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Clustering Hibird Approach Using Cooperative Artificial Fish Swarm Algorithm

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Abstract

Basic Artificial Fish Swarm(AFS) Algorithm is a new type of heuristic swarm intelligence algorithm but optimization is difficult to get a very high precision due to the randomness of the artificial fish behavior.This paper presents an extended AFS algorithm, namely the Cooperative Artificial Fish Swarm (CAFS), which significantly improves the original AFS in solving complex optimization problems. K-medoids clustering algorithm is used to classify data,but the approach is sensitive to the initial selection of the centers and the divided cluster quality is not high.A novel hibird clustering method based on the CAFS and K-medoids could be used for solving clustering problems. In this work, firstly, CAFS algorithm is used for optimizing six widely-used benchmark functions and the comparative results produced by CAFS, Particle Swarm Optimization (PSO) are studied. Secondly, K-medoids and CAFS algorithm is used for data clustering on several benchmark data sets. The performance of the hibird algorithm base on K-medoids and CAFS is compared with CAFS,PSO,and AFS algorithms on clustering problem. The simulation results show that the proposed CAFS outperforms the other two algorithms in terms of accuracy, robustness and convergence speed.

Keywords: Artificial Fish Swarm, Particle Swarm Optimization, Swarm Intellengence, Data cluster.

1. Introduction

Swarm Intelligence (SI) is an innovative artificial intelligence technique for solving complex optimization problems. In recently years, many SI algorithms have been proposed: such as Ant Colony Optimization (ACO), Particle Swarm Algorithm (PSO), Bacterial Foraging Optimization (BFO), etc. Artificial Fish Swarm (AFS) algorithm is a new swarm intelligent algorithm. The AFS algorithm imitates the behaviors of the real fishes on finding food source and sharing the information of food sources , AFS has been applied successfully to some engineering problems, such as constrained optimization problems ,neural networks and clustering.

A novel Cooperative optimization mode Artificial Fish Swarm (AFS) Algorithm is designed in this paper. AFSA use swarm intelligence of biosphere to solve optimization problems, as a generalized neighborhood search algorithm, by means of heuristic search strategy, its capacity of tracking changes rapidly gives algorithm the ability of global optimization, because of the characteristics of global convergence itself, the initial value can be set as fixed or random allowing parameters to be set in a wider scope . AFSA has strong adaptability and parallelism, many behaviors combinations can be selected due to its good flexibility, and it can get better optimization performance which genetic algorithm and particle swarm optimization does not possessed. This artificial intelligence mode which is based on biological behavior is different from classical pattern, firstly is to design a single entity perception, behavioral

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mechanisms, then placed a group of entities in the environment so that they can solve the problem in environment interaction [3-5]; however making the best reaction under the stimulation of the environment is the basic idea of AFSA. Literature [6] proposed reducing the search field to accelerate local search of artificial fish individual, but this optimization only took convergence speed into account making severe limitation of swarming and following behaviors of AFs, thus affecting the quality of the optimization.[7]introduced the K-means algorithm to speed up the iteration, but the performance was unstable because of many random processes in AFSA and it affected the practical application of the method. Using simulated annealing algorithm to improve AFSA,the approach in [8]modified preying behavior to avoid the degradation of artificial fish, although this hybrid algorithm overcame the shortcoming which easily fall into local minima, convergence time of the method was relatively long and it was not suitable to analysis huge data. Combining AFSA with clustering analysis algorithm based on grid and density, [9] obtained the number K of clusters automatically and it applied to arbitrary shape of data, better parallelism, but the quality of ultimately clustering quality was affected by the number and the size of grids which led to some limitations [10].

Cluster analysis is an important research direction of data mining; clustering is classifying data for different patterns based on the different characteristics of different objects [11],but the traditional K-medoids has greater ability of local search, but is very sensitive to the initial cluster centers and easily falling into local optimum, if outliers are randomly selected as the initial centers, the whole quality of classification will decline. AFSA is less sensitive to initial values, even if its global optimization, has bad convergence and slower iteration rate in late period. Aiming at the advantages and disadvantages of both algorithms, this paper presents a global optimization idea to improve K-medoids clustering algorithm based on AFSA, the result of the test on a small data set shows that the improved algorithm obtains clear classifications and better performance.[12-14]

In this paper, K-medoids and AFS algorithm is applied to solve clustering problem, which has been tested on a variety of data sets. The performance of the CAFS on clustering is compared with results of the AFS, PSO and CAFS algorithms on the same data sets. The above data sets are provided from the UCI database.

2. Optimized AFS Algorithm

2.1 The Original AFS Algorithm

Population of AFS is N, individual state of AF: $F = (f_1, f_2, ...f_n)$,[where f_i is optimization variables], the largest moving step is Step, vision is Visual, test time of preying behavior is Try_number, crowd factor is δ, food consistence $Y = f(F)$ (Y is the value of objective function).

a. Preying behavior

As one of the basic habits of AF, the main principle is finding the area where there is a large food concentration by sense of sight and taste. Current state of AF is F_j, select a state F_j randomly around current location within its visual field, in the process of seeking optimal solution, if $Y_i < Y_j$, then F_j is a better state than the current one and move one step to this direction, default choose a new state and judge again, test Try_number times repeatedly, if still unable to get a better solution then move a random step [15,16].

b. Swarming behavior

To ensure the survival of fish populations, AF will gather to the center of adjacent partners. F_i still corresponds to the current state, perceive the AF number nf nearby and its central location F_c .if satisfied $Y_c / n_f > \delta \bullet Y_i$,it means the position was less congestion level, more food, then step forward to F_c, or implement preying behavior [17].

c. Following behavior

In nature, when one or a few fishes have explored food, its neighbors will follow swarm to reach the food position [18]. Perceptions of the best state F_j within the vision satisfied $Y_j / n_f > \delta \bullet Y_i$ which display the location was less crowing degree, more food, then make a step to F_j, or do preying behavior. The main steps of the AFS algorithm as following.[19,20]

1:cycle=1
2:Initialize the food source positions x_i , i =1 ...SN
3:Evaluate the food sources (fitness function fit_i)
4:**repeat**
5: Preying behavior's Phase
  For each a Artificial Fish
    Produce new food source positions v_i
    Calculate the value fit_i
    Apply greedy selection mechanism
    EndFor.
6: Calulate the probability values p_i for the solution.
7: **Swarming behaviors**' Phase
  For each a Artificial Fish **Swarm**
    Chooses a food source depending on p_i
    Produce new food source positions v_i
    Calculate the value fit_i
    Apply greedy selection mechanism
  EndFor
8: **Following behaviors** Phase
  If there is an Artificial Fish becomes follow
  Then replace it with a new random source positions
9: Memorize the best solution achieved so far
10 cycle=cycle+1.
11:**until** cycle=Maximum Cycle Number

2.2 Cooperative Artificial Fish Swarm (CAFS) Algorithm

In order to find every best dimension in all individuals, we need each individual's contribution to the best solution. So, we apply cooperative search to solve the problem in the AFS algorithm and propose the Cooperative AFS algorithm. In the CAFS algorithm, we set a super-best solution vector, namely gbest and its each component of D-dimensional is the best in all populations. For *gbest*: $(g_1, g_2, \cdots, g_i, \cdots, g_D)$ g_i corresponds to the *ith* component of the *gbest*. The algorithm of improved AFS are given below:

a. In preying behavior, when a state of randomly selected F_j does not satisfy the moving condition it will choose random behavior, that is difficult to obtain high precision, AFs searching nearby the global extreme points circuitously at anaphase of convergence, which lead to an invalid calculation. In this paper, when preying failed, AFs choose to move a step to a better value comparing with the bulletin board records:

$$F_i(k+1) = F_i(k) + Step \bullet [F_{better}(k+1) - F_i(k)] \quad (1)$$

$F_i(k+1)$ and $F_i(k)$ denote respectively current position and next position after the movement, Fbetter is the better state recorded by bulletin board, comparing with random method it gives the possibility of a better forward and thus jump out of local optima, preventing AFs in the local concussion at a standstill.

b. In AFSA, the parameter crowding factor δ is to avoid overcrowding of AF and δ is a fixed value in global algorithm, this approach that make δ a constant will lead to mutual exclusion between individuals which are adjacent to global optimization solution, so AFs cannot gather to extreme points accurately and contrast crowding condition after every iteration will increase the computational cost too. Improved method defines the initial congestion factor δ =0.75, when Try_number = 180, ignoring the congestion factor namely $\delta \bullet n_f = 1$ in initial stages, it needs to limit the size of artificial fish, but in the latter part fishes have already gathered in optimum, default δ can reduce calculation amount and execution time of the algorithm, in this way not only does it improves the operation efficiency of AFS but also has no effect on convergence.

c. In order to solve the problem of centers of K-medoids by AFS, when swarming and following behavior failed, preying behavior is carried out, thus increasing the convergence time and computation. So we renew the behavior as follows: substitute random swim for preying behavior after failing in movement. And the step is adaptive step-size. The method overcomes the problem that AFs aggregated at local solution and missed the global ones and enhances the quality of solutions.The main steps of CAFS algorithm are given below:

1:cycle=1

2:Initialize the food source positions x_i , i =1 ...*SN*

3:Evaluate the amount(fitness fit_i) of food sources and find the best food source which is the initial value of *gbest*

4:**repeat**

5: For each component $j \in (1, 2,..., D)$

6: Preying behaviors ’ Phase

For each Artificial Fish i =1 ...*SN*

Replace the j component of the *gbest* by using the j component ofArtificial Fish i

Calculate the f [*newgbest*($g_1, g_2, \cdots, x_{ij}, \cdots, g_D$)]

If f (*newgbest*) better than f (*gbest*)

Then *gbest* is replaced by *newgbest*

For Artificial Fish i produce new food source positions v_i by using (2)

Calculate the value fit_i

Apply greedy selection mechanism

EndFor.

7: Calulate the probability values p_i for the solution.

8: Swarming behaviors' Phase

For each Swarm i =1 ...SN

Chooses a food source depending on p_i

Replace the j component of the *gbest* by using the j component of fish i

Calculate the f [*newgbest*(g_1 , g_2 , ⋯ , x_{ij} , ⋯ , g_D)]

If f (*newgbest*) better than f (*gbest*)

Then *gbest* is replaced by *newgbest*

For Swarm's fish i produce new food source positions v_i by using (1)

Calculate the value fit_i

Apply greedy selection mechanism

EndFor

EndFor

9: Following behaviors' Phase

If there is an fish becomes follow

Then replace it with a new random source positions

10: Memorize the best solution achieved so far

11: Compare the best solution with *gbest* and Memorize the better one.

12: cycle=cycle+1.

13:**until** cycle=Maximum Cycle Number

3. Benchmark Test

3.1 Benchmark functions

In order to compare the performance of the proposed CAFS algorithm with AFS PSO, we used 5well-known benchmark functions. One of the benchmark functions is unimodal and the minima. [21,22]

1. Sphere function

$$f_1(x)=\sum_{i=1}^{n}x_i^2 \tag{2}$$

2. Rosenbrock function

$$f_2(x)=\sum_{i=1}^{n}100\times(x_{i+1}-x_i^2)^2+(1-x_i)^2 \tag{3}$$

3. Quadric function

$$f_3(x)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i}x_j\right)^2 \tag{4}$$

4. Sum of different powers

$$f_4(x)=\sum_{i=1}^{n}\left|x_i\right|^{i+1} \tag{5}$$

5. Ackley's function

$$f_6(x)=-20\exp(-0.2\sqrt{\tfrac{1}{n}\sum_{i=1}^{n}x_i^2})-\exp(\tfrac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i)+20+e \tag{6}$$

6. Rastrigrin's function

$$f_7(x)=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10 \tag{7}$$

3.2 Parameter Settings

In the experiment, all functions are tested on 30 dimensions; and the population size of all algorithms was 100. The PSO algorithm we used is the standard PSO. In PSO algorithm, inertia weight ω varies from 0.9 to 0.7 linearly with the iterations and the acceleration factors c_1 and c_2 were both 2.0. The dimensions, initialization ranges, global optima x^*, and the corresponding fitness value $f(x^*)$ of each function are listed in Table 3.[23]

Table 1. Parameters of the test functions

	Dimensions	Initial Range	x^*	$f(x^*)$
f_1	30	$[-100,100]^D$	[0,0,…,0]	0
f_2	30	$[-30,30]^D$	[1,1,…,1]	0
f_3	30	$[-65.536, 65.536]^D$	[0,0,…,0]	0
f_4	30	$[-1,1]^D$	[0,0,…,0]	0
f_6	30	$[-32.768,32.768]^D$	[0,0,…,0]	0
f_7	30	$[-5.12, 5.12]^D$	[0,0,…,0]	0

Table 2. Results comparison of different optimal algorithms for 30 runs

30D		AFS	CAFS	PSO
Sphere	Average	1.1426e-014	**1.2346e-018**	2.2345e-008
	Best	2.11269e-015	5.9142e-019	1.7865e-009
	Worst	3.2378e-014	**2.7426e-018**	2.6754e-007
	Std	8.1226e-015	**5.3234e-019**	3.8776e-008
Rosenbrock	Average	3.2313e-001	**7.3246e+000**	2.3442e+001
	Best	1.3680e-002	2.8654e-002	7.3455e+000
	Worst	1.3357e+000	7.5632e+001	9.3535e+001
	Std	2.9874e-001	**1.0864e+001**	1.4356e+001
Quadric	Average	**6.2342e-007**	3.9523e-003	4.1956e+002
	Best	1.3549e-011	1.2465e-001	3.4355e+002
	Worst	1.7767e-005	1.2665e-001	4.3454e+002
	Std	**3.2344e-006**	2.7866e-002	2.9238e+001
Sum of different powers	Average	1.9897e+002	**3.3453e-004**	9.5252e+003
	Best	4.3453e-004	3.8183e-004	8.3453e+003
	Worst	4.7389e+002	3.3454e-004	1.0151e+004
	Std	1.1697e+002	**6.3455e-009**	3.3455e+002
Ackley	Average	6.3454e-006	**8.3455e-012**	4.2520e+000
	Best	1.5905e-006	2.5553e-012	2.3453e+000
	Worst	1.34535e-005	2.9208e-011	5.7625e+000
	Std	3.5254e-006	**7.3455e-012**	8.3370e-001

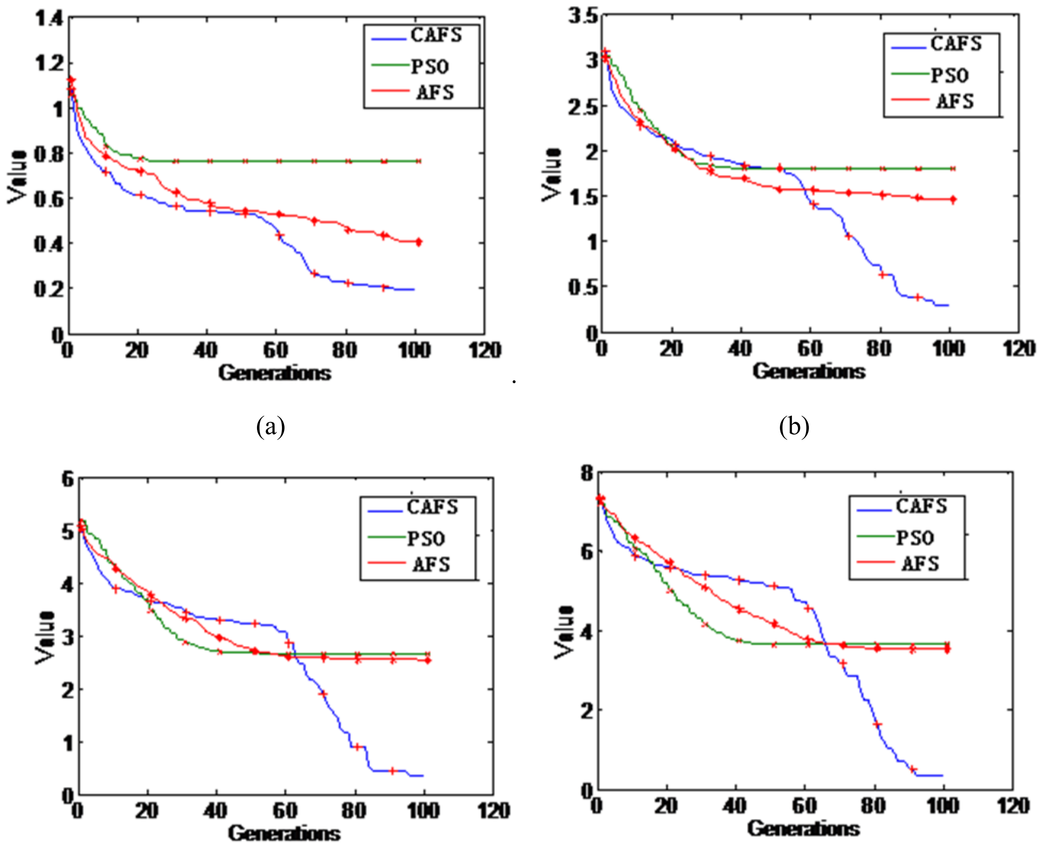
Rastrigin	Average	1.3455e-001	**1.3732e-013**	4.6671e+001
	Best	3.8257e-009	1.3453e-001	2.1889e+001
	Worst	9.34535e-001	334535e-013	834535e+001
	Std	3.6710e-001	**8.3242e-014**	1.2656e+001

3.3 Simulation Results for Benchmark Functions

The experimental results, including the best, worst, average, and standard deviation of the function values found in 30 runs are proposed in Table 1 and all algorithms were terminated after 100,000 function evaluations:

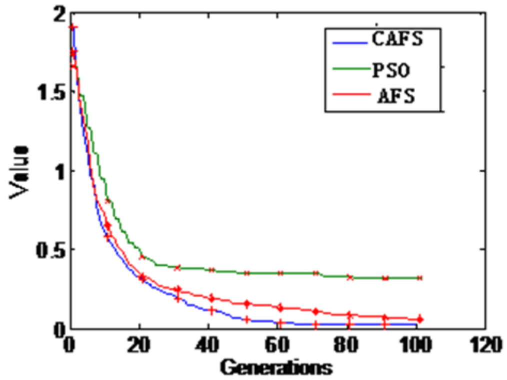
From Table 1, the CAFS algorithm is better than the other algorithms on Sphere, Ackley and Rastrigin benchmark functions while the AFS algorithm shows better performance than the other algorithms on Quadric benchmark functions. The PSO converges very slowly and its performance is very bad on all benchmark functions, as can be seen in Fig.1.

On Sphere function, all algorithms perform very well. However, Table 1 shows that the performance of CAFS is much better than the others'. The speed of convergence of CAFS is much faster, as can be seen in Fig.1.

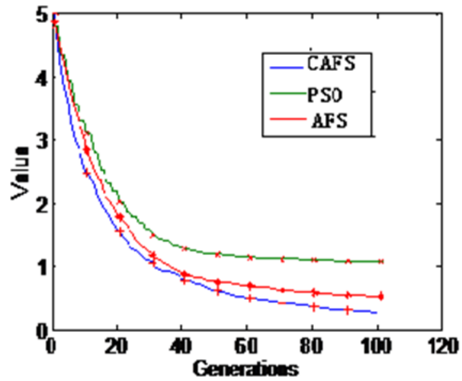


(a) (b)

(c) (d)



(e)



(f)

Figure 1. The median convergence results of 30D unimodal continuous functions.(a) Sphere function. (b) Rosenbrock function. (c) Quadric function. (d) Sum of different powers. (e) Ackley function. (f) Rastrigin function.

From Table 2 and Fig.1, the CAFS converged much faster to significantly better results than all other algorithms. The AFS is the fastest one for finding good results within relatively few generations. All algorithms were able to consistently find the minimum to functions f_1, $f_2$and f_3 within 1000 generations.

From the comparisons between CAFS and PSO algorithms, we can see that, statistically, CAFS have significantly better performance on continuous unimodal functions $f_1 \sim f_5$. From the rank values presented in Table 2. the search performance of the algorithms tested here is ordered as CAFS > AFS> PSO.

4. A Hybrid Clustering Algorithm Based on CASF

4.1 Clustering Model

$X=(x_1, x_2, \ldots x_N)$ as the N data samples, x is the data representative point, C_i is an arbitrary cluster, O_i is the center of the cluster C_i, (j=1,2…,k). Algorithm is presented as follows.

Selected k objects in set X as the initial centers arbitrarily ($O_1,O_2,\ldots O_i \ldots O_k$), assigned the remaining data except for representative centers by the proximity principle to each cluster; in each cluster (C_i), chose a noncentral point O_j randomly, calculating total cost ΔE after using non-center instead of the original center point; If ΔE<0, then replace the original O_i with a non-center O_j, performing the above steps repeatedly until k centers is fixed [11,12]. Cost function is used to evaluate the clustering quality improved. The function is defined as follows:

$$\Delta E = E_2 - E_1 \tag{8}$$

ΔE represents the change of absolute error standard, E_2 refers to the sum of dissimilarity degree between representative points and center points in the same cluster after replacing the centers, and E_1 represents the dissimilarity degree before replacing [13,14]. Calculate ΔE, if ΔE<0, the effect of clustering has been improved, then use the new center.

4.2 The Mixed Clustering Based on CASF

Definition 1: (adaptive step-size of AF) Adaptive step-size represents the moving distance of AF changing with iterations. Adaptive step-size is defined as:

$$F_{i+1} = F_i + Step \bullet Rand() \tag{9}$$

Definition 2: (clustering evaluation criterion) Objective function measures dissimilarity between representative points and objects, which means the compact degree of data distribution between classes, the objective function is defined as:

$$E = \sum_{j=1}^{k} \sum_{X \in C_j} | X - O_j |^2 \tag{10}$$

Step 1: Initialize the initial value of AF parameters, calculate food consistence at current position by objective function;

Step 2: Carry out the algorithm through behavior's condition, update the location of AFs by preying, swarming and following behaviors, data density refer to food concentration; contrast food consistence within vision distance to select solution, with its state recorded in the bulletin board, finally fishes gather in the areas of high data density;

Step 3: Each state of AF represents a decision variable, and the fitness value is computed by objective function, evaluate optimization degree and record; repeat 2) 3), update the location information of AFs until the termination condition is met;

Step 4: According to bulletin board information and the location of fishes, choose input parameters for K-medoids, namely the initial center and the number of clusters; using K-medoids for cluster analysis until meeting minimum within-class scatter of data. The minimum within-class M is presented as follows:

$$M = \min E \tag{11}$$

The flowchart shows procedure of approach in Fig. 2:

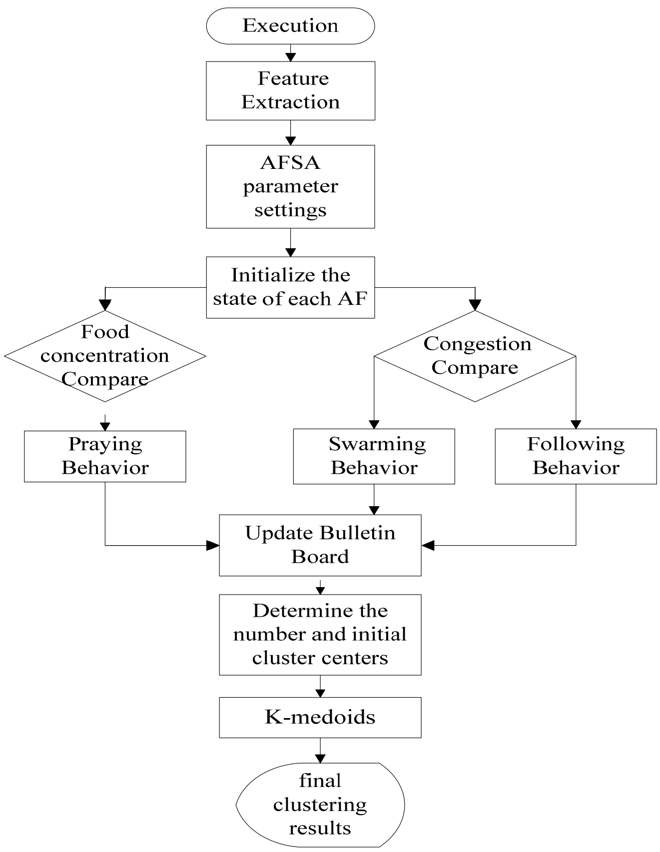


Figure 2. Flowchart of clustering algorithm based on CFSA

5. Data Clustering Experimental Results

To evaluate performance of the proposed CAFS approach for clustering, we compare the results of the PSO, AFS clustering algorithms using different data sets which are selected from the UCI machine learning repository.

5.1 Experiment by Simulation data sets

Simulation data include 300 3D data; running environment for experiment: Pentium(R),3.00G;Programming environment:Matlab(2012b);AFSA parameters are set as follows: Step is 0.2, Visual is 100, δ is 0.75, Try_number(iteration times) is 200,N (the total number of AF) is 50.

In the simulation, it classify the data by two hybrid clustering algorithms, comparison results of the approach this paper proposed and basic hybrid clustering algorithm. Operation result of classic hybrid method shown in Fig.2, Fig.3 shows performance of improved approach.

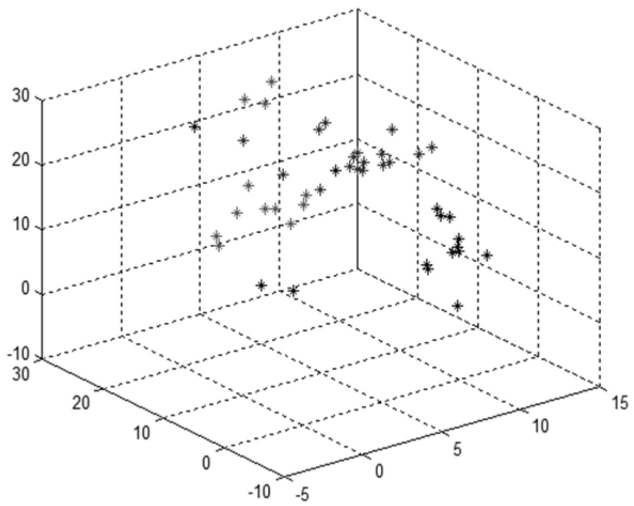


Figure 3. Optimization graph of basic clustering algorithm based on AFS

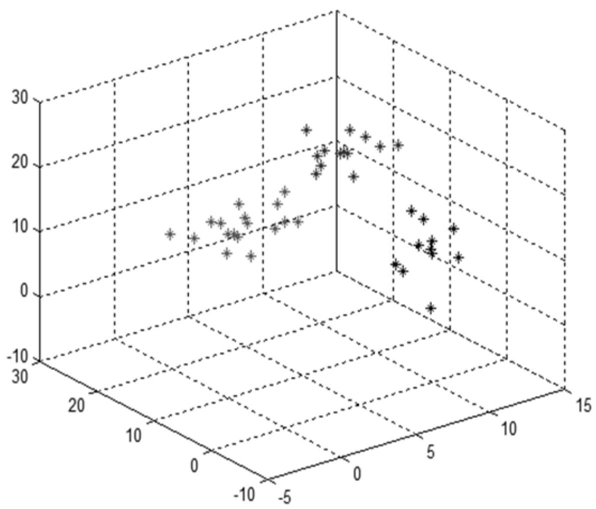


Figure 4. Optimization graph of improved method based on CAFS

AFs find the centers in the 3D data, as shown in Fig.3 aggregation effect is not clear, a few individuals moves to local clusters; optimization result approximate to global data-intensive areas that can be seen from the iteration route in Fig.4; comparison of performance shows the edge of clusters is more obvious by improved method on the same condition, the aggregation of position is closer so that we can obtain a higher accuracy of the division to verify the advantages of this algorithm.

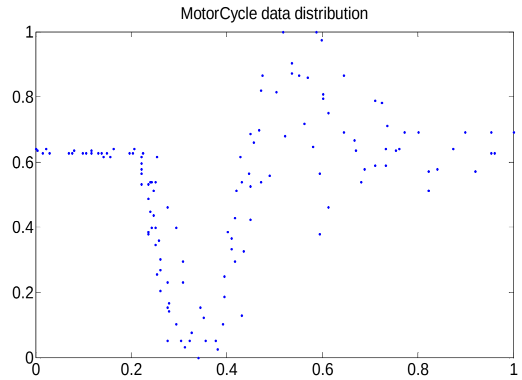
Table 3. The results of two algorithms

	Total Number of AF	Iteration Times	Iteration Time /ms	Correct Rate
Method in [6]	50	200	762	89
Proposed Method	50	200	685	93

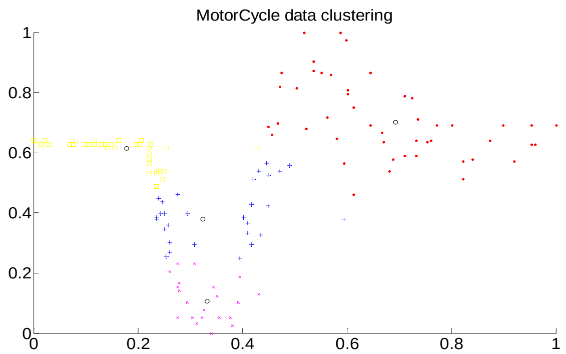
It is shown in table 3 the proposed method reduced not only the iteration time but also calculation amount on the same condition, and the accuracy is also improved.

5.2 Experiment byReal data sets

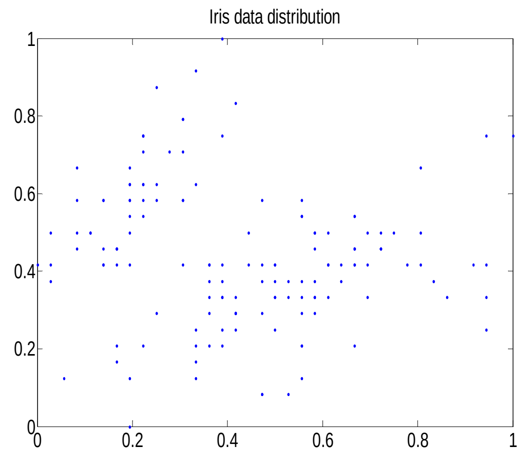
The CAFS clustering algorithm is able to provide the same partition of the data points in all runs. Motorcycle data sets and ris data are selected from the UCI machine learning repository ,Clusterting result of MotorCyle and Iris data sets by CAFS algorithm are presented in Fig 4.From the result Fig 4, for all real data sets, CAFS outperforms the other methods.



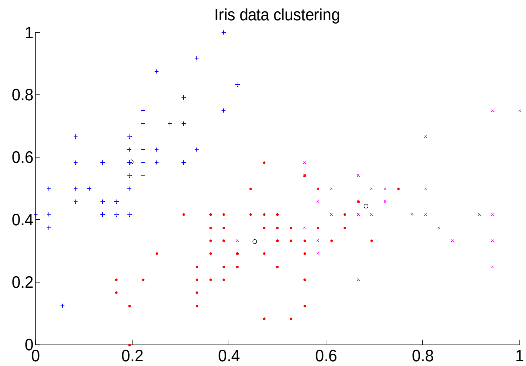
(a)Motor distribution



(b)Motor clustering result



(c)Iris distribution



(d)Iris clustering result

Figure 4. The data distribution of MotorCycle and Iris data sets and the clustering result by CAFS algorithm. (a) Motor distribution (b) Motor clustering result. (c) Iris distribution. (d) Iris clustering result.

6. Conclusion

In this paper, based on the cooperative approaches, a novel Artificial Fish Swarm(AFS) algorithm is presented, namely Cooperative Artificial Fish Swarm(CAFS) In order to demonstrate the performance of the CAFS algorithm, we compared the performance of the CAFS with those of AFS, PSO optimization algorithms on several benchmark functions. Comparison of experimental results shows the hybrid clustering algorithm base on CFSA, make similar data gather obvious, the model is more stable and accurate than the old one, distinguish samples precisely while also improving the cluster quality and obtaining better centers with clear division, reducing computation amount is also a breakthrough.

The model of modern intelligence algorithm based on animal autonomous body combines K-medoids, this novel method avoids the weakness of dependency on Cluster initialization, and overcomes slow iteration speed in late period; its good parallelism can be effectively applied in various fields, it also plays a major role in knowledge discovery, information forecast and decision analysis. However, the convergence speed issue remains to be improved and researched.

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