Image Enhancement CHPSO Processing Technology Based on Improved Particle Swarm Optimization Algorithm

Dajian Yi, Zhangping You, Wenhui Zhang

Abstract: **A colony heuristic particle swarm optimization (CHPSO) image processing technique is proposed to improve image enhancement efficiency. An adaptive weight adjustment algorithm based on particle performance and distance to the optimal position is designed, enabling real-time adjustment of inertia weights and enhancing global search effectiveness. A novel colony particle swarm optimization (CPSO) algorithm, integrating the information transmission mechanism of Ant colony optimization, is introduced to improve information sharing and collaborative search among particles. Utilizing the pheromone release mechanism of ant colony optimization, a heuristic data selection and updating algorithm is developed to enhance optimization capability and convergence speed. Experimental results show that CHPSO improves peak signal to noise Ratio (PSNR), structural similarity index (SSIM), and convergence speed by 8.7%, 7.2%, and 9.4%, respectively, compared to traditional algorithms.**

Index Terms: **enhancement; Particle swarm optimization algorithm; Ant colony algorithm; Hybrid metaheuristic algorithm**

I. INTRODUCTION

Image enhancement technology is widely used in fields such as intelligent robots, satellite remote sensing, and visual recognition [1]-[6]. Contrast enhancement is a crucial process in image processing, involving the expansion of the dynamic intensity range to reveal finer details [7]. It is an essential preprocessing step in computer vision applications such as remote sensing, fault detection, and biomedical image analysis, aimed at highlighting the differences in grayscale values between objects and backgrounds. The enhanced images thus produced not only exhibit improved visual quality but also play a crucial role in subsequent analysis. Despite its significance, the lack of a universal theory and standardized metrics for evaluating image quality makes contrast enhancement a challenging task. The subjective nature of visual perception adds complexity, requiring delicate balance between technically enhancing and maintaining content integrity. In fields such as remote sensing, contrast enhancement plays a critical role in extracting meaningful information from images, aiding in the identification of subtle environmental features. Similarly, in fault detection, enhancing contrast helps in identifying irregularities that may be associated with faults or anomalies. Ongoing research is crucial for developing robust methods adaptable to various applications and image types, reinforcing the need for subtle interactions between technical considerations and subjective factors in contrast enhancement in image processing.

Contrast enhancement plays a crucial role in two aspects: first, it helps to improve the visual contrast between objects and backgrounds in low dynamic range images, thereby enhancing the overall contrast of the entire image; second, it reveals details in the original image that are often difficult to perceive, making these details more prominent. This processing not only gives the image a more prominent and clear appearance but also allows observers to more accurately identify subtle differences between objects and backgrounds in the image. Through contrast enhancement processing, the image presents a more prominent and clear appearance, enabling observers to more accurately distinguish between objects and backgrounds in the image. This improvement not only enhances the overall quality of the image but also makes details more striking, providing observers with richer visual information. There are various classification methods for contrast enhancement methods, including gray level transformation based on nonlinear functions (such as logarithmic, power-law, gamma functions), histogram-based techniques, nonlinear quadratic filtering, and frequency domain-based methods (such as homomorphic filters). among them, histogram equalization (HE) is a widely used contrast enhancement technique, commonly used in multiple fields such as radar and medical image processing. However, while able to globally enhance images, HE may lead to over-enhancement issues because it operates based on the most frequently occurring intensity levels in the image. HE also fails to effectively handle cases where there are significant differences in brightness between the main areas of the image and other areas, while also easily leading to loss of local details and enhancement of noise. To address the issues of HE, researchers have proposed various improvement methods.[8] Among them, local histogram equalization (LHE) divides the image into small regions and performs histogram equalization

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Dajian Yi is a postgraduate student at Zhejiang Sci-Tech University, Hangzhou 310018, P. R. China (email: ydj1176540684@163.com).

Zhangping You is a professor at Lishui University and Lishui Key Laboratory of High Power Density Intelligent Drive System, Lishui 323000, P. R. China (email: 44536388@qq.com).

Wenhui Zhang is a professor at Nanjing Xiaozhuang University, Nanjing 211171, P. R. China (corresponding author to provide phone: +86-18268906955; e-mail: hit_zwh@126.com).

for each region, helping to retain local details and alleviate over-enhancement issues. On the other hand, dual histogram equalization (DSIHE) introduces additional histogram equalization steps, better addressing contrast differences in different regions of the image. Tarik Arici et al. [9] proposed a histogram equalization-based image contrast enhancement framework. By minimizing the cost function of the optimization problem, a specially designed penalty term is introduced to adjust the contrast enhancement level, achieving a more natural image effect while considering factors such as noise robustness, white/black stretching, and average brightness preservation. The proposed low-complexity algorithm performs superiorly in terms of performance. Sonali et al. [10] proposed a noise removal and contrast enhancement algorithm for fundus images. By combining filtering with contrast limited adaptive histogram equalization (CLAHE) technology, the algorithm solves the noise removal and enhancement problems of color fundus images. Wencheng Wang et al. [11] proposed a color image correction method based on nonlinear function transformation to improve the adaptability of image enhancement to low-light images. Based on the illumination-reflection model and multi-scale theory, the experimental results show that the algorithm can improve the overall brightness and contrast of the image while reducing the impact of uneven illumination.

Automatic contrast enhancement techniques are highly demanded in many applications today. However, automating algorithms is not easy, as it requires the evaluation of objective functions that measure the quality of the enhanced image. To address this issue, a series of optimization methods based on neural network evolutionary computation [12]-[20] have been proposed in recent years, aiming to achieve automatic execution of contrast enhancement tasks. The key goal of these techniques is to find the optimal parameter settings or the best input/output mapping to produce the highest quality images.

In recent years, intelligent computer vision technology has also been widely used in the field of robotics. Many studies have proposed contrast enhancement methods based on optimization algorithms. Krishna et al. [21] formulated image enhancement as an optimization problem and solved it using the natural-Inspired optimization algorithm (NIOA), ushering in a new era in the field of image enhancement. Zhuang et al. [22] developed a Bayesian retinal algorithm to enhance a single underwater image using multiple gradients prior to reflectance and illumination, converting the complex underwater image enhancement problem into two simple denoising problems. They provided their convergence analysis mathematically and derived their solutions through effective optimization algorithms. F. Orujov et al. [23] developed an image processing algorithm based on contour detection, which used Mamdani (Type-2) fuzzy rules, contrast-limited adaptive histogram equalization (CLAHE) for contrast enhancement, and median filtering for background exclusion. This method, as a flexible approach, is applicable to various edge detection/contour-based applications. Gorai et al. [24] proposed an objective criterion for measuring image enhancement considering image entropy and edge information. They optimized the parameters used in the transformation function using the Particle Swarm Algorithm to achieve the best enhanced image according to the objective criterion.

Although researchers have made significant efforts to enhance the contrast of images, research on contrast enhancement for industrial images remains relatively limited. Therefore, we propose an innovative industrial image contrast enhancement technique based on an improved PSO algorithm (named CHPSO) and apply it to local/global image enhancement. The contributions of this study are as follows:

(1) Designing a weight adaptive adjustment method based on the performance of particles and their distance to the best position to achieve real-time adjustment of the inertia weights of each particle in different dimensions, thereby improving the global search effect of the algorithm.

(2) By introducing adaptive inertia weights into the PSO algorithm, the stability of the algorithm is improved. Additionally, by utilizing the information transmission mechanism of the ant colony algorithm, we integrate the ant colony algorithm with the improved PSO to design a novel CPSO algorithm. This allows for information sharing among particles, enhancing the effect of cooperation and collaborative search.

(3) Based on the mechanism of the ant colony algorithm releasing pheromones to attract other particles to form optimal paths, we designed a Heuristic-based data selection and update algorithm. This algorithm enhances the optimization strength, improves spatial search capability, and accelerates convergence speed.

The organization of the rest of this paper is as follows: Section 2 introduces the principles of LGE enhancement transformation and the original ant colony algorithm. Section 3 provides a detailed explanation of the proposed CHPSO algorithm. Section 4 presents the experimental results and discusses them. Section 5 draws conclusions and provides suggestions for future work.

II. Image Enhancement Transformation

A. Local/Global Enhancement Transformation

The LGE transformation utilizes both local statistical information such as mean, variance, and global image information. For each pixel located at position (u,v) in an image of size M × N, the transformation T_{LGE} is applied to map the old intensity $f(u,v)$ to a new intensity value $g(u,v)$. The expression for the LGE transformation is:

$$g(u,v) = T_{LGE}[f(u,v)] = k*\frac{G_m}{\sigma(u,v)+b}\left[f(u,v)-c*m(m,v)\right]+(u,v)^a \tag{1}$$

where $u = 0,1,\ldots,M-1, v = 0,1,\ldots,$ while $N-1$ and G_m are the global mean values of the original image.

As shown in Fig. 1, the local statistics, mean Y $m(u,v)$, and standard deviation Z $\sigma(u,v)$ of window size X $n\times n$ are calculated as follows:

$$m(u,v) = \frac{1}{n^2}\sum_{i=-\text{int}\,n/2}^{\text{int}\,n/2}\sum_{j=-\text{int}\,n/2}^{\text{int}\,n/2} f(u+i,v+j) \tag{2}$$

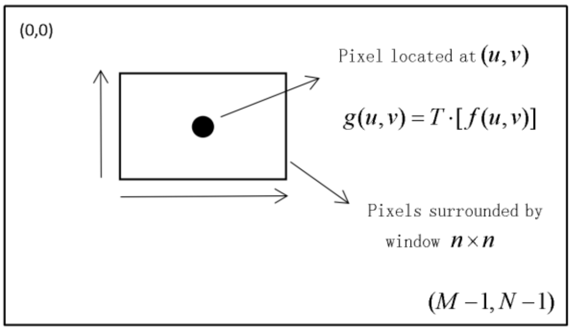


Fig. 1 Local image statistics of an n × n window

$$\sigma(u,v)=\sqrt{\frac{1}{n}\sum_{i=-\text{int}\,n/2}^{\text{int}\,n/2}\sum_{j=\text{int}\,n/2}^{\text{int}\,n/2}(f(u+i,v+j)-m(u+i,v+j))^2} \tag{3}$$

The global mean of image G_m is:

$$G_m=\frac{1}{M\times N}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}f(u,v) \tag{4}$$

According to Equation (1), four unknown parameters a, b, c, and k have a significant impact on the LGE transformation. Parameter a introduces smoothness and brightness effects in the image, while parameter b introduces an offset to the standard deviation in the neighborhood. Parameter c controls how much average value is subtracted from the image. Finally, parameter k is used to regulate the global enhancement effect of the image. The adjustment of these parameters has a significant impact on the performance of the LGE transformation. Therefore, when using the LGE transformation, it is necessary to carefully adjust these parameters to achieve the desired image enhancement effect. This understanding provides guidance for optimizing the LGE transformation, making it more accurately applicable in the field of image processing.

When parameter b is set to zero, it results in a dependency on the local variance, which can make the transformation unstable. Meanwhile, setting parameters a, c, and k to 1 limit the range of parameter choices to achieve optimal performance. If parameters a, b, and c can take any positive real values, while k remains between 0.5 and 1.5. Therefore, the goal of the optimization algorithm is to find the optimal values of these parameters based on a given objective function to achieve the best enhanced image effect. Different parameter settings may lead to different enhancement results, so the selection of parameter ranges should consider the ultimate goal and performance requirements.

B. Objective Function

In the absence of external intervention, achieving automatic measurement of enhanced image quality requires defining an objective function suitable for specific application requirements. Many papers have proposed various objective functions, including contrast, brightness equalization, structural preservation, and information entropy. Selecting the appropriate objective function is crucial for improving the accuracy of automatic image enhancement assessment. These objective functions can be used to quantify the quality of image enhancement, making it suitable for automated performance evaluation. As shown below:

$$F(I_e)=In[In(E(I_e))+\exp]*\frac{edgels(I_e)}{M\times N}\exp(H(I_e)) \tag{5}$$

In the formula, I_e represents the enhanced image generated after processing by the transformation function, $edgels(I_e)$ denotes the number of edge pixels obtained from I_e using the Sobel edge detector, $E(I_e)$ is the sum of edge strengths of the enhanced image, and $H(I_E)$ represents the entropy value of I_e.

The formula for calculating $H(I_E)$ is as follows:

$$H(I_e)=\begin{cases}-\sum_i V_i\log_2(V_i), & V_i\neq 0\\ 0, & V_i=0\end{cases} \tag{6}$$

Where $i\in\{1,2,\ldots,256\}$ is an 8-bit grayscale image, and V_i is the probability of occurrence of the i-th grayscale value.

The formula for calculating $E(I_e)$ is as follows:

$$E(I_e)=\sum_u\sum_v\sqrt{S_{h1}(u,v)^2+S_{v1}(u,v)^2} \tag{7}$$

In the formula, $S_{h1}(u,v)$ and $S_{v1}(u,v)$ are the horizontal and vertical Sobel template edge detections respectively.

The Sobel operator is widely used in image enhancement, focusing primarily on edge detection. Its core idea is based on the gradient information of the image, which effectively captures edge features in the image. The operator uses two 3x3 convolution kernels, one for detecting edges in the horizontal direction and the other for detecting edges in the vertical direction. By applying these two convolution kernels to the pixels of the image, the Sobel operator can calculate the gradient magnitude and direction of each pixel, thereby efficiently detecting edges.

Histogram equalization is a method to transform the original image into a new image with a histogram that is uniformly distributed. Let r and s represent the normalized grayscale values of the original image and the image after histogram equalization, respectively. That is, $0\le r$, $s\le 1$. For any r value in the [0, 1] interval, there is a corresponding s value, and $s=T(r)$ .The inverse transformation relationship is $r=T^{-1}(s)$ .According to probability theory, if the probability density function of the random variable r is $p_r(r)$, and the random variable s is a function of r, then the probability density $p_s(s)$ of s can be derived from $p_r(r)$. Assuming the distribution function of the random variable s is represented by $F_s(s)$, according to the definition of distribution function:

$$F_s(s)=\int_{-\infty}^{s}p_s(s)ds=\int_{-\infty}^{r}p_r(r)dr \tag{8}$$

By using the relationship that the density function is the derivative of the distribution function, we can differentiate both sides of the equation with respect to s:

$$p_s(s)=\frac{d}{ds}\left[\int_{-\infty}^{r}p_r(r)dr\right]=p_r\frac{dr}{ds}=p_r\frac{d}{ds}\left[T^{-1}(s)\right] \tag{9}$$

As can be seen, the probability density function of the output image can be adjusted to a uniformly distributed histogram by the transformation function $T(r)$. This corrected image can meet the requirements of human visual perception. The following Fig 2 shows a comparison of the example defective image after enhancement using the Sobel operator and the histogram equalization (HE) algorithm.

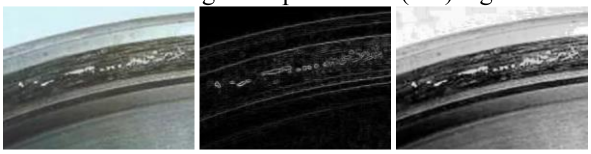


Fig. 2 shows the original image, the image enhanced by the Sobel operator, and the image enhanced by histogram equalization.

C. Ant Colony Optimization Algorithm

ACO (ant colony optimization) is a heuristic algorithm introduced by Marco Dorigo in 1997, demonstrating the potential to solve the traveling salesman problem (TSP). The algorithm simulates the natural behavior of ants in finding food through pheromone trails. In this method, agents (simulated ants) communicate through pheromones to simulate the communication between ants, transmitting information about finding the shortest path. The goal of TSP is to find the best global travel route, covering all cities and returning to the starting point. Ants accumulate information during the search process to generate short trips. They use pheromone trails on the path to select the next city to visit, preferring cities with more pheromones. In the initial stage, ants randomly select a city, and then through the iterative process, they continuously update their pheromones until the travel task is completed. Finally, using the pheromone trail update equation (11), ants with the shortest paths will update the global path GT. equation (10) is used to evaluate the path selection probability from node i to node j. Where Ω_i represents the concentration of pheromones between nodes i and j, $\tau_{i,j}$ represents the domain of the i-th node, and a and b are the adjustment parameters of the pheromones. P represents the probability that ant(k) chooses to pass through the arc (i, j), as detailed in Fig.3.

$$P^k_{i,j} = (\tau^{k-1}_{i,j})^\alpha * \eta^\beta_{i,j} + \sum_{j\int\Omega_i} (\tau^{k-1}_{i,j})^\alpha * \eta^\beta_{i,j} \tag{10}$$

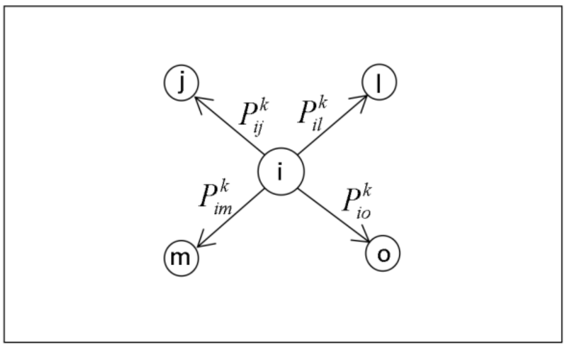


Fig. 3 Random Ant Policy

The ants need to choose $P^k_{i,o}$, $P^k_{i,j}$, $P^k_{i,l}$, and $P^k_{i,m}$ in their food search process to pass from the current city i to another city (j, l, m, o), as shown in Fig. 3. They start locally, assume a city, move from one node to another, and eventually return to the starting point, using the shortest path. Pheromones act as markers for paths in the search space, reflecting the paths most frequently used globally, helping to avoid getting stuck in local optima. To update the pheromones, formula (11) is used, where ρ is the pheromone evaporation coefficient.

$$\begin{aligned} &if\,(i,j) \in BestTour\,\tau_{ij} = (1-\rho)\tau^{(k-1)}_{ij} + \rho\Delta^k_{ij} \\ &else\,\tau^{(k-1)}_{ij} = \tau^{(k-1)}_{ij} \end{aligned} \tag{11}$$

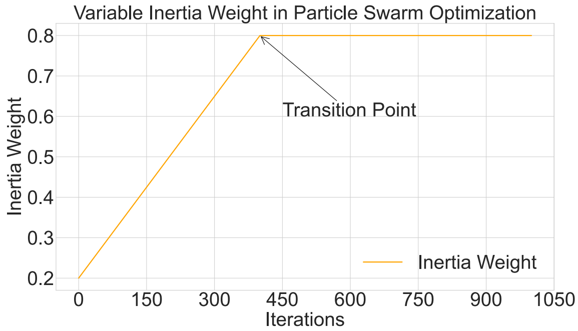


Fig. 4 Changes in Inertia Weight with Iteration Count in Standard Particle Swarm Optimization

III. The proposed CHPSO algorithm

A. Adaptive inertia weight

The adaptive inertia weight strategy in the particle swarm optimization (PSO) algorithm is crucial for balancing the algorithm's global exploration and local exploitation capabilities. Traditional PSO algorithms adjust the inertia weight linearly to balance the algorithm's exploration and exploitation capabilities to some extent. However, when dealing with complex nonlinear multidimensional function optimization problems, the algorithm is prone to being limited by local optima. This paper investigates an inertia weight determination strategy that adjusts the inertia weight (ω) based on monitoring the search situation and one or more feedback parameters [25]. During the PSO search process, the adaptive adjustment of the inertia weight is performed, considering two characteristic parameters: the velocity factor and the convergence factor. The velocity factor is defined as:

$$h^t_i = \left| \frac{\min(fit(P^{t-1}_i), fit(P^t_i))}{\max(fit(P^{t-1}_i), fit(P^t_i))} \right| \tag{12}$$

Where P^t_i is the best position found by particle i before iteration t, and $fit()$ is the function to be optimized. The clustering factor is defined as:

$$S = \left| \frac{\min(F_{tbest}, \overline{F}_t)}{\max(F_{tbest}, \overline{F}_t)} \right| \tag{13}$$

Where $\overline{F}_t$ is the average fitness of all particles in the t-th iteration group, and F_{tbest} is the best fitness achieved by a particle in the same iteration. Using the velocity and clustering factors, the inertia weight of particle i at iteration t is determined as:

$$w_i(t) = w_{\min} - \alpha(1-h^t_i) + \beta S \tag{14}$$

Where α and β are two constants usually in the range [0,1].

On the other hand, using the fitness of the particle as a feature of the particle to adjust the inertia weight of each particle. The inertia weight in each iteration is determined by the ratio of the average of the global best fitness and the particle's local best fitness.

$$w = 1.1 - \frac{fit(P_g)}{\frac{1}{n}\sum_{i=1}^{n} fit(P_i)} \tag{15}$$

Where i is the number of particles.

Assign different inertia weights to different particles based on their ranks.

$$w_i = w_{\min} + \left(w_{\max} - w_{\min}\right)\frac{Rank_i}{n} \tag{16}$$

Where $Rank_i$ represents the rank of the i-th particle when sorted based on its best fitness. The rationale behind this approach is that particles with higher fitness move more slowly in position adjustments compared to those with lower fitness:

$$P_S(t) = \frac{\sum_{i=1}^{n} S(i,t)}{n} \tag{17}$$

$$S(i,t) = \begin{cases} 1 & \text{if } fit\left(pbest_i^t\right) < fit\left(pbest_i^{t-1}\right) \\ 0 & \text{if } fit\left(pbest_i^t\right) = fit\left(pbest_i^{t-1}\right) \end{cases} \tag{18}$$

Where $P_s \in [0,1]$ represents the percentage of particles whose fitness improved in the last iteration. By using a linear function, the value of p is mapped to the possible range of inertia weights, as follows:

$$w(t) = \left(w_{\max} - w_{\min}\right)P_s(t) + w_{\min} \tag{19}$$

In this strategy, as the success rate decreases, the inertia weight decreases accordingly; conversely, as the success rate increases, the inertia weight also increases correspondingly.

A simple adaptive nonlinear strategy is introduced. The selected strategy is mainly based on the performance of each particle, specifically depending on the absolute distance between the individual best position of the particle and the global best position, which is determined during the iteration process:

$$w_i(t+1) = w_i(t) - \left(w_i(t) - 0.4\right)\times \exp\left(-\left|\left(P_g - P_i\right)\times \frac{t}{iter_{\max}}\right|\right) \tag{20}$$

This strategy considers the effects of both nonlinear and exponential inertial weights. When particles are far from the global optimum, a larger inertia weight (w) promotes more extensive exploration. However, as particles approach the global optimum, the inertia weight dynamically decreases to a smaller value (close to 0.4), facilitating deeper exploitation of the local area.

The introduced strategy covers a declining double exponential function, specifically the Gompertz function, for selecting the inertia weight.

$$w_i(t+1) = \exp(-\exp(R_i(t)))$$
$$R_i(t) = \left|P_g - P_i\right| \times \frac{iter_{\max} - t}{iter_{\max}} \tag{21}$$

Firstly, in each iteration, the performance metric (Ri) for each particle is evaluated based on its individual best position and the global best position of the swarm. These performance metrics are then fed into the Gompertz function to assess the momentum of each particle. In this strategy, the initial inertia weight is around 0.4. As iterations progress, to expedite the convergence rate, the inertia weight gradually increases, eventually reaching around 1.

This kind of strategy overcomes the limitations and assumptions of time-varying inertia weight strategies. However, it doesn't mean that adaptive methods are always superior to time-varying methods. Especially in multimodal environments, both methods can be comparable.

The inertia weight model used in this paper is the stability-based adaptive inertia weight (SAIW). The situation of each particle in the population is crucial for adjusting the inertia weight. Therefore, to adjust the inertia weight of each particle, its feedback is used. The performance of the particle reflects the trend of its memory in the last direction. In this strategy, the inertia weight value of each dimension is considered to be different, which improves the convergence speed, especially in asymmetric environments. Based on the stability condition, we use the adaptive calculation of the acceleration coefficient for each dimension's inertia weight.

The success of particle i at iteration $t+1$ is defined as:

$$\delta_i(t) = \begin{cases} 1 & \text{if } fit\left(x_i(t+1)\right) < fit\left(P_i^t\right) \\ -1 & \text{else} \end{cases} \tag{22}$$

Based on the above discussion, we introduce the following equation to determine the inertia weight:

$$W_{ij}(t+1) = \left\{\begin{array}{ll} \min\left(1, w_{ij}(t) + \left(1-w_0\right)\times \exp\left(\frac{\left(x_{ij}(t+1) - Pbest_{ij}(t)\right)^2}{-2\sigma^2}\right) + \varepsilon\right) & \text{if } \left(\delta_i(t) > 0 \text{ and } \delta_i(t-1) > 0\right) \\ \max\left(0.1, w_{ij}(t) - w_0 \times \left(\left(1 - \exp\frac{\left(x_{ij}(t+1) - Pbest_{ij}(t)\right)^2}{-2\sigma^2}\right)\right) - \varepsilon\right) & \text{if } \left(\delta_i(t) < 0 \text{ and } \delta_i(t-1) < 0\right) \\ w_{ij}(t) & \text{else} \end{array}\right\} \tag{23}$$

Where $w_{ij}(t+1)$ is the inertia weight of particle i in the $(t+1)$ iteration. w_0 is the initial inertia weight, assumed to be equal for all dimensions and particles. $x_{ij}(t+1)$ is the position of particle i in dimension j in the $(t+1)$ step. $Pbest_{ij}(t)$ is the best position of particle i in dimension j up to the $(t+1)$ step. The Gaussian kernel width (σ) is adjusted to cover the maximum particle movement. ε is a small positive number (e.g., 0.11 $\varepsilon = 0.005$) used to ensure proper increase or decrease of the inertia weight. The velocity of the particle is updated based on the neutralization of three vectors $v_i(t)$, $(P_i - x_i(t))$, and $(P_g - x_i(t))$. Their scaling parameters are w, R_1c_1, and R_2c_2.

B. Particle Swarm Optimization Algorithm

The particle swarm optimization (PSO) algorithm is a widely acclaimed optimization tool used for optimizing features by performing iterative local and global searches in feature space to find significant features. The algorithm's population consists of a group of random particles that continuously move in feature space, seeking the optimal solution through continuous iterations. This process continues until an appropriate convergence level is reached. PSO simulates the collaborative behavior of a particle swarm, enabling each particle to adjust its search position based on individual experience and information from the entire swarm, thereby efficiently finding the global optimal solution in the search space.

The basic particle swarm optimization (PSO) algorithm updates particles based on their individual historical best position (p_{best}) and the global best position of the swarm (g_{best}) to find the optimal particle. For solving an optimization problem with variables $X = \{X_1, X_2, \cdots, X_D\}$ and objective function $\min\{f(x)\}$, the basic PSO algorithm's particle update formula is given by:

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1(p_{best_{id}} - x_{id}(t)) + c_2r_2(g_{best_d} - x_{id}(t)) \tag{24}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{25}$$

The formula consists of the following variables: $v_{id}(t+1)$ and $x_{id}(t+1)$ represent the velocity and position of particle i at iteration $t+1$; w is the inertia weight, which decreases with the number of iterations in the standard PSO algorithm; c_1 and c_2 are the cognitive and social learning factors, typically set to 2; r_1 and r_2 are random numbers uniformly distributed between 0 and 1.

In the equation above, r_1 and r_2 are two increasing random numbers, ranging from 0 to 1, while c_1 and c_2 represent the weighting parameters of individual and social influences. The update velocity equation consists of three independent parts: the inertia component, the individual cognitive component, and the social contact component. In the search algorithm, the weight parameter w plays a balancing role in the inertia component. In the second part (individual cognition), information updates are based on the particle's local knowledge. Finally, in the third part, updates are made based on cooperation among particles.

C. Implementation of the Algorithm

The CHPSO algorithm is a hybrid improvement algorithm based on the particle swarm optimization (PSO) algorithm, designed specifically for image enhancement applications. This algorithm introduces an adaptive inertia weight, which improves the stability of particle positions and velocities by updating them based on the particle's position and velocity. Additionally, the CHPSO algorithm cleverly incorporates the principles of ant colony algorithms, referencing the mechanism of ants leaving pheromones when updating their positions and velocities. This makes the particle updates more efficient and accurate. Furthermore, by reselecting particles based on the pheromones left by the previous group of particles and the paths constructed, the new particle swarm is more excellent in final aggregation, resulting in better optimization results. This comprehensive improvement makes the CHPSO algorithm perform exceptionally well in image enhancement.

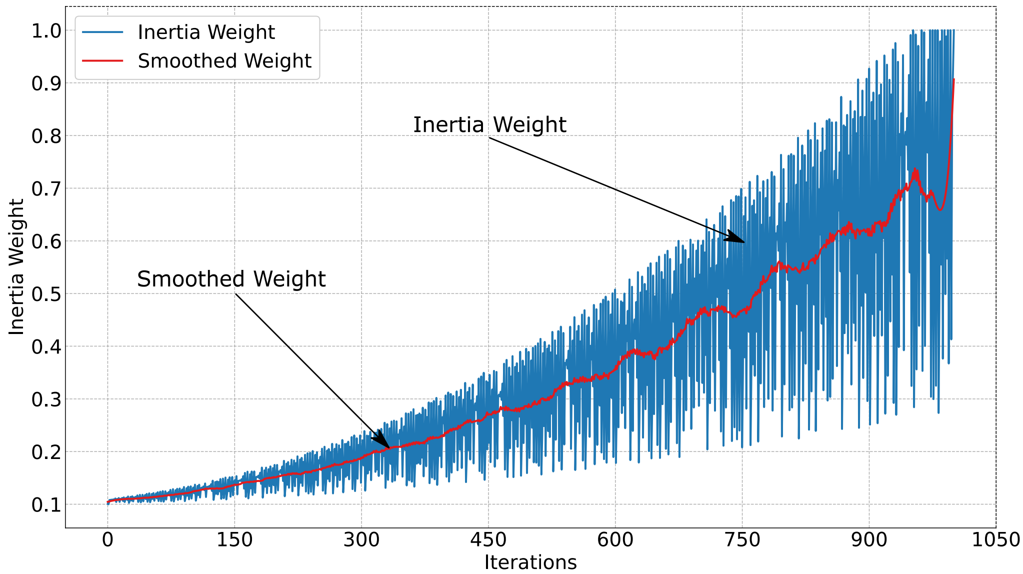


Fig. 5 Iteration-dependent transformation of adaptive inertia weight

Table I
Pseudocode of the CHPSO

```
The proposed CHPSO algorithm
Initialize the particle swarm and ant colony
Initialize the Adaptive inertia weight
Evaluate the current particle mass
while the individual particle mass has not reached the optimal quality do
    Particles randomly disperse, select a group, and leave behind pheromones
    Particles create optimal paths based on pheromones and select a new group
    if ( i > p_best ) do
        Update the Adaptive inertia weight
        Chaotic particle random distribution
      Update individual best quality and position
    end
    if ( i > g_best ) do
        Update global best quality and particle
        Update the best particle mass
    end
        Update the velocity and position of the best chaotic particle
        Define a function for updating particle positions
        Calculate the new velocity using inertia weight, individual learning factor, and social learning factor
        Calculate the new position using the new velocity
        Update the best particle swarm
end
Return the optimal solution and the objective function
```

IV. Experiments and Results Analysis

In this chapter, we tested and evaluated the performance of the proposed CHPSO algorithm through a series of industrial image enhancement experiments. Firstly, we evaluated the optimization ability of the CHPSO algorithm in image enhancement experiments using the image enhancement evaluation metrics PSNR and SSIM. Secondly, through visual comparison experiments, we intuitively demonstrated the effectiveness of the CHPSO algorithm in image enhancement. Finally, by comparing the convergence of the algorithm with various other image enhancement optimization algorithms, we comprehensively demonstrated the superiority of the CHPSO algorithm proposed in this paper. These comprehensive evaluation methods reveal the superiority of the CHPSO algorithm in industrial image enhancement.

This section compares the proposed CHPSO algorithm with some typical optimization algorithms, such as GA, ACO, original PSO, HE, and SA algorithms.

A. Evaluation Metrics

In the field of image quality assessment, peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are common standards, especially when evaluating the performance of image enhancement algorithms [26]. PSNR is used to measure the degree of loss of image quality by calculating the mean square error between the original image and the processed image, and converting it into decibels for easy understanding. A higher PSNR value indicates a higher similarity between the processed image and the original image. The formula for calculating PSNR is as follows:

$$PSNR = 20 * \log_{10}(\frac{Q-1}{RMSE}) \tag{26}$$

Where L represents the possible intensity levels in the image, and RMSE is the root mean square error, which can be determined by the following formula:

$$RMSE = \left(\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left| I_i - D_o \right|^2 \right)^{\frac{1}{2}} \tag{27}$$

Where D_o is the data of the distorted image, I_i is the input data of the original image, M and N represent the number of pixels in rows and columns, and x and y represent the respective column and row indices in the image.

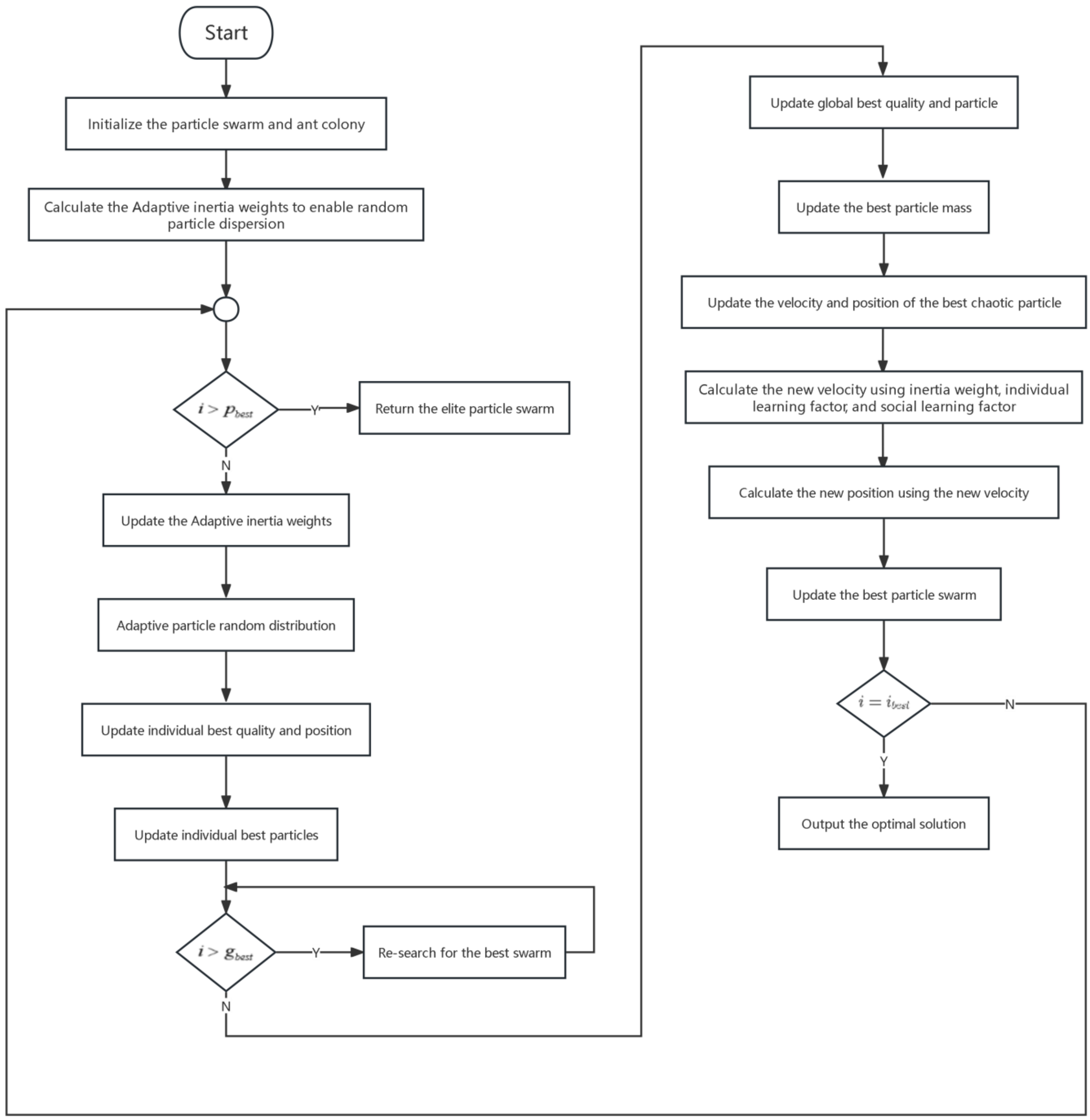


Fig. 6 Flowchart of the CHPSO

Table II

Parameter setting for GA algorithm

Parameter	Setting
Population Size	100
Crossover Probability	0.8
Mutation Probability	0.05
Number of Generations	50

Table III

Parameter setting for ACO algorithm

Parameter	Setting
Number of Ants	100
Pheromone Evaporation Rate	0.25
Pheromone Intensity	5
Heuristic Factor	3
Exploration Probability	0.25

Table IV

Parameter setting for PSO algorithm

Parameter	Setting
Number of Particles	80
Inertia Weight	0.5
Individual Learning Factor	1
Social Learning Factor	1
Max Velocity Limit	5%

Table V

Parameter setting for SA algorithm

Parameter	Setting
Initial Temperature	1000
Final Temperature	0.01
Cooling Rate	0.95
Iterations per Temperature	100

Table VI

Parameter setting for HE algorithm

Parameter	Setting
Number of Gray Levels	256

When evaluating image quality, although PSNR is widely used to measure the quality of image reconstruction, experimental results have shown that PSNR alone cannot fully reflect the actual perception of images by the human eye. Human visual sensitivity to different errors is complex and varied, and PSNR fails to comprehensively consider these perceptual factors. Therefore, to more comprehensively assess image quality, we need to combine other visual quality assessment metrics to more accurately capture the diversity of human eye perception of image details and structure.

B. Structural similarity index

The SSIM is a more comprehensive image quality assessment metric that considers not only the similarity of pixel values but also multiple factors such as luminance, contrast, and structure. Its value ranges from -1 to 1, where a value closer to 1 indicates greater similarity between the processed image and the original image. The calculation formula for SSIM includes three main components: luminance similarity, contrast similarity, and structure similarity. The final SSIM value is the weighted average of these components. Through this more comprehensive consideration, SSIM can more accurately capture the overall similarity of images in terms of luminance, contrast, and structure.

$$SSIM(x,y)=\frac{\left(2\mu_x\mu_y+d_1\right)\left(2\sigma_{xy}+d_2\right)}{\left(\mu_x^2+\mu_y^2+d_1\right)\left(\sigma_x^2+\sigma_y^2+d_2\right)} \tag{28}$$

Where x and y are the reference and segmented images, μ_x and μ_y are the mean values of x and y, σ_x and σ_y are the mean standard deviations of x and y, σ_{xy} represents the covariance of x, $d_1=(K_1L)^2$, $d_2=(K_2L)^2$, where $K_1<<1$ and $K_2<<1$.

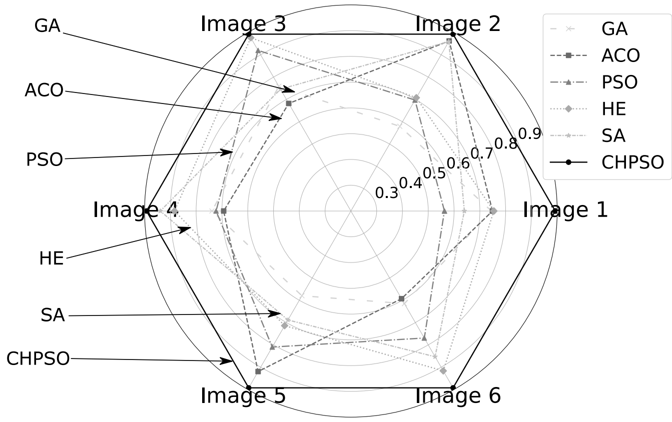


Fig. 7 presents the SSIM values of Genetic Algorithm (GA), original Ant Colony Optimization (ACO), original Particle Swarm Optimization (PSO), and CHPSO optimization algorithm in three random image enhancement experiments.

Fig 7 shows that in three random image enhancement experiments, genetic algorithm (GA) and original PSO Algorithm exhibit significant instability in SSIM values, indicating that these image enhancement methods are prone to image distortion and introduce more noise. While the original ACO algorithm shows relatively stable SSIM values in image enhancement experiments, its average SSIM value is lower compared to the CHPSO optimization algorithm proposed in this paper. The CHPSO optimization algorithm improves the SSIM index by approximately 7.2% on average compared to the other three algorithms.

Through the comparison in the above Table VII, we can clearly observe that in the six different image enhancement experiments, compared to the common genetic algorithm (GA), original ant colony optimization (ACO), histogram equalization (HE) algorithm, bat algorithm (BA), and original particle swarm optimization (PSO) algorithm, the CHPSO optimization algorithm used in this paper shows more stable and higher PSNR values in image enhancement experiments, with an average improvement of about 8.7%, demonstrating significant advantages.

Table VII

PSNR Data for Six Image Enhancement Algorithms in Six Different Image Enhancement Experiments

Image	Index	Result					
		GA	ACO	PSO	HE	BA	CHPSO
Test image 1							
	Best	34.5046	29.6829	38.1783	37.161	37.1576	39.4332
	Worst	20.2499	24.1122	26.5438	20.7892	23.5993	27.2262
	Median	26.0998	25.3786	32.017	24.0647	32.9922	33.4683
	Mean	27.6226	26.5097	32.1789	25.8219	31.57654	32.8475
	Std	6.5379	2.7511	4.1843	6.5419	4.998	2.3054
Test image 2							
	Best	37.2081	37.6031	36.5376	38.8657	35.9962	38.3247
	Worst	26.4148	20.1815	25.1869	20.2649	21.3013	25.4568
	Median	33.075	27.4819	29.1801	28.7547	25.9222	33.7525
	Mean	32.7971	29.3083	29.5440	29.0885	27.3480	36.8445
	Std	4.2696	7.9250	4.7263	7.6265	6.3257	2.9568
Test image 3							
	Best	37.9297	38.5903	39.4222	37.5099	39.7659	40.2897
	Worst	25.3297	20.6497	28.2384	20.3104	23.235	32.1879
	Median	28.5602	35.8162	29.4162	25.603	36.4522	36.1058
	Mean	29.6993	32.2211	32.5940	27.6923	32.9653	38.0875
	Std	5.0832	7.6990	5.0603	6.9974	6.9994	3.2897

Test image 4							
	Best	36.7759	34.9991	35.5712	35.7314	39.1178	43.20578
	Worst	21.9813	20.3194	25.6469	24.8766	26.3149	36.2385
	Median	31.6676	25.6514	27.0973	32.821	29.0248	40.1707
	Mean	30.9736	26.8730	29.8302	30.4046	31.4353	41.1351
	Std	5.4677	5.8270	4.5762	5.1363	5.2503	3.135
Test image 5							
	Best	32.9444	29.7943	29.2437	38.1976	39.2762	41.2487
	Worst	20.6537	23.8284	20.6799	21.9346	25.1171	36.1235
	Median	23.5131	26.7103	24.2428	25.4401	35.9632	38.2608
	Mean	26.3509	27.2312	23.9895	26.9272	33.1191	39.2672
	Std	5.4794	2.5029	3.3923	6.5158	6.1392	3.4568
Test image 6							
	Best	39.6357	39.4927	39.3635	38.3607	38.822	40.1354
	Worst	24.5062	22.1657	22.9213	20.5187	27.4642	26.2467
	Median	30.4042	27.1452	32.3793	29.784	34.1687	37.3573
	Mean	31.4111	29.3839	30.163	30.0598	33.7387	35.2655
	Std	5.4703	6.8980	6.9038	8.2243	4.7371	3.2662

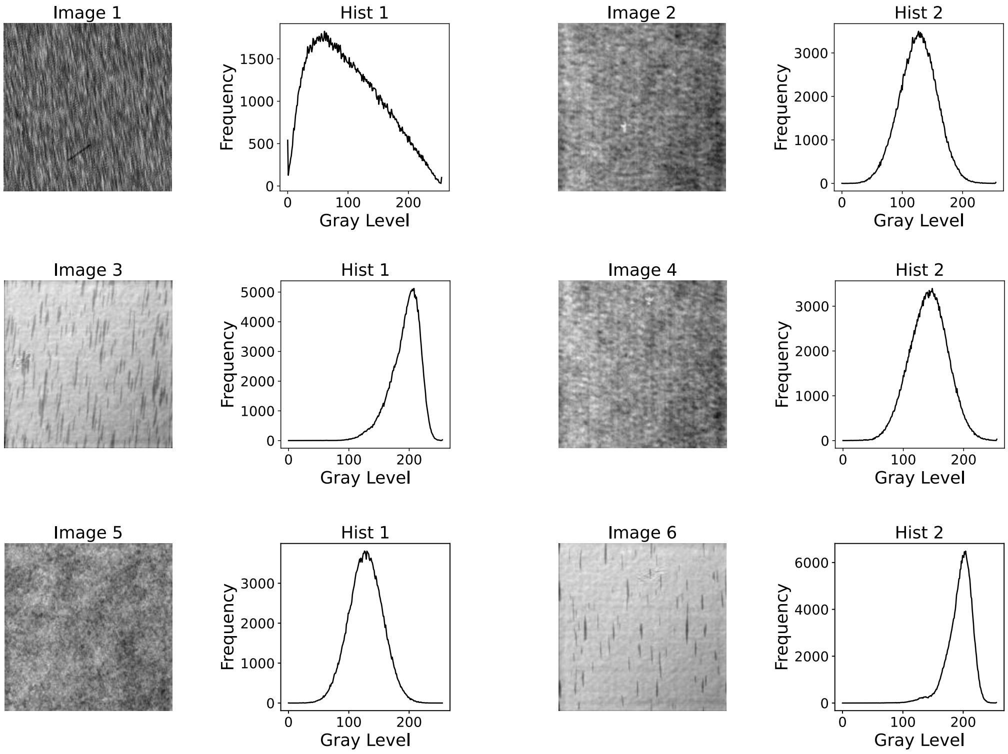


Fig. 8 Original Images of Common Defects in Various Products and Their Grayscale Histograms

C. Visualization of Image Enhancement Experiments

To verify the effectiveness of the CHPSO algorithm proposed in this paper for image enhancement, we selected six images with different defects from a network database, and one image was selected for each type of defect for the verification of the method's effectiveness. The original images and their respective grayscale histograms are shown below. To demonstrate the superiority of the image enhancement method based on the CHPSO algorithm proposed in this paper, we compared it with genetic algorithm, original ant colony algorithm, and original PSO algorithm. The following Fog.8 shows the visual comparison of the enhancement effects of surface defects in four products using genetic algorithm, original ant colony optimization algorithm, original particle swarm optimization Algorithm, and the CHPSO optimization algorithm proposed in this paper. Genetic algorithms, while capable of enhancing contrast and preserving details locally, tend to introduce issues such as over-enhancement, noise amplification, and texture distortion. Ant colony algorithms, while possessing the ability to adjust brightness and contrast, may lead to information loss, color distortion, as well as global equalization and noise enhancement. In the image enhancement experiments of surface oil stains, surface damage, and surface scratches on steel surfaces, both of these algorithms exhibited some significant flaws, such as the disappearance of defect detail features. In contrast, the product surface defect image enhancement method based on the CHPSO optimization algorithm proposed in this paper performed better. Compared to other algorithms, this method not only better preserves defect features but also has superior background processing capabilities, demonstrating better results in the image enhancement experiments of surface oil stains on steel and surface scratches on wood.

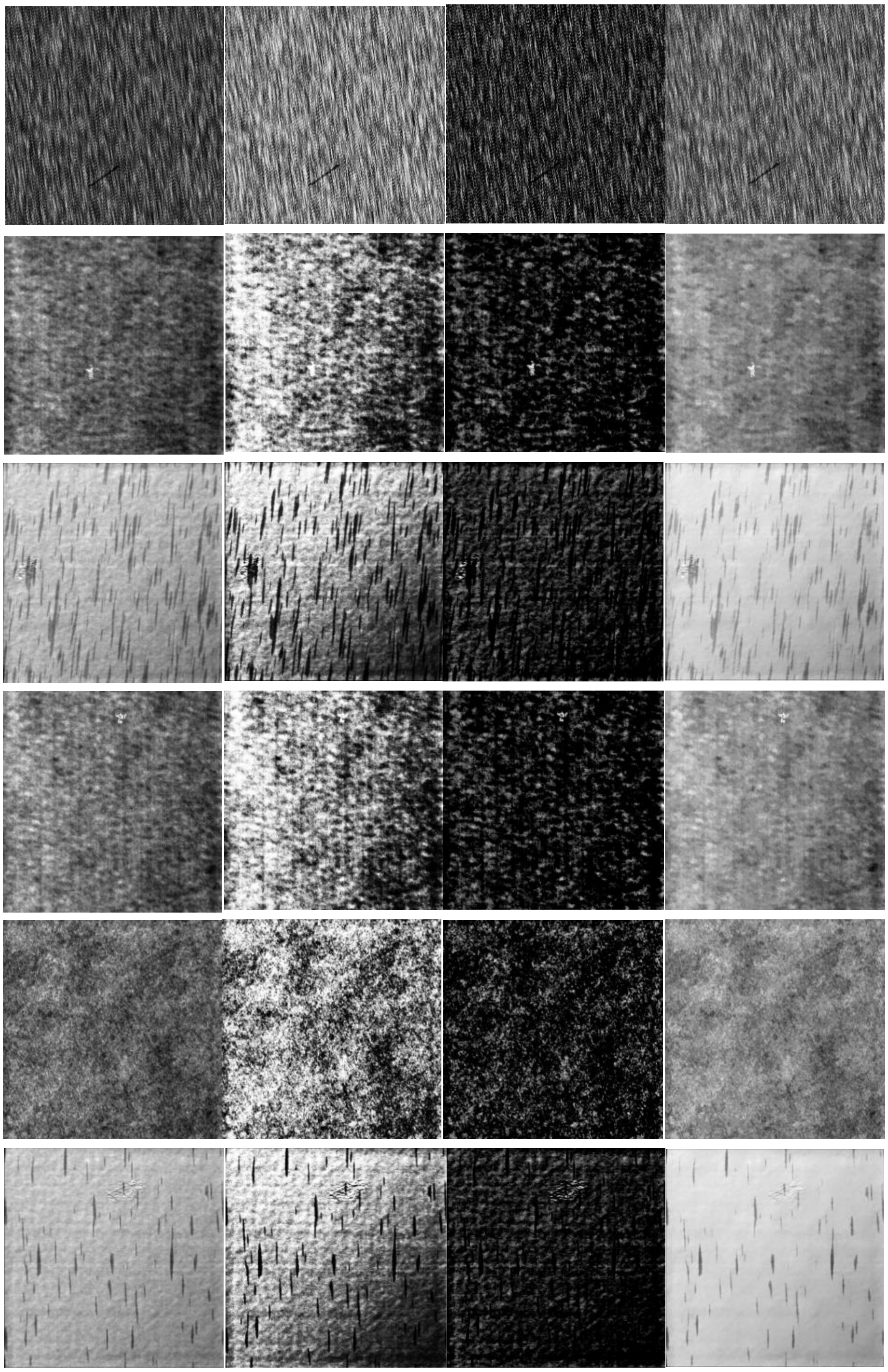
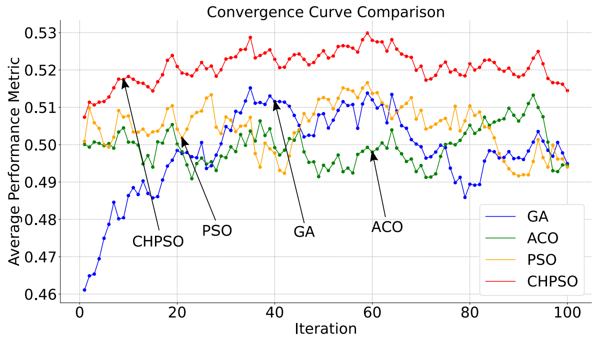


Fig. 9 Visual comparison of the effects of image enhancement methods on surface defects of four products

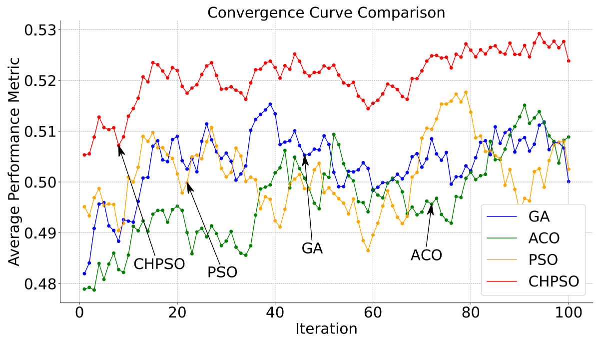
D. Convergence and Stability Comparison of Algorithms

The following Fig 10 shows a comparison of the convergence performance of four optimization algorithms. The convergence performance of the algorithms is evaluated by observing the convergence index reached within a certain number of iterations. A higher index value indicates better convergence performance.

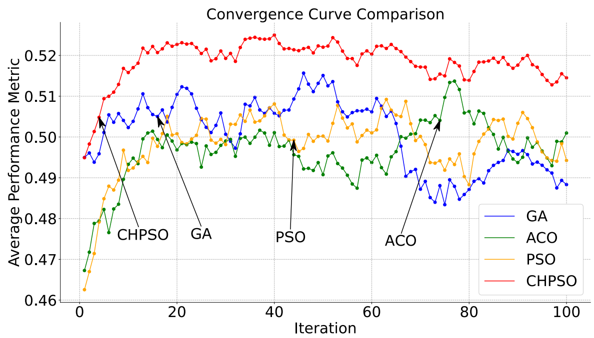
As shown in the Fig 10, in the 6 comparative experiments on the convergence of optimization algorithms, the CHPSO proposed in this paper outperforms the traditional 3 image enhancement optimization algorithms (i.e., GA, ACO, PSO algorithms) in terms of algorithm convergence performance by an average of approximately 9.4% in 100 iterations. The curves in the figure also indicate that in the 6 comparative experiments, the stability of the CHPSO algorithm is significantly better than that of the other 3 algorithms.



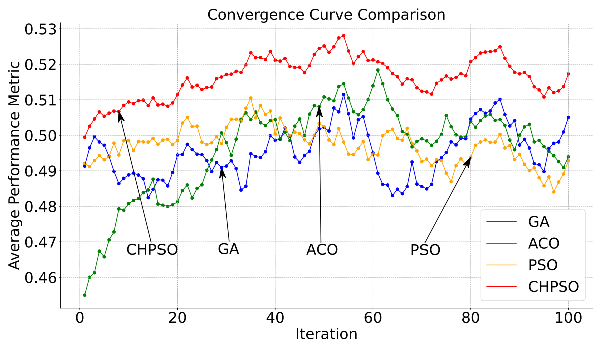
（a）Convergence curve for test image 1



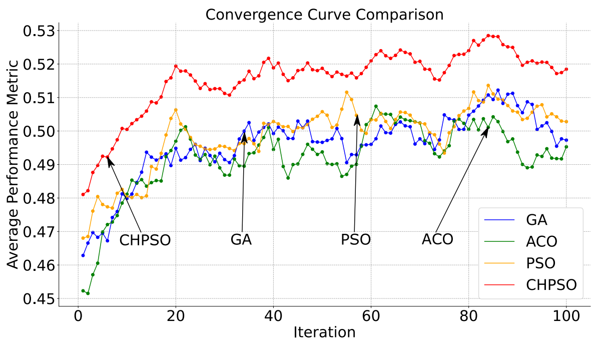
（b）Convergence curve for test image 2



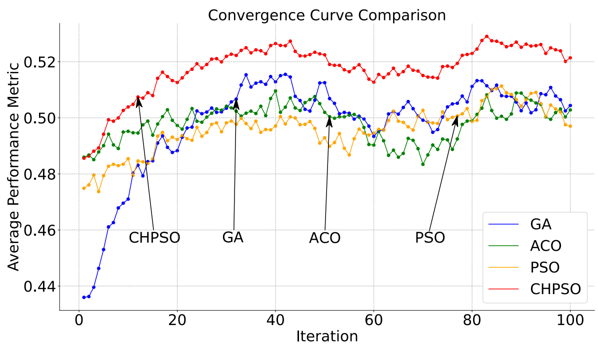
（c）Convergence curve for test image 3



（d）Convergence curve for test image 4



（e）Convergence curve for test image 5



（f）Convergence curve for test image 6

Fig. 10 Comparison of convergence performance among four algorithms using LGE transformation.

V.Conclusions

The CHPSO image processing technique proposed aims to improve image enhancement efficiency. Firstly, the algorithm improves stability by introducing a stability-based adaptive inertia weight. Secondly, it enhances cooperation and collaborative search by combining the information transmission mechanism of ant colony algorithms with PSO, enabling particles to share information. This method is based on the mechanism where ant colony algorithms release pheromones to attract other particles to form the optimal path. It selects and updates data based on the shortest path determined by pheromone concentration, thereby enhancing the algorithm's optimization strength and spatial search capability. This improvement significantly improves the algorithm's convergence speed. Experimental results show that the CHPSO algorithm outperforms traditional optimization algorithms by 8.7%, 7.2%, and 9.4% in terms of PSNR, SSIM, and algorithm convergence performance, respectively, demonstrating its significant engineering value in image enhancement. These results indicate that the CHPSO algorithm has a notable improvement effect in image enhancement tasks, demonstrating its advantages and potential in improving image quality.

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Dajian Yi is currently a master's student in the School of Mechanical Engineering at Zhejiang Sci-Tech University. He received his bachelor's degree from Lishui University in 2022. Her research focuses on Machine Vision and Mechatronics Integration.

Zhangping You works as a professor in the School of School of Engineering at Lishui University. He received a bachelor's degree in Mechanical Design, Manufacturing, and Automation from Changsha University of Science and Technology in 2001, a master's degree in in Mechanical Design and Theory in 2004, and a PhD in Mechatronic Engineering from Tongji University in 2011. His research interests include intelligent control of mechatronic systems, equipment condition monitoring, and fault diagnosis, etc.

Wenhui Zhang works as a professor in the School of Electronic Engineering at Nanjing Xiaozhuang University. He received a bachelor's degree in Mechanical Design, Manufacturing, and Automation from Harbin Institute of Technology in 2004, a master's degree in Aerospace Engineering in 2008, and a PhD in Aerospace Science and Technology in 2011. His research interests include robotics technology and intelligent control, machine vision and mechatronics integration technology, etc.