Infrared Dim Target Detection Based on Multi-Feature Fusion

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Abstract. A novel infrared(IR) dim target detection algorithm based on multi-feature fusion is proposed in this paper. Firstly, the gray residuals map is obtained by calculating the 8-directional local gray residual. Secondly, the image is divided into a series of local image patches by using a sliding window, then the intensity mean of local image patches is constrained to achieve the local intensity mean constrained map. Lastly, the local image patch is further divided into 12 directional blocks, and the gradient direction constrained saliency map can be obtained by constraining the gradient direction of the pixels in each directional block. Then, the final saliency map is obtained from the above three feature maps by dot product operation, and dim targets are separated by threshold segmentation. The experimental results show that the proposed algorithm not only can effectively suppress background clutter and eliminate false targets, but also can accurately detect dim targets with high detection rate.

1. Introduction

Infrared(IR) dim target detection as a key technology has been widely applied in many fields, such as target tracking system, monitoring system, precision guidance and early warning system, etc.[1-2]. Due to the influence of long distance and atmospheric environment, those targets in IR image are usually very small and only occupy a few pixels. In addition, dim targets have no obvious shape, texture information and the detectable signal in IR image is relatively weak[3]. On the other hand, the background of IR dim target image is also complex. Typical background includes sky background, complex cloud background, sea background and sea-sky background. Under these complex backgrounds, the signal-to-clutter ratio (SCR) of dim targets is very low, which is easily immersed in noise and strong clutter. Moreover, there are pseudo-target points similar to dim targets in the image, resulting in a high false alarm rate. Hence, these effects make the IR dim target detection a challenging task.

Recently years, the human visual system (HVS) has been introduced to IR dim target detection for getting favorable results. In human visual mechanism, IR dim targets have significant discontinuity and strong contrast compared with adjacent background[4]. Based on the properties of the HVS, a series of IR dim target detection methods have been proposed. However, these methods still can not perform well under complex backgrounds. For example, Kim et al.[5] used Laplacian of Gaussian(LOG) filter to enhance target and suppress the background. Although this algorithm performs well, it fails to filter some high-frequency cutters. Chen et al.[6] proposed a classical contrast
method called local contrast measure (LCM), which enhanced the bright targets significantly. However, its robustness is still not good enough when backgrounds involve high-bright noise and heavy clutter. In addition, Wei et al.[7] proposed a method named multiscale patch-based contrast measure (MPCM), which can detect the bright and dark targets simultaneously. But it has limited ability to suppress strong background cutters. In 2018, Zhang et al.[8] introduced a new dim target detection algorithm based on local intensity and gradient properties (LIG), which suppresses cutters well and has good robustness for various target sizes. However, in complex background infrared image, there are pseudo-target points with similar intensity or gradient characteristics to dim target. The interference of these pseudo-target points mainly includes: isolated background points and some strong edge clutters, which makes the LIG method unable to eliminate the pseudo-target completely.

Aimed at achieving a better detection result, this paper presents a novel IR dim target detection method based on multi-feature fusion. The main contributions of this paper can be summarized as follows.

1) An 8-direction local gray residuals method is introduced. It can suppress the gently background effectively.

2) A local intensity mean constraints is designed. It can eliminate the interference of isolated background points and enhance targets.

3) Gradient direction constraints of IR dim target are designed to eliminate the interference of strong edge clutters.

2. 8-direction local gray residuals
Firstly, along the direction $\theta$, the local gray residuals $I$ can be defined by

$$I(x,y,\theta) = f(x,y) - \min_{d \in (0,d_{m})} f(x-d \cdot g(\theta), y + d \cdot h(\theta))$$

where $f$ denotes the image, $f(x, y)$ is a pixel in an image, $d$ represents the distance range between the coordinates of a pixel and its surrounding pixels, $d_{m}$ is the upper bound of this distance. And $g(\theta)$ and $h(\theta)$ can be calculated by

$$g(\theta) = \begin{cases} 0 & \theta = 0 \ or \ \theta = \pi \\ 0 < \theta < \pi \\ -1 & \pi < \theta < 2\pi \end{cases}$$

$$h(\theta) = \begin{cases} 1 & 0 \leq \theta < \frac{\pi}{2} \ or \ \frac{3\pi}{2} < \theta < 2\pi \\ 0 & \theta = \frac{\pi}{2} \ or \ \theta = \frac{3\pi}{2} \\ -1 & \frac{\pi}{2} < \theta < \frac{3\pi}{2} \end{cases}$$

Furthermore, in order to suppress the background adequately, the gray value of the pixel $f(x, y)$ is expressed by the minimum response of the residuals in each direction, so the 8-direction local gray residuals can be defined as

$$B(x,y) = \min_{\theta \in [0, 2\pi]} I(x,y,\theta)$$

where $\theta \in \left\{ \frac{n\pi}{4} | n = 1, 2, 3, \ldots, 8 \right\}$.

Consequently, according to equation(1), equation(4) can be rewritten as
\[
B(x, y) = \min_{d \in \{0, 2\pi\}} \left( f(x, y) - \min_{d \in \{0, 2\pi\}} f(x - d \cdot g(\theta), y + d \cdot h(\theta)) \right)
\]

\[
= f(x, y) - \max_{d \in \{0, 2\pi\}} \left( \min_{d \in \{0, 2\pi\}} f(x - d \cdot g(\theta), y + d \cdot h(\theta)) \right)
\]

\[
= f(x, y) - \max_{d \in \{0, 2\pi\}} H(x, y, \theta) \tag{5}
\]

where

\[
H(x, y, \theta) = \min_{d \in \{0, 2\pi\}} f(x - d \cdot g(\theta), y + d \cdot h(\theta)) \tag{6}
\]

Generally speaking, the gray value of the target pixel is brighter than its surrounding background. Therefore, as in equation (5), for the target pixel \(f(x, y)\), subtracting the minimum gray value (surrounding background pixels) of all the pixels along the \(\theta\) direction, a larger \(B(x, y)\) can be obtained, and the target pixel can be enhanced.

3. Local intensity mean constraints
In this section, the image is divided into a series of local image patches by using a sliding window from left and top to right and down. The step size is 1 pixel. In this way, the mean of the intensity of each local image patch can be expressed as

\[
\bar{P} = \frac{1}{s^2} \sum_{x=1}^{s} \sum_{y=1}^{s} P_{xy} \tag{7}
\]

where \(s\) denotes the size of the sliding window, and \(P_{xy}\) is the gray intensity of each pixel in a local image patch. In IR dim target image, the pixel of target is typically brighter than isolated background clutters. Thus we need an appropriate threshold to distinguish between real target and isolated background clutter. According to the principle of \(3\sigma[9]\), the threshold can be given as the following

\[
T_i = m + k_1 \sigma \tag{8}
\]

where \(k_1\) is a constant which is determined empirically. \(m\) and \(\sigma\) denotes the mean and the standard deviation of the local image patch, respectively.

Then, the local intensity mean constrained map \(P\) can be obtained by

\[
P = \begin{cases} 
0 & \bar{P} \leq T_i \\
\max_{x,y \in \{1,2,...,s\}} P_{xy} & \bar{P} > T_i 
\end{cases} \tag{9}
\]

As shown in equation (9), once the mean value of local image patch is less than \(T_i\), then all the pixels of this image patch are set to 0, and the isolated background points are eliminated.

4. Gradient directional characteristic
In IR dim target image, the target is discontinuous with its adjacent background regions, and this discontinuity can be characterized by gradient vector field. Some research has proved that the gradient direction of dim targets points roughly to the center of them, but the gradient of strong edge clutter is generally consistent. This characteristic is called as the local gradient directional characteristic. Therefore, the gradient directional characteristic can be used to eliminate strong edge clutters.

Similarly, local image patches are achieved from the input IR image with a sliding window, and the step size is 1 pixel. The size of local image patch is \(c = 2d_m - 1\), where \(d_m\) is the upper bound of the distance between the coordinates of a pixel and its surrounding pixels when calculating 8-direction local gray residuals. In order to make the best of the difference of gradient vector field distribution
between target and strong edge clutters, Cartesian coordinate system is established with the center of
the local image patch as the origin. Then, the local image patch are further divided into 12 directional
blocks, which is presented in figure 1. Each directional block can be expressed by

$$\phi_i = \left\{ f(x,y,\theta) \mid \frac{\pi(i-1)}{6} < \theta \leq \frac{\pi i}{6}, i \in [1,2...12] \right\}$$

where \( \phi_i \) denotes the \( i \)th directional block, \( f(x,y,\theta) \) represents a pixel point in directional block, and \( x,y \) is the coordinates of a pixel.

Since the gradient of IR dim targets does not point strictly to its central region, thus the orientation
constraint of the gradient of targets in this paper is as follows

$$\omega_{\phi_i} = \left\{ g_{\phi_i}(u,\beta,x,y,\theta) \mid \pi \leq \beta < \frac{3\pi}{2}, i \in [1,2,3] \right\}$$

$$g_{\phi_i}(u,\beta,x,y,\theta) \mid \frac{3\pi}{2} \leq \beta < 2\pi, i \in [4,5,6]$$

$$g_{\phi_i}(u,\beta,x,y,\theta) \mid 0 \leq \beta < \frac{\pi}{2}, i \in [7,8,9]$$

$$g_{\phi_i}(u,\beta,x,y,\theta) \mid \frac{\pi}{2} \leq \beta < \pi, i \in [10,11,12]$$

where \( \omega_{\phi_i} \) represents the gradient set satisfying the direction constraint of gradient vector in direction
block \( \phi_i \), \( g_{\phi_i}(u,\beta,x,y,\theta) \) denotes the gradient element in the set \( \omega_{\phi_i} \), \( u \) represents the magnitude of
\( g_{\phi_i} \), and \( \beta \) is the direction of \( g_{\phi_i} \). As show in figure 2, \( g(x_1,x_1) \) and \( g(x_2,y_2) \) is the gradient element
in the directional block \( \phi_5 \) and \( \phi_6 \), respectively. According to equation (11), the direction of
\( g(x_2,y_2) \) does not meet the constraint \( \frac{3\pi}{2} \leq \beta < 2\pi \) in the block \( \phi_6 \). So \( g(x_2,y_2) \notin \phi_6 \), while
\( g(x_1,x_1) \in \phi_5 \).

Then, in each directional block, the mean square of the gradient magnitude can be calculated by

$$V_i = \frac{1}{N} \sum_{j=1}^{N} u_j^2$$

where \( N \) is the number of the gradient elements in the set \( \omega_{\phi_i} \). And minimum value and maximum
value of all \( V_i \) can be expressed as

$$V_{\min} = \min_{1 \leq i \leq 12} V_i, \quad V_{\max} = \max_{1 \leq i \leq 12} V_i$$

(13)
Finally, the gradient direction-constrained saliency map of local image patches can be represented as

\[ V(x, y) = \begin{cases} \sum_{i=1}^{12} V_i & \frac{V_{\min}}{V_{\max}} > k_2 \\ 0 & \frac{V_{\min}}{V_{\max}} \leq k_2 \end{cases} \] (14)

where \( V(x, y) \) is the central pixel of a local image patch, and \( k_2 \) is a constant. When the sliding window traversal image is completed, the final gradient direction constrained saliency map \( V \) is obtained.

5. Target detection system
The gray residuals map \( B \), the local intensity mean constrained map \( P \) and the gradient direction constrained saliency map \( V \) can be obtained by using the three-step process shown above. In this section, the final saliency map is obtained from the above three feature maps by dot product operation, and dim targets are separated by threshold segmentation. The threshold \( T_z \) can be defined by

\[ T_z = \bar{F} = \bar{B} \bullet P \bullet V \] (15)

where \( F' \) is the final saliency map, and \( \bar{F} \) represents the means of non-zero elements in \( F' \). Additionally, in order to show the proposed method intuitively, the overview of our method is shown in figure 3.

6. Experiments and results
6.1 Experimental Setup
To evaluate the performance of proposed method, four kinds of IR images with different backgrounds are used in the experiment. As shown in figure 4, (a) is sky background, (b) is complex cloud background, (c) is sea background and (d) is sea-sky background.

In this paper, the size of the sliding window \( s = 3 \) and \( c = 11 \). The range of parameter \( k_i \) is 0~1.5. And the value of \( k_j \) is set to 0.01. The LCM method[6], MPCM method[7] and LIG method[8] are used as the baseline methods.
6.2 Experimental results and discussions

From figure 4(a), we can find that its background is relatively flat, but there is interference from isolated background points. Figure 4(b) shows that a dim target overlap with heavy back clouds. In addition, the backgrounds with strong edges occupies the main part of the image. In figure 4(c) and figure 4(d), the contrast between the background and target is so low that we can hardly distinguish it.

The detection results on four kinds of infrared images with different backgrounds are shown in figure 5. We can see that background clutters of the image are fully suppressed, and the final detection results have no residual pseudo-target. Especially in Figure 5(a), the isolated background noise is completely eliminated. This means that the proposed algorithm has not only good performance of suppressing the cutters, but also robustness for various complex backgrounds.

In order to further assess the detection capability of the our algorithm, we use the receiver operation characteristic (ROC) curve[10] to indicate the performance of the method. And the ROC curves of four methods for four kinds of infrared images are presented in figure 6. By comparison, the proposed method achieve the highest detection rate at the fastest speed in all image. And the ROC curves of our algorithm is located in the upper left corner, which implies that our algorithm achieves the better detection performance compared with other methods.

7. Conclusions

In this paper, a new IR dim target detection method is proposed. An 8-direction local gray residuals method is introduced to suppress the gently background effectively. In addition, by using the local intensity mean constraints, the interference of isolated background points is eliminated. More importantly, the backgrounds with strong edges is also suppressed by using the gradient directional characteristic. The experimental results show that the proposed algorithm not only can effectively suppress background clutter, but also can accurately detect dim targets with high detection rate.
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