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An improved clustering method to evaluate teaching based on ABC-FCM

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ABSTRACT: Clustering is a popular data analysis and data mining technique. Among the many approaches developed for clustering, a popular method is the fuzzy c-means (FCM) algorithm. The artificial bee colony (ABC) algorithm is an optimisation algorithm based on a particular intelligent behaviour of honeybee swarms. In this article, a novel hybrid clustering algorithm to evaluate teaching processes based on the ABC-FCM algorithm is proposed. The novel algorithm can improve the optimisation ability of the original FCM algorithm and improve the convergence speed. Experimental results are presented to verify the feasibility and effectiveness of the proposed approach.

INTRODUCTION

As an important management method, teaching evaluation is becoming more and more popular in most schools. Especially in higher schools, student evaluation of teaching quality has been shown to have a high level of validity. There are many indexes for evaluating teaching quality. Undoubtedly, a large quantity of indexes will offer rich information for evaluation of teaching quality, while increasing the complexity of evaluation to some extent. The teaching evaluation process is a conduct that poses great challenges from a modelling perspective.

Fuzzy clustering is an important research branch of one of the many fields of knowledge discovery and pattern recognition, which is a method associated with unsupervised learning [1]. The main purpose of clustering is to group data into clusters such that the similarities among data members within the same cluster are maximal, while similarities among data members from different clusters are minimal. Because of efficiency and simplicity in implementation, the fuzzy c-means (FCM) algorithm as a popular fuzzy clustering method attracts much attention in literature and is widely used. It has been applied to pattern recognition, image processing and computer vision, as well as many other fields, but there are still some flaws.

A novel hybrid clustering algorithm to evaluate the teaching process based on ABC-FCM is proposed in this article. The focus of this work is how to combine bees' foraging behaviour and clustering techniques. The work aims to address the shortcomings of the FCM algorithm by dealing with the local minimum value and sensitivity to initialisation and noise data [2]. According to the simulation results, the proposed algorithm not only can effectively resolve the faults of FCM, it is also more accurate in clustering and is higher in efficiency.

FCM ALORITHM

The fuzzy c-means algorithm is an effective and the most popular fuzzy clustering algorithm [3]. In a simple view, it selects C points as cluster centres and assigns to each data point a fuzzy membership. The updating and reassigning process continues until a convergence criterion is met [4].

FCM partitions a given dataset $X = \{x_1, x_2, \cdots, x_n\} \in R^p$, into c fuzzy subsets by minimising the following objective function defined as Equation (1) and Equation (2).

$$J_b(U,v) = \sum_{i=1}^{n}\sum_{k=1}^{c}(\mu_{ik})^b (d_{ik})^2, \tag{1}$$

$$d_{ik} = d(x_i - v_k) = \sqrt{\sum_{j=1}^{m} (x_{ij} - v_{kj})^2} \tag{2}$$

Where d_{ik} is the Euclidean distance, which is used to measure the distance between the *i-th* sample x_i and Class *k* centre point, *c* is the number of clusters selected as a specified value $(2 \le c \le n)$, *n* is the number of data points, *m* is the number of characteristics of the sample, μ_k is the membership of X_i in class *k*, *b* is the quantity controlling clustering fuzziness $(1 \le b \le \infty)$, and *V* is the set of cluster centres $v_i \in R^p$. The matrix *U* satisfies:

$$U \in \left\{ \mu_j(x_i) \in [0,1] \middle| \sum_{j=1}^{c} \mu_j(x_i) = 1 \right\}, i = 1,2,\cdots,n \tag{3}$$

$$\mu_{ik} = 1 / \sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{b-1}} \tag{4}$$

The FCM algorithm can optimise the cost function using Equations (3) and (4) in an interactive way. When the algorithm has converged; theoretically, all types of cluster centres and various samples for each pattern class membership are obtained. Then fuzzy set division is completed. Although FCM has high search speed, FCM is a local search algorithm, and the initial value is very sensitive to the cluster centre. When the initial value is selected inappropriately, FCM will converge to a local minimum point.

The objective function of the FCM algorithm based on a gray histogram is defined by Equation (5):

$$W_b(U,V) = \sum_{m=0}^{L} \sum_{k=1}^{c} (u_{mk})^b (d_{mk})^2 h(m) \tag{5}$$

Where $h(m)$ represents a statistical value of the corresponding gradation level *k* in an image histogram, where *m* ranges from 0 to *L*, v_k is the *k*-grayscale centre.

The objective function W_b of the FCM clustering technique reveals the clustering quality of the output images in terms of the degree of compactness and uniformity of the cluster centres. Specifically, a smaller value of W_b indicates a more compact and uniform cluster centre set that leads to more desirable clustering results. Hence, different expressions of the objective function W_b are produced. Consequently, during the FCM clustering process, the formula that may be specifically used to calculate the minimum value of W_b for all types of images do not exist [5].

ARIFICIAL BEE COLONY ALGORITHM – ABC

The artificial bee colony algorithm simulates the intelligent foraging behaviour of honey bee swarms [6]. It is a very simple, robust and population-based stochastic optimisation algorithm. In the ABC algorithm, the colony of artificial bees consists of three groups of bee: employed bees, onlookers and scouts. Employed bees and onlooker bees are primarily responsible for the exploitation of food source; the scouts are primarily responsible for the exploration of food source. The ABC algorithm combines the global search and local search, so the two aspects of the exploration and exploitation of the algorithm are able to achieve a better balance [7].

In mathematical terms, the standard ABC algorithm can be formulated as follows.

In the initialisation phase, the ABC algorithm generates randomly distributed initial food source positions of *SN* solutions, where *SN* denotes the size of employed bees or onlooker bees. Each solution x_i (i =1, 2, …, *SN*) is a *D*-dimensional vector. Here, *D* is the number of optimisation parameters. Then, evaluate each nectar amount fit_i. In the ABC algorithm, nectar amount is the value of the benchmark function.

In the employed bees' phase, each employed bee finds a new food source v_i in the neighbourhood of its current source x_i. The new food source is calculated using Equation (6):

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{6}$$

where $k \in (1, 2,..., SN)$ and $j \in (1, 2,..., D)$ are randomly chosen indexes, and k has to be different from i . ϕ_{ij} is a random number between [-1,1]. Then, the employed bee compares the new one against the current solution and memorises the better one by means of a greedy selection mechanism.

In the onlooker bees' phase, each onlooker chooses a food source with a probability related to the nectar amount (fitness) of a food source shared by employed bees. Probability is calculated using Equation (7):

$$p_i = fit_i / \sum_{n=1}^{SN} fit_i \tag{7}$$

IMPROVEMENT THE FCM CLUSTERING ALGORITHM BASED ON ABC

First, the ABC-FCM algorithm uses the capability of a global search in the ABC algorithm to seek an optimal solution as initial clustering-centres for the FCM algorithm [8]. Second, the proposed model uses the FCM algorithm to optimise the initial clustering-centres and to obtain the global optimum [9].

ABC-FCM generates a randomly distributed initial population of SN solutions (food source positions), where *SN* denotes the size of employed bees or onlooker bees. So, a bee denotes a cluster centre. Each solution x_i (i = 1,2,…, *SN*) is a *D*-dimensional vector. Here, *D* is the number of optimisation parameters. A food source represents a possible solution to the problem to be optimised and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. This is calculated using Equation (8):

$$fit_i = \frac{1}{1+f_i} = \frac{1}{1+J_m(U,V)} \tag{8}$$

Where $J_m(U,V)$ is the objective function of the FCM algorithm given in Equation (1). The smaller value of $J_m(U,V)$, the higher the individual fitness fit_i and the better the clustering result.

In ABC-FCM, providing that a position cannot be improved further through a predetermined number of cycles (called the limit), the food source is assumed to be abandoned. Assume that the abandoned source is x_i, then, the scout discovers a new food source to be replaced with x_i. This operation can be defined as Equation (9):

$$x_i^j = x_{\min}^j + rand[0,1](x_{\max}^j - x_{\min}^j) \tag{9}$$

The ABC-FCM algorithm is a robust search process; exploration and exploitation processes are carried out together. The global search performance of the algorithm depends on a random search process performed by scouts and a neighbour solution production mechanism performed by employed and onlooker bees. Therefore, the ABC-FCM algorithm is an efficient optimisation tool since it combines efficiently the exploitative local search and explorative global search processes.

For clarity, the following algorithm is presented to show the steps of the proposed method. The ABC-FCM algorithm can be described as:

1. Initialise the parameters of ABC and FCM including population size *SN*, maximum cycle number *MCN*, limit, clustering number *c*, *m*, ε ;
2. Initialise the membership matrix *U* by Equation (3);
3. Generate the initial population (cluster centre) c_{ij} by Equation (4), and evaluate the fitness of the population by Equation (8);
4. with:

    a. cycle = 1;
    b. s = 1;
    c. Produce new solutions v_{ij} for the employed bees by using Equation (6) and evaluate them;
    d. Apply the greedy selection process for the employed bees;
    e. Calculate the probability values P_i for the solutions c_{ij} by Equation (7);

f. Produce the new solutions v_{ij} for the onlookers from the solutions c_{ij} selected depending on P_i and evaluate them;
g. Apply the greedy selection process for the onlookers;
h. If the searching times surrounding an employed bee exceeds a certain threshold limit and a better solution could not be found, the location vector can be reinitialised randomly according to Equation (9). Go to Step b;
i. If the iteration value is larger than the maximum number of the iteration (that is, cycle > *MCN*), output the best cluster centres. If not, go to Step a.

5. Update membership matrix $\mu_{ik}{}^{t}$ with Equation (3). Update the cluster centres $v_{ik}{}^{t}$ with Equation (4);
6. If $\max_{i,k}\left|\mu_{ik}{}^{t}-\mu_{ik}{}^{t-1}\right|\le\varepsilon$ stop. If not, go to Step 5. Stop when the condition is satisfied.

EXPERIMENTAL RESULTS

Results of the ABC-FCM Algorithm

To evaluate the performance of the proposed ABC-FCM approach for clustering, the authors compared the results of the FCM, ABC and ABC-FCM clustering algorithms using six different data sets selected from the UC Irvine Machine Learning repository 23. The data characteristics are shown in Table 1.

Table 1: Experimental data sets.

Data set name	Number of sample	Dimension	Class
Motorcycle	133	2	4
Iris	150	4	3
Wine	178	13	3
Contraceptive method choice	1473	10	3
Wisconsin breast cancer	683	9	2
Ripley's glass	214	9	6

There are three control parameters set as follows: *SN* = 100, *MCN* = 2000, limit = 30. The weighting exponent *m* is set to 2. For each data set, there are 30 tests for each algorithm. Summarised in Table 2 are the clustering results of each algorithm, also known as the cluster distance, the Std represents the standard deviation.

Table 2: Comparison of intra-cluster distances for the three clustering algorithms.

Data set	Criteria	FCM	ABC	ABC-FCM
Motorcycle	Average	3012.3	2068.9	2060.7
	Best	2446.3	2060.6	2060.6
	Worst	4683.2	2126.7	2062.4
	Std	439.06	19.118	0.32158
Iris	Average	106.05	94.607	94.603
	Best	97.333	94.603	94.603
	Worst	120.45	94.644	94.603
	Std	14.631	0.0077734	0.0000000019767
Wine	Average	18061	16298	16294
	Best	16555	16294	16292
	Worst	18563	16302	16296
	Std	793.21	6.2411	15.466
CMC	Average	5893.6	5695.4	5693.8
	Best	5842.2	5693.9	5693.7
	Worst	5934.4	5698.6	5693.9
	Std	47.165	1.3824	0.045501
Cancer	Average	3251.2	2964.4	2964.4
	Best	2999.1	2964.4	2964.4
	Worst	3521.5	2964.4	2964.4
	Std	251.14	0.010731	0.00001838
Glass	Average	235.57	225.39	223.68
	Best	215.74	210.87	212.32
	Worst	255.38	253.20	246.27
	Std	12.471	12.685	7.8323

The average, best, and worst solution of fitness from the 30 simulations and standard deviation are shown in Table 2. The comparative study of the proposed approaches with existing algorithms in the literature using the data sets from the

UC Irvine Machine Learning repository is satisfactory. It can be concluded that the results obtained by the purposed algorithm are clearly better than the other algorithms for all data sets; the search ability of the ABC-FCM algorithm has been enhanced, and its optimisation speed is faster.

Results from Evaluating Teaching

The proposed algorithm was used for the evaluation system of teaching. The teaching evaluation system contains several indexes and each index comprises several factors; each lowest-hierarchy factor can possess several options chosen by students. The detailed evaluation factors are shown in Table 3, where the evaluation data of a teacher is arranged by vector, EXP_W is the weight of indexes obtained by the experts' rating. The authors chose evaluation data for 10 teachers for testing and verifying the proposed method. The data set consists of 120 evaluation records involving 20 course groups and 100 classes [10].

Table 3: The factors of evaluation.

ID	Factors	EXP_W
1	Preparation for a lesson	0.05
2	Update of the teaching content	0.05
3	Heuristic teaching	0.05
4	Language and teaching status	0.03
5	Teaching efficiency	0.02
6	Appliance of various teaching tools	0.05
7	Interaction with students	0.04
8	Command of basic skills	0.10
9	Command of basic theory and methods	0.10
10	Personal teaching	0.08
11	Obey the schedule	0.02
12	Assignment of homework	0.05
13	Q&A 0.03 0.04	0.03
14	Educational function	0.05
15	Comprehensive teaching content	0.06
16	Highlighting difficulties	0.07
17	The level of students' understanding	0.09
18	Developing students' ideas	0.06

As shown in Table 4, the number of clusters is 4, including Excellent, Good, Moderate and Pass. Column 6 consists of the conventional evaluation score. The conventional methods have a drawback, which arises from the integrated score of each factor, i.e. for some evaluation indexes every option selected is converted into a composite score for the index according to fixed weights. Using the conventional methods, all teachers' conventional evaluation scores are excellent, but these results are not credible. Now, referring to the clusters where the weight is greatest in corresponding rows as the categories the teachers belong to, the evaluation results are more representative.

Table 4: Clustering results using EXP_W.

No.	Excellent	Good	Moderate	Pass	Exp_W
1	0.4433	0.1837	0.3175	0.0553	4.7216
2	0.0560	0.1665	0.0988	0.6768	4.6545
3	0.0914	0.5408	0.2548	0.1130	4.7933
4	0.4832	0.1738	0.2503	0.0927	4.7220
5	0.1772	0.3336	0.4082	0.0811	4.7224
6	0.7189	0.0800	0.1773	0.0237	4.7812
7	0.0850	0.1920	0.1338	0.5892	4.7258
8	0.1361	0.3842	0.2683	0.2114	4.7067
9	0.4067	0.2088	0.2876	0.0969	4.8215
10	0.0892	0.4288	0.2106	0.2714	4.7550

CONCLUSIONS

A new data clustering approach based on the bee colony algorithm was proposed in this article. The advantage of the algorithm is that it can *jump out* of the local optimal solution. Mainly, this is because the bee colony algorithm has the ability of a global search and a local search. The main focus of this algorithm is the adaptive selection of parameters and the optimal combination of various parameters.

The experimental data show that the algorithm is superior to other algorithms for various data sets. The results show that using the proposed algorithm to evaluate teaching practice can broaden the development in education of new ideas and initiatives to persuade teachers to further improve their teaching.

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