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# Image Segmentation Technique of Strip Surface Defects Based on Wolf Optimizer Algorithm Optimized by Chaotic Catfish Effect

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**Abstract**

Strip surface defect image segmentation is an important part of strip surface image processing, which is very important for subsequent strip surface image processing. On steel strip surface defect image segmentation field, the defect type is complex and it is difficult to separate the defect from the background. The traditional segmentation methods to deal with such problems are not effective. In view of the above problems, this paper proposes a Wolf Optimizer Algorithm based on Chaotic Catfish effect optimization of steel strip surface defect image segmentation technology, which avoided algorithm trapped in local optimal solution, improved the search ability of the algorithm, Finally, the global optimal solution is obtained, and its validity is verified on the benchmark function. Finally, the Wolf Optimizer Algorithm based on Chaotic Catfish effect is applied to strip surface defect image segmentation. Experimental results show that compared with traditional GA, PSO, GSA image segmentation algorithms and WPA algorithm, the proposed algorithm can obtain more details, convergence speed is faster, and segmentation effect is better.

**Keywords:** Surface defects; Image segmentation; Wolf Optimizer Algorithm; Chaotic Catfish effect

## 1. Introduction

Image segmentation is an important part of image processing, and has always been a classic problem in the field of image processing. Common image segmentation methods include threshold segmentation, edge detection, swarm intelligence algorithm and the combination of many methods.

Among them, the threshold calculation methods mainly include iterative method [1], maximum intervariance method (Otsu) [2], entropy based method [3], clustering based method [4], etc. Kapur et al. Proposed the maximum entropy threshold method, which can achieve good results in segmenting non ideal bimodal histograms without rich empirical knowledge [5]; Dunn et al. Studied the threshold selection method of homogenization error [6]; Otsu algorithm has the characteristics of simple calculation, easy understanding and high stability [7].

In terms of edge detection for image segmentation, Abidin et al. Studied an image edge detection method based on derivative, and the experiment proved that canny performs well in JPEG type image segmentation [8]. Mohammad proposed an image segmentation method based on the EECS algorithm. The technology mainly focuses on preprocessing, edge detection, enhancement, threshold and feature extraction. The advanced fuzzy k-means algorithm is used for clustering. Compared with other technologies such as cmeans clustering, the time is reduced by 71%, and the efficiency of specific target detection is increased by more than 22% [9]. Liu Yuan et al. Proposed a new edge detection algorithm for strip surface defect image. The average segmentation accuracy of the proposed algorithm is 93.5%, which can obtain better edge detection effect compared with the traditional Sobel operator edge detection method [10].

At present, many researchers have done more research on the application of intelligent algorithms to image segmentation [11]. In 2016, Vijay et al proposed enhanced Darwinian particle algorithm, which is applied to medical image segmentation and has great value in medical image segmentation [12]. In 2017, Mou Mengyuan and others improved the genetic algorithm and applied it to image segmentation. The accuracy and accuracy of the improved algorithm in image segmentation processing have been improved a lot [13]. Li Maomin et al. Proposed a new portrait image segmentation method based on the combination of improved genetic algorithm and threshold image segmentation, which improved the accuracy acquisition of image segmentation threshold and the anti-noise ability of image segmentation, and shortened the time of image segmentation [14].

The image segmentation methods for the surface defect image of strip steel mainly include threshold segmentation, edge detection and the combination of various methods. Zhao Wei improved the traditional difference image method and proposed an iterative threshold method for strip surface defect segmentation by changing the standard image in real time [15]. Yang Yongmin et al. Proposed an image segmentation algorithm based on hyper entropy and fuzzy set theory. Combined with the theory of hyper entropy and fuzzy set, the fuzzy hyper entropy is constructed. The segmentation threshold is determined by calculating the optimal membership function parameter combination corresponding to the maximum fuzzy hyper entropy of the image, and the image segmentation is completed by using this threshold. The results show that the algorithm can accurately extract defects from the background and effectively suppress the over segmentation phenomenon [16]. Xie Guangwei et al. Proposed a defect region segmentation method based on gray level morphological enhancement and adaptive threshold. The experimental results show that the segmentation effect of this method is better than the traditional segmentation method [17]. Li Xiaotong and others used the maximum correlation criterion method to select the threshold value to segment the defect image. The experimental results show that compared with the typical image enhancement and segmentation methods, the proposed method has excellent performance and has good application value for the recognition and segmentation of strip surface defect images under non-uniform illumination [18]. Zhang Hongbo proposed a strip surface defect image segmentation method based on adaptive bat algorithm (ABA). Experiments show that compared with similar algorithms, ABA algorithm can better segment defect targets and has better search performance in solving the problem of strip surface defect image segmentation [19].

To sum up, the current methods used to realize the image segmentation of strip surface defects can achieve relatively good results in the segmentation of a certain type of specific images due to the diversity of images and the uncertainty of image data, but the segmentation results for other types of images are not ideal.

The actual effect of the image segmentation method of strip surface defects based on edge detection needs to be determined through experiments. The research on the segmentation method of strip surface defect image based on threshold segmentation mainly focuses on the few threshold, while the research on multi threshold segmentation is less, and the problem of threshold selection is difficult. The image segmentation method combined with many methods has many steps and complicated process. There are few researches on the image segmentation of strip surface defects using swarm intelligence optimization algorithm. Therefore, this paper will study the image segmentation technology of strip surface defects based on the wolf swarm algorithm optimized by chaotic catfish effect. Compared with the traditional image segmentation algorithm, more detailed information is obtained, the convergence speed is faster, and the segmentation effect is better.

## 2. Image Segmentation Technology of Strip Surface Defects based on Wolf Swarm Algorithm Optimized by Chaotic Catfish Effect

### 2.1. Wolf Swarm Algorithm Principle

Wolf optimizer algorithm (WPA) is a random probability search algorithm. Inspired by the social hierarchy of gray wolf population and the collective hunting behavior of wolves, it is widely used in parameter optimization, image classification, function optimization and other fields [20]. The algorithm has the advantages of good convergence, few parameters and easy realization, and can quickly find the optimal solution with a large probability; The wolf swarm algorithm also has parallelism, which can search from multiple points at the same time without affecting each other, thus improving the efficiency of the algorithm.

The optimal solution obtained by the search individual is called $\alpha$, the second optimal solution and the third optimal solution of the search individual are called $\beta$、$\delta$ respectively, and the candidate solutions of the other search individuals are assumed to be $\omega$. The optimization process of the wolf swarm optimization algorithm is carried out under the guidance of $\alpha$、$\beta$、$\delta$, $\omega$ following the three gray wolves.

Gray wolves need to surround their prey in the process of hunting. In the model, wolves approach the optimal prey by updating the position, that is, changing the threshold. The process of rounding up is represented by formula (1) - formula (2):

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_P(\mathrm{t}) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

In the formula, t represents the current iteration number, $\vec{D}$ is the distance between the gray wolf and the prey, $\vec{X}$ is the position of the gray wolf, and $\vec{X}_{\mathrm{p}}$ represents the position of the prey. $\vec{A}$ and $\vec{C}$ are a parameter vector, which is calculated by formula (3) - formula (4):

$$\vec{A} = 2\vec{a} \cdot r_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r}_2 \tag{4}$$

In the formula, $\vec{a}$ iterates from 2 to 0 in the iterative process. $\vec{r}_1$、$\vec{r}_2$ are respectively a random vector in the interval [0,1].

The action of hunting prey is led by the wolf $\alpha$, and the wolf $\beta$、$\delta$ will constantly participate in it. It is assumed that wolves $\alpha$, wolves $\beta$ and wolves $\delta$ are more aware of the potential location of their prey. During each iteration, the positions of the currently obtained optimal solution, that is, the wolf $\alpha$, the second optimal solution wolf $\beta$ and the third optimal solution wolf $\delta$ are saved. Then the rest of the search individuals continuously update their positions according to the position information of the three gray wolves. The update formula is as shown in equations (5) to (11).

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha^t - \vec{X}^t\right| \tag{5}$$

$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta^{\mathrm{t}} - \vec{X}^t\right| \tag{6}$$

$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta^{\mathrm{t}} - \vec{X}^t\right| \tag{7}$$

$$\vec{X}_1 = \vec{X}_\alpha^{\mathrm{t}} - \vec{A}_1 \cdot \vec{D}_\alpha \tag{8}$$

$$\vec{X}_2 = \vec{X}_\beta^t - \vec{A}_2 \cdot \vec{D}_\beta \quad (9)$$

$$\vec{X}_3 = \vec{X}_\delta^t - \vec{A}_3 \cdot \vec{D}_\delta \quad (10)$$

$$\vec{X}^{t+1} = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \quad (11)$$

The steps of grey wolf optimization algorithm are as follows:

Step 1: initialize the population, set the maximum number of iterations and the population number. Initialization parameters a，A，C.

Step 2: initialize the location $X_i$ of gray wolf individuals randomly.

Step3: calculate the fitness value of each wolf and save the first three best search individuals $X_\alpha$, $X_\beta$, $X_\delta$.

Step 4: update the position $X_i$ of the current search individual according to formula (11).

Step5: update parameters a，A，C.

Step 6: calculate and update the optimal solution of all search individual location information.

Step 7: determine whether the maximum number of iterations has been reached. If the maximum number of iterations has been reached, stop and return to the optimal solution value $X_\alpha$, otherwise jump back to step 4.

### 2.2. Wolf Swarm Algorithm based on Chaos Catfish Effect Optimization

The wolf swarm algorithm is too random in the process of wolf swarm initialization, and the distribution of wolf swarm is not uniform, which may lead to unsatisfactory optimization results. According to the randomness, regularity and correlation of the chaotic system, we use chaotic mapping to extract and capture the information in the solution space, so as to enhance the diversity of the initial wolves. In this paper, Logistic chaotic map is adopted and analyzed. Its mathematical iteration equation is as follows:

$$\lambda_{t+1} = \mu \times \lambda_t (1 - \lambda_t), t = 0,1,2,\cdots,T \quad (12)$$

Where, T is a preset maximum number of chaotic iterations, $\lambda_t$ is a random number, uniformly distributed on the interval [0,1], and $\lambda_0 \notin \{0, 0.25, 0.5, 0.75, 1\}$. $\mu$ is the chaos control parameter. When $\mu = 4$, the system will be in a completely chaotic state.

First, a set of chaotic variables $\lambda_t$ is generated by using formula (12); Secondly, we use chaotic sequence to map NF d-dimensional gray wolf individual position vectors $X_i$ into the chaotic interval $[F_{\min}, F_{\max}]$ according to formula (12), where $F_{\min}$ and $F_{\max}$ respectively represent the maximum and minimum boundaries of $F_i$; Finally, the fitness value corresponding to each gray wolf individual is calculated according to equation (13).

$$f_{i,j} = f_{\min,j} + \lambda_{i,t} \left( f_{\max,j} - f_{\min,j} \right) \quad (13)$$

In the WPA algorithm, if the "limit" times do not update the nesting position, it can be seen that the algorithm falls into the local optimal solution, resulting in the failure of the algorithm to obtain the global optimal solution, and can only stop at this local solution. This not only weakens the search ability of the entire population, but also may cause the algorithm to eventually fail to converge to the global optimal value.

In this paper, the wolf swarm algorithm (CCWPA) for chaotic catfish optimization is proposed, so as to jump out of the problem of falling into the local optimal solution and finally converge to the global optimal solution. The specific steps are as follows:

***Classification and marking.***

The fitness values corresponding to the current gray wolf individual $NF$ are sorted in ascending order to mark the position of the first worst gray wolf individual $10\% \times NF$ .

***Eliminate the position of the worst gray wolf***

Eliminate the position of the worst gray wolf, and replace it with the same amount of chaotic catfish wolf. If the number of gray wolf individuals is *M*, then $M = 10\% \times NF$ .

***Produce chaotic catfish and wolves.***

Set the initial position vector of chaotic catfish wolf according to equation (14)

$$V_m^d(0) = \left(v_m^1(0), v_m^2(0), \ldots, v_m^d(0)\right), m = 0,1,2,\ldots, M \quad v_m^j(0) = \begin{cases} v_{m,j}^{\max}, & if \quad r > 0.5 \\ v_{m,j}^{\min}, & if \quad r \le 0.5 \end{cases} \tag{14}$$

Where, $v_{m,j}^{\max}$ and $v_{m,j}^{\min}$ respectively represent the maximum and minimum values in the $j$ dimension of the $m$ catfish wolf, and $r$ is a random number in $[0,1]$, and let 0.5 be the boundary point to make the value $v_m^j$ distribution at the two-level values approximate.

***Updates its position***

The chaotic catfish wolf updates its position according to equation (15), $T$ is the chaotic iteration threshold

$$\begin{cases} \mathbf{V}_m^d(t) = \mathbf{V}_{\min} + (\mathbf{V}_{\max} - \mathbf{V}_{\min}) \times \mathbf{V}_m^d(t), & \mathbf{V}_m^d \in [\mathbf{V}_{\min}, \mathbf{V}_{\max}] \\ \mathbf{V}_m^d(t+1) = \mu \times \mathbf{V}_m^d(t) \times \left(1 - \mathbf{V}_m^d(t)\right), & t = 0,1,\ldots, T \end{cases} \tag{15}$$

Equation (14) uses equation (12) and equation (13) to calculate the fitness value of the position of each chaotic catfish wolf to replace the M values with the smallest fitness in the original wolf group. After updating, the newly added chaotic catfish wolf will form a new population with the remaining wolves and enter the next cycle search process.

Finally, the steps of the wolf swarm search algorithm based on chaotic catfish effect to segment the surface defect image of strip steel are given:

Step1: input the surface defect image of the strip steel to be divided

Step 2: initialize CCWPA algorithm parameters: population size d; Maximum chaotic iteration threshold; Maximum iteration times T; Maximum iteration limit t of wolf pack update: limit; Maximum boundary $F_{\max}$ ; Minimum boundary $F_{\min}$ ;

Step3: initialize the wolf group position; The positions $X_i$ of gray wolf individuals were randomly initialized.

Step4: calculate the fitness value of each wolf and save the first three best search individuals $X_\alpha$ , $X_\beta$ , $X_\delta$ .

Step 5: enter the loop and update the position $X_i$ of the current search individual according to formula (11).

Step 6: perform local search according to CCWPA algorithm, calculate the fitness value of the position of each chaotic catfish wolf to replace the M values with the smallest fitness in the original wolf group. After updating, the newly added chaotic catfish wolf will form a new population with the remaining wolves and enter the next cycle search process.

Step 7: calculate and update the optimal solution of all search individual location information.

Step 8: if the maximum iteration limit of wolf pack update is reached, execute step 9; Otherwise, execute step 5;

Step9: output the position and fitness value of the optimal wolf.

## 3. Experimental Simulation

The hardware conditions of the experimental PC: the CPU is Intel Core i5 760 2.8 GHz, and the memory is 2 GB; Software platform: operating system windows7 ultimate, simulation software MATLAB 7.0.

In order to verify the effectiveness and universality of the improved algorithm, we compared the improved algorithm on 8 benchmark functions. The parameter settings of the 8 benchmark functions are shown in Table 1.

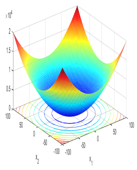
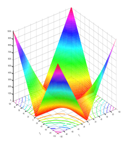
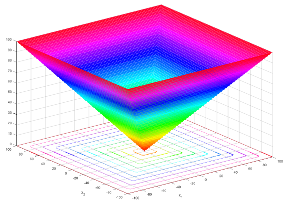
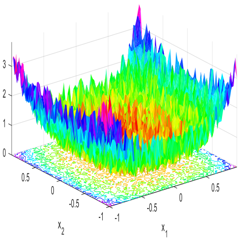
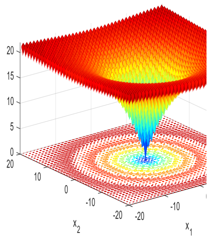
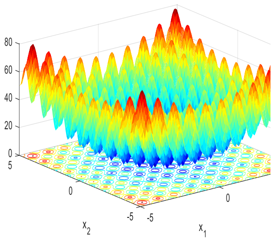
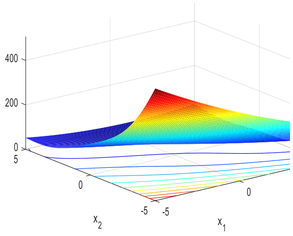
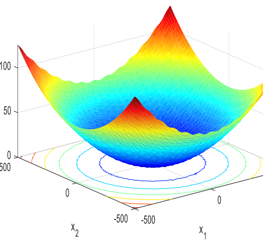
Tab.1 Base function setup

| Function | function expression | dimension | Value range | Optimal solution |
|---|---|---|---|---|
| Sphere | $f_1(x)=\sum_{i=1}^{n} x_i^2$ | 30 | [-1.5,1.5] | 0 |
| Schwefel 2.22 | $f_2(x)=\sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$ | 30 | [-10,10] | 0 |
| Schwefel 2.21 | $f_3(x)=\max_{i=1}^{n}\{\lvert x_i\rvert\}$ | 30 | [-100,100] | 0 |
| Quadric | $f_4(x)=\sum_{i=1}^{n} i x_i^4 + rand(0,1)$ | 30 | [-1.28,1.28] | 0 |
| Ackley | $f_5(x)=-20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2})-\exp(\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i)+20+e$ | 200 | [-32,32] | 0 |
| Rastrigrin | $f_6(x)=\sum_{i=1}^{D}\left[x_i^2-10\cos(2\pi x_i)+10\right]$ | 60 | [-10,10] | 0 |
| Branins's rcos | $f_7(x)=(y-\frac{5.1}{4\pi^2}x^2+\frac{5}{\pi}x-6)^2+10(1-\frac{1}{8\pi})\cos(x)+10$ | 2 | [-10,10] | 0 |
| Griewank | $f_8(x)=\sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$ | 2 | [-100,100] | 0 |

The three-dimensional characteristics of the test function are shown in Table 2.

In order to verify the performance of ccwpa algorithm, we will use ccwpa, WPA and PSO algorithms to optimize the eight benchmark functions in the simulation experiment and compare the experimental results. Parameter settings are shown in Table 3.

Tab.2 Three-dimensional characteristics of test functions

| Functions | Sphere | Schwefel 2.22 | Schwefel 2.21 | Quadric |
|---|---|---|---|---|
| Three-dimensional features |  |  |  |  |
| Functions | Ackley | Rastrigin | Branins's rcos | Griewank |
| Three-dimensional features |  |  |  |  |

Tab.3 Parameter Setting

| Population number | Maximum iteration | scaling factor range | crossover |
|---|---|---|---|
| 30 | 1000 | [0.2,0.8] | 0.5 |

When PSO, WPA and ccwpa are used for optimization, the fitness function is shown in Figure 1.

It can be seen from Fig. 1 that ccwpa algorithm converges faster than WPA algorithm and PSO algorithm.

The WPA algorithm and ccwpa algorithm are used to compare the performance indexes of the eight benchmark functions in the optimal value, average value and standard deviation. The results are shown in Table 4.

Tab.4 Comparison of optimization performance data between WPA and CCWPA

| Function | WPA | | | CCWPA | | |
|---|---|---|---|---|---|---|
| | Optimal value | Mean value | Standard deviation | Optimal value | Mean value | Standard deviation |
| $f_1$ | 1.388e-59 | 1.0575e-31 | 6.8342e-31 | 1.4626e-71 | 2.142e-39 | 7.1016e-37 |
| $f_2$ | 4.0556e-35 | 1.5876e-39 | 1.3918e-36 | 2.9372e-43 | 3.1692e-45 | 9.4977e-45 |
| $f_3$ | 6.5298e-15 | 2.5849e-15 | 5.9855e-15 | 7.4635e-17 | -4.7008e-18 | 7.5129e-17 |
| $f_4$ | 0.0015439 | 0.0047173 | 0.033156 | 0.00088055 | 0.0026007 | 0.03587 |
| $f_5$ | 1.1546e-14 | 3.764e-16 | 3.0427e-15 | 7.9936e-15 | 1.9018e-16 | 2.3655e-15 |
| $f_6$ | 0 | 1.5101e-09 | 3.6359e-09 | 0 | -2.2121e-10 | 3.9858e-09 |
| $f_7$ | 0.3979 | 5.9489 | 4.9161 | 0.39789 | 2.7082 | 0.61315 |
| $f_8$ | 0 | 7.0399e-10 | 1.8151e-08 | 0 | -4.6582e-09 | 1.5915e-08 |

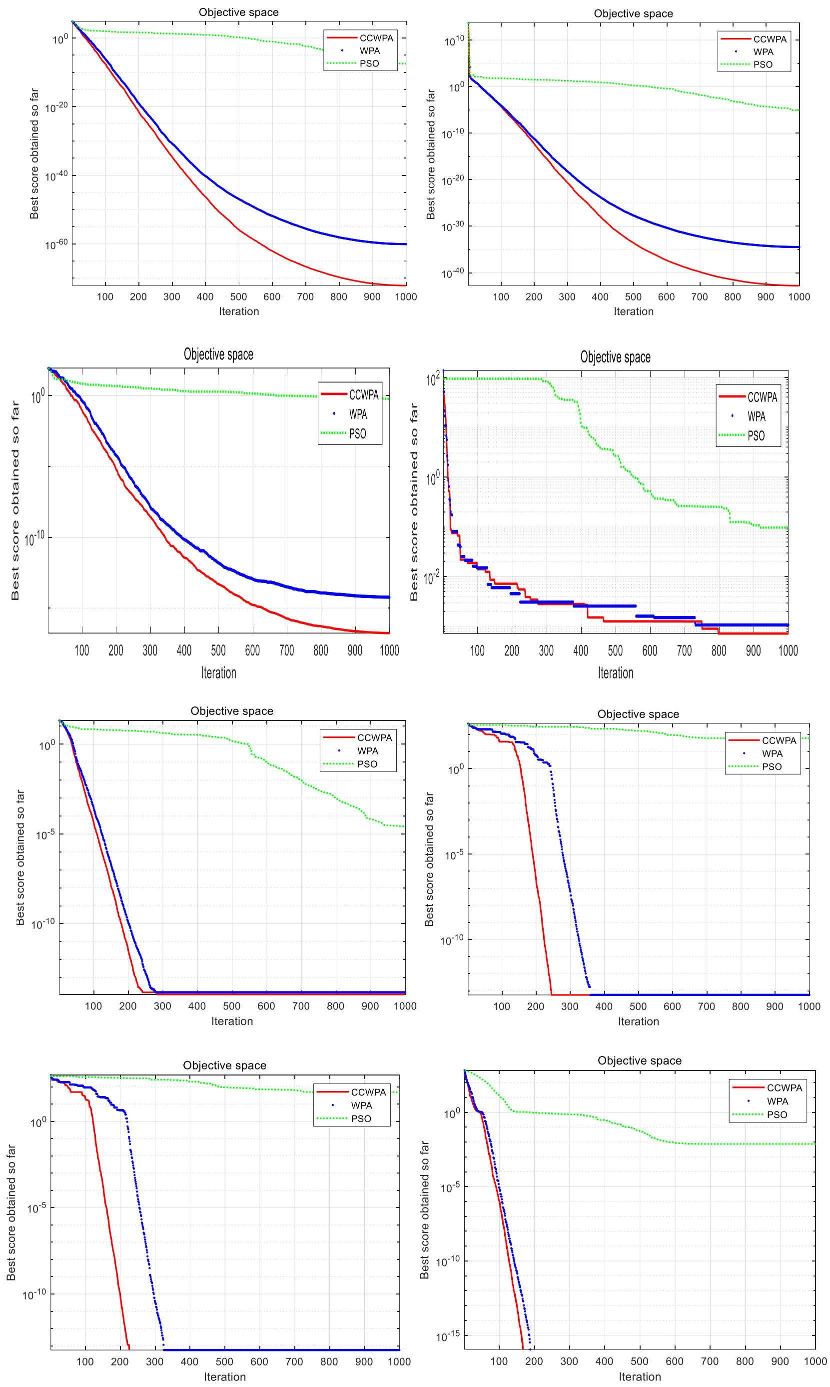



Fig.1 Convergence curve

It can be seen from table 4 that the solution obtained by the improved ccwpa algorithm is closer to the optimal solution than the WPA optimization algorithm, and the ccwpa algorithm is more stable in solving the optimal value. In conclusion, ccwpa has better performance than wolf swarm optimization algorithm and particle swarm optimization algorithm in finding the optimal solution of the function.

In this paper, the segmentation effect of ccwpa algorithm is tested and simulated by selecting three kinds of strip defect images (scratch, scratch and surface warping) collected by a steel plant. Population number of wolf swarm optimization algorithm in the experiment (search agents)_ No is set to 50, and the maximum number of iterations of the population is Max_ When iteration is set to 100, comparative experiments are conducted by setting different threshold numbers. Parameter settings are shown in Table 5.

Tab.5 Parameter Setting

| Maximum number of iterations | Population number | Upper bound | Lower bound | Threshold |
|---|---|---|---|---|
| 100 | 50 | 255 | 1 | 1，2，3，4，5，10 |

The gray level histograms of the three defect images are shown in Fig. 2.

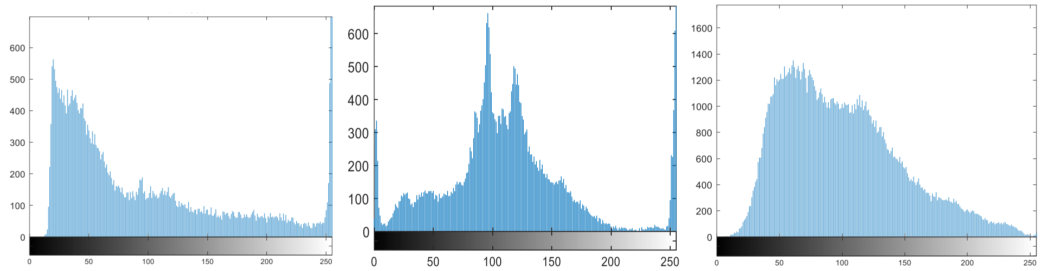
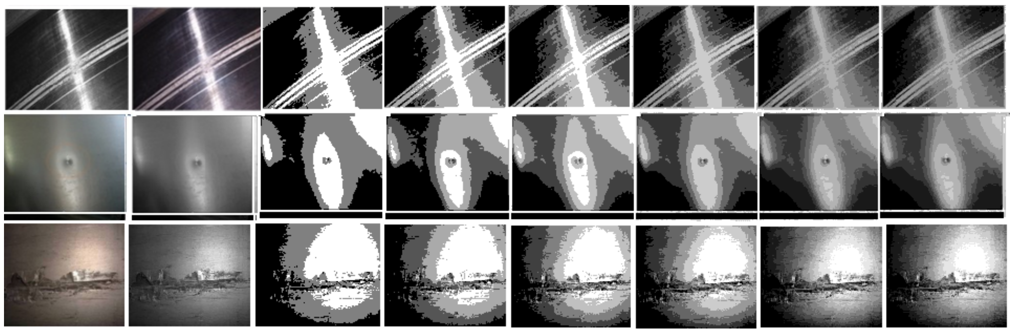



Fig. 2 Gray histogram of scrape, scratch and surface warping

Based on ccwpa algorithm, single threshold, double threshold, three threshold, four threshold, five threshold and ten threshold image segmentation are respectively adopted for three kinds of strip surface defect images (scrapes, scratches and surface warping). The image segmentation effect is shown in Fig. 3. Table 6 shows the segmentation effect measured from several performance indicators such as optimal threshold, inter class variance and average time.



(a) Original image (b) gray image (c) single threshold (d) Double threshold (e) three threshold (f) four threshold (g)five threshold (h) ten threshold

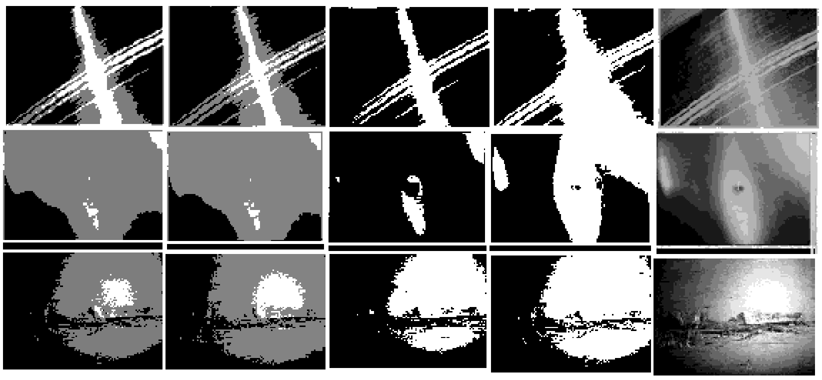
Fig. 3 Image segmentation effect of strip surface defects based on CCWPA algorithm

It can be seen from Fig. 3 and table 6 that with different types of surface defects of strip steel, the segmentation effect of the target image based on ccwpa algorithm is good and the average time is short, and with the increase of the number of thresholds, the segmentation effect of the image is getting better and better.

In order to further verify the effectiveness of the algorithm in this paper, CCWPA is compared with traditional genetic algorithm (GA), particle swarm optimization (PSO), gravitational algorithm (GSA) and WPA image segmentation algorithm using five threshold segmentation. The experimental results are shown in Fig. 4.

Tab. 6 Experimental results

| Threshold number | Performance index | scrapes | scratches | surface warping |
|---|---|---|---|---|
| Single threshold | Optimal threshold | 74 | 115 | 96 |
| | otsu | -17.4859 | -17.4922 | -20.0783 |
| | average time（s） | 1.81 | 1.70 | 1.76 |
| Double threshold | Optimal threshold | 45，116 | 98，131 | 73，118 |
| | otsu | -25.1560 | -25.1649 | -28.9955 |
| | average time（s） | 1.84 | 1.94 | 1.89 |
| Three thresholds | Optimal threshold | 40，,71,158 | 96，118，149 | 64，95，131 |
| | otsu | -32.4858 | -32.4555 | -37.5662 |
| | average time（s） | 1.92 | 2.11 | 1.99 |
| Four thresholds | Optimal threshold | 35,53,96,185 | 76，97，122，156 | 60，82，108，137 |
| | otsu | -39.5612 | -39.4912 | -45.8918 |
| | average time（s） | 1.94 | 1.91 | 2.08 |
| Five thresholds | Optimal threshold | 35，51，92，162， | 77，97，118，142， | 55，73，95，118， |
| | otsu | -46.4892 | -46.4507 | -54.0219 |
| | average time（s） | 1.70 | 1.97 | 2.09 |
| Ten thresholds | Optimal threshold | 26，36，45，55， | 49，84，96，104， | 48，60，70，81， |
| | otsu | -79.3844 | -79.2087 | -92.7029 |
| | average time（s） | 2.27 | 2.13 | 2.44 |



(a) GA (b) PSO (c) GSA (d) WPA (e) CCWPA

Fig. 4 Comparison of segmentation effects

The PSNR comparison of the output images of the three strip surface defect image segmentation methods is shown in Table 7.

Tab.7 PSNR comparison of three strip surface defect image segmentation methods

| Defect type | | GA | PSO | GSA | WPA | CCWPA |
|---|---|---|---|---|---|---|
| scratch | PSNR | 17.8820 | 18.8291 | 15.8926 | 16.1865 | 24.8181 |
| | MSE | 1058.9679 | 851.4769 | 1674.2407 | 1564.7053 | 214.4245 |
| scab | PSNR | 20.8596 | 21.5090 | 17.6351 | 17.1071 | 21.7584 |
| | MSE | 533.4866 | 459.3859 | 1120.9173 | 1265.8137 | 433.7479 |
| surface | PSNR | 18.9338 | 18.9012 | 15.8736 | 15.7644 | 20.8058 |
| warping | MSE | 831.1903 | 837.4560 | 1681.6031 | 1724.4093 | 540.1356 |

It can be seen from Fig. 4 and table 7 that the segmentation effect of ccwpa algorithm is higher than that of traditional image segmentation algorithm, that is, the image segmentation effect is better and the quality is higher.

## 5. Conclusion

In view of the poor effect of the current image segmentation method for strip steel surface defects, this paper studies the use of wolf swarm optimization algorithm for strip steel surface defects image segmentation. In view of the possibility of local optimization of wolf swarm algorithm, this paper proposes a wolf swarm algorithm for strip steel surface defects image segmentation based on chaotic catfish effect optimization, which improves the search ability of the algorithm, obtains the global optimal solution, and verifies its effectiveness on the benchmark function; Compared with traditional GA, PSO, GSA and other image segmentation algorithms and WPA algorithms, it can obtain more detailed information, converge faster and achieve better segmentation results.

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