A Feature-Based Small Target Detection System

Jong-Ho Kim[1], Young-Su Park[1], Sang-Ho Ahn[2], and Sang-Kyoon Kim[1,*]

[1] Department of Computer Engineering, Inje University, Gimhae, Gyeongsangnam-do 621-749, Republic of Korea
[2] Department of Electronic Engineering, Inje University, Gimhae, Gyeongsangnam-do 621-749, Republic of Korea
luckykjh@daum.net, pzworko@gmail.com, {elecash,skkim}@inje.ac.kr

Abstract. Existing small target detection systems generally use the difference image between a predicted background image and an original image. This method has two disadvantages. First, to predict the background image, the size of the structural element has to be carefully selected considering the size of small targets. Second, because of blurring, clutter such as clouds can occur around the edge of the background. To deal with these problems we propose a new feature-based detection system. The proposed method selects candidate pixels with Harris corner detector and then, again selects pixels that have a higher intensity than a threshold among the candidates. After labeling the selected candidates in order to obtain the number of pixels they have, the system decides which is a small target. In an experiment, our proposed method gave better results than the existing methods.

Keywords: Harris corner detector, New White Top-Hat, Labeling, Histogram.

1 Introduction

Concomitant with the development of scientific techniques, techniques and systems for the development of weapons have been making rapid progress. In particular, missiles and unmanned aerial vehicles (UAVs) that effectively strike targets over long distances have emerged as important threat elements, such that an effective counterstrategy is required.

Infrared Warning System (IRWS) and Infrared Searching and Tracking system (IRST) have been proposed as means of detecting small targets such as missiles early and to judge whether they are threats. In these systems, the difference image between a predicted background image and an original image is generally used to detect small targets from IR images that have a lot of clutter. The targets are assumed to occupy a couple of pixels.

Conventional methods utilize Max-Mean and Max-Median filters [1] and White Top-Hat(WTH) Transformation [2]. Max-Mean and Max-Median filters remove clutter and make a predicted background image from IR images while preserving the

* Corresponding author.

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edges of clouds and structural backgrounds. After extracting a difference image using the background image, small targets are then detected from candidate targets with a threshold. However, the filters are not useful in cases where a target is on the edge of clouds or an input IR image is not clear. In addition, the performance of the filters is degraded when the shape of targets is irregular or a lot of clutter is distributed.

WTH transformation [2] also removes clutter and makes a predicted background image. This morphology-based method can detect targets in real-time because it is not a time consuming job. However, it also does not work well with a variety of pixel size targets. New White Top-Hat (NWTH) transformation [3], which uses several kinds of structural elements to get better background images and to cope well with the size of targets, has been proposed. However it is not flexible with regards to size because the available number of structural elements is limited. Moreover, one of its side effects is generation of clutter on the edges of clouds. Multi-structuring elements (multi-SEs) NWTH transformation [4] has been proposed to automatically determine the optimal size of structural elements. However, all these methods that use a difference image have difficulties dealing with the size of targets and clutter on the edges of clouds.

In this paper, we propose a new feature-based detection system to deal with the problems. The proposed method classifies pixels into two groups specifically, pixels for the background and pixels for the target using Harris corner detector. The detector extracts well corner features from images, so that it is able to find pixels corresponding to the boundaries of targets. More possible pixels are subsequently screened by a threshold of intensity, while almost all clutter is eliminated. Because the pixels can be a part of clouds or a target, a target is detected by labeling and finding the number of pixels of labeled areas.

The proposed method is not restricted by the size of the targets because it uses the finds pixels for edges of targets with Harris corner detector. In addition, it clearly divides images into areas for targets and backgrounds, which improves the detection performance by excluding clutter.

2 Small Target Detection System

2.1 The Main Structure of the System

Fig. 1 shows the main structure of the proposed small target detection system. First, it extracts corner features from input images using Harris corner detector. Next, it selects more plausible pixels that have high intensity and can be regarded as pixels for targets or backgrounds. The selected pixels then are labeled and areas that can be divided into targets and backgrounds generated. Finally, small targets are detected according to the number of pixels in the labeled areas with a size threshold.

Fig. 1. Main structure of the small target detection system

2.2 Feature Point Extraction

2.2.1 Harris Corner Detector

Harris corner detector is a popular interest point detector due to its strong invariance to rotation, scale, illumination variation, and image noise. Harris corner detector is based on the local auto-correlation function of a signal [5]; where the local auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different directions. Our proposed method extracts corner features using the detector. The corner features consist of edges of targets and clouds, which are very useful in classifying images into interest areas such as targets and clouds. The detector algorithm is as follows:

Given a shift $(\Delta x, \Delta y)$ and a point (x, y), the auto-correlation function is defined as,

$$c(x, y) = \sum_W [I(x_i, y_i) - I(x_i + \Delta x, y_i + \Delta y)]^2 \tag{1}$$

Where $I(\cdot,\cdot)$ denotes the image function and (x_i, y_i) are the points in the window W (Gaussian1) centered on (x, y). The shifted image is approximated by a Taylor expansion truncated to the first order terms:

$$I(x_i + \Delta x, y_i + \Delta y) \approx I(x_i, y_i) + [I_x(x_i, y_i) I_y(x_i, y_i)] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \tag{2}$$

where $I_x(\cdot,\cdot)$ and $I_y(\cdot,\cdot)$ denote the partial derivatives in x and y, respectively. Substituting approximation Eq. (2) into Eq. (1) yields

$$c(x, y) = \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \begin{bmatrix} \sum_W (I_x(x_i, y_i))^2 & \sum_W I_x(x_i, y_i) I_y(x_i, y_i) \\ \sum_W I_x(x_i, y_i) I_x(x_i, y_i) & \sum_W (I_x(x_i, y_i))^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \tag{3}$$

The second matrix is $c(x, y)$ and degree of corner is detected. The discrimination of corner degree is determined by corner response function equations (4) [6]

$$R(x, y) = \det(C(x, y) - k[trace(C(x, y))]^2 \tag{4}$$

Threshold k is 0.04, corner response function $R(x, y)$ presents overall pixels. The tiny degree of corner response value is removed by threshold.

2.2.2 Selection of Pixels

In the pixels selection step, the pixels extracted by Harris corner detector are screened by an intensity threshold. Generally, a small target has a higher intensity than backgrounds and clutter because targets radiate a lot of heat. However, an IR image does not have a constant brightness value, which varies according to the kind of target, distance from the infrared ray sensor, and light scattering. Therefore, we screen the pixels with adaptive thresholds. To automatically obtain the adaptive thresholds, we use the following method.

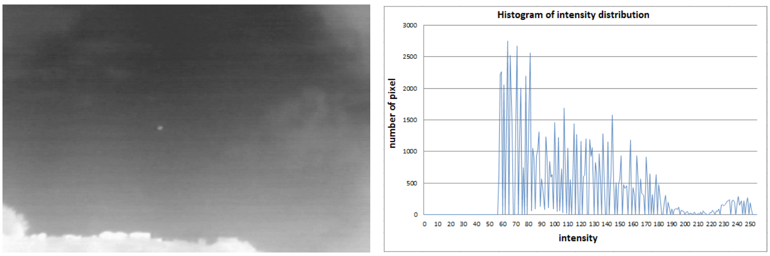
Fig. 2(b) shows the histogram of intensity distribution for the input image in Fig. 2(a). It shows that the intensity is not evenly distributed but rather biased to some values. The threshold is automatically obtained according to the distribution of intensity. Equation (5) is the method used to obtain the histogram of the intensity distribution [7]:

$$H(X_k) = n_k \tag{5}$$

Where X_k is the intensity of the k th intensity and n_k is the number of pixels that have the same value X_k . In this paper, the threshold of intensity T is determined by equation (6), which gives the median of the number of pixels in the histogram:

$$\begin{aligned} &IF\ \ N > (W \times H)/2\ \ Then \\ &T = k\ \ for\ \sum_{k=0}^{L-1} H(X_k) \end{aligned} \tag{6}$$

, where W is the width of the image and H is the height. Fig. 3 shows the threshold obtained. Fig. 4 shows that screening pixels and clutter are eliminated by the adaptive threshold. Fig. 4(a) shows the image that results after using Harris corner detector while Fig. 4(b) shows the image after clutter elimination.



(a) Input image (b) Histogram of intensity distribution

Fig. 2. Histogram of intensity distribution of an IR image

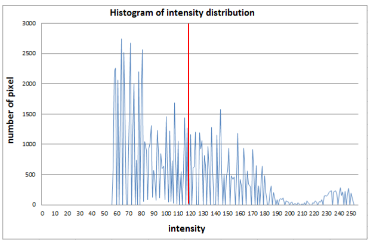
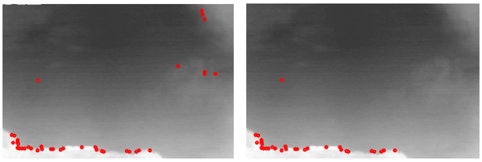


Fig. 3. An adaptive threshold

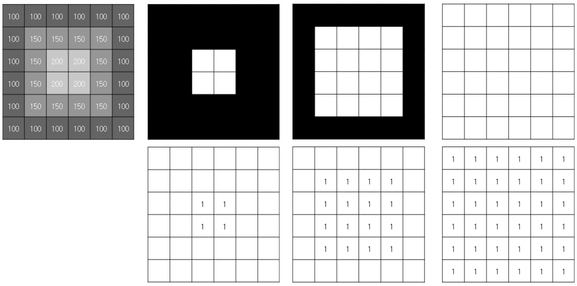


(a) (b)

Fig. 4. Screening pixels

2.3 Labeling and Making Areas

Screened pixels are labeled as a precursor to dividing them into two groups backgrounds and targets. Generally, binarization of an image is followed by labeling. However, original image information can be damaged when a fixed threshold is used in the binarization. For example, Fig. 5(a) shows how the results of binarization can differ according to the threshold used. In the labeling process, if a high threshold is used, targets or clouds can disappear.



(a) Gray Image (b) Threshold 190 (c) Threshold 140 (d) Threshold 90

Fig. 5. Labeling of binary images using thresholds

In this paper, the screened pixels are labeled using the pixel value of gray level without binarization to avoid information damage. Equation (7) shows how the neighbor in gray images is determined.

$$\begin{cases} \quad Neighbor \quad : I(j)\times\omega_{Min} \le I(p_i) \le I(j)\times\omega_{Max} \\ Non-Neighbor : \qquad\qquad otherwise \end{cases} \tag{7}$$

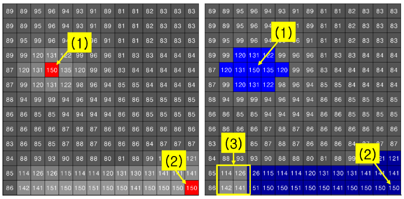
Where I is the intensity value, p_i is pixels, and i is the number of screened pixels. ω_{Min} and ω_{Max} are the minimum and maximum weights, respectively. In our experiments, we used 0.92 as the minimum weight and 1.3 as the maximum weight.

In traditional labeling methods [8], the overall pixels in an image are related. However, we perform the labeling operation only on the screened pixels. The actual size of a small target is very tiny because, for IR images, it is located a long distance away from the camera. The size of a target is usually in ranges such as 3×3, 5×5, 7×7, 9×9, and 11×11. Thus, the search areas for the neighbor is limited to a size of 21×21. The strategy used to search for a neighbor is as follows:

- If a pixel among 4-connected neighbor pixels is not labeled, the pixel is labeled as a neighbor with the same label number.

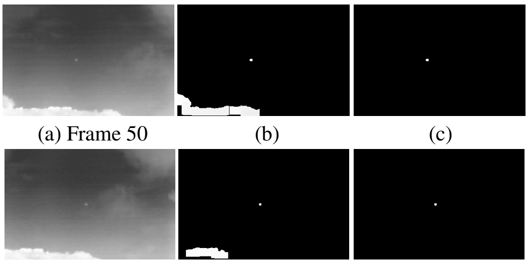
For instance, pixels (1) and (2), marked in red in the gray image of Fig. 6(a), are the screened pixels. Fig. 6(b) shows the result of our labeling. The pixels in area (3) are not included in area (2). Because of the limited search space, the larger neighbor does not need to be searched. Figs. 7(b) and 7(e) are the resultant images for the real images of Fig. 7(a) and 7(d), respectively.

In the making of areas, our labeling not only searches for only the screened pixels instead of all the pixels in the image but also limits the search areas that result from the tiny size of targets. Thus, our labeling improves traditional labeling methods and plays an important part in the performance of the entire detection system.



(a) (b)

Fig. 6. Search areas of the labeling: (a) screened pixels; (b) result of the labeling



(a) Frame 50 (b) (c)

(d) Frame 83 (e) (f)

Fig. 7. (a),(d) input images (b),(e) labeled image (c),(f) detected small targets from images (a), (d), respectively

2.4 Small Target Detection

The small targets are detected by the number of pixels in the labeled areas:

$$\begin{cases} Small\ Target : T_{Min} \le P(i) \le T_{Max} \\ \quad Clutter \quad : \quad otherwise \end{cases} \tag{8}$$

In equation (8), $P(i)$ is the number of pixels in the i th labeled area. In this paper, threshold T_{Min} is 10 and T_{Max} is 150. Figs. 7(c) and 7(f) show the small targets detected from the real IR images of Figs. 7(a) and 7(d), respectively.

3 Experimental Results

Fig. 8 shows the simulation results for WTH transformation, NWTH transformation, multi-SEs NWTH transformation, and our proposed method, respectively. The experimental IR images had resolutions of 360×240 pixels. The IR images of the first and second row had a cloudy background and only one small target, respectively. The IR image of the last row had a cloudy background and only one small target in the cloud.

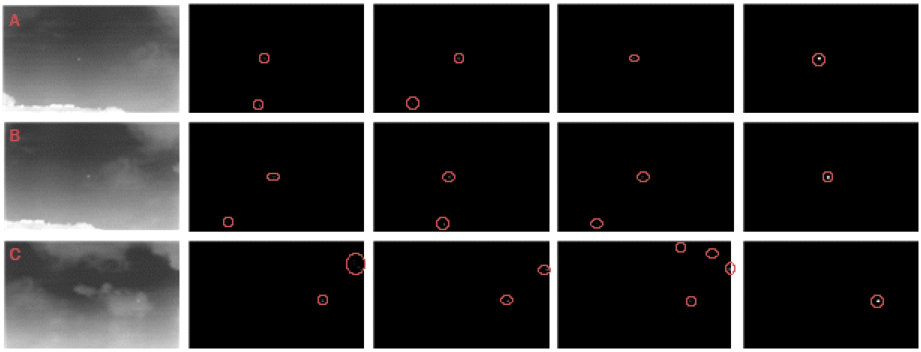


Fig. 8. (a) Input IR images; (b) WTH transformation; (c) NWTH transformation; (d) Multi-SEs NWTH transformation (e) Our proposed method

We analyzed each method in terms of processing time and correct detection rate. Table 1 shows processing times of each method for the real IR images in Fig. 8. Table 2 compares their results for correct detection rate.

The experimental results show that target detection ability of our proposed method is superior to that of WTH transformation, NWTH transformation, and multi-SEs NWTH transformation.

Table 1. Processing times

	WTH (s)	NWTH (s)	multi-SEs NWTH (s)	Proposed (s)
A	0.005	0.005	0.014	0.058
B	0.005	0.006	0.015	0.057
C	0.006	0.006	0.017	0.059

Table 2. Correct detection rate(%)

	Detection rate (%)			
	WTH	NWTH	multi-SEs NWTH	Proposed
Small target data	59.71	63.03	83.41	100.00

4 Conclusion

In this paper, we proposed a feature-based small target detection system from IR images. The system is flexible to the sizes of targets as it uses the corner features extracted with Harris corner detector. The clutter on the outside of targets and cloud regions are eliminated using a histogram of intensity distribution and adaptive thresholds. The clutter on the edges of clouds is also removed by our improved labeling technique. Experimental results show that our proposed method is more effective in detecting small targets than existing methods.

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