A method for single frame detection of infrared dim small target in complex background

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Abstract. In order to solve the problem of high false alarm rate caused by strong disturbance (the ground objects, uncertain strong noise) in complex background, we propose a novel algorithm based on density peaks searching and improved region growing. Initially, density peaks searching is employed to select the candidate targets quickly; then, improved region growing with introducing the relative local contrast and the local gray average is used to extract the features of candidate targets; finally, an adaptive threshold is applied to extract real targets. Experimental results on two real sequences show that the proposed algorithm has a better effectiveness against existing algorithms.

1. Introduction
The infrared dim small targets usually occupy only a few pixels in images and are easy to be drowned in complex background clutters and heavy noise. Accordingly, it is challenging for infrared searching and tracking system (IRST) to detect small targets from complicated background. In recent years, a large number of methods for detecting infrared dim small targets have emerged. These methods can be divided into two categories: single-frame-based methods and multi-frame-based methods. Compared with multi-frame-based methods, single-frame-based methods have the advantages of short running time and no need to consider interframe jitter and prior information. Therefore, single-frame-based methods have attracted more research attention in recent years.

Filtering-based methods are an important branch of infrared small target detection methods. Representative methods are Mean Filter [1], Median Filter [2], Top-Hat Filter [3-4], LoG Filter [5], etc. Although this type of algorithm has a short running time, it is susceptible to interference from complicated background clutters and noise, which generates more false alarms. In recent years, the contrast mechanism of human visual system (HVS) have shown great potential in the field of single-frame-based target detection. Such methods are inspired by biological mechanisms and their focus is on the contrast information between the region of interest and the background. Representative methods include LCM [6], NLCM [7], MPCM [8], RLCM [9], etc. This kind of approach has achieved good results in terms of target enhancement and background suppression by constructing contrast operator, but it computes the local feature value at each position through a rectangle sliding window so that they can hardly match different clutter shapes very well. In addition, inspired by [10] and [11], Huang et al. [12] have proposed a detection algorithm based on density peaks searching and maximum-gray region growing. This approach is novel and has great detection effect. It can suppress the continuous strong and weak edge clutters. However, the disadvantages are that it ignores the interference of isolated highlight noise pixels and does not enhance the characteristics of dim small targets. This method
improves the detection rate and at the same time the false alarm rate is relatively high. When the target signal strength is weaker, it can easily cause the target to be missed.

Aiming at the shortcomings of existing algorithms, we propose a novel algorithm based on density peaks searching and improved region growing.

The main contributions of this paper can be summarized as follows.

1) Fast searching. Extracting density peaks from an infrared image as candidate targets, and reducing the target-searching scope.
2) Feature extraction. Adopting the improved region growing method to calculate the features of all the selected density peaks.
3) Threshold operation. Separating the real targets from clutters.

2. Fast searching

2.1. Infrared dim small target features

Infrared dim small targets usually have the following obvious features: a relatively large gray value; a relatively large distance from pixels with larger gray value. As shown in Figure 1, the left side is a partial infrared image with a target, and the right side is an enlarged image of target pixels and adjoining background pixels. The numerical values on the image represent the gray value of each pixel of the target and adjoining background. Obviously, the gray values of the target pixels are larger than the gray values of the adjoining background pixels, and the distance between the target pixels and the adjoining pixels with lower gray values are relatively small. In other words, target pixels are further away from pixels with higher gray values.

![Figure 1. Gray image of target and its neighbors.](image)

2.2. Density peaks searching

According to the features of infrared dim small targets, we can use a density peaks searching method to quickly extract candidate targets. Inspired by [10], we can apply its method of finding the local maximum density point to the extraction of candidate targets in infrared images.

This method has two values that need to be calculated: the local density of the sample point, and the distance between the sample point and the point that is greater than the local density of the sample point. Here, we regard each pixel in the infrared image as a sample point, and regard the gray value of each pixel as the density of the sample point. We define the density of the pixel \( p \) in infrared images as

\[
\rho_p = g_p
\]

(1)

\( g_p \) is the gray value of the pixel \( p \). We denote the distance of the pixel \( p \) as \( \delta_p \), which represents the minimum distance between pixel \( p \) and any pixel with larger gray value.
\[ \delta_p = \min_{q, d_{pq} > r_p} \left( d_{pq} \right), \quad d_{pq} = \sqrt{\left( x_p - x_q \right)^2 + \left( y_p - y_q \right)^2} \]  

(2)

where \( x_p, y_p, x_q, y_q \) are the position coordinates of the pixel \( p \) and pixel \( q \), \( d_{pq} \) represents the Euclidean distance between two pixels. For the pixel with the biggest density in the original image, we define as

\[ \delta_p = \max_q \left( d_{pq} \right) \]  

(3)

A pixel with both large \( \rho \) and \( \delta \) in a local region is called a “density peak” here. In this letter, we calculate the product of each pixel’s \( \rho \) and \( \delta \), and sort all results of the pixels from large to small. Then we take the first \( n \) pixels as density peaks, denoted as \( s_1, s_2, \ldots, s_n \). According to the features of infrared dim small targets, the target pixels usually have large \( \rho \) and \( \delta \) in a local region. Therefore, the real target pixels are included in the density peaks, and we can narrow the target-searching range by extracting density peaks.

### 3. Feature extraction

In order to separate the real targets from all the candidate targets, we need to extract features from candidate targets after using the approach based on density peaks searching. Therefore, an improved region growing method is proposed to calculate the feature values of candidate targets.

Specifically, we record all the extracted density peaks as seeds \( s_{k(k=1,2,\ldots,n)} \), and use \( U_k \) to denote the pixel set that grows from the seed \( s_k \). The initial state of \( U_k \) is \( s_k \), which is denoted as \( U_k^0 \). We use \( U_k^i \) to denote the pixel set after \( i \) steps of the region growing from the seed \( s_k \), and define the set of all unallocated pixels that adjoin \( U_k^i \) as

\[ W_k^i = \left\{ a \mid a \not\in U_k^i, N(a) \cap U_k^i \not= \emptyset \right\} \]  

(4)

where \( a \) represents the coordinate vector of the pixel, and \( N(a) \) denotes the eight neighbors of the pixel \( a \). Throughout our proposed method, we choose the pixel \( a^* \) satisfying

\[ a^* = \arg \max_{a \in W_k^i} g(a) \]  

(5)

where \( g(a) \) represents the gray value of the pixel \( a \). Then we add the selected pixel \( a^* \) to \( U_k^i \),

\[ U_k^{i+1} = U_k^i \cup \{ a^* \} \]  

(6)

There are many isolated highlight noise pixels in the real infrared images. In order to avoid the negative effect of highlight noise pixels on the extraction of the real target, we use the gray average of the pixel set in the region growing. Here, we define the local gray average as

\[ G_m = \frac{1}{K_l+1} \sum_{i=0}^{K_l} g(a_i) \]  

(7)

where \( a_i \) denotes the pixel after \( l \) steps of the region growing from the seed \( s_k \), and \( a_{i=0} \) represents the seed \( s_k \). We use \( g(a_i) \) to denote the gray value of the pixel after \( l \) steps of the region growing.
$K$ represents the number of pixels that need to calculate the gray average except the seed $s_k$, and its optimal range is from 1 to 4.

Then, we construct the contrast operator to define the feature calculation method of the candidate targets

$$R(k) = \max_{a \in [l]} \left(\frac{G_m}{g(a)} G_m - G_m\right)$$

(8)

The maximum value of $l$ is usually set to be slightly larger than the number of pixels occupied by the target. $R(k)$ represents the feature calculation result of the seed $s_k$.

Since the size of the real target is relatively small, for the seed $s_k$ in the real target region, its pixel set will finally exceed the range of the target region. Therefore, both the high gray value pixels belonging to the real target and the low gray value pixels belonging to background will be included in the pixel set, and the ratio of $G_m$ and $g(a)$ will be greater than 1, leading to a large $R(k)$. For the seed $s_k$ in the background clutter region, its pixel set will hardly exceed the range of the background clutter region, because the background clutter is more continuous than the real target region, and the size is usually relatively large. Thus, the pixel set from the clutter seed will be filled with high gray value pixels finally, and the ratio of $G_m$ and $g(a)$ will tend to 1, leading to a relatively small $R(k)$.

4. Threshold operation

As described above, compared with the background pixels, the feature values of the real target pixels usually are large in the feature data. Accordingly, we only need to select the feature results with large values. Here, we use a threshold operation, and the threshold $T$ is adaptively defined as

$$T = \mu + k_{th} \times \sigma$$

(9)

where $\mu$ and $\sigma$ are the mean and standard deviation of the feature data, $k_{th}$ is a given parameter. Our experiments show that the optimal range of $k_{th}$ is from 1 to 5.

The pixels which have larger feature values than $T$ will be regarded as real target pixels, while the pixels with relatively small feature values are discarded.

5. Flowchart of algorithm

The whole flowchart of the proposed method is shown in Figure 2.

6. Analysis and evaluation of experimental results

All the experiments and simulations were conducted on a computer with 16-GB memory and 2.6-GHz Intel i7 processor, and the code was implemented in Matlab R2018b.
In the experiments, different scenes of infrared images [13] were used to test the detection effect of the proposed method. As shown in Figure 3, targets were marked with red circles, and the scene details were shown in Table 1.

Table 1. Details of the 2 test scenes.

| No. | Frame number | Scene description     | Target (pixels) | Image size (pixels) |
|-----|--------------|-----------------------|-----------------|--------------------|
| 1   | 100          | Grounds and sky       | 2x2             | 256x256            |
| 2   | 100          | Grounds               | 2x2             | 256x256            |

Figure 3. The representative frame of each typical scene.

In order to evaluate the performance of the proposed method intuitively, we adopted the receiver operation characteristic (ROC) curve. The ROC curve is plotted based on the true positive rate (TPR) and false positive rate (FPR), which are defined as

\[
\text{TPR} = \frac{\text{number of detected true targets}}{\text{total number of actual targets}}
\]

\[
\text{FPR} = \frac{\text{number of detected false targets}}{\text{total number of pixels}}
\]

Figure 4. ROC curves of two groups of image sequences.

Three methods were adopted for comparison, and they are Top-hat method [3], MPCM method [8] and Huang [12] method. A ROC curve closer to the top left is better. We can see that the ROC curves of the proposed method have a superior detection performance in both ROC curves from Figure 4, demonstrating the proposed methods’ effectiveness.
7. Conclusion
In this letter, we have proposed a new IR dim small target detection method based on the density peaks searching and the improved region growing. Compared with the maximum-gray region growing method, the proposed method reduces the eigenvalues of background pixels (including isolated highlight noise pixels) and enhances the eigenvalues of the real target pixels to a certain extent. First, the isolated highlight noise pixels can be suppressed by introducing the local gray average in the region growing; in addition, the difference between the true and false targets in the candidate targets is enhanced by constructing a different contrast operator. Finally, all the experiments and simulations have proved that the proposed method has a great detection effect.

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