

# Facet-based infrared small target detection method

G.-D. Wang, Ch.-Y. Chen and X.-B. Shen

The cubic facet model is applied to fit the underlying intensity surface in infrared small target detection procedure. Using the partial derivatives of the fitted surface to make decisions regarding the maximum extremum points is proposed. The experimental results demonstrate that the proposed method is efficient and robust.

**Introduction:** Small target detection is the core technology of aerial defence alertness and deep space control and guidance. These systems always need to deal in real-time. Peng and Zhou designed a  $5 \times 5$  highpass template filter for infrared small target detection [1]. Yang *et al.* provided a small target detection method called Butterworth highpass filter (BHPF) [2]. Sang *et al.* put forward the small target detection method of two-dimensional normalised least mean square (TDNLS) [3]. Ye *et al.* presented a time domain filter for small target detection [4]. The performances of the methods mentioned above are good but the time consumed is long, so they are not well fitted for real-time detection. To enhance the efficiency of small target detection, we put forward a new method based on the facet model in time domain. The experiments reflect the method as being efficient and robust.

**Cubic facet model:** Haralick's cubic facet model assumes that in each neighbourhood of an image, the underlying grey-level intensity surface can be approximated by a bivariate cubic function  $f$  [5]. 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. For a cubic function, the polynomial bases with order higher than 3 can be ignored. For example, let  $R$  be defined as  $R = \{-2, -1, 0, 1, 2\}$ , and  $C$  be defined as  $C = \{-2, -1, 0, 1, 2\}$ . Then the set of discrete orthogonal polynomials for a cubic function over  $R \times C$  is 1,  $r$ ,  $c$ ,  $r^2 - 2$ ,  $rc$ ,  $c^2 - 2$ ,  $r^3 - (17/5)r$ ,  $(r^2 - 2)c$ ,  $r(c^2 - 2)$ ,  $c^3 - (17/5)c$ .

Let  $S$  be a symmetric 2D neighbourhood defined on  $R \times C$ , and  $I(r, c)$  be the observed intensity value at  $(r, c) \in S$ . Let  $\{g_0(r, c), g_1(r, c), \dots, g_N(r, c)\}$  be the set of 2D DOP basis functions. As a result, the bivariate cubic function  $f(r, c)$ , expressed using discrete orthogonal polynomials, is [5]

$$f(r, c) = K_1 + K_2r + K_3c + K_4(r^2 - 2) + K_5rc + K_6(c^2 - 2) + K_7\left(r^3 - \frac{17}{5}r\right) + K_8(r^2 - 2)c + K_9r(c^2 - 2) + K_{10}\left(c^3 - \frac{17}{5}c\right) \quad (1)$$

where  $K_i$ ,  $i = 1, \dots, 10$ , are coefficients for the bivariate cubic function expressed in discrete orthogonal polynomials. The coefficients  $K_1, \dots, K_N$  in (1) are determined by the least-squares surface fitting and the orthogonal property of the polynomials

$$K_i = \frac{\sum_{(r,c) \in S} g_i(r, c) I(r, c)}{\sum_{(r,c) \in S} g_i^2(r, c)} \quad (2)$$

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

$$W_i = \frac{\sum_{(r,c) \in S} g_i(r, c)}{\sum_{(r,c) \in S} g_i^2(r, c)} \quad (3)$$

**Determination of potential target pixels:** In the cubic facet model, each facet centred about a given pixel may be approximated by the bivariate cubic function in canonical form, as shown in (1). Evaluating the second row and column partial derivatives at the neighbourhood centre  $(0, 0)$  (i.e.  $r=0$  and  $c=0$ ) yields the second directional derivatives

$$\frac{\partial^2 f(r, c)}{\partial r^2} = 2K_4, \quad \frac{\partial^2 f(r, c)}{\partial r \partial c} = K_5, \quad \frac{\partial^2 f(r, c)}{\partial c^2} = 2K_6 \quad (4)$$

where  $K_i$  are the fitting coefficients. Each coefficient  $K_i$  can be computed independently by convolving the image with the corresponding weight kernel computed by using (3).

Let  $R$  be defined as  $R = \{-2, -1, 0, 1, 2\}$ , and  $C$  be defined as  $C = \{-2, -1, 0, 1, 2\}$ ; then the weight kernels for each fitting coefficient over the symmetric  $5 \times 5$  neighbourhood defined on  $R \times C$  can be listed as follows:

$$W_4 = \frac{1}{70} \begin{bmatrix} 2 & 2 & 2 & 2 & 2 \\ -1 & -1 & -1 & -1 & -1 \\ -2 & -2 & -2 & -2 & -2 \\ -1 & -1 & -1 & -1 & -1 \\ 2 & 2 & 2 & 2 & 2 \end{bmatrix}, \quad W_5 = \frac{1}{90} \begin{bmatrix} 4 & 2 & 0 & -2 & -4 \\ 2 & 1 & 0 & -1 & -2 \\ 0 & 0 & 0 & 0 & 0 \\ -2 & -1 & 0 & 1 & 2 \\ -4 & -2 & 0 & 2 & 4 \end{bmatrix}, \quad W_6 = W_4^T \quad (5)$$

According to extremum theory, if

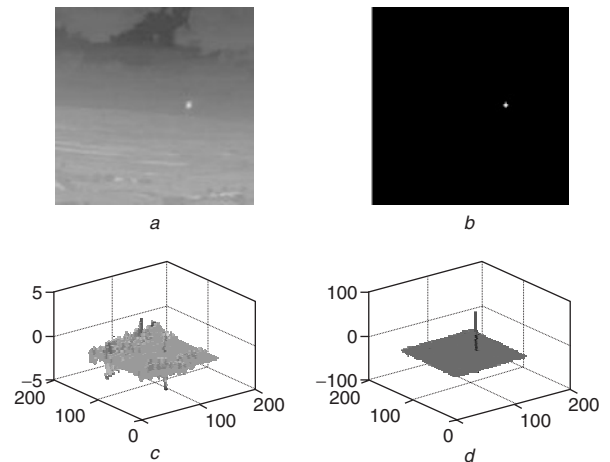
$$D_1 = 2K_4 < 0; \quad D_2 = 4K_4K_6 - K_5^2 < 0 \quad (6)$$

then the corresponding pixel  $f(r, c)$  is the maximum extremum point, i.e. a possible target pixel.

**Facet-based small target detection:** The procedure contains four steps:

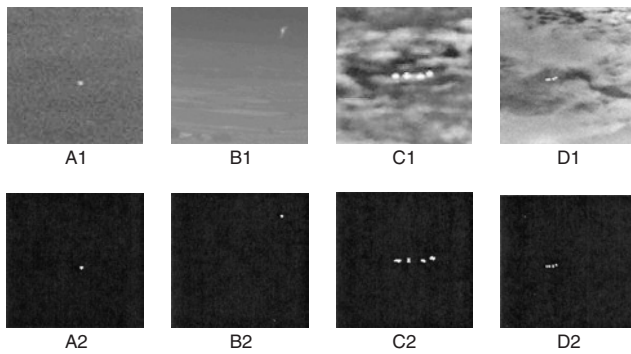
1. Calculate  $K_4, K_5, K_6$  by convolving the original image with  $W_4, W_5, W_6$  [using (5)].
2. With the calculated second directional derivatives of the fitted surface, the decision is made whether the pixel is a target point or not by using the maximum extremum conditions, (6).
3. Repeat steps 1 and 2, decide and store all the possible target pixels.
4. Using threshold to separate the target pixels. There are some other pixels satisfying the conditions of (6), so we use threshold to eliminate these pixels. According to many experiments, we set the conditions to  $D_1 < -0.1$  and  $D_2 > 0.3 \cdot \max(D_2)$ .  $\max(D_2)$  means the maximum of  $D_2$ .

**Experimental work:** For these experiments, we select typical infrared images from many images. Figs. 1 and 2 show the filtered effects of several images under different backgrounds in the facet-based method, in the experiments the kernel size ( $R \times C$ ) is  $5 \times 5$  pixels.



**Fig. 1** Infrared small target detection

- a Original image  
b Computed target position  
c Distribution of  $D_1(K_4)$   
d Distribution of  $D_2(4K_4K_6 - K_5^2)$



**Fig. 2** Original image and resulting image

A1, B1, C1, D1: Original infrared images under different background  
A2, B2, C2, D2: Computed target position

In contrast to the methods mentioned in [2, 3], the proposed approach detects a small target on a well-fitted intensity surface of the infrared image. A possible target pixel is analytically determined by extremum theory, which is accomplished just by convolving the infrared image with the three second-derivative operators. The target positions are then computed in the neighbourhood of the maximum extremum pixels. Only three fitting coefficients for each image pixel are computed, and the two-dimensional weight kernel is separable: its convolution with an image can be accomplished using two separate one-dimensional convolutions, leading to a substantial saving in computation.

The experimental data are listed in Table 1, which shows that the filtering performances of several filters differ greatly from a time consuming standpoint. In the TDNLMS, a  $5 \times 5$  pixel kernel was used. It is obvious that the facet-based method maintains better time consuming performance for small target detection under different backgrounds, therefore the facet-based method is a robust and real-time method for small target detection.

**Table 1:** Comparison of performance of different methods

Number of image	Size of image	Elapsed time using different methods for test(s)		
		Facet-model	Adaptive BHPF	TDNLMS
1	$128 \times 128$	0.07	0.701	1.352
2	$128 \times 128$	0.05	0.771	1.372
3	$128 \times 128$	0.061	0.651	1.382
4	$256 \times 256$	0.18	4.366	5.769
5	$128 \times 128$	0.09	1.833	1.362
6	$230 \times 230$	0.11	3.044	4.597

**Conclusion:** The analysis of the small target grey intensity surface was performed to establish an efficient and reliable small target detection method. According to extremum theory, the possible small target position is analytically determined by convolving the infrared image with the operators deduced from the bivariate cubic function. Experimental results demonstrate that the small target detection method is robust and efficient. Moreover, it can also be applied in small target detection not only in infrared images.

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## References

- 1 Peng, J.-X., and Zhou, W.-L.: 'Infrared background suppression for segmenting and detecting small target', *Acta Electron. Sin.*, 1999, **27**, (12), pp. 47–51
- 2 Yang, L., Yang, J., and Yang, K.: 'Adaptive detection for infrared small target under sea-sky complex background', *Electron. Lett.*, 2004, **40**, (17), pp. 1083–1085
- 3 Sang, H.-Sh., Chen, Ch.-Y., and Shen, X.-B.: 'Structural parameter of TDNLMS adaptive prediction filter used in point objects detection in digital image data', *J. Huazhong Univ. Sci. Technol. (Nature Sci. Edn.)*, 2003, **31**, (1), pp. 58–60
- 4 Ye, Z.-J., et al.: 'Detection algorithm of weak infrared point targets under complicated background of sea and sky', *J. Infrared Millim. Waves*, 2000, **19**, (2), pp. 121–124
- 5 Haralick, R.M.: 'Digital step edges from zero crossing of second directional derivatives', *IEEE Trans. Pattern Anal. Mach. Intell.*, 1984, pp. 58–68 (PAMI-6(1))