An Improved Otsu Multi-threshold Image Segmentation Algorithm Based on Pigeon-Inspired Optimization

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Abstract—**Threshold segmentation is a simple and effective method in the field of image segmentation which has the widest application domain. And the improvement of efficiency and precision of the threshold segmentation has received extensive attention and research. Inspired with the bio-inspired intelligent optimization, this paper proposes an Otsu multi-threshold segmentation based on pigeon-inspired optimization. The basic idea of this method is: the Otsu multi-threshold segmentation method is used to design the objective function, and the interclass variance function is used as the fitness function. The iterative optimization process is performed by the pigeon-inspired optimization. In this process, the fitness function is used as a criterion for the solution and corresponds to the coordinate of pigeon in the pigeon-inspired optimization. The best segmentation threshold group is obtained when the pigeon finds the global best position. This method converts the problem of finding the optimal solution into the solving problem of multi-dimensional variables and effectively optimizes the solution process. For the purpose of verifying the feasibility and segmentation accuracy of this method, the multiple segmentation parameters of several classical images of this method are compared with parameters of other classic algorithms such as particle swarm optimization and fireworks algorithm. The experiments show that the improved Otsu segmentation method based on pigeon-inspired optimization can effectively improve the speed of threshold solution, and the double operators ensures the accuracy of the segmentation. The method has the advantages of superior convergence and convenience of implementation. Simultaneously, the segmentation effect is ideal with this modus.**

Keywords-component; Image segmentation; Otsu; Multi-threshold segmentation; Pigeon-Inspired Optimization

I. INTRODUCTION

In the image recognition process, the signal processing process includes steps such as target detection and target classification. [1] Target detection is the basic condition for target recognition, and image segmentation is an important method for image recognition. Image segmentation is essentially a classification problem, and one or more objects in the image are extracted by dividing the pixels in the image into two or more category areas of practical significance. After image segmentation, important features such as the orientation of the target and the shape of the target can be determined, providing the basis for subsequent image recognition. At the same time, image segmentation is a prerequisite step for image analysis, understanding and description. It is applied to fields including machine vision, text recognition, biomedicine, and image analysis. Image segmentation is a classical problem in the field of image processing and analysis, and it is also one of the difficulties in this field. [2]

The image is divided into different objects or regions during the segmentation process, and these objects or regions are closely related to the target objects in the image, and the segmentation process stops when the target object is divided. Pixels with similar properties are divided into one class, and the actual demand determines the subdivision level. Image segmentation criteria are often based on the fundamental characteristics of intensity values such as discontinuities or similarities. The similarity-based segmentation algorithm uses similar regions to divide images according to predetermined criteria. Threshold processing is a commonly used segmentation method for obtaining relevant information from images in the field of image processing. Its principle is based on a histogram in which pixels in a region can share their intensity, so it separates bright and dark regions. Because of its high efficiency and ease of use, threshold processing has become one of the most commonly used techniques in image segmentation. Since the image segmentation process has many benchmarks, including color, intensity, and texture, these criteria divide the image into sections. Therefore, threshold processing is considered to be the best segmentation method for our experiment. The key to threshold segmentation is the selection of the optimal threshold, which is used to separate one or more desired objects from their application-dependent background. It is always a problem that people are concerned about seeking an efficient global optimal threshold selection method. [3]

The largest between-class variance method (Otsu) [5] was proposed by Japanese scientist Otsu. Its main idea is to

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segment the image into two regions based on the grayscale information of the image. [6] The multi-threshold method is widely used for higher-demand image segmentation, and the optimal threshold is obtained by minimizing or maximizing certain parameters. Otsu is one of the best threshold selection criteria, and the optimal threshold obtained by this method is the threshold that maximizes the variance between the foreground and background regions. Otsu is most suitable for two situations: one is that the image has a bimodal histogram distribution; the other is that there is a significant difference between the foreground and the background. The traditional Otsu method is considered to be one of the effective techniques for providing excellent segmentation results for ordinary images. However, due to the huge amount of computation after the multi-threshold is raised, the actual applications are very few. Chen, K et al, proposed a method of image threshold based on firefly algorithm (FA) in 2014. [7, 8]. Chen, M et al proposed an improved Otsu image segmented based on particle swarm optimization (PSO) in 2009. [9, 10] These two algorithms have been widely used in optimizing image segmentation, and their accuracy and segmentation efficiency have been highly recognized. This provides an idea for optimizing Otsu using other algorithms.

The pigeon-inspired optimization is Duan's first new swarm intelligence optimization algorithm proposed in 2014. [4] It was inspired by the autonomous homing behavior of pigeons in nature. The optimization algorithm mainly relies on two operators—the map and the compass operator and the landmark operator to complete the target solution search process. In this paper, the Otsu segmentation criterion is improved using a pigeon-inspired optimization, which effectively improves the segmentation efficiency and segmentation accuracy of the original algorithm. And the results obtained by the new algorithm are compared with the above two classic algorithms PSO and FA to further verify the feasibility and segmentation performance of the improved Otsu multi-threshold segmentation based on pigeon-inspired optimization.

II. METHODS

A. Otsu segmentation Algorithm

In the Otsu algorithm, the key is finding the thresholds for dividing the image into two parts, the foreground and the background. Assuming that the total number of pixels of the image is S , i represents the gray value, and S_i is the corresponding pixel number. The probability of occurrence of the number of pixels corresponding to the specific gray value is:

$$P_i = S_i / S \tag{1}$$

Setting the threshold for dividing the image into foreground and background is x, then the probability of occurrence of pixels in the two regions is:

$$t_0 = \sum\nolimits_{i=0}^{k} P_i = t(k) \tag{2}$$

$$t_1 = \sum\nolimits_{i=k+1}^{L-1} P_i = 1 - t(k) \tag{3}$$

The total mean value of the image is expressed as μ , μ_0 and μ_1 respectively represent the average of the foreground and background. The calculation method for the variance between the foreground and the background as formula (4):

$$\sigma(x) = t_0 (\mu_0 - \mu)^2 + t_1 (\mu_1 - \mu)^2 \tag{4}$$

where, in the case where the threshold number is 1, The condition that the method obtains the optimal solution x is $\sigma(x)$ taking the maximum value.

It is assumed that the image gray level is M , and the threshold group is denoted as $x_1, x_2, \ldots, x_n \left(0 \le x_1 \le x_2 \ldots \le x_n \le M-1\right)$. We can decrement that n thresholds will divide the image into $n+1$ different intervals, and the total variance between the classes of the segmentation intervals in the case of multi-threshold:

$$\sigma(x_1, x_2, \ldots, x_n) = \sum_{i=0}^{n-1} \sum_{j=i+1}^{n} t_i t_j (\mu_i - \mu_j)^2 \tag{5}$$

In the formula (5), when $\sigma(x_1, x_2, \ldots, x_n)$ takes the maximum value, $(x_1, x_2, \ldots, x_n)$ is the optimal solution obtained with the Otsu. Where, μ_i and μ_j represent the average values of certain two regions respectively. t_i and t_j are respectively the probability of occurrence of pixels in the certain two regions.

B. Pigeon-Inspired Optimization

Based on the special navigational behavior of the pigeons during the homing process, Duan et al. proposed a pigeon-inspired optimization. [11] pigeon-inspired optimization has been widely used recently. Zhang, B. and Duan, H. proposed a UAV's path planning method based on pigeon-inspired optimization in 2014. [12] Zhang, S. and Duan, H. used pigeon-inspired optimization (PIO) approach to orbital spacecraft formation reconfiguration in 2015. [13] Duan, H. and Wang, X. found an image restoration method by using echo state networks with orthogonal pigeon-inspired optimization. [14] Xue, Q. and Duan, H. proposed a way to control robust attitude for reusable launch vehicles based on fractional calculus and pigeon-inspired optimization. [15]

In the algorithm, two different operator models are proposed by mimicking the mechanism by which pigeons use different navigation tools in different stages of finding the target:

(a) Map and compass operator

Pigeons can use magnetic objects to sense the magnetic field and then form a map in the mind. They use the sun's altitude as a compass to adjust the direction of flight. When they approach the destination, their dependence on the sun and magnetic objects decreases.

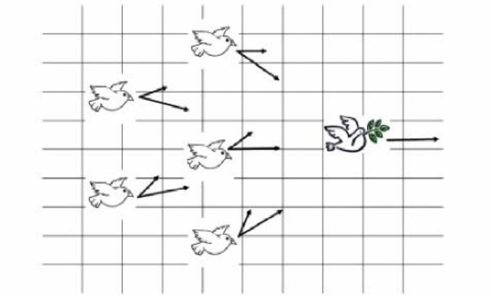

Figure 1. Map and compass operator model

(b) Landmark operator

Landmark operator is used to simulate the effect of landmarks on pigeons in navigation tools. As the pigeons fly closer to their destination, they will rely more on nearby landmarks. If the pigeon is familiar with the landmark, it will fly directly to the destination. Otherwise, they will follow the pigeons familiar with the landmark.

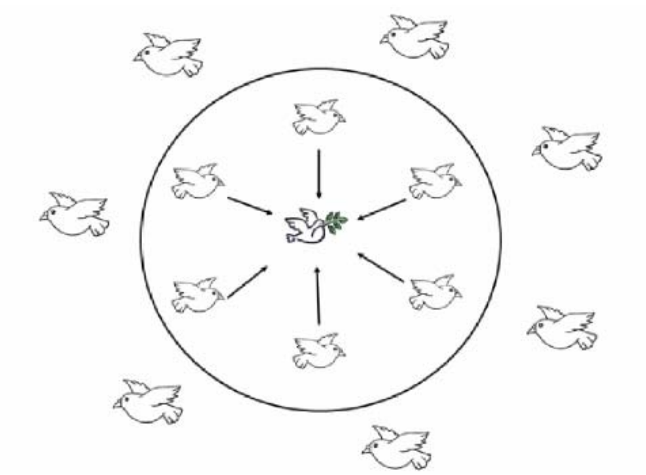

Figure 2. Landmark operator model

In a pigeon-inspired optimization model, virtual pigeons are used to simulate the navigation process. According to the principle of the map and compass operator, the position and speed of the pigeon are initialized. And in the multidimensional search space, the position and speed of the pigeon are updated in each iteration.

Its position and speed are recorded as

$$X_i = [x_{i1}, x_{i2}, \cdots, x_{iN}] \tag{6}$$

$$V_i = [v_{i1}, v_{i2}, \cdots, v_{iN}] \tag{7}$$

In the formula, $i = 1, 2 \cdots, N$. means each pigeon. And each pigeon updates its position X_i and speed V_i according to

$$V_i^{N_c} = V_i^{N_c-1} e^{-R\times N_c} + rand(X_{gbest} - X_i^{N_c-1}) \tag{8}$$

$$X_i^{N_c} = X_i^{N_c-1} + V_i^{N_c} \tag{9}$$

where, R is the factor of map and compass, the value range is set to 0 to 1; $rand$ is a random number in the range of 0 to 1; N_c is the current number of iterations; X_{gbest} is the globally optimal position obtained by comparing the positions of all the pigeons after the $N_c - 1$ iterations, When the number of iterations reaches the required number of iterations, the work of the map and the compass operator is stopped and the work continues in the landmark operator.

In the landmark operator, the number of pigeons is reduced by half after each iteration. Those pigeons far from the destination are unfamiliar with the landmarks. They will no longer have the ability to distinguish the routes and will be sacrificed. X_{center} is the center position of the remaining pigeons and will be used as a landmark, which is the reference direction for the flight. Based on the following equation, the pigeon's position X_i is updated.

$$X_{center}^{N_c-1} = \frac{\sum_{i=1}^{N^{N_c-1}} X_i^{N_c-1} F(X_i^{N_c-1})}{N^{N_c-1} \sum_{i=1}^{N^{N_c-1}} F(X_i^{N_c-1})} \tag{10}$$

$$N^{N_c} = \frac{N^{N_c-1}}{2} \tag{11}$$

$$X_i = X_i^{N_c-1} + rand(X_{center}^{N_c-1} - X_i^{N_c-1}) \tag{12}$$

where,

$$F(X_i^{N_c-1}) = \begin{cases} \dfrac{1}{fitness(X_i^{N_c-1}) + \varepsilon}, & for \quad the\ minimization\ problem \\ fitness(X_i^{N_c-1}), & for \quad the\ maximization\ problem \end{cases}$$

$$fitness(X_i^{N_c-1}) > 0$$

Similarly, after the iteration loop above the maximum number of iterations, the landmark operator also stops working.

C. Improved Otsu Multi-threshold Segmentation Based on Pigeon-Inspired Optimization

1. Read in and preprocess the image to be divided.
2. Initialize the pigeon group coordinates and randomly generate the initial speed, set the parameters.
3. Update the speed and flight path of the pigeons using the landmark operator and the compass operator.
4. Use formula (4) to calculate the fitness of each pigeon's coordinates, compare all pigeons' fitness and find the best path.
5. That the best individual coordinate obtained after reaching the set number of iterations is the optimal threshold group. And the image segmentation is performed according to the requested threshold group.

III. RESULTS & DISCUSSION

The experiment environment for Win10, Intel i5-3210 CPU 4*2.5GHz, and the programming tool used is Matlab2016b. The sample plots and their gray distribution histograms（GDH）used in this experiment are as figure 3:

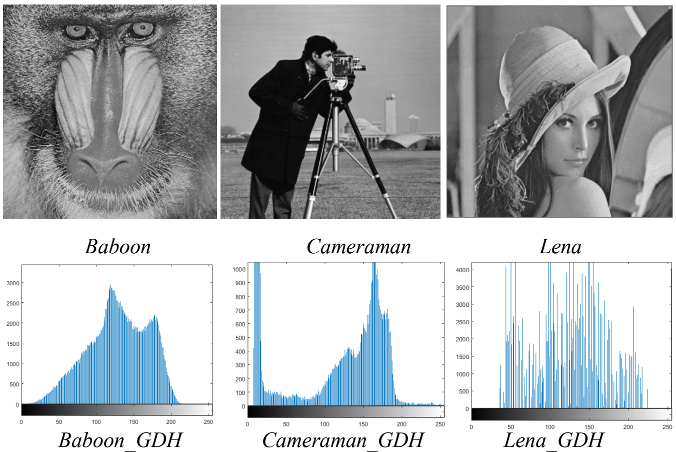

Figure 3. The sample plots and their gray distribution histograms（GDH）.

Figures 4 show the results of image segmentation based on pigeon-inspired optimization for different thresholds (the number of thresholds n = 1, 2, 3, 4) for Otsu multi-threshold segmentation.

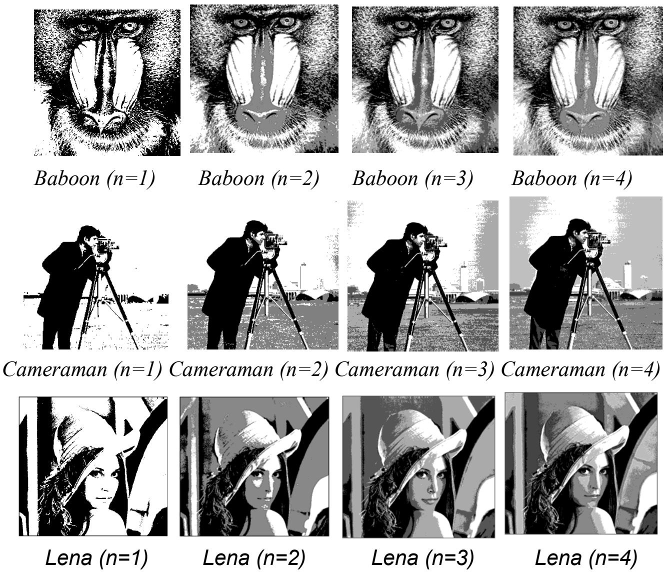

Figure 4. The segmentation effect of PIO in the case that thresholds number n = 1, 2, 3, 4 in each of the three sample images.

In order to further verify the feasibility and accuracy of the proposed algorithm, we use the classic algorithm PSO and FA threshold for the same three sample plots with n=1, 2, 3, 4 thresholds. Their segmentation effects are shown in Figure 5 and Figure 6, and the data we obtain is as TABLE I.

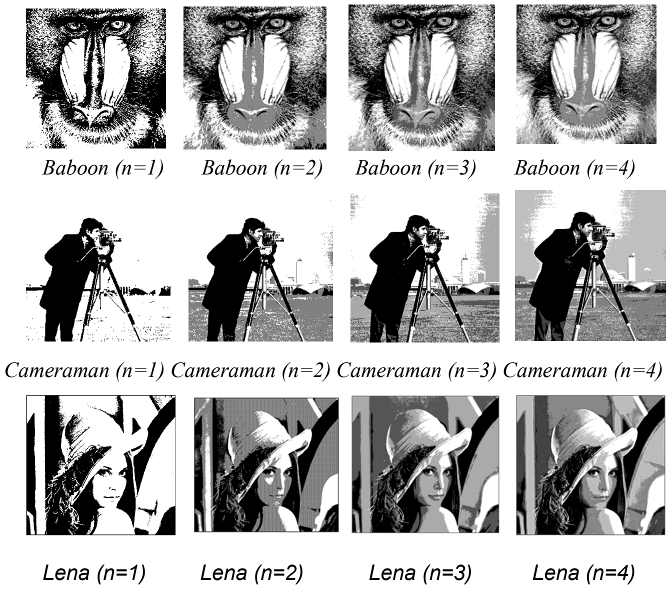

Figure 5. The segmentation effect of PSO in the case that thresholds number n = 1, 2, 3, 4 in each of the three sample images.

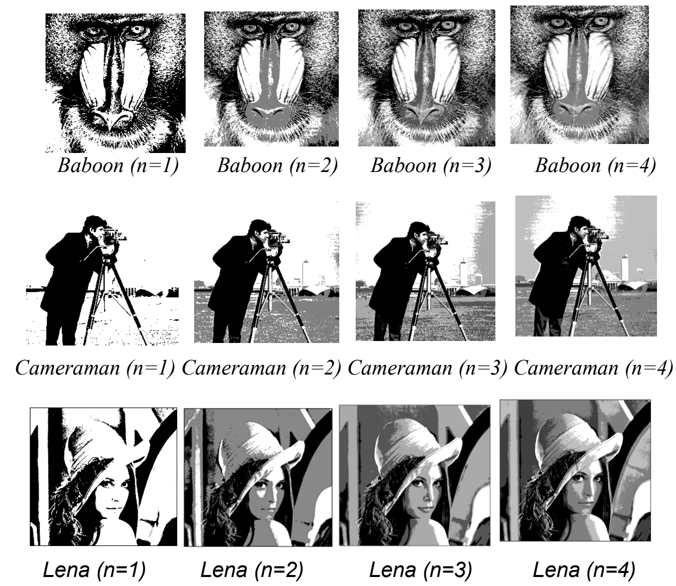

Figure 6. The segmentation effect of FA in the case that thresholds number n = 1, 2, 3, 4 in each of the three sample images.

TABLE I. THE FITNESS VALUE AND OPTIMAL THRESHOLD GROUP OF THREE ALGORITHMS WHEN N=1, 2

Pic	Baboon			Cameraman			Lena		
algorithm	PIO	PSO	FA	PIO	PSO	FA	PIO	PSO	FA
Fitness	1069.15	1069.15	1069.15	3289.12	3289.12	3289.12	1568.57	1568.57	1568.57
n=1	128	128	128	89	89	89	120	120	120
Fitness	1367.25	1367.28	1367.25	3650.34	3650.34	3650.34	1978.48	1978.48	1978.48
n=2	99,148	98,148	99,148	70,144	70,144	70,144	104,166	104,166	104,166

It can be seen from Table 1 that when n=1, 2, the effect of the three algorithms divided is not obvious. Because PSO and

FA have been widely used in image segmentation, it shows that the pigeon-inspired optimization is also suitable for Otsu's multi-threshold segmentation. In order to measure the differences among the three algorithms, we set the number of runs of the three algorithms to be 100 when the higher dimension n=3, 4, and list their maximum and minimum values for the calculated fitness values. And calculate their average and standard deviation.

TABLE II. THE FITNESS VALUE OF THREE ALGORITHMS WHEN N=3

Pic	Baboon			Cameraman			Lena		
algorithm	PIO	PSO	FA	PIO	PSO	FA	PIO	PSO	FA
max	1454.58	1454.58	1454.58	3725.72	3725.72	3725.72	2163.27	2163.27	2163.27
min	1454.52	1454.52	1452.81	3725.63	3725.70	3723.79	2163.27	2048.74	2162.34
mean	1454.57	1454.57	1454.21	3725.71	3725.71	3725.4	2163.27	2160.98	2163.00
std	0.0232	0.0163	0.3679	0.0164	0.0025	0.3953	0.0000	16.1966	0.2420

TABLE III. THE FITNESS VALUE OF THREE ALGORITHMS WHEN N=4

Pic	Baboon			Cameraman			Lena		
algorithm	PIO	PSO	FA	PIO	PSO	FA	PIO	PSO	FA
max	1503.91	1503.91	1503.71	3780.69	3780.69	3780.63	2234.35	2234.35	2234.29
min	1503.88	1503.62	1489.09	3780.65	3779.55	3764.46	2234.29	2212.28	2211.14
mean	1503.9	1503.89	1502.45	3780.68	3780.63	3778.74	2234.35	2233.03	2230.24
std	0.0096	0.0442	2.2708	0.0087	0.1800	2.7733	0.0086	5.2556	7.1389

Through the fitness value analysis of Table 2 and Table 3, it can be seen that the maximum fitness value and the minimum fitness value obtained by the three algorithms in the case of full iteration are relatively close. However, through analyzing the standard deviation of fitness values of three algorithms, the maximum standard deviation of PSO and FA has reached more than 1. In particular, Table 2 shows that when PSO is applied to Lena to perform segmentation with a threshold number of 3, the standard deviation of fitness value reaches 16.1966.Since the gray level distribution of the Lena image is more discrete than that of the other two images. It is also explained that the stability of the PSO algorithm is poor. While the maximum standard deviation of the PIO algorithm in these two sets of experiments does not exceed 0.0232, and the minimum value is only 0. It can be seen that the global search ability of the pigeon-inspired optimization is better, and its stability is better than the PSO algorithm and the FA algorithm under the same segmentation conditions.

IV. CONCLUSION

This paper proposes a multi-threshold Otsu image segmentation algorithm based on pigeon-inspired optimization to solve the problem of inefficiency and prematureness of classic optimization methods in image processing field to some extent. The comparative data show that the segmentation effect can be obtained with PIO same as the classical PSO and FA when the threshold is low. It is not easy to be premature and has better stability when the threshold is large. In light of the few applications of the PIO algorithm in image processing, it is possible to propose targeted optimization in the future and to further improve the dimensions and segmentation accuracy.

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