection of all the methods. Besides, the runtime is also employed to verify the efficiency of our proposed method.

Thirty real IR images with six different categories of backgrounds (five for each category) are chosen as our test images. Five simulated point targets are randomly added to each image, the SNR of targets for each category scene is randomly selected within a range, illustrated in Table 1. GSNR and BSF are chosen as objective standard to evaluate the performance of background suppression. We have

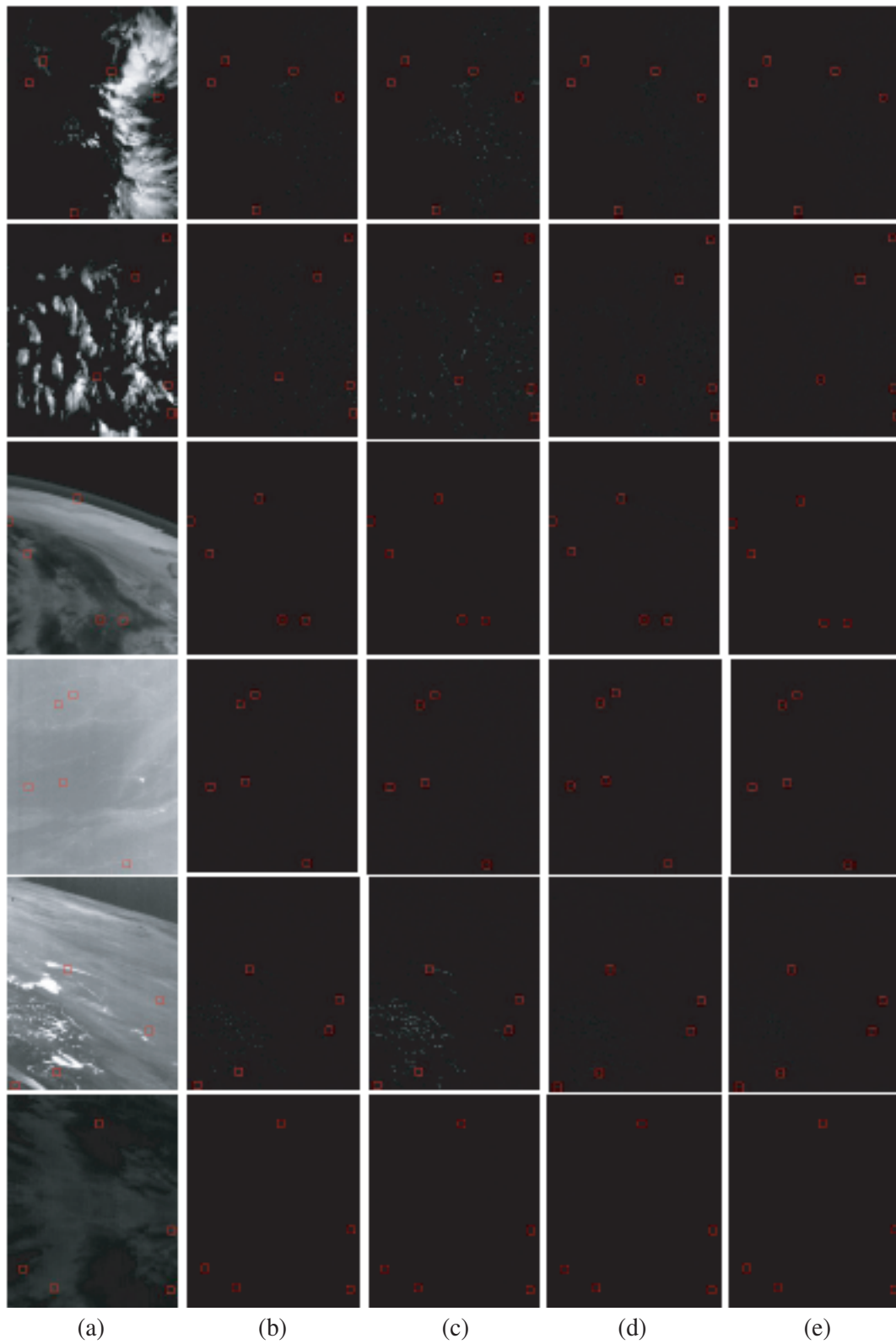
**Table 1.** SNR range of simulated targets for each category scene.

Scenes	Cirrus cloud	Ragged cloud	Earth edge	Ice	Lake	Dark background
Range of SNR	[1, 2]	[1, 2]	[2, 3]	[3, 6]	[2, 3]	[8, 10]

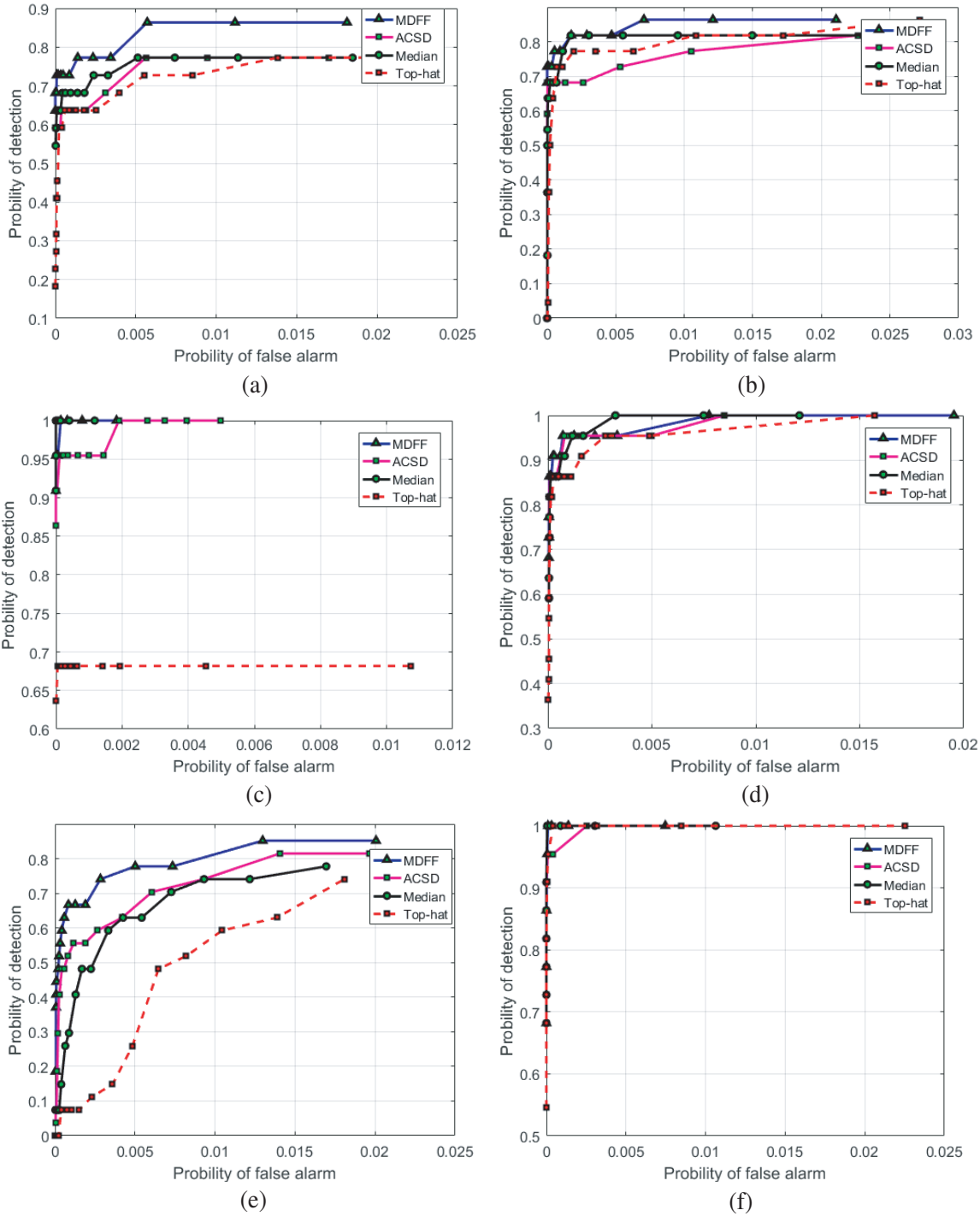


**Figure 5.** Quantitative comparison of 4 methods in 6 different categories of images.





**Figure 6.** Comparison of experimental results by 4 methods, red rectangles contain simulated point targets. (a) Original image, (b) median, (c) top-hat, (d) ACSD, (e) MDFF.



**Figure 7.** ROC curves obtained from IR images with different backgrounds: (a) cirrus cloud, (b) ragged cloud, (c) earth edge, (d) ice, (e) lake, (f) dark ground.

repeated the experiments for five times, and the average results are shown in Fig. 5. Examples of the six categories scenes and the comparison of background suppression results among four methods are shown in Fig. 6, where the red rectangles contain simulated point targets.

From Figs. 5 and 6, we can see that for the images with homogeneous backgrounds such as earth edge, ice and dark background, all of the four methods can achieve good performance on background

suppression. But for the images with heterogeneous backgrounds such as cirrus cloud, ragged cloud and lake, the proposed method MDFF outperforms the other three methods obviously in terms of objective evaluation as shown in Fig. 5 and human vision as shown in Fig. 6.

To verify the detection performance of the proposed method, we take the six images shown in Fig. 6(a) as our test data. Fifty one-pixel synthetic targets are inserted to each image for detection, where the synthetic targets are randomly distributed. The ROC curves of the proposed method MDFF, Median filter, ACSD and Top-hat are shown in Fig. 7. It is demonstrated that for homogeneous backgrounds such as earth edge, ice and dark ground, all the methods can obtain a good detection performance, and there are no much differences among the four methods. However, for the images with heterogeneous backgrounds such as cirrus cloud, ragged cloud and lake, the proposed method MDFF outperforms the other three methods obviously in terms of detection probability.

To verify the effectiveness and real time property of our proposed algorithm, we run the target detection under the same environment (Intel Core i5-6500 at 3.2 GHz, 8-GB Memory) and implement the algorithms in Matlab 2016a. Four different sizes of images ( $320 \times 256$ ,  $500 \times 300$ ,  $800 \times 600$ , and  $1024 \times 1024$ ) are chosen as our test data. We conduct six groups of experiments on different scenes and take the average time as the final results. The comparison results are summarized in Table 2. It is obvious that our proposed method MDFF outperforms the other three methods in terms of efficiency.

**Table 2.** Runtime comparison of four methods/s.

Images size	Median	Top-hat	ACSD	MDFF
$320 \times 256$	0.241848	0.395773	0.577148	0.151661
$500 \times 300$	0.461591	0.773955	1.105268	0.291063
$800 \times 600$	1.450455	2.487889	3.627889	0.919919
$1024 \times 1024$	2.987221	5.002599	8.62599	1.939649

## 5. CONCLUSIONS

In this paper, we propose a novel background suppression method based on multi-direction filtering fusion aiming at the problem of point target detection in space-based IR imaging systems. The proposed method contains two main ideas: 1) the strong correlation between adjacent background pixels is simply assumed as linear relationship to simplify algorithm's calculation, and 2) the background gray value of each pixel is predicted along 8 different directions, which make the predicted results of heterogeneous background, homogeneous background and point targets all different. We conduct several groups of experiments on real IR images with six different categories of backgrounds, and the final experimental results demonstrate that our proposed method MDFF outperforms other methods in terms of efficiency and accuracy.

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