

MORPHOLOGY INFRARED IMAGE TARGET DETECTION ALGORITHM OPTIMIZED BY GENETIC THEORY

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ABSTRACT:

This paper proposes a novel morphology algorithm for target detection of the infrared images, which is optimized by the genetic algorithm. First, several improvements have been adopted for genetic algorithm (GA). The improvements include the auto-regulation of genetic evolution crossover probability and mutation probability which based on population difference; A more reasonable target characteristic variable according the feature of infrared image has been designed to train structure elements. So the efficiency of the algorithm can be improved obviously, at same time, the optimized trained structural elements could reflect the sample's true structure information. Then the background and objectives structural elements could be got by inputting background and target samples into the GA model. Using it as a priori knowledge of the morphology operation, it does favor to improve the algorithm's accuracy and adaptability. Experiment shows that this method can achieve a higher detection efficiency and accuracy.

1. INTRODUCTION

Infrared has been widely used in the target detection technology for its special recognition capability and the anti-jamming ability. However, due to the detection range of the infrared detectors and other conditions, infrared images are characterized by severe noise pollution and low signal-to-noise ratio. Therefore there is a growing interest in the research of the methods which are used in the target detection of the infrared images. In recent years, mathematical morphology which based on shape and structure information has been paid more and more attention in the area of target detection for its superior performance in the field of infrared target detection, however, the results of the target detection are due to the choice of the structural information mentioned above.

The idea of the genetic algorithms (GAs) which derived from the theory of evolution is different from the traditional optimization methods. GAs can be used to solve complex unstructured problems for its global optimal search capability and parallel computing characteristic. Using GAs, we can get the optimal structure elements which contain samples' information by training the Genetic Evolution Model (GEM) with only a small sample of the origin images. This paper demonstrates how multi-populations GA can be employed in the target detection using improved mathematical morphology.

2. IMPROVED GENETIC ALGORITHM

GA has particular advantages in solving the problem of multi-parameter optimization for its global search mechanism, but on contrary to traditional GA there are also some shortcomings that can not be ignored, such as the powerful global search capability while poor local search ability, premature problem, the contradictions between the search efficiency and accuracy. Aiming at improving these weaknesses, many scholars have done a lot of work to improve its performance, such as the introduction of population difference, improved genetic operators and so on. In

this paper, the genetic algorithms is used into the field of target detection and a new fitness measurement methods based on target characteristics value is proposed for the specific needs of detection. For the premature problem, basing on the population difference which is proposed by predecessors, the introduction of the male and female parents dynamic clustering based on individual differences makes crossover operate more reasonable; The strategy of multi-population parallel evolution and best individual transplant merge the best individual retention strategy and the best gene retention strategy effectively, which accelerate the speed of convergence of the algorithm and meanwhile ensure the global search capability.

2.1 Population Difference

From the perspective natural evolution, if the group owns a great diversity larger crossover and smaller mutation ratio is the best choice. On the contrary, smaller cross scale and larger mutation probability is better choice, so we can see population difference is a useful variable in determining evolution parameters. Details refer to the references [1].

2.2 Encoding Method

In this paper, we have chosen a real-parameter coding method which avoids information loss during the encoding and decoding process. Compared to binary coding method, every individual in the population contains original information of the structure elements. In the abstract this coding method has a more appropriate complexity and higher accuracy result.

2.3 Group Initialization

This paper discusses a new method to get initial population which calls division of feasible solution space. Its detail can be shown as follows.

- 1) Division the solution space into n subintervals. Both symmetrical division and unsymmetrical division are permitted.

- 2) Generate a random number in every subinterval.
- 3) With the assistant of the n number's random combination in step.2 n^m individuals can be got. Among the n^m individuals N ones will be randomly selected as the initial population.

This initialized approach has do great favor to the group's quality increase. According to the method, similar individual won't be chosen and the population has larger probability to include optimal solution. With a proper initial result the algorithm's search efficiency and the probability of convergence to global optimum are improved.

2.4 Fitness Function

Fitness function reflects individual's adaptable ability to environment, it is the controller of evolution trend of genetic algorithm. During the process of designing genetic algorithm fitness function only has to meet non-negative and comparable conditions. Before introducing our own fitness function, we define an new variation to describe target's character——target characteristics value. It can be calculated following formula (4):

$$g_{(a)} = \sum_{f_{(i)} \in \Omega} e^{f_{(a)}/f_{(i)}} \quad (4)$$

Where, Ω presents a local area, its central point a is point-target. $f_{(a)}$ is the gray value of central point a , $f'_{(i)}$ is the local area point's gray value. In order to reflect the difference between target and background we use the gray value contrast of target and background, the accumulation step can partially reduce the noise effect. Exponent function used here acts as an amplifying lens to amplify the difference between background and target. Objective function can be defined as:

$$tag_{(X)} = \frac{1}{N} \sum_{i=1}^N (f'_{(i)} - g_{(a)}^i)^2 \quad (5)$$

Where, N is the size of population, $f'_{(i)}$ is the output value of the i th sample's morphology operation. $g_{(a)}^i$ is the i th sample's normalized target characteristics value. Here our fitness function can be defined as the reciprocal of objective function:

$$fit_{(X)} = \frac{1}{tag_{(X)}} \quad (6)$$

2.5 Crossover Operator

2.5.1 Adaptive Crossover Probability: In this paper, the crossover probability is based on the population difference and evolution time. The crossover probability $Cross$ is defined as follows

$$Crossr = \begin{cases} Rat \times \frac{1}{1+T} \times P & \text{if } Rat \leq 0.95 \\ 0.95 \times \frac{1}{1+T} \times P & \text{others} \end{cases} \quad Rat = k_1 + k_2 \cdot dif \quad (7)$$

Where, $k_1 > 0, k_2 > 0$ and $k_1 + k_2 = 1$. t is the current evolution time, T is the maximum evolution time, P is an adjustable parameter which is used to limited the scale of crossover. dif presents the population difference.

2.5.2 Custom Crossover Approach: According to natural evolution theory, the combination of individuals who have similar genotypes will greatly increase the probability of pathogenic generation. In order to simulate this natural phenomenon, we add an classification step in crossover. According to the individual's difference the population is divided into two spaces male and female using K-means clustering analysis method. the difference between two individuals is measured by formula(9), where \bar{X}_i is the vector form of individual X_i .

$$dif_{(X_i, X_j)} = \begin{cases} \frac{|\bar{X}_i|}{|\bar{X}_j|} & \text{if } |\bar{X}_i| \geq |\bar{X}_j| \\ \frac{|\bar{X}_j|}{|\bar{X}_i|} & \text{others} \end{cases} \quad (9)$$

This classification method doesn't base on the individual's fitness value, the two parent space only represents two kinds of individuals which own different characters. Therefore excellent individuals are distributed randomly in the two species. As we do crossover operation the parent are selected separately from male and female space. This crossover approach has great advantages in mining potential high-fitness individual and enhancing the algorithm's search capability.

So as to enhance the algorithm's detecting ability, the formulas we choose in crossover step is a combination approach of mathematical method and heuristic method. The formal one is good at generating linear combination offspring of two complementary parental individuals, yet heuristic crossover can generate the parent's linear extrapolation according to individual's fitness. Their formula is as follows:

$$a \begin{cases} Y_1 = X_i + r(X_i - X_j) \\ Y_2 = X_i \end{cases} \quad b \begin{cases} Y_1 = rX_i + (1-r)X_j \\ Y_2 = (1-r)X_i + rX_j \end{cases} \quad (10)$$

Where r is a random number in (0,1). If $fit_{(X_i)} \geq fit_{(X_j)}$ do as formula(a), otherwise formula(b) should be used.

If offspring meet one of the following two conditions, the current crossover operation is invalid, try again.

- 1) Y_1, Y_2 are beyond the solution space;
- 2) The better one's fitness in Y_1, Y_2 is smaller the worse in X_i, X_j .

The better one in parents and filial generation will be selected. This crossover operation ensures that excellent genes have been inherited by offspring. So a sub-optimal individual in parental generation and a sub-optimal individual in the next generation will be rejected when choosing the next generation. As a result of this operation, the population size will be stable, poor indi-

vidual will be eliminated as soon as possible, we will get a more effective algorithm.

2.6 Mutation Operator

Although the probability is very small, it plays an important role in preventing premature convergence and enhancing the algorithm's global search capability.

2.6.1 Adaptive Mutation Probability: In our algorithm the population's mutation probability is determined by two variations: the difference of population genes and the individual's mutation. It can be defined as follows:

$$\ell = \begin{cases} 0.01 \times k_m \times (1 - dif) \times \left(\frac{fit(x)}{fit_ave} \right)^a \times \frac{1}{1 + \frac{1}{t}} \times Mut_{max} \\ Mut_{min} \end{cases}$$

$$Mut = \begin{cases} \ell & \text{if } \ell > Mut_{min} \\ Mut_{min} & \text{others} \end{cases} \quad (12)$$

Let's put ℓ as a temporal variable, dif as the population difference, $fit(x)$ as the individual's fitness, fit_ave as the average fitness, a , k_m ($k_m > 0, a > 0$) are adjustable parameters, a control the degree of individual fitness which effects mutation probability. Usually it is 1, 0.5 or 2. Mut_{max} is maximum mutation probability, Mut_{min} is minimum mutation probability, t represents the current generation number, T is the maximum generation number.

2.6.2 Custom Mutation Approach: As for the mutation operator, the step is very difficult to determine: small step is helpful in getting the global optimal solution, yet increases computing time; the big one consumes shorter time but is unable to guarantee the global optimal solution. This paper adds a partial perturbation tracking operation to the Multi-variable inhomogeneous mutation operator for real-coding method which presented by Michalewicz, this method could determine the most appropriate mutation direction and enhance the search efficiency at the same time guarantee the result's accuracy. Mutation formula is as follows:

$$\begin{cases} X_i + P_{(t)} * (b_i - X_i) & \text{if } i = j, r_1 < 0.5 \\ X_i - P_{(t)} * (a_i + X_i) & \text{if } i = j, r_1 < 0.5 \\ X_i & \text{others} \end{cases} \quad P_{(t)} = (r_2 * (1 - t/T))^b \quad (13)$$

In the formula, a_i, b_i stands for the parameter boundary, r_1, r_2 as the random variable in (0,1), j means an random number, t is the current algebra, t represents current generation number, T is the maximum generation number. b is the attribute variation step of the curve shape factor which drops along with the generation. The step in this method has the features as follows: the bigger step in the initial evolution period is greatly advantageous as enhancing the search efficiency, while the shorter one in the later evolution period when the population tends to stably and searches nearby the optimum value, can guarantee solution

optimality.

The aim of using partial perturbation tracking is to find a high convergence rate searching route. That is to say to increase or reduce some times of the step such as $X_i \pm k * (X_i - X'_i)$, so we can obtain some new candidates. The most sufficient one will be chosen as the final result.

2.7 Selection Strategy

In this paper, we use the synchronous selection strategy on multi-subpopulations. First, the original population is divided into two classes: "stable subpopulation" and "exploring subpopulation". Different class has different evolution strategy and operators. Concretely, in the former we set a bigger probability of crossover and mutation, make full use of its exploring ability; In stable subpopulation avoiding excellent gene to be destroyed is our main purpose. In order to guarantee the population's diversity, excellent individuals in the two subpopulations should be exchanged in every generation so they could share the advantages of each other. Individuals in Middle generation comes from the above two subpopulations, the most outstanding individual in each population will be selected as candidate directly, the remains will be chosen by competitive selection method. For the sake of fusing the genetic characteristic of the two subpopulations, middle population is endowed with small probability of crossover and mutation. So that the best gene will be merged adequately and it is more likely to find new potential excellent genes.

The synchronous selection strategy on multi-subpopulation is a eclectic method between avoiding premature and destroying excellent individuals. Simultaneously the optimal gene reserved strategy and the optimal individual reserved strategy are merged properly.

2.8 Evolution Control Parameters:

Population Size: Usually it is a constant and even number.

Crossover Probability: reference to section 2.5, usually it is not more than 0.75;

Mutation Probability: reference to section 2.6, usually it does not exceed 0.05;

Generation Number: In view of the population evolution and the algorithm's efficiency, generally set it around 100 generations

Termination Criteria: if any of the following conditions are met, terminating the algorithm.

- 1) The population difference is smaller than threshold.
- 2) The best individual is sufficient to meet the fitness requirements.
- 3) Achieved maximum evolution algebra.

3. MORPHOLOGY FILTER

There are two important aspects in image processing using morphology: Morphological operation and Structural element chosen. Morphological open operation is good at removing bright details which is smaller than structure element and main-

taining characters stable of the whole image and big bright area. Whereas Morphological close operation could remove dark details which is smaller than structure element and maintain characters stable of the whole image and big dark area. Structure element with circle shape has good suitability. Taking all above factors we design our morphological filter algorithm like follows:

Step 1: Employ circular structural element which is bigger then the target, training it with background samples, after the Morphological opening operation noise and target both will be removed. The final result is considered as the background.

Step 2: The opening operation is acted on the primary image with the structural element which was trained by target samples. The bright noise whose size is smaller then the structure element is filtrated .And the background is consistent with Step 1. Thanks to the trained structure elements own target information, target will not be filtrated

Step 3: The result of the image from the step 2 subtracts the background images in step 1 is the final target.

4. MORPHOLOGY ALGORITHM OPTIMIZED BY GENETIC THEORY

The collectivity flow chart of target detection algorithm is shown in Figure 1. Figure 2 is a detailed introduction to the “Genetic Evolution” part of Figure 1

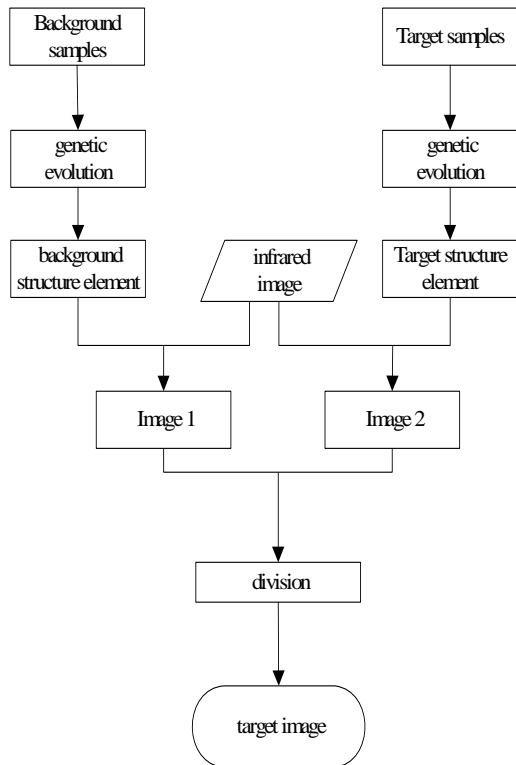


Figure 1 Optimized morphology target detection algorithm by genetic theory

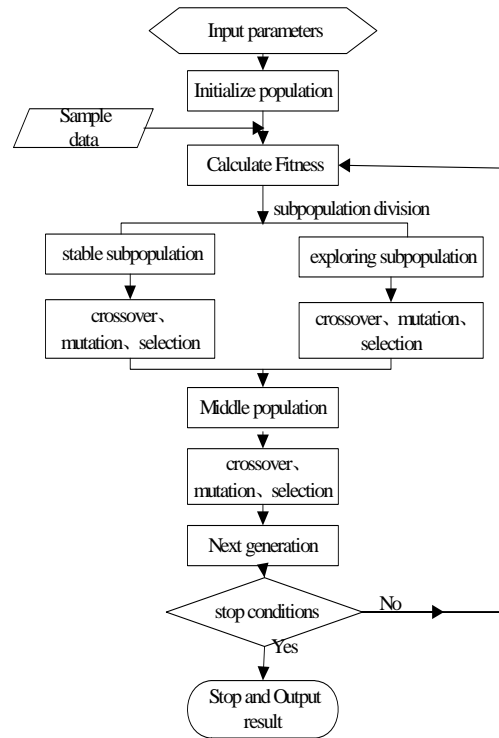
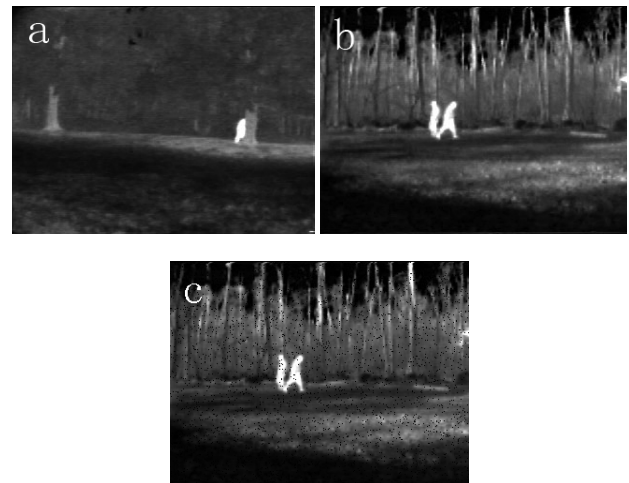


Figure 2 Genetic evolution algorithm flow chart

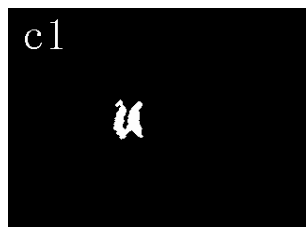
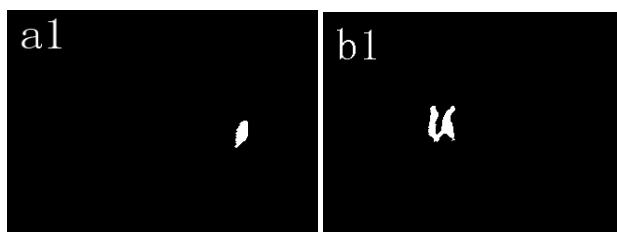
5. THE APPLICATION OF ALGORITHM

In order to verify the validity of the algorithm, in this paper, two kinds of natural background infrared image were used to the experiment.



a. single objective infrared image b. multi-objective infrared image c. salt and pepper noise image

Figure 3.Original infrared image



a1. single objective detection b1. multi-objective detection
c1. salt and pepper noise detection

Figure 4. Result of detection

During the analysis of experiment result, occasionally the target we got has small fracture in the center. It can be attributed to the effect of the structure element's shape which can't fit to the objective details. Fortunately, binary morphology opening and closing operator are good at removing burrs and filling the holes. The experiments have proved that this algorithm is efficient to detecting target in complex background images, and can commendably meet the detection needs of different backgrounds or noised images.

6. CONCLUSION REMARKS

In this paper, the optimized genetic evolution model which characteristic with the multi-strategy integration and parallel evolutionary strategy is helpful to improve its premature convergence fault. Moreover the local explorative ability of the algorithm is enhanced obviously, as well as the algorithm's efficiency and the results' accuracy. Experimental results show that the structure element which has been trained through GA does contain the information of training samples. With the assistant of those trained structure elements and morphology target detection method the complex natural background can be re-

moved properly, salt and pepper noise also can be effectively restrained. On the whole, the algorithm we have designed is an effective method for infrared image target detection.

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