Infrared Physics & Technology 55 (2012) 403–408

Contents lists available at SciVerse ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

An improved infrared dim and small target detection algorithm based on the contrast mechanism of human visual system

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HIGHLIGHTS

- ▶ A dim and small target detection approach is based on the contrast mechanism of HVS.
- ▶ LoG filter suppresses the background and enhances the target simultaneously.
- ▶ Morphological processing further removes the residual background clutter and noise.
- ▶ The algorithm proposed yields high detection rate and low false alarm rate.

ARTICLE INFO

Article history:
Received 27 July 2011
Available online 15 June 2012

Keywords:
Small target detection
Human visual system contrast mechanism
LoG filter
Morphological processing

ABSTRACT

To achieve higher detection rate and lower false alarm rate in dim and small target detection, this paper proposed an improved algorithm based on the contrast mechanism of human visual system (HVS) for infrared small target detection in an image with complicated background. According to the contrast mechanism of HVS, Laplacian of Gaussian (LoG) filter is exploited to deal with the input image, which can not only suppress the background noise and clutter but also enhances the target intensity significantly. As a result it increases the contrast ratio between target and background. To further eliminate residual clutter, we process the filtered image with morphological method in all directions. True target is finally obtained by applying local thresholding segmentation to the pre-processed image. Experimental results demonstrate its superior and reliable detection performance by high detection rate and low false alarm rate.

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1. Introduction

Infrared imaging technology has found wide applications in military. As an important technique in infrared searching and tracking, precision guidance, pre-warning, etc. infrared dim and small target detection has received a lot of attentions [1–5].

Existing detection algorithms for infrared small targets can be categorized into two classes: individual frame detection and sequence detection. Small target detection in a single infrared image frame is of great importance due to the nature of early-warning. Median filter [6,7], high-pass filter [8], matched filter [9], as well as algorithms based on Bayes estimation [10] and maximum likelihood estimation [11], are widely used in single frame detection. However, median filter is ineffective when the image is heavily cluttered; high-pass filter works well only for point target detection in images with homogeneous background; matched filter can only detect targets that are relatively large and bright enough; Bayes estimation and maximum likelihood estimation methods are applied with huge computational cost. Based on the contrast mechanism of human visual system, some small target detection methods only focus on the reduction of background noise and clutter, such as median filter [6,7], least mean square filter [12,13], mean subtraction filter [14] and Max-Mean/Max-Median filter [15,16]. Sungho Kim et al. [17] proposed a novel HVS contrast mechanism based detecting algorithm, which is capable of increasing target intensity as well as suppressing background clutter and noise. Although their method is more effective than those traditional detecting algorithms, when it comes to images with heavily cluttered background, their detection results are not satisfying. Thus an improved algorithm is proposed in this paper. We make use of Kim's LoG filter to increase image contrast. Then based on the fact that small target energy scatters in all direction, namely it lacks directivity information [18], morphological method is employed to deal with the filtered image in all directions, which ensures that target can be easily distinguished from background. In order to obtain true targets, local thresholding is utilized to segment the pre-processed image considering the characteristic that

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http://dx.doi.org/10.1016/j.infrared.2012.06.001

a target is the brightest among its local domain. Experimental results indicate the effectiveness of the strategy proposed in this paper.

The rest of the paper is organized as follows. In Section 2, we introduce the concept of HVS contrast mechanism. In Section 3, an improved strategy based on HVS contrast mechanism is put forward and described in details. Section 4 presents experimental results obtained by applying our algorithm, Kim's algorithm [17], Top-hat and Max-Mean methods to infrared imagery, respectively. Finally, some concluding remarks are given in Section 5.

2. Contrast mechanism of HVS

Given four images as shown in Fig. 1, where each square target is of the same intensity but accompanied with intensity-varied backgrounds, HVS feels that the target with darker background is brighter and the target with brighter background is darker.

What can be further deduced from this are [19]:

(1) When targets with different intensity are set in backgrounds which are also of different intensity, HVS perceives target brightness according to the contrast between target and background.
(2) HVS considers that the brightness of two targets approximate if they have similar contrast.

In other words, it is the contrast between the target and background rather than the intensity of targets that plays an important role in HVS perception of visual signal and the reorganization of the target from its background later. Scientists draw a conclusion from neuro-physiological researches that the response of ganglion cells to contrast is linear to contrast and that contrast is the most important quantity in the streams of HVS [17].

Contrast means the difference between target intensity and background intensity, and it is usually defined as follows:

$$C_1 = (g_t - g_b)/(g_t + g_b) \tag{1}$$

or

$$C_2 = (g_t - g_b)/g_b \tag{2}$$

where g_t and g_b are the intensity of target and background respectively.

What needs to be considered is that the definition of contrast given above only applies to local area of image instead of the entire image.

3. An improved dim target detection algorithm based on the contrast mechanism of HVS

Sungho Kim proposed a small target detection method based on the contrast mechanism of HVS [17]. Experimental results show the effectiveness of Kim's strategy, but this method will lead to false alarms when it comes to infrared image with complicated background. This drives us to modify the algorithm. Fig. 2 depicts the processing flow of our algorithm. The improved method consists of three parts: LoG filtration, morphological processing and local thresholding segmentation.

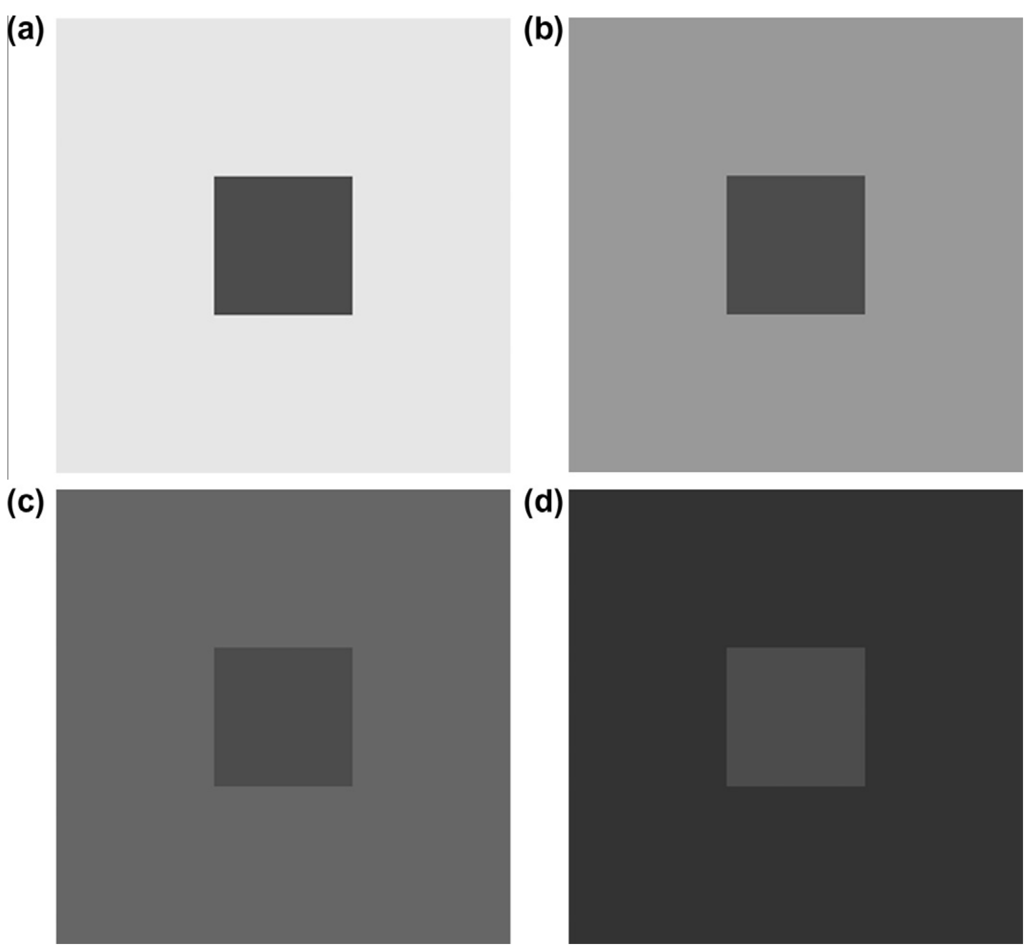

Fig. 1. The same target in different backgrounds.

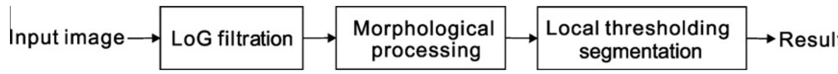

Fig. 2. The outline of the proposed algorithm.

3.1. LoG filtration

Distant targets can be blurred due to atmospheric refraction, dispersion, optical defocusing, detector tilt, lens aberration, diffraction and deformation of mirror. These effects have been modeled as point spread function [20]. Therefore, Sungho Kim et al. put forward a parametric model of point spread function defined as Eq. (3) for small target detection [17].

$$T(x,y|x_c,y_c,s) = I_P \cdot \exp\{[(x-x_c)^2 + (y-y_c)^2]/(2*s^2)\} \quad (3)$$

where (x_c, y_c) is the position of target center pixel, s is the scale parameter in Gaussian kernel function, I_P is defined as the peak intensity illustrated in Fig. 2a.

2D Gaussian function has circular symmetry, namely Gaussian filter smooth signal identically in all directions. In general, it's hard to decide which direction needs more smoothing than others, but the circular symmetry ensures that the filter is not partial to any orientation. In addition, Gaussian function is a single-valued function, which means that it replaces a given pixel with the weighted average of its neighborhood, and the weighting reduces with the increasing of distance between the center pixel and its neighbor. The property is of the essence, because the image can avoid being over-smoothed with the weighting.

Eq. (4) is the 2D Laplacian transformation of Gaussian kernel function shown in Eq. (3). Processing an input image with Eq. (4) by means of convolution, we can get the different intensity between target and background ($|I_t - I_b|$). As shown in Fig. 2b, on-center coefficient (+) is used to estimate the target intensity, while off-center coefficient (−) is for background intensity.

$$LoG(x,y,s) = (1/\pi s^4) * [1-(x^2+y^2)/(2*s^2)] * \exp[(x^2+y^2)/(2*s^2)] \quad (4)$$

Fig. 3 demonstrates that LoG filter not only suppresses noise and clutter in the background but also intensifies the target, resulting in a significant increment of contrast, which is closely related to the contrast mechanism of HVS. As comparison, conventional filters [6,7,12–16] merely put emphasis on background suppression.

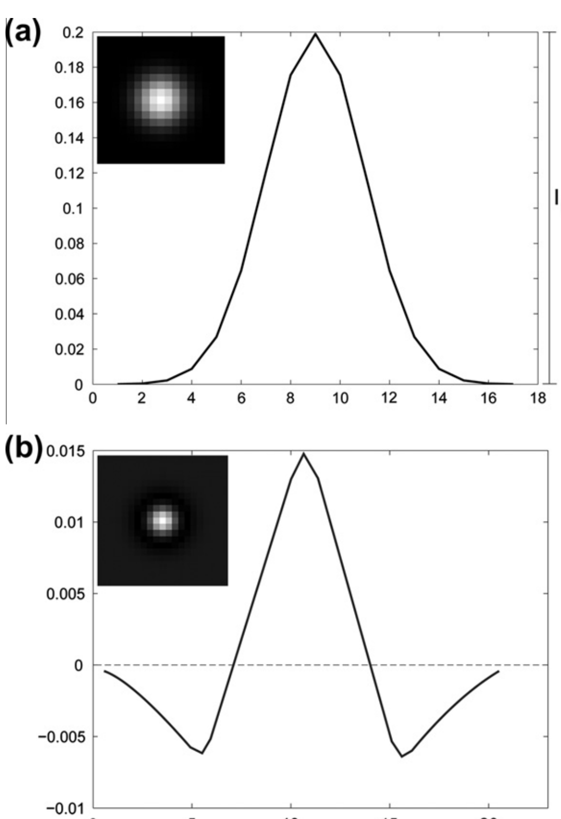

Fig. 3. LoG filtration: (a) Parametric target model. (b) Laplacian of Gaussian for target filtering.

3.2. Morphological processing

Due to the long distance between imaging system and target, small target usually occupies only a few pixels. And there is no structure information such as shape and texture. Additionally, target energy scatters in all directions with point spread characteristic, which is shown in Fig. 4. Consequently, small target is not sensitive to direction. So we exploit morphological method to deal

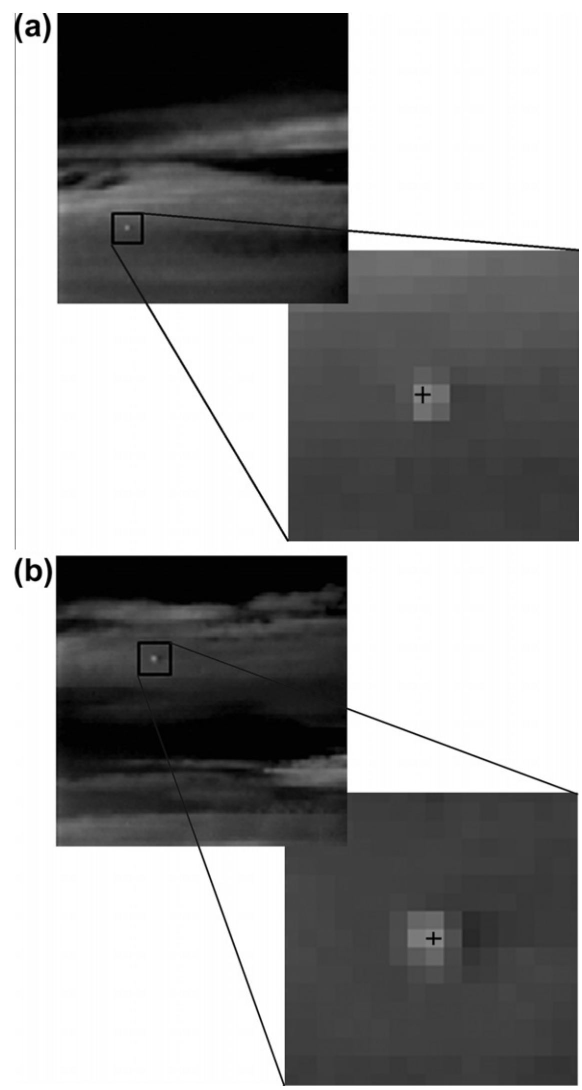

Fig. 4. Target in infrared images.

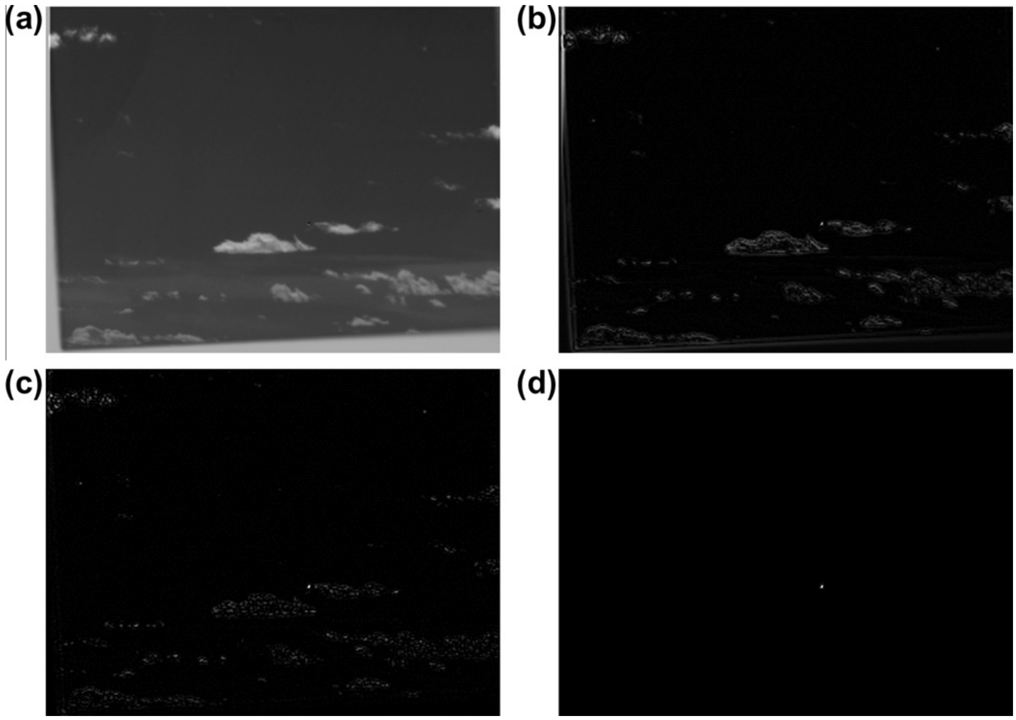

Fig. 5. Process of small target detection: (a) Input image. (b) Image after LoG filtration. (c) Image after morphological processing. (d) Detection result.

with the LoG-filtered image in each direction in order to further eliminate residual clutter and noise.

In Eq. (5), the input image is convolved with LoG function defined in Eq. (4), as a result, the filtered image with enhanced target and suppressed background is obtained, and then we process it by utilizing morphological linear erosive structural element in each direction as depicted in Eq. (6).

$$h = |LoG(x,y,s) * I(x,y)| \tag{5}$$

$$\begin{aligned} h_1 &= h\Theta B_1 = \{Z|(B_1)_Z \cap I^c \neq \emptyset\} \\ h_2 &= h\Theta B_2 = \{Z|(B_2)_Z \cap I^c \neq \emptyset\} \\ h_3 &= h\Theta B_3 = \{Z|(B_3)_Z \cap I^c \neq \emptyset\} \\ &\vdots \\ h_n &= h\Theta B_n = \{Z|(B_n)_Z \cap I^c \neq \emptyset\} \\ &\vdots \end{aligned} \tag{6}$$

where $\emptyset$ is empty set, $B_1, B_2, \ldots, B_n, \ldots$ is structuring element in each direction respectively.

These structural operators enable us to erode clutter with corresponding directivities. And the best corrosion result is selected as the final morphological filtration result according to Eq. (7). Therefore, the majority of residual clutter and remained false targets are removed in the final filtered image.

$$I(x,y) = \min(h_1(x,y), h_2(x,y), \ldots h_n(x,y), \ldots) \tag{7}$$

3.3. Local thresholding segmentation

Infrared imaging technology is a wavelength conversion technology transforming infrared radiation into visible light. Due to the direct proportional relationship between object infrared radiation and detected image intensity, the infrared image intensity increases as object temperature rises. Usually a small target has a higher temperature than the background does. With background suppressed and target enhanced by the above processing, small target has the maximum intensity within its local region in an image. Given that, this paper applies local thresholding segmentation to detect true target. Two steps are designed to accomplish this:

Step 1: In order to eliminate false targets, a threshold is defined as Eq. (8).

$$Thr = m \times \max(I(x,y)), \quad m \in (0,1) \tag{8}$$

in which, m is a coefficient related to threshold, and $I(x,y)$ is the preprocessed image obtained.

Table 1
Contrast of original image and image processed.

Frame	C_{in}	C_{out}
1	0.0279	0.8970
10	0.0334	0.8898
19	0.0298	0.8781
28	0.0354	0.9004
37	0.0297	0.8702
46	0.0360	0.8946
55	0.0315	0.8725
64	0.0307	0.8810
73	0.0278	0.8853
82	0.0293	0.8890
90	0.0285	0.8801

Table 2
The detection rate of different detection methods for Fig. 6a1–a4.

Image	Method			
	Our method (%)	Kim's method [17] (%)	Top-hat (%)	Max-Mean (%)
Fig. 6a1	100	0	0	0
Fig. 6a2	100	100	100	100
Fig. 6a3	100	100	100	100
Fig. 6a4	100	100	100	100

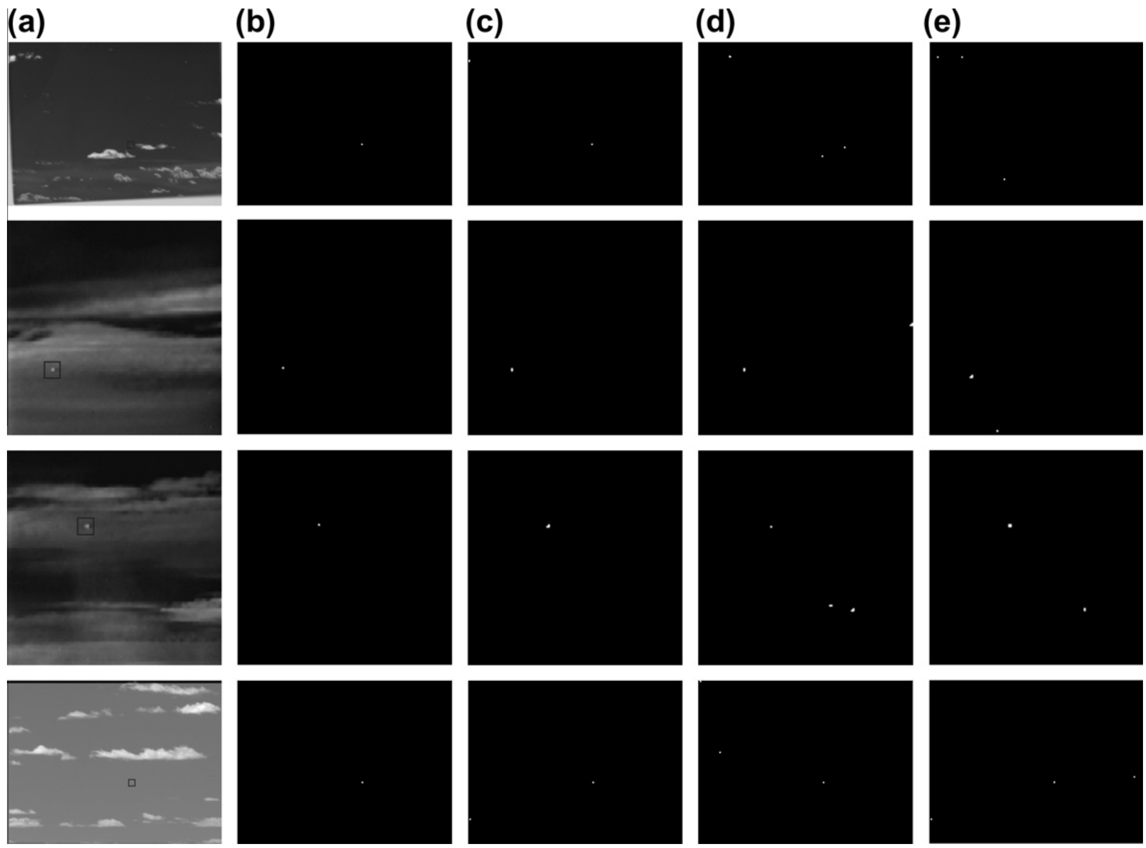

Fig. 6. Results of detection algorithms mentioned above: (a1)–(a4) are one given frame from input image Seq1–Seq4 respectively, (b1)–(b4) are the detection results of our methods, (c1)–(c4) represent detection results of Kim's algorithm [17], (d1)–(d4) denote detection results derived by utilizing Top-hat method, (e1)–(e4) mean the detection results obtained by Max-Mean algorithm.

Step 2: As shown in Eq. (9), if the pixel is the brightest one among its 5×5 neighborhood W and its gray level is higher than *Thr*, the value is set as 1; else as 0.

$$I(x,y) = \begin{cases} 1, \text{if } (I(x,y) \geqslant I(x_w, y_w) \text{ and } I(x,y) \geqslant Thr, (x_w, y_w) \in W) \\ 0, \text{ others} \end{cases} \quad (9)$$

The pixel marked as 1 is where the center of small target is, and thus small target is detected.

4. Experimental results

The width of Gaussian filter is characterized by parameter s, and s is strongly related to the smoothness of background. The larger the s, the wider the filter band is, and thus the better smoothness will be conducted. Adjusting the parameter s, we can obtain an appropriately smoothed image. In our experiments, we select an s with the value of 0.7, an m with 0.85, and choose 0°, 45°, 90° and 135° these four directions for morphological processing.

In order to evaluate the performance of the proposed method, four sequence images (Seq1, Seq2, Seq3 and Seq4) are used. Seq1 and Seq4 are both heavily cluttered and with a size of 320×244 pixels. Seq1 has 90 frames and Seq4 has 86 frames. Seq2 and Seq3 with 128×128 size both consist of 101 frames.

We perform LoG filtering, morphological processing and local thresholding segmenting to one given frame from Seq1 successively. The results are shown in Fig. 5.

According to the mathematical definition of the contrast given in Eq. (1), the image contrast is calculated every nine frames for both the original Seq1 and the processed Seq1. The calculation results are displayed in Table 1.

Conclusion can be drawn from Table 2 that the algorithm presented performs well in improving image contrast based on the contrast mechanism of HVS.

To test the effectiveness of our algorithm, we deal with several different original infrared images by means of our algorithm, Kim's

Table 3
The false alarm rate of different detection methods for Fig. 6a1–a4.

Image	Method			
	Our method (%)	Kim's method [17] (%)	Top-hat (%)	Max-Mean (%)
Fig. 6a1	0	100	100	100
Fig. 6a2	0	0	50	50
Fig. 6a3	0	0	66.7	50
Fig. 6a4	0	50	66.7	66.7

Table 4
The detection rate of different detection methods for Seq1–Seq4.

Sequence	Method			
	Our method (%)	Kim's method [17] (%)	Top-hat (%)	Max-Mean (%)
1	97.8	81.1	35.6	42.2
2	100	88.1	52.5	59.4
3	100	90.1	56.4	63.4
4	97.7	82.6	38.4	46.5

Table 5
The false alarm rate of different detection methods for Seq1–Seq4.

Sequence	Method			
	Our method (%)	Kim's method [17] (%)	Top-hat (%)	Max-Mean (%)
1	4.3	29.1	83.4	79.5
2	1.0	13.6	72.1	67.6
3	1.9	11.7	69.4	64.4
4	3.4	26.0	82.0	77.5

algorithm [17], Top-hat and Max-Mean filter respectively. The results are depicted in Fig. 6. Table 2 and Table 3 respectively show P_d (detection rate, defined in Eq. (10)) and P_f (false alarm rate, defined in Eq. (11)) of these four different strategies for Fig. 6a1–a4. To further prove the superiority of our algorithm, statistical calculations of P_d and P_f are made for Seq1–Seq4 as listed in Tables 4 and Table 5.

$$P_d = \frac{\text{Quantity of true targets detected in images}}{\text{Quantity of true targets existing in images}} \times 100\% \qquad (10)$$

$$P_f = \frac{\text{Quantity of false targets detected in images}}{\text{Quantity of targets detected in images}} \times 100\% \qquad (11)$$

Fig. 6 and Tables 2–5 depict that Top-hat and Max-Mean methods are not fully competent in dim and small target detection because they produce several false detections and even miss the interesting target, especially in heavily cluttered image cases. And their detection effect depends a lot on the selection of the threshold, because a larger threshold leads to a low P_d and a smaller one leads to a high P_f, Kim's algorithm performs better in terms of detection rate and false alarm rate because their filter not only suppresses background noise and clutter but also enhances the target intensity. However, there also exist false alarms when input images are under complicated background for that some clutters still survive after tune-max of SCR [17]. The experimental results indicate that the strategy put forward in this paper outperforms the other three methods in its significant increment of detection rate and reduction of false alarms, because the residual clutter can be further removed by morphological processing utilizing the target feature and diversity between target and background clutter.

5. Conclusions

Small target detection as an essential part in infrared image processing, an improved detecting algorithm based on the contrast mechanism of human visual system is proposed in this paper. The LoG filter enhances target intensity and suppresses background clutter and noise simultaneously leading to a large improvement of the contrast between target and background. Morphological method is employed to further eliminate false targets introduced by unwanted clutter. The algorithm presented can detect potential targets with much lower false alarm. From the experimental results it is clear that the algorithm proposed achieves satisfying performance, in terms of detection rate and false alarm rate.

Acknowledgment

This project is supported by the National Defense Pre-Research Foundation of China (9140A01060110DZ0125).

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