Point Target Detection Based on Quantum Genetic Algorithm with Morphological Contrast Operation

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Abstract. Robust small target detection of infrared clutter background has drawn great interest of scholars. Recently, morphological filter is playing a significant role in detecting infrared point target. Generally, the background clutter and targets are diverse in the case of each image. Traditional fixed structural elements cannot acquire to successful point target detection in complex background. Therefore, a new method is introduced based on quantum genetic algorithm to optimize and obtain structural element which is used as morphological filter for point target detection in original Infrared images. Then, morphological contrast operation is proposed to enhance areas of point targets after the filtered image is obtained. Thus, an enormous background clutter and noise are suppressed and the contrast between target and background are observably increased. Finally, by setting proper threshold, the point targets can be detected perfectly. Experimental evaluation results show that the proposed method is effective and robust with respect to detection accuracy.

Keywords: Structural elements · Quantum genetic algorithm · Morphological contrast operation · Background suppression

1 Introduction

Detection technology of weak point target has become the focus of scientists in recent decades, especially in the field of military monitoring and the application. When the target is far away from the infrared detection system, it is considered as a point target, and the area in the image only occupies 1–3 pixels and lacks obvious information of size, shape and texture. The gray value is low. Therefore, it is easy to be submerged in complicated background. In order to detect point target accurately, various algorithms of point target detection have been proposed in the past few decades. Some approaches, such as Max-mean filter and Max-median filter [1, 3], are proposed by Deshpande et al. in 1999, which are simple and easy to accomplish. However, it cannot remove edges of the clouds and structural backgrounds. In 1988, Hadhoud and Thomas proposed two dimensional least mean square filter (TDLMS) [1, 4, 9] to predict the background based on iteration. This is a typical adaptive filter that is estimated by the weighted average of neighboring pixels. Objectively, TDLMS filter is very effective as the background

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condition is relatively homogeneous or self-correlated. Unfortunately, there is a high false alarm rate to the strong fluctuation of background clutters and low Signal-to-Clutter-Ratio (SCR) [1–3, 6, 8]. In addition, the operation procedure of TDLMS is complex. Mathematical morphology was founded by French mathematicians Matheron G and Serra J in 1964. Mathematical morphology filter is an excellent method used that has obtained satisfactory effects in infrared point target detection. The choices of structural element size and shape will seriously affect the processing of digital images. In the traditional morphological filter, a fixed size and shape of the structural elements are chosen entirely by the designer's experience, so it is difficult to guarantee different targets detection from diverse infrared images and help to detect the targets precisely.

As this issue, the paper proposed a new and adaptive improved combination based on Top-hat [1, 2, 6, 7, 9, 10] and Bottom-hat transformations after using quantum genetic algorithm (QGA) [5, 10] to optimize the size and shape of structural elements from learning and training the samples. Therefore, different images use optimized structural elements to eliminate effects from complex background and certain noises. QGA is suitable for finding global optimal solution in searching spaces. If the binary mode is the structural elements of 4×4 size, the searching spaces will have 2^{16} = 65,536 search in each image, the structural elements must be adapted with the background features and targets so that the targets can be detected by lower false alarm rate. Due to the huge searching space, the QGA is used for designing adaptive structural elements to match the desired features in the infrared images.

The filtered effect of the optimized structural elements is significantly better than that of the unoptimized ones. Morphological contrast operation (MCO) is proposed in this paper, which exploits the original infrared image to add the Top-hat and then subtract the Bottom-hat to augment sensitive areas of the targets. Finally, binary images are obtained by threshold segmentation method. This also verifies the correctness of combination Top-hat and Bottom-hat transformations to enhance the target ideas proposed in this paper. The point target detection algorithm based on QGA with MCO is evidently effective and robust for complex background and noise clutter.

2 Feature Analysis for Point Target Image

The image of point target under complex conditions can be described as three parts [6, 9]:

$$I(x, y, t) = B(x, y, t) + T(x, y, t) + N(x, y, t) \tag{1}$$

where $I(x, y, t)$ represents infrared image contained point target, $B(x, y, t)$ represents the background, $T(x, y, t)$ represents dim point targets, $N(x, y, t)$ represents random noise clutter, (x, y) represents the pixel location, t denotes different intervals of frames. For infrared weak point target detection, signal-to-clutter ratio (SCR) [1–4, 6, 8, 10] is a key factor affecting the quality of detection, it is defined as follow:

$$SCR = \frac{\mu_t - \mu_b}{\sigma_b} \tag{2}$$

Where μ_t is the average gray value of target region, μ_b is the local area pixels' average intensity, σ_b is standard deviation of neighboring area pixels. Increasing of SCR value leads to high contrast of target area which is easier to detect. Moreover, raising of large background suppression factor (BSF) value can lightly eliminate background clutter and reduce false alarms. The SCR gain (SCRG) [1–4, 6, 8, 10] and BSF [1, 2, 8, 10] are defined as Eqs. (3) and (4) respectively.

$$SCRG = \frac{SCR_{\mathrm{out}}}{SCR_{in}} \tag{3}$$

$$\mathrm{B}SF = \frac{\sigma_{in}}{\sigma_{out}} \tag{4}$$

$\sigma_{\mathrm{i}in}$ and σ_{out} are the clutter standard deviations of the infrared image before and after filter respectively. SCRG represents the enlargement of target signal relative to background in the detection image. BSF represents the suppression level of background. The bigger values of SCRG and BSF are, the better the results of performance are.

3 Morphological Contrast Operation (MCO)

Recently, mathematical morphology filter for image enhancement and segmentation has been applied quickly and is playing a great potential role in weak point target detection. Mathematical morphology has four basic operations: dilation, erosion, opening and closing operations. The opening and closing operations are able to respectively remove off the bright and dark regions which are smaller than the size of structural elements. The opening and closing operators of morphology are described as:

$$(I \circ b)(x,y) = [I(x,y)\,\Theta\, b(s,t)] \oplus b(s,t) \tag{5}$$

$$(I \bullet b)(x,y) = [I(x,y) \oplus b(s,t)]\,\Theta\, b(s,t) \tag{6}$$

where $\oplus$ and Θ are defined as dilation and erosion operations, $b(s,t)$ is structural elements, $I(x,y)$ is original infrared image. Top-hat and Bottom-hat are defined as follows:

$$TH(x,y) = [I(x,y) - (I \circ b)(x,y)] \tag{7}$$

$$BH(x,y) = [(I \bullet b)(x,y) - I(x,y)] \tag{8}$$

For *TH* is the sensitive area of bright target, *BH* is the sensitive area of dark target, generally, small targets are brighter than local background areas. The Top-hat transform can be used for bright targets on dark background, while Bottom-hat transformation is applied for the opposite case.

Contrast enhancement mainly refers to enhancing or sharpening the characteristics of an image. This paper proposes a MCO to enhance point target regions. It can be achieved by assembling the filtered image from Top-hat and Bottom-hat in parallel. The original image added Top-hat to enhance the bright target, and Bottom-hat is subtracted from the resulting image to enhance the dark target. In other words, MCO is that original image plus *TH* minus *BH*, which is defined as Eq. (9).

$$\begin{aligned} MCO(x,y) &= I(x,y) + TH(x,y) - BH(x,y) \\ &= I(x,y) + I(x,y) - (I \circ b)(x,y) - ((I \bullet b)(x,y) - I(x,y)) \\ &= 3I(x,y) - (I \circ b)(x,y) - (I \bullet b)(x,y) \end{aligned} \tag{9}$$

Some potential point targets are enhanced through the above operations. Experiment shows that MCO can effectively enhance weak point target by suppressing background clutter and random noise to lower level to achieve success.

The key of point target detection relies on choice of structural elements. Traditional fixed structural elements are unsuitable for different targets detection from diverse infrared images. Based on this reason, the choice of structural elements should be adaptive as the background and small targets change in order to gain accurate detection. In this paper, a method of point target contrast enhancement based on MCO is proposed after having been employed by adaptive structural element filter, in which QGA below is proposed to optimize the structural elements, which attributes to its ability on searching global optimal solution.

4 Structure Element of Optimization by QGA

Narayanan first proposed QGA. Han et al. introduced quantum bits and quantum revolving gates into genetic algorithms. Quantum bits are defined as a vector existed on the unit circle which is depicted on two-dimensional plane composed of a pair of orthogonal basis of the two quantum states $\{|0\rangle, |1\rangle\}$. Quantum bits can be expressed as $|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle$, $|\varphi\rangle$ is a representation of a quantum state, α, β is a pair of plural defined probability amplitude. For example, a chromosome length [2] of m, it can be defined as binary encoding string $Q(t) = \left(\left| \frac{\alpha_1}{\beta_1} \right| \frac{\alpha_2}{\beta_2} \left| \frac{\alpha_3}{\beta_3} \right| \frac{\cdots}{\cdots} \left| \frac{\alpha_m}{\beta_m} \right| \right)$ and $\alpha_i^2 + \beta_i^2 = 1(i = 1, 2, \ldots, m)$.

An encoding with m-bit quantum bits can be expressed as 2^m different states, and the number of genes in chromosome [2] is the length of the chromosome. In this method, each binary bit in the structure element is modelled with a gene in the chromosome. The figure below shows that the 4×4 structure element is modelled with a chromosome length of 16 bits. For example, a chromosome equals [0,1,0,0;0, 1,1,0;0,1,1,0;0,0,0,0], structural elements are shown as follow in the Fig. 1.

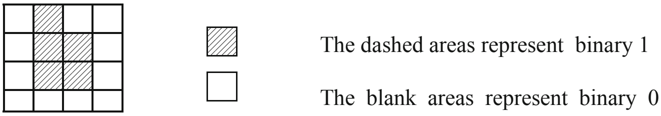

Fig. 1. A structure element is modeled with the chromosome.

After quantum bits of chromosome have been encoded by a matrix of probability amplitude pair, quantum rotation gate will be implemented. It is a main adjustment strategy for updating population in QGA, which is defined as common matrix U.

$$U = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

Quantum rotation operation is shown as follow:

$$\begin{bmatrix} \alpha_i^{t+1} \\ \beta_i^{t+1} \end{bmatrix} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \bullet \begin{bmatrix} \alpha_i^t \\ \beta_i^t \end{bmatrix}$$

Where $\left(\alpha_{\mathrm{i},}^t\ \beta_i^t\right)$ is quantum coding at the ith quantum bits from the tth generation in the structure of chromosome and θ_{i} is the rotation angle. The size and direction are executed based on a pre-designed adjustment strategy. The purpose of the rotation operation is to achieve the transition between states and speed up convergence rate to realize an optimal solution of point target detection. Compared with traditional genetic algorithms, QGA can quickly converge to global optimal solutions at a smaller population.

5 The Fitness Function [10]

Since the fitness function is the only certain indicator of the choice of individual survival opportunity in the population, it directly determines the evolutionary behavior of the population. The fitness function plays a decisive role in describing quantum bit, it offers an optimizing criterion such as convergence criterion and termination criterion of QGA. In other words, the fitness function not only plays the evolutionary behavior of the population, but also acts a decisive part in describing quantum bits.

In this paper, the fitness function is established based on the Minimum Mean Squared Error (MMSE), under criterion of MMSE, the objective adaptive function is defined as $E = \frac{1}{MN}\sum_{t=1}^{L}(Y_t - d_t)^2$, where MN is the number of training samples, Y_t is the expectation of output signal, and d_t is the expectation of output corresponding to the tth value of input, t is the maximal value of tth output matrix after each morphological filter. The flow chart of algorithm [5] using MCO with the structural elements optimized by QGA to detect point target is shown as follow in the Fig. 2.

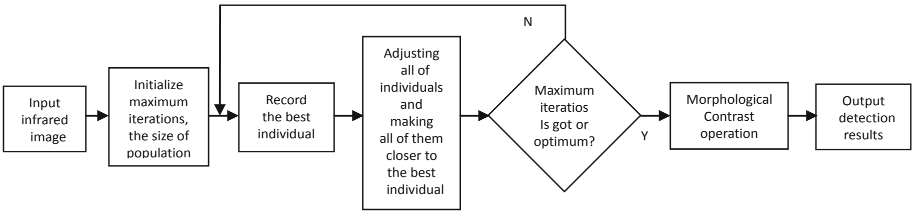

Fig. 2. The flow chart of using QGA with MCO to detect point target.

6 Compare to Several Methods

6.1 Experiment 1

To compare the results of the proposed methods with other approaches based on TDLMS filter, Max-median filter, Top-hat transformation, and Fixed structural elements filter, four different backgrounds are given in different clutter and noisy background respectively. The point targets are marked with red circles. The results of 3D maps in the Fig. 3 are shown as following after background clutter are suppressed.

Comparisons of experiment result between the classical methods and the proposed method are shown in the Fig. 3. It can be inferred that the TDLMS, Max-median filter, Top-hat transformation, and Fixed structural elements cannot well enhance the target areas and still there is a lot of background clutter around the target areas. While the QGA with CMO has better performance compared with the previous methods by improving the contrast between target and background. It is shown three-dimensional (3D) graphs in the seventh row in the Fig. 3.

6.2 Experiment 2 (BSF and SCRG Comparisons)

The results of SCRG and BSF evaluation parameters for the TDLMS, Max-median filter, Top-hat transformation, Fixed structural elements filter and Proposed methods are shown respectively as Tables 1 and 2.

As shown in Tables 1 and 2, it can be seen that Top-Hat transformation and Fixed structure element filter achieve bigger values of BSF and SCRG than other traditional methods. However two metrics are not stable and consistent. TDLMS and Max-median filter have poor ability to suppress complex background and the effects are relatively insignificant for point target enhancement. Compared to TDLMS, Max-median filter, Top-hat transformation, and Fixed structural elements filter, it is indicated clearly that the proposed algorithm achieves the best performance on two metrics for different clutter and noisy backgrounds. In which the values in boldface indicate the higher quality. From the Table 1, it is also exhibited clearly that the proposed method not only has better effect in terms of improving image-contrast enhancement, but also has stronger clutter suppression ability, especially for lower SCR images.

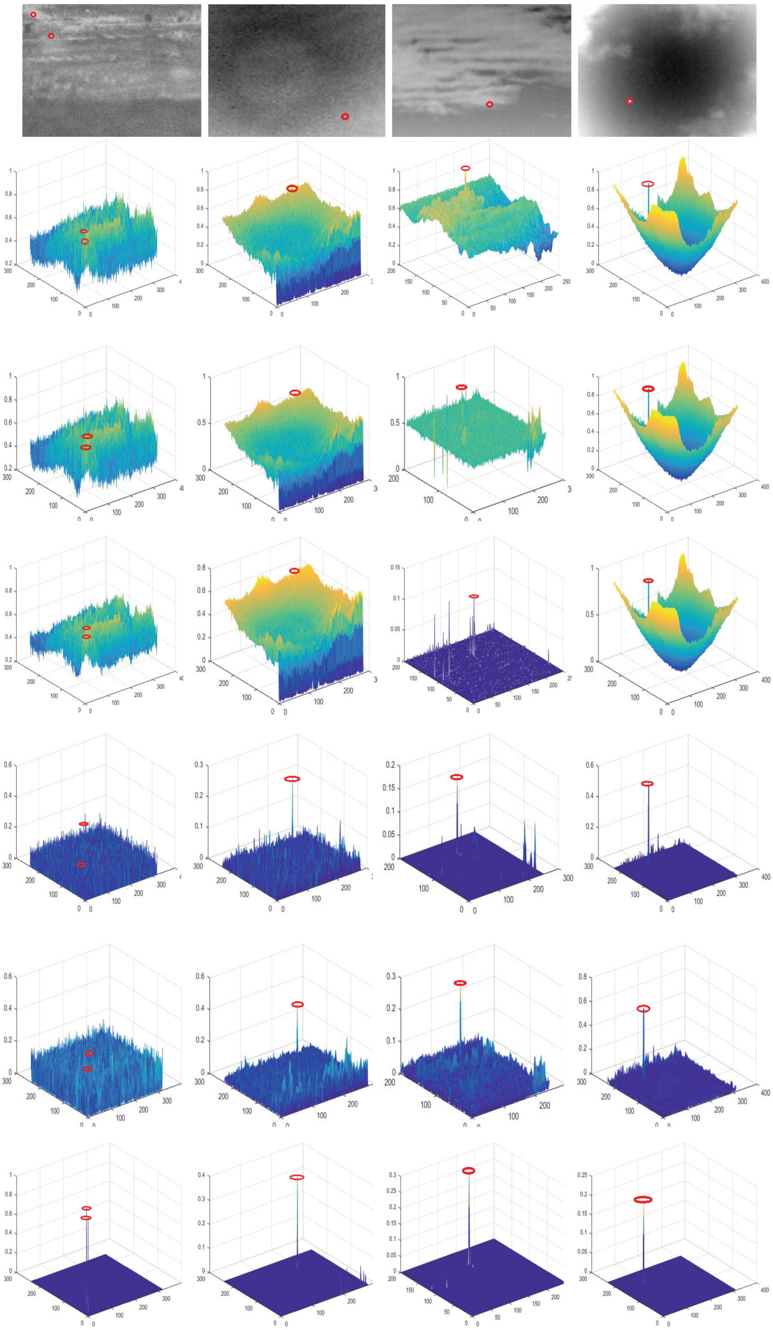

Fig. 3. Comparison of five algorithms. The first row indicates original infrared figures shown as image a1, a2, a3 and a4 in different clutter and noisy background respectively; The second row (b1–b4) indicates the 3D gray distribution of original infrared figures; The third row (c1–c4) to the seventh row (g1–g4) indicates filtered results of the 3D feature graphs of TDLMS, Max-median filter, Fixed structure element filter, Top-Hat transformation and Proposed method respectively.

Table 1. SCRG values in different algorithms for diverse infrared images.

SCRG	Image a1	Image a2	Image a3	Image a4
TDLMS	1.4394	2.4061	1.5816	1.9034
Max-median filter	1.0632	1.6491	1.2827	1.9098
Top-Hat transformation	1.7652	2.9174	5.3710	2.0417
Fixed structure element filter	5.7556	8.4635	9.3173	1.9143
Proposed method (QGA with MCO)	**36.7845**	**12.0662**	**10.004**	**3.2693**

Table 2. BSF values in different algorithms for diverse infrared images.

BSF	Image a1	Image a2	Image a3	Image a4
TDLMS	1.0130	1.005	1.1125	1.0016
Max-median filter	1.1184	1.0148	1.0052	1.0001
Top-Hat transformation	6.4431	12.6274	12.9605	7.5506
Fixed structural elements filter	1.8336	4.4161	6.5789	19.8621
Proposed method (QGA with MCO)	**18.1753**	**56.6755**	**43.5512**	**146.8314**

7 Threshold Segmentation Method

After MCO, final input infrared image is obtained, in order to extract the point target, a segmentation method is used in the result image, which is defined as Eq. (10).

$$T = \mu + k \times \sigma \tag{10}$$

Where μ is the average value of the image, σ is the standard variance of the image, k is a constant determined experientially. The results of 3D maps below are shown in Fig. 4 after threshold segmentation. Red circles marked represent point target in every image of segmentation.

Above experiments with different background show the results of the threshold segmentation. Top-hat transformation seems to be more effective for figure k3 and k4 in the Fig. 4, but for figure k1 and k2 in the Fig. 4, it does not filter out residual clutters successfully. Fixed structural elements filter can detect point target successfully for figure j3 in the Fig. 4, but for figure j1 and j4 in the Fig. 4, the background with high brightness cannot be suppressed effectively. TDLMS and Max-median filter have a large number of false targets in the Fig. 4, it fails to filter out the messy clutter. Compared with TDLMS, Max-median filter, Top-hat transformation, Fixed structural elements filter. The results of the threshold segmentation can be seen obviously that our method have the superiority on clutter suppress and point target enhancement. Finally it can successfully extract point target in different clutter backgrounds respectively.

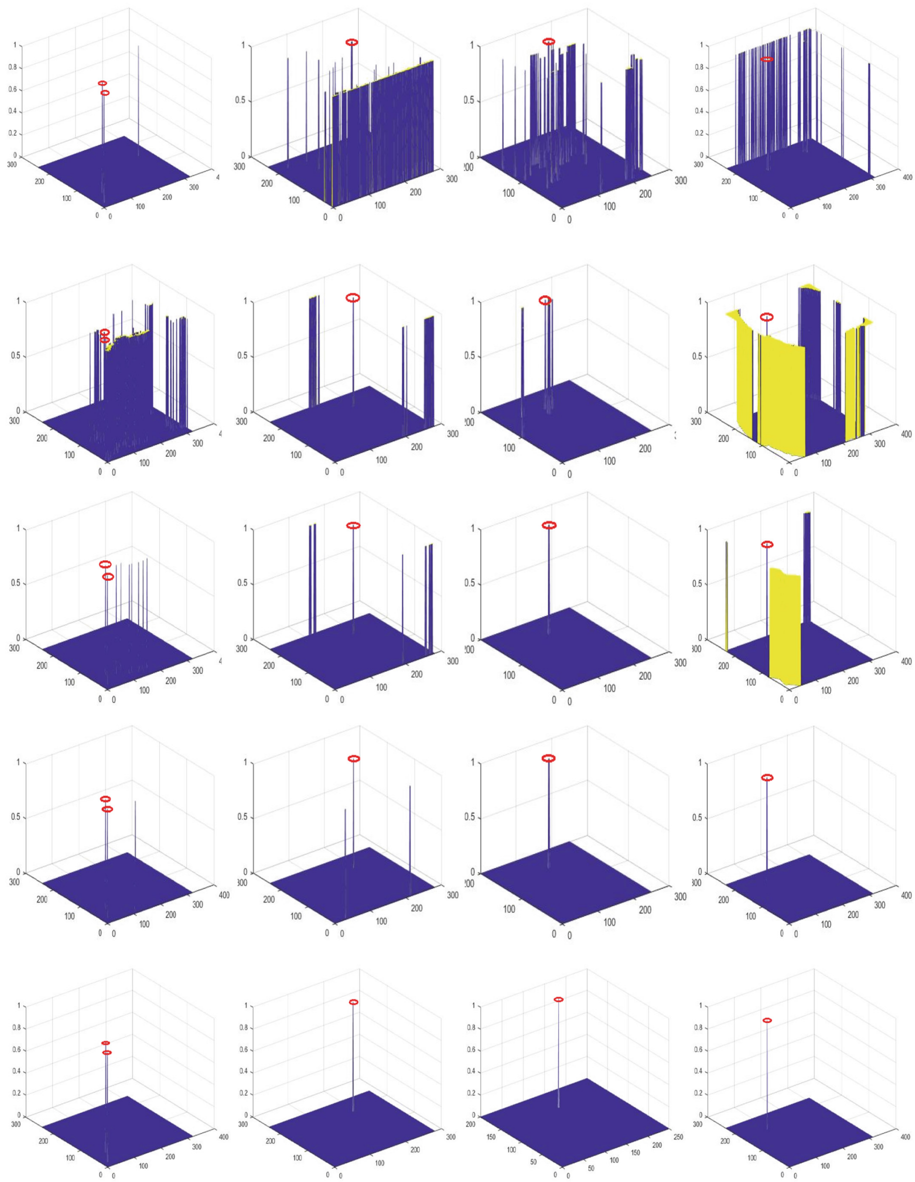

Fig. 4. The results of threshold segmentation. The first row to fifth row indicate 3D maps corresponding to threshold segmentation of TDLMS method (h1–h4), Max-mean filter (i1–i4), Fixed structural elements' filtering method (j1–j4), Top-hat transformation (k1–k4) and Proposed method (l1–l4) respectively. (Color figure online)

8 Conclusion

Qualitative and quantitative experimental results have shown the superiority of the MCO with the structural elements optimized by QGA. In this paper, Structural elements are modeled by genes in chromosome, individual survival is determined by fitness function, quantum revolving gate implements the population updating. The preferred structural elements can be used for morphological filtering to adapt to the target and background characteristics preferably in different images. The contrast enhancement algorithm was used to enhance sensitivity of the target areas. Finally, threshold segmentation method was employed to extract the point target successfully. Compared with several classical detection methods, the proposed method based on QGA with MCO have high reliability and good robustness under different clutter backgrounds for size of target tend to point in support domain.

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