A Performance of Modified Fuzzy C-Means (FCM) and Chicken Swarm Optimization (CSO)

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***Abstract*—Numerous research and related applications of fuzzy clustering are still interesting and important. In this paper, modified Fuzzy C-Means (FCM) and Chicken Swarm Optimization (CSO) algorithm in order to improve local optima of Fuzzy Clustering presented by using UCI dataset. In this study, the proposed FCMCSO performance is also compared with three methods i.e. FCM based on Particle Swarm Optimization (FCMPSO), FCM based on Artificial Bee Colony (FCMABC), and also FCM. The simulation results indicated that the FCMCSO method have better performance than three other compared methods.**

Keywords—fuzzy clustering; FCM; CSO; FCMPSO; FCMCSO; FCMABC

I. Introduction

An algorithm analysis of data clustering in order to get better performance is indispensable. Moreover, the clustering algorithm has been able to solve various data mining problems, i.e. exploration data analysis [1 - 3], mathematical techniques [4], and image segmentation [5]. In addition, many clustering techniques have been effectively presented in order to overwhelm the problem of learning algorithm scalability [5], where before and during the training were grouped and selected as cluster samples for training in order to improve traditional clustering processes. The goal is to facilitate the training process and improve the performance of generalizations [6 - 9].

Several clustering methods have been proposed such as K-Means, Self-organizing Maps (SOM), Fuzzy Clustering and so forth. Unfortunately, the FCM algorithm tends to fall into local optimum. Hence, FCM algorithm performance optimally depends on initialization is indispensable. Numerous optimization FCM based on metaheuristic approaches i.e. genetic algorithm (GA), PSO, ABC were conducted that aim to avoid local optima. In order to have better performance in fuzzy clustering, several metaheuristic methods as an optimization algorithm i.e. single swarm optimization have been proposed and developed [7].

Moreover, Xianbing Meng et.al, were proposed optimization algorithm called Chicken Swarm Optimization (CSO) [7]. The researchers stated that CSO better than single swarm optimization algorithm in problem optimization, especially in local and global optimum. Hence, in this study, CSO approach that mimicking chicken swarm i.e. roosters, hens and chicks behavior will be adopted then implemented to optimize the FCM.

Furthermore, the rest of paper are Section II briefly presents the FCM. Section III briefly the PSO. Section IV, the FCMPSO is presented. Section V, the principle of CSO is presented. The FCMCSO and experimental results are presents and analyzed in Section VI and VII. Lastly, the conclusion and future works.

II. Principle of Fuzzy C-Means

Other famous techniques clustering in machine learning called Fuzzy C-Means (FCM) that was introduced by Dunn, 1973, and increased by Bezdek, 1981. In principle, FCM clustering process is based on a partition of a set of data into a similar clusters with minimum similarity between different clusters [3]. The FCM formula can been seen in (1) and (2).

$$J_m = \sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{ij}^{m} d_{ij} \tag{1}$$

$$z_j = \frac{\sum_{i=1}^{n} \mu_{ij}^{m} o_i}{\sum_{i=1}^{n} \mu_{ij}^{m}} \tag{2}$$

Where, $d_{ij}=|o_i - z_j|$, m is is a real number that controls cluster uncertainty, μ_{ij} is membership of o_i in the cluster j, o_i is the i-th of d- data dimensional, z_j is the d-cluster center dimensional, d_{ij} is the Euclidean distance between o_i and z_j; z_j is cluster centroid of the j-th.

The following data clustering techniques using the FCM algorithm as follows.

1. Choose $m > 1$, initialization of membership function values $\mu_{ij}, i = 1,2, \dots, n; j = 1,2, \dots, c$.
2. Compute the cluster centers $z_j, j = 1,2, \dots, c$.
3. Calculate the euclidian distance d_{ij}.
4. Update the membership function μ_{ij} using the following formula (3).

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{3}$$

5. If not met, go to step 2.

III. Principle of Particle Swarm Optimization

PSO stands for Particle swarm optimization that inventor by Eberhart and Kennedy, 1995 [7]. In principle, the PSO is a metaheuristic technique. In other word, the PSO is to solve the problem in the search space based on generations. In general, the steps of PSO algorithm, consist of, first, initialization population of particles that represent solutions. Second, randomly initialized in the search space as a velocities. Third, updating search position by using the particle velocities, best or *pbest* and global or *gbest* (positions) and fitness. Fourth, conditions of velocity and position particles is met. The PSO algorithm formula by using (4) and (5).

$$V(t+1) = wV(t) + c_1r_1(pbest(t) - X(t)) + c_2r_2(gbest(t) - X(t)) \tag{4}$$

Where, c_1 and c_2 are positive constants of *pbest* and *gbest*, r_1 and r_2 are randomly values in range [0, 1], w is weight.

$$X(t+1) = X(t) + V(t+1) \tag{5}$$

Where, X and V are velocity and position particles.

IV. Principle of FCM-PSO

A modified of FCM based on PSO called FCMPSO have been proposed that for Traveling Salesman Problem (TSP) by Pang et al. [6]. In principle, the FCMPSO is redefined the cluster position and velocity to find related particles. However, the FCM algorithm process is relatively quicker than the FCMPSO algorithm due to FCM simpler functionality. Nevertheless, FCM algorithm tends to reach its local optima. The researchers [8] have been proposed FCM integrated PSO, called FCMPSO in order to get better performance. This studied revealed that PSO have been applied in cluster reposition and fitness value of every single FCM particle. The optimized algorithm is detailed as the following steps.

1. Initialization of PSO and FCM parameters: population size P, $c1$, $c2$, w, and m.
2. Creating a swarm with P particles (X, *pbest*, *gbest* and V are $n\times c$ matrices).
3. Initializion of X, V, *pbest* for each particle and *gbest* for the swarm.
4. PSO algorithm:
   a. Using Eq. 6 to calculate the cluster centers for each particle.
   b. Using Eq. 14 to calculate the fitness value of each particle.
   c. Calculating e *pbest* for each particle.
   d. Calculating *gbest* for the swarm.
   e. Using Eq. 11 to update the each particle.
   f. velocity matrix.
   g. Using Eq. 12 to update the every particle position matrix.
   h. Processing the 4th step while PSO terminating condition is not reached.
5. FCM algorithm
   a. Using Eq. 6 to compute the cluster centers for each particle.
   b. Using Eq. to calculate Euclidian distance dij , i = 1,2,..., n; j = 1,2,..., c; for each particle.
   c. Applying Eq. 7 to tpdate the membership function μij ,i = 1,2,..., n; j = 1,2,..., c; for each particle.
   d. Calculating pbest for each particle.
   e. Calculating *gbest* for the swarm.
   f. Going back to step 5 if FCM terminating condition is not met.
6. Step 2 is accessed If FCMFPSO terminating condition is not met.

V. Principle of Chicken Swarm Optimization

CSO stands for Chicken Swarm Optimization. This chicken behavioristic optimization method is proposed by [7] in 2014 with at least four following rules.

- The chicken swarm consists of several groups. The member of each group is a dominant rooster, a couple of hens, and chicks.
- The chicken swarm groupings depend on the chicken fitness values. The fit chickens may become roosters, is dominant in their own group. On the other hand, the less fit chickens would be selected as chicks. The rest of the group would be classified as hens, liv in random groups. As consequence, the random mother-child relationship of hens and chicks is also formed.
- The dominance relationship and mother-child relationship in a group will be kept to be hierarchically unchanged. In every several (G) time steps, these statuses could be updated.
- In general food searching events, chicks are around hens that follow their dominant group-mate rooster. Naturally, chickens would randomly steal others' food as well as stops others to steal their food. In this food searching competition, the stronger individuals have more. advantage than their competitors.

The most fit roosters have food access priority since they may explore wider range of places than the weaker roosters. The CSO formula can be viewed in (6) and (7).

$$x_{i,j}^{t+1} = x_{i,j}^{t} * \left(1 + Randn(0,\sigma^2)\right). \tag{6}$$

$$\sigma^2 = \begin{cases} 1 & f_i \le f_k \\ \exp\left(\frac{f_k - f_i}{|f_i| + \varepsilon}\right) & otherwise \end{cases} \quad k \in [1,N], k \ne i. \tag{7}$$

Where, *Randn* $(0,\sigma^2)$ is a Gaussian and standard deviation, ε is error values, f_k is the lowest constant, k is a randomly rooster value, f is the fitness value of x.

Furthermore, hens on the track of group roosters to search the food casually. Thus, the attractive hens would be win the food. These phenomena can be formulated in (8), (9) and (10).

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 * Rand * \left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S2 * Rand * \left(x_{r2,j}^{t} - x_{i,j}^{t}\right). \tag{8}$$

$$S1 = \exp\left(\frac{f_i - f_{r1}}{abs(f_i) + \varepsilon}\right). \tag{9}$$

$$S2 = \exp(f_{r2} - f_i). \tag{10}$$

Rand is a uniform-random number over [0, 1], $r1 \in [1 \dots N]$ is a rooster index, which is the *i*th hen's group-mate, while $r2 \in [1 \dots N]$ is an index of the chicken (rooster or hen), which is randomly chosen from the swarm $r1 \ne r2$.

Next, (11) models the chicks food finding movements in around their mother.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right). \tag{11}$$

Where, $x_{m,j}^{t}$, are hens position in i-th $(m \in [1,N])$, *FL* $(FL \in (0,2))$ is a values [0..2] randomly for the chicks.

VI. Proposed Method

In this paper, a modified FCM and CSO called FCMCSO in order to explain the TSP have been presented. In this study, the FCMCSO propose to redefined identity and dominance relationship of chickens. In this section, we describe FCMCSO method. In FCMCSO algorithm, X is chicken position shows *th*-fuzzy relation from datasets $o = \{o_1, o_2, \dots, o_n\}$, $Z = \{z_1, z_2, \dots, z_n\}$, is a set of cluster centers. X is expressed by (12).

$$X = \begin{bmatrix} \mu_{11} & \cdots & \mu_{1c} \\ \vdots & \ddots & \vdots \\ \mu_{n1} & \cdots & \mu_{nc} \end{bmatrix} \tag{12}$$

Where, μ_{ij} is datasets of the i-th in j-th cluster constrains by using (13) and (14).

$$\mu_{ij} \in [0,1], \quad \forall i = 1,2,\dots,n; \ \forall j = 1,2,\dots,c \tag{13}$$

(14)

Afterward, the position matrix μ of each chicken is obtained. Thus, updating of each particle by using a matrix *n x c* in a range [0, 1] is utilized. Furthermore, updating the rooster, hens and chicks positions respectively based on matrix operations by using (15), (16) and (17).

$$x_{i,j} = x_{i,j} \otimes \left(I \oplus Randn(0,\sigma^2)\right). \tag{15}$$

$$x_{i,j} = x_{i,j} \oplus S1 \otimes Rand \otimes \left(x_{r1,j} \ominus x_{i,j}\right) \oplus S2 \otimes Rand \otimes \left(x_{r2,j} \ominus x_{i,j}\right) \tag{16}$$

$$x_{i,j} = x_{i,j} \oplus FL \otimes \left(x_{m,j} \ominus x_{i,j}\right). \tag{17}$$

The updating matrix position process may violate the constraints given in Eq. 13, 14. Thus, normalization the matrix position is necessary by using Eq. 12. Then, evaluation the fitness function for generalized solutions by using (18).

$$f(X) = \frac{K}{J_m} \tag{18}$$

The value K is constant while J_m represents the FCM objective function (Eq. 1).

In this study, the best model of FCMCSO indicate by the smaller J_m. It means that similarity of clustering and also higher individual fitness $f(X)$ have good performance. Furthermore, the steps of FCMCSO algorithm as follows.

1. Initialization parameters *P*,
2. Creating a chicken swarm with P chicken groups (roosters, hens and chicks) in matrix using Eq. 12,
3. Initialization X for the swarm for each chicken group,
4. Calculate the cluster centers,
5. Calculate the fitness values,
6. Update the matrix position by using Eq. 15 for roosters, using Eq. 16 for Hens and using Eq. 17 for chicks,
7. Return to step 4,
8. Until terminating condition is met.

In this method, the maximum iteration of fitness value is proposed as a termination condition.

VII. Experimental Result

This section presents the empirical work, performed by seven datasets that documented from the UCI website. The, datasets analysis have been used MATLAB Ver. 7.10.0 (R2010a) with Windows 7 Professional 32-bit as an operating system. The datasets were captured from the UCI that can be viewed in Table I.

TABLE I. Data Set

Data	The Number of Object	The Number of attribute	Data Size
Yeast	1484	8	11872
Cancer	683	9	6147
Ecoli	336	7	2352
ionosphere	351	34	11934
spambace	4601	57	262257
Vowel	990	12	11880
Iris	150	4	600

All the size of selected data is horizontally or vertically different. Selecting data process is using to the proposed technique performance. Then, some datasets were modified by deleting the sample had incomplete data. Experiment running with the specified number of 50 with a population of 100 with a maximum number of iterations fuzziness index variations are $m \in [1.1, 2.0]$, and then the average purity, index and Davies Bouldin index rank is calculated.

TABLE II. DAVIES BOULDIN INDEX

Data	FCM	FCMPSO	FCMCSO	FCMABC
Yeast	0	0.4872	0	0.4909
Cancer	0	3.5686	0	3.5532
Ecoli	0.1944	0.6395	0.2107	0.6481
ionosphere	0.0184	1.9951	0.0147	2.0275
spambace	0	22.4644	0	25.1852
Vowel	0.0749	0.6757	0.0671	0.6823
Iris	0.0064	3.8999	0	3.8272
Average	0.042014	4.818629	0.041786	5.202057

Based on the Table II, it shows that the FCM CSO has the lowest davied Bouldin index compared to other methods. Only the data Ecoli Davies Bouldin index only slightly higher compared with FCM. Overall average of davied Bouldin index is the smallest FCMCSO i.e. 0.041786.

TABLE III. PURITY

Data	FCM	FCMPSO	FCMCSO	FCMABC
Yeast	0.2606	0.0067	0.2606	0.0067
Cancer	0.7536	0.9001	0.7536	0.9001
Ecoli	0.3295	0.0235	0.3295	0.0235
ionosphere	0.7632	0.7017	0.7632	0.7017
spambace	0.7133	0.2003	0.7133	0.2003
Vowel	0.2661	0.0108	0.2661	0.0108
Iris	0.6380	0.0200	0.6380	0.02
Average	0.5320	0.2662	0.5320	0.2662

Based on Table III, it can be viewed that the FCM, and FCM CSO has a higher purity compared to other methods. Only on data from cancer has a lower purity than the method FCMPSO and FCMABC. Overall average FCMCSO Purity is the highest of 0.532043

TABLE IV. RANK INDEX

Data	FCM	FCMPSO	FCMCSO	FCMABC
Yeast	13.2008	13.1604	72.188	72.1757
Cancer	51.1859	50.7321	49.9705	49.941
Ecoli	17.7381	19.0179	67.1567	67.2425
ionosphere	51.4245	52.2507	49.9201	50.02
spambace	19.6479	19.9239	50.0002	49.9987
Vowel	12.5960	12.1111	83.5559	83.5284
Iris	38.1333	37.5333	55.6421	55.506
Average	29.1324	29.2471	61.2048	61.2018

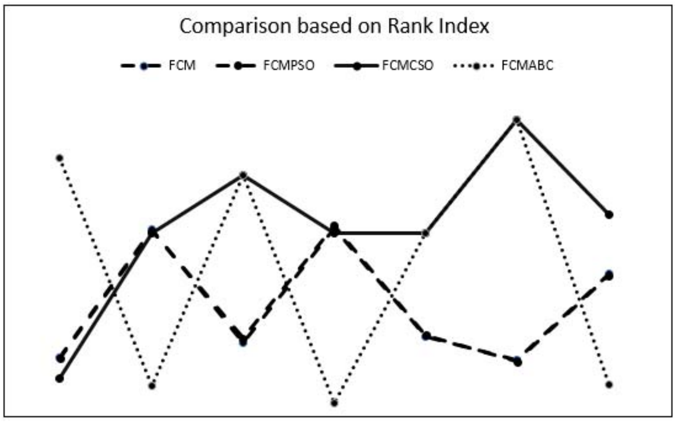

Fig. 1. Comparison of Rank Index

Based on the Table IV, it shows that the index Rank FCMABC and CSO FCM are higher compared to other methods. Overall average FCMCSO Rank Index is the highest of 61.2048. The illustration of the Rank Index is shown in fig. 1.

VIII. CONCLUSION

In this paper, FCM clustering with emphasizes on CSO technique, called FCMCSO have been implemented as an alternative approach in the fuzzy clustering problem. Furthermore, the CSO algorithm have been successfully utilized by using UCI datasets. Then, the optimization of artificial neural networks (ANN) by using CSO is one of the future works.

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