A new point target detection method

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Abstract. This paper proposes a new point target detection method based on multiscale morphological filtering and local characteristic criterion. First 8-directions morphological Top-hat transform are used to detect all the possible targets with different scales. Next, the adaptive threshold is adopt to obtain the Region of Interest (RoI) of the target and improve signal to noise ratio (SNR). Secondly, we remove the remaining background edges according to the local characteristic criterion between background edges and point targets. Finally, we make use of the matching relationship of interframe to remove noise and obtain point target trajectory. And the point target is successfully detected out in motion control system. The results show that the proposed method has a good performance to suppress complex background and meet real-time requirement.

1 Introduction

Infrared dim point target detection technology is a key technique in infrared search and track (IRST). Since the aircraft is at long ranges from infrared focal plane array (IRFPA) detector, point target’s imaging size and detail information are very small. More seriously, the background is temporally nonstationary such as atmospheric radiation, complex clouds, buildings and heavy noise, which is likely to cause the radiation intensity of some scene in the infrared image over the point target\textsuperscript{[1-3]}. Therefore, the first step in target detection is to suppress the background.

A large amount of researches in the point target detection have been carried out for decades. Bae\textsuperscript{[4]} proposed a bilateral filter which was made toward predicting backgrounds. Gu\textsuperscript{[5]} work to predict and eliminate background clutters by using a kernel-based nonparametric regression model. A detection method based on Karhunen-Loeve transform has been proposed to manage a typical maritime scenario recently\textsuperscript{[6]}. Kim\textsuperscript{[7]} presented a spatial filter constructed by decomposing the original 2D LoG filter, but the computational complexity is high. Also many scholars use wavelet transform in different scales to distinguish the target and background\textsuperscript{[8]}. Laure\textsuperscript{[9]} proposed a target detection algorithm of background’s block matching 3D (BM3D) model by calculating the covariance of image block to estimate the similarity distribution, then the Gaussian mixture model was used to model the background. The background suppression effect is very good, but the algorithm is complicated and it’s difficult to realize. Secondly, there are commonly used methods such as the max-median filtering\textsuperscript{[10]}, dynamic programming algorithm\textsuperscript{[11]}, and particle filter\textsuperscript{[12]}. Many algorithms can suppress the complex background well but the complexity of algorithm is high and can’t meet the real-time requirement. Some algorithms not only highlight the goal, but also remain high-frequency background edges and isolated noise when predicting the background, which resulting in a high false alarm probability\textsuperscript{[13-15]}.
Recently, a lot of people use morphological filtering\cite{16} to detect point target in complex background. Top-hat transform in morphological filtering is used to extract the similar structure in the image with a certain morphological structure element. The effect of background suppression for morphological filtering depends on the size and shape of structural element. The role of structural element in morphological operations is similar to the filtering window. The conventional Top-hat transform algorithm only uses a structural element, which ignoring the target details in different directions. Recently, some people use multiscale morphological algorithm to detect weak and small seismic wave. In this paper, we propose a new detection method based on multiscale morphological Top-hat transform and local characteristic criterion. The complex background and noise are eliminated clearly and the point target is detected out using this method. The results prove that our algorithm is effective and meets the requirements of the parallel properties needed for easy implementation in a real-time hardware system.

2 Multiscale morphological filtering

Aircraft with long distance from infrared detector in the image is rarely accounted for 1 pixel, more often spreading into horizontal or vertical direction of 2 pixels, or 3×3 pixels, as shown in Figure 1. It is because that long distance imaging produces optical diffraction, and point target will diffuse into Eyre spot, causing energy diffusion to neighboring pixels. The size and shape of point target in the motion are changing, and the strong mobility of point target is more likely to occur in the complex scenes with different scales.

![Figure 1: Morphological information of point target](image)

In this paper, we adopt a kind of omnidirectional multiscale structural elements to cover the point targets in every direction as far as possible. The open operation in morphological filtering can get rid of the region which is less than the structure element sub domain. We set \( I(x, y) \) as the input of the original image, \( b(s, t) \) is the structure element. \( \oplus \) represents dilation operation, and \( \ominus \) represents erosion operation. The open operation is as follows:

\[
(I \circ b_n)(x, y) = [I(x, y) \ominus b(s, t)] \oplus b(s, t).
\]  

We use the larger structural element than the target to make open operation, so as to obtain the image background. Then we subtract the background image from the original image, which is the Top-hat transform.

The proposed multiscale Top-hat transform is defined as follows:

\[
TH_n = I(x, y) - (I \circ b_n)(x, y),
\]  

where \( b_n \) represents different structural element, and \( n = 1, 2, \ldots, N \).

We design the structural elements of 8 directions: horizontal, vertical, diagonal, and so on, to extract the point targets of different gray levels. The structural elements of 8-directions \( b_n(n = 1, 2, \ldots, 8) \) which are 3×3 dimensions are shown below:

\[
\begin{bmatrix}
0 & 0 & 0 \\
0 & 0 & 1 \\
0 & 1 & 0 \\
1 & 0 & 0 \\
0 & 1 & 1 \\
0 & 1 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]
The designed structural elements cover almost all the morphological information of point target. For each $b_n$, the $ROI_n$ can be obtained from the Top-hat transform.

We construct a large filter with $ROI_n$, and get the results of suspected point target images with different Morphological distribution shown as formula (12).

$$ROI = [ROI_1 \oplus ROI_2 \oplus \cdots \oplus ROI_n].$$

The constant false alarm rate (CFAR) is used to deal with the above $ROI$ and we get the candidate targets. The threshold is calculated as:

$$Th = \mu + k\sigma,$$

where $\mu$ is the mean value of the image, $\sigma$ the standard deviation, and $Th$ is the adaptive threshold, and $k$ is a fixed constant, which can be regarded as the threshold of SNR. We make binaryzation to the image by $Th$. To show the results of the algorithm, we assign $k$ is 1.5 according to the SNR of point target to be detected. The results of the above process may also remain residual strong fluctuation background edges and noise. We use the local characteristic criterion between background edges and point targets to remove the interference point.

3 Local characteristic criterion

The remaining points not only consist of point target, but also exist high-frequency background edges in the image. In order to detect out point target instead of the edges, we use the 4-directions weighted filter algorithm in $5 \times 5$ window centered at $I(i, j)$, as shown in Figure 3. We define $L_m$ (m=1 to 4) as the direction vector consisting of four coordinates around $I(i, j)$ in the $m$th direction, which are given in (5).

$$L_1 = \{I(i-2, j-2), I(i-1, j-1), I(i+1, j+1), I(i+2, j+2)\}$$
$$L_2 = \{I(i, j-2), I(i, j-1), I(i, j+1), I(i, j+2)\}$$
$$L_3 = \{I(i+2, j-2), I(i+1, j-1), I(i-1, j+1), I(i-2, j+2)\}$$
$$L_4 = \{I(i-2, j), I(i-1, j), I(i+1, j), I(i+2, j)\}.$$

$$d_{i,j}^{(x)} = \sum_{(x,y)\in L} w_{x,y} \left| I(i + x, j + y) - I(i, j) \right|,$$
where \( w_{x,y} \) is the weighted kernel to weight the absolute differences between \( t \) \( I(i+x, j+y) \) and \( I(i, j) \). We normally think that the closest four-neighbor pixels are more likely to the center pixel, so we assign the larger value 4 to them. We let \( w_{x,y}=2 \) to the second closest pixels. And so on, we assign the small value 1 to the four far points whose coordinates \( x \) and \( y \) are both ±2. We combine \( L_i \) to \( L_f \) into a column vector \( L \). The weighted kernel \( w_{x,y} \) corresponding to elements of \( L \) are obtained as follows:

\[
L = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ L_4 \end{bmatrix}, \quad w_{x,y} = \frac{1}{36} \begin{bmatrix} 1 & 2 & 2 & 1 \\ 2 & 4 & 4 & 2 \\ 1 & 2 & 2 & 1 \\ 2 & 4 & 4 & 2 \end{bmatrix}.
\]  

We define a new variable named direction ratio (DR) to distinguish point target from background edges. The direction ratio is calculated as the maximum of \( d_{i,j}^{(e)} \) divided by the minimum of \( d_{i,j}^{(e)} \) shown as follows:

\[
DR = \frac{\max(d_{i,j}^{(e)})}{\min(d_{i,j}^{(e)})}, \quad (1 \leq m \leq 4).
\]  

When it comes to an edge pixel, there exist at least one very small \( d_{i,j}^{(e)} \) and one very large \( d_{i,j}^{(e)} \). Together, they give rise to the large \( DR \). When it comes to a point target, all the four direction differences of gray values are large and near-equal. Hence the \( DR \) of point target is about 1. Considering the difference of \( DR \) value, we can distinguish point target from edges by setting a threshold \( T \), and the choosing threshold is slightly larger than 1. Thus, we obtain the point target detector as follows: if \( DR \) is less than \( T \), it is a point target, otherwise it is an edge pixel. In order to visually display experimental results, the threshold \( T \) is set to 2 in this paper.

There may also remain some noise in the detected points, while the position of noise is fixed or out of order. In the actual case, fixed-base detector acquisition device is easy to eliminate the noise according to the continuity of the moving point target, and we can obtain the target trajectory using multi frame accumulation. If we use the moving base detector to grab point target image, the speed of turntable is known always, and the fixed noise can be eliminated within 5 frames due to the high frame rate. The random flicker noise can’t establish relationship in the interframe, so it’s easy to remove it. The point target uniform an approximate linear motion in a very short time, and the number of passed pixels in the interframe can be regarded as a fixed value. We can use Hough line detection method[17] to detect out the point target and obtain the target trajectory.

4 Result analysis

Figure 4 (a) is an original image from infrared image sequence of clouds background, and the sequence contains 1000 frames. We use the proposed algorithm to detect point target in the sequence. Image processing finished in MATLAB R2014a, and PC configuration is i7-4790 CPU (3.60GHz). Figure 4 (b) is obtained by multiscale morphological transform and the adaptive threshold. The candidate points are mainly residual strong fluctuation background edges and noise, which will disappear after using the local characteristic criterion. There remain about 5 candidate points in each frame which marked in red as shown in Figure 4 (c). The trajectories of each point target are obtained by using the interframe correlation shown in Figure 4 (d). The results of image processing prove that the proposed algorithm is effective to suppress complex background. In the following we analyze the proposed algorithm through the specific data.
Figure 4: (a) Original image;(b) CFAR result;(c) Result of local characteristic criterion and noise eliminated; (d) The target trajectory

The formula of calculating the SNR of point target in infrared image engineering is as follows:

$$SNR = \frac{\mu_t - \mu_b}{\sigma_b},$$  \hspace{1cm} (9)

where \(\mu_t\) is gray mean of the target area, and \(\mu_b\) is gray mean of the local background area, so the molecular is the absolute energy of point target. \(\sigma_b\) is the standard deviation of the local background area. By calculating the SNR of point target in the whole moving phase, the SNR varies between 0.4-2.9, which is very low that the naked eye can’t find the target in infrared image.

In order to further measure the effectiveness of the proposed algorithm, we compare the proposed algorithm with common algorithms such as the max-median filtering, DoG space-scale, BM3D, and Gaussian Mixture Model (GMM). The target detection probability \(P_d\), false alarm probability \(P_{fa}\) and the running time of the algorithm are selected as the evaluation indexes of the results, which are defined as following:

$$P_d = \left(\frac{N_c}{N_t}\right) \times 100\%,$$  \hspace{1cm} (10)

$$P_{fa} = \left[\frac{N_f}{(N_f + N_t)}\right] \times 100\%,$$  \hspace{1cm} (11)

where \(N_c\) is the number of detected true points, \(N_f\) is the number of false alarms and \(N_t\) is the total number of point targets. The statistical results are shown in Table 1.
Max-median filtering and DoG are simple and meet real-time requirement, but they are not good at background suppression, so the false alarm probability is a little high. BM3D and GMM are very effective for complex background suppression, but the algorithm is complex. The proposed algorithm has high detection probability and low false alarm rate. At the same time, the proposed algorithm has low complexity and short running time.

5 Conclusion
This paper proposes a new method of point target detection based on omnidirectional multiscale morphological filtering and local characteristic criterion. First we use the 8-directions 3×3 structural elements to detect all the possible targets with different scales. Next, the adaptive threshold is adopt to obtain the RoI of the target and improve SNR. And then, we use the local characteristic criterion to eliminate the residual strong fluctuation background edges. Finally, the trajectory of point target is obtained after using the interframe correlation. The experimental results show that the proposed algorithm is effective and has a good inhibition effect on the complex background, and the running time of the algorithm is short, which meets the requirements of real-time for engineering.

Acknowledgements
This work was supported by National Science Foundation of China (NSFC) (61675202).

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