Flower Pollination Algorithm with Bee Pollinator for Cluster Analysis

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Abstract: Clustering is a popular data analysis and data mining technique. The K-Means clustering algorithm is one of the most commonly used method. However, it highly depends on the initial solution and is easy to trap into the local optimal. For overcoming these disadvantages of the k-means method, Flower Pollination Algorithm with Bee Pollinator is proposed. Discard pollen operator and crossover operator are applied to increase diversity of the population, and local searching ability is enhanced by using elite based mutation operator. Ten data sets are selected to evaluate the performance of proposed algorithm. Compared with DE, CS, ABC, PSO, FPA and K-Means, the experiment results show that Flower Pollination Algorithm with Bee Pollinator has not only higher accuracy but also higher level of stability. And the faster convergence speed can also be validated by statistical results.

Keywords: flower pollination algorithm; discard pollen operator; elite based mutation operator; crossover operator; clustering problem.

1. Introduction

Data clustering is the process of grouping together similar multi-dimensional data vectors into a number of clusters. Clustering algorithms have been applied to a wide range of problems, including exploratory data analysis, data mining [1], image segmentation [2] and mathematical programming [3]. Clustering techniques have been used successfully to address the scalability problem of machine learning and data mining algorithms, where prior to, and during training, training data is clustered, and samples from these clusters are selected for training, thereby reducing the computational complexity of training process, and even improving generalization performance [4] [5].

Clustering algorithms can be grouped into two main classes of algorithms, namely hierarchical and partitional. The k-means clustering method [6] is one of the most commonly used partitional methods. However the results of k-means solving the clustering problems highly depend on the initial solution and it is easy to fall into local optimal solutions. For overcoming this problem, many scholars began to solve the clustering problem using meta-heuristic algorithms. Nikam et al have proposed an efficient hybrid evolutionary algorithm based on combining ACO and SA (simulated annealing algorithm, 1989 [7] for clustering problem [8] [9]. In 1991, Colorni A et al have presented ant colony optimization (ACO) algorithm based on the behavior of ants seeking a path between their colony and a source of food. Then P. S. Shelokar and Y. Kao solved the clustering problem using the ACO algorithm [10] [11]. Kennedy J and Eberhart RC have proposed particle swarm optimization (PSO) algorithm which simulates the movement of organisms in bird flock or fish school in 1995 [12]. The algorithm also has been adopted to solve this problem by M. Omran and V. D. Merwe [13] [14]. Kao et al have presented

a hybrid approach according to combination of the k-means algorithm, Nelder-Mead simplex search and PSO for clustering analysis [15]. Kevin et al have used an evolutionary-based rough clustering algorithm for the clustering problem [16].

In this paper, a variant of the flower pollination algorithm is used to solve the data clustering problem. Flower Pollination Algorithm (proposed by Yang in 2012) [17] is a new population-based intelligent optimization algorithm by simulating flower pollination behavior in nature. And it has been extensively researched in last two years by scholars. Yang and Xingshi He have used FPA to solve multi-objective optimization problem in 2013 [18]. Marwa Sharawi has applied FPA for solving Wireless Sensor Network Lifetime global optimization in 2014 [19]. Osama Abdel-Raouf has used an improved FPA to solve Sudoku Puzzles in 2014 [20]. And FPA has been used to solve Large Integer Programming Problems by Ibrahim El-henawy in 2014 [21].

The remainder of this paper is organized as follows. Section 2 introduces the mathematical model of clustering; Section 3 describes the principle of basic flower pollination algorithm; while section 4 specified implementation procedure of our proposed Flower Pollination Algorithm with Bee Pollinator (BPFPA); in section 5, Series of comparison experiments are conducted; Result analysis will be given in Section 6; Our conclusion and future works are described in section 7; and acknowledgements are shown in section 8.

2. The mathematical model of clustering

2.1 Mathematical definition of data clustering

The goal of data clustering is grouping data into a number of clusters, clustering problems can be seen in practice frequently. In this subsection, a mathematical definition of data clustering is presented. In order to explain the definition clearly, we supposed that there exists a data set $D = \{d_1, d_2, \dots, d_n\}$. And each individual d_i ($i = 1, 2, \dots, n$) has many features. If the dimension is m , each individual can be shown as $d_i = (l_1, l_2, \dots, l_m)$. Data clustering is a process which can classify the given data set D into a certain numbers of clusters $G_1, G_2, \dots, G_K$ (assume K clusters) based on the similarity of individuals. And $G_1, G_2, \dots, G_K$ should satisfy the following formulas:

$$1). G_i \neq \emptyset, i = 1, 2, \dots, K.$$

$$2). G_i \cap G_j = \emptyset, i, j = 1, 2, \dots, K, i \neq j.$$

$$3). \bigcup_{i=1}^K G_i = \{d_1, d_2, \dots, d_n\}.$$

2.2 The principle of data clustering

In the clustering process, if the given data set D should be divided into K clusters $(G_1, G_2, \dots, G_K)$, and each cluster must have one center c_j ($j = 1, 2, \dots, K$). It is supposed that $C = (c_1, c_2, \dots, c_K)$ are the centers of $(G_1, G_2, \dots, G_K)$. Where c_j is the center of subset G_j .

The main idea of clustering is to define K centers, one for each cluster. These centers should be placed in a crafty way, because different location will causes different result. Therefore, the better choice is to place them as far away from each other as possible. In this paper, we will use Euclidian metric as a distance metric. The expression is given as follows:

$$d(d_i, c_j) = \sqrt{\sum_{k=1}^m (d_{ik} - c_{jk})^2} \quad (1)$$

where d_i ($i=1,2,\dots,n$) is an individual in the given data set D , m is the number of individual features; c_j ($j=1,2,\dots,K$) is the center of j th subset. Because individual has m features, c_j can be presented by $(c_{j,1}, c_{j,2}, \dots, c_{j,m})$. In order to confirm which subset d_i belongs to, the distances between d_i and c_j ($j=1,2,\dots,K$) should be calculated via (1). If the distance between d_i and c_{best} ($best=1,2,\dots,K$) is smaller than the distances between d_i and other centers (except c_{best}), we can make the decision that d_i should belongs to G_{best} . For example, if the value of $d(d_1, c_2)$ is smaller than $d(d_1, c_j)$, ($j \neq 2$), we can draw the conclusion that d_1 should be distributed to G_1 .

2.3 The performance evaluation function of data clustering

In this paper, data clustering problem is solved by population based algorithm (Flower Pollination Algorithm and Flower Pollination Algorithm with Bee Pollinator). For explaining the evaluation process explicitly, we suppose that given data set D should be divided into K subsets. And the dimension of individual of data set D is m . In order to optimize the coordinates of centers of K subsets, it is easily to find that the dimension of solution should be $K*m$. The individual in the population can be described as $s = (c_1, c_2, \dots, c_K)$. A great classification should minimize the sum of distances value. So we should try to minimize the distance between individual d_i and the center (c_j) of subset it belongs to. Finally, the proposed algorithm aims at minimizing the objective function, which can be expressed as following:

$$f(D, C) = \sum_{i=1}^n \text{Min}\{ \|d_i - c_k\| \mid k=1, 2, \dots, K \} \quad (2)$$

where $D = (d_1, d_2, \dots, d_n)$ is the given data set, $C = (c_1, c_2, \dots, c_K)$ is the centers of subsets $(G_1, G_2, \dots, G_K)$.

3. Flower Pollination Algorithm (FPA)

Flower Pollination Algorithm (FPA) was founded by Yang in the year 2012. Inspired by the flow pollination process of flowering plants are the following rules [22] [17]:

Rule 1: Biotic and cross-pollination can be considered as a process of global pollination process, and pollen-carrying pollinators move in a way that obeys Lévy flights.

Rule 2: For local pollination, a biotic and self-pollination are used.

Rule 3: Pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved.

Rule 4: The interaction or switching of local pollination and global pollination can be controlled by a switch probability, with a slight bias toward local pollination.

In order to formulate updating formulas, we have to convert the aforementioned rules into updating equations. For example, in the global pollination step, flower pollen gametes are carried by pollinators such as insects, and pollen can travel over a long distance because insects can often fly and move in a much longer range. Therefore, Rule 1 and flower constancy can be represented mathematically as:

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(x_i^t - B) \quad (3)$$

Where x_i^t is pollen i or solution vector x_i at iteration t , and B is the current best solution found among all solutions at the current generation/iteration. Here γ is a scaling factor to control the step size.

In addition, $L(\lambda)$ is the parameter that corresponds to the strength of the pollination, which essentially is also the step size. Since insects may move over a long distance with various distance steps, we can use a Lévy flight to imitate this characteristic efficiently. That is, we draw $L > 0$ from a Levy distribution:

$$L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{S^{1+\lambda}}, (S \gg S_0 > 0) \quad (4)$$

Here, $\Gamma(\lambda)$ is the standard gamma function, and this distribution is valid for large steps $s > 0$. Then, to model the local pollination, both Rule 2 and Rule 3 can be represented as

$$x_i^{t+1} = x_i^t + U(x_j^t - x_k^t) \quad (5)$$

Where x_j^t and x_k^t are pollen from different flowers of the same plant species. This essentially imitates the flower constancy in a limited neighborhood. Mathematically, if x_j^t and x_k^t comes from the same species or selected from the same population, this equivalently becomes a local random walk if we draw U from a uniform distribution in $[0,1]$. Though flower pollination activities can occur at all scales, both local and global, adjacent flower patches or flowers in the not-so-far-away neighborhood are more likely to be pollinated by local flower pollen than those faraway. In order to imitate this, we can effectively use the switch probability like in Rule 4 or the proximity probability p to switch between common global pollination to intensive local pollination. To begin with, we can use a naïve value of $p = 0.5$ as an initially value. A preliminary parametric showed that $p = 0.8$ might work better for most applications [17].

4. Flower Pollination Algorithm with Bee Pollinator (BPFPA)

For strengthening the global searching and local searching abilities, three optimization strategies are applied to the basic flower pollination algorithm (FPA). As we all know that honey bees usually act as pollinators of flower plants in nature. And there exists a discard solution operator in artificial bee colony algorithm (ABC) [23]. In this paper, that operator is selected to enhance the global searching ability of proposed Flower Pollination Algorithm with Bee Pollinator. Other two optimization strategies (Elite Based Mutation Operator and Crossover Operator) used in local search process to enhance its local searching ability.

4.1 Discard Pollen Operator

In natural, Bees usually act as the pollinators of flowers. And there exists a discard solution operator in ABC [23] to enhance the diversity of population and the global searching ability. In ABC, *limit* is an important controls parameter. If a solution can't be improved after *limit* generation continuously, and it is not the global best in the population, we should discard it and generate a new solution in a random way.

Honey bees use levy flight to do global search in proposed Flower Pollination Algorithm with Bee Pollinator. And discard pollen operator is chosen to enhance its global searching ability. If a pollen is not improved after *limit* generations continuously, and it is not the global best, we should discard it and generate a new pollen use simplex method. The steps of simplex method [26] [25] are shown as follows (Fig.1):

Fig.1 The simplex method searches the difference points

Step 1: Evaluate all the solutions in the population, and choose the global best x_g , and the second best x_b . It is supposed that x_s is the pollen should be discarded. $f(x_g), f(x_b), f(x_s)$ are the fitness value of x_g, x_b, x_s .

Step 2: Find the center point x_c between x_g and x_s by the expression below:

$$x_c = \frac{x_g + x_s}{2} \quad (6)$$

Step 3: Carry out the reflecting operation by expression below:

$$x_r = x_c + \alpha(x_c - x_s) \quad (7)$$

where x_r is the reflecting point of x_s . α is the reflecting coefficient, which is set to 1 in this paper.

Step 4: If the fitness value of x_r is smaller than that of x_g ($f(x_r) < f(x_g)$), extension operation should be carried out according to the expression below:

$$x_e = x_c + \gamma(x_r - x_c) \quad (8)$$

where x_e is the extension point. And the extension coefficient γ should be set to 2. If the fitness value of x_e is smaller than the fitness of x_g , x_s should be replaced by x_r , otherwise x_r will be used to substitute x_s .

Step 5: If $f(x_r) > f(x_s)$, the compression operation should be used via expression below:

$$x_t = x_c + \beta(x_s - x_c) \quad (9)$$

where x_t is the compression point of x_s , the compression coefficient β should be set to 0.5. If $f(x_t) < f(x_s)$, x_s should be replaced by x_t .

Step 6: If $f(x_s) > f(x_r) > f(x_g)$, shrink operation should be carried out according to expression below:

$$x_w = x_c - \beta(x_s - x_c) \quad (10)$$

where x_w is the shrink point. Shrink coefficient β is set to 0.5 in this paper. If $f(x_w) < f(x_s)$, x_s should be replaced by x_w , otherwise, we use x_r to substitute x_s .

In global search process of Flower Pollination Algorithm with Bee Pollinator, the discard pollen operator is used to jump out local minima, which enhance its global searching ability significantly. And simplex method is used to generate new pollen to substitute the bad one. New pollen generated by simplex method usually has a better fitness, which can speed up the convergence speed.

4.2 Elite Based Mutation Operator

Flower Pollination Algorithm (developed by Yang) carries out local search in a similar way to the step in differential evolution (DE). And experiment results show that local search ability of DE is limited. Thus, we add Elite Based Mutation Operator to local search process to enhance its exploitation ability. And that operator can be expressed in the following formula:

$$X_{i,G+1} = X_{i,G} + \alpha(X_{best} - X_{i,G}) + \beta(X_{p,G} - X_{q,G}) \quad (11)$$

where X_{best} is the best vector of the whole population, $p, q \in [1, n]$, n is the population size. α, β obey uniform distribution. The exploitation ability of proposed algorithms is enhanced by this mutation operator.

4.3 Crossover Operator

In subsection 4.2, Elite Based Mutation Operator is used to the local search process. EBMO can increase its exploitation ability, and it can also speed up the convergence speed. But another aspect should be taken into account. EBMO make it easier to trap in local minima. So crossover operator is chosen to increase the diversity of population. And the crossover operator can be expressed in the following formula:

$$X_{i,j} = \begin{cases} X_{i,j}, & rand_{i,j}[0,1] < C_r \\ X_{k,j}, & k \neq i \text{ else} \end{cases} \quad i, k = 1, 2, 3 \dots n; j = 1, 2, \dots d. \quad (12)$$

where $X_{k,j}$ is the j th variable of k th pollen; C_r is the crossover rate, which is set to 0.15 in this paper. The crossover operator helps to increase the diversity of population in local search process, and avoid trapping into local optimal. Specific implementation steps of Flower Pollination Algorithm with Bee Pollinator (BPFPA) for clustering can be summarized in the pseudo code shown in Algorithm 1.

Algorithm1 .Flower Pollination Algorithm with Bee Pollinator for clustering problem

Initialize a population (X) of n flowers/pollen gametes with random solutions.

Each flower represents all center points of clusters.

Initialize the vector $counter = zeros(1, n)$; it is used to record the generation of unimproved flowers.

Set $limit = 10$;

Find the best solution B in the initial population

Define a switch probability $p \in (0, 1)$

Define a stopping criterion (either a fixed number of generations/iterations or accuracy)

while ($t < MaxGeneration$)

for $i = 1:n$ (all n flowers in the population)

if $rand < p$

 (Global search process)

 Draw a (d-dimensional) step vector L which obeys a Lévy distribution.

 Global pollination via equation (3) and get new solution x_i .

if $counter(1, i) = limit$

 Generate a new solution via simplex methods (discussed in section 4.1);

$counter(1, i) = 0$;

end if

else

 (Local search process)

 Carry out Elite Based Mutation Operation via equation (11).

 Carry out Crossover Operation via equation (12).

end if

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    Evaluate the new solution  $x_i$  via equation (2);
    if  $fitness(x_{i,G+1}) < fitness(x_{i,G})$ 
        update flower  $x_i$ ;
         $counter(1,i) = 0$ ;
    else
         $counter(1,i) = counter(1,i) + 1$ ;
    end if
end for
    Find the current best solution  $B$ 
end while
Output the best solution found.

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5. Simulation Experiments

5.1 Experimental setup

All of the algorithm was programmed in MATLAB R2012a, numerical experiment was set up on AMD Athlont (tm) II*4640 processor and 2 GB memory.

5.2 Numerical Comparison of each algorithm performance

The proposed Flower Pollination Algorithm with Bee Pollinator compared with mainstream swarm intelligence algorithms DE [24], CS [27], PSO [12], ABC [23], FPA [17] and K-means [6], respectively using the mean and standard deviation to compare their optimal performance. The setting values of algorithm control parameters of the mentioned algorithms are given below.

DE setting: $F = 0.5$ and $CR = 0.9$ in accordance with the suggestions given in [24], the population size is 50.

CS setting: $p_a = 0.25$ have been used as recommended in [27], the population size is 50.

PSO setting: weight factor $\omega = 0.7298$, $c_1 = c_2 = 1.4962$ [12], the population size is 50.

ABC setting: limit = 5D has been used as recommended in [23], the population size is 50.

FPA setting: switch probability $p = 0.8$ in accordance with the suggestions given in [17], the population size is 50. And the maximum generations of all algorithms are set 200.

In this section, ten data sets are selected to testify the effectiveness of proposed algorithm, including two artificial data sets and eight real-life data sets (selected from the UCI machine learning repository [28]). There are artificial set one, artificial set two, Iris, Wisconsin breast cancer, Contraceptive Method Choice (CMC), Statlog (Heart), Balance Scale, Seeds, Haberman's Survival, Wine.

For these data sets, each algorithm is applied 20 times individually with random initial solution. For art1 and art2 data sets, once the randomly generated parameters are determined, the same parameters are used to test the performance of three algorithms. The best value, the worst value, the mean value and standard deviation are recorded in Table 1 to 10. Bold and italicized results mean that BPFPA is better, while underlined results mean that other algorithm is better. The results are kept four digits after the decimal point.

5.2.1 Artificial data set one

Artificial data set one ($N = 250, d = 3, K = 5$). This is a three-featured problem with five classes,

where every feature of the classes was distributed according to Class 1-Uniform(85,100), Class 2-Uniform(70,85), Class 3-Uniform(55,70), Class 4-Uniform(40,55), Class 5-Uniform(25,40) [29]. The comparison of algorithms for artificial data set one is listed in Table 1. And the convergence curves of algorithms are shown in Fig.2. In Fig.3, it is the result of anova test for artificial data set one.

Table 1. Results obtained by the algorithms for 20 different runs on Artificial data set one

Algorithm	Best	Worst	Mean	Std.
BPFPA	1718.2538	2386.5104	1783.5147	200.9330
FPA	1977.7401	2418.7069	2173.4082	115.4865
CS	1725.2482	<u>1995.5823</u>	1806.2505	<u>75.4400</u>
PSO	1718.2538	2444.8930	2153.7595	344.4796
ABC	1788.2069	2059.1212	1899.4503	77.49667
DE	1718.4592	2495.0929	1974.5335	346.0330
K-means	1747.3859	2507.9091	1991.9351	342.2974

Fig.2 The convergence curves of algorithms for art1

Fig.3 The anova test of algorithms for art1

From Table 1, the best value and the mean value of BPFPA are much better than those of other algorithms mentioned in this paper can be found. Though the standard deviation of CS is smaller, the mean value of CS is not good enough. Six convergence curves can be seen in Fig.2, which is the comparison for artificial data set one. We can discover that the curve of BPFPA is much smoother than other algorithms. And its convergence speed is faster. Fig.3 is the anova test for data set art1. We can find that the stability of BPFPA is well, the reason of its large deviation is two outliers shown in Fig.3.

5.2.2 Artificial data set two

Artificial data set two ($N = 600, d = 2, K = 4$). This is a two-featured problem with four unique classes. A total of 600 patterns were drawn from four independent bivariate normal distributions, where classes were distributed according to

$$N_2\left(\mu = \begin{pmatrix} m_i \\ 0 \end{pmatrix}, \Sigma = \begin{bmatrix} 0.5 & 0.05 \\ 0.05 & 0.5 \end{bmatrix}\right)$$

$$i = 1, 2, 3, 4 \quad m_1 = -3, \quad m_2 = 0, \quad m_3 = 3, \quad m_4 = 6.$$

μ and Σ being mean vector and covariance matrix, respectively [29]. The comparison of algorithms for artificial data set two is listed in Table 2. And the convergence curves of algorithms are shown in Fig.4. In Fig.5, it is the result of anova test for artificial data set two.

Table 2. Results obtained by the algorithms for 20 different runs on Artificial data set two

Algorithm	Best	Worst	Mean	Std.
BPFPA	513.9035	513.9035	513.9035	1.33E-13
FPA	517.1823	568.8652	538.6455	14.9615
CS	513.9037	515.931	514.1077	0.5302
PSO	513.9035	513.9035	513.9035	2.14E-08
ABC	514.6936	534.4247	518.3271	4.430872
DE	513.9035	514.2079	513.9463	0.0781
K-means	525.5957	907.1413	694.4421	191.4831

Fig.4 The convergence curves of algorithms for art2

Fig.5 The anova test of algorithms for art2

From Table 2, we can discover that the best value, worst value, mean value and standard deviation of BPFPA are the best in seven algorithms. And six convergence curves for artificial data set two are shown in Fig.4. The curve of BPFPA is smoother than others can be discovered easily. Faster convergence speed of BPFPA can be found as well. Fig.5 shows that BPFPA has a high degree of stability.

5.2.3 Data set Iris

Iris data ($N=150, d=4, K=3$): this data set with 150 random samples of flowers from the iris species setosa, versicolor, and virginica collected by Anderson (1995). From each species there are 50 observations for sepal length, sepal width, petal length, and petal width in cm. This data set was used by Fisher (1936) in his initiation of the linear-discriminant-function technique [28] [29]. The comparison of algorithms for data set Iris is listed in Table 3. And the convergence curves of algorithms are shown in Fig.6. In Fig.7, it is the result of anova test for Iris.

Table 3. Results obtained by the algorithms for 20 different runs on Iris

Algorithm	Best	Worst	Mean	Std.
BPFPA	96.6555	96.6555	96.6555	8.2E-13
FPA	97.4786	103.5763	99.7933	1.6846
CS	96.6569	97.1995	96.7242	0.1260
PSO	96.6554	127.6677	105.9627	14.5783
ABC	97.1362	100.2921	98.1047	0.6856
DE	96.6571	105.8550	97.5744	2.0035
K-means	97.1901	121.3554	100.8866	8.7805

Table 3 shows that the best value, worst value, mean value and standard deviation of BPFPA are all better than other algorithms. Convergence curves of six algorithms for data set Iris are shown in Fig.6. The curves in Fig.6 show that BPFPA has a faster convergence speed. And the convergence curve of BPFPA is smoother. Higher level of stability of BPFPA can be discovered in Fig.7, which shows the anova test result for Iris.

Fig.6 The convergence curves of algorithms for Iris **Fig.7** The anova test of algorithms for Iris

5.2.4 Data set Wisconsin Breast Cancer

Wisconsin breast cancer ($N = 683, d = 9, K = 2$): which consists of 683 objects characterized by nine features: clump thickness, cell size uniformity, cell shape uniformity, marginal adhesion, single epithelial cell size, bare nuclei, bland chromatin, normal nucleoli, and mitoses. There are two categories in the data: malignant (444 objects) and benign (239 objects) [28] [29]. The comparison of algorithms for data set Cancer is listed in Table 4. And the convergence curves of algorithms are shown in Fig.8. In Fig.9, it is the result of anova test for cancer.

Table 4. Results obtained by the algorithms for 20 different runs on Cancer

Algorithm	Best	Worst	Mean	Std.
BPFPA	2964.3869	2964.3869	2964.3869	9.0041E-12
FPA	2970.7424	3033.8020	2987.5210	14.3143
CS	2964.5318	2966.6399	2964.9456	0.4996
PSO	2964.3871	4728.7901	3140.8281	543.0715
ABC	2982.8207	3190.5028	3046.3477	48.8843
DE	2970.7369	3119.2544	3025.7756	49.3631
K-means	2976.9441	2988.4278	2983.3164	4.8661

Fig.8 The convergence curves of algorithms for Cancer

Fig.9 The anova test of algorithms for Cancer

The best value, worst value, mean value and the standard deviation of BPFPA are the best of seven algorithms listed can be easily discovered from Table 4. From the numerical comparison in Table 4, we also can find that CS performs second best. Convergence curves for data set Cancer shown in Fig.8 clearly show that BPFPA has a faster convergence speed. And its high degree of stability can be discovered in Fig.9, which is the anova test for Cancer.

5.2.5 Data set Contraceptive Method Choice (CMC)

Contraceptive Method Choice ($N = 1473, d = 10, K = 3$): this data set is a subset of the 1987 National Indonesia Contraceptive Prevalence Survey. The samples are married women who were either not pregnant or do not know if they were at the time of interview. The problem is to predict the current contraceptive method choice (no use, long-term methods, or short-term methods) of a woman based on her demographic and socioeconomic characteristics [28] [29]. The comparison of algorithms for data set CMC is listed in Table 5. And the convergence curves of algorithms are shown in Fig.10. In Fig.11, it is the result of anova test for CMC.

Table 5. Results obtained by the algorithms for 20 different runs on CMC

Algorithm	Best	Worst	Mean	Std.
BPFPA	5693.7239	5693.7283	5693.7246	0.0016
FPA	5796.7620	6100.1095	5927.0751	80.9424
CS	5704.1720	5738.4765	5721.1617	9.9204
PSO	5693.7779	5694.6504	5694.1109	0.2400
ABC	5848.2889	6320.9353	6041.8898	123.7676
DE	5720.3057	6089.6187	5811.6135	95.0982
K-means	5703.3444	5705.2747	5704.0770	0.9012

Fig.10 The convergence curves of algorithms for CMC

Fig.11 The anova test of algorithms for CMC

From Table 5, we can discover that the best value, worst value, mean value and standard deviation of BPFPA are the best in seven algorithms. ABC performs worst can also be seen from that table. And six convergence curves for data set CMC are shown in Fig.10. The curve of BPFPA is smoother than those of other algorithms can be found easily. Faster convergence speed of BPFPA can be found as well. Fig.11 shows that the stability of BPFPA and PSO are in high level.

5.2.6 Data set Statlog (Heart)

Statlog (Heart) data set ($N = 270, d = 13, K = 2$): this data set is a heart disease database similar to a database already present in the repository (Heart Disease databases) but in a slightly different form [28]. The comparison of algorithms for data set Heart is listed in Table 6. And the convergence curves of algorithms are shown in Fig.12. In Fig.13, it is the result of anova test for Heart.

Table 6. Results obtained by the algorithms for 20 different runs on Heart

Algorithm	Best	Worst	Mean	Std.
BPFPA	10622.9824	10623.1824	10622.9924	0.0447
FPA	10630.4063	10646.4106	10639.9882	4.0078
CS	10623.3314	10624.6019	10623.7067	0.3131
PSO	10622.9886	10623.4230	10623.0434	0.1120
ABC	10673.4980	11148.8039	10795.8489	110.1501
DE	10628.3745	11283.5839	10739.1109	173.6192
K-means	10682.0809	10700.8385	10691.7056	8.2080

Fig.12 The convergence curves of algorithms for Heart

Fig.13 The anova test of algorithms for Heart

Table 3 shows that all four indicators listed of BPFPA are smaller than those of other algorithms for data set Heart. And PSO performs the second best. ABC shows the weakness of its ability to solving clustering problem for data set Heart. Convergence curves for Heart are shown in Fig.12. The curves in Fig.12 shows the fact that BPFPA has a faster convergence speed. High level of stability of BPFPA can be discovered in Fig.13, which shows the anova test result for Heart.

5.2.7 Data set Balance Scale

Balance Scale data ($N = 625, d = 4, K = 3$): this data set was generated to model psychological experimental results. Each example is classified as having the balance scale tip to the right, tip to the left, or be balanced. The attributes are the left weight, the left distance, the right weight, and the right distance. The correct way to find the class is the greater of (left-distance * left-weight) and (right-distance * right-weight). If they are equal, it is balanced [28]. The comparison of algorithms for data set Scale is listed in Table 7. And the convergence curves of algorithms are shown in Fig.14. In Fig.15, it is the result of anova test for Scale.

Table 7. Results obtained by the algorithms for 20 different runs on Scale

Algorithm	Best	Worst	Mean	Std.
BPFPA	1423.8204	1425.7726	1424.3949	0.8473
FPA	1427.2209	1431.0778	1428.8768	1.0186
CS	1424.7429	1427.7458	1426.6609	0.9433
PSO	1423.8204	<u>1425.7714</u>	1424.8512	0.9363
ABC	1424.6303	1427.7899	1426.9782	<u>0.7207</u>
DE	1424.1447	1432.2318	1427.1192	2.0181
K-means	1423.8514	1434.0441	1426.7539	3.1208

Fig.14 The convergence curves of algorithms for Scale

Fig.15 The anova test of algorithms for Scale

From Table 7, the best value and the mean value of BPFPA are the best can be discovered. And the worst value of PSO and the standard deviation of ABC are better than other algorithms. Fig.14 shows the convergence curves of mentioned population based algorithms. Faster convergence speed can be discovered easily from it.

5.2.8 Data set Seeds

Seeds data ($N=210, d=7, K=3$): this data set consists of 210 patterns belonging to three different varieties of wheat: Kama, Rosa and Canadian. From each species there are 70 observations for area A, perimeter P, compactness $C (C=4 * \pi * A / P^2)$, length of kernel, width of kernel, asymmetry coefficient, length of kernel groove[28]. The comparison of algorithms for data set Seeds is listed in Table 8. And the convergence curves of algorithms are shown in Fig.16. In Fig.17, it is the result of anova test for Seeds.

Table 8. Results obtained by the algorithms for 20 different runs on Seeds

Algorithm	Best	Worst	Mean	Std.
BPFPA	311.7978	311.7978	311.7978	2.8E-10
FPA	317.0426	335.7757	328.0480	4.8174
CS	311.9915	313.3699	312.6202	0.4634
PSO	311.7979	420.1676	328.0546	39.7004
ABC	318.0697	339.3141	327.5305	6.2071
DE	312.4527	323.5514	316.3921	3.9990
K-means	313.1428	313.7343	313.4799	0.26879

From Table 8, we can discover that the best value, worst value, mean value and standard deviation of BPFPA are the best. And CS performs the second best in all algorithms. It is can be seen clearly that PSO performs the worst. Fig.16 is the convergence curves of algorithms for data set Seeds. The curve of BPFPA is smoother than others can be discovered easily. Faster convergence speed of BPFPA can be found as well. From Fig.17, we can find that the stability of BPFPA, PSO and CS are in really high level.

Fig.16 The convergence curves of algorithms for Seeds

Fig.17 The anova test of algorithms for Seeds

5.2.9 Data set Haberman's Survival

Haberman's Survival ($N=306, d=3, K=2$): the data set contains cases from a study that was conducted between 1958 and 1970 at the University of Chicago's Billings Hospital on the survival of

patients who had undergone surgery for breast cancer. It records two survival status patients with age of patient at time of operation, patient's year of operation and number of positive axillary nodes detected [28]. The comparison of algorithms for data set Survival is listed in Table 9. And the convergence curves of algorithms are shown in Fig.18. In Fig.19, it is the result of anova test for Survival.

Table 9. Results obtained by the algorithms for 20 different runs on Survival

Algorithm	Best	Worst	Mean	Std.
BPFPA	2566.9889	2567.8248	2567.0307	0.1869
FPA	2566.9926	2567.4245	2567.0727	0.103246
CS	2566.9889	<u>2566.9889</u>	<u>2566.9889</u>	<u>3.492E-07</u>
PSO	2566.9889	2567.8248	2567.1561	0.3430
ABC	2566.9921	2567.6142	2567.1368	0.2107
DE	2566.9889	2569.2452	2567.8519	0.9110
K-means	2625.1076	3193.5941	2655.1274	126.7500

Fig.18 The convergence curves of algorithms for Survival

Fig.19 The anova test of algorithms for Survival

From Table 9, best value of BPFPA is the best in mentioned algorithms can be seen. But CS performs the best in worst value, mean value and standard deviation. These three indicators of BPFPA are the second best. Fig.18 shows the convergence curves for data set Survival. It shows the clear fact that BPFPA converges faster than another population based algorithms. High degree stability of BPFPA can be found from Fig.19 easily.

5.2.10 Data set Wine

Wine data ($N=178, d=13, K=3$): this is the wine data set, which is also taken from MCI laboratory. These data are the results of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars. The analysis determined the quantities of 13 constituents found in each of the three types of wines. There are 178 instances with 13 numeric attributes in wine data set. All attributes are continuous. There is no missing attribute value [28] [29]. The comparison of algorithms for data set Wine is listed in Table 10. And the convergence curves are shown in Fig.20. In Fig.21, it is the result of anova test for Wine.

Table 10. Results obtained by the algorithms for 20 different runs on Wine

Algorithm	Best	Worst	Mean	Std.
BPFPA	16292.1847	16294.1727	16292.9230	0.7663
FPA	16322.0613	16381.6074	16343.7325	16.1486
CS	16296.4098	16306.4835	16299.4568	2.1980
PSO	16292.3974	16297.6153	16294.2251	1.1983
ABC	16391.4522	17439.2544	16706.4996	249.1459
DE	16336.3502	18124.0392	16876.5229	512.3944
K-means	16325.1202	18436.9520	17452.9957	1003.6327

Fig.20 The convergence curves of algorithms for Wine **Fig.21** The anova test of algorithms for Wine

We can discover that the best value, worst value, mean value and standard deviation of BPFPA are the best from Table 10. And PSO performs the second best. All of these methods, K-mean may be the worst one for solving clustering problems for data set Wine. Fig.20 shows that the curves of algorithms are all smooth. The curve of BPFPA converges faster than other five. Fig.21 shows that BPFPA, PSO and CS are the algorithms with high level of stability.

5.3 Graphical Experiment of Clustering

In section 5.2, large number of numerical simulation experiment is done. Table 1-10 show that BPFPA is an efficient population algorithm for solving clustering problems. Another fact that BPFPA is an algorithm with faster convergence speed and high level of stability can be discovered from Fig.2-21, but the results of numerical experiment are not easy to understand. Therefore, some graphical clustering comparison will be carried out in this section. In subsection 5.3.1, the clustering process of proposed BPFPA is shown. In subsection 5.3.2, five data sets (artificial data set one, artificial data set two, Iris, Contraceptive Method Choice, Survival) are selected to show the graphical result comparison of clustering by proposed BPFPA and another algorithm mentioned here.

5.3.1 The clustering process of BPFPA

In this subsection, artificial data set one is selected to show the clustering process of proposed Flower Pollination Algorithm with Bee Pollinator. In order to show the whole process of clustering, the clustering results of BPFPA are selected respectively when iterations are 0,10,15,50, which are shown in Fig.22-25. In these figures, every color represents one class.

Fig.22 The distribution of artificial data set 1.

Fig.23 The clustering result of BPFPA for art1, iteration is 10.

Fig.24 The clustering result of BPFPA for art1, iteration is 15.

Fig.25 The clustering result of BPFPA for art1, iteration is 50.

Fig.22 shows the distribution of artificial data set one, Fig.23 is the clustering result when iteration is 10, chaotic classes are shown in it. Class colored red mingled with the class colored blue, class colored green and class colored red are mixed together. When the iteration is 15, result shown in Fig.24 can be obtained. In Fig.24, the classifications are much clearer than Fig.23. When iteration reaches 50, these five classes are separated successfully by proposed BPFPA, the result is shown in Fig.25.

5.3.2 Graphical results comparison

In this subsection, five data sets (artificial data set one, artificial data set two, Iris, Contraceptive Method Choice, Survival) are selected to carried out the graphical comparison between proposed BPFPA and other algorithms. The maximum generations are set to 20 to see the differences between algorithms because of their efficient ability of optimization.

Fig.26 and Fig.27 are the comparison for artificial data set one. BPFPA and CS perform well for art1 from table 1, so CS is selected. In Fig.26, class colored green and the class colored pink mixed together. But in Fig.27, five classes are separated clearly.

Fig.26 The clustering result of CS for art1, the iteration is 20.

Fig.27 The clustering result of BPFPA for art1, the iteration is 20.

Fig.28 and Fig.29 are the comparison for artificial data set two. BPFPA and PSO are selected because of the great performance for artificial data set two, which shows in Table 2. In Fig.28, class colored red mingled with the class colored azure. And the data set is divided into four categories clearly in Fig.29.

Fig.28 The clustering result of PSO for art2, the iteration is 20.

Fig.29 The clustering result of BPFPA for art2, the iteration is 20.

In order to carrying out the comparison for data set Iris, CS and proposed BPFPA are selected, Fig.30 and Fig.31 are the clustering results of these two population-based algorithms. In Fig.30, two classes those colored red and azure mixed together. The classification of BPFPA (shown in Fig.31) is distinct.

Fig.30 The clustering result of CS for Iris, the iteration is 20.

Fig.31 The clustering result of BPFPA for Iris, the iteration is 20.

These two figures below show the comparison for data set Contraceptive Method Choice (CMC). From Table 5, we can discover that BPFPA and CS perform better than other algorithms. So CS is selected here to compare with BPFPA. Seen from Fig.32 and Fig.33, it can be found that the clustering ability of BPFPA is slightly better than CS.

Fig.32 The clustering result of PSO for CMC, iteration is 20.

Fig.33 The clustering result of BPFPA for CMC, iteration is 20.

Fig.34 and Fig.35 are the comparison for data set Survival. In Table 9, CS and BPFPA are the better ones for clustering Survival can be easily found. The boundary of two classes is not apparent in Fig.24. And in Fig.35, the two classes are separated apparently.

Fig.34 The clustering result of CS for Survival, iteration is 20.

Fig.35 The clustering result of BPFPA for Survival, iteration is 20.

6. Results Analysis

In section 5, sufficient experiment has been carried out to test the ability of proposed Flower Pollination Algorithm with Bee Pollinator for solving clustering problems. For validating BPFPA comprehensively, ten data sets are used.

Table1-10 shows the numerical result of several mainstream population based algorithms (PSO, DE, ABC, CS, FPA). Best value, worst value, mean value and standard deviation are listed respectively in these tables. From these tables, we can discover that BPFPA performs the best in most data set cases. Fig.2-21 shows the comparison of convergence curves and the anova test results for different data sets. From these comparison figures, we can easily find that the convergence speed of BPFPA is faster than other algorithms mentioned in this paper in most cases. Another fact can be found that the stability of BPFPA can reach a relatively high level as well.

In section 5.2, graphical comparisons of algorithms are carried out for five of these data sets (artificial data set one, artificial data set two, Iris, Contraceptive Method Choice, Survival). Fig.22-35 show the graphical comparison results directly. The classification obtained by BPFPA is much clearer than that of other algorithms can be easily found from these figures.

7. Conclusion and Future Works

Flower Pollination Algorithm is a new population based algorithm, its outstanding advantage is that it has a strong ability of exploitation. But it often traps in the local minima in the searching process. In

another words, its exploration ability is not good enough. In this paper, Flower Pollination Algorithm with Bee Pollinator is proposed to overcome the shortage of standard FPA. In global search process, the discard pollen operator is introduced to help jumping out of the local minima, which enhance its exploration ability. In local search process, Elite based mutation operator and crossover operator are used to improve the convergence speed and the diversity of population. In view of the clustering problem, a pollen represents all the centers of clusters. In this paper, two artificial data sets and 8 real instances are selected to compare with other algorithms (k-means, PSO, DE, CS, ABC, FPA). Both numerical experiments results and the graphical experiment results show that Flower Pollination algorithm with Bee Pollinator is more competitive than other algorithms for solving the clustering problem. Future studies will extend the fitness function to also explicitly optimize the intra-cluster distances. More elaborate tests on higher dimensional problems and large number of patterns will be done. The BPFPA clustering algorithm will also be extended to dynamically determine the optimal number of clusters.

Acknowledgements

This work is supported by National Science Foundation of China under Grants No. 61165015, 6143007. Key Project of Guangxi Science Foundation under Grant No. 2012GXNSFDA053028, Key Project of Guangxi High School Science Foundation under Grant No. 20121ZD008.

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