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Single-threshold Image Segmentation Algorithm Based on Improved Bat Algorithm

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Abstract

The Improved Bat Algorithm (IBA) is proposed for the image segmentation based on the maximum interclass variance method. Firstly, the principle of image segmentation based on the maximum interclass variance method is explained, and secondly, the bat algorithm is improved by using chaotic logistic mapping to initialize the population to improve the diversity of solutions, using adaptive parameter optimization to avoid falling into local optimum, using Monkey algorithm for individual selection, and finally, the image segmentation function in image segmentation is used as the individual fitness function of the bat algorithm for solving. The simulation experiments show that compared with the bat algorithm and the monkey group algorithm, this algorithm has better segmentation effect under different threshold values.

Keywords: *Image segmentation, single thresholding, bat algorithm, chaotic logistic, monkey algorithm*

I. Introduction

Among all kinds of information in the Internet era, image information is the information that we have the most contact with, it has the advantages of intuitive, easy to understand, and large amount of information and is widely accepted by people. However, not all information is needed by people, in most cases, people are usually only interested in a certain region or some regions of the image, so image segmentation was born in such a context, image segmentation [1] is a technique to separate specific regions from other regions, which directly affects the problem of feature extraction and target recognition. Scholars at home and abroad have studied image segmentation to different degrees. Literature [2] used Improved Moth-Flame Optimization Algorithm to optimize the Otsu algorithm for threshold segmentation of infrared images before fault diagnosis, and the results showed that the method was able to determine the temperature range of each part; Literature [3] used Symbiotic Organisms Search The results show that the algorithm can obtain accurate segmentation thresholds; Literature [4] proposed a dragonfly algorithm based on chaotic initialization and backward learning strategy applied to multi-threshold color image segmentation, and the experimental results show that the algorithm ensures the stability while the accuracy of image segmentation is effectively improved; Literature [5] proposed a multi-objective particle swarm and artificial The experimental results show that the algorithm can achieve the ideal segmentation results; Literature [6] proposed to use the improved bat algorithm (BA) to search for the optimal solution of the threshold, and applied the improved bat algorithm to the minimum cross-entropy multi-threshold image segmentation, and the experimental results show that the algorithm in the speed and segmentation accuracy effect is significantly improved; Literature [7] proposed a new Drosophila optimization algorithm and optimized the image segmentation thresholds. The experiments show that the improved algorithm achieves better results than other algorithms in the application of image segmentation.

From the above study, it is found that the image segmentation using bionic algorithm has achieved better results. In view of the above results, this paper adopts the improved bat algorithm for image segmentation processing. Firstly, the definition of image segmentation by the maximum interclass variance method is explained, then the performance improvement measures of the bat algorithm are proposed, and the experiments show that the improved bat algorithm achieves better results in image segmentation.

II. Image Segmentation Based on the Maximum Inter-Class Variance Method

Image segmentation is the process of dividing an image into several different regions, where the similarity of color, shape and information of the images in the same region is relatively high and the similarity between different regions is very low. Considering an image as a set R, each region of the segmentation is a non-empty subset $R_1 R_2, \cdots R_n$, and these subsets satisfy the following conditions. Condition 1: $\cup_{i=1}^{n} R_i = R$, means that the sum of pixels in n subregions contains all pixels of the original image and all pixels in the same subregion are connected; Condition 2: for all i and j, when $i \neq j$, $R_i \cap R_j = \varnothing$, means that no pixel in the image can belong to different subregions at the same time; Condition 3: for $i = 1, 2 \cdots n$, $P(R_i) = True$, means that the pixel values in the same subregion have high similarity in some condition 4: for $i \neq j$, $P(R_i \cup R_j) = False$ means that the pixels in different sub-regions should have different features in some aspect.

The maximum interclass variance method is a simple and efficient single threshold segmentation algorithm proposed by Otsu [8], a Japanese scholar, in 1979. The principle is that since the grayscale values of the same region are of the same size or close to each other, and the grayscale values of different regions are more obviously different, the larger the variance of each region is, the greater the difference between them, so it can be regarded as different classes to divide the image into several parts. Specifically, there are m thresholds $t_1, t_2 \cdots t_m$ to divide the gray space $\{0, 1, 2, \cdots L-1\}$ into $k_0, k_1, k_2 \cdots k_m$ regions. Let there be n_i pixels in the image with gray value i, the total number of pixels is N, the frequency of pixels is p_i, and μ_i is the image gray value, expressed as follows.

$$N = \sum_{i=0}^{L-1} n_i \tag{1}$$

$$p_i = \frac{n_i}{N} \tag{2}$$

Set the interclass variance be.

$$f(t) = \sum_{i=0}^{m} \sigma_i \tag{3}$$

Where σ_i is defined as follows:

$$\begin{cases} \sigma_0 = \omega_0 (\mu_0 - \mu_T)^2, \mu_0 = \sum_{i=0}^{t_1 - 1} \frac{i p_i}{\omega_i}, \omega_0 = \sum_{i=0}^{t_1 - 1} \frac{n_i}{N} = \sum_{i=0}^{t_1 - 1} p_i \\ \sigma_1 = \omega_1 (\mu_1 - \mu_T)^2, \mu_1 = \sum_{i=t_1}^{t_1 - 1} \frac{i p_i}{\omega_i}, \omega_1 = \sum_{i=t_1}^{t_2 - 1} \frac{n_i}{N} = \sum_{i=t_1}^{t_2 - 1} p_i \\ \sigma_2 = \omega_2 (\mu_2 - \mu_T)^2, \mu_2 = \sum_{i=t_2}^{t_3 - 1} \frac{i p_i}{\omega_i}, \omega_2 = \sum_{i=t_2}^{t_3 - 1} \frac{n_i}{N} = \sum_{i=t_2}^{t_3 - 1} p_i \\ \sigma_j = \omega_j (\mu_j - \mu_T)^2, \mu_j = \sum_{i=t_j}^{t_{j+1} - 1} \frac{i p_i}{\omega_i}, \omega_j = \sum_{i=t_j}^{t_{j+1} - 1} \frac{n_i}{N} = \sum_{i=t_j}^{t_{j+1} - 1} p_i \\ \sigma_m = \omega_m (\mu_m - \mu_T)^2, \mu_m = \sum_{i=t_m}^{t_{m+1} - 1} \frac{i p_i}{\omega_i}, \omega_m = \sum_{i=t_m}^{t_{m+1} - 1} \frac{n_i}{N} = \sum_{i=t_m}^{t_{m+1} - 1} p_i \end{cases} \tag{4}$$

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Then the optimal threshold is the maximum interclass variance when t is expressed as follows.

$$(t_1^*, t_2^*, \cdots t_m^*) = \arg\max f(t) \tag{5}$$

Ⅲ. Bat Algorithm

In 2010, Yang developed a new meta-heuristic algorithm, Bat Algorithm (BA) [9], by imitating the echolocation function of bats in nature. The principle of this algorithm is to treat individual bats as solutions in the search space, and rely on the loudness and pulse rate of individual bats to search for food through continuous iterations to obtain the optimal solution. The principle of the BA algorithm is as follows: set the N -dimensional search space, the frequency range of the bat is $[f_{\min}, f_{\max}]$, the corresponding wavelength range is $[\lambda_{\min}, \lambda_{\max}]$, the bat loudness is A, the pulse frequency is r, and the position l_i^t and velocity v_i^t of the i the bat at the moment of t are updated as follows.

$$f_i = f_{\min} + (f_{\max} - f_{\min}) \bullet \beta \tag{6}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x^*) \bullet f_i \tag{7}$$

$$l_i^t = l_i^{t-1} + v_i^t \tag{8}$$

In the above equation, f_i denotes the bat frequency, $\beta \in [0,1]$ is a random variable subject to uniform distribution, and x^* denotes the optimal position after each iteration. During the operation of the algorithm, but the individual bats perform local search, the algorithm will generate an optimal solution from the current local search, so that each bat will get a new position at random, and its expression is shown in (9).

$$l_{new} = l_{old} + \alpha \overline{A^t} \tag{9}$$

In formula (9), the value of α is between [-1, 1], and $\overline{A^t}$ represents the average loudness of all bats at time t. The bat's speed and position are constantly updated as the iterations continue. Once the prey is found, the loudness decreases and the pulse frequency increases.

$$A_i^{t+1} = \alpha A_i^t \tag{10}$$

$$r_i^{t+1} = r_i^0 \bullet [1 - \exp(-\kappa t)] \tag{11}$$

Ⅳ. Image Segmentation Based on Improved Bat Algorithm

Like other meta-heuristic algorithms, the bat algorithm also has the problem of easily falling into local optimality and insufficient global search ability. Therefore, in order to be better used in image segmentation, this article uses population initialization, adaptive parameters and individual screening. Aspects are optimized.

4.1 Population initialization

In order to obtain the optimal solution, the population needs to be evenly distributed in the search space. Initializing the algorithm through a chaotic algorithm also has better solution diversity. The idea is to rely on the mapping relationship to generate a chaotic sequence in the interval [0,1], and then correspond to the individual

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search space. This paper uses the chaotic sequence generated by the Logistics map to initialize the bat algorithm population. The mathematical expression of Logistics mapping is:

$$y_{j+1}^{i} = \mu y_{j}^{i}(1-y_{j}^{i}) \quad y_{j}^{i} < 0.5 \tag{12}$$

In the formula, $\mu \in [0,4]$ is a chaotic parameter, and its value is related to the quality of the chaotic effect. The larger the value, the better the chaotic effect, and vice versa, the worse the effect. In this paper, the maximum value of μ is selected, and $i = 1,2,3\cdots$ and N represent the population size; $j = 1,2,\cdots,$ d represents the sequence number of the chaotic variable

4.2 Adaptive parameter optimization

The adaptive parameter α is a fixed value. Obviously, it cannot adapt to the transformation of the algorithm during operation. The step size becomes larger, which is conducive to improving the algorithm's global exploration ability, and the step size becomes smaller, which is conducive to the local development ability of the algorithm and improves the search capability. Therefore, this paper uses exponential decline factor instead of adaptive parameters, which improves the accuracy of the algorithm and makes the step size adaptive. The specific update formula is shown in (13):

$$\alpha = \begin{cases} \alpha_{\max} - 0.1 \times (\alpha_{\max} + \alpha_{\min}) \times e^{\frac{t}{N}} & t < 0.5N \\ \alpha_{\min} + (\alpha_{\max} + \alpha_{\min}) \times \dfrac{t}{N} & t \geq 0.5N \end{cases} \tag{13}$$

In the formula, t is the current iteration number, G is the overall iteration number, and $\alpha_{\max}$ and $\alpha_{\min}$ represent the maximum and minimum values of factor α , respectively.

4.3 Global optimization

The bat algorithm does not perform individual screening after each iteration, resulting in a lot of redundant individuals. These redundant individuals participate in the next iteration process, which will seriously affect the quality of the solution and cannot effectively produce the optimal solution. The advantage of the Monkey algorithm is that it has a better global search capability. Therefore, in this paper, monkey swarm algorithm is used for individual selection in the algorithm after each iteration, and the monkey swarm algorithm has better individual selection ability to select whale individuals, and retains better population individuals for the next iteration.

(1) Crawling process

The process of finding the objective function value of the optimization problem by each monkey by crawling in the current range continuously through the process of crawling step by step is as follows.

Step 1: Randomly generate vectors $\Delta X_i = (\Delta x_{i1}, \Delta x_{i2}, \cdots, \Delta x_{in})$ and $i = 1,2,\cdots M$. Component Δx_{ij} takes a with equal probability, where $j = 1,2\cdots,n,a(a>0)$ is the step length of the monkeys each time they climb.

Step 2: Calculate $f_{ij}^{'}(X_i) = \dfrac{f(X_i + \Delta X_i) - f(X_i - \Delta X_i)}{2\Delta x_{ij}}$, where $j = 1,2\cdots,n,a(a>0)$ and vector $f_i^{'}(X_i) = (f_{i1}^{'}(X_i), f_{i2}^{'}(X_i),\cdots f_{in}^{'}(X_i))$ are the pseudo gradients at the location of the objective function.

Step 3: Set $Y_i = X_i + a \times sign(f'_{ij}(X_i))$, where $j = 1, 2 \cdots, n$ and $sign$ are symbolic functions

Step 4: When vector $Y_i = (y_{i1}, y_{i2}, \cdots y_{in})$ is in the range of $[x_{\min}, x_{\max}]$ and $f(Y_i) < f(X_i)$, change Y_i to, otherwise it will not change.

(2) Hope process
Each monkey reached the highest peak in its respective range through the climbing process. After reaching the peak, it looked for a higher mountain than the current one by looking in all directions around it. When the highest mountain appeared, it moved towards the highest peak. , Otherwise stay in place. Therefore, the specific process is as follows:

Step 1: Randomly generate a real number $(x_{ij} - b, x_{ij} + b)$ within the range that the monkey can observe, randomly generate a real number y_{ij}, set $Y_i = (y_{i1}, y_{i2}, \cdots y_{in})$, then $Y = (Y_1, Y_2, \cdots Y_M)$, where b is the length of the observation range.

Step 2: When the vector $Y_i = (y_{i1}, y_{i2}, \cdots y_{in})$ is in the variable range and $f(Y_i) < f(X_i)$, change Y_i to X_i, otherwise perform step 1 until a feasible Y_i is found.

(3) Jump process
The jumping process in the monkey algorithm is to re-search in a new field in order to obtain a better solution. The specific operations are as follows:

Step 1: Generate a real number θ in the limited interval $[c, d]$ of the monkey jump.

Step 2: Set $y_{ij} = x_{ij} + \theta \times (p_j - x_{ij})$, where $p_j = \frac{1}{M}\sum_{i=1}^{M} x_{ij}$, where $j = 1, 2 \cdots, n$, where $p = (p_1, p_2, \cdots p_n)$ is the pivot.

Step 3: When the vector $Y_i = (y_{i1}, y_{i2}, \cdots y_{in})$ is in the range of $[x_{\min}, x_{\max}]$ and $f(Y_i) < f(X_i)$, change Y_i to X_i, otherwise perform steps 1 and 2 until a feasible Y_i is found.

4.4 Algorithm steps

Step 1: The image to be segmented is converted to grayscale image to obtain the grayscale distribution, and according to the grayscale value of the image between [0,255], the position bound of the improved bat algorithm is also located in this interval.

Step 2: Initialize a certain number of bat individuals in a specific solution space, the initialization process represents the population size, dimension and number of iterations, and each individual represents a solution in the solution space.

Step 3: Calculate the fitness function of each bat individual according to Equation (3)

Step 4: The bat algorithm population is initialized according to section 3.1, the parameters are optimized according to section 3.2, and the individuals are filtered using the monkey colony algorithm according to section 3.3.

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Step 5: When the individuals do not satisfy the termination condition, the next iteration is required according to steps 3-4, and the optimal result is obtained continuously through repeated operations until the termination condition is satisfied, and the image is segmented and evaluated according to the optimal threshold vector $(t_1,t_2,\cdots t_m)$ found.

V. Experimental Simulation

In order to further verify the segmentation effect of the algorithm in this paper, the monkey swarm algorithm was selected, and the bat algorithm was used as a comparison algorithm for image segmentation, using the maximum inter-class variance and the structural similarity SSIM [10] values reflecting subjective evaluation as the image segmentation quality evaluation criteria. the range of SSIM is between [0,1], and the larger the value means the better the segmentation quality.

$$SSIM(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{14}$$

μ_x, μ_y is the mean of the image x,y, σ_x^2,σ_y^2 is the variance of the image, σ_{xy} is the covariance of x,y, and c_1 and c_2 are constants. In this paper, the SSIM value and segmentation time are chosen as the comparison indexes, and the hardware platform is Matlab 2012, CPU is Core i5 with 8GDDR3 memory, and the operating system is Windows 7 running on the host computer. In this paper, three images from Berkeley Segmentation Data Set and Benchmarks 500 (BSDS500) were randomly selected as segmentation objects, and the segmentation threshold was set to 3. The segmentation effects of threshold 1-3 are shown in Figure 1 (a)-Figure 3 (c).

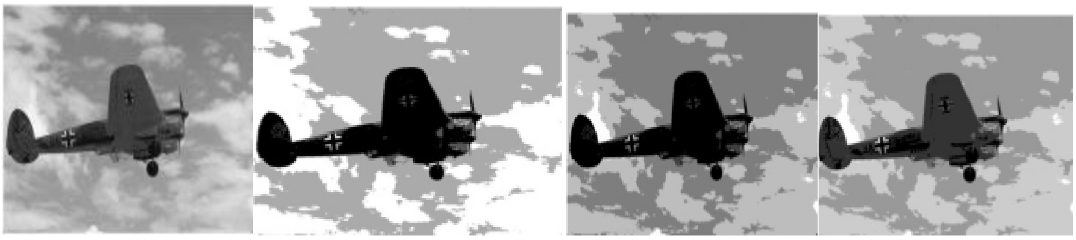

Fig.1: Plane Image ***Fig.1 (a): threshold=1*** ***Fig.1 (b): threshold=2*** ***Fig.1 (c): threshold=3***

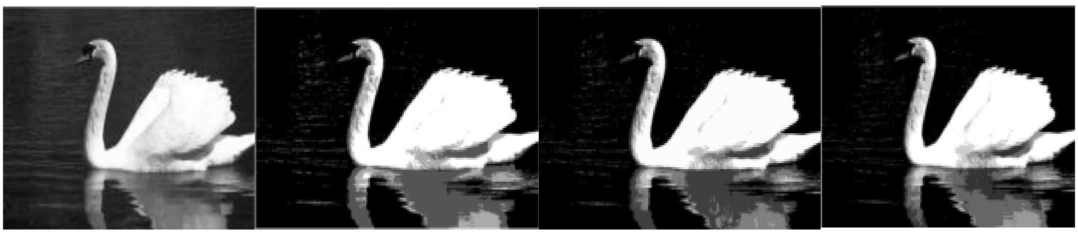

Fig.2: Swan Image ***Fig.2 (a): threshold=1*** ***Fig.2 (b): threshold=2*** ***Fig.2 (c): threshold=3***

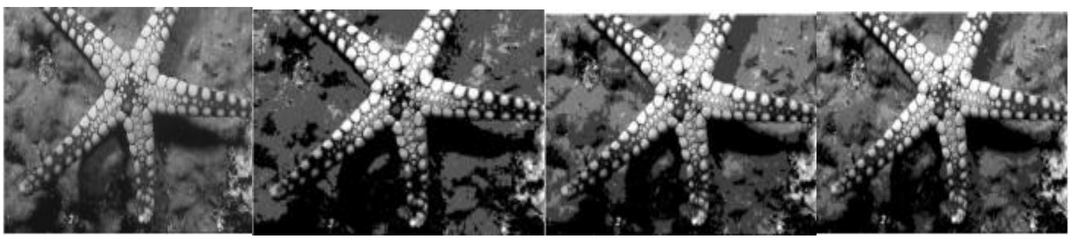

Fig.3: SeaStar Image ***Fig.3 (a): threshold=1*** ***Fig.3 (b): threshold=2*** ***Fig.3 (c): threshold=3***

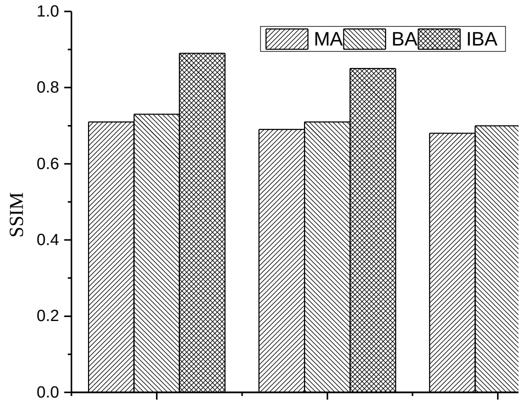

Fig. 4: SSIM contrast values for the three algorithms with a threshold of 1

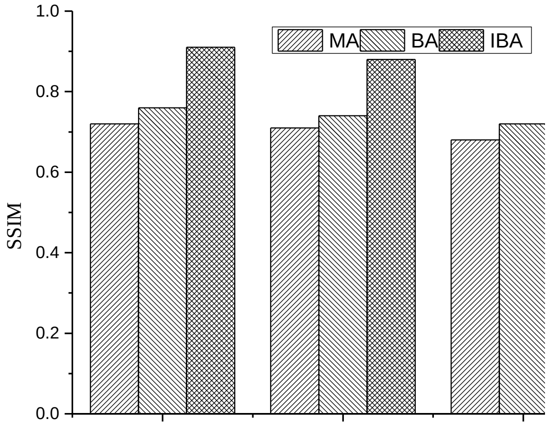

Fig.5: SSIM contrast values for the three algorithms with a threshold of 2

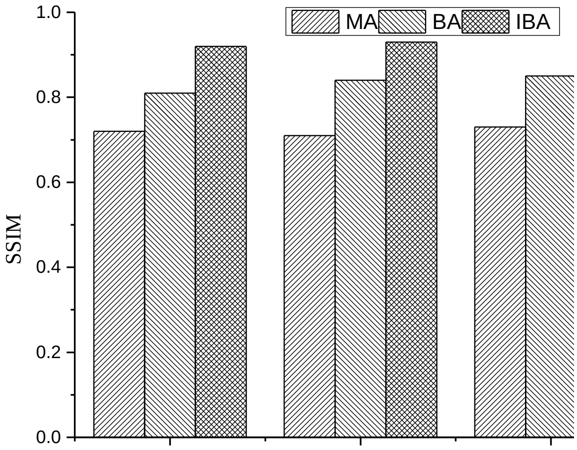

Fig.6: SSIM contrast values for the three algorithms with a threshold of 3

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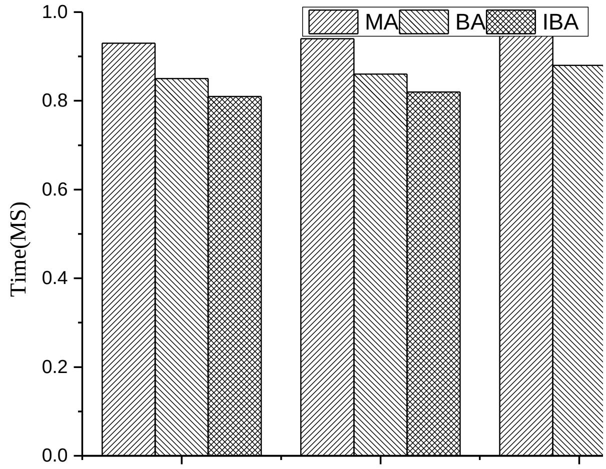

Fig.7: Comparison of segmentation time of three algorithms with a threshold value of 1

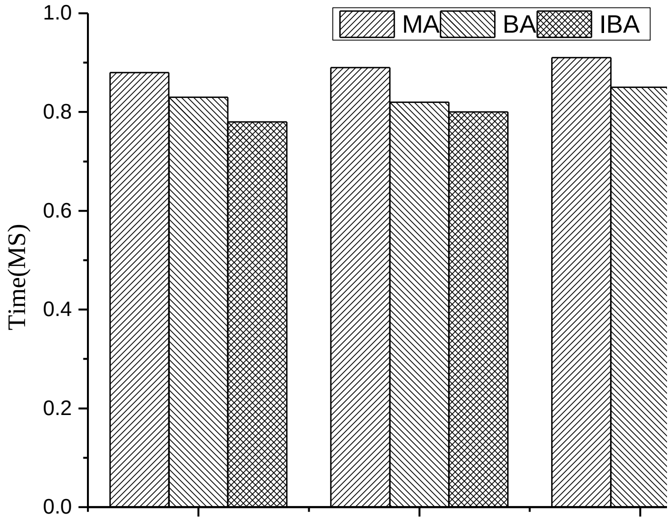

Fig.8: Comparison of segmentation time of three algorithms with a threshold value of 2

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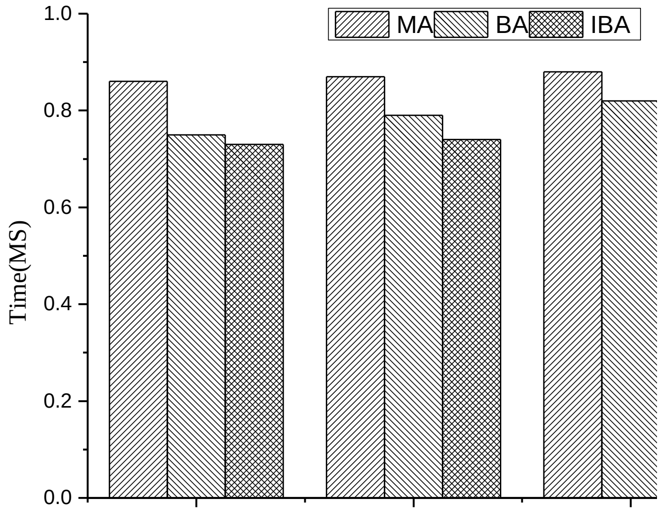

Fig.9: Comparison of segmentation time of three algorithms with a threshold value of 3

Figure 4-6 shows the comparison of the image segmentation quality of the three algorithms for different threshold values, when the threshold value is equal to 1, the segmentation quality of this algorithm is significantly better than the other three algorithms, which indicates that the improved algorithm can indeed improve the quality of segmentation. The SSIM value of this algorithm is always the smallest. On the whole, the algorithm in this paper does achieve good results in terms of segmentation quality under different thresholds, and it has obvious advantages over the BA algorithm, which indicates that the improvement of the algorithm has certain effect on improving the segmentation quality. Figures 7-9 show the time required for image segmentation under the three algorithms. Although the time spent by the algorithm in this paper is the least overall, the time required for optimization is indeed unavoidable due to the improved performance of the algorithm in this paper, especially after the operations of initializing the population, adaptive parameter optimization, and individual screening, the complexity of the algorithm has increased, but the time used for segmentation is relatively Therefore, from the overall comparison results, the time consumption of this algorithm is the least compared with the other two algorithms, which indicates that this algorithm can improve the performance of the algorithm after optimization, making it better in terms of image segmentation performance.

Ⅵ. Conclusion

In this paper, we propose an improved bat algorithm for image segmentation processing strategy, firstly, we describe the image segmentation based on the maximum inter-class variance method, and secondly, we optimize the bat algorithm by using chaotic initialization population, adaptive parameters, individual selection, etc. The experiments show that the algorithm achieves better results in image segmentation, and the next step will be to consider how to adopt the algorithm of this paper under multi-threshold conditions. The next step will be to consider how to adopt the effect of the algorithm in multi-threshold conditions, and to think more about both segmentation quality and segmentation time.

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