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RESEARCH ARTICLE

Research on Threshold Segmentation Method of Two-Dimensional Otsu Image Based on Improved Sparrow Search Algorithm

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ABSTRACT Aiming at the issues of complex calculation and low accuracy of two-dimensional (2D) Otsu segmentation images, an image threshold segmentation means of 2D Otsu ground on a modified sparrow search algorithm is proposed. Firstly, in the initialization stage, the tent chaos mapping is added to enhance the multiformity of the population, and the population elite strategy is introduced to enhance the quality of the initial solution. Secondly, in the local search stage, the elite reverse learning strategy is applied to renewal the sparrow location to solve the issue of getting into local optimality. Eventually, the modified sparrow search algorithm is fused with 2D Otsu and the image threshold is segmented to enhance the accuracy of image segmentation. Compared with the traditional 2D Otsu algorithm, 2D Otsu genetic algorithm (GA-Otsu), 2D Otsu seagull optimization algorithm (SOA-Otsu), 2D Otsu particle swarm algorithm (PSO-Otsu) and 2D Otsu sparrow search algorithm (SSA-Otsu), the mean square error (MSE) value is reduced by 40.84%, 2.68%, 1.57%, 0.77% and 1.04%, respectively, and the peak signal-to-noise ratio (PSNR) value is increased by 24.48%, 1.24%, 0.83%, 0.40% and 0.45%, respectively. Moreover, the optimal threshold of the proposed algorithm is better than the other five algorithms. It is verified that the algorithm in this paper has faster convergence speed and higher accuracy, and effectively improves the quality of image segmentation.

INDEX TERMS Tent chaos mapping, elite reverse learning strategy, sparrow search algorithm (SSA), two-dimensional Otsu, seagull optimization algorithm.

I. INTRODUCTION

Computer vision technology has grown fast in recent years, the image segmentation is the basis of computer vision and has evolved into a crucial area of study in the realm of computer vision. It has broad applications in varieties of realms, for example, fingerprint recognition [1], satellite remote sensing image processing [2], communication field [3] and medical image diagnosis [4] and other fields. Image segmentation is the separation and extraction of valuable areas of an image for further utilization. The method of image segmentation can be divided into a threshold segmentation means, an area segmentation means, and an edge segmentation means [5], [6], [7], which is widely used due to the features of simple image calculation, high computational efficiency, easy implementation and fast speed of threshold segmentation method. Commonly used threshold segmentation algorithms include the Otsu method, maximum entropy algorithm, and iterative method. Among them, Otsu is the maximum between-class difference in the analyzed target area, and the threshold for image segmentation is selected by calculation [8], [9], which has the advantages of adapting to various scenes and stability, so it is widely used in image segmentation. However, traditional 2D Otsu has the disadvantages of complicated compute, sensitive to noise and background, and low segmentation accuracy. Therefore, with the increase of the complicated of image segmentation, it is difficult for traditional 2D Otsu to achieve ideal results in image segmentation.

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At the same time as the rise and development of artificial intelligence, evolutionary computing (EC) is widely used to solve threshold-based image segmentation problems, EC mainly includes evolutionary algorithms, swarm intelligence algorithms and other algorithms [10], [11], by optimizing different objective functions to find the optimal threshold [12], many image segmentation methods based on EC have been proposed. For example, genetic algorithm [13], particle swarm algorithm [14], seagull optimization algorithm [15], artificial fish group optimization algorithm [16], wolf pack optimization algorithm [17], whale optimization algorithm [18], improved firefly algorithm [19], etc., EC can effectively optimize the 2D Otsu algorithm and improve the segmentation effect of the image. However, the local search ability of the genetic algorithm is weak and the convergence speed is slow, and the particle swarm algorithm is easy to get into the partial optimum. The seagull optimization algorithm has poor global optimization ability and low convergence accuracy, artificial fish group algorithm fails to be applied to general images, wolf pack optimization algorithm has shortcomings such as unclear image edges after segmentation, and segmentation quality needs to be improved, etc., and the traditional firefly algorithm is easy to get into partial optimization, which affects the segmentation results.

Compared with the above algorithms, Sparrow Search Algorithm (SSA) [20] possesses strong local search capability, better accuracy, convergence rate and stability, and is used to solve various optimization issues [21]. However, SSA is prone to getting into local optimality. In order to further enhance the property of SSA, some scholars have proposed various solutions. For instance, Zhang and Ding [22] incorporated logical mapping, adaptive hyperparameter, and mutation operator into SSA. Advanced [23] optimizes SSA by introducing Tent chaos graph, random search capability, and greedy strategy. The modified SSA proposed by Wu and Yuan [24] combined Levy flight and nonlinear inertia weights, and an adaptive SSA with modified circular chaotic mapping, T-distribution variation and similarity was proposed by Liu and Wang [25].

In this article, a modified sparrows search algorithm combining Tent chaos mapping, elite strategy and elite reverse learning strategy (SSAN) is proposed, which enhances initiation and position update of SSA, enhances species group diversity and initial solution quality, accelerates convergence rate, and the problem of getting into local optima is solved. In the next place, it is proposed that the image threshold segmentation by SSAN optimized 2D Otsu algorithm, change the solution issue of the objective function of 2D Otsu into the optimal solution issue by using SSA, obtain the best threshold of segmentation images, and then segment images. The segmentation effect obtained by this method is more accurate.

The major contributions of this article are summarized as follows:

1) In the initialization stage of sparrow species group, Tent chaos mapping is added to raise the multiplicity of the species group, and at the meantime, combined with the species group elite strategy, the initial solution quality is improved.

2) In view of the issue that SSA is easy to get into the optimum, the elite reverse learning strategy is applied to renew the position of sparrows. When the sparrows are updated, the elite solution is selected and the dynamic boundary of the elite sparrows is gained at the meantime. The reverse learning strategy is applied to solve the reverse solution, and the sparrow before and after the update is compared. If it is better, the sparrow before and after the update is replaced, which not only raises the convergence speed, but also solves the issue of getting into the partial optimal.

3) Change the issue of solving the objective function of 2D Otsu into solving the optimal solution by making use of SSA, and optimize threshold segmentation of images by SSAN, which can obtain a more accurate optimal threshold and enhance the segmentation effect of images.

The configuration of our article is structured in the following manner, the second part introduces the 2D Otsu, the third part proposes the improvement measures for the SSA and give a description of the whole system, the fourth part provides the experimental consequence and analysis, and the fifth part concludes the article by summarizing the overall content.

II. THRESHOLD SEGMENTATION OF 2D OTSU IMAGE

The 2D Otsu [26], [27], [28] in order to resolve the issue of low anti-interference ability of one-dimensional Otsu image threshold segmentation means, the neighborhood average gray value is introduced, and gray value of that point and its neighborhood average gray value are combined into a binary group to found a 2D histogram.

For an image, hypothesise that $f(x, y)$ represents the image, includes $M \times N$ pixels, and the L represents gray level, Then the average gray level of each pixel neighborhood is also regarded as L. Therefore, a dualistic group (i, j) is formed by the gray value i of the pixel and the gray value j of the image neighborhood. If f_{ij} can be set to the frequency of (i, j), then the joint probability density P_{ij} corresponding to (i, j) can be expressed as

$$P_{ij} = \frac{f_{ij}}{M \times N} \tag{1}$$

Thereinto, $i = 0, 1, 2, \ldots, L-1; j = 0, 1, 2, \ldots, L-1$. The sum of the probability distribution densities is

$$\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P_{ij} = 1 \tag{2}$$

Assuming that s represents the grayscale threshold in the image, the mean grayscale threshold for neighborhoods is t, and the two-region segmentation threshold is (s, t). This is shown in Fig. 1, the image 2D histogram can be split into four areas: A, B, C, and D, among areas C and D represent the target and background, in several, and regions A and B are far from the diagonal, representing edges and noise, respectively.

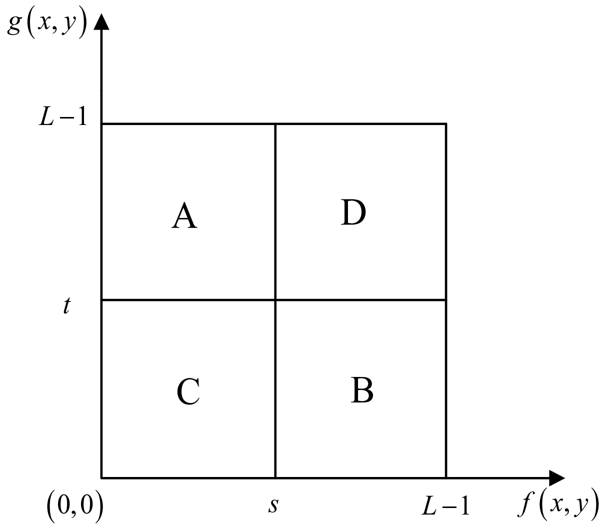


FIGURE 1. 2D Otsu histogram.

And thus it can be obtained that the interclass discrete measures S_b for target C and background D are

$$S_b = P_C\left(\mu_0 - \mu_T\right)^T\left(\mu_0 - \mu_T\right) + P_D\left(\mu_1 - \mu_T\right)^T\left(\mu_1 - \mu_T\right) \tag{3}$$

where P_C is the probability of occurrence in the target area, P_D is the probability of occurrence in the background area, s is the gray threshold, t is the mean gray value threshold of the neighborhood, and P_{ij} is the joint probability density. μ_0 is the mean vector of target C, μ_1 is the mean vector of background D, and μ_T is the total mean vector of the 2D histogram.

The trace of the dispersion matrix $tr\left(S_b\right)$ can be used to represent the range measurement function between objective C and background D:

$$tr\left(S_b\right) = P_C\left[\left(\mu_{0i} - \mu_{Ti}\right)^2 + \left(\mu_{0j} - \mu_{Tj}\right)^2\right] + P_D\left[\left(\mu_{1i} - \mu_{Ti}\right)^2 + \left(\mu_{1j} - \mu_{Tj}\right)^2\right] \tag{4}$$

When the trace $tr\left(S_b\right)$ of the between-class dispersion matrix is the maximal, the segmentation threshold obtained is the optimal threshold (s^*, t^*), and the distinction between target C and background D is the best, and the equation should be satisfied

$$tr\left(S_{((s^*,t^*))}\right) = \max\left(tr\left(S_{(s,t)}\right)\right) \tag{5}$$

III. THRESHOLD SEGMENTATION OF 2D OTSU IMAGE BASED ON IMPROVED SSA

A. SPARROW SEARCH ALGORITHM

SSA [20] is a population optimization method proposed by Jiankai Xue in 2020, which completes the acquisition of food by constantly updating the position of the discoverer, follower and vigilant in the process of foraging [29], [30], and the location of the optimal food is the optimal solution discovered.

If there are n sparrows in the population, amount vigilantes accounts for $10\% \sim 20\%$ of the species group, and amount discoverers and followers is dynamically changing.

The population of all individuals is

$$X = [x_1, x_2, \ldots, x_n] \tag{6}$$

The appropriate function of the individual corresponds is

$$F = [f(x_1), f(x_2), \ldots, f(x_n)] \tag{7}$$

1) FINDER LOCATION UPDATES

The location renewal formula of the discoverer is as follows:

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^t \cdot \exp\left(\dfrac{-i}{\alpha \times iter_{\max}}\right) & R_2 < ST \\ x_{ij}^t + Q \cdot L & R_2 \geq ST \end{cases} \tag{8}$$

Among them, t represents the number of current iterations, x_{ij}^t denotes the position of the i-th sparrow in the j dimension in the t generation, and $\alpha \in (0, 1)$, $iter_{\max}$ represents the maximum number of iterations, R_2 denotes the alarm value, the safety threshold is ST, Q denotes the random number that follows the normal distribution, L denotes the identity matrix of $1 \times \dim$, and dim is the dimension.

2) FOLLOWER LOCATION UPDATES

The location renewal of the follower is as follows:

$$x_{ij}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{x_{worst}^t - x_{ij}^t}{i^2}\right) & i \in (n/2, +\infty) \\ x_p^{t+1} + \left|x_{ij}^t - x_p^{t+1}\right| \cdot Z^+ \cdot L & i \in [0, n/2] \end{cases} \tag{9}$$

Among them, x_{worst}^t denotes the individual position with the worst adaptation of the t, x_p^{t+1} is the individual position with the best adaptation in $t+1$, Z is a matrix of $1 \times \dim$, and each element in the matrix is stochastically preset to -1 or 1, $Z^+ = Z^T\left(ZZ^T\right)^{-1}$. When $i > n/2$, it means that the i-th entrant has not got food and is in hungry extremely condition. The current fitness value is low and it needs to fly to somewhere else to feed for more energy.

3) VIGILANTE LOCATION UPDATES

The location renewal of the vigilantes is as follows:

$$x_{ij}^{t+1} = \begin{cases} x_{best}^t + \beta \cdot \left|x_{ij}^t - x_{best}^t\right| & f_i \neq f_g \\ x_{best}^t + k \cdot \left(\dfrac{x_{ij}^t - x_{best}^t}{|f_i - f_w| + \varepsilon}\right) & f_i = f_g \end{cases} \tag{10}$$

Among them, x_{best}^t is the location of the global optimal in generation t, the control step is β, $k \in [-1, 1]$, obeys the normal distribution of mean 0 and variance of 1, ε is constant, f_i is the fitness value of the current individual, f_g denotes the fitness value of the current global optimal individual, and f_w represents the fitness value of the current global worst individual.

B. IMPROVED THE SSA

For the sake of resolve the issue of SSA easily getting into local optimality, the classical SSA is proposed.

Tent chaos mapping [31], [32], [33] and population elite strategy were used to initialize sparrow population to raise the multiplicity and initial solution quality of the sparrow population.

Tent chaos mapping is defined as:

$$x_{m+1} = f(x_m) = \begin{cases} x_m/\beta & x_m \in [0, \beta) \\ (1 - x_m)/(1 - \beta) & x_m \in [\beta, 1] \end{cases} \tag{11}$$

Among them, the system is in a short-cycle state, when $\beta = 1/2$, therefore, the value is generally not taken. In order to avoid conversion to a cyclical system, the initial values x_m of the system and the system parameters β must be different.

The elite reverse learning [34], [35], [36], [37] approach is employed to replace the sparrow position. While selecting the elite sparrow according to the fitness of the updated sparrow, and the dynamic boundary of the elite sparrow is obtained, the reverse anti-sparrow population is obtained by having access to the reverse learning approach to solve the elite solution, and the new sparrow population is constructed from the sparrows before and after the update, and the better sparrows are selected as new generation individuals to solve the problem of being in part of the local optimality.

Hypothesis that the extreme points corresponding to ordinary individuals in the population are elite individuals, that is

$$Y^e_{m,n} = \left(Y^e_{m,1}, Y^e_{m,2}, \ldots, Y^e_{m,D}\right) \tag{12}$$

Its reverse solution is

$$\overline{Y^e_{m,n}} = \left(\overline{Y^e_{m,1}}, \overline{Y^e_{m,2}}, \ldots, \overline{Y^e_{m,D}}\right) \tag{13}$$

The elite reverse solution can be defined as

$$\overline{Y^e_{m,n}} = K(\alpha_n + \beta_n) - Y^e_{m,n} \tag{14}$$

where K denotes a stochastic figure on the interval (0, 1) and α_n, β_n represent the dynamic boundary, and $Y^e_{m,n} \in [\alpha_n, \beta_n]$. The dynamic boundary solves the shortcomings of the difficulty of preservation of the fixed boundary search experience, so that the elite reverse solution can be searched in a narrow space to avoid being in the best part.

C. IMAGE SEGMENTATION STEPS TO IMPROVE THE ALGORITHM

The steps of 2D Otsu image threshold segmentation to refine the SSA are as follows:

Step 1: Enter the desired image to be segmented.

Step 2: Initialize the parameters of the SSA: the number of sparrow species group Search Agents-no, the amount of finders PD, the amount of vigilantes SD, the maximum amount of iterations Max-iteration, and the alarm value ST, lower boundary lb, upper boundary ub.

Step 3: Tent chaos mapping is added according to equation (11) and elite strategies are introduced to initialize the species group.

Step 4: Calculate objective function value to the image to be segmented, obtain sparrow population individual fitness values, and sort fitness values obtained.

Step 5: Update positions of predators, followers and vigilantes based on equations (8), (9) and (10) respectively, find and update the fitness values of each sparrow, and rank the updated sparrows.

Step 6: Obtain elite sparrows and dynamic boundaries, update population positions, and update optimal population with elite reverse learning strategy.

Step 7: Check whether the number of iterations that the current algorithm runs is the maximum number of iterations is the maximum number of iterations, and if so, obtain the optimal threshold (s^*, t^*) of 2D Otsu; otherwise, go to step 3.

Step 8: Export the segmented image.

The flowchart is shown in Fig. 2.

IV. SIMULATION RESULTS AND ANALYSIS

In order to verify the improvement of the accuracy and convergence speed of image segmentation, this article uses three types of human images, scene images and animal images, and performs multiple threshold segmentation experiments on four different images. A set of random experimental results were selected to compare and analyze the threshold segmentation of traditional 2D Otsu algorithm (2D-Otsu), the 2D Otsu threshold segmentation ground on genetic algorithm (GA-Otsu), the 2D Otsu threshold segmentation ground on seagull optimization algorithm (SOA-Otsu), the 2D Otsu threshold segmentation ground on particle swarm algorithm (PSO-Otsu), the 2D Otsu threshold segmentation of standard SSA algorithm (SSA-Otsu), and algorithm in this article (SSAN-Otsu). MATLAB R2019a was selected to write the program and completed the simulation experiment on the 11th Gen Intel (R) Core (TM) i7-11800H @ 2.30GHz, 16GB, Windows 10 64-bit operating system.

A. SIMULATION RESULTS

The maximum number of iterations of all algorithms in this article is set to 50, the species group size of the SSAN is set to 30, and the safety threshold is set to 0.6, the proportion of discoverers is set to 0.7, the proportion of joiners is set to 0.3, and the proportion of alerts is set to 0.2 after reading [25], [38], [39], [40]. Details of the other algorithm parameters compared in this article are listed in Table 1. The segmentation effect obtained is shown in Fig. 3 to Fig. 9.

B. COMPARISON OF SEGMENTATION EFFECTS

It can be seen from the comparative observation of Fig. 3 to Fig. 9 that the algorithm in this article can efficaciously distinguish the person in the character image from the background, detail in animal image and the bullet holes on the wall in the scene image are clearly displayed, the segmented image is clearer and more complete, the target and background

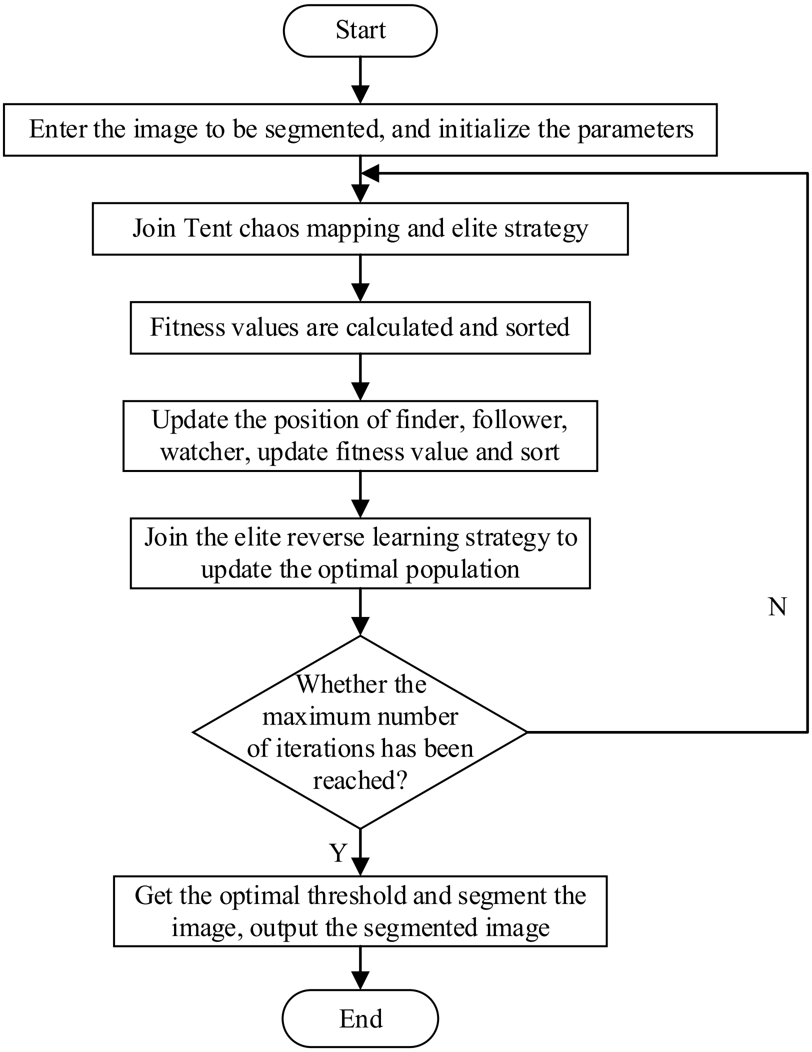
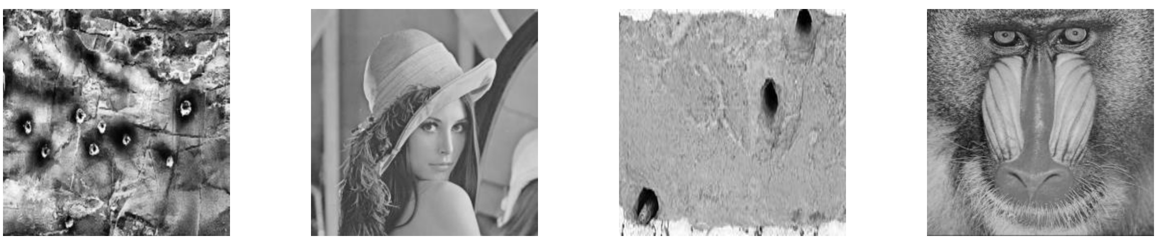


FIGURE 2. Flow chart of the segmentation algorithm in this paper.



(a) Bullet hole wall (b) Lena (c) Bullet hole wall partial (d) Baboon

FIGURE 3. Original image.

segmentation are more accurate, and the inaccuracy segmentation area of the image is effectively reduced. For example, the outline of the figure in Lena is clearer, the noise around the bullet holes is significantly reduced in the bullet hole wall image and the partial bullet hole wall image, and the facial organs in the Baboon image are more accurately segmented. Therefore, the SSAN-Otsu is obviously better than the traditional 2D Otsu algorithm, GA-Otsu SOA-Otsu, PSO-Otsu and SSA-Otsu in respects of details and accuracy.

C. CONVERGENCE SPEED COMPARISON

Since the traditional 2D Otsu uses the exhaustive method to search for thresholds, Table 2 and Fig. 10 only compare the five algorithms of GA-Otsu, SOA-Otsu, PSO-Otsu, SSA-Otsu and SSAN-Otsu. It can be seen from Table 2 and Fig. 10

TABLE 1. Initial parameters of the algorithm.

Algorithm	Main parameter	Value
GA	Population size N	30
	Crossover probability P_C	0.7
	Mutation probability P_M	0.05
SOA	Number of seagulls N	30
	frequency variable f_C	4
	correlation constants of spiral shape μ	2
	correlation constants of spiral shape v	2
PSO	Number of particles N	30
	Maximum velocity $V_{\max}$	3
	Individual learning factors C_1	2
	Social learning factors C_2	2
	Minimum inertia weight $\omega_{\min}$	0.6
	Maximum inertia weight $\omega_{\max}$	0.5
SSA	Number of sparrows N	30
	Security thresholds ST	0.6
	Proportion of vigilants SD	0.2
	Proportion of finders PD	0.7
SSAN	Number of sparrows N	30
	Security thresholds ST	0.6
	Proportion of vigilants SD	0.7
	Proportion of finders PD	0.2

(a) Bullet hole wall **(b)** Lena **(c)** Bullet hole wall partial **(d)** Baboon

FIGURE 4. Threshold segmentation image segmentation results of traditional two-dimensional Otsu algorithm.

(a) Bullet hole wall **(b)** Lena **(c)** Bullet hole wall partial **(d)** Baboon

FIGURE 5. Threshold segmentation image segmentation results of two-dimensional Otsu genetic algorithm.

(a) Bullet hole wall (b) Lena (c) Bullet hole wall partial (d) Baboon

FIGURE 6. Threshold segmentation image segmentation results of two-dimensional Otsu seagull optimization algorithm.

(a) Bullet hole wall (b) Lena (c) Bullet hole wall partial (d) Baboon

FIGURE 7. Threshold segmentation image segmentation results of two-dimensional Otsu particle swarm algorithm.

(a) Bullet hole wall (b) Lena (c) Bullet hole wall partial (d) Baboon

FIGURE 8. Threshold segmentation image segmentation results of two-dimensional Otsu sparrow search algorithm.

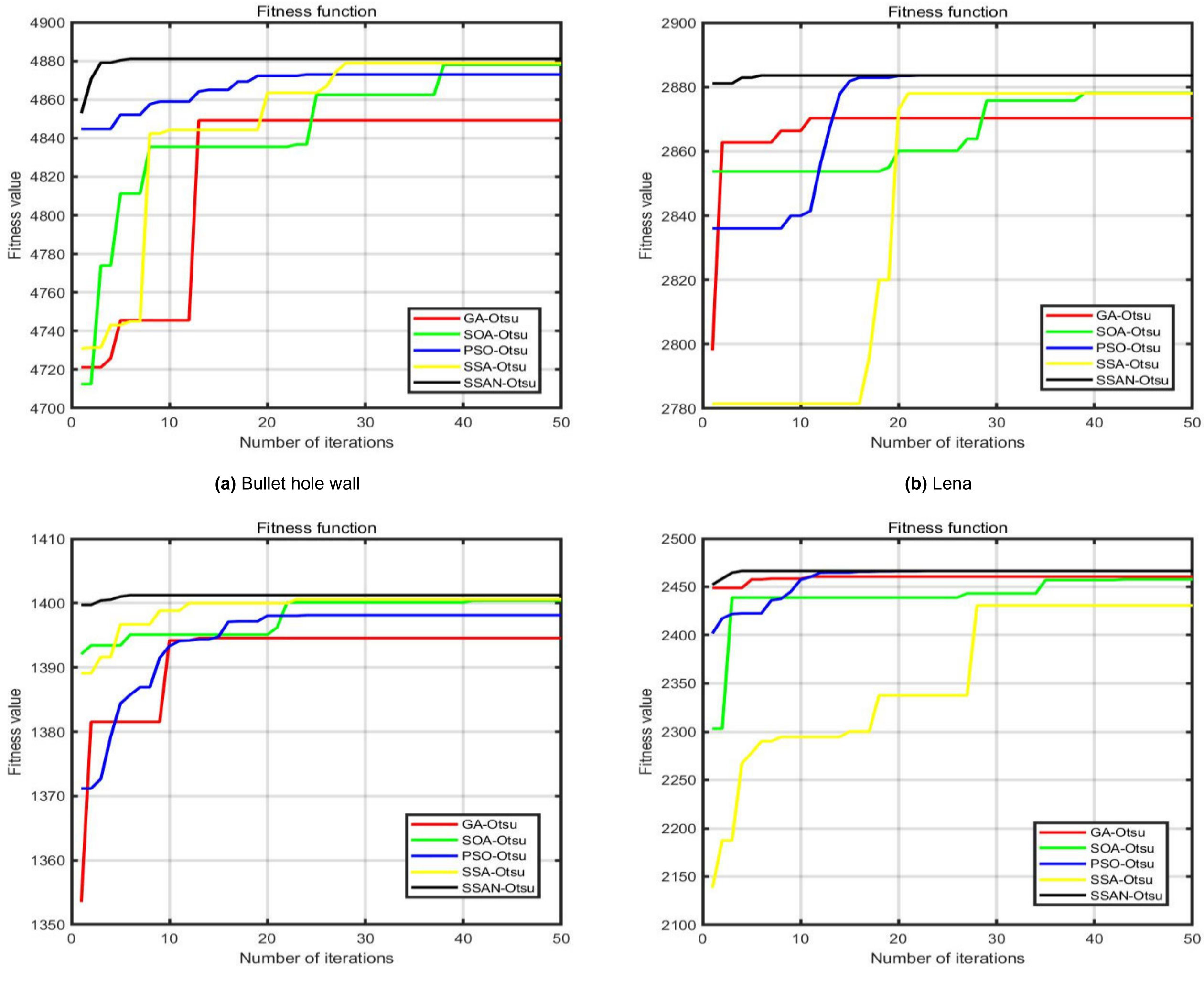
(a) Bullet hole wall (b) Lena (c) Bullet hole wall partial (d) Baboon

FIGURE 9. The image segmentation results of this article algorithm.

that for the four images, the SSAN-Otsu can quickly achieve the highest fitness value, while the number of iterations when the other four algorithms converge is significantly higher, and the convergence tends to be stable, and it takes multiple iterations to jump out of the partial optimal. It can be seen that the SSAN-Otsu modifies the standard SSA algorithm, adds Tent chaos mapping and population elite strategy in the initialization stage, which improves the species group diversity and the initial solution quality of the species group, and enhances the global search ability. By adding the elite reverse learning strategy, the algorithm is easy to jump out of the partial optimal value, so that the convergence can quickly achieve stability, raise the convergence efficiency, and effectively solve the issue that it is easy to get into the partial optimum.

D. SEGMENTATION ACCURACY COMPARISON

In order to quantitatively evaluate each optimization algorithm, this paper takes the optimal threshold, mean square error (MSE), peak signal-to-noise ratio (PSNR) and



(a) Bullet hole wall

(b) Lena

(c) Bullet hole wall partial

(d) Baboon

FIGURE 10. Image segmentation fitness value comparison graph.

TABLE 2. Comparison of iterations during convergence of the three algorithms.

Algorithm	Bullet hole wall	Lena diagram	Bullet hole wall partial	Baboon diagram
GA-Otsu	13	11	13	11
SOA-Otsu	38	39	41	43
PSO-Otsu	24	22	24	23
SSA-Otsu	28	21	23	28
SSAN-Otsu	6	6	6	4

interclass variance value of the four images obtained by the six algorithms through the experiment as the objective evaluation basis. The performance of traditional 2D Otsu algorithm, GA-Otsu, SOA-Otsu, PSO-Otsu, SSA-Otsu and this algorithm in image segmentation is discussed. It can be seen from Table 3 that for each image, the optimal threshold

TABLE 3. Performance comparison of six algorithms.

Evaluation indicators	Algorithm	Bullet hole wall	Lena diagram	Bullet hole wall partial	Baboon diagram
Optimal threshold	2-D Otsu	(94.157)	(106,156)	(105,205)	(101,148)
	GA-Otsu	(99.99,156.55)	(102.09,153.02)	(118.00,207.30)	(101.59,144.91)
	SOA-Otsu	(93.65,157.99)	(106.09,154.50)	(111.64,207.51)	(97.56,153.68)
	PSO-Otsu	(91.43,156.35)	(107.79,157.06)	(100.74,198.98)	(106.16,153.96)
	SSA-Otsu	(96.20,156.40)	(106.44,154.68)	(112.99,205.20)	(101.00,147.93)
	SSAN-Otsu	(95.78,158.66)	(107.92,157.38)	(111.80,205.62)	(106.47,153.18)
MSE	2-D Otsu	8439.9065	9477.4492	25675.5099	9979.1020
	GA-Otsu	7254.4553	8840.2907	7160.0370	9313.1629
	SOA-Otsu	7253.9446	8777.6125	7007.8224	9162.8935
	PSO-Otsu	7436.7973	8761.8936	6996.9259	8746.4813
	SSA-Otsu	7203.6141	8777.6125	7004.8605	9043.9871
	SSAN-Otsu	7199.3672	8761.8936	6988.0300	8746.4813
PSNR	2-D Otsu	8.9140	8.3639	4.0356	8.1399
	GA-Otsu	9.5248	8.6661	9.5817	8.4398
	SOA-Otsu	9.5251	8.6970	9.6750	8.4626
	PSO-Otsu	9.4169	8.7048	9.6817	8.7125
	SSA-Otsu	9.5553	8.6970	9.6768	8.5672
	SSAN-Otsu	9.5579	8.7048	9.6873	8.7125
Inter-class variance value	2-D Otsu	4889.2741	2885.4101	1409.5652	2483.8719
	GA-Otsu	4849.1548	2870.3163	1394.5625	2460.5513
	SOA-Otsu	4878.0179	2878.1559	1400.3971	2457.7651
	PSO-Otsu	4872.9700	2883.6021	1398.1220	2466.4607
	SSA-Otsu	4878.8543	2878.0579	1400.5848	2430.8562
	SSAN-Otsu	4881.1020	2883.6021	1401.2331	2466.4607

of the algorithm in this article can reach the highest, and it has better performance than the other five algorithms in respects of MSE value and PSNR value, low image distortion, strong noise immunity, and can retain more original image information. The between-class variance values of the four images segmented by the algorithm in this article are close to the traditional 2D Otsu method, and they are all better than the four algorithms of GA-Otsu, SOA-Otsu, PSO-Otsu and SSA-Otsu, but it can be observed from Fig. 4 and Fig. 9 that the segmentation effect of the proposed algorithm is more obvious, reflecting the shortcomings of the low accuracy of traditional 2D Otsu segmentation images. It is explained that by modifying the algorithm, the algorithm in this article is easier to jump out of the partial optimality, obtain a better inter-class variance value, stronger optimization ability, higher segmentation quality, and more obvious segmentation effect, which can enhance the accuracy of image segmentation.

The aforementioned experiments showcase that the proposed algorithm of this article has a better segmentation effect and accuracy in images of different categories and backgrounds. And iteration speed is better. Therefore, the algorithm of this article is better in respects of segmentation effect, accuracy and iterative speed.

V. CONCLUSION

In view of the issues of complex computation and low accuracy of 2D Otsu image threshold segmentation algorithm, this article proposes a method to optimize 2D Otsu image threshold segmentation ground on the SSAN. Tent chaotic mapping and population elite strategy were introduced to initialize the sparrow species group, which raised the multiformity of the species group and the quality of the initial solution. By updating the sparrow position with the elite reverse learning strategy, the algorithm can easily jump out of the partial optimal. The SSAN is applied to partition the image threshold, which improved the accuracy of segmentation and image quality. By comparing the traditional 2D Otsu algorithm, GA-Otsu, SOA-Otsu, PSO-Otsu, SSA-Otsu and SSAN-Otsu in three respects of segmentation effect, convergence speed and segmentation accuracy of images of different scenes. As can be seen from the consequences of the experiment, SSAN-Otsu has a better segmentation effect, which effectively improves the accuracy of segmentation images and solves the issue of low segmentation accuracy of traditional 2D Otsu algorithm.

The algorithm of this article has the advantage of better image segmentation and has a broad application prospect, but it still has some shortcomings in terms of running time. In future studies, more optimization algorithms will be adopted to further enhance the accuracy of image segmentation and decrease the segmentation time.

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