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Adaptive top-hat filter based on quantum genetic algorithm for infrared small target detection

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Abstract With the development of infrared technology, infrared small targets detection has attracted great interest of researchers. Top-hat filter is one of widely used methods for detecting infrared small target, and the structure elements have great influence on the performance of detection. The structure elements are desired to be adjusted adaptively. To this end, an adaptive structure elements optimization method based on quantum genetic algorithm (QGA) is introduced, and the convergence of QGA reveals the effectiveness of QGA. Experimental results show that the proposed adaptive top-hat filter based on QGA can achieve more stable infrared small target detection performance compared with the traditional top-hat filter.

Keywords Infrared small target detection · Top-hat filter · Quantum genetic algorithm · Convergence analysis

1 Introduction

With the popularization of the infrared monitoring and the application of infrared thermography technology, the infrared small target detection technology has become a hot topic in recent decades [4, 9, 16, 28]. Because of the long-distance between targets and the infrared imaging sensor, targets appear as some dim and small speckles embedded in the complicated background. Under these circumstances, the small target is easily confused with the clutter, such as it is submerged in the clutter and also has no obvious features such as colors, scales, shapes and

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textures. Different from the high-resolution remote sensing image processing task [17], for infrared small target detection, only the unknown intensity of the target is the usable cue. Therefore, it is difficult to detect the target from the complicated background.

Various methods of small target detection have been proposed in the past [5, 18–20]. These methods is approximately divided into two classes: spatial-based filtering methods and temporal-based filtering methods. The linear spatial-based filtering methods have some impressive results when the background is homogeneous, and the non-linear spatial-based filtering methods can suppress structural background clutter for small target detection [8], but cannot have well results in noise-dominated background. In 1999, Deshpande et al. [7] proposed Max-mean and Max-median filters to preserve edges of clouds and structural backgrounds in infrared images for detecting moving targets. The variance weighted information entropy followed by a region growing technique is introduced to detect the target in the IR image after background suppression in Ref. [15]. Qi et al. [23] proposed an infrared small-target detection measure using a robust directional saliency method inspired by visual effect of human eyes between targets and backgrounds. The target can be segmented in Ref. [14, 18, 21, 22]. Unfortunately, those spatial-based methods can't work well, especially when the signal-clutter-noise ratio is very low.

Some temporal-based methods have been used to detect infrared small target. The triple temporal filter [3] has been proved that it can detect target effectively. An adaptive Butterworth high-pass filter is offered [26] to detect target since small targets is the high frequency components in infrared images. In Ref. [1], Bae has adopted a bilateral filter for predicting infrared clutter background. Taking advantage of the ability of adjusting the weights for similar intensity and surrounding pixels, the bilateral filter is able to preserve edge details of the image effectively. Other target detection methods detect target by subtracting the predicted image from the original image, and the detection performance lies on the quality of the predicted images. If the background details are retained well, the target are always excluded in the predicted image, and the target can be detected clearly from the subtracted image; and if the predicted image is blur, the subtracted image also has lots of information such as edges, so that the target cannot be detected easily. Many other techniques have also been used for infrared target detection. The information entropy [6] as an important method is developed to small target detection. Top-hat operator as one of excellent tool has also been used in infrared small object detection [2, 27]. It is evident that selection of the structure elements plays a key role on infrared object detection performance. In Ref. 11, the authors demonstrated the feasibility of optimizing the structure elements of the top-hat filters using the genetic algorithm. Genetic algorithm is a random search global optimization algorithm, and gets high efficiency when it is used to find the optimal solution of searching problem or optimization problem.

In this paper, a structure elements selection method is proposed through using quantum genetic algorithm (QGA) to optimize the structure elements, and the top-hat filter with optimal structure elements is further used to detect infrared small target. Quantum technique is proposed firstly by Shor [25] and quantum computing is a novel emerging interdisciplinary method in information science and quantum science. Quantum genetic algorithm is proposed by combining quantum computing and genetic algorithm (GA) to get better performance on finding optimal solution in search spaces.

The outline of this paper is as follows. In section 2, the theory of top-hat filter on image processing is reviewed briefly. In section 3, the process of using QGA to optimize structure elements is described in detail, and then the optimal structure elements are used in the top-hat filter for enhancing infrared small target. The convergence of QGA is proved in section 4. In section 5, the infrared small target detection performance of top-hat filter with optimal structure elements is verified, and section 6 gives the conclusion.

2 Target detection based on top-hat morphological filter

In the early twenty-first century, Serra et al. firstly proposed mathematical morphology for image processing [24] and it has been applied for target detection quickly. Particularly, the top-hat transformation operator in the mathematical morphology has become an important tool in infrared target detection [2, 27]. Given a gray-level image $I = \{(x, I(x)), x \in P, P \subseteq E^2\}$ and structure elements $B = \{(m, b(m)), m \in S, S \subseteq E^2\}$, the opening operator and the closing operator of morphology are defined as

$$I \circ B = (I \Theta B) \oplus B \tag{1}$$

and

$$I \bullet B = (I \oplus B) \Theta B \tag{2}$$

where $I \oplus B$ and $I \Theta B$ are named as dilation and erosion operation, and they are defined as

$$(I \oplus B)(x) = \sup_{m \in S, x-m \in P} \{I(x-m) + b(m)\} \tag{3}$$

and

$$(I \Theta B)(x) = \inf_{m \in S, x+m \in P} \{I(x+m) - b(m)\} \tag{4}$$

where $I(x)$is the grayscale of coordinate point x, and $b(m)$is structuring function.

Based on above operations, the opening operation and closing operation and closing operators of top-hat for a gray-level images are defined as follows,

$$OTH(x) = I(x) - (I \circ B)(x) \tag{5}$$

and

$$CTH(x) = (I \bullet B)(x) - I(x) \tag{6}$$

The opening and closing operations can respectively wipe off the bright and dark regions that smaller than the size of structure elements. Due to small candidate targets are usually small bright or black regions in infrared image, some potential target regions can be extracted by combining using the two operations [2, 27].

The performance of target detection from infrared images based on top-hat operation mostly depends on structure elements. The fixed structure elements cannot be suitable for different targets detection from different infrared images. Based on this, adaptive structure elements are critical for improving the performance of target detection. In this paper, a infrared target detection method based on top-hat operation is proposed by using adaptive structure elements, in which quantum genetic algorithm is used to optimize the structure elements due to its ability on searching global optimal solution.

3 Adaptive structure element optimized by qGa

GA has been used to estimate structure elements, and got good performance. Due to QGA has stronger convergence ability than GA for solving global optimization problem [10, 13], QGA is used to optimize structure elements in this paper. Then the optimized adaptive structure elements are used in top-hat filter for detecting infrared small target. The flow chart of using adaptive top-hat filter to detect target is shown as Fig. 1.

The detailed process of using QGA to optimize structure elements is shown as following. Firstly, we should make quantum coding. The algorithm would maintain a population of chromosomes which can be denoted as $Q(t) = \left\{q_1^t, q_2^t, q_3^t, \ldots q_i^t, \ldots q_N^t\right\}$ at the tth generation. In QGA, chromosome is encoded by using quantum bits, and each quantum bit is represented by a pair of plural. Usually, quantum bit is at the superposition of 0 and 1, so it is always defined as a vector on the unit circle which is defined on the plane consisted of a pair of orthogonal basis of the two quantum states $\{|0\rangle, |1\rangle\}$. Each quantum bit state can be expressed by the linear combination of $\{|0\rangle, |1\rangle\}$, for example, $|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle$. For a chromosome length of N, it can be expressed as binary encoding string $q_i^t = \left[\alpha_1^t \quad \beta_1^t| \quad \alpha_2^t \quad \beta_2^t| \quad \ldots \quad \ldots| \quad \alpha_i^t \quad \beta_i^t| \quad \ldots \quad \ldots|\,\alpha_N^t \quad \beta_N^t\right]$, and $\left|\alpha_i^t\right|^2 + \left|\beta_i^t\right|^2 = 1$. Furthermore, α_i^t and β_i^t can also be defined as $\alpha_i^t = \cos\varphi$ and $\beta_i^t = \sin\varphi$ called probability amplitude. In other words, the probabilities of any bit in the chromosome coding taking 0 and 1 are $\left|\alpha_i^t\right|^2$ and $\left|\beta_i^t\right|^2$, respectively. The structure of chromosome with quantum coding at the tth generation is shown as Fig. 2.

After quantum bits string have been encoded by an array of probability amplitude pair, quantum rotation gate will be performed. Quantum rotation is a main update strategy for updating population, which is defined as $U(\Delta\gamma) = [\cos\Delta\gamma \quad -\sin\Delta\gamma \quad \sin\Delta\gamma \cos\Delta\gamma]$, where $\Delta\gamma$ is the rotation angle. Using the quantum rotation gate, each quantum bit is updated by

$$\begin{bmatrix} \alpha_i^{t+1} \\ \beta_i^{t+1} \end{bmatrix} = \begin{bmatrix} \cos(\Delta\gamma) & -\sin(\Delta\gamma) \\ \sin(\Delta\gamma) & \cos(\Delta\gamma) \end{bmatrix} \cdot \begin{bmatrix} \alpha_i^t \\ \beta_i^t \end{bmatrix} \tag{7}$$

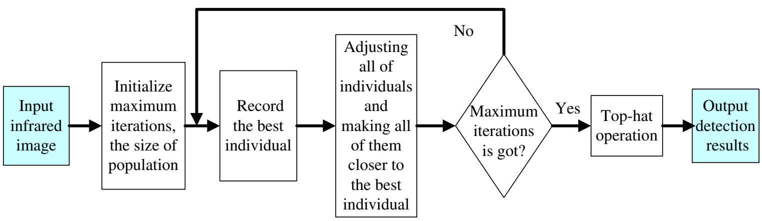

Fig. 1 The flow chart of using adaptive top-hat filter to detect target

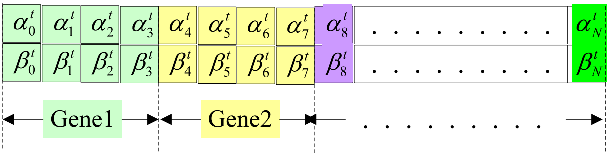

Fig. 2 The structure of chromosome with quantum coding at the tth generation

So we get

$$\begin{cases} \alpha_i^{t+1} = \cos(\Delta\gamma)\cos\varphi - \sin(\Delta\gamma)\sin\varphi = \cos(\Delta\gamma+\varphi) \\ \beta_i^{t+1} = \sin(\Delta\gamma)\cos\varphi + \cos(\Delta\gamma)\sin\varphi = \sin(\Delta\gamma+\varphi) \end{cases} \tag{8}$$

In the whole process, the update strategy of quantum rotation gates is very important, and this operation can change the amplitude of individuals and further improve the performance of QGA. The purpose of updating is making all of individuals closer to the best individual. $\Delta\gamma$as one of most important parameters can control the convergence rate. If $\Delta\gamma$is small, the convergence rate would be slow, but the globe search ability would be strong; otherwise, the convergence rate would be fast, but it would be get local optimum.

In order to control the convergence rate of QGA, a convergence factor $k$is introduced in this paper, and $\Delta\gamma = \Delta\gamma \times k$. By a numbers of simulation experiments, it can be found that the convergence rate can be improved and the solution will not trap in local optimum.

Moreover, the fitness function plays a decisive role on describing quantum bits, it provides the optimizing criterion such as convergence criterion and termination criterion of QGA. In this paper, the adaptive function is denoted as $E = \frac{1}{2L}\sum_{t=1}^{L}(Y_t - d_t)^2$, where $L$is the number of training samples, $Y_t$is the maximal value of tth output matrix after each top-hat operation, and $d_t$is the expected value of output corresponding to the tth input [27].

The algorithm of using top-hat operator with the structure element optimized by QGA to detect small target is shown as Table 1.

Table 1 The algorithm of adaptive top-hat filter for target detection

Input: infrared image.

Step 1: Initialize: Maximum iteration, the size of population and the structure of chromosome with quantum coding,

$$\begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \cdots & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \cdots & \frac{1}{\sqrt{2}} \end{bmatrix}$$

Step 2: Computing the fitness of all individuals and recording the best individual;

Step 3: According to the updating strategy of quantum rotation gates, making all of individuals closer to the best individual;

Step 4: whether the maximum iterations or convergence condition is got or not; if it is, output the best individual, or else, switch to step 3;

Output: The detection results (Top-hat filter is operated by the best individual which is the best structure elements).

4 Convergence analyss of quantum genetic algorithm

Definition 1 The population of qubit chromosomes is denoted as $Q(t) = \{q_1^t, q_2^t, q_3^t, ...q_i^t, ...q_N^t\}$ at generation t on the basis of Equ. (7) and $|\alpha_i^t|^2 + |\beta_i^t|^2 = 1$.

$$q_i^t = \begin{cases} 1 & \text{rand}(r) > (\alpha_i^t)^2 \\ 0 & \text{rand}(r) \leq (\alpha_i^t)^2 \end{cases} \tag{9}$$

Definition 2 We can define a random variable $Z_t(Z_t = \max\{f(q_k^t(i))\ |k = 1, 2\cdots N\})$ as the best fitness on at generation t, and the algorithm is converge to the global optimal solution. If $\lim_{t\to\infty} P\{Z_t = Z^*\}$ is equal to 1, $Z^* = \max\ \{f(q)|q \in S\}$ is the global optimal solution.

Definition 3 If $A = \{t : t \geq 1, P_{ii}^{(t)} > 0, \forall i \in S\}$ was non-empty, and the greatest common divisor of A is 1, then the markov chain is nonperiodic.

Definition 4 For any state i, j. $P_{ij}^{(n)}$ is the probability of starting from J to I by n steps and $P_{ij}^{(0)} = 0$.

$$P_{ij}^{(n)} = P\{Q_n = j, Q_k \neq j, k = 1, 2\cdots n-1 | Q_0 = i\}, n \geq 1. \tag{10}$$

If $\sum_{n=1}^{\infty} P_{jj}^{(n)} = 1$, the state j can be regarded as the persistent state; and if $\sum_{n=1}^{\infty} P_{jj}^{(n)} < 1$, the state j will be not the persistent state.

Definition 5 For the persistent status i, we can define that $u_i = \sum_{n=1}^{\infty} nP_{ii}^{(n)}$; if$u_i < +\infty$, the state i can be denoted as a positive persistent state. Especially if the state i is a positively persistent or a non-periodic state, it will be called as the ergodic Markov chain.

Lemma 1 The renewal process of each individual is a Markov process, and it can be show as:

$$P\{q_i^{t+1} = q | q_i^1 = q_1, q_i^2 = q_2 \cdots q_i^t = q_t\} = P\{q_i^{t+1} = q | q_i^t = q_t\}. \tag{11}$$

Proof

$$q_i^{t+1} = \begin{cases} q_i^t & \text{if } q_i = q_{bi} \\ q_i^t \bullet \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} & \text{if } q_i \neq q_{bi} \end{cases} \tag{12}$$

We can know that the new individual q_i^{t+1} only depends on the conditional probability of the current individual q_i^t, and the transfer probability of the individual is not related to the starting point of time. So the renewal process of each individual is a Markov process.

Lemma 2 Quantum genetic algorithm is a non periodic Markov chain.

Proof Because $P_{jj} > 0$, when $\exists j \in S$. We can combine the Def. 3 and $t = 1$, so the greatest common divisor of D is 1.

Lemma 3 Quantum genetic algorithm is ergodic chain.

Proof We define than $\varepsilon = \max\{P_{ij} : \forall\, i, j \in S\}$ when $0 < p_{ij} < 1$, so

$$\therefore u_i = \sum_{n=1}^{\infty} nP_{ii}^{(n)} \leq \sum_{n=1}^{\infty} n\varepsilon^n < \infty \tag{13}$$

According to lemma 2 and definition 5, we can know that quantum genetic algorithm is ergodic chain.

Theorem 1 Quantum genetic algorithm with quantum gate updating strategy can converge to the global optimal solution.

Proof According to the characteristics of quantum gates,

$$f\left(q_i^{t+1}\right) \geq f\left(q_i^t\right). \tag{14}$$

By Lemma 3, it is easy to prove that $\left\{Q_t^+, t \geq 1\right\}$ still is homogeneous Markov chain, and it is ergodic.

$$P_j^+(t) = \sum_{i \in S} P_i^+(1) P_{ij}^+(t). \tag{15}$$

We assume that the optimal solution state isS_0,

$$P_{ij}^+ > 0 \quad (\forall i \in S, \forall j \in S_0). \tag{16}$$

$$P_{ij}^+ = 0 \quad (\forall i \in S, \forall j \notin S_0). \tag{17}$$

It is shown that the transition probability from the optimal solution to the any non-optimal solution is 0, on the contrary, the transition probability is greater than 0. When$\forall i \in S$, $\forall j \notin S_0$, there is

$$\left(P_{ij}^+\right)^t \to 0 \qquad (t \to \infty). \tag{18}$$

$$P_j^+(\infty) \to 0 \qquad (j \notin S_0). \tag{19}$$

$$\lim_{t \to \infty} P\left(Z_t = Z^*\right) = 1. \tag{20}$$

According to definition 2, the algorithm converges to the global optimal solution.

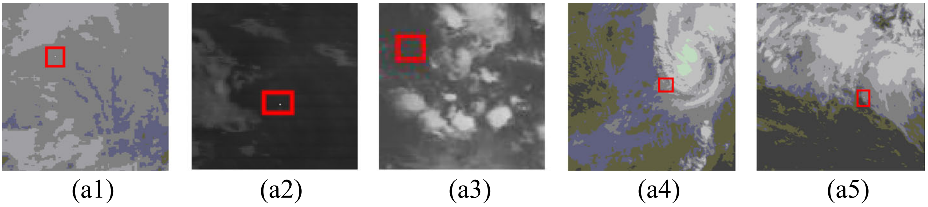

Fig. 3 Original infrared images. (**a1**) Infrared image 1, (**a2**) Infrared image 2, (**a3**) Infrared image 3, (**a4**) Infrared image 4, (**a5**) Infrared image 5

5 Experiments

To evaluate the performance of adaptive Top-hat filter on detection small target, some targets in clutter background are detected. Firstly, several original infrared images are given in Fig. 3, and the targets are marked with red box.

Top-hat filter with different structure elements are used to detect targets shown in Fig. 3, and the detection results are shown in Fig. 4 using different methods. Figure 4(a1)-(a5) are the results of using square structure element produced by command "strel ('square', w)" of Matlab. (b1)-(b5) are the results of Top-hat filter with the structure elements optimized by GA, and (c1)-(a5) are the results of using the structure elements optimized by QGA. In order to see more clearly, Fig. 5 give the 3D maps of detection results corresponding to Fig. 4. From the detection results, we can clearly find that for the six images, the detection results of using

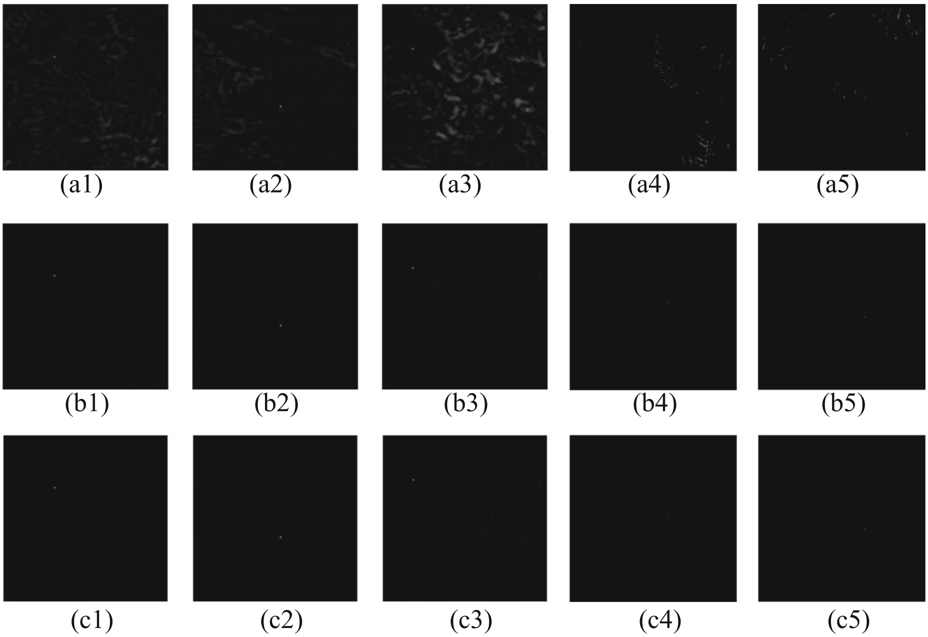

Fig. 4 The detection results of images Fig. 3 (**a1**)-(**a5**) using Top-hat filter with different structure elements. (**a1**)- (**a5**) are detection results using fix structure elements; (**b1**)-(**b5**) are detection results using adaptive structure elements optimized by GA; (**c1**)-(**c5**) are detection results using adaptive structure elements optimized by QGA

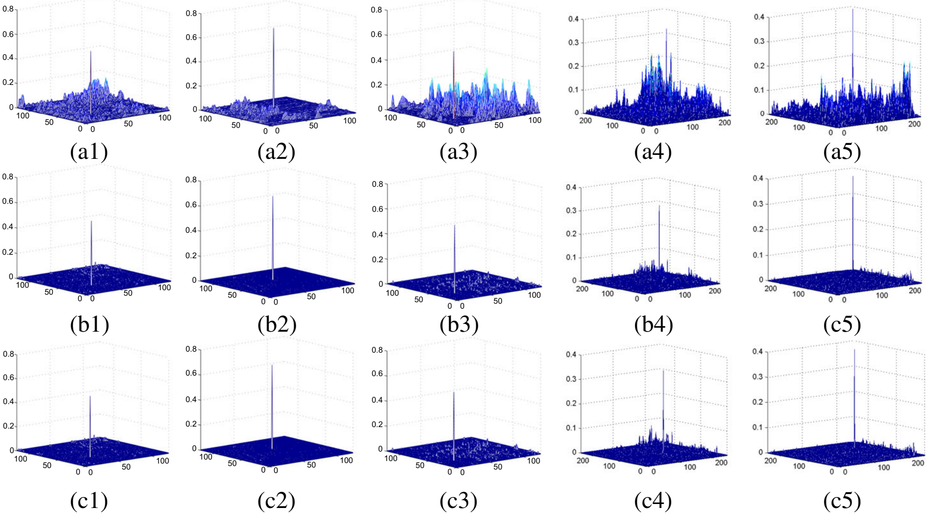

Fig. 5 The 3D maps corresponding to Fig. 4

structure elements obtained by QGA and GA are better than that of using the one obtained by "strel ('square', w)" function. It means that using the structured elements optimized by QGA and GA can get good adaptability. In simulation experiments, in order to verify the stability, 50 times repeated tests are made for each algorithm and each image.

For quantitative comparison the merits of above detection results, two objective metrics of the background suppression factor (BSF) and signal-to-background ratio gain (SBRG) are defined [12]

$$\mathrm{SBRG} = \frac{\left(S/B\right)_{\mathrm{out}}}{\left(S/B\right)_{\mathrm{in}}} \tag{21}$$

and

$$BSF = \frac{B_{\mathrm{in}}}{B_{\mathrm{out}}} \tag{22}$$

where S is the signal amplitude and $B$is the background standard deviation, and $B_{in}$and $B_{out}$are the background standard deviations of the input image and the output image, respectively.

Table 2 Performance comparison of using different structure elements

Structure elements	obtained by" *strel*"		obtained by GA		obtained by QGA	
Test terms	BSF	SBRG	BSF	SBRG	BSF	SBRG
image 1	4.6573	2.4108	39.3825	20.0774	40.8516	20.8263
image 2	4.0407	3.2903	74.2519	60.4623	75.4808	61.4629
image 3	4.4728	2.9606	47.6109	31.5139	48.8629	32.3426
image 4	9.4808	3.9647	69.8124	27.2126	72.8295	28.4697
image 5	11.1273	5.2734	100.1076	44.8308	101.2814	45.3565

Using BSF and SBRG to evaluate the performance of above different detection algorithm, and the objective comparison results are shown in Table 2. It can be found that under the same circumstances, the Top-hat filter with the structure element optimized by QGA can get better performance on small target detection.

6 Conclusion

Top-hat filter is one of widely used infrared small target detection methods. Adaptive structure elements are critical for top-hat filters. Considering that QGA has an excellent ability on searching the global optimal solution, QGA is used to optimize the structure element of the top-hat filter in this paper. The convergence of QGA for optimizing structure elements are proved. Some experimental results show the superiority of the Top-hat filter with the structure element optimized by QGA. With the consideration that the current algorithm can't meet the real-time detection need, we will explore the parallel computation of QGA based multi-GPU to accelerate our method in the future work.

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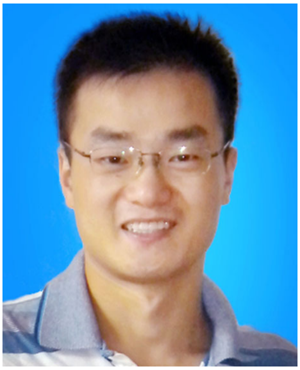

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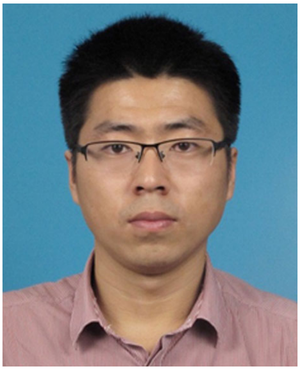

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