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An Improved PSO-FCM Algorithm for Image Segmentation

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Abstract. FCM algorithm is a kind of soft clustering method widely used in image segmentation, but the algorithm is prone to fall into local minimum and sensitive to initial value. In this paper, considering the local and global optimization capabilities, an improved PSO algorithm is proposed. Image segmentation experimental results show that the improved algorithm not only can effectively avoid the local optimal value due to the manual setting of FCM initial value, but also has better accuracy and anti-noise performance than traditional FCM.

1. Introduction

Fuzzy c-means (FCM) Clustering algorithm is an iterative optimization method combining unsupervised clustering and fuzzy set concepts, and was first proposed by Dunn and popularized by Bezdek[1]. At present, FCM is one of the most widely used methods in clustering analysis, and can effectively solve the problem of image segmentation with uncertainty and fuzziness. In recent years, many scholars have tried to solve the problem of FCM initial value falling into local extreme value[2-4].

Particle swarm optimization (PSO) is an effective global optimization algorithm proposed by James Kennedy and Russell Eberhart. PSO algorithm can converge to the optimal solution quickly, which not only has global optimization ability, but also has strong local optimization ability. Because PSO requires relatively few parameters to be set and is not easy to fall into local convergence, it is widely used in many fields such as function optimization, neural network training and image processing[5].

In this paper, an FCM clustering image segmentation algorithm based on improved PSO algorithm is proposed. The strong global search ability of PSO is utilized to obtain the optimized initial FCM clustering center and the number of clustering categories, so as to effectively avoid the local optimal value trap.

2. Introduction to FCM

FCM turns hard classification into fuzzy classification on the basis of c-means[6-8]. The objective function of c-means is shown in (1):

$$J_{\mathrm{e}} = \sum_{i=1}^{c} \sum_{y \in \Gamma_i} \left\| y - m_i \right\|^2$$

$$(1)$$

.

The goal of the c-means method is the minimum value of J_e, where m_i is the sample mean of the i-th class samples, Γ_i is the i-th class clustering, and $y \in \Gamma_i$ is all samples classified to the i-th class. Each parameter is marked in the FCM algorithm，$x_i, i = 1,2,3...n$ is the sample space composed of n samples, c is the specified number of categories, $m_i, i = 1,2,3...c$ is the center of each cluster, and $\mu_j(x_i)$ is the membership function of the i-th sample to the j-th class. The objective function defined by membership degree is

$$J_e = \sum_{i=1}^{c} \sum_{i=1}^{n} [\mu_j(x_i)]^b \left\| x_i - m_j \right\|^2 \tag{2}$$

where b is a constant representing the degree of ambiguity, and the iterative method is used to calculate (3)and(5)[9]. The algorithm of objective function steps are as follows:

a) Set clustering number c and parameter b.

b) Initialize each cluster m_i.

c) Repeat the following steps until the membership function of each sample is stable.

d) Substitute the current clustering center and calculate the membership function through (3)and(4),

$$\mu_j(x_i) = \frac{(1 / \left\| x_i - m_k \right\|^2)^{1/b-1}}{\sum_{k=1}^{c} (1 / \left\| x_i - m_k \right\|^2)^{1/b-1}}, \quad j = 1,2,...,c, \quad i = 1,2,...,n, \tag{3}$$

$$\text{and} \quad \sum_{j=1}^{c} [\mu_j(x_i)] = 1, \quad i = 1,2,...,n \tag{4}$$

e) The membership function is used to calculate and update the clustering centers according to (5),

$$m_j = \frac{\sum_{i=1}^{n} [\mu_j(x_i)]^b x_i}{\sum_{i=1}^{n} [\mu_j(x_i)]^b}, \quad j = 1,2,...,c \tag{5}$$

3. Improved PSO FCM algorithm

In the view of PSO, the solution to each optimization problem can be regarded as a bird in the search space, namely "particle". The particle is abstracted as an individual, and the solution of the problem is the optimal position of the particle in space[10]. Let the particle swarm search in an n-dimensional space, composed of m particles $Z = \{Z_1, Z_2, ..., Z_m\}$, where each particle's position $Z_i = \{Z_{i1}, Z_{i2}, ..., Z_{in}\}$ represents a solution to the problem. Particles search for new solutions by adjusting their positions. Each particle can remember the best solution it has found, let's call it p_{id}, and the best position that the whole particle swarm has experienced, the best solution so far, let's call it p_{gd}, and the velocity of each particle is $V_i = \{v_{i1}, v_{i2}, ..., v_{in}\}$. The particle updates its speed and position according to

$$v_{id}(k+1) = \omega v_{id}(k) + c_1 rand \ (P_{id} - Z_{id}(k)) + c_2 rand \ (P_{gd} - Z_{id}(k))$$
$$Z_{id}(k+1) = Z_{id}(k) + v_{id}(k+1) \tag{6}$$

where ω is the inertia weight, c_1 and c_2 is the learning factor, and $rand$ is the random number on [0,1]. The inertia weight w makes the particle maintain the inertia of motion[11]. W generally takes the random number between 0 and 1, but not 0. Through (7),

$$\omega = \omega_{max} - iter \frac{\omega_{max} - \omega_{min}}{iter_{max}} \tag{7}$$

the inertia weight changes with the position of the particle, so the algorithm is not easy to fall into local extreme, where $iter$ is the current iteration number and $iter_{max}$ is the maximum iteration number. For the problem of slow convergence speed and low efficiency in the late evolution of PSO, the study factor c_1, and c_2 is segmented, which is also conducive to avoid too long search time. Compared with the early stage, the late stage of the local search ability is smaller, while the late stage of the global search ability should be larger. In the early stage, the algorithm can search the global particles quickly, and in the later stage, the local particles tend to be global particles. Show that

$$\begin{cases} c_{1f} = \left(e^{-\frac{iter}{iter_{max}}} \right) c_1 & \frac{iter}{iter_{max}} > 0.4 \\ \\ c_{2f} = c_2 + 1 - e^{-\frac{iter}{iter_{max}}} & \frac{iter}{iter_{max}} > 0.4 \end{cases} \tag{8}$$

with which $iter$ is the current iteration number, $iter_{max}$ is the maximum iteration number, and when $\frac{iter}{iter_{max}} \le 0.4$, the learning factor remains unchanged. The algorithm flow of PSO-FCM is as follows:

Step 1. Initialize and encode n clustering centers to form the first generation of particles. The initial velocity of particles is given.

Step 2. Calculate Euclidean distance according to the initial clustering center, and initialize the membership matrix.

Step 3. Update the value of the root objective function J_e according to (2), update the clustering center as the next generation particle according to (3), and update the membership matrix according to equation 5.

Step 4. Take function $f(z_i) = \frac{1}{J_e + 1}$ as the fitness of particles. If the fitness reaches the maximum threshold $iter_{max}$ or the number of iterations reaches the maximum, the iteration will be terminated and the current clustering center will be returned as the global optimal clustering center. Otherwise, it will enter the next Step.

Step 5. Search the local optimal particle according to the current clustering center, and its position is denoted as p_{id}; search the global optimal particle, and its position is denoted as p_{gd}.

Step 6. Calculate iteration number update ω and learning factor c_1, c_2. Update particle velocities and positions according to equations 6 and 7.

Step 7. If the clustering frequency reaches the maximum clustering category $c\,max$, the iteration is stopped and the current particle is returned as the global optimal clustering center. The current clustering frequency is the number of optimal clustering categories. Otherwise go back to step3.

Parameter description is as follow: maximum value of clustering category $c\,max$, fuzzy index b, particle swarm size n, learning factor c_1, c_2, maximum value of inertia weight ω_{max}, minimum value of inertia weight ω_{min}, maximum speed v_{max} and maximum number of iterations $iter_{max}$.

4. The experimental results

The software used in this experiment is Matlab 2017R, and the selected 3 images are all from the network standard image data set. Because the FCM algorithm does not consider the spatial characteristics of the image, the segmentation result is easily affected by the noise, abnormal points and texture in the image [8]. In order to verify the image segmentation quality, different levels of Gaussian noise were added to two images, and the other one was texture image. The algorithm in this paper is compared with traditional FCM. The PSO-FCM algorithm adopted in this paper has the same FCM parameter setting as the traditional FCM: the maximum number of clustering categories $c\max = 10$, the maximum number of iterations $iter_{\max} = 100$, the fuzzy index b=2, and the threshold value $\xi = 1e-5$. Other parameters of the improved algorithm are set as follows: the particle swarm size is n=20, and the initial value is $c_1 = 0.4$, $c_2 = 0.4$, $\omega_{\max} = 1$, $\omega_{\min} = 0$, $v_{\max} = 1.5$.

(a) The original image   (b) FCM image segmentation   (c) improved PSO-FCM image segmentation

Figure 1 The result of FCM and improved PSO-FCM cameraman image segmentation with C=2.

（a）C=5   （b）C=7   （c）C=9

Figure 2 The result of improved PSO-FCM cameraman image segmentation.

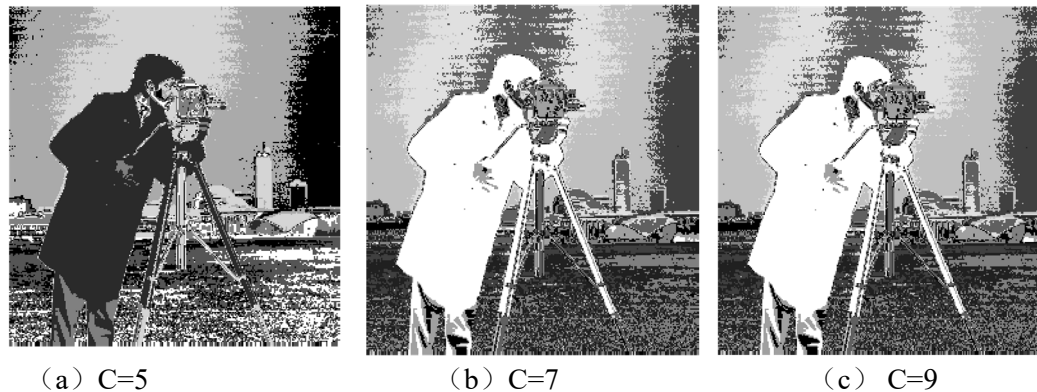（a）C=5   （b）C=7   （c）C=9

Figure 3 The result of FCM cameraman image segmentation.

When segmenting standard cameraman images, it is found that the segmentation effect is very similar when the number of clustering categories is small, as shown in figure 1, when C=2. When the number of clustering categories is large, it can better reflect the optimization effect of improved PSO-FCM, as shown in figure 2 and 3. C=5, C=7 and C=9 are respectively taken to compare the segmentation results of FCM and improved PSO-FCM. In figure 3, there is no difference in FCM segmentation when C=7 and C=9, and the algorithm falls into the local optimal value, while the improved PSO-FCM global optimization ability is reflected in figure 2, and the algorithm returns C=7 as the number of optimal clustering categories. The experimental data in figure 2 and 3 are shown in table 1 for comparison. The number of iterations and objective function of the algorithm in this paper are small, but the total time is long.

C=4 was selected for comparison when clustering and segmentation were carried out for standard tooth ultrasonic images. The segmentation results are shown in figure 4, and the image segmentation data are shown in table 2. The segmentation image shows that figure 4 (c) image has a good segmentation, which can fully display the shape of teeth and distinguish them from the background. However, figure 4 (b) shows that the selection of FCM clustering center is slightly worse.

Table 1 The result of cameraman image segmentation with C=7.

algorithm	Time（s）	The number of iterations	Theobjective function	The clustering center
FCM	4.7653	23	3.1037e+06	149.0707, 13.6481, 127.0244, 53.1898, 165.6034, 182.8878, 102.8695
the improved PSO-FCM	9.007824	20	2.2783e+06	13.7539, 113.4352, 210.6862, 146.3355, 178.6433, 55.4851, 167.5340

(a) The original image   (b) FCM image segmentation   (c) Improved PSO-FCM image segmentation
Figure 4 The result of tooth ultrasonic image segmentation with C=4

Table 2 The result of cameraman image segmentation with C=7.

| algorithm	Time（s）	The number of iterations	The objective function	The clustering center
FCM	41.7022	27	8.6262e+07	212.0332, 125.1470, 72.0929, 184.3657
the improved PSO-FCM	123.561	23	1.0395e+07	204.0365, 195.3976, 125.0144, 71.8177

In order to test the anti-noise performance of the algorithm, Gaussian noise with the addition square difference of 0.002 and 0.052 in the original figure of figure5 and 6 was added when other algorithm parameters were the same. The segmentation results show that there are few noise points in the tooth area of figure (c) in figure 5, figure (b) and (c) in figure 6, cannot distinguish between people and background. Figure 5(c) has obvious contour with distant buildings. The experimental results show that the algorithm proposed in this paper has better anti-noise performance than FCM.

Figure7 shows the selection of texture images. When the simulation parameters are the same (C=2, number of iterations), the algorithm in this paper can better shield interference terms and highlight texture features, while figure7 (b) shows that the results of FCM algorithm are worse than the algorithm in this paper.
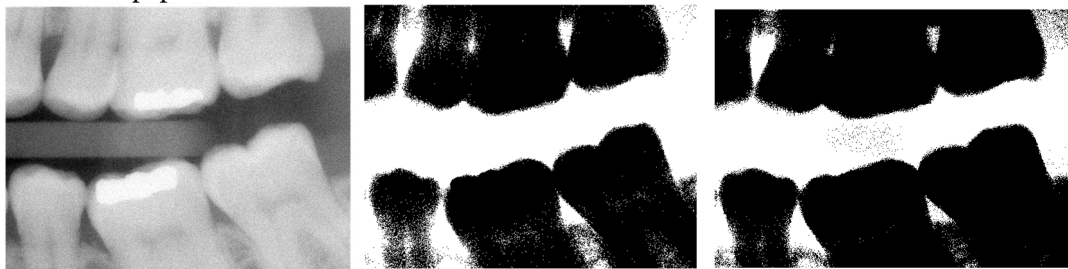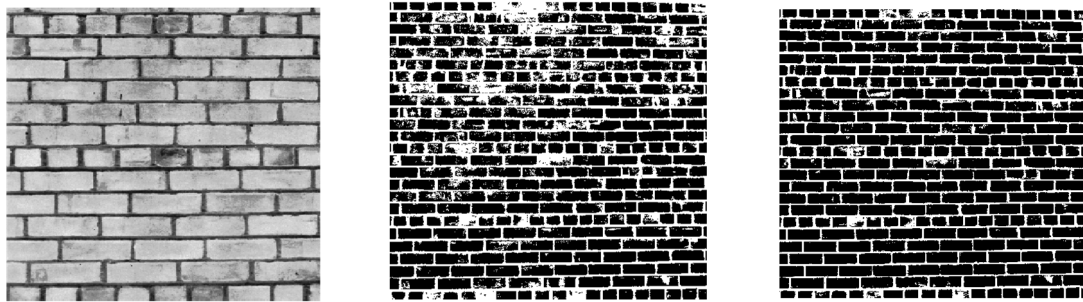

(a)The image with Gaussian noise （b）FCM segmentation （c）Improved PSO-FCM segmentation
Figure 5 The segmentation results of ultrasonic teeth images with Gaussian noise.
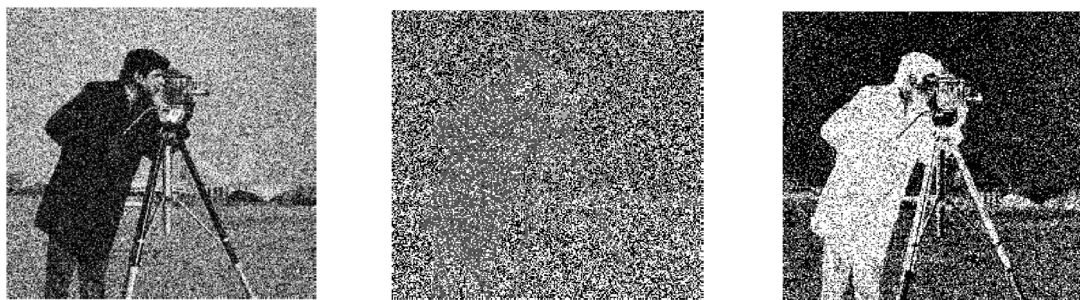
(a)The image with Gaussian noise （b）FCM segmentation （c）Improved PSO-FCM segmentation
Figure 6 The segmentation results of the cameraman images with Gaussian noise.

(a)The image with Gaussian noise　（b）FCM segmentation　（c）Improved PSO-FCM segmentation
Figure 7 The segmentation results of the texture images with Gaussian noise and c=5.

5. Conclusion

In this paper, a clustering segmentation algorithm based on FCM combined with improved PSO is proposed for image segmentation. This algorithm can effectively perform global optimization and has high accuracy and noise resistance. The test results on the actual image data show that the improved FCM-PSO method proposed in this paper has a better image segmentation effect under the same conditions.

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