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Small target detection based on accumulated center-surround difference measure

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HIGHLIGHTS

- We propose novel method to detect infrared small targets in heavy clutter.
- The method can distinguish target region and inhomogeneous region.
- The method needs no prior knowledge and no sensitive parameters.

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ABSTRACT

Small target detection is a critical problem in the Infrared Search And Track (IRST) system. Although it has been studied for years, there are some difficulties remained due to the clutter environment such as the cloud edge and the horizontal line. In the homogeneous area such as sky, cloud-inner area and sea surface area, target can easily be detected, but in heterogeneous area which contains cloud edge, sky-sea line the target may be falsely detected. This paper proposes a novel method called accumulated center-surround difference measure to detect infrared small target in heavy clutter. Each pixel's accumulated center-surround difference measure is computed by using sliding window manner. The measure can effectively distinguish target region and heterogeneous region. Experimental results show our method achieves better performance.

1. Introduction

Small target detection is a critical problem in the Infrared Search And Track (IRST) system. Although it has been studied for years [1–5], there are some difficulties remained. The reasons are as follows: first, features such as texture and color are unavailable for small targets when they are far away from the infrared sensor. Second, heterogeneous areas such as cloud edge and sky-sea line may be falsely detected as small targets.

Background estimation based small target detection method is widely studied in recent years [6–9]. These methods detect small targets in the residual image which subtracts the estimation image from original image. The detection performance depends on how well the background estimation image can achieve. The 2-D least mean square (TDLMS) method [6] minimizes the difference between an input image and a background image that is estimated by the weighted average of neighboring pixels. The TopHat method [7] estimates background by a morphological opening operator with structure element.

Existing background suppression methods for single-frame infrared image are mainly based on the filtering methods [10,11]. The LS-SVM [11] method uses filter templates, which can suppress most part of the correlative background but may be easily interfered because of the strong fluctuation of background clutters.

Recently, a small target detection algorithm based on sparse representation has been proposed [12]. They modeled small infrared targets by Gaussian intensity model for dictionary generation, and solved a sparse $l0$-minimization problem at any candidate point of target when a detection window scans over the test image.

The main drawback of conventional filtering based methods for small target detection is they could not guarantee sufficient suppression ability towards those high frequency components belonging to background, such as strong corners and edges. In recent years, a method based on local connectedness constrains [13] was proposed to overcome such problems.

Heterogeneous areas such as cloud edge and sky-sea line make small target detection more difficult. These methods may achieve

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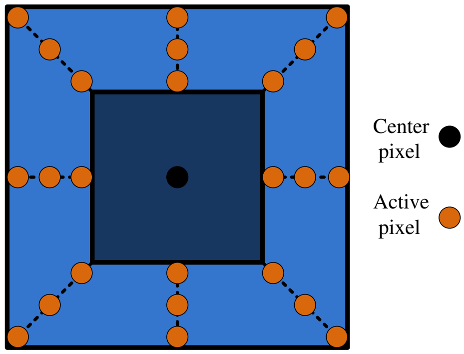

Fig. 1. Illustration of calculating accumulated center-surround difference measure.

good results on simple background, but not on heavy clutter background. The main reason is they cannot distinguish small targets from heavy clutter effectively. We propose a novel method called accumulated center-surround difference measure to detect infrared small targets in heavy clutter. When compared with TDLMS [6], TopHat [7], LS-SVM [11], SP [12], LCC [13], our method achieve better performance, especially in the heterogeneous area.

2. The proposed method

We propose a single-frame infrared small target detection method. We calculate each pixel's accumulated center-surround difference measure. A measure map is obtained, which indicates the probability of a pixel belonging to target regions. We then can detect small target by implementing a proper threshold.

Generally, the IR image model can be formulated as:

$$f(x,y) = f_T(x,y) + f_B(x,y) + n(x,y) \tag{1}$$

where f, f_T, f_B, n and (x,y) are IR image, target image, background image, random noise and pixel's coordinate, respectively. n is assumed to follow Gaussian distribution with mean 0 and variance σ^2 [8].

According to (1), IR image can be divided into 3 different components: target region, homogeneous region and inhomogeneous region. Homogeneous region usually locates inside the cloud, the sea surface and the sky, whereas inhomogeneous region may appear in the sky-sea line and cloud edge. Conventional background estimation method may regard inhomogeneous region as target mistakenly, because features of inhomogeneous and target region are highly similar. Based on the observation above, we propose accumulated center-surround difference measure to distinguish target region and inhomogeneous region.

Fig. 1 describes the proposed accumulated center-surround difference measure for a certain pixel (i,j) . An outer window of the size $N*N$ and an inner window of the size $M*M$ are defined around the reference pixel. Along 8 orientations (i.e. $0^\circ, 45^\circ, \ldots, 270^\circ, 315^\circ$), the accumulated difference measurement is carried out respectively.

For example, along 0° orientation the accumulated center-surround difference is:

$$\sum_{\substack{ii=i \\ j+M/2\leqslant jj\leqslant j+N/2}} \tau[(ii,jj),(i,j)] * |l(ii,jj) - l(i,j)| \tag{2}$$

where $\tau(\cdot)$ can be certain monotone increasing function. In this paper,

$$\tau[(ii,jj),(i,j)] = 1 - e^{-c*\|(ii,jj)-(i,j)\|_2^2} \tag{3}$$

(i,j) is the coordinate of the central pixel (i.e. the reference pixel), and (ii,jj) is active pixel's coordinate. $l(\cdot)$ represents pixel's intensity. Here M is a constant smaller than N. Accumulated center-surround difference measure can distinguish target region and inhomogeneous region. Fig. 2 represents results of accumulated

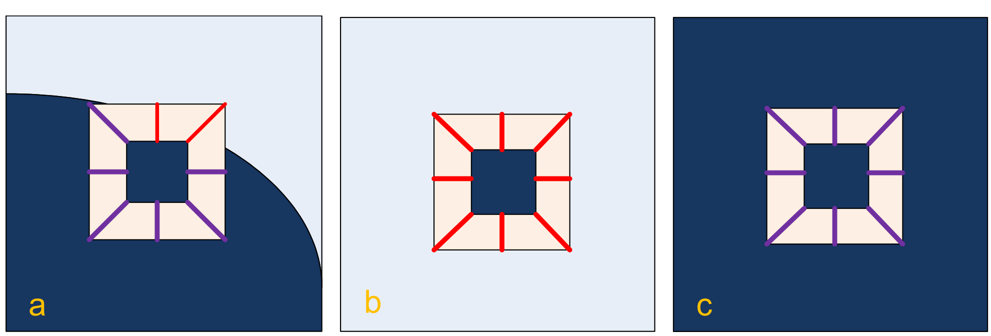

Fig. 2. Results of accumulated center-surround difference in 3 different pixels.

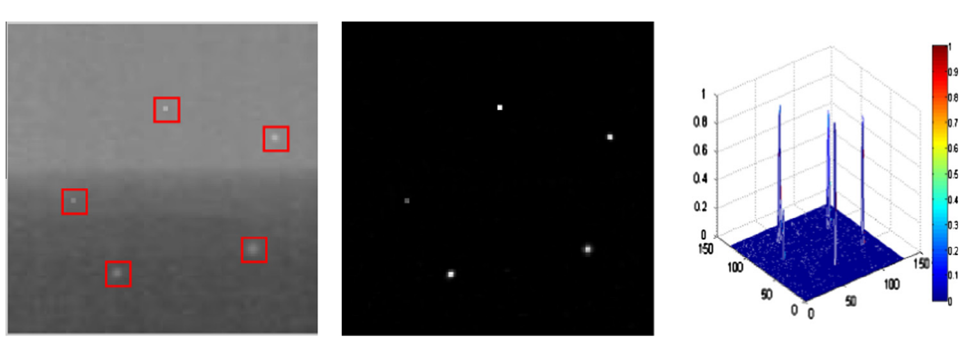

Fig. 3. An IR image and its accumulated center-surround difference measure. From left to right: original image, accumulated center-surround difference measure and its 3d-plot.

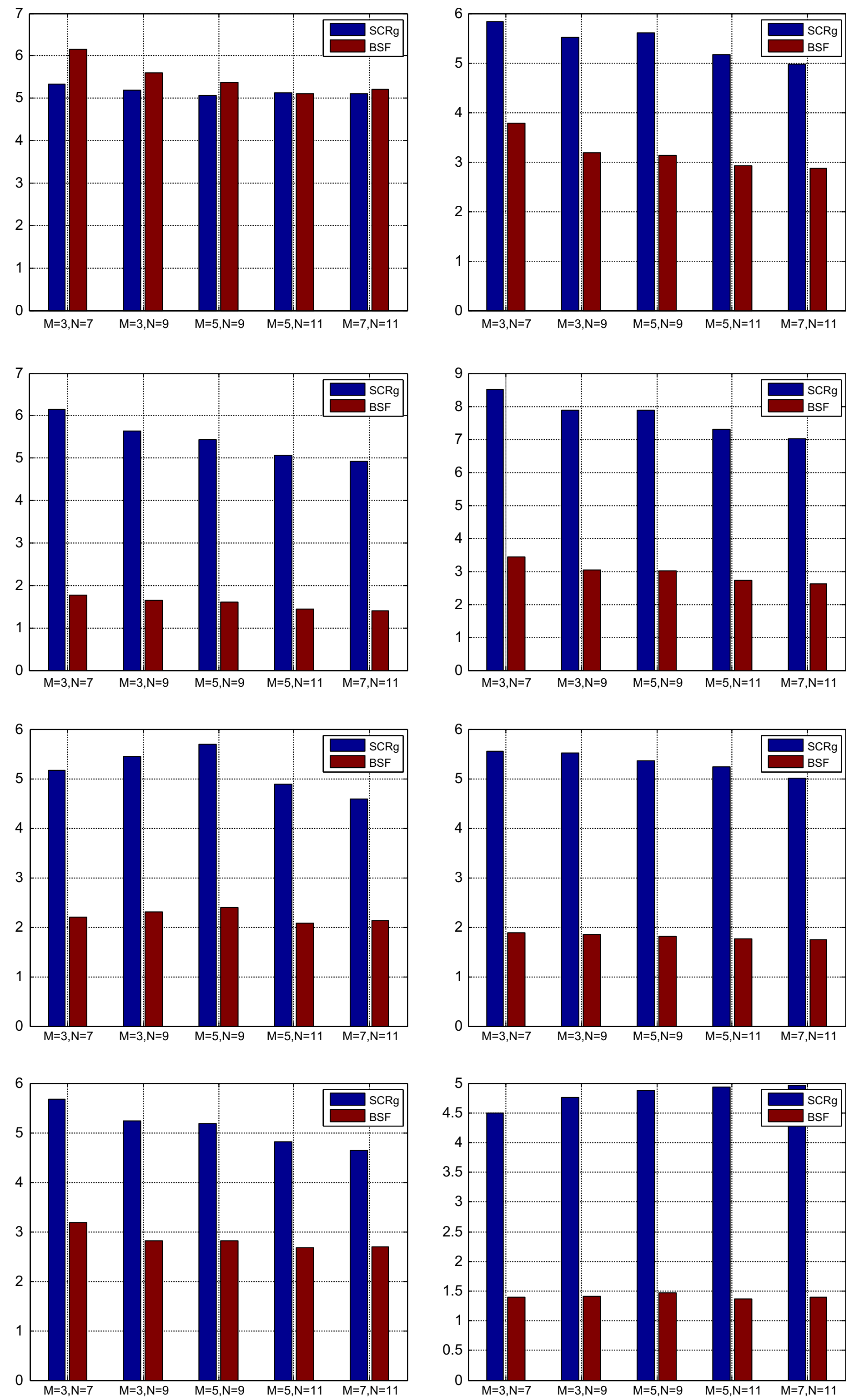

Fig. 4. SCRg and BSF of 5 groups of parameters that configurations are $M = 3,\ N = 7;\ M = 3,\ N = 9;\ M = 5,\ N = 9;\ M = 5,\ N = 11;\ M = 7,\ N = 11$ in 8 different categories of images.

center-surround difference measure on 3 different pixels. From left to right, they are inhomogeneous region, target region and homogenous region, respectively. Blue color represents high intensity region, white color represents low intensity region, purple color represents a small accumulated value and red color represents a large accumulated value. When the window is located in the inhomogeneous region, e.g. cloud edge, the accumulated center-surround differences along certain orientations are large, as shown in Fig. 2(a). When center pixel is on the target region, the accumulated center-surround differences along all orientations are larger, as described in Fig. 2(b). When center pixel is on the homogenous region, the accumulated center-surround differences along all orientations are small, as described in Fig. 2(c).

8-orientation accumulated center-surround differences are defined as $ACSD_0$–$ACSD_{315}$. The subscript stands of the angle of the orientation. Thus, we define accumulated center-surround difference measure as:

$$min(ACSD_0, ACSD_{45}, \ldots, ACSD_{315}) \tag{4}$$

As we can see, 8-orientation results in different pixels contain different distinguishing features. The final accumulated center-surround difference measure is the minimum of the results along all orientations. Thus, accumulated center-surround difference measure is large when center pixel is on target region; is small when center pixel is on inhomogeneous region or homogeneous region. Fig. 3 represents an IR image and its accumulated center-surround difference measure. From left to right, they are original image, accumulated center-surround difference measure and its 3d-plot.

We apply accumulated center-surround difference measure on IR image using sliding window manner, we can obtain a measure map $m(i,j)$ of the same size of original image.

We normalize the value $m(i,j)$ to $[0,1]$. A large $m(i,j)$ value indicates that the pixel at (i,j) very likely belongs to target region.

3. Experiments

In this section, we firstly introduce the evaluation method and the methods for comparison in this paper. Then we perform experiments to demonstrate the different effects when using different parameters of the proposed method. Finally, we compare the proposed method with the baseline methods.

3.1. Evaluation and comparison methods

The most important metrics of evaluating the detection performance are ROC curve (receiver operating characteristic curves). The ROC curve represents the varying relationship of the detection probability and false alarm rate. This curve can provide a quantitative comparison of the detection performance. Detection probability is defined as the ratio of the number of detected pixels to the number of real target pixels. False alarm rate defined as the ratio of the number of false alarms to the total number of pixels in the whole image. At the same false alarm rate, the higher the detection probability is, the better the performance of this algorithm is.

To compare the performance of methods quantitatively, signal clutter ratio gain (SCRg) and background suppression factor (BSF) are employed and defined as the follows [14]:

$$SCR = \frac{|I_t - \mu_b|}{\sigma_c}, \quad SCRg = \frac{SCR_{out}}{SCR_{in}}, \quad BSF = \frac{\sigma_{in}}{\sigma_{out}} \tag{5}$$

where I_t is the signal amplitude, μ_b and σ_c are the average intensity and standard deviation of the pixels in the neighboring area around a reference location (excluding the target), and σ_{in} and σ_{out} are the background standard deviations of the original image and the measure image, respectively.

We choose the TopHat [7] and TDLMS [6] filtering method as two baseline methods. Moveover, LS-SVM [11] filtering method is also chosen as the comparison method in this paper since the method is well studied and has a good performance. In recent years, two new methods based on sparse representation [12] and local connectedness constrains [13] were proposed to overcome the constrain when dealing with heavy clutter. They are chosen as the comparison methods.

The images chosen in the experiments contain more than one hundred targets and eight different categories of clutter environments. We take these images as test data.

3.2. Analysis on effects of parameters

The proposed method have three key parameters: M, N and c: M determines the size of inner window. The inner window should be big enough to cover the reference object. N determines the size of outer window, and must be larger than M. A larger N implies that more pixels are considered for calculating accumulated center-surround difference and vice versa. We have to make a tradeoff in this issue: using larger N is robust to outlier and noise contained in pixels. However, correlation between pixels decreases when using a larger N. This will make a false detection in non-target region. A restriction should be posed on M and N: $N - M$ is set as 4 or 6 in our experiments. It is a tradeoff between large N and small N. c is

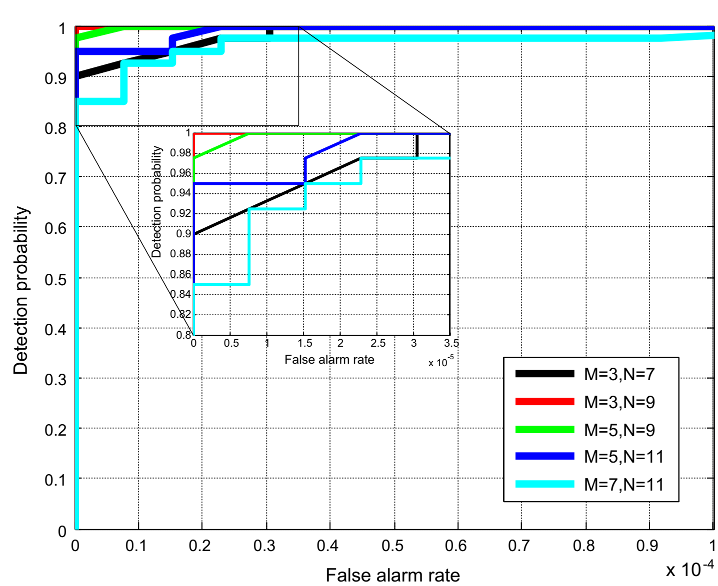

Fig. 5. ROC curve of 5 groups of parameters that configurations are $M = 3,\ N = 7;\ M = 3,\ N = 9;\ M = 5,\ N = 9;\ M = 5,\ N = 11;\ M = 7,\ N = 11$ in test data.

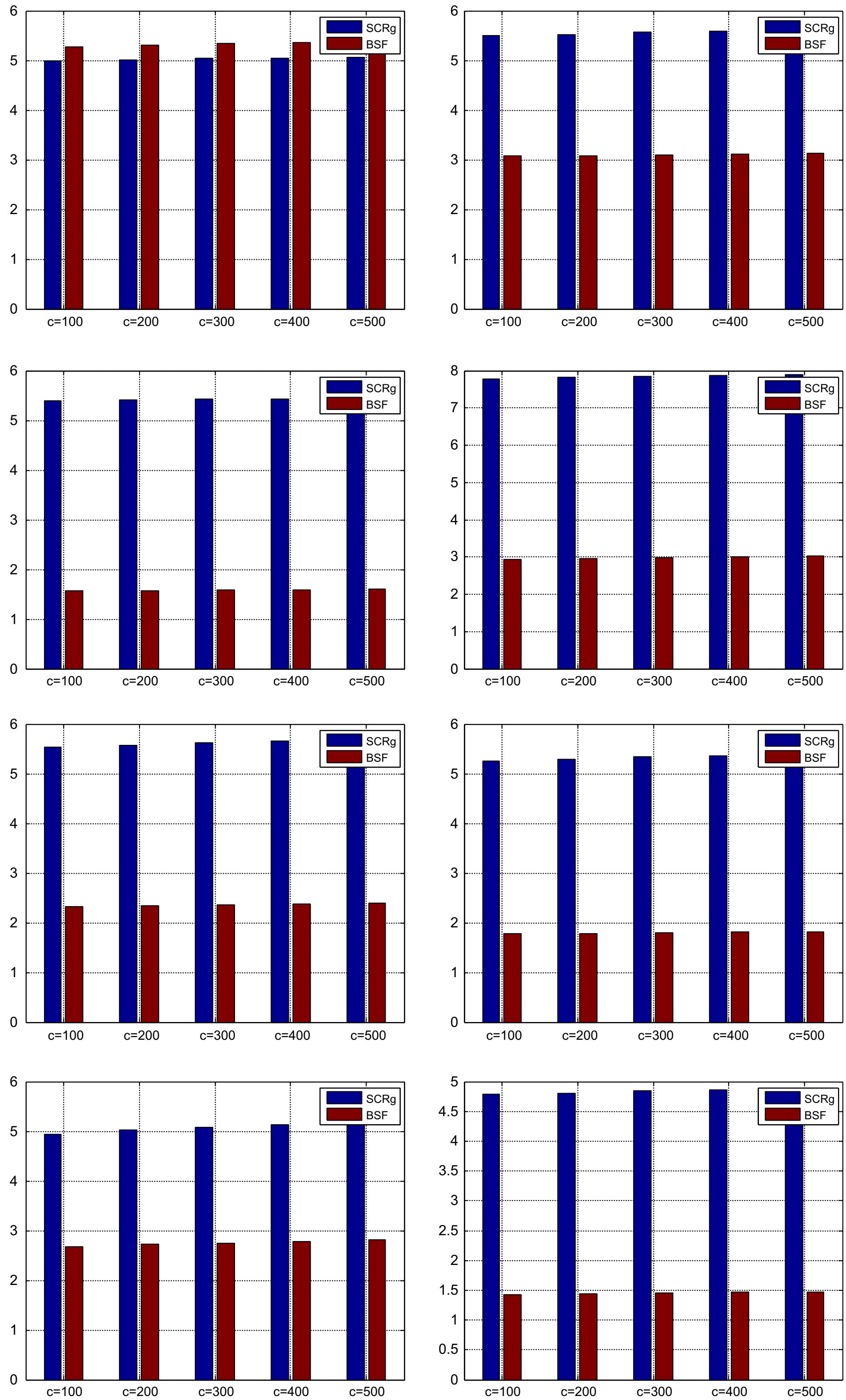

Fig. 6. SCRg and BSF of 5 groups of parameters that configurations are $c = 100,\ c = 200,\ c = 300,\ c = 400,\ c = 500$ in 8 different categories of images.

the parameter that controls accumulated weights of different pixels. Larger value makes difference between weights bigger, and vice versa.

We carry out two experiments to show the effects of the three parameters. In the first experiment, we fix c as 500, and choose 5 groups of M and N to test the proposed method. The evaluation results are shown in Figs. 4 and 5.

From Fig. 4, we can see that BSF in different categories is different from each other and SCRg has only slight difference. In each categories, SCRg and BSF change not significantly.

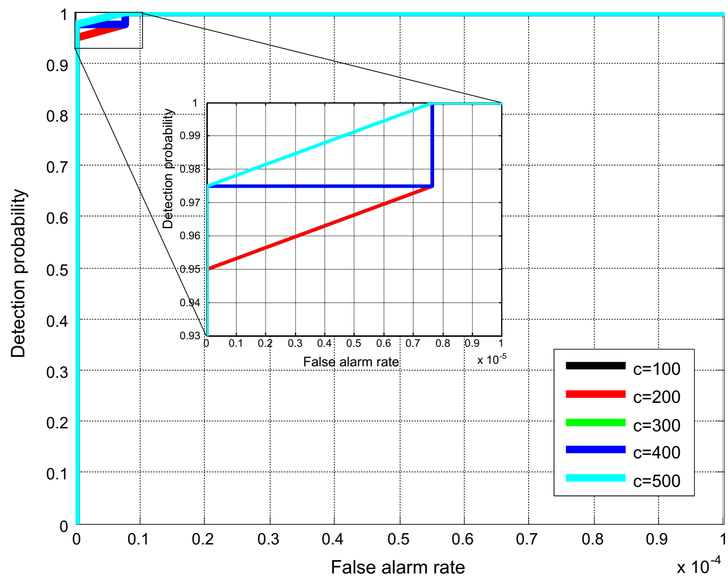

Fig. 7. ROC curve of 5 groups of parameters that configurations are $c = 100,\ c = 200,\ c = 300,\ c = 400,\ c = 500$ in test data.

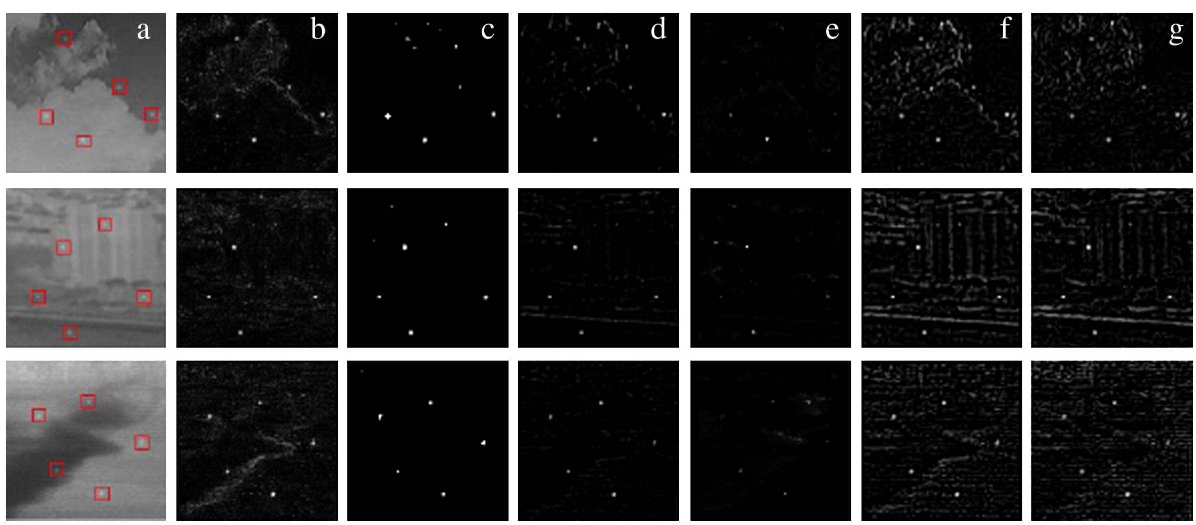

Fig. 8. Comparison between 6 methods. Red rectangles contain ground truths of small targets. (a) Original image, (b) ACSDM (our method), (c) LCC, (d) LS-SVM, (e) SR, (f) TDLMS, and (g) TopHat.

From Fig. 5, we can see that ROC curve is influenced by both M and N. From the results, we can see that for M smaller than the size of the object, a larger N is required to achieve good performance. For M equal to or larger than the size of object, smaller N is helpful.

In the second experiment, we fix $M = 5,\ N = 9$, and choose 5 groups of c to test the proposed method, respectively. The evaluation results are shown in Figs. 6 and 7.

From Fig. 6, in different categories, SCRg change slowly with different groups of parameters. But BSF have clear differences. It implies that different clutter background causes different difficulty degree of background suppression. For example, heterogeneous background is difficult to achieve high BSF.

From Fig. 7, we can see that ROC curve only shows minor difference when using different parameters. Large c makes a better performance.

3.3. Comparison to baseline methods

Fig. 8 gives comparisons between the proposed method with parameter configuration of $M = 5,\ N = 9,\ c = 500$ and the baseline methods TopHat [7], TDLMS [6], LS-SVM [11], SR [12], LCC [13] whose parameters are well set to achieve their best performances in test data. We can see that our method highlights target region, meanwhile suppresses clutters in background.

To compare the performance of these methods quantitatively, ROC curve, SCRg and BSF were employed. For LCC could directly detect small targets from original image, its decision map is a binary image. We choose SCRg and BSF to evaluate the comparison performance between the propose method and the rest of 4 methods, shown in Figs. 9 and 10.

From Figs. 9 and 10, we can see that although our method is not the best on SCRg and BSF but outperforms all the other methods

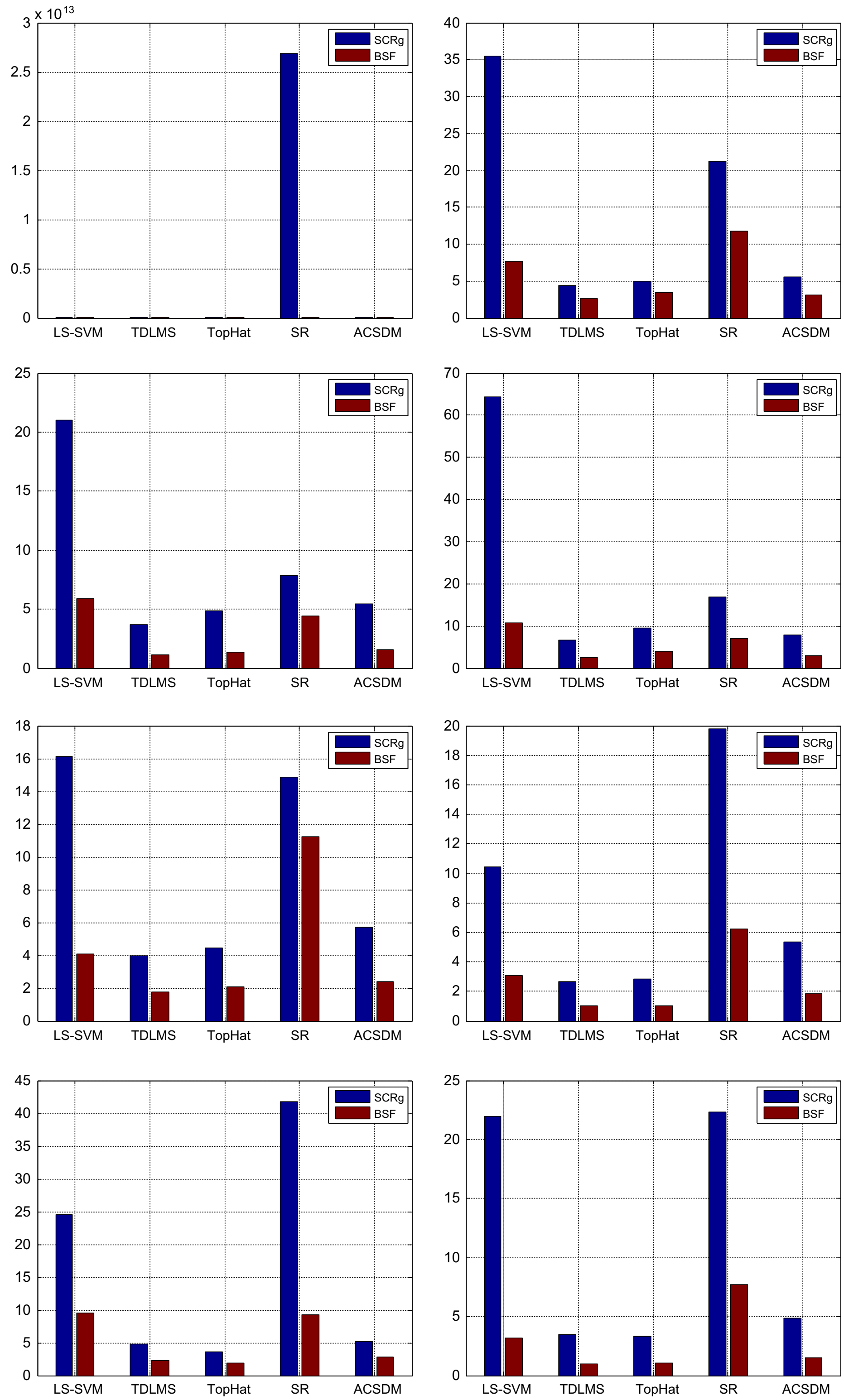

Fig. 9. SCRg and BSF of 5 methods in 8 different categories of images.

according to ROC curve. LS-SVM and SR could achieve high SCRg and BSF but they may suppress target area which causes high miss alarm.

For comparison of method complexity, 6 algorithms are implemented using MATLAB. The algorithms run on 2.4 GHz CPU with 2G RAM, the results are shown in Table 1. In our experiment, all

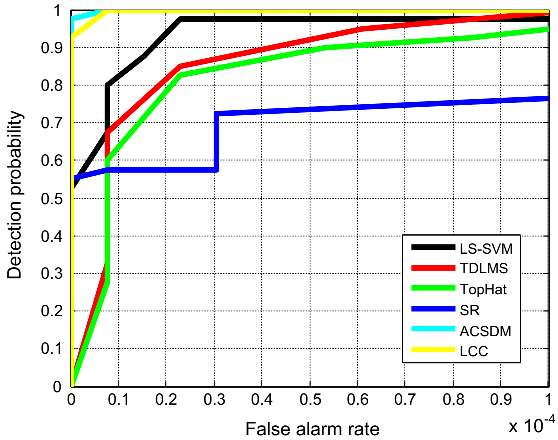

Fig. 10. ROC curve of 6 methods in test data.

Table 1
Comparison of computation time.

Method	LCC	ACSDM	SR	LS-SVM	TDLMS	TopHat
Computation time (s)	1.0139	0.3896	53.6898	0.0477	0.1234	0.0465

algorithms are performed on $128 * 128$ image, the average time per image is adopted.

4. Conclusions

In this paper, we propose a new small target detection algorithm based on accumulated center-surround difference measure. Accumulated center-surround difference measure calculates a measure map to indicate the probability that a pixel belongs to target region. The experimental results show our method outperforms other methods.

Conflict of interest

There is no conflict of interest among authors.

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References

[1] H. Deng, J. Liu, Infrared small target detection based on the self-information map, Infrared Phys Technol 54 (2) (2011) 100–107.
[2] T.-W. Bae, Small target detection using bilateral filter and temporal cross product in infrared images, Infrared Phys Technol 54 (5) (2011) 403–411.
[3] S.D. Deshpande, H.E. Meng, R. Venkateswarlu, P. Chan, Max-mean and max-median filters for detection of small targets, in: SPIE's International Symposium on Optical Science, Engineering, and Instrumentation, International Society for Optics and Photonics, 1999, pp. 74–83.
[4] X. Dong, X. Huang, Y. Zheng, L. Shen, S. Bai, Infrared dim and small target detecting and tracking method inspired by human visual system, Infrared Phys Technol 62 (2014) 100–109.
[5] R. Liu, Y. Lu, C. Gong, Y. Liu, Infrared point target detection with improved template matching, Infrared Phys Technol 55 (4) (2012) 380–387.
[6] M.M. Hadhoud, D.W. Thomas, The two-dimensional adaptive LMS (TDLMS) algorithm, IEEE Trans Circ Syst 35 (5) (1988) 485–494.
[7] X. Bai, F. Zhou, Analysis of new top-hat transformation and the application for infrared dim small target detection, Pattern Recognit. 43 (6) (2010) 2145–2156.
[8] F. Zhao, H. Lu, Z. Zhang, S. Xiao, Complex background suppression based on fusion of morphological open filter and nucleus similar pixels bilateral filter, Infrared Phys. Technol. 55 (6) (2012) 454–461.
[9] Y. Zhao, H. Pan, C. Du, Y. Peng, Y. Zheng, Bilateral two-dimensional least mean square filter for infrared small target detection, Infrared Phys. Technol. 65 (2014) 17–23.
[10] L. Yang, J. Yang, K. Yang, Adaptive detection for infrared small target under sea-sky complex background, Electron. Lett. 40 (17) (2004) 1083–1085.
[11] P. Wang, J. Tian, C.Q. Gao, Infrared small target detection using directional highpass filters based on LS-SVM, Electron. Lett. 45 (3) (2009) 156–158.
[12] J. Zhao, Z. Tang, J. Yang, E. Liu, Infrared small target detection using sparse representation, J. Syst. Eng. Electron. 22 (6) (2011) 897–904.
[13] K. Fu, K. Xie, C. Gong, I.Y. Gu, J. Yang, Effective small dim target detection by local connectedness constraint, in: IEEE Int'l. Conf. ASSP (ICASSP 2014), 2014.
[14] B. Zhang, T. Zhang, Z. Cao, K. Zhang, Fast new small-target detection algorithm based on a modified partial differential equation in infrared clutter, Opt. Eng. 46 (10) (2007) 106401–106402.