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Maximum Entropy Image Segmentation Method Based On Improved Firefly Algorithm

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Abstract. An adaptive parametric firefly algorithm is proposed for the premature convergence of the firefly algorithm itself and the late oscillation of the algorithm iteration. In the image threshold segmentation test experiment, the algorithm is used to optimize the maximum entropy image segmentation, and the maximum entropy and the basic firefly improved maximum entropy algorithm are compared. At the same time, two important indicators of image segmentation evaluation index regional consistency are used to evaluate the results. It shows that the experimental results of the algorithm have better intra-regional consistency and noise immunity.

1. Introduction

As one of the traditional image segmentation algorithms, maximum entropy is flexible in feature selection and easy to replace. The contribution of feature probability distribution can be obtained by iterative training of the algorithm, which is easy to realize. It has been widely used in image segmentation. However, in large-scale data sets, the computational complexity and time problems caused by sequential traversal of the algorithm are particularly prominent. Firefly algorithm [1] is a kind of local optimization algorithm. It does not need to traverse all the data sequentially. It combines multi-local optimization information to get the final solution. It has a good advantage for large-scale data sets as image watermarking and medical detection[2,3]. However, the traditional firefly algorithm has less control over the mobile control of fireflies, and the algorithm is easy to be premature. Moreover, there is no cooperation between fireflies, and the efficiency of the algorithm is low. Therefore, the algorithm needs to be improved urgently. Reference [4] improves FA and adjusts its parameters. The accuracy of the algorithm is improved, but the running speed is slower. Literature [5] uses cubic mapping to readjust the initialization of fireflies, which improves the speed and accuracy of operation. Reference [6] improves chaotic firefly algorithm, designs local search operator in chaotic sequence, and tries to solve the premature problem of basic firefly. Document [7] combines the firefly algorithm with simulated annealing algorithm, and divides the results of local optimization into better solutions and worse solutions. The better solution probability is acceptable, while the worse solution probability is rejected. The accuracy of the firefly algorithm has been greatly improved. The common problem of these methods is that when the algorithm approaches the optimal solution, it will oscillate at the optimal solution of the algorithm, which will affect the speed of the algorithm and the final result generation.

In this paper, an adaptive firefly algorithm is proposed. When this algorithm is used to optimize the optimal threshold function of maximum entropy, it has better application value in image processing with higher complexity.



2. Material and Methods

2.1. Maximum Entropy Image Segmentation

Let the threshold of image segmentation be t and the gray level be $L, X \in \{0, 1, 2, \dots, th\}$ be probability distribution for prospects, $Y \in \{th+1, th+2, \dots, L-1\}$ be background gray distribution, the probability density function of the corresponding region is:

$$X: \frac{P_0}{P_m}, \frac{P_1}{P_m}, \dots, \frac{P_t}{P_m} \quad (1)$$

$$Y: \frac{P_{t+1}}{1-P_m}, \frac{P_{t+2}}{1-P_m}, \dots, \frac{P_{L-1}}{1-P_m} \quad (2)$$

In equations (1) and (2):

$$P_m = \sum_{i=0}^t P_i \quad (3)$$

Then the corresponding entropy is:

$$H(X) = - \sum_{i=0}^t \frac{P_i}{P_m} \ln \frac{P_i}{P_m} \quad (4)$$

$$H(Y) = - \sum_{i=t+1}^{L-1} \frac{P_i}{1-P_m} \ln \frac{P_i}{1-P_m} \quad (5)$$

Sm and SL are information entropy respectively. Then the optimal threshold function is $\phi(t) = H(X) + H(Y)$.

Maximum Entropy Threshold Segmentation obtains the optimal solution of threshold function by traversing, which takes a long time to calculate, especially when the segmentation area increases, the computational complexity becomes more obvious. For the actual image segmentation, it cannot meet its application requirements.

2.2. Firefly algorithm

In the basic firefly algorithm (FA), all fireflies are gender-neutral, and their attractiveness is related to their brightness. In the solution domain, the objective function value determined the attractiveness of fireflies. Fireflies influence the surrounding individuals through their own fluorescein. Individuals with small fluorescein value are more likely to be attracted by individuals with large fluorescein value. The movement mode of position change is shown in equation (6):

$$x_i(t+1) = x_i(t) + \beta_{ij} [x_j(t) - x_i(t)] + \alpha(\varepsilon^t) \quad (6)$$

In the equation, the number of iterations is t , β_{ij} the relative fluorescein value between the x_i and x_j , α is the quantization factor of the moving step, and the value is the random number in the $[0, 1]$ interval, which controls the search radius of each firefly. ε is a random factor obeying uniform distribution.

When updating β_{ij} , follow the rule as shown in equation (7):

$$\beta_{ij} = \beta_0 e^{-\lambda r_{ij}^2} \quad (7)$$

In the equation, the maximum initial fluorescein value is β_0 , r_{ij} is the Euclidean distance between two fireflies, and λ is the light attenuation parameter.

The disadvantage of this method is that the information exchange between fireflies is affected by their search range. In the practice of basic FA, the initial positions of fireflies are randomly allocated, and the independence between fireflies is relatively large. It is possible that the fluorescein values set by fireflies are too discrete to cause relatively slow operation. Secondly, in FA, the parameters controlling the search range are randomly set. The simulation results are also random. Furthermore, the update of FA search points is always determined by the generated neighborhood. In order to effectively solve the search problem, we also need to improve the algorithm.

3. Adaptive firefly algorithm

3.1. Symmetric Matrix Transform

The traditional firefly algorithm has the characteristics of low discovery rate and low accuracy. In this paper, a parametric firefly algorithm is proposed. Because the traditional firefly algorithm needs to set the initial position of the firefly randomly before it runs, and this kind of random setting easily leads to less correlation between fireflies and local optimum. In this paper, symmetric matrix transformation is used to correlate the initial firefly location randomly set, as shown in equation (8):

$$\begin{pmatrix} x_{k2} \\ x_{k2} \end{pmatrix} = \begin{pmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{pmatrix} \bullet \begin{pmatrix} x_i \\ x_j \end{pmatrix} \quad (8)$$

In equation (8), the range of γ is (0,1), x_{k1} and x_{k2} is generated by the corresponding values, which are used as the initial parameters of the firefly algorithm. This method ensures that the number of fireflies generated is consistent with the initial number of fireflies, and the fireflies generated by this method have a stronger correlation, thus speeding up the operation of FA.

3.2. Parametric Variable Adjustment

In order to further improve the algorithm, step size quantization factor α and motion parameter adjustment β_{ij} are considered to improve the accuracy of the algorithm by using the advantages of the two in different regions. In the neighbourhood of the firefly, the influence of light attenuation on the movement of the firefly β_{ij} is dominant, so the influence factor is dominant at this time. As can be seen from equation (7), it is related to the attenuation of light.

In the basic FA, the optical attenuation parameter λ is set to 1, and the attenuation will change with the distance due to the influence of medium. Therefore, this paper adjusts the parameters in the form of (9). From Fig.1, we can see the relationship between β and λ .

$$\lambda_i = \frac{-\ln(\beta_{\min} / \beta_0)}{\|x_i^t - X_k^t\|^2} \quad (9)$$

therefore:

$$\beta(t)_{ij} = \beta_0 e^{\frac{\ln(\beta_{\min} / \beta_0)}{\|x_i^t - X_k^t\|^2} \bullet r_{ij}^2} \quad (10)$$

In equation (9), the position of the K first reference point, the corresponding position of the search point, and the minimum amount of movement are the optical attenuation of the first search point relative to the reference point in the neighborhood.

The migration of fireflies is not only affected by the attenuation of light, but also by the mutual attraction of fireflies. At this time, the iteration speed of the algorithm is the main factor. Considering the parameters, the moving step controls the moving speed of two fireflies, that is, the iteration speed. As the number of iterations increases, the location of all fireflies gradually approaches the optimal solution, and the search range should also gradually decrease. Thus, the parameters are set as linear decreasing functions, as shown in equation (11):

$$\alpha(t) = \alpha_{\max} - \frac{t}{T_{\max}} (\alpha_{\max} - \alpha_{\min}) \quad (11)$$

In equation (11), α_{\max} is the maximum quantization step for the initial setting, α_{\min} is the minimum quantization step, and T_{\max} is the maximum number of iterations.

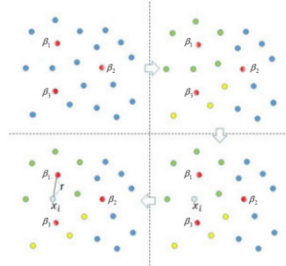


Fig. 1 The relationship between motion parameters and light attenuation

3.3. Improved Maximum Entropy Threshold Segmentation Based on AFA

The method for determining the luminance of fluorescein is shown in equation (12):

$$\begin{cases} \frac{\varphi(t)_{\max}}{\varphi(t)_i} = \frac{1}{\beta(t)_i} \\ \beta(t)_{ij} = \frac{\varphi(t)_i}{\varphi(t)_j} = \frac{\varphi(t)_i / \varphi(t)_{\max}}{\varphi(t)_j / \varphi(t)_{\max}} = \frac{1/\beta(t)_j}{1/\beta(t)_i} = \frac{\beta(t)_i}{\beta(t)_j} \end{cases} \quad (12)$$

In equation (12), the maximum entropy in the search range of each firefly at the current moment is not the final result.

The specific optimization steps are as follows:

According to the algorithm steps of FA and the improved method in this paper, the improved algorithm is determined as follows:

(1) Set the initial parameters τ 、 n 、 α_{\max} 、 β_0 、 T_{\max} in the solution domain. For the initial number of fireflies set.

(2) Initialize the location of fireflies randomly.

(3) Initialized fireflies are grouped into two groups in order of position from small to large, and then symmetrical matrix transformation is carried out to generate offspring and calculate the attractiveness of offspring β_{ij} .

(4) Update the location of the next generation of fireflies according to the attraction, moving step and motion control parameters.

(5) Disturb the firefly in the best position and update the parameters α and β_{ij} .

When the number of interference T_{\max} reaches, output the best value at this time, otherwise jump step (4).

4. Results

The initial parameters of this algorithm are set as follows: $\beta_0=1, \alpha_{\max}=0.5, n=50, T_{\max}=100, \alpha=0.5$ is Fixed in the basic firefly algorithm. As shown in Fig. 2, the test was carried out using Fig.(a₁) and the format of the picture was 690*459. We use maximum entropy segmentation and the optimized maximum entropy segmentation of the basic firefly algorithm to compare with the algorithm in this paper. Fig.(a₂) is the result of the same processing after adding white Gaussian noise.

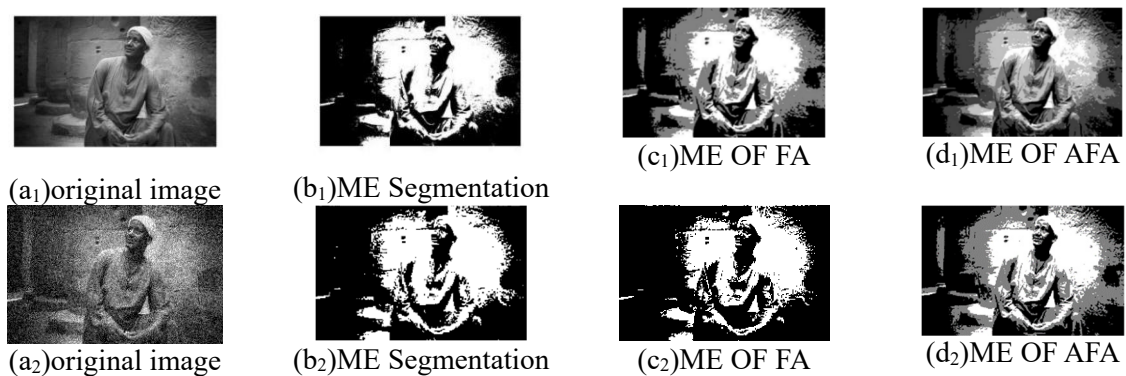


Fig.2 Comparisons of algorithm results

The naked eye is not convincing to evaluate the algorithm. Therefore, this paper uses the image segmentation evaluation index regional consistency [8] for qualitative evaluation. The evaluation criteria are as follows:

$$G = 1 - \frac{1}{c} \sum \left\{ \sum_{(x,y) \in R_i} \left[f(x,y) - \frac{1}{A_i} \sum_{(x,y) \in R_i} f(x,y) \right]^2 \right\} \quad G \in [0,1] \quad (13)$$

Table 1 Performance comparison of algorithm results

ME			ME OF FA			ME OF AFA		
Threshold	G	Time(s)	Threshold	G	Time(s)	Threshold	G	Time(s)
108	0.831	10.8	115	0.822	3.8	106	0.936	1.1
118	0.428	12.5	120	0.512	5.3	110	0.833	1.8

From Fig.2 and Table 1, we can see that the segmentation results in this paper have better intra-region consistency and better anti-noise ability for low noise ratio images. At the same time, in the image with the same noise ratio, the image segmentation effect and the operation of the algorithm show great advantages.

5. Conclusion

An adaptive firefly algorithm based on parameter control is proposed for local optimum caused by prematurity of basic firefly algorithm. The algorithm uses symmetric matrix transformation to associate the first generation of randomly set fireflies, so as to reduce the independence brought by randomization. In the iteration of the firefly algorithm, it is divided into two parts: the neighborhood of firefly and the intersection of firefly. In the intersection of firefly points, the adaptive moving step parameters are used to reduce the later oscillation of the algorithm. In the neighbourhood of firefly points, the optical attenuation parameters are controlled to enhance the accuracy of the algorithm. The experimental results show that the algorithm can speed up the operation of maximum entropy and the image processing results are more accurate.

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