Journal of Agricultural Science and Engineering
Vol. 1, No. 2, 2015, pp. 46-53
http://www.publicscienceframework.org/journal/jase

Fuzzy Artificial Bee Colony for Clustering

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Abstract

In this paper, "fuzzy artificial bee algorithm (FABC)" has been proposed for clustering data, this method is an algorithm derived from honeybees to find food in the global and local search to find the best centres in clusters. This algorithm in comparison with other well-known modern heuristic algorithms such as ABC, GA, TS, SA, ACO, K-means, FCM, and PSO improved significantly that fuzzy ABC algorithm had the best performance among other algorithms for the best, average and worst inter-cluster distances. Experiments on Iris and Wine data sets show that the new method is better. On the other hand, we checked Fuzzy ABC algorithm by two well-known functions "Gaussian and Cauchy", that among Fuzzy algorithm and exclusive Honey Bee algorithm, Fuzzy algorithm has better improvement and among Gaussian function and Cauchy function, Gaussian function has better improvement, too.

Keywords

Fuzzy, Honey Bee, Colony, Clustering

Received: December 16, 2014 / Accepted: March 27, 2015 / Published online: April 10, 2015

1. Introduction

Please The main characteristic of clustering algorithms to find useful information about the relationship between data, without being labeled as a nun supervise clustering. Clustering algorithms can be divided into two general categories: exclusive clustering and fuzzy clustering.

In exclusive clustering, the data belongs to exactly one cluster, such as K-Means clustering algorithm. The most popular class of clustering algorithms is K-means algorithm which is a center based, simple and fast algorithm [1]. However, K-means algorithm highly depends on the initial states and always converges to the nearest local optimum from the starting position of the search. In order to overcome local optima problem, the researchers from diverse fields are applying fuzzy clustering, partition-based clustering, density-based clustering, and artificial intelligence based clustering methods, such as: statistics [2], graph theory [3], expectation-maximization algorithms [4], artificial neural networks [5-8], evolutionary algorithms [9, 10], swarm intelligence algorithms [11-16] and so on.

In the method of fuzzy clustering, the clustering of the data is attributed to a degree of belonging to each cluster. A sense of belonging to a given data can be attributed to several different clusters[17]. Fuzzy theory was introduced by LotfiZadeh in 1965[18]. A fuzzy clustering is a method to divide the data into separate groups, with a degree of membership to a given cluster can be assigned to one or more. One of these algorithms, FCM algorithm, which was first introduced in 1973 by Dunn [19] and improved by Bezdek gained [20].This method is applied in many fields as a popular tool in numerical clustering was used. In recent years intelligent clustering methods such as clustering of data using neural networks [21], ant colony algorithm [22], PSO [23] and genetics [24]. Bee colony algorithm [25, 26]is a technique that makes use of collective intelligence. This algorithm was introduced in 2006 by Karaboga that food searching behaviour of honey bee groups was simulated. In this way, the algorithm performs a local search is combined with random search.

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The algorithm consists of three types of bees: worker bee, scouts bee and spectators. Half the colony is worker bees and the other half are spectators. Worker bees are responsible for the operation of the nectar sources that have already been discovered and to other bees in the hive spectators waiting to receive information about the quality of food sources are good, they give information. Spectator bees stay in hive and the worker bees are sharing information about food sources to use when making their decision. Scout bees as a food source by a random environment for a new search.

In this paper, the proposed algorithm for optimization of fuzzy bee is applied to data clustering. Iris and Wine data sets examined by the algorithm, and are compared with the good clustering algorithms.

The rest of this paper is organized as follows. Section 2 presents the clustering algorithms, in Section 3 we describe fuzzy artificial bee algorithm. The effectiveness of the purposed method and experimental results for clustering are demonstrated in Section 4, and finally, the paper is concluded in Section 5.

2. Clustering Algorithms

In this paper, a fuzzy algorithm for clustering n sample or model in a d-dimensional space into k clusters or groups is used. Although different clustering criteria can also be adapted for clustering,in this paper, the minimum inter-cluster distance, or average Euclidean distance of all samples to the cluster centers in the objective function (1) is used:

$$\mathrm{Fitness}_{SN} = \frac{1}{1+\sum_{i=1}^{K}\left(\frac{1}{D_{Train}}\sum_{j=1}^{D_{Train}} U_{jk}X_j\right)_i} \tag{1}$$

If X is an example of D-dimension and C cluster centers, Euclidean distance (2) is calculated using the following formula:

$$\mathrm{Distance}(X,C) = \sqrt{(X_1 - C_1)^2 + \ldots + (X_D - C_D)^2} \tag{2}$$

One of the most used methods for clustering is based on K-means. Although the K-means algorithm is simple to implement and in most cases is faster, but the big problem is that the algorithm converges to a local minimum usually. Algorithm starts with an initial random partition and tries to assign each of the instances to different clusters. This is done using the similarities between each of sample with centroids. After averaging the central elements of the cluster centres, new centres of each cluster is calculated and replaced the previous ones. This process continues it gets a convergence criterion. Some of the disadvantages of the algorithm are as follows:

- The final result will depend on the initial position.
- Number of clusters is unknown.
- During the algorithm process it is possible that a data point would not assign to a cluster.

Traditional clustering methods generate partitions. In this partition each sample belongs to one and only one cluster, but the FCM algorithm with a membership function of each sample can be attributed to each of the clusters.

The sum of the probabilities for each of the clusters is equal to one. Namely:

$$\sum_{i=1}^{c} u_{ik} = 1, \forall k = 1,\ldots,n$$

Using the above conditions and the minimum objective function, centers update formulas (3) and FCM membership function (4) are as follows:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}} \tag{3}$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}} \tag{4}$$

Where C is the number of clusters and N is the number of patterns. FCM algorithm is an algorithm that always converges, but has the following disadvantages:

- Much computation time.
- Is sensitive to initial guesses and may be stopped at a local minimum.
- Is sensitive to noise.

Honeybee fuzzy clustering algorithm is a new algorithm for finding the best centers in the algorithm, each point in the space of possible responses will be evaluated as a source of food. "The scout bees" or simulated agents, generate randomly answers in the state space by fitness function, quality and location visited. Spectators are another batch of new forces to improve the worker bees's answer by local search. The algorithm searches other source to find the point of maximum fitness function will search for the best spots to be converged.

The algorithm compared with other algorithm, for example Genetic Algorithms (GA) [27] that are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem, Simulated annealing (SA) [28] is a generic probabilisticmeta-heuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space. It is often used when the search space is discrete and ants colony algorithm (ACO) [14] proposed by Marco Dorigo in 1992 in his PhD thesis, to search for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food and taboo search algorithm (TS) [29] which that enhances the performance by using memory structures that describe the visited solutions or user-provided sets of rules If a potential solution has been previously visited within a certain short-term period or if it has violated a rule, it is marked as "taboo so that the algorithm does not consider that possibility repeatedly, Finally, Particle swarm optimization (PSO) [22, 30] is a population based stochastic optimization technique developed by Dr.Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

3. Fuzzy Artificial Bee Colony Algorithm

A honey bee colony can skillfully choose among nectar sources. It will selectively exploit the most profitable source in an array and will rapidly shift its foraging efforts following changes in the array. How does this colony-level ability emerge from the behaviour of individual bees? The answer lies in understanding how bees modulate their colony's rates of recruitment and abandonment for nectar sources in accordance with the profitability of each source. A worker modulates its behaviour in relation to nectar source profitability: as profitability increases, the tempo of foraging increases, the intensity of dancing increases, and the probability of abandoning the source decreases. How does a worker assess the profitability of its nectar source? Bees accomplish this without making comparisons among nectar Sources. Neither do the workers compare different nectar sources to determine the relative profitability of any one source, nor do the food scorers compare different nectar loads and indicate the relative profitability of each load to the workers. Instead, each worker knows only about its particular nectar source and independently calculates the absolute profitability of its source. Even though each of a colony's workers operates with extremely limited information about the colony's food sources, together they will generate a coherent colony-level response to different food sources in which better ones are heavily exploited and poorer ones are abandoned.

Nectar-source selection by honey bee colonies is a process of natural selection among alternative nectar sources as workers from more profitable sources "survive" (continue visiting their source) longer and ' reproduce" (recruit other workers) better than do workers from less profitable sources. Hence this colonial decision-making is based on decentralized control.

In this algorithm, the colony consists of three groups of bees: worker bee, scouts bee and spectators. The first half of the colony includes artificial worker bees and the second half includes spectators. For every food source, there is just a worker bee. Each worker bee has a solution for the problem of clustering with cluster centres.

Worker bees are called scout bees at the beginning of a random search. Worker bees search a food source near their food source memory (previous solutions). In other words, they modify themselves in their search for finding a better solution according to the formula (5):

$$V_{ij} = Z_{ij} + \sum_{h=1}^{h=NC} (\varphi_h \Psi_{ij}(Z_{ij} - Z_{kj})) \qquad (5)$$

In formula (5), Z is the centre of cluster,Vij is a new position and is a random number between the range of (-1, 1). It controls the production of neighbour food sources around Zij. k is determined randomly and it has to be different from i. As can be seen from (6), as the difference between the parameters of the Zi,j and Zk,j decreases, the perturbation on the position Zi,j decreases, too. In this relation, we try to select one dimension of one of the positions based on its extent; there will be a movement occurs towards it or against it.

Thus, as the search approaches to the optimum solution in the search space, the step length is adaptively reduced. In this paper, we can use a number of fuzzy membership function. Popular membership function choices include the triangular, trapezoidal, Gaussian and Cauchy membership function. The Cauchy function has a "wider tail" Compare to the Gaussian function. NC is number of clusters index a Cauchy's value for each cluster.

In this paper we use a membership function based on the Cauchy function (6). Let h be one of the NC-clusters in a given neighbourhood and let f(pg) refer to the fitness of the best solution for the neighbourhood under consideration.

We compute the clusters NC as:

$$\varphi_h = \frac{1}{1+\left(\frac{f(p_h)-f(p_g)}{\beta}\right)^2} \quad (6)$$

We set: $\beta = \frac{f(p_g)}{1}$

Two used functions (Gaussian and Cauchy) are showninFig. 1.

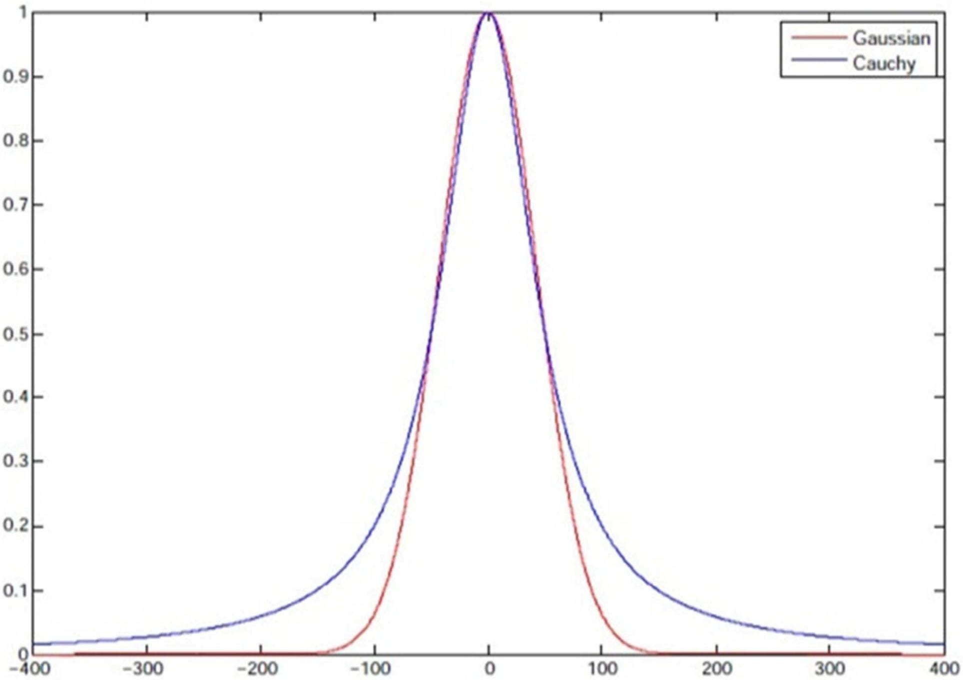

Fig. 1. A plot of a Gaussian function (solid line) anda Cauchy function (dashed line)

By performing this dance, successful Worker bees share the information about the direction and distance to patches of flower and the amount of nectar within this flower with their spectators. So this is a successful mechanism which foragers can recruit other bees in their colony to productive locations to collect various resources. Bee colony can quickly and precisely adjust its searching pattern in time and space according to changing nectar sources.

The information exchange among individual insects is the most important part of the collective knowledge. Communication among bees about the quality of food sources is being achieved in the dancing area by performing waggle dance, then spectators will select one of them according to formula (7).

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (7)$$

In formula (7), fiti is fitness of ith food source associated with bees. SN is equal to the number of bees.

Spectator bees search a food source neat to the food source selected in previous step based on the formula (5). When source is finished, the worker bee leaves the source and become a scout and start a random search for a food source according to formula (8) is.

$$\begin{aligned} &Z_i = Z_{min} + \Gamma(Z_{max} - Z_{min}) \\ &\Gamma \in [0,1] \end{aligned} \quad (8)$$

Each cycle of the search consists of three steps: moving worker bees and spectators to the food sources and calculating their fitness (nectar) and their random movement towards possible food source. A food source is a possible solution to problem and the nectar amount of a food source corresponds to the quality of solutions presented. In this method, spectators select more suitable food source based on a selection mechanism.

In Bee proprietary algorithm, the sample belongs to one and only one cluster. Clustering algorithms proposed in the context added that each sample can be attributed by a membership function to each of the clusters. In Fuzzy Honey Bee algorithm, Uik represents the amount of accrued ith example in kth cluster but the difference is that it has a fuzzy function. The sum of the probabilities of each cluster is to be equal to one.

Namely:

Each data by its center space takes a membership function on a value between zero and one; the average distance of the data from each solution obtains Fitness Centres.

$$\sum_{i=1}^{c} u_{ik} = 1, \forall k = 1, \ldots, n$$

$$\text{Fitness}_{SN} = \frac{1}{1 + \sum_{i=1}^{K} \left(\frac{1}{D_{Train}} \sum_{j=1}^{D_{Train}} U_{jk} X_j \right)_i} \tag{9}$$

Where DTrain is the number of training patterns which is used to normalize the sum that will range any distance within [0.0, 1.0] and Ujk defines the probability of class that instance (Xj) belongs to according to database.Pseudo-code of the Fuzzy ABC algorithm is:

Procedure FABC:

Generate the initial population

Evaluate the fitness by (9)

REPEAT

REPEAT

Produce new solution for employed bee by (5)

Calculate the value fitness by (9)

Calculate the probability values by (7)

UNTIL n= worker bees

REPEAT

Select a solution by rollet wheel by (7)

Calculate the value fitness by (9)

UNTIL m= spectators bees

If there is an abandoned solution for scout

replace new random solution by (8)

Memorize the best solution;

UNTIL meet the stop criteria

4. Results of Experiments

In this paper, the novel algorithm of fuzzy ABC were compared with the best algorithms including ABC, SA, GA, ‹FCM‹K-Means ‹TS‹ ACO, K-NM-PSO to evaluate function. This experiment is performed on a system with 266 GHz and 4 GB of Ram. Two sets of data i.e. Wine and Iris are used.

The set of Iris data is a set of data including three samples of iris flowers that is presented in 1936 by Fisher to show linear separation techniques. Hence, this dataset is also called Fisher iris flower dataset. Iris is one the well-known database including 150 samples of clusters. Each cluster includes 50 petals, 4 numerical features, sepal length, sepal width, petal length, and petal width.

Wine dataset is a dataset that includes chemical analysis of grown elements of similar wines in similar circumstances. Attribute vectors have 13 components. There are 178 patterns of three distinct classes in this dataset. Samples in contain 59 data in the first class, 71 data in the second class, and 48 data in the third class.

In this algorithm, the number of worker bees and spectator bees is equal with 10 and 600 iterations were carried out for 10 food source or centre clusters. Setup values of the rest of the algorithms are presented in the current paper

In Figure 2, the graph of three algorithms of K-means, FCM and the proposed algorithm for two datasets is shown. As you can see, the fuzzy ABC algorithm could achieve its most efficient function in both data sets, and this is due to the nature of the local and global search in this algorithm.In Figure 3, the centres of the Iris data set obtained by the fuzzy ABC algorithm are shown.

In Table 1, as it can be seen, fuzzy ABC algorithm has the best performance among other algorithms for the best, average and worst inter-cluster distances. For Iris data set, the maximum intra-cluster distance is the worst performance obtained by GA which is 113.98, while the best performance is for the fuzzy ABC algorithm and is 75.51. The worst performance for the second data set is related to the performance of the FCM algorithm, while the best performance belongs to Fuzzy ABC, again. According to the results, the proposed algorithm has the best performance among algorithms, and can find the best or near-best solutions to clustering of N data to K clusters. The parameter settings of ABC, ACO, GA, TS, SA and K–NM–PSO are set the same as their original paper.

On the other hand, we checked Fuzzy ABC algorithm by two well-known functions "Gaussian and Cauchy". In Figure 1 the diagram of two functions is shown. Among these two functions, the average, worst and the best inner-distance of iris dataset belongs to Gaussianfunction. In second data set like the first data set, the average and the best inner-distance belongs to Gaussian function. In 2th dataset, the optimal amount of the worst interior distance is related to Cauchy function.

In general form, among Fuzzy algorithm and exclusive Honey Bee algorithm, Fuzzy algorithm has better improvement and among Gaussian function and Cauchy function, Gaussian function has better improvement, too.

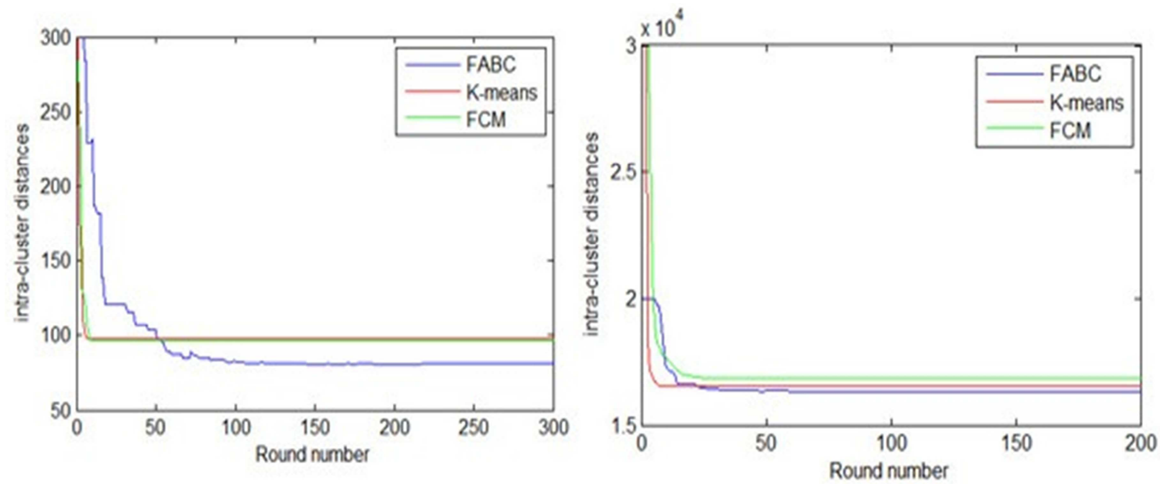

Fig. 2. Comparison of performance for K-means, FCM (two basic algorithm) and propose algorithm

Table 1. Comparison of intra-cluster distances for the ten algorithms

Data set	Criteria	GA	TS	SA	ACO	K–NM–PSO	K-Means	FCM	ABC	FABC-G	FABC-C
	Average	125.19	97.86	97.13	97.17	96.67	97.324	96.92	78.94	75.51	75.80
Iris	Worst	139.78	98.57	97.26	97.81	97.01	97.34	96.92	78.94	75.51	75.80
	Best	113.98	97.36	97.10	97.10	96.66	97.32	96.92	78.94	75.51	75.80
	Average	16530.53	16785.46	16530.53	16530.53	16293.00	16555.67	16856.16	16260.52	16254.41	16258.32
Wine	Worst	16530.53	16837.54	16530.53	16530.53	16295.46	16555.67	16856.16	16279.46	16273.24	16271.12
	Best	16530.53	16666.22	16530.53	16530.53	16292.00	16555.67	16856.16	16257.28	16241.67	16249.87

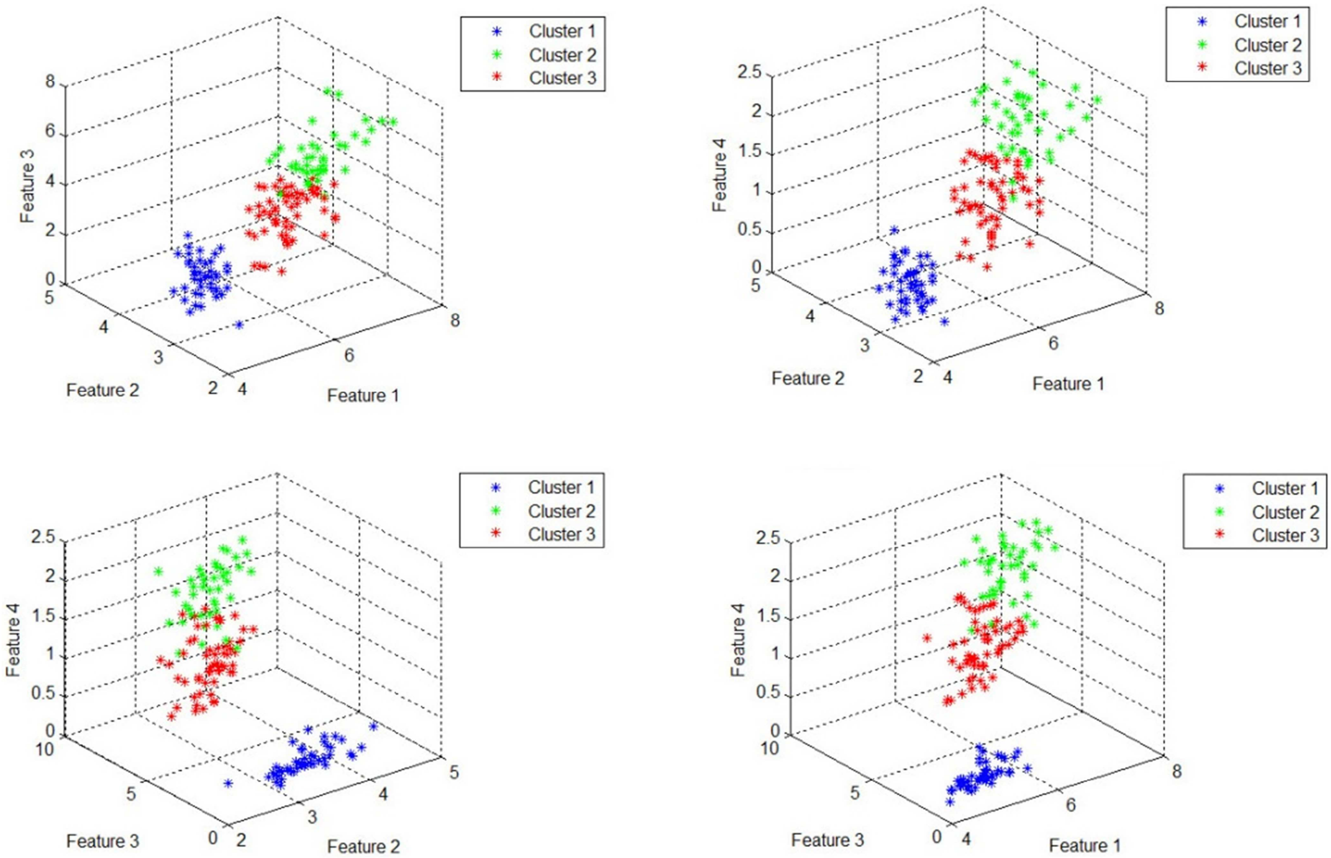

Fig. 3. Clustering result of Iris data by Fuzzy ABC algorithm.

5. Conclusion

Swarm intelligence is an emerging area in the field of optimization and researchers have developed various algorithms by modeling the behaviors of different swarm of animals and insects such as ants, termites, bees, birds, fishes. In 1990, Ant Colony Optimization based on ant swarm and Particle Swarm Optimization based on bird flocks and fish schools have been introduced and they have been applied to solve optimization problems in various areas within a time of two decade. The foraging behavior, learning, memorizing and information sharing characteristics of bees have recently been one of the most interesting research areas in swarm intelligence.

Studies on honey bees are in an increasing trend in the literature during the last few years. In this paper, a fuzzy artificial bee colony algorithm which is a new, simple optimization method is used to solve clustering problems which is inspired by the bees' forage behaviour. As mentioned above, the algorithm has the best performance; the performance of the FABC algorithm is compared with ABC algorithm and other seven techniques which are widely used by the researchers. It can be a good option to find the best or close to best use.

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