

Image Segmentation Algorithm Based On Improved Constrained Chicken Swarm Optimization Algorithm

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【Abstract】 The chicken swarm optimization algorithm(CSO) has the problems of the slow convergence rate and easy to fall into local optimum. In this paper, an improved constrained chicken swarm optimization algorithm(ICCSO) is proposed to improve the evolutionary mechanisms of the basic chicken swarm optimization, and the convergence rate and global search ability of the algorithm are improved. The comparison of simulation experiment with other algorithms proves the rationality and validity of the proposed optimization algorithm. Then using the maximum variance between classes in otsu algorithm on the improved constrained chicken swarm optimization algorithm as a fitness function, which is optimized to get the best threshold value for image segmentation, and compared with other image segmentation algorithm has the better use of the computing rate and convergence rate.

【Key words】 Chicken Swarm Optimization; evolutionary mechanism; constraint function; otsu

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I INTRODUCTION

Image segmentation is one of the most important technologies in the field of digital image processing. It has been widely applied in many theoretical researches and practical applications. The accuracy and efficiency of image segmentation often determine the effects of image analysis and image understanding. Efficient and accurate image segmentation can make higher-level image analysis and understanding become a reality. In the image segmentation technique, the otsu algorithm is able to find a gray value t that maximizes the variance between classes to split the target area and background area [1]. No other prior information is needed in this process. A lot of manpower supervision operations are omitted, so there are many areas for practical application.

Image segmentation can essentially be regarded as the problem of finding the best parameter value to segment the image in a complex data space. However, in the image segmentation process, since otsu algorithm is necessary to obtain an optimal segmentation threshold by traversing all the gray levels, the algorithm has a large amount of calculation and takes too much time, and cannot satisfy the requirement of real-time performance. The swarm intelligence optimization algorithm has unique advantages in solving complex nonlinear multi-modal function optimization problems. It not only can obtain the global optimal solution, and the optimization time is shorter than the traditional methods. With the development of intelligent optimization algorithms, more intelligent optimization algorithms have been used to solve complex engineering problems with large scale and high dimensions, such as particle swarm optimization algorithm [2-5], firefly algorithm [6-8] and ant colony algorithm [9-10]. The application of swarm intelligence optimization algorithm in image segmentation has made more and more research results, especially image threshold segmentation. More intelligent optimization algorithms have natural advantages in solving this kind of problem [11-15].

In this paper, an improved constrained chicken swarm optimization algorithm is proposed to solve the problems of slow convergence rate and easy to fall into local optimal [16-17]. The basic chicken swarm optimization algorithm is improved from two aspects of constraint function and evolutionary mechanism, and the convergence rate and global searching ability of the algorithm are improved. Then using the maximum variance between classes in otsu algorithm on the improved constrained chicken swarm optimization algorithm as a fitness function, which is optimized to get the best threshold value for image segmentation, and compared with other image segmentation algorithms has the better use of the computing rate and convergence rate.

II THE IMPROVED CONSTRAINED CHICKEN SWARM OPTIMIZATION ALGORITHM

2.1 The chicken swarm optimization algorithm

Chicken Swarm Optimization is a swarm intelligence algorithm based on chicken group search behavior, which is proposed by MENG Xianbing in 2014 [18]. In the basic chicken swarm optimization algorithm, the chicken group is divided into several subgroups. Each subgroup is composed of a rooster, a few

hens and chicks. In chickens, some of the best individuals are roosters, with the least adapted individuals as chicks and the remaining individuals as hens. The mother hen chooses the rooster randomly, and the mother-son relationship between the hens and the chicks is also randomly established, and this hierarchy, domination relationship and mother son relationship remain unchanged until several generations to be updated. Individuals in each subgroup look for food around the rooster in this subgroup, while roosters move randomly and iteratively update the population to get the target eventually.

When solving the optimization problem, each individual in the chicken group corresponds to a solution to the optimization problem. Assuming that all the individuals in the chicken population are N , the number of roosters, hens, chicks and mother hens respectively is N_R, N_H, N_C and N_M . $X_{i,j}^t (i \in [1, N], j \in [1, D])$ represents the position of the individual i in the D -dimensional search space at the t iteration. Roosters are the best individuals in the group. They find food in a wider space. The corresponding formula for roosters is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t * (1 + randn(0, \sigma^2)) \quad (1)$$

$$\sigma^2 = \begin{cases} 1, & \text{if } f_i \leq f_k \\ \exp\left(\frac{f_k - f_i}{|f_i| + \epsilon}\right), & \text{else} \end{cases} \quad (2)$$

In the formula: $randn(0, \sigma^2)$ is a Gauss distribution with a mean value of 0 and a standard deviation of σ^2 ; ϵ is a very small constant; $(k \in [1, N], k \neq i)$ is a rooster index and is randomly selected from all non-self roosters; f is a corresponding fitness value for x .

The formula for the location of the hens is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + S_1 * rand * (x_{r_1,j}^t - x_{i,j}^t) + S_2 * rand * (x_{r_2,j}^t - x_{r_1,j}^t) \quad (3)$$

$$S_1 = \exp\left(\frac{f_i - f_{r_1}}{abs(f_i) + \epsilon}\right) \quad (4)$$

$$S_2 = \exp(f_{r_2} - f_i) \quad (5)$$

In the formula: $rand$ is a random number between $[0, 1]$; r_1 is the rooster of the i th hen's own subgroup; r_2 is a randomly selected rooster or individual hen, and $r_1 \neq r_2$.

The position update formula for chicks is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + FL * (x_{m,j}^t - x_{i,j}^t) \quad (6)$$

In the formula, m is the hen corresponding to the i th chick; $FL (FL \in [0, 2])$ is the following coefficient, indicating that the chick follows its corresponding hen for food.

2.2 The improved constrained chicken swarm optimization algorithm

The basic chicken swarm optimization algorithm has the problems of slow convergence rate and easy to fall into the local optimality. In this paper, the basic chicken swarm optimization algorithm is improved from the constraint function and the evolutionary mechanism.

2.2.1 Improvement of constraint function

In the basic chicken swarm optimization algorithm, if the individual exceeds the search scope, the individual will restart the search from the nearest boundary. The mathematical description is as follows:

$$x_{i,j}^t = \begin{cases} Lb_j, & x_{i,j}^t < Lb_j \\ Ub_j, & x_{i,j}^t > Ub_j \end{cases} \quad (7)$$

In the formula, Lb_j, Ub_j respectively denote the lower boundary and upper boundary of the j dimension.

The chicken swarm optimization algorithm uses the upper and lower bound instead of the constraint value, and the convergence rate is slow. This paper proposes replacing the constraint value with the random movement of the corresponding value of the best group in the current population, so as to improve the convergence rate of the algorithm. Describe the following:

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if  $x_{i,j}^t < Lb_j \parallel x_{i,j}^t > Ub_j$ 
    temp =  $x_{h,j}^t + w_1 * randn(0,1)$ 
    if  $Lb_j \leq temp \leq Ub_j$ 
         $x_{i,j}^t = temp$ 
    else
         $x_{i,j}^t = x_{h,j}^t$ 
end
end
where
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$$w_1 = \begin{cases} 0.2 * (x_{h,j}^t - x_{i,j}^t), & i \leq (N - N_C) \\ 0.2 * (x_{h,j}^t - x_{g,j}^t), & i > (N - N_C) \end{cases} \quad (8)$$

w_1 is the step length, $\text{randn}(0,1)$ is the standard normal distribution, $x_{h,j}^t$ is chosen randomly from the best $N_{well}(N_{well}=N_R)$ individual, $x_{g,j}^t$ is selected randomly from the current best $N_{good}(N_{good}=N-N_C)$ individuals.

2.2.2 Improvement of evolutionary mechanism

According to the position updating formula of the 3 types of chicken, the individual in each subgroup finds food around the rooster in the subgroup, and the rooster moves at random. If the roosters fall into a local optimum, the entire subgroup may also fall into a local optimum. Furthermore, there is no information exchange between the roosters and the convergence rate is slow. In response to these shortcomings, we have increased the traction effect of the whole chicken population on the roosters and hens, so as to improve the convergence rate and global search ability of the algorithm. The position update formula of the improved rooster is as follows:

$$x_{i,j}^{t+1} = w_{01} * x_{i,j}^t * (1 + \text{rand}(0, \sigma^2)) + w_{02} * (x_{best,j}^t - x_{i,j}^t) \quad (9)$$

where

$$w_{01} = w_{max} - (w_{max} - w_{min}) * (1 - t/M) \quad (10)$$

$$w_{02} = w_{min} + (w_{max} - w_{min}) * (1 - t/M) \quad (11)$$

In the formula, w_2 is an adaptive adjustment factor, w_{min} , w_{max} are the minimum and maximum of adjustment factors respectively, M is the maximum number of iterations.

The updated formula for the position of the improved hen is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + S_1 * \text{rand} * (x_{r1,j}^t - x_{r2,j}^t) + S_2 * \text{rand} * (x_{best,j}^t - x_{i,j}^t) + w_{02} * (x_{best,j}^t - x_{i,j}^t) \quad (12)$$

The improved algorithm steps are shown as follows:

- 1) Initialization. Determine the initial parameters N , N_R , N_H , N_C , N_M , M , generating the initial position x of each individual of the group randomly in the solution space, its fitness, and initializing the individual's current best position P_{best} and the best global position of the flock I_{best} are calculated;
- 2) If $t \% G = 1$, the ranking system, dominance relationship and mother child relationship were established by ranking the fitness of chickens;
- 3) The positions of roosters, hens and chicks were updated by formula (9), (11) and (6) respectively, and their fitness values were calculated;
- 4) Update the best location and the best position of the chicken population;
- 5) Step (2) - (4) determine the maximum number of iterations after completion of an iteration process. If so, terminate the cycle, otherwise continue to loop.

III. IMAGE SEGMENTATION ALGORITHM BASED ON IMPROVED CONSTRAINED CHICKEN SWARM OPTIMIZATION ALGORITHM.

The otsu algorithm is proposed by Nobuyuki Otsu, and the greater the variance between classes based on the target and the background, the greater the difference between the background and the target area, and easier to distinguish. This method is based on the principle of discrimination and least squares. At this time, the best threshold value is the gray value when the value of the variance between classes is the maximum. The improved constrained chicken swarm optimization algorithm is optimized by using the variance of the inter class variance in the otsu algorithm as the fitness function to get the best threshold for image segmentation. The algorithm is implemented as follows:

- 1) Input image and calculate the probability of each pixel in the image;
- 2) Initialize the initial parameters, the image segmentation threshold is set as the corresponding position of each individual in the chicken group. The variance between classes in the Otsu algorithm is set as the objective function, which is the fitness function of the chicken group. The initial position x of each individual of the group is randomly generated in the entire solution space, the corresponding fitness is calculated, and the individual's current best position P_{best} and the global best position I_{best} of the flock are initialized;
- 3) If $t \% G = 1$, the ranking system, dominance relationship and mother child relationship were established by ranking the fitness of chickens;
- 4) The positions of roosters, hens and chicks were updated by formula (9), (11) and (6) respectively, and their fitness values were calculated;
- 5) Update the best location and the best position of the chicken population;
- 6) Step (2) - (4) determine the maximum number of iterations after completion of an iteration process. If so, terminate the cycle, otherwise continue to loop;
- 7) According to the best segmentation threshold, the gray image is segmented and the segmented image is obtained.

IV. EXPERIMENTAL SIMULATION AND ANALYSIS

4.1 The simulation of chicken swarm optimization algorithm

This article uses the five standard test functions listed in Table 1 to analyze and verify the actual performance of the ICCSO algorithm, and compares the results with the ICSO [19] and CSO algorithms.

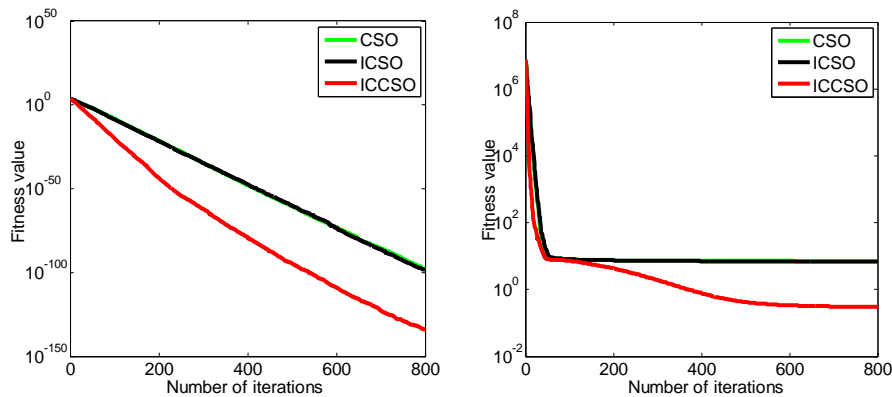
Table 1 Standard Test Functions for Testing Algorithm Performance

Test function	Code number	Ranges	Optimal solution
Sphere	$F1(x) = \sum_{i=1}^D x_i^2$	[-100,100]	0
Ackley	$F2(x) = \sum_{i=1}^D (100(x_i^2 - x_{i=1})^2 + (x_i - 1)^2)$	[-30,30]	0
High Conditioned Elliptic	$F3(x) = \sum_{i=1}^D (10^6)^{\frac{i-1}{D-1}} x_i^2$	[-100,100]	0
Bent Cigar	$F4(x) = x_1^2 + 10^6 \sum_{i=2}^D x_i^2$	[-100,100]	0
Discus	$F5(x) = 10^6 x_1^2 + \sum_{i=2}^D x_i^2$	[-100,100]	0

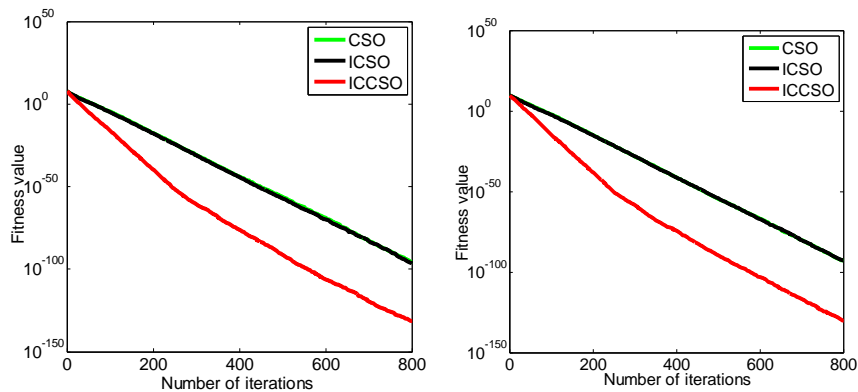
In this experiment, the population size N of the ICCSO algorithm is 100, the dimension D is 10, and the maximum number of iterations M is 800. N_R , N_H , N_C , N_M are respectively $0.2N$, $0.6N$, $0.1N$, $0.1 * N_H$. FL is a random number between [0.4,1], $G=10$, $w_{min}=0.8$, $w_{max}=1.0$. Each test function runs independently 50 times to eliminate randomness, Comparing the calculated optimal value, worst value, average value, and standard deviation value with those of CSO and ICSO, as shown in Table 2. The test results are shown in Figure 1.

Table 2 Comparison of test results of the algorithm

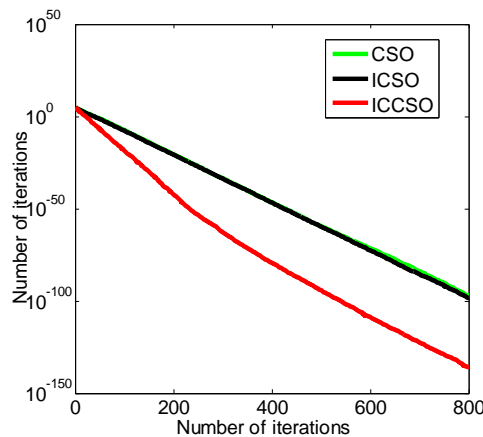
Test function	Algorithm	The optimal value	The worst walue	average value	Standard deviation
F1	CSO	4.8424e-107	2.9993e-97	1.2087e-98	5.8146e-98
	ICSO	8.2764e-106	9.3290e-98	3.9592e-99	1.7636e-98
	ICCSO	3.1284e-150	4.3856e-133	8.8268e-135	6.2014e-134
F2	CSO	6.1811	8.0498	7.0382	0.3841
	ICSO	6.3319	7.2062	6.9288	0.2602
	ICCSO	9.8240e-06	3.1808	0.2996	0.6934
F3	CSO	1.5646e-102	4.5937e-95	1.7700e-96	6.9608e-96
	ICSO	3.6136e-104	4.5163e-96	3.4820e-97	9.3182e-97
	ICCSO	2.3057e-146	1.1718e-130	2.3661e-132	1.6569e-131
F4	CSO	2.6906e-100	2.6191e-92	8.8646e-94	3.9650e-93
	ICSO	4.0327e-100	3.2484e-92	1.2397e-93	4.9659e-93
	ICCSO	1.3431e-142	5.4875e-129	1.1426e-130	7.7569e-130
F5	CSO	4.3402e-106	2.0361e-96	7.9139e-98	3.2048e-97
	ICSO	1.4989e-105	5.7117e-98	2.8675e-99	1.0660e-98
	ICCSO	1.1532e-152	3.3527e-135	1.5076e-136	6.5884e-136



a) The test results of F1 function b) The test results of F2function



c) The test results of F3 function d) The test results of F4 function



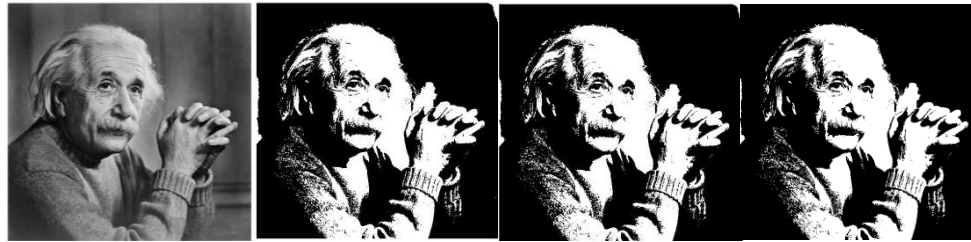
e) The test results of F5 function

Figure 1 The test results of five test functions

As can be seen from **Table 2**, for these 5 standard test functions, the ICCSO algorithm has achieved better value, the maximum difference, the average value and the standard difference compared with the CSO and ICSO algorithms. From **Figure 1**, we can see that ICCSO is superior to CSO algorithm and ICSO algorithm in terms of accuracy and convergence rate, especially for many extreme points. For example, for F2 functions with many extreme points, the CSO algorithm and the ICSO algorithm fall into the local optimal value, while the ICCSO algorithm avoids the local optimal and has a higher convergence precision. In summary, the ICCSO algorithm is superior to the CSO algorithm and the ICSO algorithm in terms of global search ability and convergence rate.

4.2 Test results and analysis of image segmentation

The images of Einstein, Lenna and Xianzi are used as segmentation objects, we compared the otsu algorithm basedonthe basic chicken swarmoptimization algorithm(CSO-Otsu), the otsu algorithm basedon the improved chicken swarm optimization algorithm(ICSO-Otsu), and the otsu algorithm basedon the improved constrained chicken swarm optimization algorithm (ICCSO-Otsu).The maximum number of iterations M is 100, the total number of population $N = 20$, other parameters as above.The algorithm is iteratively executed until the algorithm finishes the algorithm after finding the optimal threshold. We use the number of iterations and execution time as indicators to measure the algorithm. The fewer the number of iterations and the shorter the execution time, the better the algorithm. Each algorithm independently runs more than 20 times to eliminate randomness.**Table 3**, **Table 4**, and **Table 5**are the average number of iterations and execution time of the three experimental images.**Figures 2**, **Figures 3**, and **Figures 4** are segmented images of three experimental images.



(a) The original image (b)CSO-Otsu (c) ICSO-Otsu (d) ICCSO-Otsu
 Figure 2 The threshold segmentation image of Einstein image

Table 3 Image threshold segmentation iterations and execution time(Einstein)

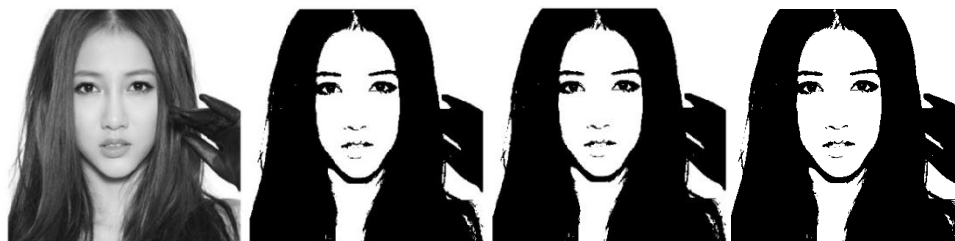
Algorithm	Number of iterations	Execution time (ms)
CSO-otsu	13	0.0159
ICSO-otsu	12	0.0158
ICCSO-otsu	3	0.0140



(a) The original image (b) CSO-Otsu (c) ICSO-Otsu (d) ICCSO-Otsu
 Figure 3 The threshold segmentation image of Lena image

Table 4 Image threshold segmentation iterations and execution time(Lena)

Algorithm	Number of iterations	Execution time (ms)
CSO-otsu	6	0.0083
ICSO-otsu	9	0.0109
ICCSO-otsu	3	0.0062



(a) The original image (b) CSO-Otsu (c) ICSO-Otsu (d) ICCSO-Otsu
 Figure 4 The threshold segmentation image of Xianzi image

Table 5 Image threshold segmentation iterations and execution time(Xianzi)

Algorithm	Number of iterations	Execution time (ms)
CSO-otsu	5	0.0062
ICSO-otsu	8	0.0106
ICCSO-otsu	3	0.0046

Table 3, Table 4, and Table 5 clearly show that the average number of ICCSO-Otsu iterations and average execution time are lower than those of CSO-Otsu and ICSO-Otsu. As can be seen from Figure 2 to Figure 4, ICCSO-Otsu, CSO-Otsu, and ICSO-Otsu can all find the optimal image segmentation threshold. In summary, compared with CSO-Otsu and ICSO-Otsu, ICCSO-Otsu has better convergence rate and operation rate in image threshold segmentation.

V. CONCLUSION

The basic chicken swarm optimization algorithm has the advantages of high convergence accuracy and good robustness, but there are some problems such as slow convergence rate and easy to fall into local optimum. By using the maximum variance between classes in otsu algorithm on the improved constrained chicken swarm optimization algorithm as a fitness function, which is optimized to get the best threshold value

for image segmentation, The result shows that theotsu algorithmbased on the improved constrained chicken swarm optimization algorithm has has the better use of the computing rate and convergence rate than the improved chicken swarm optimization algorithm and the basic chickenswarm optimization algorithm.

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