Journal of Computers Vol. 34 No. 2, April 2023, pp. 1-17
doi: 10.53106/199115992023043402001

Image Segmentation Method Based on Improved PSO Optimized FCM Algorithm and Its Application

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Received 1 February 2021; Revised 2 June 2021; Accepted 2 July 2021

Abstract. In image segmentation, FCM clustering algorithm can not find the optimal initial clustering center and fall into local extremum, which leads to the decrease of image segmentation accuracy. The PSO algorithm has strong optimization ability, so a new method based on improved PSO algorithm is proposed to optimize the FCM clustering center selection. Firstly, the optimization performance of the PSO algorithm is improved. The distance difference between each particle and the optimal particle is calculated, and the maximum distance difference is selected. The ratio of the distance difference to the maximum distance difference and the aggregation degree of particles are used to construct the natural exponential function. This natural exponential function is used to improve the calculation method of inertia weight value of PSO algorithm, so that the farther the particle is away from the optimal position, the larger the inertia weight value it will get, the stronger the global search ability of particle; on the contrary, the smaller the inertia weight value, the stronger the local search ability of particle, so as to improve the optimization ability of PSO algorithm. The improved PSO algorithm is called DDPSO (Distance Difference PSO). Then the optimized FCM algorithm is applied to the segmentation of standard image and eggshell damaged image to improve the accuracy of image segmentation. Finally, the experimental results show that the FCM algorithm optimized by DDPSO has higher segmentation accuracy than the traditional method.

Keywords: PSO algorithm, inertia weight, FCM algorithm, image segmentation

1 Introduction

With the development of computer vision technology, image segmentation technology has been paid more and more attention. It has a wide range of applications in medical, agricultural, meteorological and other fields. Image segmentation is to divide the image into non overlapping sub regions according to the characteristics of different regions. The same region has the largest similar features, and the different regions have the smallest similar features. Therefore, the process of image segmentation is also a process of clustering according to the characteristics of image regions. In recent years, with the increase of image complexity and data volume, image segmentation has higher requirements for segmentation accuracy. The accuracy of image segmentation is still one of the research hotspots in the field of machine vision. In the research of image segmentation, the commonly used methods are segmentation method based threshold, segmentation method based edge, segmentation method based clustering and so on. Among these methods, the image segmentation method based on clustering is widely used because of its simple algorithm and good segmentation effect. The most commonly used algorithm in clustering is fuzzy C-means (FCM) clustering algorithm [1-3]. FCM algorithm was proposed by Bezdek in 1973. It is a clustering algorithm based on objective function and membership degree. FCM algorithm in image segmentation, according to the characteristics of the image pixels gathered into several classes, so that the same pixels gathered in the same area, to achieve image segmentation [4-5]. Based on the demand of "earth thesis project" for egg quality detection, the cluster center of FCM algorithm is selected by the optimized PSO algorithm, so as to improve the accuracy of image segmentation.

Although FCM algorithm has strong clustering performance, but it also has some problems, such as the selection of the initial clustering center has a great impact on the clustering results, prone to local convergence and sensitive to noise. Many researchers have optimized the shortcomings of FCM in application. For example, Ding et al used improved adaptive genetic algorithm and kernel optimization technology to optimize the initial clustering center of FCM algorithm [6]; Shamshirband et al used the comparison of the size of each sample density

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value to select the clustering center of FCM algorithm [7]; Zarinbal et al. added relative entropy as regularization function into the objective function of FCM algorithm to increase the difference between clusters [8]; Kannan et al. introduced a stable non Euclidean distance measure into the original data space to derive a new objective function, so as to cluster the non Euclidean structure in the data, which improved the robustness of FCM algorithm and reduced the noise and outliers [9]; In the early years, Krishnapuram et al. reduced the original membership constraint to [0,1] to overcome the noise sensitivity of FCM algorithm [10]; Cherkasky et al. further optimized the membership constraint based on Krishnapuram [11].

These researchers have done a lot of work on the optimization of FCM algorithm clustering performance. In many researches on FCM performance optimization, it is an important research direction to combine other algorithms, such as PSO algorithm, to optimize FCM algorithm. For example, many scholars have optimized the initial clustering center selection of FCM algorithm. Among many optimization methods, particle swarm optimization (PSO) is the most widely used. This is because PSO algorithm is easy to implement, needs to set fewer parameters. It has the advantages of efficient parallel search, which can effectively solve complex optimization problems. The initial clustering center selection of FCM algorithm is just an optimization problem [12-13]. However, PSO algorithm is also easy to fall into local optimum, which affects the accuracy of FCM algorithm initial cluster center selection. Therefore, in the research, the optimization performance of PSO algorithm is usually improved first, and then the improved PSO algorithm is used to optimize FCM algorithm, so as to improve the accuracy of initial clustering center selection of FCM algorithm. Such studies as Peng X proposed an improved PSO algorithm by considering the local and global optimization capabilities. The improved algorithm can not only effectively avoid the algorithm falling into local optimal value, that is mainly due to the manual setting of FCM initial value, but also has better accuracy and anti-noise performance than traditional FCM [14]. Hanuman Verma proposed a hybrid FCM-PSO algorithm by combining the excellent features of FCM and PSO algorithm. The new algorithm solves the problem that FCM frequently trapped into local minima during execution, which leads the undesired clustering results, while dealing with complex problems such as medical image data. Experimental results show that the proposed hybrid FCM-PSO algorithm is effective [15]. Telmo M. Silva Filho proposed two hybrid fuzzy clustering methods to solve these problems. The methods combine FCM with the IDPSO, which adjusts PSO parameters dynamically during execution. It can provide a better balance between exploration and exploitation. That can avoid falling into local minima quickly. [16]. Gao Qinqing tries to achieve the best image enhancement function with the help of improved PSO. In the paper, parameterized transformation function is used, which uses global and local information of the image. In the paper, an objective criterion for image enhancement is proposed, which considers both image entropy and edge information [17]. These studies have achieved very good results.

Not limited to the above introduction, many researchers have done a lot of work on FCM clustering performance optimization using PSO algorithm. Based on the summary of these works, this paper presents a new method to calculate the inertia weight of PSO algorithm. This method considers the distance difference between the particle and the optimal particle in each iteration. The iteration of the algorithm is guided by the optimal particle, and the aggregation degree of particles is also considered. So that the particle has a dynamic balance between the global search and local search, and the particle has a better optimization ability. The improved PSO algorithm DDPSO is applied to the selection of FCM initial clustering center, to improve the clustering accuracy of FCM algorithm. In this paper, DDPSO-FCM is compared with FCM, IPSO-FCM and HFCM-PSO in segmentation of standard image and eggshell damaged image. The results show that compared with the other three methods, the DDPSO-FCM algorithm has clearer image boundary, more complete details and better segmentation of the target and background. At the same time, this paper also makes a quantitative comparison between VBX and um. The results show that the Vbx and UM values of DDPSO-FCM algorithm are the smallest among the four algorithms, which shows that the segmentation effect of DDPSO-FCM algorithm is the best among the four algorithms. DDPSO algorithm selects an excellent clustering center for FCM algorithm, and the optimization performance of DDPSO algorithm is improved in this paper.

2. Analysis and Improvement of PSO Algorithm

2.1. Improvement of PSO Algorithm

Particle swarm optimization (PSO) is an efficient global optimization algorithm, which simulates the principle of birds foraging in nature to find the optimal solution of a solution space. The algorithm first selects a group of particles, these particles are like birds, to search for food in the solution space, that is, to find the optimal solution, all particles have to pass through the objective function to evaluate the fitness, through the fitness to adjust the speed and direction of particles, gradually close to the optimal solution, and finally reach the optimal solution. The mathematical model of the algorithm is as follows [18].

Suppose that the space solved by PSO algorithm is N-dimensional, that is, there are N particles representing the solution, then the position of the i-th particle in the D-dimensional search space is $x_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{iD}\}^T$, and the velocity of the particle is $v_i = \{v_{i1}, v_{i2}, v_{i3}, \ldots, v_{iD}\}^T$. In each iteration process, the particle position and velocity should be changed according to the individual optimal value Pbest and the population optimal value Gbest to make the particle approach the optimal solution. We use $pb_i = \{pb_{i1}, pb_{i2}, pb_{i3}, \ldots, pb_{iD}\}^T$ as the individual optimal value and $pg = \{pg_{i1}, pg_{i2}, pg_{i3}, \ldots, pg_{iD}\}^T$ as the group optimal value. When the i-th particle is in the m-th iteration, its next iteration speed is expressed by formula (1), and its position is expressed by formula (2). Through this step-by-step iteration, the particle tends to the optimal solution.

$$v_i(k+1) = wv_i(k) + c_1 r_1 (pb_i - x_i(k)) + c_2 r_2 (pg - x_i(k)), \tag{1}$$

$$x_i(k+1) = x_i(k) + v_i(k+1). \tag{2}$$

Where, ω is inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers between [0,1].

In formula (1), the particle velocity is composed of three parts, $wv_i(k)$ is the inertia of the particle's previous motion, which is the influence of the particle's previous search state on the current search behavior, and ω is the inertia weight; $c_1r_1 (pb_i - x_i (k))$ is the particle's self cognition part, which is the influence of the particle's self search experience; $c_2r_2 (pg - x_i (k))$ is the particle's group cognition, which is the sharing of particle group search information. Formula (2) is an update of the position, which is determined by the current position and velocity of the particle. Then the individual extreme value pb_i and population extreme value pg in PSO algorithm are updated by formula (3) and formula (4), Formula (5) is used to describe the aggregation degree of particles, f is the fitness function and τ is the adjustment factor. [19-20].

$$pb_i = \begin{cases} x_i, & if(x_i) < if(pb_i) \\ pb_i, & \text{others} \end{cases}, \tag{3}$$

$$pg = \begin{cases} x_i, & if(x_i) < if(pg) \\ pg, & \text{others} \end{cases}, \tag{4}$$

$$\lambda(t) = \tau(t) \cdot f(pg(t)) / f\overline{(pb_i(t))}. \tag{5}$$

Based on the above model, we can know that the inertia weight ω plays a crucial role in regulating the convergence performance of the whole particle swarm. When the value of ω is too large, the global convergence performance of the particle swarm will be greatly improved, and the particle swarm will converge rapidly, but the accuracy of searching the optimal solution will be greatly reduced; On the contrary, if the value of ω is too small, the local convergence performance of the particle will be greatly improved, the algorithm will converge to the optimal solution very well, but it will also increase the probability of the particle falling into the local optimal solution, and the optimization efficiency will be greatly reduced. To solve these problems, we discuss how to adjust the convergence rate of particles by improving the inertia weight ω to balance the local and global convergence performance of each particle [21].

In the PSO algorithm, the optimization state of each particle after each iteration is different, but from formula (1), it can be seen that the biggest external influence on the optimization ability of each particle is the optimal position of the population, except for itself. Therefore, the gap ratio between the particle and the optimal position is considered, as shown in formula (8), the adaptive inertia weight $\omega_i(t)$ of the particle is set, which is calculated by formula (9). In formula (9), in order to change the previous linear setting of inertia weight, the exponential relation is introduced. Formula (6) calculates the distance between the current position and the optimal position of the particle.

$$l_i(t) = \sqrt{\sum_{d=1}^{D} (x_{id}(t) - g_d)^2} , \tag{6}$$

$$\Delta l_i(t) = \max\{l_i(t)\} - l_i(t), \tag{7}$$

$$G_i(t) = -\frac{\lambda(t)\Delta l_i(t)}{\max\{\Delta l_i(t)\}}, \tag{8}$$

$$w_i(t) = w_{\min} + (w_{\max} - w_{\min}) \cdot e^{G_i(t)}. \tag{9}$$

Among them, g_d is the optimal position of the population. t is the current iteration number, ω_{max} is the maximum value of inertia weight setting, ω_{min} is the minimum value of inertia weight setting, and max{ } is the maximum value.

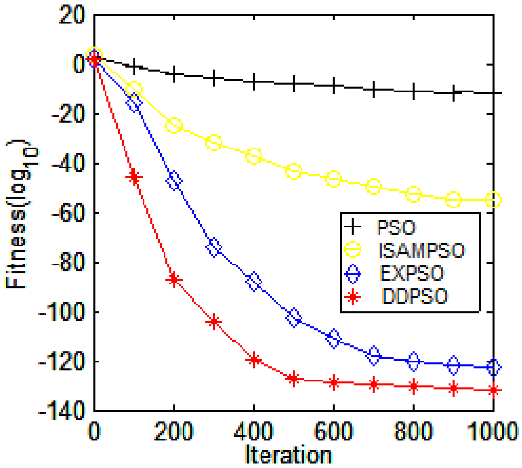
From formula (6), it can be found that the farther the current particle position is from the optimal position, the greater the value of $l_i(t)$; In formula (7), compared with other particles, the larger the value of $l_i(t)$, the smaller the value of $\Delta l_i(t)$; Similarly, in formula (8), the smaller the value of Δl_i (t), the larger the value of $G_i(t)$, and the larger the value of $e^{Gi(t)}$ when it is an increasing function, thus the larger the value of $\omega_i(t)$. To sum up, the farther the particle is away from the optimal position, the greater the inertia weight value it will get, so the particle will get stronger global search ability, make the particle converge to the global optimal solution quickly, and improve the convergence speed of the algorithm; On the contrary, the particle will get stronger local search ability, make the particle have higher search accuracy, improve the accuracy of the algorithm.

2.2. Performance Analysis of Improved PSO Algorithm

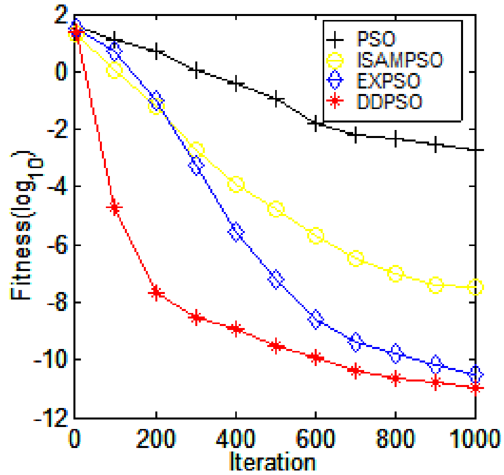
In order to verify the performance of the improved PSO algorithm in this paper, based on the above improved PSO algorithm DDPSO, compared with the improved PSO algorithm ISAMPSO in reference [22] and the improved PSO algorithm EXPSO in reference [23]. In the experiment, Sphere, Griewank, Rastrigrin, Ackley, Rosenbrock and DeJong's six standard test functions are used to compare the optimization performance of standard PSO algorithm, ISAMPSO algorithm, EXPSO algorithm and DDPSO algorithm. The specific function parameters are shown in Table 1, and the minimum value of the six standard functions is 0. In the experiment, the original parameters in reference [22] and reference [23] are selected, and the thresholds are unified. For the stability of the experimental results, 30 experiments are carried out, and the final result is the average of the 20 experimental results. The comparison curve of optimization convergence effect is shown in Fig. 1.

Table 1. Standard test function

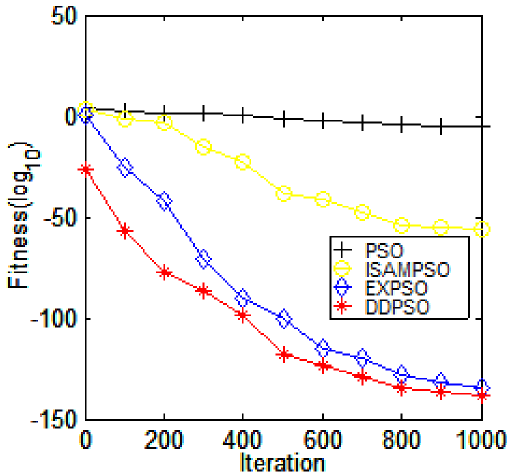
Function name	Function	Threshold	Optimal value
Sphere	f_1	(-100,100)	0
Griewank	f_2	(-600,600)	0
Rastrigin	f_3	(-5.12,5.12)	0
Ackley	f_4	(-32,32)	0
Rosenbrock	f_5	(-5.12,5.12)	0
DeJong's	f_6	(-100,100)	0



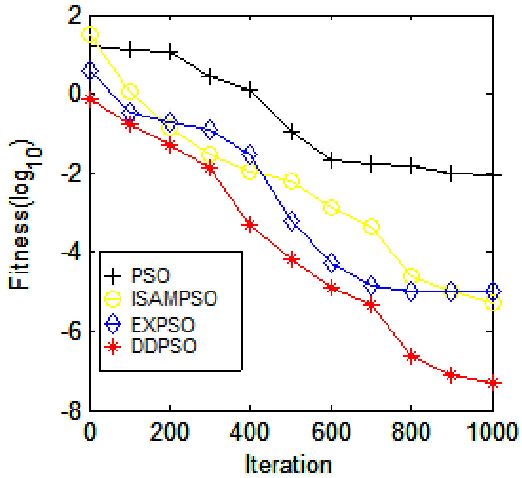
(a) f1 convergence curve



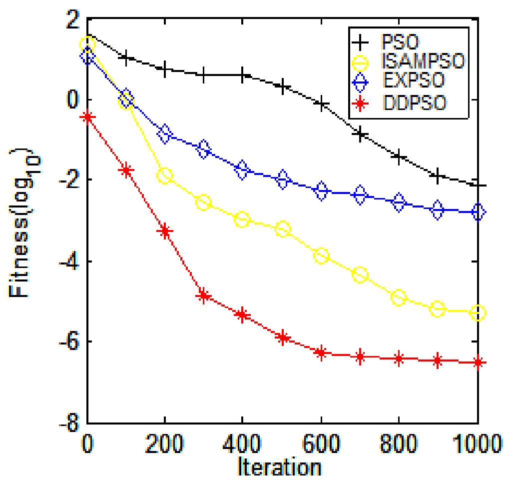
(b) f2 convergence curve



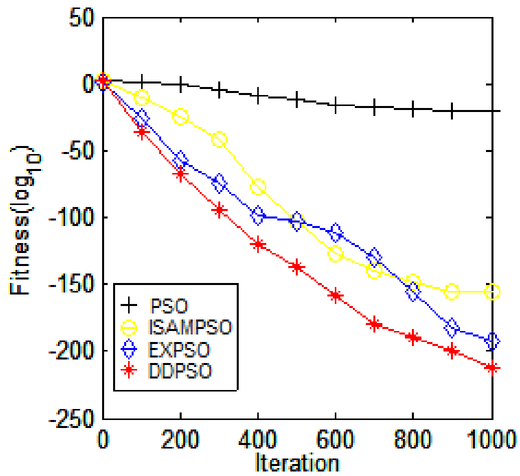
(c) f_3 convergence curve



(d) f_4 convergence curve



(e) f_5 convergence curve



(f) f_6 convergence curve

Fig. 1. Comparison of convergence of function f_1~f_6

From the simulation results of the convergence of six standard functions in Fig. 1, it can be concluded that the improved PSO algorithm DDPSO, on the basis of 1000 iterations, is better than the standard PSO algorithm, ISAMPSO algorithm and EXPSO algorithm in the optimization effect of functions $f_1 \sim f_6$. Especially for functions f_1, f_2, f_3 and f_5, the improved PSO algorithm has faster convergence speed than the other three algorithms in the first 200 iterations. In the final 1000th optimization result, DDPSO algorithm is the smallest and the best, except for f_2 and f_3 function, the effect is very significant in the other four functions. In the experiment, the standard PSO algorithm is the worst for the six standard functions, while ISAMPSO algorithm and EXPSO algorithm have their own advantages and disadvantages. In the optimization of function $f_1 \sim f_3$, EXPSO algorithm is obviously better than ISAMPSO algorithm; in the optimization of function f_5, ISAMPSO algorithm is obviously better than EXPSO algorithm; in the optimization of function f_6, EXPSO algorithm is slightly better than ISAMPSO algorithm; in the optimization of function f_4, there is not much difference between them.

In the final optimization results of $f_1 \sim f_6$ standard functions, the improved PSO algorithm DDPSO is the best. This is mainly because the PSO algorithm in this paper fully considers the influence of the optimal position of the particle population on the global optimization, such as formula (5). Finally, the optimal position of population is set by the ratio of the gap between particle and optimal position, such as formula (7). Therefore, the particle can quickly approach the optimal solution and improve the convergence speed of the algorithm. In addition, the original linear inertia weight coefficient setting method is changed, and the exponential relationship particle inertia weight coefficient $\omega_i(t)$ setting method based on the gap ratio between the particle and the optimal position, such as formula (8), is introduced to enhance the optimization ability of the particle.

3. DDPSO Optimized FCM Clustering Center Selection

FCM algorithm, due to its own fuzziness and unsupervised, can achieve good image segmentation results when applied in image segmentation. In FCM algorithm, there are n samples of data set $X=(x_1,x_2,\ldots,x_n)$. If the samples of X data set are divided into s classes, the optimization objective function J of FCM algorithm is as follows:

$$J_{FCM}^{m}(U,C,X)=\sum_{i=1}^{s}\sum_{j=1}^{n}u_{ij}^{m}d_{ij}^{2}. \tag{10}$$

Where C is the cluster center, $C=\{c_1,c_2,c_3,\ldots,c_s\}$, sample x_i has a membership degree u_{ij} in each cluster center, and m is the weighted index. In formula (10), d_{ij} is the distance between the i-th center and the j-th sample point, as shown in formula (11) [24-25].

$$d_{ij}=\left\|c_i-x_j\right\|. \tag{11}$$

Generally, u_{ij} should satisfy the following constraints:

$$\sum_{i=1}^{s}u_{ij}=1 \quad (1\le j\le n), \tag{12}$$

$$\begin{aligned}&\sum_{i=1}^{s}u_{ij}=1 \ (1\le j\le n),\\ &u_{ij}\ge 0 \ \ (1\le i\le s,\ 1\le j\le n).\end{aligned} \tag{13}$$

FCM algorithm is a local search algorithm. When FCM algorithm is used for image segmentation, it is easy to fall into local optimum. One of the key factors affecting the convergence of the algorithm is the selection of the initial clustering center. FCM algorithm is very sensitive to the selection of the initial clustering center, which will have a direct impact on the convergence and efficiency of the algorithm. The PSO algorithm has better global optimization ability. Therefore, we choose DDPSO algorithm to select the FCM optimal cluster center, which can reduce the probability of the algorithm falling into local optimal, and improve the classification accuracy and convergence efficiency of FCM algorithm. When using DDPSO to optimize FCM clustering centers, each particle p_i of DDPSO contains s clustering centers, and each particle represents the possible solution of a clustering center selection scheme. $x_i=(v_{i1}, v_{i2}, v_{i3}\ldots v_{is})$, where $v_{ij}(j=1,2,3,\ldots,s)$ represents the j-th central coordinate of the i-th particle.

In order to meet the need of optimizing FCM clustering center by DDPSO, a particle fitness function f is constructed. In DDPSO algorithm, the larger the fitness value f is, the better the result is; The smaller J is expected to be, the better the FCM algorithm is. The smaller J is, the higher the clustering accuracy of FCM algorithm is. In conclusion, the fitness value f of particles is inversely proportional to the value J of FCM clustering objective function. Therefore, the fitness function f of DDPSO algorithm is constructed as follows [26]:

$$f(p_i)=\frac{1}{J_{FCM}^{m}(U,C,X)+\theta}. \quad \textbf{(14)}$$

Where, the parameter θ in formula (14) is the adjusted value of the fitness function f of the particle, and is taken as $\theta \sim U(0.8,\ 1.2)$.

The above formula (14) is used as the particle fitness function of the improved PSO algorithm to optimize the FCM initial clustering center. When f value reaches the end of optimization, DDPSO algorithm converges to the optimal value, that is, DDPSO algorithm searches the optimal initial clustering center of FCM. In this paper, the improved PSO algorithm is used to optimize the FCM algorithm clustering center selection. The steps are as follows:

Table 2. The steps of FCM clustering center selection

Algorithm. DDPSO optimizes FCM clustering center
Input: Data set X, cluster number s, DDPSO parameters and stop conditions
Output: Optimal cluster center
(1) Initial cluster number s, weighted index m, DDPSO population size N, maximum number of iterations t_{max},maximum and minimum value of inertia weight ω, ω_{max} and ω_{min}, learning factors c_1, c_2 and other parameters.
(2) The population P is obtained by coding the particles. The individual and global optimal positions of the particle swarm are initialized.
(3) The fitness value f of particles is calculated by formula (14).
(4) The inertia coefficient $\omega_i(t)$ is updated by formulas (6) - (9).
(5) The individual optimal value pb_{iD} and global optimal value pg of particles are updated by formulas (3) - (4).
(6) If the maximum number of iterations is reached, the algorithm ends and the initial clustering center is obtained. Otherwise, go to step (3) to continue.

4. Segmentation of Eggshell Damaged Image Based on Optimized FCM Algorithm

In order to improve the speed of FCM algorithm for image segmentation, the eggshell damaged images are processed into gray images, the gray level is 256. In order to improve the efficiency of image segmentation, the gray histogram of image is introduced into the optimization objective function J of FCM algorithm. After introducing the gray histogram, the expression of objective function J of FCM is shown in formula (15), and the termination condition of FCM is shown in formula (16).

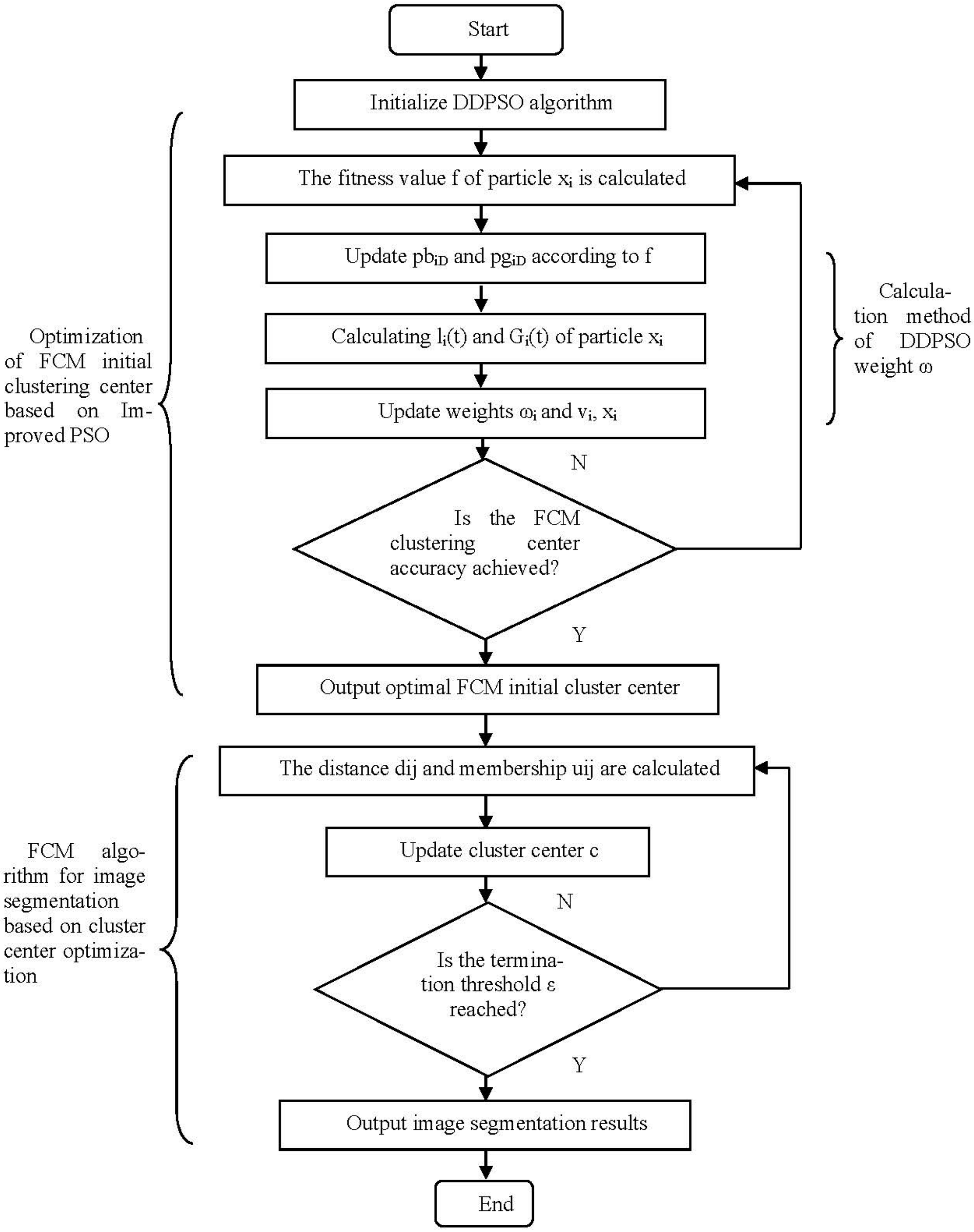


Fig. 2. Flow chart of image segmentation based on DDPSO optimized FCM

$$J_{FCM}^{m}(U,C,X)=\sum_{i=1}^{s}\sum_{j=0}^{r}u_{ij}^{m}d_{ij}^{2}h(j)\,, \tag{15}$$

$$\begin{aligned}&J_{FCM}^{m}(U,C,X)=\sum_{i=1}^{s}\sum_{j=0}^{r}u_{ij}^{m}d_{ij}^{2}h(j),\\&\left\|c_i-c_{i+1}\right\|<\varepsilon.\end{aligned} \tag{16}$$

Where r is the gray level of the image and h(j) is the gray histogram. c_i, c_{i+1} represents the clustering center of the i-th and (i+1)-th iterations of FCM [27].

By introducing gray histogram into the objective function J of FCM algorithm, and combining with the improved PSO algorithm above, a more appropriate FCM clustering center can be selected to achieve more accurate segmentation of eggshell damaged image. For gray image, $x_i,v_i \in [0,255]$ in DDPSO, the segmentation process of eggshell damaged image based on DDPSO optimized FCM is shown in Fig. 2.

5. Experiment and Result Analysis

In order to verify the performance of FCM algorithm optimized by DDPSO algorithm for eggshell damaged image segmentation, the performance of FCM algorithm optimized by DDPSO algorithm (DDPSO-FCM) is compared with standard FCM algorithm, FCM algorithm in reference [14] (IPSO-FCM) and FCM algorithm in reference [15] (HFCM-PSO). The platform environment parameters used in the comparative experiment are shown in Table 3, and the parameter settings of the four FCM algorithms are shown in Table 4. All FCM algorithms combine local spatial information and gray level information. The experiment was divided into two groups. The first group selected the standard images commonly used in image processing for segmentation and contrast, the lena, the peppers and the camera man image were selected for the experiment. The second group was to segment and contrast the damaged egg shell images. In the experiment, 300 samples of damaged eggshell were collected. According to the statistics of damaged eggshell shape, the 300 samples were divided into three categories: 68 cracks, 135 holes, 97 cracks and holes. In the experiment, the damaged eggshell images were all processed into gray images. The experiment and data analysis are based on the above sample set.

In the experiment, the visual effects of four FCM algorithms on three standard images and three kinds of eggshell damaged images segmentation are compared, and different eggshell damaged situations are compared, such as crack damaged, hole damaged, crack and hole damaged eggshell image, the segmentation effect is shown in Fig. 3 to Fig. 8. At the same time, the experiment also compares the performance of four FCM algorithms, mainly compares the Xie-Beni index Vxb and the uniformity measure index UM of the four algorithms, as shown in Fig. 9 to Fig. 14. The specific experimental results and analysis are shown in sections 5.1 and 5.2.

Table 3. Experimental environment configuration

Experimental environment	Configure
Operating system	Windows 10
CPU	intel core i7-6700HQ 2.6GHz
RAM	8G
Data processing tool	MATLAB R2012a

Table 4. Algorithm parameter list

Algorithm	Parameter	Parameter value
FCM	Number of clusters	c=3
	Maximum number of iterations	k_{max}=100
	Weighted index	m=2
	Termination threshold	ε=0.0001
IPSO-FCM	Population size	N=20
	Learning factors	c_1=c_2=0.4
	Maximum number of iterations	k_{max}=100
	Maximum inertia weight value	ω_{max}=1
	Minimum inertia weight value	ω_{min}=0
	Weighted index	m=2
	Termination threshold	ε=0.0001
HFCM-PSO	Population size	N=700
	Learning factors	c_1=c_2=2
	Maximum number of iterations	k_{max}=20
	Inertia weight value	ω_{max}=1
	Weighted index	m=2
	Termination threshold	ε=0.0001
DDPSO-FCM	Population size	N=50
	Learning factors	c_1=c_2=2
	Maximum number of iterations	k_{max}=100
	Maximum inertia weight value	ω_{max}=0.9
	Minimum inertia weight value	ω_{min}=0.4
	Weighted index	m=2
	Termination threshold	ε=0.0001

5.1. Contrast Experiment of Image Segmentation Effect

Standard Image Segmentation Effect. In this section, in order to test the optimization performance of the proposed DDPSO algorithm for FCM clustering center, FCM, IPSO-FCM, HFCM-PSO and DDPSO-FCM algorithm are used for image segmentation experiments. Four FCM algorithms are used to segment the standard test image lena, peppers and camera man. The segmentation effect of the four FCM algorithms on three standard images is shown in Fig. 3 to Fig. 5.

(a) Original picture (b) FCM (c) IPSO-FCM (d) HFCM-PSO (e) DDPSO-FCM

Fig. 3. Lena image

(a) Original picture (b) FCM (c) IPSO-FCM (d) HFCM-PSO (e) DDPSO-FCM

Fig. 4. Peppers image

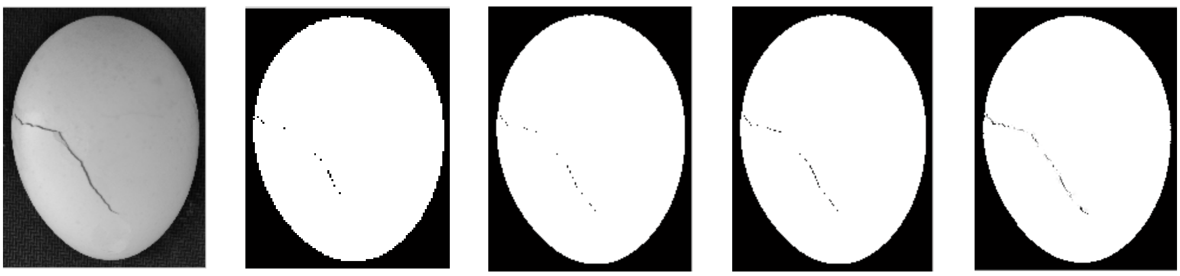
(a) Original picture (b) FCM (c) IPSO-FCM (d) HFCM-PSO (e) DDPSO-FCM

Fig. 5. Camera man image

Fig. 3 to Fig. 5 above are the experimental results of four different FCM algorithms for lena, peppers and camera man image segmentation. From the segmentation effect of subgraph (b)~(e) in Fig. 3 to Fig. 5, it can be observed that all four FCM algorithms have partial information loss in image segmentation, but FCM algorithm has the most information loss. However, the IPSO-FCM algorithm of subgraph (c) and HFCM-PSO algorithm of subgraph (d) are the second. The DDPSO-FCM algorithm in this paper has the best segmentation effect. IPSO-FCM algorithm, HFCM-PSO algorithm and DDPSO-FCM algorithm have little difference in the vision.

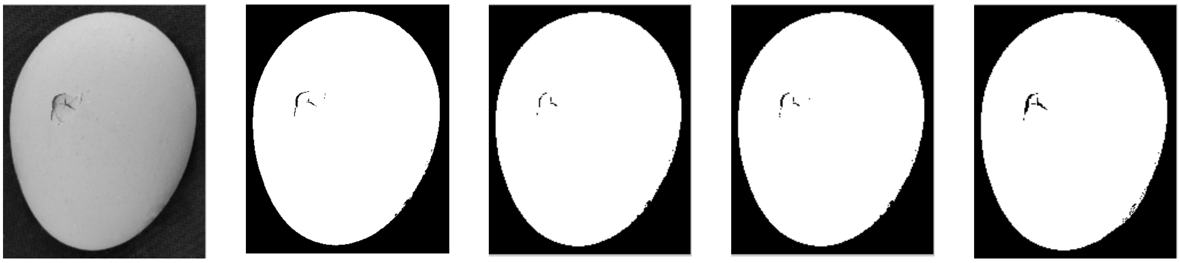
FCM algorithm has defects in the edge information of three standard images, and the degree of background discrimination has great influence on the segmentation effect. The IPSO-FCM algorithm and HFCM-PSO algorithm are better, the background and target segmentation are clear, and the segmentation effect is very similar. The segmentation effect of DDPSO-FCM algorithm is better than the other three algorithms in contour details. This is mainly due to the difference in the selection of clustering centers of the four algorithms. FCM algorithm is easy to fall into local optimization. DDPSO-FCM algorithm in this paper has strong global optimization ability, and it can retain more complete details of the segmented image, so the segmentation effect will be better.

Eggshell Image Segmentation Effect. In order to analyze the segmentation effect of eggshell damaged image from an intuitive point of view, the experiment firstly selects three kinds of sample images of eggshell damaged image, and then compares DDPSO-FCM algorithm with FCM, IPSO-FCM, HFCM-PSO algorithm for three kinds of image segmentation effect. The segmentation results are shown in Fig. 6 to Fig. 8.



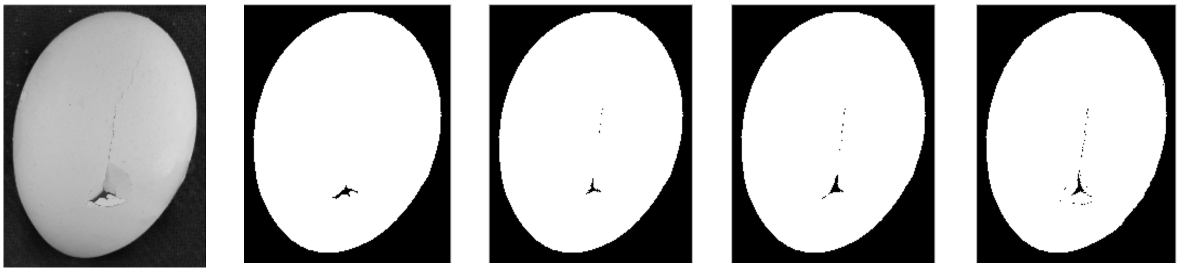
(a) Original picture (b) FCM (c) IPSO-FCM (d) HFCM-PSO (e) DDPSO-FCM

Fig. 6. Image segmentation of eggshell crack



(a) Original picture (b) FCM (c) IPSO-FCM (d) HFCM-PSO (e) DDPSO-FCM

Fig. 7. Image segmentation of eggshell hole



(a) Original picture (b) FCM (c) IPSO-FCM (d) HFCM-PSO (e) DDPSO-FCM

Fig. 8. Image segmentation of eggshell crack and hole

By using four different FCM algorithms to segment three kinds of eggshell damaged images, the effect pictures are shown in Fig. 6 to Fig. 8, which can be seen directly, in Fig. 6, the FCM algorithm of (b) subgraph has a lot of information loss and more isolated points; the IPSO-FCM algorithm of (c) subgraph is relatively complete, with less information loss than FCM algorithm, but there are still more isolated points; the HFCM-PSO algorithm of (d) subgraph is relatively more complete, with less isolated points of cracks; the DDPSO-FCM algorithm of (e) subgraph has the best segmentation effect, with basically complete crack information. There are few outliers isolated points.

In Fig. 7, for the hole image segmentation, the FCM algorithm segmentation of (b) subgraph and IPSO-FCM algorithm segmentation of (c) subgraph are similar in visual effect, the segmented images have more information loss, obviously a lot of edge information loss. There is a phenomenon of incomplete segmentation. the HFCM-PSO algorithm segmentation of (d) subgraph has more complete image edge information, but there is still a lot of information loss inside the hole. In the (e) subgraph, although there are local edge information missing and discrete points on the right side of the hole edge, the overall edge is clear, and the micro crack information inside the hole is intact.

In Fig. 8, the FCM algorithm of (b) subgraph keeps the center information of the hole basically complete, but the edge is not segmented, the segmented area is smaller than the actual target area, and the crack information is also lost; In the IPSO-FCM algorithm of (c) subgraph, the center information of the hole is complete, the center edge is clear, but the crack is discrete; In the HFCM-PSO algorithm of (d) subgraph, the center information of the hole is relatively complete , however, the edge information of the hole is completely lost, and there are many discrete points of the crack; And the effect of the DDPSO-FCM algorithm of (e) subgraph is that the information of the hole and the crack is relatively complete, even the information of the outer edge of the hole is basically visible.

To sum up, from the visual observation, the DDPSO-FCM algorithm is better than the standard FCM, IPSO-FCM and HFCM-PSO algorithm in the segmentation of three kinds of eggshell images. Compared with the other three FCM algorithms, the optimized FCM algorithm can achieve better segmentation results.

5.2. Contrast Experiment of Image Segmentation Index

Image Segmentation Index. According to the FCM algorithm described in formula (10) - (13) in Section 3, this paper uses Xie-Beni index Vxb and the partition uniformity measurement index UM to measure the image segmentation performance of DDPSO-FCM algorithm, and compares the performance with standard FCM, IPSO-FCM and HFCM-PSO respectively. The definition of Vxb and UM index is shown in formula (17)-(18).

(1) Vxb index

$$V_{xb} = \frac{\sum_{i=1}^{s}\sum_{k=1}^{n} u_{ik}^{m} \left\| x_k - c_i \right\|^2}{n \min_{i \neq j} \left\| c_i - c_i \right\|^2} . \tag{17}$$

Vxb index describes the relationship between the distance center of each sub class pixel. The smaller the Vxb is, the better the clustering effect is.

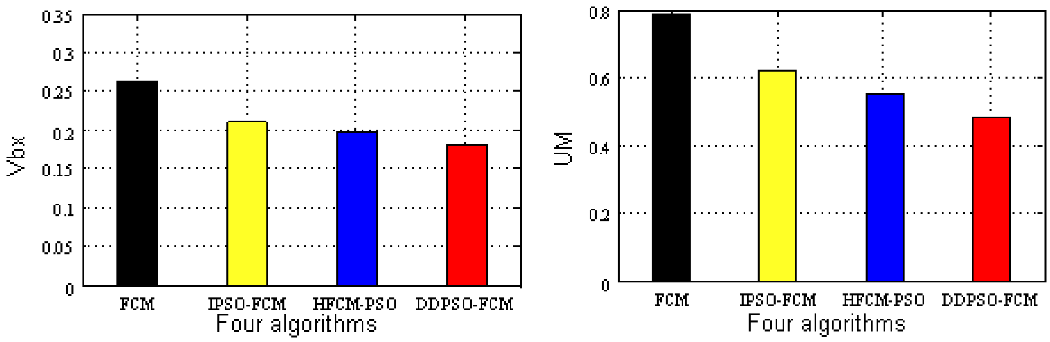
(2) UM index

In the experiment, the partition uniformity measurement index UM of each image segmentation is calculated. The UM index measures the internal uniformity of each partition class, which is used to evaluate the uniformity of sample distribution in the cluster. The calculation of UM is shown in formula (18) [28].

$$UM = \frac{1}{n}\sum_{i=1}^{s}\left\{\sum_{k \in R_i}\left[x_k - \frac{1}{A_i}\sum_{k \in R_i} x_k\right]^2\right\}. \tag{18}$$

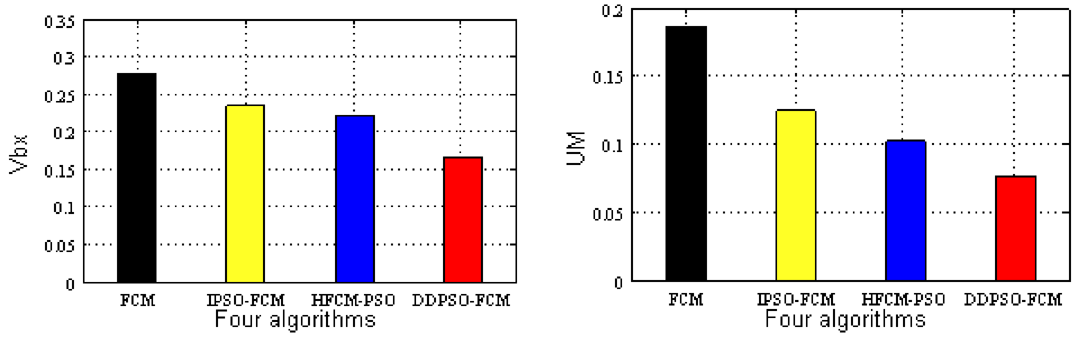
Where n is the total number of samples, that is, the total number of pixels in the image, s is the number of clusters, R_i is the i-th cluster, and A_i is the number of samples in the R_i cluster. From the analysis of equation (18), we can know that the more balanced the distribution of samples in the cluster, that is, the smaller the difference between the sample x_k and other samples in the cluster, the smaller the UM value, indicating that the segmentation effect of the algorithm is better. If there are more misclassified samples, the larger the UM value will be, indicating that the segmentation effect of the algorithm is worse. Therefore, the calculation of UM value can reflect the segmentation effect of the algorithm on each subclass.

Comparison of Standard Image Segmentation Indexes. In the previous section, the segmentation results of three standard images segmented by four FCM algorithms are compared. Based on the segmentation experiments in the previous section, this section compares the Vxb and UM segmentation index values of three standard image segmentation, to further verifies the segmentation performance of DDPSO-FCM algorithm proposed in this paper from a quantitative point of view. The statistical results of Vxb and UM segmentation index values of three standard images are shown in Fig. 3 to Fig. 5. Because the Vxb and UM value of the same image using different segmentation algorithms has little difference, so in order to show the experimental results more intuitively, the histogram and line chart are drawn in the experimental statistical chart at the same time.



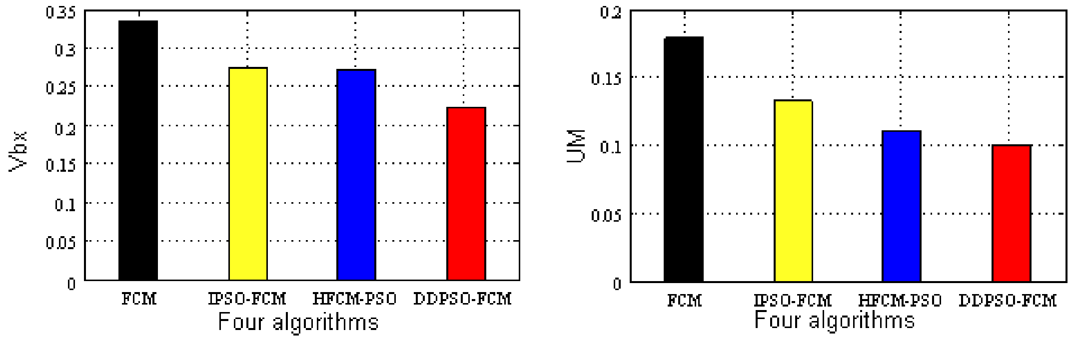
(a) Vbx (b) UM

Fig. 9. Lena image



(a) Vbx (b) UM

Fig. 10. Peppers image

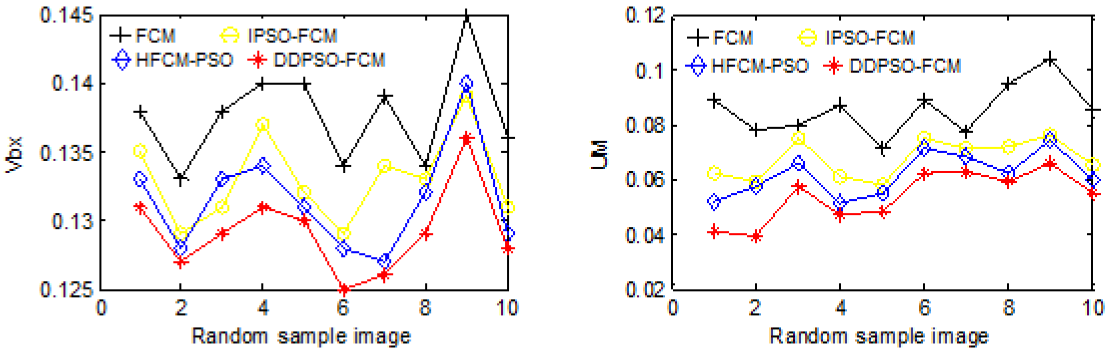


(a) Vbx (b) UM

Fig. 11. Camera man image

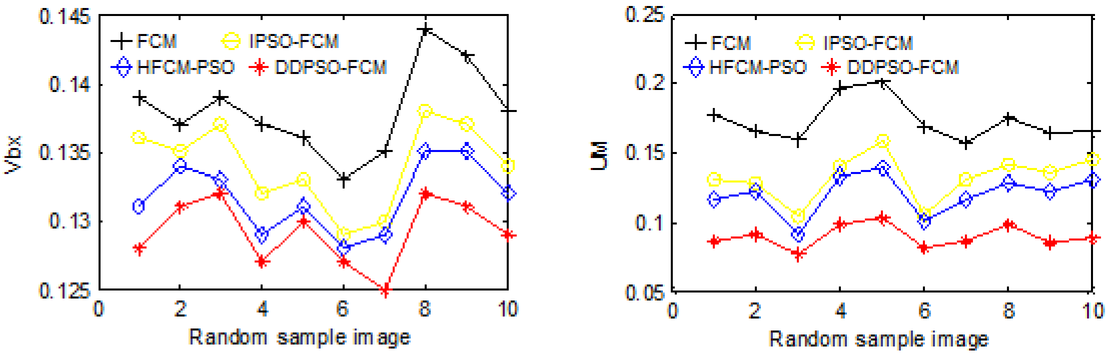
It can be concluded from the above experimental results that the four FCM algorithms have achieved good quantitative results in the segmentation of lena, pepper and camera man images. From the comparison of Vxb and UM index values, it can be found that the Vxb and UM values of FCM algorithm are the largest among the four algorithms, and it is quite different from that of IPSO-FCM algorithm, HFCM-PSO algorithm and DDPSO-FCM algorithm, which indicates that the image segmentation performance of FCM algorithm is the lowest among the four FCM algorithms. The Vxb and UM values of the DDPSO-FCM algorithm are the smallest among the four algorithms, which shows that the image segmentation performance of the DDPSO-FCM algorithm is the highest among the four FCM algorithms. Furthermore, it shows that the optimization ability of DDPSO algorithm proposed in this paper has been optimized. Compared with the other three algorithms, it can better find the clustering center of FCM algorithm in image segmentation, so as to improve the clustering performance of DDPSO-FCM algorithm.

Comparison of Eggshell Image Segmentation Indexes. Based on the intuitive comparison of the four FCM algorithms in the previous section, this section conducts several random eggshell image segmentation experiments, and then carries out statistical analysis to further verify the effectiveness of the algorithm. In the experiment, 10 images of each class are randomly selected from the three kinds of eggshell damaged images in the sample set to carry out the comparative experiments of the four algorithms. After the experiment, according to the data statistics, the Vxb and UM values of three kinds of eggshell damage images are shown in Fig. 12, Fig. 13 and Fig. 14 respectively.



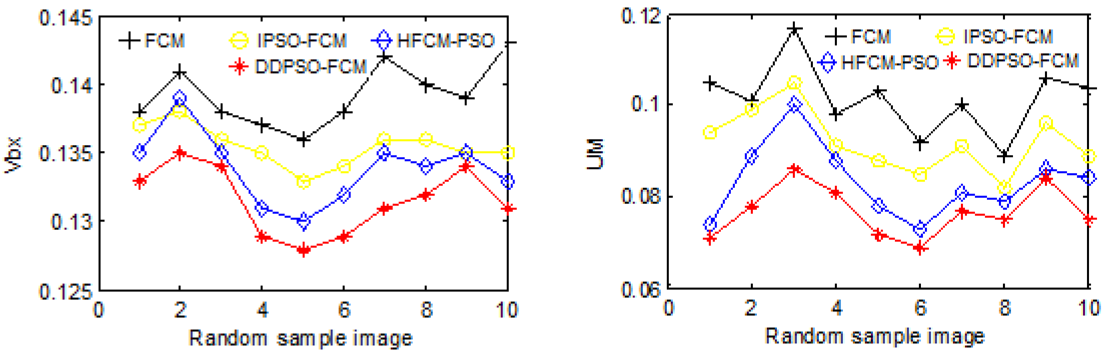
(a) Vbx (b) UM

Fig. 12. Comparison of segmentation indexes value in crack damage image



(a) Vbx (b) UM

Fig. 13. Comparison of segmentation indexes value in hole damage image



(a) Vbx (b) UM

Fig. 14. Comparison of segmentation indexes value in crack and hole damage image

From the above experimental results, it can be clearly found that the Vbx and UM values of the three types of randomly selected images fluctuate greatly due to the different complexity of the images. However, when segmenting the same eggshell damaged image, the Vbx and UM values of the optimized FCM algorithm is the smallest, followed by IPSO-FCM and HFCM-PSO algorithm, and the Vbx and UM value of the standard FCM algorithm is the largest. This is mainly because the improved PSO algorithm can search the optimal FCM clustering center, which improves the accuracy of eggshell broken image segmentation. Because the smaller the Vbx and UM image segmentation index values, the better, so from the above experimental results, we can conclude that the DDPSO-FCM algorithm proposed in this paper is better than the other three algorithms in segmentation effect, the optimization ability of DDPSO algorithm is improved.

6. Conclusions

When the FCM algorithm is used for image segmentation, the convergence effect of FCM algorithm is greatly affected by the selection of initial clustering center. In this paper, The PSO algorithm is used to optimize the selection of clustering center of FCM algorithm. The PSO algorithm has excellent optimization performance, but it is easy to fall into the local optimal solution. In this paper, the inertia weight of particles is dynamically adjusted by considering the distance difference between each particle and the optimal particle in the iteration of the PSO algorithm. This method is used to adjust the global and local search performance of particles, and then improve the optimization ability of PSO algorithm. The improved PSO algorithm DDPSO is compared with the standard PSO algorithm, ISAMPSO algorithm and EXPSO algorithm. The experimental results show that DDPSO algorithm can find a better solution than the other three algorithms, which shows that the optimization ability of DDPSO algorithm has been improved. Finally, FCM algorithm is used to segment the standard images and the eggshell damaged images. In the application, the improved PSO algorithm DDPSO is used to optimize the selection of FCM initial clustering center. The experimental results show that the optimized FCM algorithm (DDPSO-FCM) has relatively small Vbx value and UM value in three kinds of eggshell damaged image segmentation, which shows that the optimized FCM algorithm has higher segmentation accuracy in image segmentation.

Acknowledgement

This work were the achievements of the key project of 2022 school level scientific research fund of Guizhou Education University (2022ZD004); the project “earth thesis project” of Guizhou Education University (20DDZ001); And it was supported by the Guizhou Province Science and Technology Foundation (No. QianKeHeJiChu-ZK [2021] YiBan 334); Guzhou Education Department Youth Science and Technology Talent Growth Project (QianJiaoHeKY-Zi [2021] 249); Key Disciplines of Guizhou Province-Computer Science and Technology (ZDXK [2018] 007); Key Supported Disciplines of Guizhou Province-Computer Application Technology (No. QianXueWeiHeZi ZDXK [2016] 20).

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