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An Improved Whale Optimization Algorithm for Optimal Multi-threshold Image Segmentation

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Abstract. *The whale optimization algorithm (WOA) is a recently developed swarm intelligence algorithm with popular engineering applications as its advantages of a few parameters and understandable optimization concepts. WOA still has drawbacks, e.g., low convergence accuracy and lack of local optimal escape ability. This paper introduces an improving whale optimization algorithm (IWOA) by updating the individual whale positions method by adding an energy control factor and using the oscillatory mutation strategy to increase the probability of the algorithm jumping out of the local optimum. In the experiment section, the IWOA is applied to experiments on multi-threshold image segmentation. Compared results of findings demonstrate that the IWOA algorithm can pick high-quality thresholds and enhance the efficiency of image segmentation.*
Keywords: Image segmentation; Whale optimization algorithm; Energy control factor; Cauchy variation; Multi-threshold.

1. Introduction.

One of the critical components of image processing is picture segmentation, and studies like object identification and edge extraction need the use of high-quality image segmentation technologies [1]. Threshold factors separate the object and background domains in threshold-based image segmentation [2]. Maximum inter-class variance approaches, e.g., the Ostu, Renyi entropy, minimal cross-entropy [3], etc., are a few of the frequently used picture segmentation techniques [4]. However, image technology research has recently witnessed various swarm intelligence algorithms based on biological activities [5]. Researchers have presented mathematical rules to tackle optimization challenges in theoretical research and real-world engineering difficulties [6].
Compared with traditional algorithms, swarm intelligence algorithms are widely used in many fields [7]. The advantages of solid optimization ability and high optimization efficiency [8]. The literature proposes a threshold image segmentation based on the Harris Eagle algorithm (HEA) [9], which uses the strategy of mutual benefit and lens imaging

to improve its accuracy. The literature proposes a method based on the improved multi-threshold image segmentation technology of the leapfrog algorithm, and the experiment proves that the practice has higher optimization efficiency. The literature proposes a firefly algorithm (FA)[10] based on the mixed cell membrane strategy and applies it to the multi-threshold Otsu segmentation, and the experiment proves the improvement. The grey wolf optimization algorithm (GWO) [11] was developed for multi-threshold [12]. The particle swarm optimization algorithm (PSO) applied multi-threshold of medical images [13]. The artificial bee colony (ABC) algorithm is to compute the image multi-thresholds [14].

The whale optimization algorithm (WOA) [15] is a recently developed swarm intelligence algorithm with a simple three-layer structure and a small number of control factors that has the advantages of powerful optimization ability a good performance in actual combat tasks [16, 17]. However, it still has effectively reduced the probability of the model falling into the local optimum whenever facing dealing with complex problems [18].

This work suggests an improved whale optimization algorithm-based multi-threshold picture segmentation technique (IWOA). Multi-threshold based on the Otsu segmentation method with the ideal searching threshold combination is implemented by applying IWOAalgorithm. The suggested approach is evaluated its segmentation effect through the RPSN index. The IWOA is introduced by adding an energy control factor into individual whale positions to improve the update method of respective whale positions, avoid the trap optimal local solution and improve the convergence accuracy of the algorithm.

2. Whale optimization algorithm.

The whale optimization algorithm (WOA) includes three search methods, such as wrapping, shrinking, and non-direction, to make the population search for the optimal solution of the target, and each search strategy represents a stage [11]. The transition of each stage is affected by the control factors symbolized as A and P: surround phase, contraction stage, and undirected search phase [16].

Surround Phase: the whale population starts to execute the surround strategy whenever, $|A| < 1$ and $P < 0.5$, selects the whale with the best fitness as the hunting object, and the remaining whales refer to the optimal individual position, gradually approach it and complete the surround of the prey,

$$X(t+1) = X^*(t) - A.D, \tag{1}$$

In the formula: X_t^* and X_t are the prey position and the whale position to be updated in the current cycle, respectively; t is the current number of cycles; A and C are the control factors for position movement; D is the current cycle Its position update method is shown in formula (1) and formula (2):

$$D = |CX^*(t) - X(t)|, \tag{2}$$

The distance vector between the next best solution and the whale individual.

$$\begin{cases} A = 2ar_1 - a \\ C = 2r_2 \end{cases} \tag{3}$$

where r_1 and r_2 are random numbers, and the value range is (0,1); a is the adjustment factor.

$$a = 2(1 - \frac{t}{T}), \tag{4}$$

where T is the maximum number of cycles.

Contraction stage: when $P > 0.5$, the whale population approaches the prey as planned and completes the hunt, and all individuals complete their position update in a spiral shrinking fashion:

$$X(t+1) = X^*(t) + D_p e^{bl} \cos(2\pi l), \tag{5}$$

In the formula: D_p is the straight-line distance between the whale and the prey; b is the parameter that determines the range of the shrinking route; l is a random number, the value range is $[-1, 1]$.

Undirected Search Phase: when $|A| > 1$ and $P < 0.5$, each individual in the whale population has the autonomy of the search direction, and the individual whale will randomly select other individuals in the population and move with reference to its spatial position. In order to increase the search efficiency of the population The randomness improves the convergence accuracy of the whole population. The search method at this stage is shown in formula (6) and formula (7):

$$D_n = |C \times X^*(t) - X(t)|, \tag{6}$$

$$X_n(t+1) = X_n(t) - A.D_n, \tag{7}$$

In the formula: D_n is the moving distance of the nth individual; n is a random number within the set range; $X_n(t+1)$ and $X_n(t)$ are the positions of the individual before and after the iteration, respectively.

3. **Improve whale optimization algorithm.**

3.1. **Energy control factor.**

The swarm intelligence algorithm is an optimization algorithm inspired by biological behavior. The action speed of a creature during the hunting process is often affected by its own physical performance. In order to be more in line with the principle of bionics and improve the convergence of the optimization algorithm, a whale was simulated in this study. The energy change during hunting is shown in Eq. (8):

$$E = \alpha(1 + \frac{t}{T})^{\beta}, \tag{8}$$

In the formula: α and β are energy adjustment parameters, and their values are both 1 in this study. In the early stage of optimization, the whale's energy value is relatively large, and the whale has sufficient physical strength to surround the prey, shrink hunting and other behaviors, and its position update scale is also relatively large, which is conducive to the extensive global exploration of the whale group. With the iteration round t increases, the whale's energy value decreases, and its activity decreases. At this time, the whale group will conduct a detailed local search around the prey to increase the optimization accuracy. For complex multi-peak fitness functions, the parameter β should be appropriately reduced to make the group in the whole A sufficient search is carried out in the target space to improve the probability of finding the global optimum; on the contrary, for simple functions, the parameter β should be appropriately increased to strengthen the local development capability of the population, thereby improving its convergence speed. The update method of the stage position is shown in formula (9) - formula (11):

$$X(t+1) = X^*(t)E - A.D, \tag{9}$$

$$X(t+1) = X^*(t)E + D_p e^{bl} \cos(2\pi l), \tag{10}$$

$$X(t+1) = X_n(t)E - A.D_n, \tag{11}$$

3.2. **Oscillating Cauchy mutation strategy.**

Although WOA has a non-directional search strategy, its function fitness surface structure is complex, so it is difficult to play a practical role [11]. Whales will move in the direction of the current optimal individual from the beginning of the iteration, so it is easy to fall into local optimality, resulting in reduced accuracy. In response to this problem, this study introduces an individual position disturbance mechanism, and implements the Cauchy mutation strategy on the elite population to improve the probability of WOA jumping out of the local optimum. The standard Cauchy distribution function is shown in formula (12):

$$f(x) = \frac{1}{\pi(x^2+1)}, x \in (-\infty, +\infty), \tag{12}$$

where x is the independent variable in the Cauchy function expression. In the standard Cauchy mutation [19], the variable asynchronous length has nothing to do with the number of iterations, and the adaptability of the search step size and the optimization process is difficult to determine. To solve this problem, an oscillation factor is introduced into the original Cauchy mutation formula to make the variable asynchronous length approximately alternately change In the early stage of the algorithm, a larger oscillation factor is generated to expand the search range of the population and ensure the diversity of the population; in the later stage of the algorithm, a smaller oscillation factor is generated to enhance the attractiveness of the optimal solution to the population, and to improve the convergence speed and local development ability of the algorithm. The random number generated by the Cauchy distribution function perturbs a specific individual, and the individual position adjustment strategy is shown in formula (12):

$$x_t^* = x_t(1 + v \cdot cauchy(0,1)), \tag{13}$$

$$v = \begin{cases} \dfrac{(r_1^2+1)r_2}{2}, t \leq \dfrac{T}{2} \\ \dfrac{r_1 r_2}{2}, t > \dfrac{T}{2} \end{cases} \tag{14}$$

where x_t^* is the number of mutant individuals in t iterations; x_t is the number of mutant individuals in N iterations; cauchy (0,1) is the Cauchy mutation operator; v is the oscillation factor. The Cauchy function has a smaller value in the middle and larger values on both sides compared to the typical Gaussian process, which increases the likelihood of generating a more significant random number and lengthens the fluctuation period of each individual disturbance. The range is more expansive as the elite population in this study is set to be 10% of the entire population. The oscillatory Cauchy mutation approach to complete, the individuals with the highest fitness both before and after the mutation are kept in each iteration. As the mentioned whale optimization algorithm has some advantages, e.g., a solid ability to explore and converge, still, the method is insufficient for convergence whenever dealing with a complex problem because its the mechanism for updating population position, the use of elite individual information, and the mutation are suitable setting with the specified issue. To increase the convergence accuracy and stability of the WOA, an energy control factor is first added to simulate the energy change of the whale hunting process [20].

The oscillatory Cauchy mutation and greedy retention strategies are then implemented for the elite population to increase the likelihood of the algorithm deviating from the local optimum. The computational effectiveness of the algorithm is reflected in the temporal complexity, which can be used to assess the algorithm's performance. The WOA's temporal complexity is influenced by variables like the number of individuals, the length of the sequence, and the maximum number of cycles. The IWOA is the energy control element to enhance individual position movement. The algorithm maintains the original complexity and does not increase the calculation time of the single fitness function. Assuming that the proportion of individuals that need to oscillate Cauchy mutation Eq(13) is h, then the whale mutation complexity.

4. **Experimental result and Discussion.**

4.1. **Otsu segmentation with the IWOA for Multi-threshold.**

Otsu is an unsupervised threshold segmentation algorithm that uses inter-class variance as the standard. For a given gray threshold $[0, L-1]$ and the number of categories $(1, 2, 3, ..., k)$, the gray value The probability Pi of i is the proportion of this value in the total number of pixels, M is various thresholds, and the relationship between the probability P of each category and the gray mean value μ is shown in formula (15) and formula (16):

$$P_k = \sum_{i=M_k}^{M_{k+1}-1} P_i, \tag{15}$$

$$\mu_k = \frac{1}{p_k} \sum_{i=M_k}^{M_{k+1}-1} iP_i, \tag{16}$$

The calculation of the between-class variance Σ is shown in equation (17):

$$\delta_k^2 = \sum_{i=M_k}^{M_{k+1}-1} (i-\mu_k)^2 \frac{P_i}{P_k}, \tag{17}$$

Figure 1 shows the flow chart of the application IOWA for optimizing multi-threshold image segmentation.

The procedures for order-image threshold optimization by using the IWOA algorithm is presented as follows.

(1) Initialization the algorithm's population individual size is randomly distributed in the search range, and the new solution is searched to identify the whale positions;

(2) The degree of high-quality picture segmentation is calculated using the high-quality image segmentation method.

(3) Using the revised search formula, the whale positions that come after them for new sources of prey and determine the fitness of the high-quality level of individuals. The C high value replaces the low value of C as the whale position for the next iteration of whale positions.

(4) After a given number of iterations, the answer to the question of updating Eqs. (9), (10), and (11) are repeated. A new location must be mutated to replace the associated with Eq(13) if a position is present.

(5) Check termination; if condition iterMax is not, repeat steps (2); otherwise, continue step (6).

(6) Output the best solution: the best threshold for image threshold segmentation is the threshold that then corresponds to the global best solution.

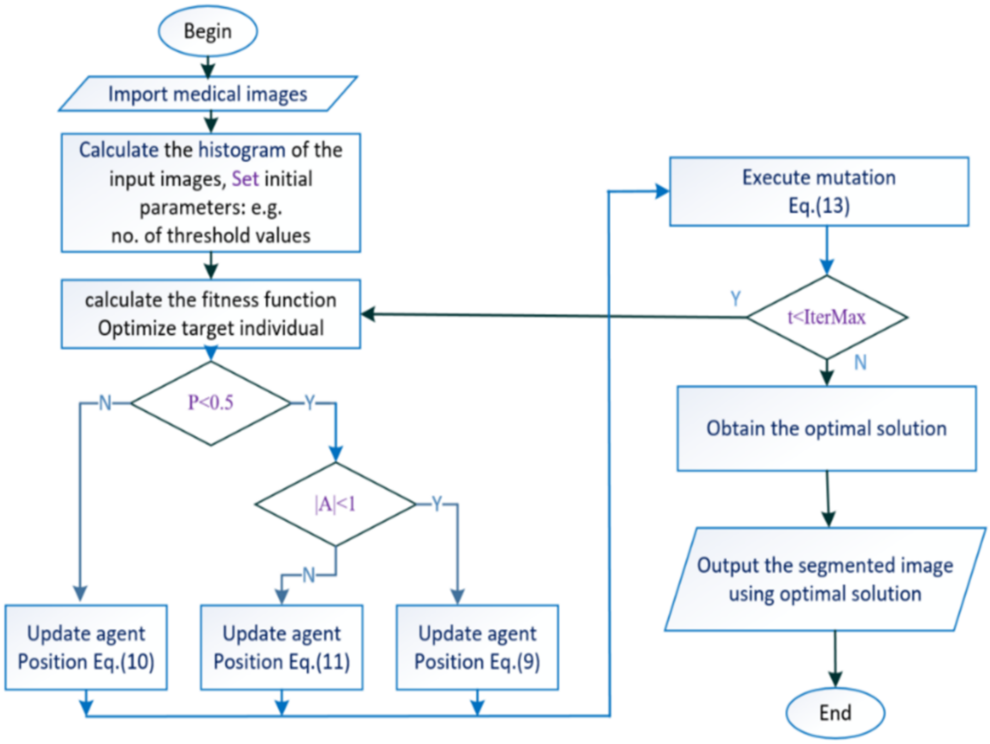

Figure 1. A flowchart of the application IOWA for optimizing multi-threshold image segmentation.

4.2. Experiment effect evaluation for Multi-threshold.

Each whale in the population represents a feasible solution. The fitness value of each feasible solution can be obtained through the fitness function, and the feasible solution with the optimal fitness value is reserved to solve the optimization problem. In order to evaluate the image segmentation quality, the peak signal to noise ratio (R_{PSN}) is selected as the evaluation index. (R_{PSN}) can measure the degree of image distortion. The larger the value, the higher the image quality after segmentation. The calculation formula is shown in Equation (18, 19):

$$R_{PSN} = 20lg\frac{255^2}{S_{ME}}, \tag{18}$$

$$S_{ME} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(f(i,j) - g(i,j))^2}{mp}, \tag{19}$$

where: S_{ME} is the original image; mean square error with the new image g; m and p are the number of rows and columns of the image; *f(i,j)* and *g(i,j)* are the grayscales before and after image segmentation, respectively.

The selected images are used to evaluate the IWOA algorithm for multi-threshold image segmentation. Figure 2 lists the chosen images with serial numbers to verify the effectiveness of IWOA in multi-threshold image segmentation. The obtained results of the IWOA algorithm are compared with the other algorithms, e.g., the PSO [13], ABC [16], and WOA [20] algorithms for the multi-threshold image segmentation effects.

The thresholds are set to 2, 3, 4, and 5 respectively. The parameters are setting the population number is set to 10, the maximum number of iterations is set to 500, and the experimental results. Among them, the threshold column is the best segmentation

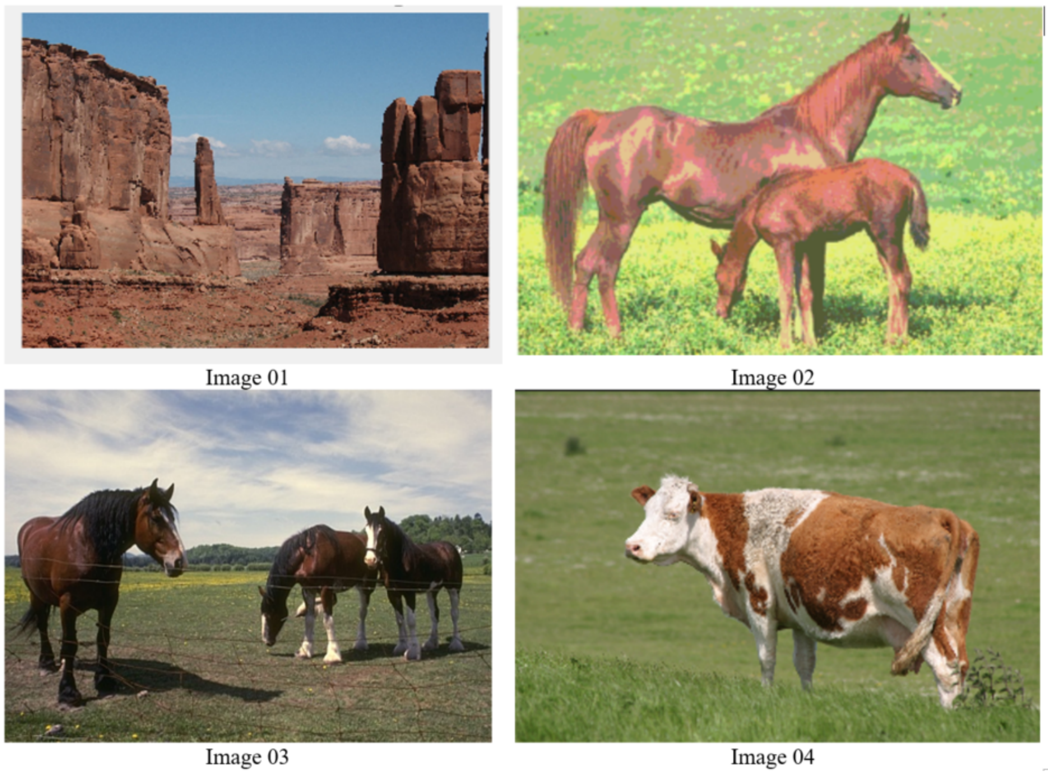

FIGURE 2. The chosen images with serial numbers.

threshold combination belonging to the IWOA scheme optimization. When the number of thresholds is small, the improvement strategy is that the impact on the algorithm is evident. Among them, the IWOA has apparent advantages in the image segmentation of the selected images, which verifies the effectiveness of the improved strategy.

Figure 3 shows the experimental threshold of the image segmentation results of the IWOA approach is contrasted with the PSO and WOA schemes. Among them, the IWOA has apparent advantages in optimization accuracy in the images with more detailed features.

For each image, the procedures must be performed 25 times, and the objective function derived from the objective function is determined for the peak signal-to-noise ratio selected as the evaluation index, the standard deviation, and the average values of the mean square error. It can be seen from Table 1 that for the test images, the IWOA can achieve a large PSNR value.

Figure 4 shows the performed image segmentation of the IWOA in experiments on selected image 01. It is the performed image segmentation of the IWOA in experiments on selected image 01. The experimental parameters are set as above, and the scheme's experimental results are visually shown.

Table 2 shows the comparing the obtained optimal experimental threshold results of the IWOA approach with the schemes PSO, ABC, and WOA algorithm for image segmentation's multi-thresholds. Among them, the IWOA has apparent advantages in optimization accuracy in images 01 and 02 with more detailed features. As can be seen from Table 2, the number of thresholds of the segmentation visualization effect of each algorithm has little difference. However, it can still be observed that IWOA has more advantages in detail in capturing the optimal thresholds. The above experiments show that IWOA can find higher-quality threshold combinations, which verifies the better performance of the IWOA ability.

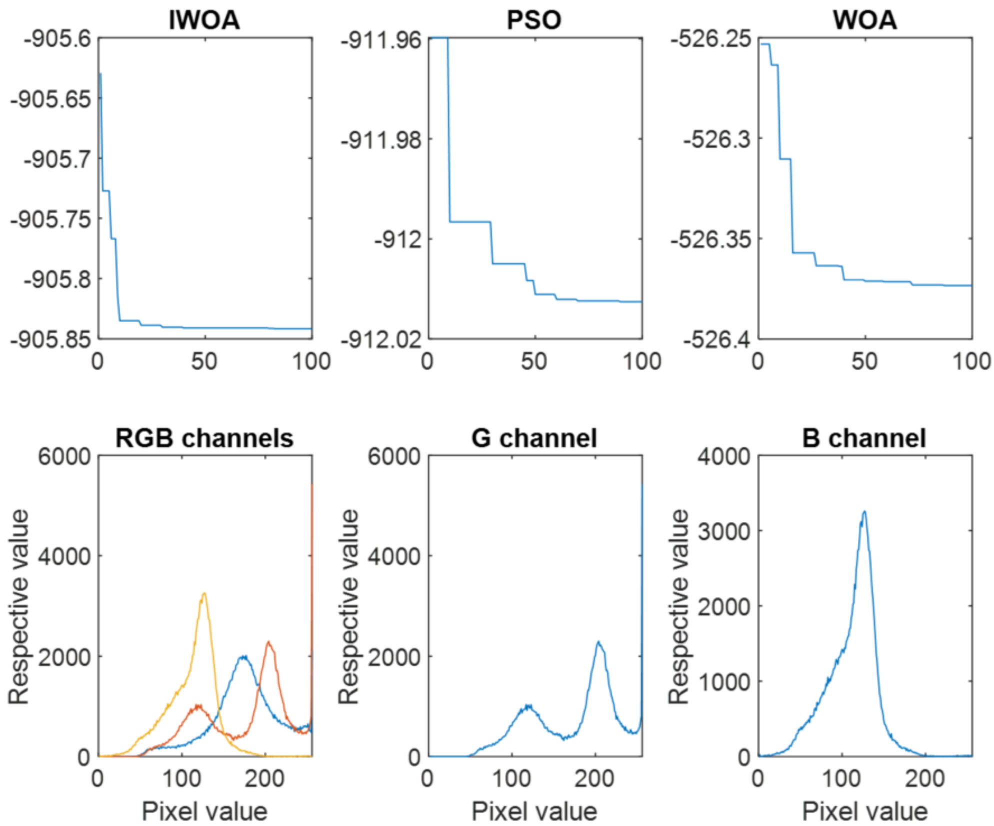

FIGURE 3. The experimental threshold visually of the image segmentation results of the IWOA approach contrasted with the PSO and WOA schemes.

TABLE 1. The obtained experimental threshold results of the IWOA approach for image segmentation.

No. Images	k	No. Thresholds	R_{PSN}/dB	ϵ_{std}.	S_{ME}
Image-01	2	9/89	1.44E+01	0.72	1.58E+01
	3	14/45/125	2.10E+01	1.13	2.23E+01
	4	23/52/104/145	1.99E+01	1.47	2.77E+01
	5	39/76/120/145/189	2.26E+01	1.67	3.26E+01
Image-02	2	24/123	1.36E+01	1.11	1.58E+01
	3	64/120/165	1.70E+01	0.46	2.36E+01
	4	43/75/120/172	2.01E+01	1.25	2.79E+01
	5	45/89/123/156/187	2.14E+01	1.54	3.26E+01
Image-03	2	67/142	1.56E+01	0.73	1.80E+01
	3	35/101/151	2.10E+01	0.46	2.47E+01
	4	41/76/102/165	2.11E+01	0.84	2.90E+01
	5	23/56/87/121/186	2.25E+01	0.96	3.22E+01
Image-04	2	8/89	1.44E+01	0.72	1.58E+01
	3	24/45/125	2.10E+01	1.13	2.23E+01
	4	23/52/104/145	1.99E+01	1.47	2.77E+01
	5	39/76/120/145/189	2.26E+01	1.67	3.29E+01

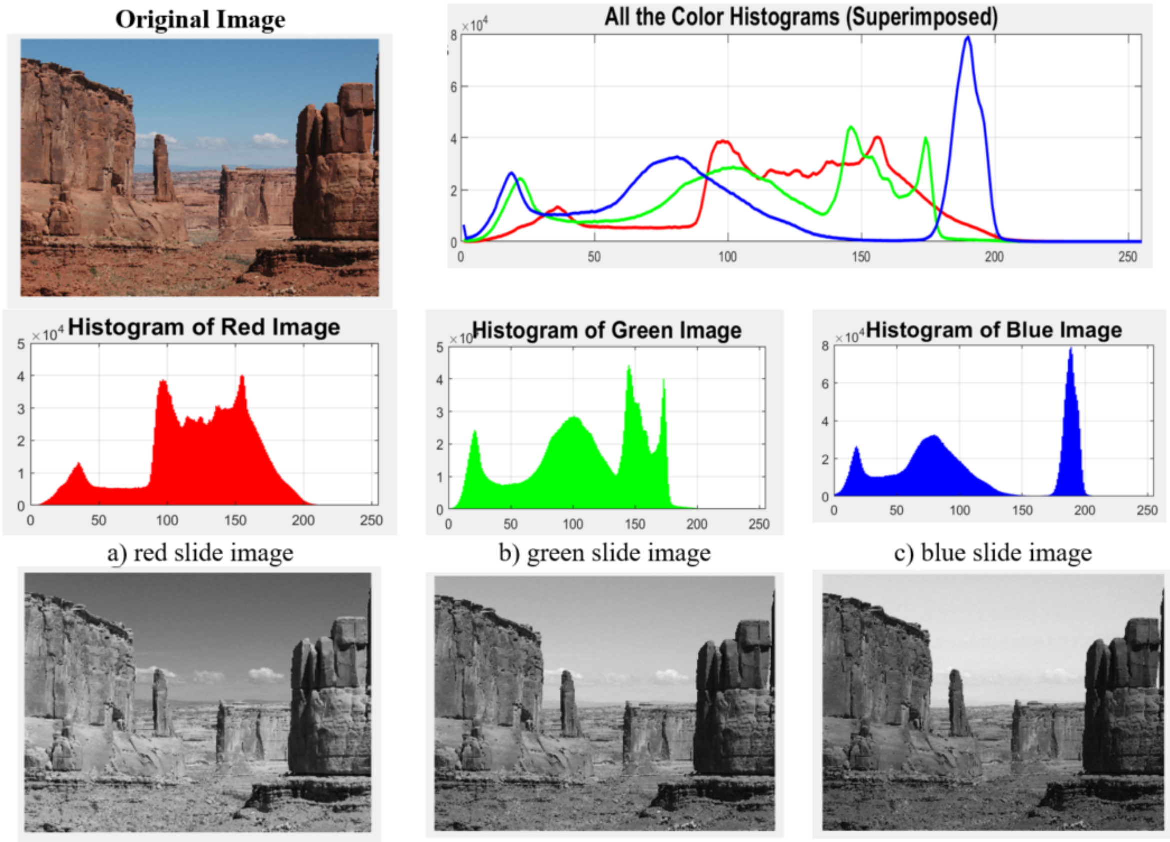

FIGURE 4. The performed image segmentation of the IWOA in experiments on selected image 01.

TABLE 2. The comparison of effectiveness of the IWOA scheme with the other algorithms, e.g., PSO, WOA, and ABC for multi-threshold image segmentation.

No. Images	ABC	PSO	WOA	**IWOA**
Image 01	18.87573	18.98945	18.97572	19.02629
Image 02	19.99228	20.07941	19.98401	20.23406
Image 03	23.32012	22.98054	22.99621	23.10218
Image 04	20.10887	20.10096	19.99452	20.30349

5. Conclusion.

This paper suggested an improved whale optimization algorithm (IWOA) by adding an energy control element to the WOA and employing an oscillatory Cauchy mutation method to boost the chance of jumping out of the local optimum to address the issue of WOA's low convergence ability. In the experiment section, the multi-threshold image segmentation problem is used to evaluate the suggested scheme of the IWOA applied to experiments. Compared results of findings demonstrate that the IWOA algorithm can pick high-quality thresholds and enhance the efficiency of image segmentation. The threshold segmentation experiments on the test-selected images show that the enhanced method can balance the algorithm's development and exploration capabilities while enhancing accuracy. Therefore, the IWOA is a stable and well-optimized swarm intelligence algorithm compared to others.

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