Fuzzy Clustering with Improved Swarm Optimization and Genetic Algorithm: Hybrid Approach

Bighnaraj Naik, Sarita Mahapatra, Janmenjoy Nayak and H.S. Behera

Abstract Fuzzy c-means clustering is one of the popularly used algorithms in various diversified areas of applications due to its ease of implementation and suitability of parameter selection, but it suffers from one major limitation like easy stuck at local optima positions. Particle swarm optimization is a globally adopted metaheuristic technique used to solve complex optimization problems. However, this technique needs a lot of fitness evaluations to get the desired optimal solution. In this paper, hybridization between the improved particle swarm optimization and genetic algorithm has been performed with fuzzy c-means algorithm for data clustering. The proposed method has been compared with some of the existing algorithms like genetic algorithm, PSO, and K-means method. Simulation result shows that the proposed method is efficient and can divulge encouraging results for finding global optimal solutions.

Keywords Fuzzy c-means · Particle swarm optimization · Genetic algorithm · Differential evolution

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1 Introduction

Clustering is one of the current active researches among all the other data mining tasks in the pattern recognition community. It is based on the principle of unsupervised learning which is intended to grouping the patterns in different restricted classes. There are two basic clustering techniques: (a) K-means and (b) Fuzzy c-means (FCM) used by a number of researchers for solving different problems. K-means is one of the popular algorithms in which the data clusters or points are classified into k points and the number of points is being chosen in well advance, but this algorithm suffers at a point where there is no any selected boundary value [1]. After the development of fuzzy theory by Zadeh [2], many researchers have shown the interest toward fuzzy theory for solving clustering problem. The fuzzy clustering problems have been expansively studied and the foundation of fuzzy clustering was being proposed by Bellman et al. [3] and Ruspini [4]. The fuzzy clustering based on the objective function is quite popularly known to be fuzzy c-means clustering (FCM) [5]. In FCM, the group of the pattern is decided based on many certain fuzzy membership grades [6]. Hoppner et al. [7] made a good effort towards the survey of FCM. FCM has been successfully applied in various application areas such as image segmentation [8], color clustering [9], real-time applications [10], signal analysis [11], spike detection [12], biology [13], forecasting [14], disease analysis [15], software engg. [16], damage detection [17], document analysis [18], cluster analysis [19], remote sensing [20, 21], etc.

FCM is an efficient algorithm for problem solving. But as the cluster center points are being chosen randomly, so the algorithm struck at local optima. Also, it has slow convergence rate and highly sensitive to initialization. To solve such problems, researchers have applied various optimization algorithms like genetic algorithm (GA) [22] and particle swarm optimization (PSO) [1, 23–25]. Particle swarm optimization is a bird-inspired metaheuristic algorithm proposed by Kennedy and Eberhart [26]. Basic idea for exploration and exploitation in PSO is found to be the backbone for development of other metaheuristic optimization techniques. Also complexity of this optimization technique is found to be fairly less than others, due to the fact that it requires minor parameter settings. But early convergence is one of the key drawbacks. So, in this paper an improved PSO with the genetic algorithm has been proposed for clustering real-world data. The suitability and effectiveness of selection of parameters in the PSO algorithm makes this method more efficient than the original PSO.

The rest of the paper is organized as follows: Sect. 2 elaborates the basic preliminaries like FCM, PSO and ISO. Section 3 describes the proposed methodology. In Sect. 4 experimental analysis and result are being described. Finally Sect. 5 concludes our work.

2 Basic Preliminaries

2.1 Fuzzy c-Means Algorithm (FCM)

FCM is a soft clustering algorithm. In general, if any clustering algorithm is able to minimize an error function [27], then that algorithm is called c-Means where 'c' is the number of classes or clusters, and if the concerned classes will use the fuzzy technique or fuzzy theory, then it is known to be FCM. In fuzzy c-means method, a fuzzy membership function is used to assign a degree of membership for each class. FCM is able to the form new clusters having close membership values to existing classes of the data points [28]. The FCM approach relies on three basic operators such as fuzzy membership function, partition matrix and the objective function. FCM is used to partition a set of 'N' clusters through a minimization of the objective function [29] w.r.t the fuzzy partition matrix:

$$J(U,V) = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^{m} \, ||x_j - v_i||^2 , \tag{1}$$

where x_j denotes the jth cluster point and v_i represents the ith cluster center.

'$u_{i,j}$' is the membership value of 'x_j' w.r.t. cluster i. 'm' denotes the fuzzy controlling parameter, i.e. for the value 1, it tends to hard partition and for the value of ∞ and it tends towards the complete fuzziness. $\|.\|$ indicates the norm function.

The iterative method is used to compute the membership function and cluster center as

$$u_{ij} = \left[\sum_{k=1}^{c} \left(\frac{||x_j - v_i||}{||x_j - v_k||} \right)^{\frac{2}{m-1}} \right]^{-1} \tag{2}$$

$$v_i = \sum_{j=1}^{N} u_{ij}^{m} x_j \Big/ \sum_{j=1}^{N} u_{ij}^{m} \quad \text{where } i \geq 1, i \leq c. \tag{3}$$

The steps of FCM algorithm are as follows:

1. Initialize the number of clusters centers v.
2. Select an inner product metric Euclidean norm and the weighting metric (fuzziness).
3. Compute U (partition matrix) using Eq. (2).
4. Update the fuzzy cluster centers using Eq. (3).
5. Compute the new objective function J using Eq. (1).
6. If $||J_{new} - J_{old}|| \leq \in$ then stop.
7. Else repeat steps 3–5.

2.2 Improved Particle Swarm Optimization

PSO [26] is an evolutionary optimization algorithm, inspired by the behavior of flying birds. Unlike other evolutionary algorithms, PSO has less parameter tuning and its complexity is also less. The algorithm of PSO is carried out with some basic assumptions such as follows [30, 31]: (i) In a multidimensional space, the birds are flying, at some position having no mass or dimension. They fly by adjusting their velocities and positions by exchanging information about the particle current position, local best particle position and global best particle position and their velocities in search space [32]; (ii) During the travel for either food or shelter [33], they are supposed to not to collide with each other by adjusting their velocity and position. In PSO, all birds in a group are assumed as population of particles in imaginary space, and velocity and position of each particle are initialized randomly according to the problem being solved. In the first generation, all the particles in current population are assumed as local best particles (lbest). From the second generation onward, local best particles are selected by comparing fitness of particles in current population and previous population. Among local best particles, a particle with maximum fitness is selected as global best particle (gbest). According to the current velocity of particles $\left(V_i^{(t)}\right)$ and position of particles in current population $\left(X_i^{(t)}\right)$, local best particles and global best particle, the next velocities $\left(V_i^{(t+1)}\right)$ of the particle are computed (Eq. 4). After obtaining next velocity, next position $\left(X_i^{(t+1)}\right)$ of all the particles in the population is updated (Eq. 5) using current position $\left(X_i^{(t)}\right)$ and next velocity $\left(V_i^{(t+1)}\right)$ of all the particles. These steps are continued until no further improvement in gbest is noticed or problem-specific stopping criteria are reached:

$$V_i^{(t+1)} = V_i^{(t)} + c_1 * rand(1) * \left(l_{best_i}^{(t)} - X_i^{(t)}\right) + c_2 * rand(1) * \left(g_{best}^{(t)} - X_i^{(t)}\right) \quad (4)$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)}. \quad (5)$$

Here, c_1 and c_2 are the constants which values may be from the range 0–2 and $rand(1)$ generates a uniform random number between 0 and 1.

ISO uses the basic concept of standard PSO algorithm to address the issues such as (i) not efficient in adjusting solution for improvisation and (ii) low searching ability near by the global optima solutions [34].

So, in ISO an inertia weight λ is introduced (Eq. 6) for addressing the above issues. By incorporating this in ISO, the search space may be significantly reduced with the increase in number of generations [35].

The improvement in both the velocity and position may be illustrated through Eqs. (6) and (7):

$$V_i^{(t+1)} = \lambda * V_i^{(t)} + c_1 * rand(1) * \left(l_{best_i}^{(t)} - X_i^{(t)}\right) + c_2 * rand(1) * \left(g_{best}^{(t)} - X_i^{(t)}\right) \quad (6)$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)}. \quad (7)$$

2.3 Genetic Algorithm

GA is one of the popular evolutionary algorithms that have been a keen interest of all types of research. Holland [36] and Goldberg [37] contributed significantly towards the development of GA. GA is a metaheuristic optimization based on Darwin's evolutionary principle. While solving a problem using GA, the chromosome represents an individual solution vector and the population is considered as predefined number of such chromosomes. Encoding of these chromosomes is purely depending on the structure of the problem and its solution. GA follows four basic steps such as fitness evaluation, selection, crossover and mutation. Here, the objective is to promote fittest chromosomes (survival of fittest) for the next generation by excluding weak chromosome from the population. The fitness evaluation reasonably depends on problem being solved and independent to computational procedure [38].

3 Proposed Hybrid GA–ISO–FCM Approach

In this section, a hybrid GA–ISO–FCM algorithm has been proposed based on the hybridization of GA, improved PSO and FCM algorithm for clustering the real-world data. In fact, FCM technique is efficient to find the optimal cluster centers. However, initially, the FCM uses randomly generated cluster centers for clustering through fuzzy membership grade. Without excluding this fact, still FCM is good in finding optimal cluster centers in a data set. However, in this proposed method, we have made an attempt to make the performance of FCM better by speeding up the convergence rate. This is achieved using metaheuristic algorithms GA and PSO for finding optimal cluster centers for the initialization of cluster centers process in FCM. On the other hand, both GA and PSO have their own limitations like complex parameter tuning (GA) and slow convergence (PSO). So we have hybridized both GA and improved PSO for fuzzy clustering to improve the convergence rate and quality of the solution. The objective of this proposed method is to select the optimal initial cluster centers from population of predefined number of cluster center in a population, thereby avoiding the usage of randomly generated initial cluster centers for FCM algorithm.

This proposed method uses an objective function (Eq. 8) to evaluate the quality of cluster centers. So, in the context of clustering, a single individual in the population represents the ‘m’ number of cluster center. And the entire population of individuals is initialized with ‘n’ number of cluster center vectors $P = \{C_1, C_2 \ldots C_n\}$, where each cluster center vector consists of ‘m’ number of cluster centers $C_1 = (c_1, c_2 \ldots c_m)$. Here, each c_i represents a single-cluster center. This is considered as a minimization problem and we have the objective function (Eq. 8) of K-means [27] for calculating the fitness:

$$\begin{aligned} F(C_i) &= \frac{k}{\left(\sum_{l=1}^{r} \|o_l - C_i\|^2\right) + d} \\ &= \frac{k}{\left(\sum_{j=1}^{m} \sum_{l=1}^{r} \|o_l - C_{i,j}\|^2\right) + d}. \end{aligned} \tag{8}$$

Here $F(.)$ is a function to evaluate the generalized solutions called fitness function, ‘k’ and ‘d’ are user-defined constants, o_l is the lth data point, C_i is the ith cluster center vector, $C_{i,j}$ is the ith cluster center of jth cluster center vector, ‘r’ is the number of data point in the data set and $\|.\|$ is the Euclidean distance norm. The pseudocode of the proposed approach is illustrated as follows.

1. **Initialize** the population of ‘n’ no. of cluster center vectors $P = \{C_1, C_2 ... C_n\}$, each cluster center vector with ‘m’ no. of random cluster center $C_1 = (c_1, c_2 ... c_m)$. An individual firefly signifies a cluster center vector C_i.
2. Iter=1;
3. **While** (iter<=maxIter)
    Compute fitness of all particles in population P by using the objective function eq. (8).
    If (iter==1)
        Assign Local best particle l_{best}=P.
    Else
        Evaluate fitness of P and P’.
        Compare the fitness of particles based on their fitness in P and P’.
        If fitness of i^{th} particle X_i in P is less that fitness of a particle in P′
            Then assign L_{best} (i) = P′(i).
        Else assign L_{best} (i) = P(i).
        End of if
    End of if
    Select particles with best fitness value from L_{best} as G_{best} particle.
    Compute new velocity Vnew of the particle by using P, Lbest and gbest by using eq. (6).
    Generate next positions of particles P’ by using P and V_{new} as follows by using eq. (7).
    Create a Mating pool of particles by replacing weak particles in the current population with global best Gbest particle.
    Perform two point crossovers on particles in P’ to generate new feasible solutions P′′.
    If (P′ is same as P′′)
        Then perform mutation on P′.
    End if
    P′=P′′.
    Update P based on P’’.
    Iter = iter+1;
   End of while
4. **Rank** the cluster center vectors based on their fitness, obtain the best cluster center vector.
5. **Initialize** the cluster centers of FCM with position of the best cluster center vector. Then using this cluster centers, iterate the FCM algorithm.
6. **Do** Update the membership matrix by eq.(2)
7. Refine the cluster centers by eq.(3),
8. **While (**until it meets the convergence criteria)
9. **Exit**

4 Experimental Setup and Result Analysis

The proposed GA–ISO–FCM has been implemented in the environment of MATLAB 9.0. The real-world data sets for experimentation have been considered from UCI repository [39] and the details about the data set are given in Table 1. For

Table 1 Data set information

Data sets	No. of pattern	No. of clusters	No. of attributes
Iris	150	3	4
Lenses	24	3	4
Haberman	306	2	3
Balance scale	625	3	4
Wisconsin breast cancer	699	2	10
Contraceptive method choice	1473	3	9
Hayesrotli	132	3	5
Robot navigation	5456	4	2
Spect heart	80	2	22

experimental analysis and performance comparison, we have compared the performance of the proposed hybrid method with some other standard techniques such as FCM, GA-FCM and PSO-FCM. However, as K-means is also considered as one of the standard methods for data clustering, we have compared the results of K-means, GA-K-means, PSO-K-means [40] and GA-ISO-K-means [41] (Table 2).

The value for the fuzzy coefficient (m) is set as 2. The acceleration coefficients (c1 and c2) are set to 1.4 and the inertia weight (λ) is set between 1.8 and 2 during ISO iteration [42]. For executing the cross over step of GA, two point crossovers have been used. After the crossover step, if population of particle remains unchanged, then mutation operation is applied on the particles in order to explore other solution in solution space. This proposed scheme produces effective cluster centers of a particle. During execution of this scheme, the cluster centers (initially chosen) are attracted towards the center of corresponding group of similar data point in successive iterations.

Table 2 Performance comparison of FCM with the other clustering methods

Data sets	Fitness values of clustering algorithms				
	FCM	GA-FCM	PSO-FCM	ISO-FCM	GA-ISO-FCM
Iris	0.012738542	0.014154986	0.014624876	0.014620135	0.014628271
Lenses	0.381339952	0.390354824	0.425698354	0.425658963	0.428734522
Haberman	0.000316547	0.000330542	0.000372865	0.000372814	0.000376875
Balance scale	0.003332606	0.003425487	0.003535478	0.003541256	0.003612873
Wisconsin breast cancer	7.48861E-14	7.50236E-14	7.52487E-14	7.53458E-14	7.53826E-14
Contraceptive method choice	7.69432E-05	8.13254E-05	8.20398E-05	8.22003E-05	8.23687E-05
Hayesrotli	4.43056E-05	4.71657E-05	4.74493E-05	4.74689E-05	4.74821E-05
Robot navigation	0.002000381	0.002258745	0.002454781	0.002468954	0.002562114
Spect heart	0.077804472	0.079365885	0.080456544	0.080569877	0.081428643

5 Conclusion

FCM is quite popular for data clustering, but as it is sensitive to the initialization, there is maximum chance to get rapped at local minima. In this paper, a hybrid approach of two popular optimization techniques like GA and improved PSO has been proposed for fuzzy clustering. The positive insights of both the algorithms help the FCM to get some quality values in terms of fitness values. The performance of the proposed method is compared with some other approaches such as FCM, GA-FCM, and ISO-FCM. For all the nine considered data sets, the performance of GA–ISO–FCM found to be better than the others.

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RF-Based Thermal Validation and Monitoring Software for Temperature Sensitive Products

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Abstract Pharmaceutical and healthcare industries are highly controlled industries all around the world. Nowadays, millions of temperature sensitive products are manufactured, warehoused, or circulated all over the world. For all these sensitive products, the control of temperature is essential. In some developing nations, they are offering no automated processes such as manual recordings of sensed information by supervisors of the organization or thermometers or USB Data loggers-means bringing the sensor node in contact with USB Data reader which aids as the interface between loggers and the system software and also enables pre-study programming and data can be download only after the study completion in some cases proved inefficient and most of the cases as burdensome. To overcome the problems raised by non-automated processes in this paper, RF-based temperature validation and monitoring software for Pharma, food processing, and warehouses is introduced. Reliant on the nature of the application, sensor nodes are deployed into the area of sensing where base station and loggers communicate by means of radio waves and temperature reading is recorded from base station which is connected to PC through Ethernet or USB.

Keywords Sensor probes · Temperature and humidity monitoring · RF-based loggers · Base station

1 Introduction

Various categories of products need to be controlled under measured environmental circumstances, which include temperature, humidity, and also factors like voltage and current. Among those parameters, the temperature and humidity is often a most

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