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A Image Segmentation Algorithm Based on Differential Evolution Particle Swarm Optimization Fuzzy C-Means Clustering

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Abstract. This paper presents a hybrid differential evolution, particle swarm optimization and fuzzy c-means clustering algorithm called DEPSO-FCM for image segmentation. By the use of the differential evolution (DE) algorithm and particle swarm optimization to solve the FCM image segmentation influenced by the initial cluster centers and easily into a local optimum. Empirical results show that the proposed DEPSO-FCM has strong anti-noise ability; it can improve FCM and get better image segmentation results. In particular, for the HSI color image segmentation, the DEPSO-FCM can effectively solve the instability of FCM and the error split because of the singularity of the H component.

Keywords: differential evolution particle swarm optimization, fuzzy c-means clustering, image segmentation, HSI color space.

1. Introduction

Digital image processing can be defined as processing image information by computer to satisfy the human visual psychology or the application requirements. The 21st century is an era of information, as the basis of human visual perception of the world, image processing and analysis is an important method of human expression information and impart information. With the development of computer science and technology, image processing and analysis gradually formed its own scientific system and a lot of new approaches have been formed. In spite of short history, image processing has attracted more and more concern. First of all digital image processing technology can help people to objective and accurate understand the world, human visual system can help humans get 3/4 or more information from the outside world, and images, graphics and visual information is the carrier of above all. The human eye can identify thousands of colors and has a high resolution, but in many cases the image is blurred or invisible to human eye. Through the image enhancement techniques these blurred or invisible images become clear and bright. On the other hand, through digital image processing pattern recognition technology a variety of objects which cannot recognize by human eyes can be quickly and accurately retrieved by computer. Therefore digital images processing has become an important visual perception tools for psychology, physiology, computer science and many other areas.

Image segmentation is an important part of image processing, it is the basis of image analysis and pattern recognition to simplify or change the representation of the image, making the image easier to understand and analyze, typically used to locate images of objects and boundary. The classical image segmentation method [1]:

a) The boundary detection, including edge detection, boundary tracing, etc. These methods make use at the edge of the image pixel gray value discontinuity is detected by the derivative; for the step-like edge, its position corresponding to the extreme points of the first order derivative, and the second derivative is zero; the differential operator is also a common method of edge detection.
b) The region segmentation, including threshold segmentation, region growing, classification merger, etc. In these methods, the whole area is constituted by the combine to have the same or similar data, the key to these methods is to determine the threshold value, and if we can determine the appropriate threshold value can be accurately image segmentation.

Because the influence of light and noise, there is ambiguity between the target and gray background of pictures, the classical segmentation algorithm is difficult to split it and the result is not satisfactory. The fuzzy clustering method can effectively deal with the fuzziness of the image; the image segmentation method based on fuzzy clustering has been extensively studied.

The Fuzzy C-means clustering (FCM) is one of the most common algorithms of fuzzy clustering algorithm; it is an unsupervised algorithm with self-adaptive and fast convergence. When use FCM to split the image, the uncertain information in the image can be split and get better segmentation. The introduction of fuzzy clustering method can effectively deal with the fuzziness of the image, and therefore subject to a wide range of applied research ([2], [3] and [31]). Compared to the traditional image segmentation algorithm, the FCM image segmentation algorithm can solve the problems of traditional segmentation algorithm cannot split the image fuzzy or uncertain area; FCM image segmentation algorithm using unsupervised automatic segmentation can automatically adjust the threshold to avoid split due to threshold selection improper impact; the FCM image segmentation algorithm do not need to know that the image grayscale data of first and second order derivative information to avoid complex mathematical seeking.

However, this algorithm is influenced by the initial cluster centers and can fall into local optimal value easily. In order to change the disadvantages of the FCM, the major improvement strategies have: the introduction of adaptive threshold method ([4], [5]); the construction of the new membership function [6]; the introduction of new weight calculation method ([7], [8]); the introduction of other distance calculation methods [9]; the introduction of intelligent compute methods ([10], [11], [12]), and the others [34].

In this paper, we use the differential evolution (DE) algorithm global convergence and the optimization characteristics of the PSO, proposed an image segmentation algorithm based on differential evolution particle swarm optimization fuzzy C-means clustering (DEPSO-FCM).

2. Brief introduction of FCM

The Fuzzy C-means clustering (FCM) is an unsupervised learning based on fuzzy math theory, proposed by Bezdek [13].

Let vectors $x_i(i=1,2,...,n)$ into c fuzzy groups, seeking cluster center of each packet to find the function of the value of the similarity index is the minimum, the value function of the FCM is defined as:

$$J(U,c)=\sum_{i=1}^{c}J_i=\sum_{i=1}^{c}\sum_{j}^{n}u_{ij}^{m}d_{ij}^{2} \quad (1)$$

where $m\in[1,+\infty)$ is weighting exponent; d_{ij} is the distance between the $i-th$ center c_i and the $j-th$ data x_j, and $d_{ij}=\|x_j-c_i\|$; $u_{ij}\in[0,1]$ represents the fuzzy membership from the $i-th$ center to the $j-th$ data, to determine the degree of membership of each packet, and $\sum_{i=1}^{c}u_{ij}=1,\ j=1,...,n$. For the value of the equation (1) is the minimum, the cluster center and the degree of membership must meet the equation (2) (3):

$$c_i=\sum_{j=1}^{n}u_{ij}^{m}x_j/\sum_{j=1}^{n}u_{ij}^{m} \quad (2)$$

$$u_{ij}=\left(\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}\right)^{-1} \quad (3)$$

The FCM clustering steps are as follows:

Step 1: Initialize the membership matrix U, generate randomly from 0~1, to satisfy the degree of membership constraints.

Step 2: calculate c_i with equation (2), $i=1,...,c$.

Step 3: According to equation (1) to compute the objective function value. If it is less than the ε, where ε is the threshold value, or relative to the last objective function value, the change of it is less than the threshold value, the algorithm will stop.

Step 4: Calculate the new matrix U using equation (3) and return to Step 2.

This algorithm is particularly strong dependence of the initial cluster centers; the initial cluster centers improper selection will cause a clustering search into local extreme, when the number of clusters of samples, the drawback is more significant.

The FCM has been applied to the image segmentation algorithm, like the FCM image segmentation based on histogram (QFCM) ([14], [30], [33]). It is mainly based on the weighted similarity between the pixels in the image and different clustering centers and to optimize the objective function. With the introduction of the image histogram, the FCM and the objective function can be rewritten as:

$$J(U,c)=\sum_{i=1}^{c}\sum_{k=0}^{L}u_{ik}^{m}d_{ik}^{2}h(k) \quad (4)$$

where $h(k)$ is the image histogram, k is a gray level, u_{ik} represents the fuzzy membership from the $i-th$ cluster center to the grayscale value k, d_{ik} is the Euclidean distance between the gray value of the $i-th$ cluster center c_i and the grayscale value k, $d_{ik}=\| k-c_i \|$. By using $\| c^{(t+1)}-c^{(t)} \|<\varepsilon$ to determine whether the algorithm converges, $c^{(t)}$ is the center of the clustering of the t-th iteration and $c^{(t+1)}$ is the next iteration.

The FCM image segmentation based on gray histogram can split the image quickly, but it still has the problems in the FCM algorithm inevitably. So we propose DEPSO-FCM. Use the PSO to reduce the impact of the initial value set for the FCM, and consider the particle swarm optimization precocious ([15], [32]), we use the differential evolution algorithm to avoid it. Meanwhile, the DE algorithm lacks the local search ability [16] and the algorithm late convergence rate is slow, the PSO can control it effectively.

3. DEPSO-FCM algorithm for image segmentation

3.1. Differential Evolution

The differential evolution (DE) is first proposed to solve optimization problems of the real number by Storn and Price [17], is an adaptive global optimization algorithm, which is similar to the genetic algorithm. It belongs to the evolutionary algorithm is currently the most efficient optimization algorithm; it has simple structure, fast convergence and robustness. In DE, the differential mutation operator is used mainly by using the differences in different particles mutation, and using the hybridization process to select better-population particle, thus achieving the goal of global optimum. In this paper we use the $DE/rand/1/bin$ mutation operator.

A brief working may be described as: For population $X=\{x_i \mid i=1,2,...,NP\}$, use three different particles, through the equation (5) to produce a new particle z.

$$z_i=x_{r1}+F*(x_{r2}-x_{r3}) \quad (5)$$

where x_{r1},x_{r2},x_{r3} are chosen from X, to ensure the differences of the three particles, the number of X must be more than four, and $r1\neq r2\neq r3\neq i$, F is the scaling factor, which is usually a positive number between $(0,1)$. Use the binomial crossover particle z_i and the individual x_i to generate the final particle u_i according to the equation (6).

$$u_i^d = \begin{cases} z_i^d, if\ (rand_i \le CR) \quad or \quad d == j_{rand} \\ x_i^d, others \end{cases} \qquad (6)$$

where x_i^d, z_i^d and u_i^d are the $d-th$ dimensional components of the particle x_i, z_i and u_i, CR is the crossover probability and the value belongs to $[0,1]$, $j_{rand} \in (1,2,...D)$ is a randomly generated positive integer. Finally, similar to the laws of natural selection of the fittest, u_i will be compared with x_i, and the better one will be saved as a member of the DE population for the next generation.

The differential evolution is a one-to-one selection operator algorithm and belongs to the steady-state evolutionary algorithm. The differential evolution algorithm flowchart is shown in Figure 1.

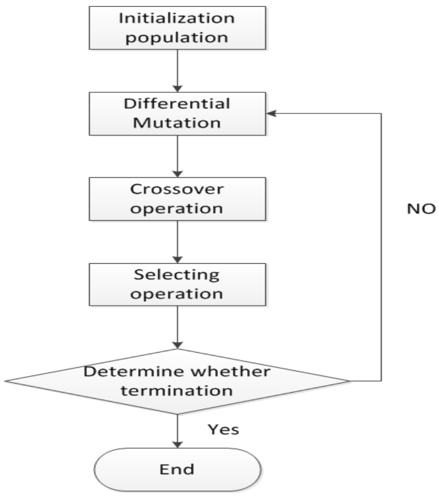


Fig. 1. Differential evolution algorithm flowchart

Compared to other evolutionary algorithms, the differential evolution has the following advantages ([16], [17]): In solving non-convex, multimodal, nonlinear function optimization problem, it has a very strong soundness; fast convergence algorithm under the same accuracy requirements; especially good at solving the multivariate function optimization problem; operation simple and easy programming.

In recent years, many experts and scholars tried to use for the optimization of the fuzzy clustering algorithm, such as Su Qinghua [18] tried to take advantage of the differential evolution algorithm to optimize the K-means clustering algorithm, and Chen Yuling [19] used DE to optimize the fuzzy c-means clustering.

3.2. Particle swarm optimization

The particle swarm optimization (PSO) is proposed by Eberhart and Kennedy [20] in 1995, it is an optimization algorithm based on swarm intelligence theory, through inter-group cooperation and competition between individuals optimize. It retains the populations of the global search ability of the algorithm, by using the velocity - displacement model to avoid the operation of complex genetic algorithm. In addition, its unique memory function can be dynamically tracking current search, then adjust the local and global search capability.

In the PSO, each optimization problem can be regarded as a bird of the search space. For randomly generated initial population $Z = \{Z_i \mid i = 1,2,..., NP\}$, each population particle location $Z_i = \{Z_{i1}, Z_{i2},..., Z_{in}\}$, and the velocity of the particles $V = \{V_i \mid i = 1,2,..., NP\}$ in feasible solution space. According to the objective function to calculate the fitness of each particle in the population, and find the optimal solution of the particle itself and global optimal solution in the population, denoted as p_{ibest} and p_{gbest}. Then update current velocity and location of the particles according to the equation (7) and (8). Use the new velocity and position to looking for the better results, until converges.

$$v_{id} = \omega v_{id} + c_1 r_1 (p_{ibest} - z_{id}) + c_2 r_2 (p_{gbest} - z_{id}) \tag{7}$$

$$z_{id} = z_{id} + v_{id} \tag{8}$$

where c_1, c_2 are the acceleration factors, $r_1, r_2 \in (0,1)$ are randomly generated constants, $\omega \in [0,1]$ is the inertia weight to keep the particles moving, the large ω is suitable for a large range and the small one is suitable for a small range, if $\omega = 0$ the particles will lose their memory capacity, the population will shrink to the current optimal position, thus losing the ability of global search. In this article, use the current number of iterations $iter$, the maximum number of iterations $iter_{\max}$, we define ω as $\omega = \omega_{\max} - iter * (\omega_{\max} - \omega_{\min}) / iter_{\max}$, ω will decrease with the increase of the number of searches. The PSO algorithm flow chart is shown in Figure 2.

The PSO has the following advantages ([29], [32]): easy to describe and understand; no special requirements on the continuity of the optimization problem defined; only very few parameters need to be adjusted; simple and fast; relative to other evolutionary algorithm the PSO only needs of smaller groups of evolution; compared to other evolutionary algorithm, it is easy convergence and only the number of times you can achieve convergence require and less evaluation function calculation; without centralized control constraints affect the entire problem solving, not due to the fault of the individual, to ensure that the system has strong robustness.

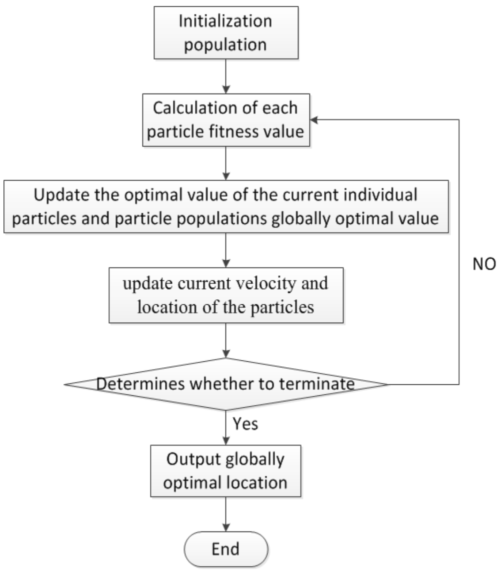


Fig. 2. Particle Swarm Optimization flowchart

The PSO has been widely used in function optimization, neural network training, fuzzy system control, multi-objective optimization, and other genetic algorithm ([21], [22], [23]).

3.3. The DEPSO-FCM image segmentation design

The characteristics of the PSO are the ability of local search, fast convergence, but premature, the DE is characterized by global search ability, but poor convergence and the lack of local search ability. In order to achieve better optimization results, in recent years, more and more experts tried to mix these two algorithms with other algorithms [24-29]. We propose the use of the respective merits of these two algorithms and learn from each other, and use it in the FCM. On the one hand, the DEPSO-FCM can avoid the local extremum of the FCM; on the other hand, can make use of the PSO to solve the DE's poor convergence.

The PSO and the DE are required to evaluate the individual particles, when the initial cluster centers close to the target cluster centers, indicating that the convergence of the algorithm, in this article we define the fitness function as:

$$diff = \frac{k}{J(U,c)} \tag{9}$$

here k is a positive constant number, in order to obtain the maximum objective function, we need to get the minimum value of $J(U,c)$.

The image as the search space, in the course of the campaign, the particles cannot exceed the range of the image, during the search, according to the fitness function, the particle search global optimal solution as image segmentation threshold based on the fitness function. The DEPSO-FCM image segmentation as follows:

Step 1: Read the image gray histogram and set parameters: the number of clusters c, the population numbers N, fuzzy index m, scaling factor F, the cross rate CR, accelerating factors c_1 and c_2, the maximum and minimum inertia weights $\omega_{\max}$ and $\omega_{\min}$, the maximum number of iterations $iter_{\max}$, the maximum velocity $V_{\max}$.

Step 2: Initialize population. Randomly generate the initial population and its flight velocity, use equation (2) and (3) to calculate the degree of membership and the cluster centers of all the particles in the population, compute the fitness of all the particles in the population according to equation (9), record all current particle individual extremum p_{ibest} and groups extremum p_{gbest}, set the initial mutation particle value Z.

Step 3: According to equation (6) to judge whether the crossover operation. If the crossover operation is not satisfied, the process proceeds to the step 4, otherwise to generate a variation of the particle in accordance with equation (5).

Step 4: According to equation (9) to calculate the current degree of adaptation of the variation particle, and compared with the current population extremum. If this particle is better than the current population optimal, update the initial individual extreme p_{ibest}, record the current population extreme value p_{gbest} and go to the step 6, otherwise go to the step 5.

Step 5: According to the formula (7) (8) to update the particle velocity and position, control the velocity and position of the new particles to movement within the space. Calculate the degree of membership, the cluster centers, and the fitness. Update the p_{ibest}, if it's better than the initial individual extremum, Update the p_{gbest}, if it's better than the group extremum.

Step 6: Judge whether the algorithm has reached the maximum number of iterations. If it has been reached, output the global optimal solution; Otherwise, skip to the step 3 for the next iteration.

The pseudo code of the DEPSO-FCM Algorithm is:

Parameter setting: C is the classification number, N is the population size, X is gray image numerical at 0-255, M is the fuzzy index, F is the scaling factor, CR is the cross rate, ω is the inertia weights;

Initialize a population X that contains N particles with random positions and each particle is clamped within $[X_{\min}, X_{\max}]$;

Initialize the particles' velocities V_{speed} and each particle's velocity is clamped within [-1, 1];

Evaluate U and $diff$ for all particles according to (2), (3) and (9), record all the particle's current individual extreme value $diff(p_{ibest})$ and the current global optimal value $diff(p_{gbest})$; p_{ibest} is he particle's current individual extreme location and p_{gbest} is the global optimal location.

```
while (cnt < iter)
// cnt is the current iteration times, iter is the maximum
     number of iterations.
  For i=1: N                                       // Do DE.
    Select x_r1, x_r2, x_r3 ∈ N randomly;
      If ((rand()<CR) || i==j_rand)
      Change u_i according to (5) and (6);
  // Adjust the value of u_i to prevent cross the border;
      If u_i > X_max then u_i = X_max ; End
      If u_i < X_min then u_i = X_min ; End
    Evaluate U(u_i) and diff(u_i) for u_i according to the
    equation (2), (3) and (9);
      If diff(u_i) is better than diff(current_gbest)
       Update current_gbest with u_i ; End
      Else      //Do PSO
       ω = ω_max − cnt*(ω_max − ω_min)/iter ;
       Evaluate the current velocity v_i according to the
       equation (7) ;
// adjust the value of v_i to prevent cross the border.
       If v_i > 1 then v_i = 1; End
       If v_i < −1 then z_i = −1; End
        Evaluate the current location z_i according to the
        equation (8) ;
// adjust the value of z_i to prevent cross the border.
       If z_i > X_max then z_i = X_max ; End
       If v_i < X_min then v_i = X_min ; End
       Evaluate U(z_i) and diff(z_i) according to the equation
       (2), (3) and (9);
       If diff(z_i) is better than diff(p_ibest)
         Update p_ibest with z_i ; End
       If diff(z_i) is better than diff(p_gbest)
        Update p_gbest with z_i ;End
     End if
```

```
    End for
    X_gbest = p_gbest ;
    // X_gbest as the best segmentation threshold value.
    cnt = cnt+1;
End
Do segmentation by using X_gbest .
```

3.4. Simulation and Analysis

All the test were implemented using MATLAB 7.8 on a PC compatible with Core i5, a 2.5GHz processor and 4 GB of RAM. The parameters were set as: the initialization population size $N = 30$, the inertia weight $\omega_{\max} = 0.9$ and $\omega_{\min} = 0.4$, the fuzzy index $m = 2$, the acceleration factors $c_1 = c_2 = 2$, the scaling factor $F = 0.5$, the cross rate $CR = 0.3$, the velocity $V_{speed} \in [-1,1]$ and the range of motion $x \in [0,255]$.

The gray image segmentation based on DEPSO. In gray image, we add noise in the original image and get a new image, then blur it. In order to judge the superiority of the algorithm, we introduce the peak signal to noise ratio (PSNR). Set the image contains $m \times n$ pixels:

$$PSNR = 10\log\frac{255^2}{MSE}$$
$$MSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}[I_{original}(i,j) - I_{split}(i,j)]^2}{m \times n} \tag{10}$$

where $I_{original}(i,j)$ is the original image pixel value without noise and blur, and $I_{split}(i,j)$ is the pixel value of the image segmentation. The bigger $PSNR$ means the divided image closer to the original image, and the better ability of anti-noise.

We split the image Cameraman, Rice, Lena with the DEPSO-FCM, and compared with the FCM and PSO-FCM. The histograms of the original image were show as Figure 3. We add salt and pepper noise to the image and blur it, and get the new image histograms as Figure 4.

The initial clustering center of FCM, the DE-FCM, PSO-FCM and the DEPSO-FCM is randomly generated and the maximum number of iterations *iter*=160. The table I lists the best cluster center with *c*=2 and the results of image segmentation are shown as Figure 5. The table 2 lists the best cluster center with *c*=5 and the results of image segmentation are shown as Figure 6. The table 3 lists the PSNR of the different algorithms.

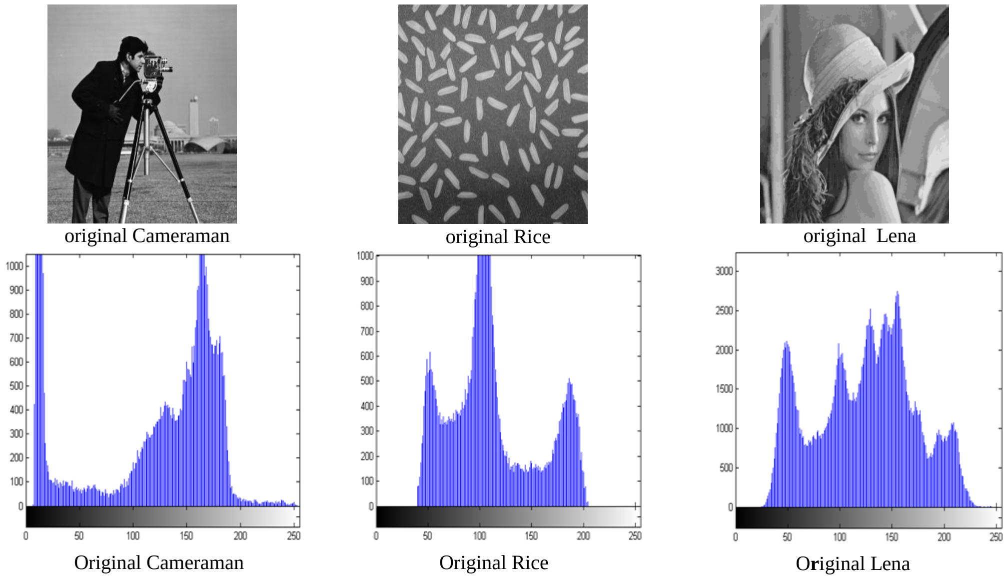


Fig. 3. The original Cameraman, Rice and Lena's histogram

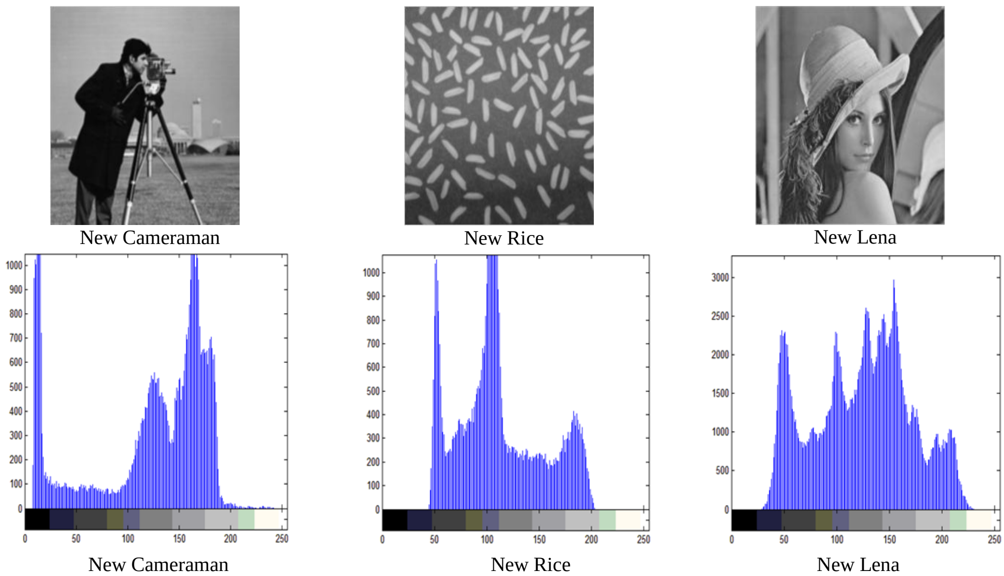


Fig. 4. The new Cameraman, Rice and Lena's histogram

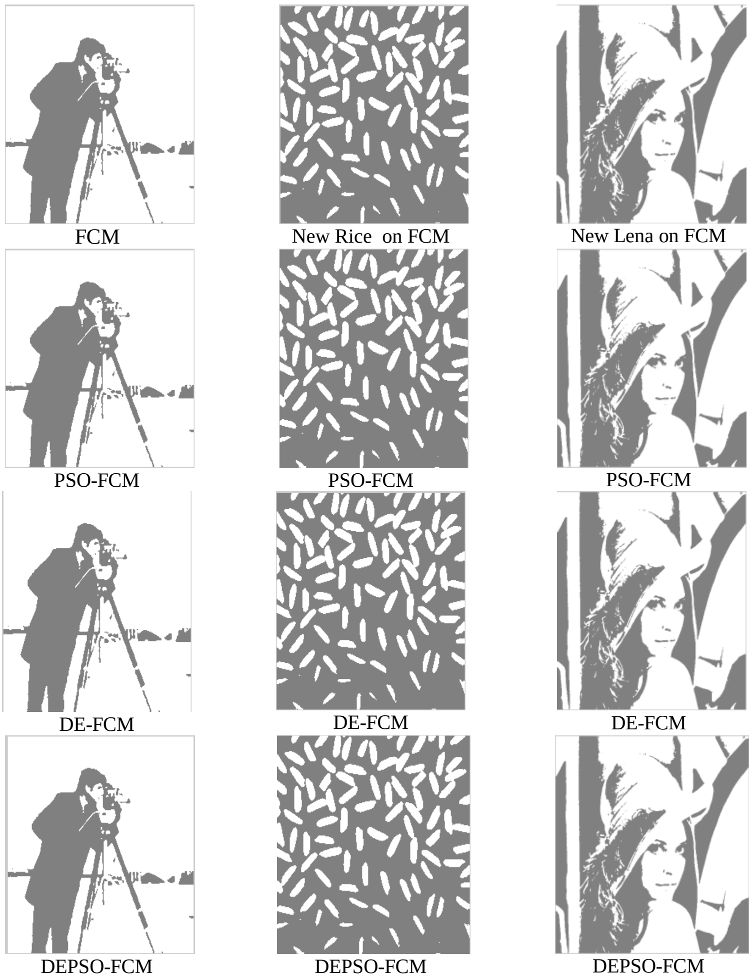


Fig. 5. The results of image segmentation based on different algorithms with C=2

Table 1. The comparison of the optimal cluster center of the different algorithms with C=2

Image	Cameraman	Rice	Lena
FCM	(26.5811,154.4875)	(90.7999,168.2538)	(77.4335,160.1558)
PSO-FCM	(26.1471,154.4076)	(90.1918,167.9582)	(77.3923,160.1371)
DE-FCM	(26.3111,154.3134)	(90.7696,168.1519)	(77.8900,160.3529)
DEPSO-FCM	(26.5863,154.4060)	(90.8900,168.3529)	(77.6001,160.2476)

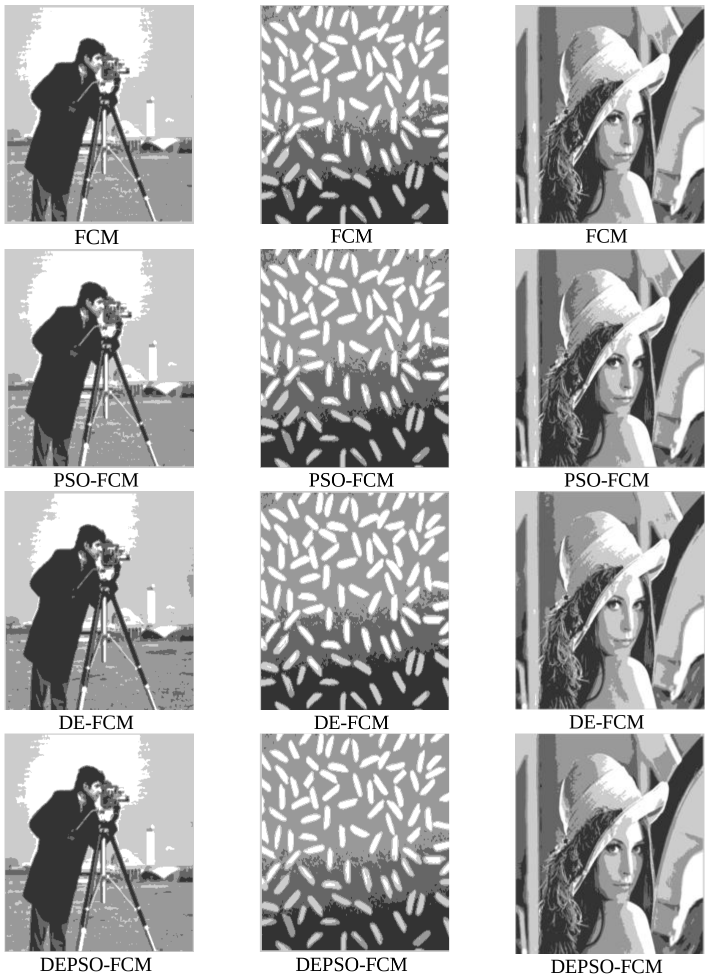


Fig. 6. The results of image segmentation based on different algorithms with C=5

Above the figures and tables, we find that all kinds of segmentation methods have the same effect when c=2. When c=5, we can see the DEPSO-FCM has the best ability of anti-noise and can get best results in the four algorithms.

Figure 7 shows use the PSO-FCM, the DE-FCM and the DEPSO-FCM to segment the Cameraman image, and the changes of the cluster centers in the same initial population and 600 iterations. Obviously, the convergence rate of the DEPSO-FCM algorithm is the best in all. From the Figure 8 and Figure 9, we can see that the more the number of peaks of the gray-scale image histogram, the advantage of the DEPSO-FCM is more obvious.

Table 2. The comparison of the optimal cluster center of the different algorithms with C=5

Image	Camera--man	Rice	Lena
FCM	(15.8154,66.9201, 122.8481,158.363, 179.0340)	(55.9146,85.4695, 107.8236,145.5002, 183.9177)	(54.0167,97.2855, 130.5054, 159.2682, 201.6038)
PSO-FCM	(17.1111,74.3400, 124.5780,159.9312, 180.9697)	(56.4884,88.6676, 108.4027,147.3045, 184.8857)	(55.7062,99.4954, 132.0255,159.6482, 201.7871)
DE-FCM	(15.8291,66.9386, 122.8169,158.3525, 179.0773)	(59.3405,89.0625, 106.2658,146.3129, 183.4174)	(55.5577,98.3903, 128.6414, 159.4831, 202.5555)
DEPSO-FCM	(15.9971,83.1323, 125.3749,161.4510, 181.1450)	(54.9073,88.5200, 108.8697,156.5483, 187.5816)	(52.7146,97.3412, 135.1057,161.4538, 203.5498)

Table 3. The comparison of the psnr of the different algorithms with C=2 and C=5

PSNR	Cameraman		Rice		Lena	
	C=2	C=5	C=2	C=5	C=2	C=5
FCM	7.61	14.08	12.62	14.74	9.58	17.83
PSOFCM	7.61	14.49	12.62	15.01	9.58	18.03
DEFCM	7.61	14.59	12.61	15.31	9.58	18.39
DEPSOFCM	7.61	14.72	12.62	15.47	9.58	18.54

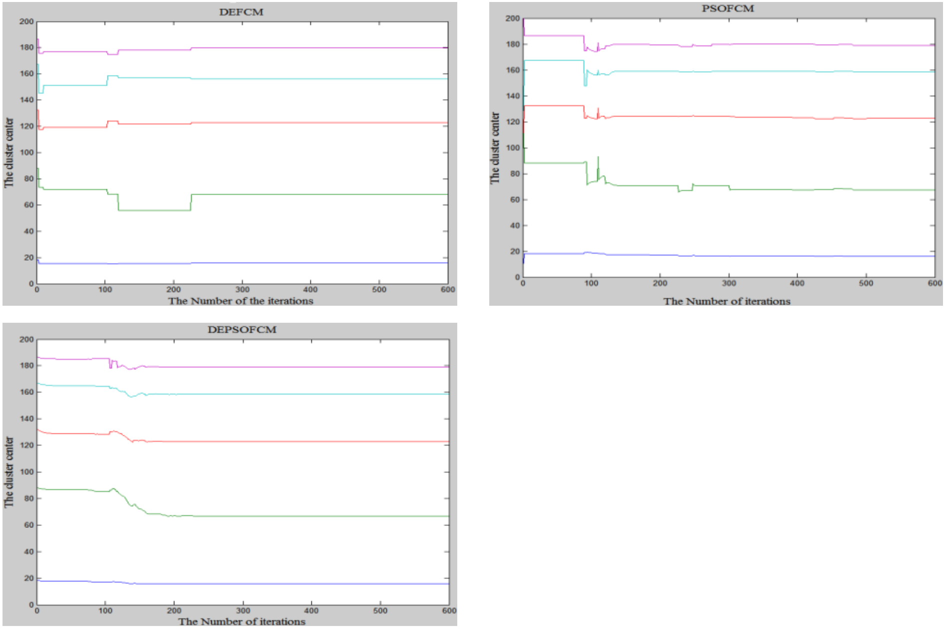


Fig. 7. The cluster center changes in DEFCM, PSOFCM and DEPSOFCM for Cameraman

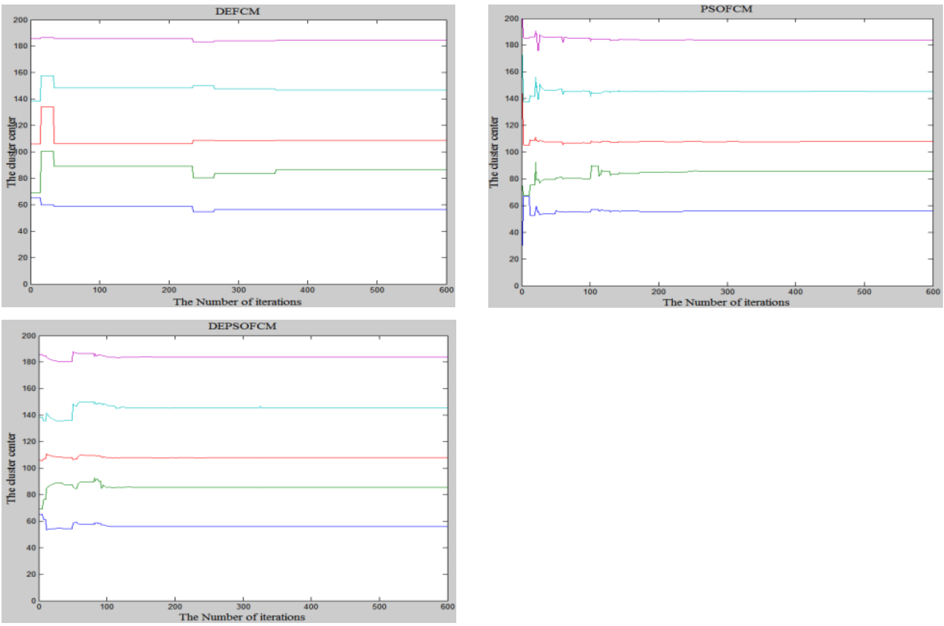


Fig. 8. The cluster center changes in DEFCM, PSOFCM and DEPSOFCM for Rice

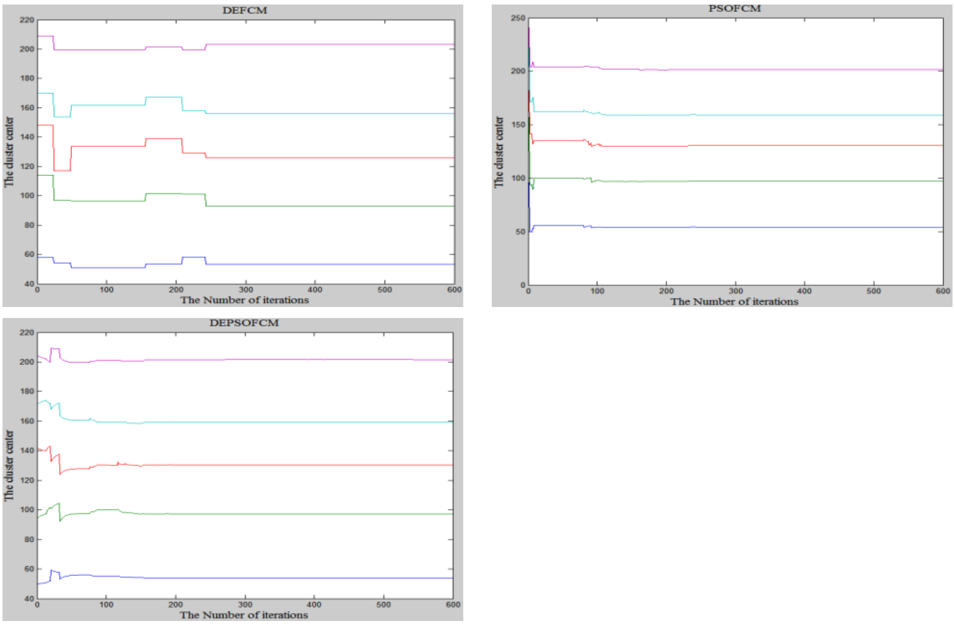
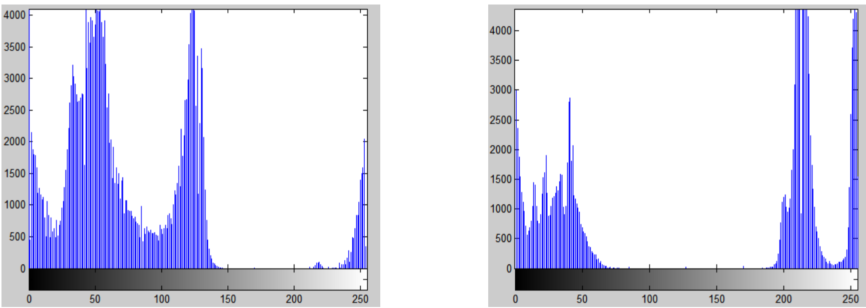


Fig. 9. The cluster center changes in DEFCM, PSOFCM and DEPSOFCM for Lena

Color image segmentation based on DEPSO in HSI space. Color image is more complicated than grayscale image, in general, we put it to a specific color space to process. HSI (Hue, Saturation, Intensity) is a color space that can be separated luminance information and color information of the image, it is an ideal space for color image rendering and processing. However, in the HSI space, some images contain a number of meaningless points that will affect the segmentation, espacailly in the H component.



House Peppers

Fig. 10. The H component histogram of House and Peppers

Original House J(u, c)=257.4 in H (a) J(u, c)=545.6 in H (b)

Fig. 11. The FCM segmentation results with C=3 for House

The initial clustering center of FCM, the DE-FCM, PSO-FCM and the DEPSO-FCM is randomly generated; the maximum number of iterations iter=200 and the center numbers C=3 in House, and iter=500 with C=5 in Peppers. And the initial clustering centers of DE-FCM, PSO-FCM and DEPSO-FCM are the same.

Original peppers J(u, c)=29.5 in H (a) J(u, c)=32.1 in H (b)

Fig. 12. The FCM segmentation results with C=5 for peppers

DEPSOFCM DEPSOFCM DEPSOFCM

Fig. 13. The results of different algorithms with C=3 and iter=200 in House

Figure 11 and Figure 12 show the effect of the color image segmentation by FCM. There are two different effects with different initial values. The figure 10(b) and figure 11(b) are caught in local minima.


DEPSOFCM


DEPSOFCM


DEPSOFCM

Fig. 14. The results of different algorithms with C=5 and iter=500 in peppers

Table 4. The comparison of the different algorithms in House in the H component with C=3 iter=200

J(u,c) in H	Mean	Max	Min	Errors	Error rate
FCM	305.4975	546.0756	257.3819	7	35%
PSO-FCM	258.0987	261.2646	257.3826	1	5%
DE-FCM	257.8241	**258.8733**	257.3962	0	0
DEPSO-FCM	**257.5019**	259.5329	**257.2075**	0	0

Table 5. The comparison of the different algorithms in peppers in the H component with C=5 iter=500

J(u,c) in H	Mean	Max	min	Error	Error rate
FCM	30.7452	**32.0031**	**29.4874**	10	50%
PSO-FCM	30.4316	53.8285	29.5291	5	25%
DE-FCM	30.1653	32.6461	29.4875	4	20%
DEPSO-FCM	**30.0772**	33.0680	**29.4874**	4	20%

Figure 13 and Figure 14 show the effects of the color image segmentation by DEPSO-FCM, DEF-CM and PSO-FCM. Table 4 and Table 5 show the objective function $J(U,c)$ of H component of House and Peppers in different algorithms. The results in the table are obtained by running twenty times, and we consider the data that seriously deviate from the optimum is error.

Analyzing the above table 4 and table 5, DEPSO-FCM is the best in the optimization. In House and Peppers, the DEPSO-FCM can get the smallest mean and the smallest minimum. From the number of successful search, the algorithm of this paper close to DE, can effectively improve the number of failures.

4. Conclusion

In this paper, we analyze the characteristics of the FCM image segmentation, the advantages and disadvantages of the PSO and the DE. Then an image segmentation method named DEPSO-FCM is introduced, which improves the effect of image segmentation by introducing differential evolution and particle swarm optimization. From the results we can see that the DEPSO-FCM has strong robustness and practicality; the DEPSO-FCM can help FCM to improve the dependence of the initial cluster centers to improve easy to fall into the local extremum. In the same initial population, the same parameters and the sufficient number of iterations, the convergence of DEPSO-FCM is the best in all and in the multi-peak gray level histogram the advantage of DEPSO-FCM is more obvious. In HSI color space segmentation, the algorithm in this paper can effectively find the global optimum, and avoid error split, and get more stable and better segmentation results.

However, this algorithm is more complex than the other two and the setting of each parameter needs for further research.

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