An improved algorithm for facet-based infrared small target detection

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The facet-based small target detection method is shown as robust and efficient, but it does not perform well in target preservation. In this paper an improved algorithm is proposed. The algorithm uses facet model to fit local intensity surface and detects potential bright and dark targets using extremum theory, then the zero-crossings of the second partial derivatives of the fitting function in each potential target's neighborhood are found, the pixels inside the zero-crossing contour are restored to the potential target. In experiments involving typical infrared images target intensity distribution information is well preserved.

(ReceivedFebruary 20, 2012; accepted April 11, 2012)

Keywords: Small target detection, Target preservation, Cubic facet model, Extremum theory, Zero-crossing

1. Introduction

A crucial problem in Infrared Search and Track systems is the detection of moving point targets. There are many algorithms reported in the open literature for this problem [1, 2], yet none of them yield acceptable results under all situations. Spatial algorithms include various linear and nonlinear filters in one-dimension and two-dimension coordinates. Anti-mean filter, multi level filter and Laplacian filter are typical linear filters. There are many nonlinear filters, such as anti-median filter, anti max-median filter, anisotropic filter, morphological filter, Wiener filter and so on. Anti-mean filter [3] computes the difference between the intensity of current pixel and the average intensity of its neighbor pixels as the filtered result. For multi level filter, small target is regard as the intermediate frequency components of original image, first multi cascaded mean filters are applied to original image to obtain a smoothed image, then the difference subtracting the smoothed image from original image is processed by other multi cascaded mean filters. Compared to anti-mean filter, Anti-median filter [3] computes the difference between the intensity of current pixel and the median value rather than average value of its neighbor pixels as the filtered result. For anti max-median filter, we firstly find a window of odd size that centered at each pixel, then the four median intensity values are found for the column vector, the row vector and the two diagonal vectors which also focus at the pixel. The maximum of these four median values is determined to be the filtered output intensity value. The max-median filter performs well in preserving the edges of structural background, and then the filtered output is subtracted from the original image to increase the signal to clutter ratio (SCR), so as to enhance the potential targets and suppress the regions of high variance and smooth ones in the result image. Algorithms based on spatial linear filter techniques have given good results in homogeneous background; on the other hand, non-linear filters are capable of non-stationary clutter suppression for small target detection [4].

In this research area the facet-based method is a novel algorithm. Haralick introduced a cubic facet model for detecting digital edges [5]. Sheng Zheng [6] and G.D. Wang [7] developed the facet-based method for infrared small target detection by using the facet model. The model assumes that in each neighborhood of an image the underlying grey-level intensity surface can be approximated by a bivariate cubic function. Potential small target can be detected from background by applying extemum theory [7]. The facet-based method is shown as robust and efficient, but target detected by the method tends to be shrunk and thus lose information of target intensity distribution. This affects severely post processing of detection, such as target tracking and recognition, which means the method's target preservation performance needs to be improved. In this paper the detection behavior of the facet model is further analyzed and an improved algorithm for target preservation is proposed.

This paper is organized as follows. Section 2 introduces the facet model and the traditional facet-based method for small target detection. In Section 3 the detection behavior of the traditional method is discussed, the shortcoming on target preservation is analyzed and an improved algorithm is proposed in detail. Dark target detection is also considered in this section. Section 4 presents experimental results obtained by applying our improved algorithm, as well as the traditional facet-based method. Finally, our conclusions are summarized in sec.5.

2. Facet-based small target detection

The facet-based small target detection method is introduced in this section [6, 7]. In Haralick's cubic facet model, the underlying grey-level intensity surface in each neighborhood of an image can be approximated by a bivariate cubic function f . For example let R be defined as $R = \{-2 \quad -1 \quad 0 \quad 1 \quad 2\}$, and C be defined as $C = \{-2 \quad -1 \quad 0 \quad 1 \quad 2\}$. The two-dimensional discrete orthogonal polynomial (DOP) basis set can be constructed from the tensor product of the two sets of one-dimensional discrete polynomials. Let S be a symmetric $2D$ neighborhood defined on $R \times C$, and $I(r,c)$ be the observed intensity value at $(r,c) \in S$. As a result, the bivariate cubic function $f(r,c)$, expressed using discrete orthogonal polynomials, is

$$\begin{aligned} f(r,c) &= \sum_{i=0}^{9} k_{i+1} P_i(r,c) \\ &= k_1 + k_2 r + k_3 c + k_4 (r^2 - 2) + k_5 rc + k_6 (c^2 - 2) \\ &+ k_7 (r^3 - \frac{17}{5} r) + k_8 (r^2 - 2)c + k_9 r(c^2 - 2) + k_{10} (c^3 - \frac{17}{5} c) \end{aligned} \tag{1}$$

The fitting coefficients $k_1, ..., k_n$ are determined through the least-squares surface fitting and according to the orthogonal property of the polynomials,

$$k_i = \frac{\sum_{(r,c)\in S} P_{i\text{-}1}(r,c) I(r,c)}{\sum_{(r,c)\in S} P_{i\text{-}1}^2(r,c)} \tag{2}$$

Equation (2) shows that each fitting coefficient k_i can be computed individually as a linear combination of the intensity values $I(r,c)$ on $R \times C$. The weight associate with each $I(r,c)$ for the i'th coefficient is determined by

$$w_i = \frac{P_{i\text{-}1}(r,c)}{\sum_{(r,c)\in S} P_{i\text{-}1}^2(r,c)} \tag{3}$$

In fact evaluating the first, second row and column partial derivatives of $f(r,c)$ at the neighborhood centre $(0,0)$ (i.e. r = 0 and c = 0) yields

$$\begin{aligned} &\frac{\partial f}{\partial r} = k_2, \ \frac{\partial f}{\partial c} = k_3 \\ &\frac{\partial^2 f}{\partial r^2} = 2k_4, \ \frac{\partial^2 f}{\partial r \partial c} = k_5, \ \frac{\partial^2 f}{\partial c^2} = 2k_6 \end{aligned} \tag{4}$$

where k_i are the fitting coefficients. For an original image k_2, k_3, k_4, k_5, k_6 can be computed independently by convolving the image with the corresponding weight kernel computed using (3). For example the weight kernels for each fitting coefficient over the symmetric 5×5 neighborhood defined on $R \times C$ can be listed as follows:

$$W_2 = \frac{1}{50}\begin{bmatrix} -2 & -1 & 0 & 1 & 2 \\ -2 & -1 & 0 & 1 & 2 \\ -2 & -1 & 0 & 1 & 2 \\ -2 & -1 & 0 & 1 & 2 \\ -2 & -1 & 0 & 1 & 2 \end{bmatrix}, \ W_3 = \frac{1}{50}\begin{bmatrix} -2 & -2 & -2 & -2 & -2 \\ -1 & -1 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 \end{bmatrix}$$
$$W_4 = \frac{1}{70}\begin{bmatrix} 2 & 2 & 2 & 2 & 2 \\ -1 & -1 & -1 & -1 & -1 \\ -2 & -2 & -2 & -2 & -2 \\ -1 & -1 & -1 & -1 & -1 \\ 2 & 2 & 2 & 2 & 2 \end{bmatrix}, \ W_5 = \frac{1}{90}\begin{bmatrix} 4 & 2 & 0 & -2 & -4 \\ 2 & 1 & 0 & -1 & -2 \\ 0 & 0 & 0 & 0 & 0 \\ -2 & -1 & 0 & 1 & 2 \\ -4 & -2 & 0 & 2 & 4 \end{bmatrix}, \ W_6 = W_4^T \tag{5}$$

Small target is considered as maximum extremum point of the fitting function. According to extremum theory, a potential small target satisfies

$$D1 = k_2 = k_3 = 0 \tag{6}$$

$$D_2 = 2k_4 < 0 \tag{7}$$

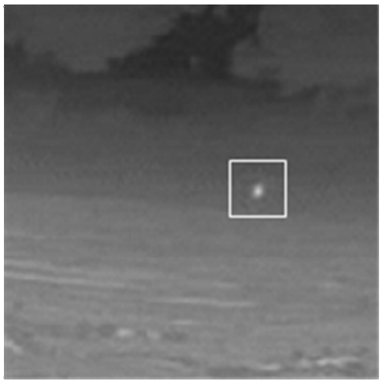
$$D_3 = 4k_4 k_6 - k_5^2 > 0 \tag{8}$$

For detection of small target the above conditions are modified by setting empirical thresholds, and then each neighborhood in original image is examined to see if the center pixel satisfies these conditions, if so the center pixel is extracted as potential target.

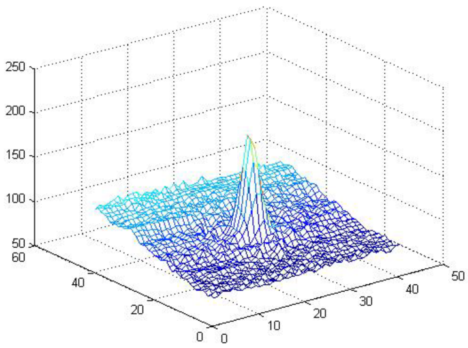
3. Improved algorithm for target preservation

The facet-based method can detect vertex of small target but ignore its peripheral pixels. In infrared image small target's intensity distribution always assumes gradual change, pixels near the target center have high intensity while peripheral pixels of target have low intensity, and therefore peripheral pixels are excluded from the target in detection result because indeed they are not local maximum extrema. Information loss of peripheral pixels may severely affect target characterization and post process of detection, such as target tracking and recognition. Modifying extremum conditions by appropriate empirical thresholds can deal with this problem in a certain extent, but to find an adaptive threshold for different practical images is difficult and inappropriate thresholds tend to produce false detections.

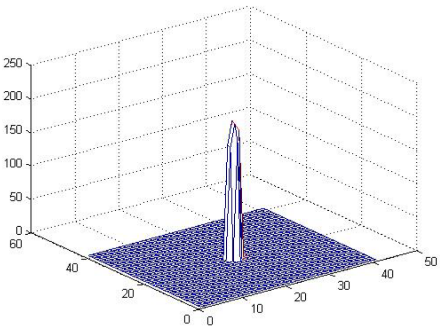
To improve the performance of facet-based method against information loss of target, zero-crossing analysis of the second partial derivative of the fitting function is incorporated. The integration of the facet model and zero-crossing detector is often used for edge detection in digital image [5]. Here a neighborhood containing small target can be regarded as a composition of the target and local background, and target region is surrounded by background region. The edge of two regions and therefore target extent can be represented by zero-crossing. Figure 1 illustrates this idea. The target determined by zeros-crossings appears more completely than the detected target by using the traditional facet-based method.



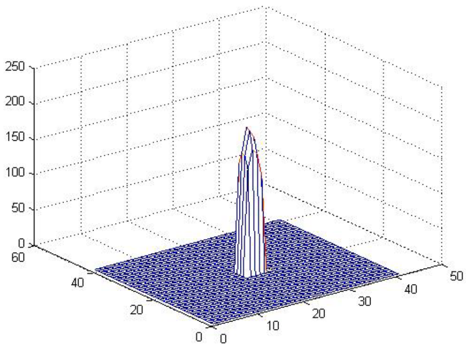
(a)



(b)



(c)



(d)

Fig. 1. Small target preservation. (a): Original image that contains a small target. (b): Three dimensional description of target region. (c): The detected target using the traditional facet-based method. (d) The target determined by zero-crossing analysis.

After potential targets are detected the zero-crossing of the second partial derivatives of the fitting function in each potential target's neighborhood are found and the pixels inside the zero-crossing contour are restored to the potential target. In practice this process can be accomplished concisely by determining the region connected with potential target with minus second partial derivatives, because the second partial derivatives at target vertex are minus values from the second condition of maximum extremum.

Furthermore, small targets often appear as dark ones, which means target intensity is lower than background, so besides target preservation issue is addressed in this paper, dark target detection is also considered by employing minimum extremum theory. Compared to detection of bright target with maxmum intensity, dark target is treated as minimum point in local image, thus

$$\frac{\partial^2 f}{\partial r^2} > 0, \frac{\partial^2 f}{\partial c^2} > 0 \tag{9}$$

Correspondingly, dark target satisfies (10)

$$D_2 = 2k_4 > 0 \tag{10}$$

4. Metrics and experimental results

The performance of the proposed algorithm for small target detection and preservation is evaluated by using infrared images. Experiments involving a variety of situations with varying background and target types are performed to demonstrate the proposed algorithm's robustness.

In comparative experiments involving typical infrared images, the proposed algorithm has the same target detection ability with the traditional facet-based method and performs better on target preservation, it provides more integrated information of target intensity distribution, just as indicated by theoretical analysis.

Three metrics are used to evaluate target preservation performance of target detection algorithm. The first one is target entropy, which is defined as

$$E_T = -\sum_i p_i \log p_i \tag{11}$$

where T represents target, i is intensity value of the target. E_T reflects information abundance thus a higher indicates more information contained in a detected target. The second metric is σ_C^2, which is variance of clutter in a neighborhood with 21×21 pixels centered at the centroid of target. If there are target pixels that are considered as clutter, which means target cannot be preserved well, σ_C^2 will have a higher value that reflects abnormal variation of clutter. The third metric is between-class variance, which is defined as

$$\sigma_B^2 = \omega_T (1 - \omega_T)(\mu_T - \mu_C)^2 \tag{12}$$

where ω_T is target probabilities, μ_T is mean value of target intensities and μ_C is mean value of clutter intensities.

Figure 2 illustrates the performance of the proposed algorithm. Original infrared images from Wang [7] contain one or more small targets. The traditional facet-based method detects well the position of small target while loses essential peripheral pixels of target. Small target that seems like a spot in infrared image, such as in Fig. 2 (a1) and (b1), tends to be severely shrunken by the traditional method, which can be seen from Fig. 2 (a4) and (b4). Targets that have distinct shape, such as in Fig. 2 (c1), (d1) and (e1) are also shrunken and lose their shape information more or less, which are shown in Fig. 2 (c4), (d4) and (e4). Compared to the traditional facet-based method, the proposed algorithm preserves more information of target. Detected target has almost the full size as in original image. In Fig. 2 (c5) the target shape information is preserved obviously. Three dimensional descriptions of K4 and K6 values show distribution of the second row partial derivative and the second column partial derivative respectively. Minus biggish values of K4 and K6 together indicate occurrence of small target and zero-crossings represents target contour.

E_T, σ_C^2 and σ_B^2 values of detected small targets are given in Table 1. Image No. is the same as Fig. 2. Target No. is defined as a label initiated from 1 from left to right when an original image contains more than one target. From target 3 in image (d1) the traditional facet-based method has detected two targets, the left one has only one pixel and its metric values are not shown in Table 1, the corresponding metric value is the right one's metric values.

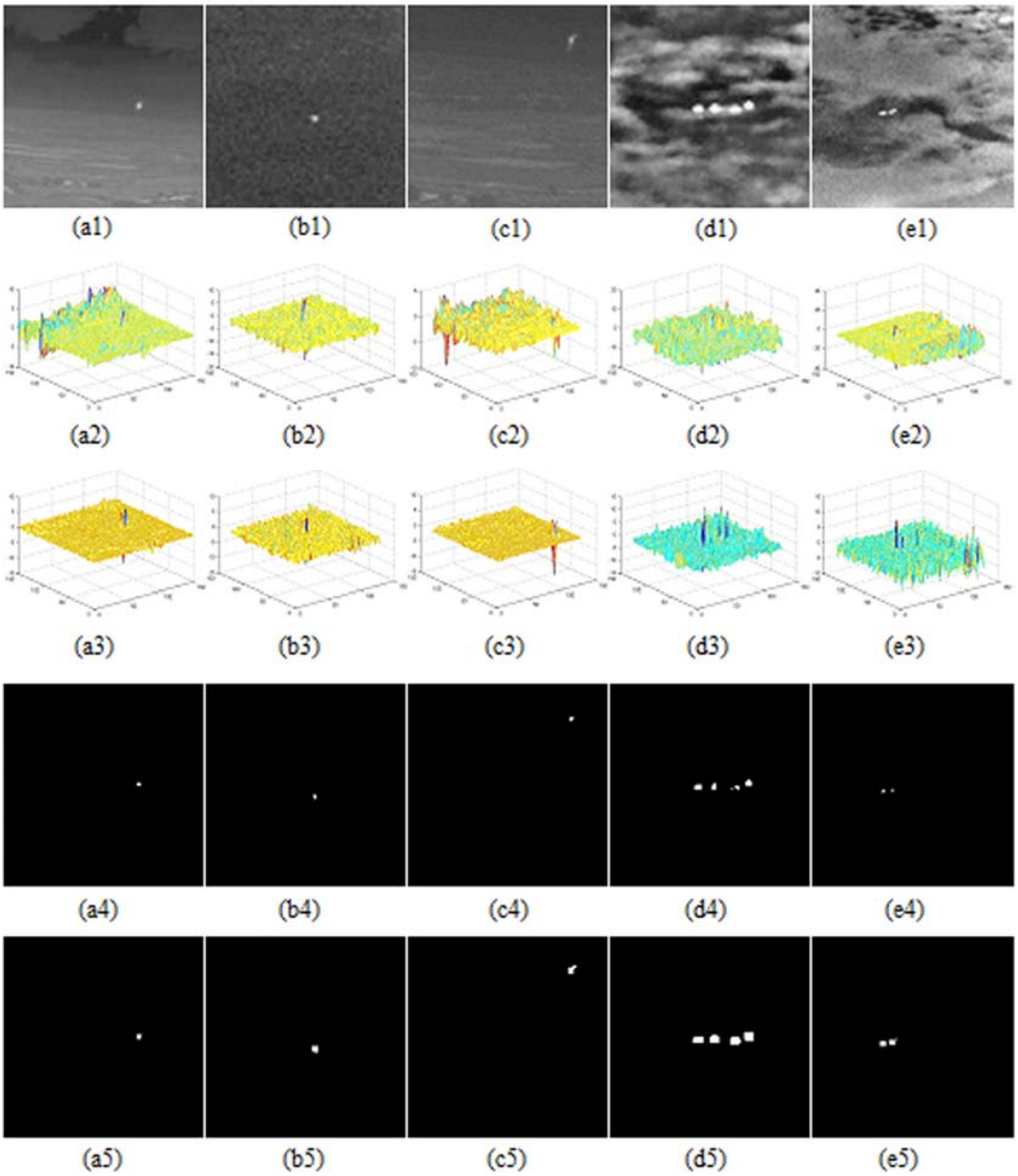


Fig. 2. Original images and processed results of the two algorithms. First row (a1)~(e1): Original images. Second row (a2)~(e2): Three dimensional description of K4 values. Third row (a3)~(e3): Three dimensional description of K6 values. Fourth row (a4)~(e4): Detection results of the traditional facet-based algorithm. Fifth row (a5)~(e5): Detection results of the improved algorithm.

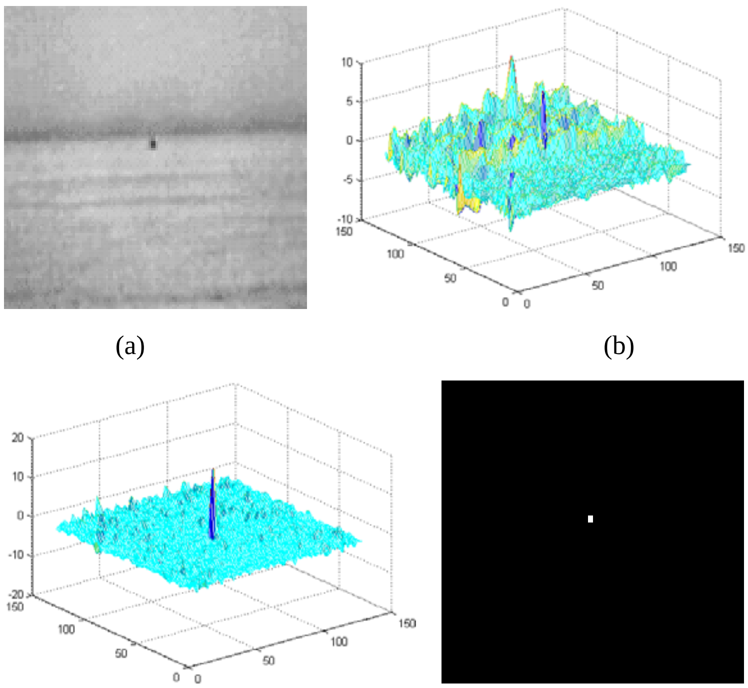
Table 1. Target preservation performance of the traditional facet-based method and the improved algorithm

Image No.	Target No.	target entropy		variance of clutter		between-class variance	
		Traditional	Improved	Traditional	Improved	Traditional	Improved
a1	1	2.8	3.7	146.3	101.6	2.4	3.1
b1	1	2.3	3.5	174.0	63.0	4.0	6.5
c1	1	2.6	4.0	101.0	55.6	2.3	3.3
d1	1	3.2	4.2	2488.4	2167.7	20.2	28.3
	2	2.9	4.4	2940.4	2317.5	12.6	29.1
	3	1.9	4.7	3324.1	2642.0	6.7	29.5
	4	3.8	5.0	2550.0	2179.2	18.5	29.4
e1	1	1.6	3.3	750.6	647.5	3.1	5.4
	2	1.0	3.5	944.5	817.5	1.5	4.0

The improved algorithm preserves well small targets, so target entropy which reflects target information abundance

is higher. In the detection results of the traditional facet-based method part of target pixels are treated as clutter pixels, thus the clutter is inhomogeneous and the calculated variance of clutter is high; while the improved algorithm detects more completely target so that its value is low. The same analysis can be made for values of between-class variance; its higher value which is produced by the improved algorithm reflects good separability between target and clutter.

Fig. 3 shows experimental result of dark target detection. Target entropy, variance of clutter and between-class variance of the detected dark target are 2.3, 538.6 and 3.4 respectively.



(a) (b)

(c) (d)

Fig. 3. Experimental results with dark target. (a): Original image. (b): Three dimensional description of K4 values. (c): Three dimensional description of K6 values. (d): Detection result.

5. Conclusions

We present an improved algorithm for facet-based detection of infrared small target. The algorithm consists of intensity surface fitting and extremum point extraction followed by target preservation process based on zero-crossing analysis of the second partial derivative of fitting function. Besides target preservation an important feature of the proposed algorithm is that it detects both bright and dark targets with the same efficiency. The performance of this algorithm has been evaluated on typical infrared images and compared with traditional facet-based and other small target detection algorithms. Experimental results show that the proposed algorithm yields satisfactory results. Future work will be focused on determining adaptively par ameters of the algorithm to detect targets within a range of int-ensities and sizes.

Acknowledgement

This work is supported by the Project of the National Natural Science Foundation of China under Grant No. 60736010 and the Defense Advanced Research Foundation of the General Armaments Department of the PLA under Grant No.9140A01060110JW0515.

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