

A Kind of Chaotic Particle Swarm and Fuzzy C- mean Clustering Based on Genetic Algorithm

Zhang Chun-na¹ and Li Yi-ran²

¹*School of Software, University of Science and Technology Liaoning, Anshan
Liaoning 114051, China*

²*College of Applied Technology, University of Science and Technology Liaoning,
Anshan Liaoning 114011, China
zcn1979@163.com*

Abstract

This paper proposes a new clustering algorithm that combines genetic algorithm and chaotic particle swarm optimization with fuzzy C- means (GCQPSO-FCM), in order to solve the issue that the fuzzy C- mean algorithm is sensitive to the initial value. First, make full use of genetic algorithms to calculate the optimal number of clusters of sample population and select a valid criterion function as a fitness function; Furthermore, introduce chaos strategy in particle swarm algorithm to improve the algorithm global search ability, also contribute to the particles are more easily jump out of local bondage. Two speed factors are defined to accelerate the convergence, which also improves the performance of the algorithm. Experimental results show that our improved GCQPSO-FCM algorithm is better in efficiency and quality than the original algorithm.

Keywords: *quantum particle swarm; chaotic sequence; FCM; GCQPSO-FCM*

1. Introduction

Clustering analysis as an important method of data mining has been widely applied in various fields of scientific research, fuzzy C- means (fuzzy c-means, FCM) algorithm is a classical algorithm in clustering analysis, which was first proposed in 1971 by Bezdek. According to some similarity, the algorithm divides the data in the sample space, homogeneous data is classified as a collection, and gives the degree of membership about each sample data for the collection. Algorithm's advantage is obvious, it is able to handle large-scale data sets, its defects is that the selection of initial value is sensitive, and the objective function use the method of gradient descent, the execution of the algorithm is easy to fall into local optimum.

There are many ways to solve the inherent defects of fuzzy C-means, some scholars introduced the intelligent algorithm in the algorithm, reference [1] put forward a kind of C-means algorithm based on chaos particle swarm, it utilized chaos sequence to determine the position of a particle, for the problem of local optimum, the adaptive inertia weight factor is defined to escape from the local constraints, The experiments prove that the algorithm has fast convergence speed and can adaptively find the optimal solution, but the algorithm does not optimize the cluster center, easily lead to the optimal solution is not stable. Reference [2] is also a mixed strategy, introduced a simple search in this paper and proposed K-NM-PSO algorithm, the method improved the speed of searching optimal solution. Reference [3] is introduced quantum particle swarm in the FCM, the algorithm is concise, fewer parameters

and global search capability is strong, but it still did not consider the effects of initial value. In the paper, according to the above combination of factors, we proposed the GCQPSO-FCM algorithm. In order to improve the global search ability of the algorithm, introduce chaos particle swarm algorithm in fuzzy C- means, so that the particles are regularly fast search the optimal solution, At the same time in the algorithm combined with genetic algorithm, using the validity criterion function as fitness function to find a reasonable initial value by an adaptive way, avoid the sensitivity of the algorithm.

2. The Quantum Particle Swarm Based on Chaotic Sequence

Particle Swarm Optimization, referred to as PSO, is a novel evolutionary algorithm, it's thought originated from the foraging behavior of birds, fish and other groups. The algorithm may turn sample data into particles, each particle has its own speed and position, while the particle is a solution, each search can be understood as a foraging, position and its speed changing in the iteration. When following the optimal particle, itself also searches and finally finds the individual and global extremum [4-6].

2.1 Chaotic Sequence

Chaotic phenomena are nonlinear areas, its most significant feature is the ergodicity and regularity, traverse the hash point in a given sample space according to certain laws, the search does not repeat in the process. It is obvious that the efficiency will be greatly improved and enhances the global search ability if use chaos strategy in the particle movement [7]. The specific steps are as follows:

(1) Define initial region, given n - vector $R_0 = (R_{01}, R_{02}, \dots, R_{0N})$, each value of R_0 is adjacent each other, and the difference is very small.

(2) To calculate the initial vector R_0 by using the logistics equation, generating chaotic sequence m_1, m_2, \dots, m_n . After several iterations, the system will be fully in a chaotic state. Vector layer can be expressed as:

$$m_{i+1} = m_i(1 - m_{i-1})\lambda \quad (1)$$

In the formula, λ is an iterative control parameters.

(3) X_i is the space particles, Using formula (1) to get the better location of X_i , denoted as X_i' .

$$X_i' = r \cdot rnd \cdot m_j + X_i \quad (2)$$

In the formula, r is the movable radius of particles X_i , $rnd \in [-1, 1]$, $j \in [0, n]$.

2.2 The Quantum Particle Swarm Algorithm with Chaos

Looking for individual and global extremum movement of particles in the PSO algorithm has some randomness, when the particle are in the search process, if arrived at the local optimal solution, followed by the other particles, have fallen into the region; the motion of the particle may not be able to make it out of the local optimal bound, and so it is easy to fall into partial optimal solutions. Chaos is introduced, so that the motion of the particle is regular and ergodic. At the same time, introducing the concept of the quantum particle swarm, the particles are placed in a quantum space by the expression of the wave function, the particles are free to search for possible solutions, its state is not affected by the position and velocity vector. The following is the wave function that mark particle state:

$$\int_{-\infty}^{+\infty} L_p dx dy dz = 1 \quad (3)$$

The iterative formula of particles obtained by Monte Carlo algorithm converted the quantum state:

$$P_{mb} = \frac{1}{l} \sum_{i=1}^l P_i \quad (4)$$

$$P_{mk} = \theta P_{ik} + (1 - \theta) P_{gk} \quad (5)$$

$$L_p(t+1) = P_{ik} \pm a | P_{mk} - L_p(t) | \ln^{\frac{1}{\lambda}} \quad (6)$$

In the above formula, P_i is current position of particle, P_{gb} is the global extremum, P_{mb} is the optimal intermediate values, l is the number of particles, P_{mk} is a random point between P_{ik} and P_{gk} , a is the expansion contraction factor and a quantitative index, used to control the convergent speed of the algorithm, get a random number from $(0,1)$ in the iterative process, if $a > 0.5$, then take positive values, else take negative values.

In the quantum particle swarm algorithm, a particle can be defined as $x_i^0 = \{v_{i1}, \dots, v_{ij}, \dots, v_{im}\}$. In the formula, v_{ij} represents the j cluster center vectors of the i particles, the fitness function is still using the particle swarm optimization objective function $J(u, Z)$, The steps of the algorithm are as follows:

(1) The initialization of Particle Swarm parameter: Including the spatial dimension of particle swarm, namely the size of population. The iteration times of search, the length of the chaotic sequence and other necessary parameters.

(2) The computation of the fitness value: calculated the fitness value of current particle, if the individual current value is better than the previous value, then update the position of the particle; Sequentially count current value of all particles, if the optimal solution of individual extreme is better than the previous global optimal solution, then replace.

(3) Chaos Optimization: Assuming the current optimal solution is $P_b = (P_{b1}, P_{b2}, \dots, P_{bk})$, denoted as P_{bi} , $i \in [1, k]$, mapped to the formula (1), obtained $m_i = (P_{bi} - a_i) / (b_i - a_i)$, then take advantage of the logistics equation are iteratively obtain chaotic variable sequences, and inverse mapping solution space obtained extremal solutions $P_b' = (P_{b1}', P_{b2}', \dots, P_{bk}')$. Finally, traverse each solution in the solution space, calculate the fitness value, obtain the alternative solution P_b'' .

(4) Search each particle in the groups, if the optimized solution is better than the current solution, then the current position is replaced by P_b'' .

(5) Check whether or not the current state satisfies the search conditions, if satisfied, the current solution is the optimal solution; then it returns continue to calculate the fitness value.

It is note that the algorithm only use a to describe the particle state, referencing the quantum particle swarm type (6) configured a , if $a > 0.5$, the formula is:

$$L_p(t+1) = P_{ik} + a | P_{mk} - L_p(t) | \ln^{\frac{1}{\lambda}}, \text{ else is : } L_p(t+1) = P_{ik} - a | P_{mk} - L_p(t) | \ln^{\frac{1}{\lambda}}$$

3. Optimization of Fuzzy C- means Algorithm

3.1 FCM Algorithm

Fuzzy C- means clustering algorithm (FCM) is essentially a kind of data classification, according to the principle of least square method of Lagrange repeatedly calculate clustering center of sampling data by using the iteration method and values of each elements in classification Matrix, so that its membership meets conditions and with the smallest variance within clusters.

Hypothesis in Q dimension space S^Q has a limit set $X = \{x_1, x_2, \dots, x_n \mid x_i \in S^Q\}$, using the fuzzy matrix u to divide the vector into m classes, $m \in (1, n)$, the center of initialization cluster is $Z = \{Z_1, Z_2, \dots, Z_m\}$, define the objective function as follows:

$$J(u, Z) = \sum_j \sum_i u_{ji}^r D_{x_i, Z_j}^2 \quad (7)$$

In the formula, u_{ji}^r is Membership, *i.e.*, membership of the i text belongs to the j class; D_{x_i, Z_j}^2 is distance of the i text to the j cluster center; r is weighting factor, it affects the ambiguity of the fuzzy matrix, this paper set $r \in [1, 3]$.

In addition, the fuzzy matrix element u_{ji}^r in formula (3) should be met the following formula:

$$\sum_{j=1}^m u_{ji}^r = 1, \quad \sum_{i=1}^n u_{ji}^r > 1 \quad (8)$$

In the formula, $u_{ji}^r \in [0, 1]$, $0 \leq i \leq n$, and $0 \leq \sum_i u_{ji}^r \leq n$.

By the above formula, it is known that, under ultimate circumstances, when $J(u, Z)$ obtain the minimum value, u_{ji}^r and D_{x_i, Z_j}^2 can get the optimal value. Here, according to principle of least square method of Lagrange adjusted u , Z in the $J(u, Z)$ referring to the following formula:

$$u_{ji} = \frac{1}{\sum_{k=1}^m \left(\frac{D_{x_i, Z_j}}{D_{x_i, Z_k}} \right)^{2(r-1)}} \quad (9)$$

$$Z_j = \frac{\sum_{i=1}^n (u_{ji})^r x_i}{\sum_{i=1}^n (u_{ji})^r} \quad (10)$$

In the formula, if $\|x_i - Z_j\| = 0$, then $u_{ji} = 1$.

The formula (5), (6) continuous iterate and adjust the value of u_{ji} and Z_j ; when $J(u, Z)$ converge enough, *i.e.* to meet the conditions, then get the final result of the clustering. The algorithm steps are as follows:

Step 1 initialize the sample set of training, randomly generate m cluster centers, denoted as $Z^1 = \{Z_{11}, Z_{12}, \dots, Z_{1m}\}$;

Step 2 According to the formula (5) and given the initial cluster centers z^1 is calculated the membership u^1 ;

Step 3 Re-calculate the cluster center z^k ;

Step 4 Set the conditions of iteration, if $|\max(u^{k+1}) - \max(u^k)| < \delta$, then stop; else progressively increase the iterative operator k and return step 2.

3.2 Optimization of Particle Velocity

The effect of clustering is to examine the satisfaction of convergence, each particle of groups has its own speed and constantly adjusted, its trajectory comes from its own flying experience and it is influenced by the other particles. Therefore, the analysis of the algorithm should not be regarded the individual as isolated point, but they were interrelated and interact on each other.

Definition 1: the acceleration factor

Usually, along with the population movement, if speed is reduced too fast, groups are easy to fall into local optimum. Experiment measured that this phenomenon is particularly obvious in FCM, and it is often convergent fast when the algorithm is far from over. The key reason is that the speed will gradually decline, and ultimately will be reduced to 0 in the iterative process; when rate drops to a certain time, search ability will decline, resulting in not enough to jump out of the local optimum. Here, set threshold ε ,if the speed is less than this value, then adjust the current speed, $v_i < \varepsilon$, then $v_i = \lambda v_0 \cdot v_0$ is the initial velocity, the maximum velocity of particles; λ is the acceleration factor, set $0 < \lambda < 1$.

Definition 2: escape factor

Species have a property called clustering, when a population gathered a large number of individuals, if the space is relatively narrow, part of the group will be separated out, and then construct the new community. The position of the particle is also based on this consideration, turn to acceleration factor, if speed is less than the threshold value ε , this paper set up an escape factor γ , the selection of a location as the current position to replace the best position of particles, and to the current rate of iteration, $v_i < \varepsilon$,then $p_g = p_i$. Here, the selection of alternative position need to be put forward specially should adopt the random strategy, which can guarantee the stability of the original groups, yet the diversity of population.

Now exists Q dimensional space, set up the i particle, can be expressed as $q_i = (q_{1Q}, q_{2Q}, \dots, q_{iQ})$, its adaptive value can be expressed as $p_i = (p_{1Q}, p_{2Q}, \dots, p_{iQ})$,with a velocity $v_i = (v_{1Q}, v_{2Q}, \dots, v_{iQ})$,for each iteration of the k ($1 \leq k \leq Q$) dimensional equation as shown below:

$$v_{ik}^n = \lambda v_{ik}^{n-1} + \alpha_1 \beta_1^{n-1} (p_{ik}^{n-1} - q_{ik}^{n-1}) + \alpha_2 \beta_2^{n-1} (p_{gk}^{n-1} - q_{ik}^{n-1}) \quad (11)$$

$$q_{ik}^n = q_{ik}^{n-1} + v_{ik}^n \quad (12)$$

In the formula, λ is acceleration factor, its value should be adaptive, not large or small, and be adjusted timely in the iterative process. $\alpha_1, \alpha_2; \beta_1, \beta_2$ are correction factors, α_1, α_2 are set the same value, $\in [0, 3]$; β_1, β_2 are random numbers, $\in (0, 1)$.

Through the correction of velocity, freedom degree of particles in the Q dimension space search process is greater, and not easy to fall into local optimum, moderate convergence rate, number of iterations is defined by conditions.

4. GCQPSO-FCM Algorithm

4.1 The Effective Criterion Function

The division of the effective criterion function based on two indicators: compactness and separation. The former is used to represent the compactness of sample point in a class; the latter is the degree of dispersion between classes. In this way, the validity criterion function is divided into two categories: based on the membership and based on the membership and data collection. In this paper, using the function optimize the initial number of clusters, namely initial value of FCM. Function is defined as follows:

$$VC(u, Z, m) = Tigs(m) + \frac{Sepn(m)}{Sepn(m_{max})} \quad (13)$$

$$Tigs(m) = \frac{\frac{1}{m} \sum_{i=1}^m \|\sigma(X_i)\|}{\|\sigma(X)\|} \quad (14)$$

$$Sepn(m) = \frac{(\max \|Z_i - Z_j\|_{i \neq j})^2}{\sum_{i=1}^m \sum_{j=1}^m \|Z_i - Z_j\|^2 (\min \|Z_i - Z_j\|_{i \neq j})^2} \quad (15)$$

In the formula, $\sigma(X) = \{\sigma(X)^1, \sigma(X)^2, \dots, \sigma(X)^m, \}$, $\sigma(X)^t = \frac{1}{n} \sum_{j=1}^n (x_j^t - \bar{x}^t)^2$, $\bar{x} = \frac{1}{n} \sum_{j=1}^n x_j$, $Tigs(m)$ used to indicate the closeness of the data in sample space, The range of value is [0,1]. The more the data and the smaller $Tigs(m)$ is, the more closely between the data; $Sepn(m)$ indicates the degree of separation between the classes, the effect depends on $VC(u, V, m)$.

4.2 Algorithm Analysis

The ultimate goal of genetic algorithm is to obtain a best individual of fitness value, First need to create a fitness function, to evaluate the population of containing one or more solutions, and through breeding of many generations, the algorithm stops when the genetic variation meet the requirements. This paper presents the algorithm of GCQPSO-FCM using adaptive of genetic algorithm to obtain the number of clusters, effective criterion function as fitness function; the PSO algorithm is used to improve the efficiency and global searching ability of the algorithm, the specific steps of the algorithm are as follows:

Step 1 Set binary populations $Y = \{Y_1^k, Y_2^k, \dots, Y_n^k\}$, the length is $l+2$, the initial state is $k=0$, the top l bits represent data encoding, the encoding corresponding decimal is represented by the $l+1$ bits, the adaptive value correspond the $l+2$ bits;

Step 2 To calculate the adaptive value of individual Y_i^k by using genetic algorithm, denoted as m_i^k ;

Step 3 Encode the clustering center Z , initialize the size n of the particle swarm, set the maximum number of iterations k_{max} , generate population $x = \{x_1^k, x_2^k, \dots, x_n^k\}$, set the particle's position $(x_i^k | x_i^1, x_i^2, \dots, x_i^N)$ and velocity $(v_i^k | v_i^1, v_i^2, \dots, v_i^N)$, The activities radius of

particle is r in chaotic sequence, the correction factor is $\alpha_1, \alpha_2, \beta_1, \beta_2$, the position of the i particle is represented by a matrix $m_i^k \times n$;

Step 4 According to formula (9) to calculate the membership, judge $\max |u_{ji}^k - u_{ji}^{k-1}| < \varepsilon$, if establish, skip to step 5;

Step 5 Calculate the initial fitness, select the best position of each particle (the best fitness value), move particle, this position as the initial iterative position of each particle, namely $P_{bi}^k = X_{bi}^k$. At the same time, the fitness function also need to make corresponding changes, namely $f(P_{bi}^k) = f(X_{bi}^k)$;

Step 6 According to the formula (1), (2) introduced the chaotic sequence in the current iteration, to calculate its particle position, and compared with the current location, if excellent, replace it. In the replacement of the position process, on the premise of considering the acceleration factor and escape operator, speed according to the formula (11), (12) to be updated;

Step 7 Constantly compare the global fitness of particle swarm in the iteration, select the global best fitness value in the history, replace the current global optimal position of the particles with this position;

Step 8 Calculate the effective criterion function $VC(u, Z, m)$, for the populations implement genetic manipulation, by selection, crossover and mutation to obtain a new generation of population $Y = \{Y_1^{k+1}, Y_2^{k+1}, \dots, Y_n^{k+1}\}$, return to step 2;

Step 9 The end condition of algorithm is:

- 1) The number of iterations to reach the maximum number of iterations k_{max} ;
- 2) Effective criterion function convergent.

5. Experimental Analysis

5.1 Experiment Contents

Experimental data are taken from three data sets in the universal database UCI: Similar, Iris, Same. Among them, Similar is a high dimensional data set, the dimension is 16090, sample number is 288, each data set contains 6 attributes, the optimal clustering number is 6; Iris is a low dimensional data set, the dimension is 4, sample number is 165, each data set contains 3 attributes, the optimal clustering number is 3; Same is a high dimensional data set, the dimension is 16090, sample number is 290, each data set contains 8 attributes, the optimal clustering number is 3; using three kinds of index evaluate the algorithm: the effect of clustering and performance of the algorithm. The former includes the accuracy of clustering, calculate the maximum, minimum and average values in selected experiments; the optimal number of clusters, under a certain number of experiments, get the total number of the optimal clustering; the pairwise comprehensive measure combines the accuracy rate and the recall rate, range set $[0,1]$, the greater the value that better clustering effect. The latter includes the average run time, it is time to obtain the optimal clustering number; convergence test the stability and speed of algorithm, ensure speed while the more gentle the better. This paper compares three kinds of algorithms: FCM、CPSO-FCM and GCQPSO-FCM, for each data set conduct 15 times simulation, the iterative number is 400. Among them, the accurate rate of clustering refer to Table 1, the average running time is shown in Table 2, the optimal number of clusters as shown in Figure 1, the pairwise comprehensive measure shown in Figure 2, the convergence shown in Figure 3.

Table 1. The Clustering Accuracy of Algorithm

Data set	Category	FCM(%)	CPSO-FCM(%)	GCPSO-FCM(%)
Similar	max	89.7.	91.2	95.3
	min	84.2	87.8	93.6
	average	87.3	89.4	94.3
Iris	max	76.6	78.5	85.4
	min	72.5	75.1	83.3
	average	74.1	77.1	84.1
Same	max	83.4	86.9	90.2
	min	77.3	83.6	88.7
	average	80.9	84.1	89.1

Table 2. The Average Running Time of Algorithm

Data set	the optimal cluster number	FCM(s)	CPSO-FCM(s)	GCPSO-FCM(s)
Similar	6	3	12	15
Iris	3	4	13	17
Same	3	4	14	16

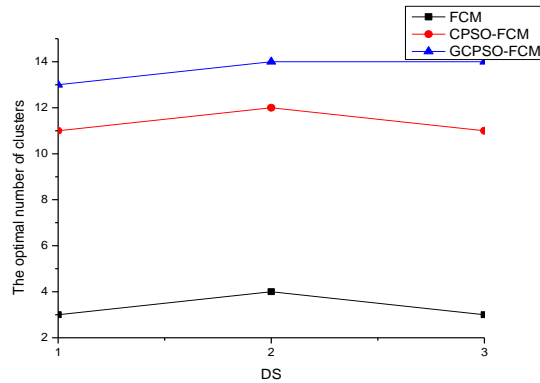
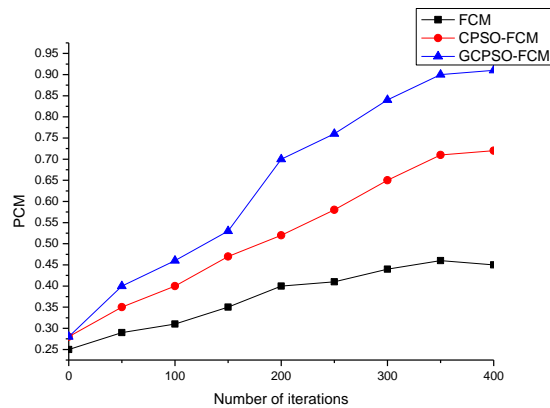
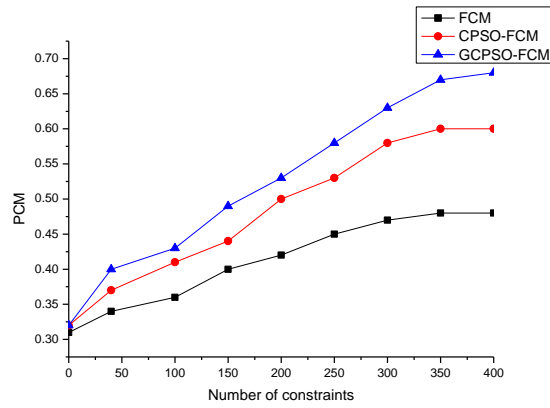


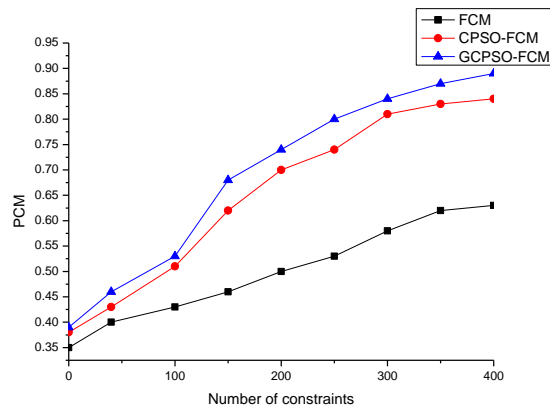
Figure 1. The Comparison of the Optimal Cluster Number



(a) The Comparison of PCM Value in the Similar Data Set



(b) The Comparison of PCM Value in the Iris Data Set



(c) The Comparison of PCM Value in the Same Data Set

Figure 2. The Comparison Results of PCM Value in the Data Set

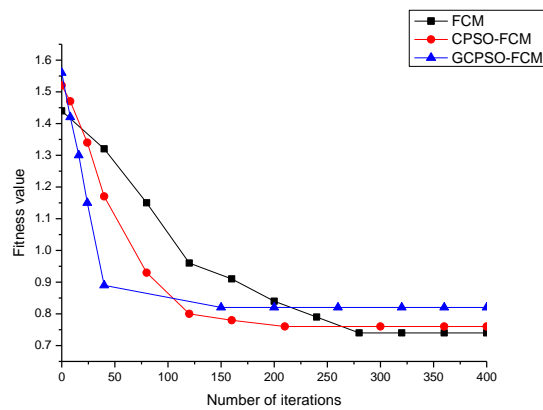


Figure 3. The Comparison Results of Convergence

5.2 Experimental Analysis

The comparison results obtained in the clustering effect and performance of the algorithm in the experiment. From the Table 1, CPSO-FCM and GCQPSO-FCM are more stable than FCM, mainly due to the introduction of the quantum particle swarm algorithm strengthen itself optimization ability and improve the stability, clustering effect is improved obviously. GCQPSO-FCM has the best performance in the three algorithms, it explains that hybrid genetic algorithm FCM has solved the problem of initial value sensitivity, therefore, the clustering effect is better. Table 2 gives the average value of the optimal clustering number needed to run time, among them, FCM spent the shortest time, GCQPSO-FCM spent the longest time, however, in terms of the overall time, the difference is not very obvious. Considering the stability of the algorithm and the clustering effect, apparently a slightly longer time-consuming can be accepted. Figure 1 shows algorithm in the three data sets obtained the average value of the optimal number of clusters, from the data analysis, CPSO-FCM and GCQPSO-FCM is better than FCM, for the number of categories in a calculation, hybrid genetic algorithm can obtain optimal cluster number as the division standard, while the FCM the corresponding number of clusters may not be optimal, and the clustering center is optimized by PSO in the optimized algorithm, clustering algorithm is more accurate; figure 2 shows a comparison of three algorithms in PCM value, comprehensive analysis the three groups data, the advantage of GCQPSO-FCM increased with the number of iterations gradually reflected, when the number of iterations to reach 100 after the slope steep rise, and then continue to maintain the upward trend, thus the algorithm improvement effect is prominent. Figure 3 is the comparison of convergence results, from the analysis of speed, convergence speed of GCQPSO-FCM is higher than the other two algorithms; in the stability analysis, the improved algorithm in the iteration number reached 150 remained stable, the improved algorithm performance is greatly improved.

6. Conclusion

In this paper, the PSO-FCM hybrid genetic algorithm to solve the problem that the algorithm dependent on the initial value. In the experiment, according to the three groups of simulation data compare FCM, CPSO-FCM, GCQPSO-FCM, results are displayed in the clustering accuracy and the optimal clustering number two indicators, the best effect is GCQPSO-FCM, and it spent the longest time to obtain the optimal clustering number, but consider the overall performance of algorithm is acceptable. From the analysis of the final results of the clustering accuracy, the optimized algorithm in the three data sets on the performance are different, it has a certain relation with the fitness function, the direction of next step should consider to adapt the adopting effective criterion function to different data sets, to obtain the best effect of clustering. The direction of future work should start with three aspects. first, select the effective criterion function to adapt to different data sets, in order to reflect the clustering effect. Second, design a new hybrid algorithm: SFLA-PSO. And finally, consider balance issues about the rapid convergence of the algorithm.

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Authors



C. N. Zhang, received the Master's degree in computer application technology from University of Science and Technology Liaoning, in 2007. Currently, she is a lecturer at School of Software Engineering at University of Science and Technology Liaoning. Her research interests include Distributed computing and data mining.



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