An Improved Fuzzy C-means Clustering Algorithm based on PSO

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***Abstract*—To deal with the problem of premature convergence of the fuzzy c-means clustering algorithm based on particle swarm optimization, which is sensitive to noise and less effective when handling the data set that dimensions greater than the number of samples, a novel fuzzy c-means clustering method based on the enhanced Particle Swarm Optimization algorithm is presented. Firstly, this approach distributes the memberships on the basis of the distance between the sample and cluster centers, making memberships meet the constraints of FCM. Then, optimization strategy is presented that the optimal particle can be guided to close the group effectively. The experimental results show the proposed method significantly improves the clustering effect of the PSO-based FCM that encoded in membership.**

***Index Terms*—clustering, particle swarm algorithm, fuzzy C means, membership, constraint strategy**

I. INTRODUCTION

Generally speaking, clustering is in accordance with certain requirements and rules to distinguish between things, and classification of the process. Clustering algorithm is a set of classification of the data that distribution is unknown, the aim is to find the structure hidden in data, and as much as possible to make the data that have same nature attributed to the same class according to some measure of similarity degree.

Clustering is a form of unsupervised learning whereby objects that similar to each other are put into the same cluster. It is the first stage of knowledge acquisition concerning a group of objects that is obtaining knowledge of classes.

Fuzzy clustering methods that based on the objective function is the most studied in the literature and the most widely used in practice, such algorithm takes the clustering problem as a constrained optimization problem, by solving the optimization problem to determine the fuzzy partition and the clustering results in data set. Such algorithms are characterized by simple and easy to apply and clustering performance is good, can take use of the classical optimization theory as its theoretical support, and easy for the programming.

Fuzzy c-means clustering algorithm (FCM) [1-2] is an effective algorithm and is one of the most used clustering methods. But when the data set has a higher dimension, the clustering effect of FCM is poor, and it is difficult to find the global optimum [3-4].

Particle Swarm Optimization (PSO) [11] is one of the modern heuristic algorithms under the evolutionary algorithms, and has proved to be very effective for solving global optimization, and gained lots of attention in various engineering applications. It is not only a recently invented high-performance optimizer that is easy to understand and implement, but it also requires little computational bookkeeping and generally only a few lines of code. It is a stochastic search technique with reduced memory requirement, computationally effective and easier to implement compared to other evolutionary algorithms.

Clustering problems can be attributed to optimization problems under certain conditions, Particle Swarm Optimization is an optimization algorithm based on the theory of swarm intelligence, which could be implemented and applied easily to solve various function optimization problems, or the problems that can be transformed to function optimization problems. PSO is easy to describe and implement, it also has a strong global search capability and a faster convergence [12]. Many PSO-based Fuzzy Clustering Algorithms are proposed [5-9]. However, in most of these algorithms the particle is encoded by cluster centers, less of these algorithms use the method that the particle is encoded by membership.

If a data set has n samples and c clusters, each sample has d dimensions. While encoded by membership, a particle is an one-dimensional row vector with $n \times c$ rows. While encoded by cluster centers, a particle is an one-dimensional row vector with $c \times d$ rows. In a data set, d is

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usually less than n, then c×d is less than n×c, so most of PSO-based FCM is encoded by cluster centers. But when the particle is encoded by cluster centers, the range of particle is difficult to confirm for different clusters have different centers. When the particle is encoded by membership, the rang of particle is [0,1], and the PSO-based FCM is better than FCM on processing the data that d is more than n [9]. When the particle is encoded by membership, the sum of the membership between a sample and all cluters should be one, this is the constraint. Thomas A. Runkler et al. put forward a method for Fuzzy clustering constraints when the particle is encoded by membership in [9]. When the sum of membership between a sample and all cluters is not one, the method in [9] increases or decreases the insufficient or extra parts evenly. And their method is sensitive to noise, and less effective when handling the data set that dimensions less than the number of samples [9].

In order to solve the above problems, this paper proposes an improved method for the distribution of membership, having a better effect on handling the data containing noise, and also on low dimensional and high dimensional data sets. At the same time, optimization strategy is presented that the optimal particle can be guided to close the group effectively.

The rest of the paper is organized as follows. After the introduction, Section II gives a description of the generalized FCM clustering. In Section III, PSO is briefly described, and the improved method is introduced. Section IV provides the experiments conducted over three different data sets and discusses the results. Finally, Section V concludes the paper.

II. Fuzzy C-means Clustring Algorithm

Different clustering criteria can produce different clustering methods. Clustering algorithm can be put into traditional hard clustering and fuzzy clustering algorithm if in accordance with the range of membership. Traditional hard clustering division is “either-or” type of a division, namely the membership for a sample to a clustering is either 0 or 1. Since fuzzy clustering algorithm extends the range of membership, so that it can take any value within 0 to 1, which has better clustering effect and data expression, has become a hot research in this field. Fuzzy C-means algorithm theory is substantially complete, applications are relatively wide. The following is a brief introduction on fuzzy C means clustering algorithm.

The data set $X=\{X_1, X_2, \cdots X_n\}$ has n samples and c clusters, and $X_i \in R^p$. The objective function of FCM is:

$$J_m(U,E)=\sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^m \| x_k - e_i \|^2 \tag{2.1}$$

m is constant, and m>1. Cluster i is expressed as $e_i(i=1,2,\cdots,c)$. The membership between sample k and cluster i is expressed as $\mu_{ik}(i=1,2,\cdots,c,k=1,2,\cdots,n)$

$$\mu_{ik}\in\{0,1\}, \forall i,k; \sum_{i=1}^{c}\mu_{ik}=1, \forall k \tag{2.2}$$

The method to optimize the FCM model is alternating optimization through the necessary conditions:

$$\mu_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{\| x_k - e_i \|}{\| x_k - e_j \|}\right)^{\frac{2}{m-1}}} \tag{2.3}$$

$$e_i=\frac{\sum_{k=1}^{n}(\mu_{ik})^m x_k}{\sum_{k=1}^{n}(\mu_{ik})^m}, 1\le i\le c \tag{2.4}$$

The final aim is minimizing (2.1) [10].

The specific steps for FCM:

Step 1: set the number of clusters c (2≤c < n) and fuzzy index m (m>1), initializing the matrix of membership (or initializing cluster centers), set the maximum iterations n.

Step 2: calculate various cluster centers (or the matrix of membership).

Step 3: calculate the matrix of membership (or various cluster centers).

Step 4: repeat step 2 and step 3, until the completion of the maximum number of iterations. It can also set a convergence precision as the condition for a loop terminates.

III. Improved FCM Clustering Algorithm Based on PSO

A. Fuzzy c means algorithm based on PSO

Particle swarm optimization (PSO) [11] is an optimization algorithm based on the theory of swarm intelligence, the cooperation and competition among particles produced swarm intelligence to guide the optimization search. PSO is easy to describe and implement, it also has a strong global search capability and fast convergence. But PSO also has defects, as in convergence condition, all particles are in the direction of the optimal, if optimal particle is not good enough, it can easily fall into local optimum [12].

In the D-dimensional space, the number of the particle is m. $X_i=[X_{i_1}, X_{i_2}, \ldots, X_{i_D}]$ is the position of particle i, its velocity is $V_i=[V_{i_1}, V_{i_2}, \ldots, V_{i_D}]$, its best position is $P_i=[P_{i_1}, P_{i_2}, \ldots, P_{i_D}]$. $P_g=[P_{i_1}, P_{i_2}, \ldots, P_{i_D}]$ is the best position of all particles. Each particle velocity is updated by (3.1), then each particle position is updated by (3.2).

$$V_i^{n+1}=V_i^n + c_1 r_1\left(P_i - X_i^n\right)+c_2 r_2\left(P_g - X_i^n\right) \tag{3.1}$$

$$X_i^{n+1}=X_i^n + V_i^n \tag{3.2}$$

In (3.1) and (3.2), i=1,2, ⋯ ,m expresses different particles, c_1 and c_2 are acceleration constants; r_1 and r_2 are random real numbers drawn from [0,1]; n denotes evolutionary epochs [13]. From a sociological point of view, the first part of (3.1) as "Memory" entry, is the previous velocity, that the current velocity is by the impact of previous velocity; the second part is "cognitive" entry, represents particles itself thinking; the third part is the "social" entry, reflects the collaboration between the particles and information sharing, which guide the particles toward the optimal position in the entire group.

PSO algorithm steps:

Step 1: initialize the particle swarm, including population size, initial position and velocity of particles, etc.

Step 2: calculate fitness for each particle, storage each particle best position P_{best} and its fitness, and choose the particle that has the best fitness as G_{best};

Step 3: update the velocity and the position of each particle according to (3.1) and (3.2);

Step 4: calculate the fitness of each particle after update the position, compare the fitness of each particle with its best previous fitness P_{best}, if better than it, then set the current position as P_{best};

Step 5: compare the fitness of each particle with the group best previous fitness, if better than it, then set the current position as G_{best};

Step 6: search algorithm to determine whether the results meet the conditions set by the end of (usually good enough to adapt to a preset value or the maximum number of iterations), if preconditions not met, then return to Step 3; if preconditions are met, then stop iteration, output the optimal solution.

While PSO is used in FCM, particle can be encoded by membership or by cluster centers. If the data set has n samples and c clusters, each sample has d dimensions. When particle is encoded by membership, a particle is an one-dimensional row vector with n × c rows, that is $\{x_{11}, x_{12}, \cdots, x_{1c}, \cdots, x_{n1}, x_{n2}, \cdots, x_{nc}\}$, x_{ij} means the membership between sample i and cluster j. When particle is encoded by cluster centers, a particle is an one-dimensional row vector with c × d rows, that is $\{x_{11}, x_{12} \cdots x_{1d}, \cdots, x_{c1}, x_{c2}, \cdots, x_{cd}\}$, x_{ij} means the value of cluster i in dimension j. If n>d, encoded by cluster centers is simple, and could better handle data sets that n>d. If n<d, encoded by membership is simple, and could better handle data sets that n<d, the value of particle should meet the constraint of FCM (i.e. (2.2)). The step of PSO based FCM that encoded by membership is: the cluster centers are computed by the value of the particle with (2.4) firstly, then the value of objective function can be computed by the particle and its corresponding clustering centers according to (2.1).

The detailed steps of PSO based FCM is:

Step 1: initialize the particle swarm and the parameters of fuzzy clustering, including population size, initial position of particles, initial velocity of particles, sample size, sample dimension, the number of clustering centers and fuzzy index etc.;

Step 2: for each particle, calculate the corresponding clustering center according to the value of initial position, then the value of objective function can be computed by the particle and its corresponding clustering centers according to (2.1), storage each position as best position P_{best} and each particle fitness, then choose the particle that has the best fitness as G_{best};

Step 3: update the velocity and the position of each particle according to (3.1) and (3.2);

Step 4: using constraint strategy to make the value of particle meet the constraints of fuzzy clustering. Then calculate the corresponding clustering center according to the value of each particle, calculate the fitness of each particle according to the particle and its corresponding clustering centers according to (2.1), compare the fitness of each particle with its best previous fitness P_{best}, if better than it, then set the current position as P_{best};

Step 5: compare the fitness of each particle with the group best previous fitness, if better than it, then set the current position as G_{best};

Step 6: search algorithm to determine whether the results meet the conditions set by the end of (usually good enough to adapt to a preset value or the maximum number of iterations), if preconditions not met, then return to Step 3; preconditions are met, then stop iteration, output the optimal solution.

Paper [9] discussed the two different encoding, and put forward constraint method for fuzzy clustering when encoded by membership:

w_{ik} means the membership between sample k and cluster i, and is restricted to a range [-5,5]. Transform w_{ik} into $u_{ik} \in [0,1]$ using the sigmoid function (i.e. (3.3)) firstly,

$$u_{ik} = \left(1 + e^{-2 \cdot w_{ik}}\right)^{-1} \tag{3.3}$$

then use (3.4) making $\sum_{i=1}^{c} u'_{ik} = 1$ (c is the number of cluster).

$$u'_{ik} = \frac{u_{ik}}{\sum_{j=1}^{c} u_{jk}} \tag{3.4}$$

B. Improved FCM clustering algorithm based on PSO

When the sum of membership between a sample and all clusters is not one, the method in [9] increases or decreases the insufficient or extra parts evenly, giving equal treatment to clusters that near the sample and clusters that away from the sample, do not take the distance between the sample and different cluster centers into consideration, then slow convergence and less effective. The improved method in this paper has two steps:

Firstly, the constraint of PSO based FCM is improved.

The distance between sample k and cluster i is l_i, the membership between sample k and cluster i is u_{ik}, $u_{ik} \in [0,1]$. If $\sum_{i=1}^{c} u_{ik} \neq 1$, the change of u_{ik} is determined by l_i.

If $\sum_{i=1}^{c} u_{ik} < 1$, use (3.5), smaller distance, more plus; greater distance, less plus.

$$u_{ik} = u_{ik} + (1 - \sum_{i=1}^{c} u_{ik}) \times (1 - \frac{l_i}{\sum_{i=1}^{c} l_i}) \tag{3.5}$$

If $\sum_{i=1}^{c} u_{ik} > 1$, use (3.6), greater distance, more reduction; smaller distance, less reduction.

$$u_{ik} = u_{ik} + (1 - \sum_{i=1}^{c} u_{ik}) \times \frac{l_i}{\sum_{i=1}^{c} l_i} \tag{3.6}$$

Secondly, for optimal particle in PSO has an important role in guiding the group, if can get better optimal particle in each iteration, then can speed up the convergence and optimize cluster results, so this paper puts forward a new optimization method for optimal particle. The new method optimizes optimal particle through optimizing the worst sample in the optimal particle.

Data set $X = \{x_1, x_2, ..., x_n\}$ has n samples and $c(2 \le c < n)$ clusters, m>1 is constant, μ_{ik} means the membership between sample k and cluster i, e_i means cluster i. Using (3.7) get the fitness of sample k, that is $L(k)$, to fix the worst sample in the optimal particle. Greater fitness, the worse the sample.

$$L(k) = \sum_{i=1}^{c} (\mu_{ik})^m \|x_k - e_i\|^2 \tag{3.7}$$

η_n means the membership between the worst sample and cluster n, d_n means the distance between the worst sample and cluster n. The irrational distribution of membership cause the worst sample, the most reasonable distribution is that η_n and d_n are proportional.

Let $\eta_1 d_1 = \eta_2 d_2 = \cdots = \eta_n d_n$ and $\eta_1 + \eta_2 + \cdots + \eta_n = 1$, gets $\eta_k' = \frac{t_k}{t_1 + t_2 \cdots + t_n}$, $t_k = d_1 d_2 d_3 \cdots d_{k-1} d_{k+1} \cdots d_n$, so η_n and d_n are proportional.

This improved method firstly considers the distance between sample and different clusters. For the clusters near the sample, if the sum less than one, plus more, if the sum more than one, decreased less; for the clusters away from the sample, if the sum less than one, plus less, if the sum more than one, decreased more. Improved constraint method makes the sample anear its closer clusters and away from clusters that far from it in each iteration. Then, optimizing the worst sample in the optimal particle, to ensure the membership in near clusters big and the membership in far clusters small, optimization of the worst sample means optimizing the optimal particle at the same time, serve to the purpose that speeding up the convergence and optimizing cluster results. Compare to method in [9], the improved method adds the process of computing the distance, but gives up the process of using the sigmoid function (i.e. (3.3)), so the computed amount between the improved method and method in [9] is not obviously.

IV. Experiment Testing and Comparative Analysis

Hardware environment of experiment is PC with Intel(R) Core(TM)2 Duo, CPU E7400 2.80GHz, 2GB RAM. Operating system is Windows XP Professional, program code is achieved in platform of Visual Studio 2005 using C#.

Test data sets are: (1) Single outlier data set: [-1.2,0.5,0.6,0.7,1.5,1.6,1.7], 7 group with 1dimension data, one with the point [0.5,0.6,0.7], one with the point [1.5,1.6,1.7], a single outlier at -1.2. (2) Iris data set: 150 vectors with 4 features, has 3 clusters, each cluster has 50 samples. (3) Lung cancer data set: 32 vectors with 56 features (for containing 5 unknown data, only use 32 vectors with 54 features), has 3 clusters, the first contains 9 samples, the second contains 13 samples, the third contains 10 samples.

When the number of particle is 10 and with 100 iterations, table 1 to table 3 show the index of average clustering effect after running various methods. DIC stands for average distance inside clusters, DBC stands for average distance between clusters, OFV stands for objective function value, SCR stands for successful classification rate.

TABLE I.
Single Outlier Data Set

	FCM	Paper [9]	Improved method
DIC	0.28	0.56±0.05	0.26±0.01
DBC	2.28	0.44±0.24	2.29±0.03
OFV	1.54	2.79±0.11	1.53±0.07
SCR (%)	85.71	82.86±11.43	85.71

TABLE II.
Iris Data Set

	FCM	Paper [9]	Improved method
DIC	0.65	1.93±0.03	0.67±0.02
DBC	3.30	0.13±0.12	2.98±0.04
OFV	160.51±0.01	227.36±0.03	155.92±8.52
SCR (%)	89.33	46.60±2.07	90.47±2.33

TABLE III.
Lung Cancer Data Set

	FCM	Paper [9]	Improved method
DIC	4.24±0.37	4.32±0.04	4.07±0.10
DBC	0.04±0.01	0.23±0.06	2.07±0.47
OFV	204.32	200.49±0.03	123.01±8.72
SCR (%)	42.81±7.19	61.25±7.50	69.38±3.75

Table I shows the improved method is better than the method in [9] in various performance, and better than FCM in DIC and DBC. From table I, the improved method is better than FCM in various performances except in SCR. The improved method is obviously better than method in [9] in various performances too. Also, the method in [9] is worse than FCM in all performances. So, we can know the improved method has the best effect in data sets that has noise, and we can know the difference between the improved method and FCM when handling small data sets is not obvious.

Table II shows the improved method is better than the method in [9] obviously, and also better than FCM in the iris data set. Comparing FCM with method in [9], we can know FCM is better than method in [9], and the difference is obviously, because when PSO based FCM is encoded by membership, the algorithm can only better handle data sets that dimension greater than the number of sample, do not has a better performance in handling data sets that dimension less than the number of sample, like iris data set. However, table II shows the improved method makes the PSO based FCM that encoded by membership can also have a better effect in handling data sets that dimension less than the number of sample, and the advantages are obvious.

Table III shows the improved method is better than the method in [9] and FCM obvious in lung cancer data sets. From the comparation between FCM and the method in [9], we can see FCM is not suitable for data sets that dimension better than the number of sample, PSO based FCM that encoded by membership can better handle them, and the improved method is obviously better than the method in [9].

Table I to table III show the improved method is better than FCM and method in [9] not only in data sets that have noise, but also in data sets that have a low dimension or a high dimension, when the iteration is taken at 100.

Take the number of particle at 10, increasing iteration from 1 to 100, Fig. 1 to Fig. 6 show the change of successful classification rate and objective function value by using different methods. OFV means objective function value, SCR means successful classification rate.

Fig. 1 shows the method in [9] is worse than the other two methods in successful classification rate, the difference between FCM and the improved method is not obvious too when the iteration is change. So we can see the method in [9] is more sensitive to noise than the other two methods.

From Fig. 2, we can see the improved method has a faster convergence than the method in [9], and finally better than FCM. The change of objective function value in the improved method has a clear trend that is the value of objective function in the improved method decrease with the increase of iterations.

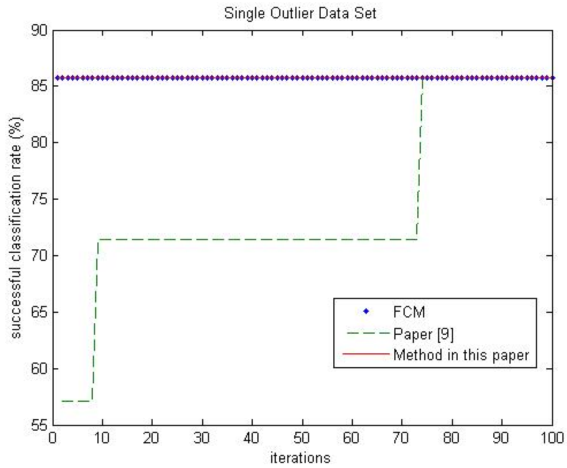

Figure 1. Comparation of SCR in single outlier data set.

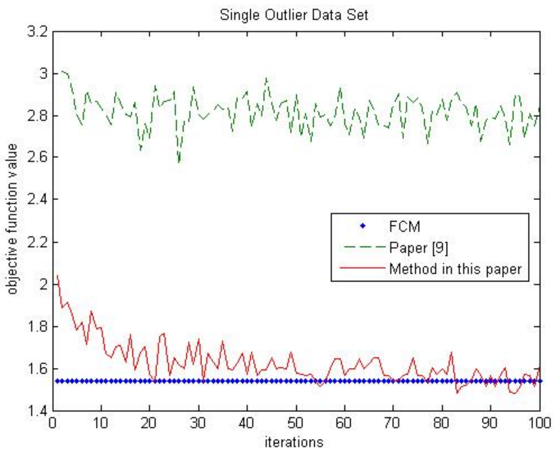

Figure 2. Comparation of OFV in single outlier data set.

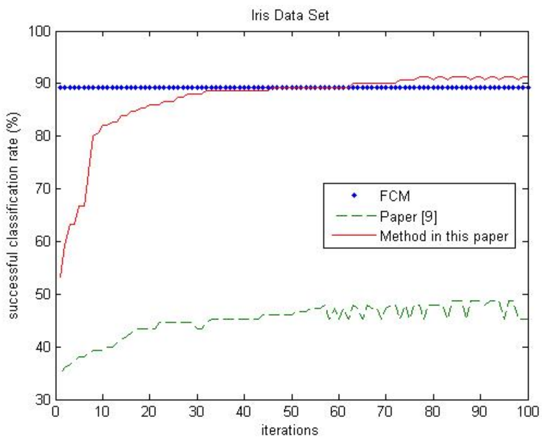

Figure 3. Comparation of SCR in iris data set.

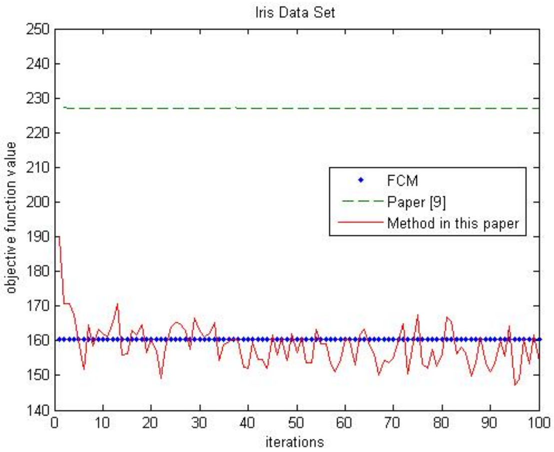

Figure 4. Comparation of OFV in iris data set.

From Fig. 3, knows the improved method is better than the method in [9] obviously, successful classification rate in the improved method and the method in [9] is not at the same level, and the improved method has a faster convergence with the increase of iterations, then finally better than FCM. When the iteration is 32, the improved method nearly has a convergence, compare to the method in [9] with a convergence number at 56. While the number of iteration increases to 70, the successful classification rate of the improved method is better than FCM.

From Fig. 4, knows objective function value in the improved method and the method in [9] is not at the same level too, and the improved method has a fast convergence with the increase of iterations, using less than 10 iterations. The overall level of the improved method is significantly lower than FCM, but the overall trend of the improved method in objective function value is not stable enough. The trend that PSO based FCM encoded by membership can also has a good effect on data sets that dimension less than the number of sample is obviously.

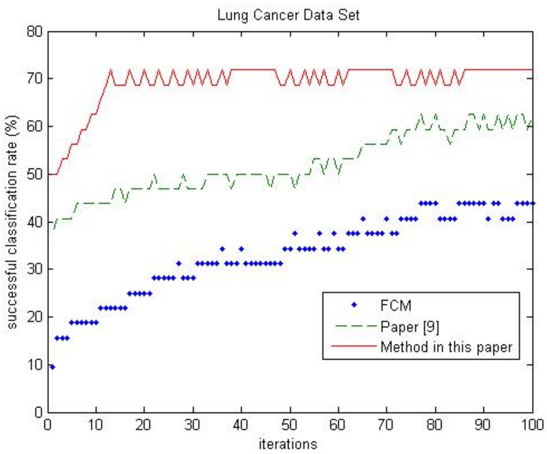

Figure 5. Comparation of SCR in lung cancer data set.

Fig. 5 shows the performance of FCM is worse, the improved method is better than the method in [9] obviously, and having a faster convergence. From Fig. 5, knows the curve of FCM is the worst one, having the lowest successful classification rate, using 78 iterations to come to a convergence. The method in [9] has a middle level successful classification rate, but the rate of coming to convergence is the biggest one, using 80 iterations. The improved method only uses 12 iterations to come to a convergence, the successful classification rate is significantly high than others, is the best one.

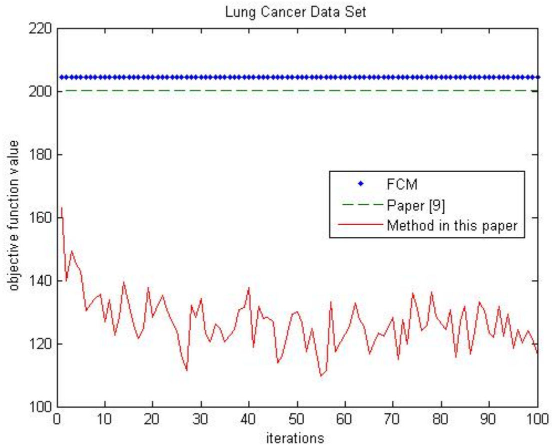

Figure 6. Comparation of OFV in lung cancer data set.

Fig. 6 displays the performance of FCM is the worst one, the method in [9] is little better than FCM, but worse than the improved method obviously. The performance of FCM and the method in [9] is stable enough in objective function value, but they are so worse. The improved method in objective function value has a fast convergence that only uses 18 iterations, and with the increase of iteration, the volatility of the curve decreased.

To sum up, the experiment using single outlier data set show the method in [9] is sensitive to noise, the improved method and FCM can handle the noise better; the experiment using iris data set show the new method improves the clustering effect of PSO based FCM better than FCM in data sets that dimensions less than the number of samples; the experiment using lung cancer data set show FCM is not suitable for high-dimensional data sets, the improved method gets the best clustering effect. So the improved method is better than the method in [9] obviously, having a faster convergence, and better than FCM in various data sets.

V. Conclusions

For the problems when PSO-based fuzzy clustering algorithm is encoded by membership, this paper improves the method of achieving constraint and puts forward an optimization method for optimal particle. In the previous, PSO-based FCM that encoded by membership can only better handle data sets that dimensions greater than the number of samples, but not suitable for data sets that dimensions less than the number of samples.

Three typical data sets are used to verify different algorithms. Experiments show that the improved method can handle the noise better than previous methods, further improves clustering effect in data sets that dimensions greater than the number of samples, and gets better effect than FCM in data sets that dimensions less than the number of samples at the same time, making PSO based FCM encoded by membership can better handle data sets that dimensions less than the number of samples too. The desired effect is achieved

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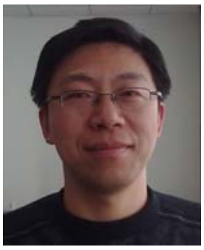

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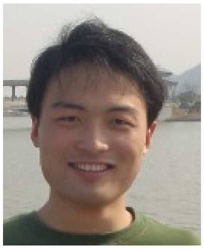

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