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Adaptive Cuckoo Search Algorithm Based on Dynamic Adjustment Mechanism

Yang Yang, Xukun Zuo, Maosheng Fu, Shuhao Yu, Chaochuan Jia*

College of Electronics and Information Engineering, West Anhui University, Lu' an, People's Republic of China
yangyy@wxc.edu.cn, 1693368@qq.com, 49593838@qq.com, 1956345025@qq.com, ccjia@hfcas.ac.cn

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Abstract. Cuckoo Search (CS) algorithm, a simple and effective global optimization algorithm, has been widely used to deal with practical optimization problems. So as to improvethe standard cuckoo search algorithm, such as slow convergence and easy convergence to local optimal value, an Adaptive Cuckoo Search algorithm on the basis of Dynamic Adjustment Mechanism (ACS-DAM) has been proposed. Based on exponential function and logarithmic function, the dynamic adjustment is made for updating step size and discovering probability. During the optimization process, updating step size and discovering probability of each nest are adjusted according to the number of iterations of each nest, so as to equilibrate the global detection and local capacity of the algorithm. Then 23 standard test functions will be selected for a simulation experiment, and compared with other CS variant algorithms, ACS-DAM effectively improved the rate of convergence and the algorithmic precision. ACS-DAM algorithm was employed to optimize the Support Vector Machine (SVM). The experiment proves that the convergence rate with ACS-DAM is better than that with CS obviously and ACS-DAM has stronger optimization ability and higher efficiency than CS.

Keywords: cuckoo search algorithm, dynamic adjustment mechanism, updating step size, discovery probability, support vector machine

1 Introduction

The Cuckoo Search algorithm (CS) is proposed by scholars Yangand Deb in year of 2009. It is an intelligent optimization algorithm, which is inspired by the parasitic breeding behavior of cuckoo birds in nature [1]. Based on long-term study of cuckoo life habits, this algorithm is proposed, and it largely takes advantage of the characteristics of cuckoo breed parasitic eggs and Levy flight. Its characteristics include good adaptability, few parameters, optimal random search path and strong optimization ability [2].

At present, CS algorithm has been used in a variety of engineering optimization problems [3], with potential research value. Although CS algorithm has few control parameters and simple structure and being easy to implement, like other biological heuristic algorithms, it also has a slow convergence rate in the late stage and is easy to fall into the local minimum problem. Therefore, many scholars at home and abroad have carried out researches and proposed some improved algorithms [4] in view of these problems.

Li X et al. [5] used some variational rules on the basis of rand and the best individual in the whole population, and balanced the development and exploration. The linear decreasing probability rules was combined. Then, in the light of the relative success rate of the new parameters in the former stage, it introduced the adaptive parameter as same random value to increase the multiformity of the population. Cheung N J et al. [6] proposed a new variant of non-homogeneous search strategy CS algorithm on the basis of quantum mechanism, so as to improve the search ability of traditional CS algorithm. Chen L et al. [7] presented a new multi-objective CS algorithm based on decomposition. Two different operators are

* Corresponding Author

proposed from the basic algorithm. Naik and Panda [8] put forward a new algorithm. According to the value of step fitness function and the current position of step length in the search space, it is adaptive, which is faster than CS algorithm. Cheung R et al. [9] put forward an improved multi-objective CS (MOCS/D) algorithm. A free gradient algorithm cuckoo search has been proposed in the paper [10], which avoids the problem of slow convergence.

Song Y et al. [11] introduced an improved cuckoo algorithm on the basis of adaptive mechanism. Chen C et al. [12] introduced population distribution entropy, new step size factor and discovery probability of dynamic change, and proposed a double-cuckoo search algorithm with dynamic adjustment probability, which improved local and global optimization ability. Wong F et al. [13] presented a cuckoo search algorithm by adding Gaussian interference in the iterative process. Lau Z et al. [14] put forward an improved cuckoo algorithm on the basis of adaptive differential interference. Yip Yet al. [15] used a cuckoo search algorithm on the basis of adaptive step size random interference. Du L et al. [16] put forward a CS algorithm on the basis of conjugate gradient, which made cuckoo population decrease rapidly along the conjugate directions after the evolution of Levi flight mechanism and elimination mechanism. It greatly improved the convergence ability of the algorithm. Chia H et al. [17] used an improved CS algorithm (APCS) on the basis of the exploration and development of equilibrium. Cheung H et al. [4] introduced an interactive learning CS algorithm (ILCSA), which improved the speed. Lo D et al. [18] put forward an improved CS algorithm (ICS), which introduced the dynamic decrement factor of the function and the adaptively adjusted search step size and the discovery probability.

So as to deal with the problem that the standard CS uses the parameter updating step size and the discovering probability into the function with fixed value, which leads to slow convergence speed and the local optimal Adjustment Mechanism, it proposes an Adaptive Cuckoo Search algorithm on the basis of Dynamic Adjustment Mechanism (ACS-DAM). The second part introduces the standard CS, and the third part elaborates the strategy of the improved algorithm ACS-DAM, and the fourth part compares the solution and convergence of the improved algorithm with other algorithms through simulation experiments, highlighting the advantages of the improved algorithm and improving the convergence speed and solving accuracy.

2 Cuckoo Search Algorithm

In nature, cuckoo birds have a special way of breeding. They do not build nests, and their offspring have to raise their offspring in the way of parasitism by quietly placing eggs in other's nest. Other birds will raise their offspring. However, if the host bird finds an foreignone, it will give it up or build another nest. To simulate cuckoo nesting and reproduction behavior, Yang X S and Deb S [1] hypothesized the three rules:

(1) Cuckoos lay only one egg one time and hatch them at random;

(2) reservethe best nests for the next generation;

(3) the probability interval of host bird finding foreign eggs, $P_a \in (0,1)$;

Based on the above three ideal states, Yang et al. adopted Formula (1) to replace the nest of the next generation:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus levy(\lambda) \quad i = 1, 2, ..., n \tag{1}$$

Where, $x_i^{(t+1)}$ and $x_i^{(t)}$ respectively represent the nest locations of Generation t+1 and Generation t; α is the step length; $\oplus$ is point-to-point multiplication; $levy(\lambda)$ is the random search path. The Formula (2) is as follows:

$$levy(\lambda e \sim \mu) = t^{-\lambda} (1 < \lambda \le 3) \tag{2}$$

Literature [13] uses (3) to calculate Levi's random numbers:

$$levy(\lambda) = \frac{\varphi * \mu}{|\upsilon|^{\frac{1}{\beta}}} \tag{3}$$

υ, μ are all the normal distribution of the standard, $\beta = 1.5$.

$$\varphi = \left[\Gamma\left(\left(\frac{1+\beta}{2} \right) \times \beta \times 2^{\frac{1+\beta}{2}} \right) \right] \quad \textbf{(4)}$$

So as to facilitate the calculation of Levy flight, the step length factor in literature [19] was adopted:

$$\alpha = \alpha_0 * (x_i^{(t)} - x_{best}) \quad \textbf{(5)}$$

Where, α_0 is 0.01, x_{best} is the best value this generation .

Combined with formulas (1)~(5), CS algorithm uses Formula (6) to update the new nest position through Levi flight:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha_0 \frac{\varphi * \mu}{|\upsilon|^{\frac{1}{\beta}}} * \varphi * (x_i^{(t+1)} - x_{best}) \quad \textbf{(6)}$$

The probability of discovery P_a is expressed as the rate that the host one finds an foreign egg. If the foreign eggs are found, the host bird will discard them or nest again. That is, after the CS algorithm updates the position by levy flight, γ is in the interval of (0, 1). If $\gamma > P_a$, the preference walk $x_i^{(t+1)}$ is shown in (7):

$$x_i^{(t+1)} = x_i^{(t)} + \gamma * (x_i^{(t)} - x_k^{(t)}) \quad \textbf{(7)}$$

Where, γ is in the interval of (0, 1), $x_i^{(t+1)}$ and $x_k^{(t)}$ are two random value of generation t.

3 Adaptive Cuckoo Search algorithm on the basis of Dynamic Adjustment Mechanism

3.1 Dynamic Adjustment of Step Size

In the early iteration, so as to ensure the population multiformity and develop the global search ability, the step size factor should be set large. But as the iteration goes on, so as todevelop the local search capability, step size factor should be set small. So it is needful to dynamically adjust the value of step size to fully equilibrate the global and local search capability.

ACS-DAM algorithm proposes modifyof step length, as shown in Formula (8):

$$a_0 = 1 - \frac{1}{1.5 + \exp\left(\frac{t - t\max}{t\max} \right)^2} \quad \textbf{(8)}$$

t and *t*max are the current and the maximum number of iterations. In the iteration, step size is large initially, which keeps the population multiformity and enables better global exploration. Gradually to the later stage, the step size is small, and local optimization is carried out, and the convergence speed is fast.

3.2 Dynamic Adjustment of Discovery Probability

In early iteration of CS, so as to ensure the update of more solutions, and the population multiformity, and develop the global search capability, a small probability of discovery should be set. The larger the search range of each iteration is, the stronger the global search capability is, and the faster the convergence speeds. With the expansion of the search scale, the local optimization ability will reduce, so will the search precision. Therefore, in the later stage of iteration, a relatively high probability of discovery should be set, so that the search scope of each iteration will be reduced. The local optimization ability will be enhanced, and the search accuracy will also be improved. Inspired by the s-type function weight adjustment strategy proposed by the particle swarm optimization algorithm in literature [20], ACS-DAM algorithm proposed the dynamic adjustment discovery probability and introduced the dynamic adjustment factor into the discovery probability, as shown in Equation (9):

$$P_w = \frac{1}{1+\exp\left(\ln 1.5 - \ln 19 * \frac{t}{t\max}\right)^2} \tag{9}$$

Where, t and $t$max are the current and the maximum number of iterations. In the early iteration, P_W is small, which enhances the global exploration capability. In the later stage, P_W is larger, which is conducive to local optimization. The value of the discovery probability P_a is dynamically adjusted by the factor, as shown in Equation (10):

$$P_a = P_0 * P_w \tag{10}$$

3.3 ACS-DAM Algorithm Flow

Here is the description of ACS-DAM algorithm process:

Step one Initialize the bird population, the number of nests, the initial location of nests, and the number of iterations;

Step two Count the corresponding objective function to get the fitness value;

Step three Use the dynamic adjustment step size (Formula (8)) of Levi flight to update the nest position and make corresponding changes;

Step fourUses the dynamically adjusted discovery probability (formula (9) and (10)) to calculate the parameters and compare with the random value r. If $\gamma > P_a$, enter the random walk to get the new nest location;

Step five If the optimal nest location in Step fouris satisfied with the termination condition, the result will be output; otherwise, return to step two to continue searching.

The flow chart of ACS-DAM algorithm is shown in Fig. 1.

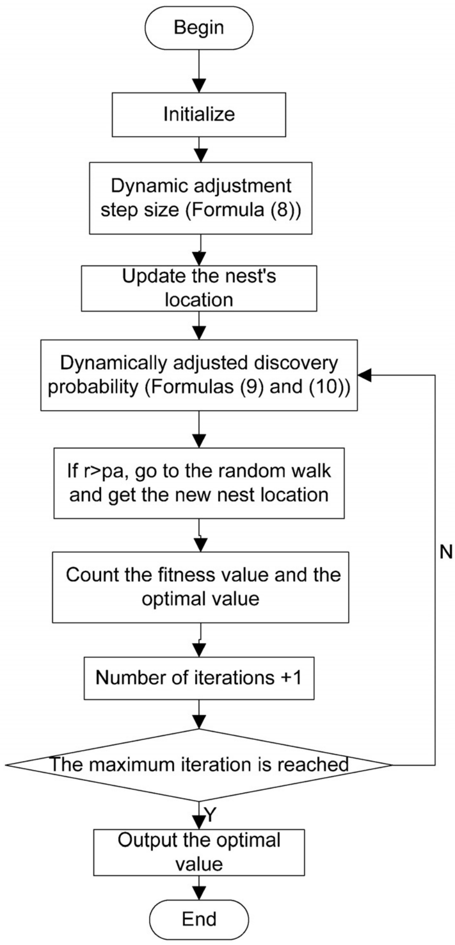


Fig. 1. Process of adaptive CS algorithm for dynamic adjustment mechanism

4 Experiment and Discussion

So as to check the ACS - DAM performance, this article selected 23 functions of standard test in literature [21] (Table 2 to Table 3), did the simulation experiments, and compared the test results with CS, literature [17] (APCS), literature [4] (ILCSA), literature [18] (ICS).

The solution accuracy and convergence speed of curve are analyzed. Then, CS and ACS-DAM were used to optimize Support Vector Machine classification methods respectively, and the classification accuracy curves of the two optimized test sets were compared.

4.1 Algorithm Accuracy Analysis

The parameters include: bird nests n=30, the maximum value of iterations $t$max = 600, and range of dynamically adjusted step a_0 size is (0.762, 0.6). The interval of discovery probability P_0 is (0, 1). After a lot of experimental tests, when

$P_0 = 0.4$, and dynamically adjusted discovery probability P_a is in the interval of (0.16, 0.376), the convergence speed is faster and the fitness value is better of the ACS-DAM algorithm.

Because the optimization algorithm is random, algorithms of 23 functions were executed 50 times, and the best, worst, average value and variance were recorded in Table 1, Table 2 and Table 3.

Table 1. Simulation results of unimodal benchmark functions

f	algorithm	best	worst	mean	std
f1	CS	0.5831	2.4172	1.6311	0.5292
	ICS	0.0245	0.1080	0.0635	0.0279
	APCS	0.3617	2.3334	1.2700	0.4493
	ILCSA	0.3309	1.5417	0.9982	0.3998
	ACS-DAM	0.0016	0.0055	0.0034	0.0012
f2	CS	2.6043	9.3598	5.1294	2.1280
	ICS	0.4004	1.3042	0.7559	0.2768
	APCS	2.5458	1.0000e+10	1.3615e+09	3.8322e+09
	ILCSA	1.9140	8.1766	4.4522	1.7102
	ACS-DAM	0.0501	0.2471	0.1463	0.0634
f3	CS	944.4108	1.6238e+03	1.2621e+03	527.7342
	ICS	7.9769e+03	1.4258e+04	1.2490e+04	2.1988e+03
	APCS	27.5483	783.0678	157.2952	1.5771e+03
	ILCSA	503.1526	1.8894e+03	998.2732	320.9306
	ACS-DAM	885.5144	1.4590e+03	1.6433e+03	800.8444
f4	CS	5.3994	15.0695	8.7246	2.7960
	ICS	4.5866	12.3916	9.6010	1.4483
	APCS	5.4583	14.8629	11.8786	2.8396
	ILCSA	5.1956	13.1106	9.4481	2.4223
	ACS-DAM	2.9895	5.0396	3.5360	0.7099
f5	CS	6.1253	585.5169	66.4940	182.376
	ICS	5.2926	208.1099	30.1728	62.5343
	APCS	4.5458	283.0597	46.9982	83.0669
	ILCSA	5.7504	90.2075	16.6170	25.9703
	ACS-DAM	2.6593	31.1444	6.2537	8.7732
f6	CS	0.4918	2.7015	1.4916	0.6908
	ICS	0.0513	0.2215	0.0988	0.0521
	APCS	0.4776	2.4961	1.2540	0.5864
	ILCSA	0.4739	1.6821	0.8975	0.3159
	ACS-DAM	0.0015	0.0077	0.0049	0.0018
f7	CS	0.0475	0.1412	0.0747	0.0279
	ICS	0.0402	0.1067	0.0698	0.0209
	APCS	0.0442	0.1622	0.0794	0.0375
	ILCSA	0.0347	0.1229	0.0667	0.0272
	ACS-DAM	0.0194	0.0508	0.0360	0.0110

Table 2. Simulation results of multimodal benchmark functions

f	algorithm	best	worst	mean	std
f8	CS	-8.6864e + 03	-7.9267e + 03	-8.1348e + 03	133.8808
	ICS	-6.8330e + 03	-6.8063e + 03	-7.2324e + 03	374.9420
	APCS	-7.8130e + 03	-7.7015e + 03	-8.0682e + 03	250.0307
	ILCSA	-8.0626e + 03	-7.6928e + 03	-8.2249e + 03	319.0977
	ACS-DAM	-7.2554e + 03	-6.2031e + 03	-7.1063e + 03	689.4235
f9	CS	82.5502	121.3861	98.0715	10.7863
	ICS	121.4052	165.4204	140.5548	14.0832
	APCS	67.9421	115.0026	80.7564	10.0048
	ILCSA	89.7988	118.2744	99.7827	11.8830
	ACS-DAM	97.7152	123.7461	103.7606	28.0353
f10	CS	3.8294	7.6915	5.1340	1.7288
	ICS	1.0073	4.3044	2.9001	1.2806
	APCS	2.7235	5.9502	4.6697	1.5457
	ILCSA	2.2207	5.1578	4.0895	0.7274
	ACS-DAM	0.0683	0.8838	0.4216	0.3587
f11	CS	0.9745	1.0695	1.0397	1.1696
	ICS	0.3164	0.5625	0.3934	0.5458
	APCS	0.9349	1.8629	1.4958	1.7092
	ILCSA	0.9034	1.0076	0.0866	1.3981
	ACS-DAM	0.0670	0.1396	0.1059	0.2851
f12	CS	1.2419	3.7415	2.6751	0.8695
	ICS	0.2300	2.2229	0.8712	0.6692
	APCS	1.1923	3.0053	2.2988	0.8039
	ILCSA	1.1241	2.6696	1.8409	0.8335
	ACS-DAM	6.3513e-04	0.1093	0.0307	0.0312
f13	CS	1.7137	18.0695	5.3480	5.0535
	ICS	0.2243	0.8625	0.4776	0.4141
	APCS	2.1156	27.8629	16.9812	14.5956
	ILCSA	0.5223	8.1106	3.6621	3.1090
	ACS-DAM	0.0100	0.1196	0.0544	0.0291

Table 3. Simulation results of fixed-dimension multimodal benchmark functions

f	algorithm	best	worst	mean	std
f14	CS	0.9980	0.9980	0.9980	1.6550e-16
	ICS	0.9980	0.9980	0.9980	0
	APCS	0.9980	0.9980	0.9980	1.0467e-16
	ILCSA	0.9980	0.9980	0.9980	1.2820e-16
	ACS-DAM	0.9980	0.9980	0.9980	0
f15	CS	3.0816e-04	4.6359e-04	3.3214e-04	4.6958e-05
	ICS	4.4313e-04	7.7504e-04	6.2142e-04	1.1356e-04
	APCS	3.0749e-04	3.0755e-04	3.0753e-04	5.1390e- 12
	ILCSA	3.0784e-04	4.0519e-04	3.3681e-04	3.8825e-05
	ACS-DAM	3.0749e-04	4.6069e-04	3.2300e-04	4.6378e-05
f16	CS	-1.0316	-1.0316	-1.0316	1.2820e-16
	ICS	-1.0316	-1.0316	-1.0316	7.4015e-16
	APCS	-1.0316	-1.0316	-1.0316	1.6550e-16
	ILCSA	-1.0316	-1.0316	-1.0316	1.4803e-16
	ACS-DAM	-1.0316	-1.0316	-1.0316	0
f17	CS	0.3979	0.3979	0.3979	0
	ICS	0.3979	0.3979	0.3979	0
	APCS	0.3979	0.3979	0.3979	0
	ILCSA	0.3979	0.3979	0.3979	0
	ACS-DAM	0.3979	0.3979	0.3979	0

Table 3. Simulation results of fixed-dimension multimodal benchmark functions (continued)

f	algorithm	best	worst	mean	std
f18	CS	3.0000	3.0000	3.0000	7.4015e-16
	ICS	3.0000	3.0000	3.0000	8.6315e-16
	APCS	3.0000	3.0000	3.0000	1.1842e-15
	ILCSA	3.0000	3.0000	3.0000	1.1466e-15
	ACS-DAM	3.0000	3.0000	3.0000	6.9432e-16
f19	CS	-3.8628	-3.8628	-3.8628	9.0043e-16
	ICS	-3.8628	-3.8628	-3.8628	9.3622e-16
	APCS	-3.8628	-3.8628	-3.8628	9.3622e-16
	ILCSA	-3.8628	-3.8628	-3.8628	9.3622e-16
	ACS-DAM	-3.8628	-3.8628	-3.8628	9.3622e-16
f20	CS	-3.3220	-3.3220	-3.3220	2.1355e-08
	ICS	-3.3220	-3.3220	-3.3220	4.6811e-16
	APCS	-3.3220	-3.3220	-3.3220	2.0668e-11
	ILCSA	-3.3220	-3.3220	-3.3220	1.8644e-08
	ACS-DAM	-3.3220	-3.3220	-3.3220	4.6811e-16
f21	CS	-10.1532	-10.1532	-10.1532	6.8107e-09
	ICS	-10.1532	-10.1532	-10.1532	1.3240e-15
	APCS	-10.1532	-10.1532	-10.1532	1.4450e-13
	ILCSA	-10.1532	-10.1532	-10.1532	3.0944e-09
	ACS-DAM	-10.1532	-10.1532	-10.1532	1.1842e-15
f22	CS	-10.4029	-10.4029	-10.4029	7.5716e-09
	ICS	-10.4029	-10.4029	-10.4029	1.7764e-15
	APCS	-10.4029	-10.4029	-10.4029	3.7871e-11
	ILCSA	-10.4029	-10.4029	-10.4029	2.8516e-09
	ACS-DAM	-10.4029	-10.4029	-10.4029	1.6748e-15
f23	CS	-10.5364	-10.5364	-10.5364	6.2258e-07
	ICS	-10.5364	-10.5364	-10.5364	1.3240e-15
	APCS	-10.5364	-10.5364	-10.5364	3.0044e-11
	ILCSA	-10.5364	-10.5364	-10.5364	6.7538e-08
	ACS-DAM	-10.5364	-10.5364	-10.5364	1.6748e-15

Among them, functionsf1-f7, are unimodal reference functions, and there is only one best value in every function. In f1-f6 and f7, the best, worst, average value and variance searched by ACS-DAM are all smaller than those of the other four algorithms, which shows that ACS-DAM has higher solving accuracy and optimization ability.

Functions f8-f13, are multi-peak functions. In f10-f13, the global optimal value, worst value, average value and variance searched by ACS-DAM are all superior to the other four algorithms, indicating that ACS-DAM has strong stability and ability to deal with complex optimization process.

Functionsf14-f23, are multimodal functions with fixed dimensions. In F15, the global optimal value of ACS-DAM is the smallest. In f14, f16, f18 and f20-f23, ACS-DAM and the other four algorithms can all search for the global optimal value. However, from the perspective of variance, ACS-DAM is far less than other algorithms, indicating that the solution result of ACS-DAM is more stable. ACS-DAM and the other four algorithms can all search for the global optimal value. However, from the perspective of variance, ACS-DAM is far less than other algorithms, indicating that the solution result of ACS-DAM is more stable. Results of experiment prove that global detection capability of ACS-DAM and processing ability of complex optimization process is stronger, and the precision finding the solution is higher and the process is more stable.

4.2 Convergence Analysis of the Algorithm

Fig. 2 shows some convergence curves of ACS-DAM, CS, ICS, APCS, and ILCSA. It can be seen that ACS-DAM shows convergence when the test function is searching for the optimal fitness value.

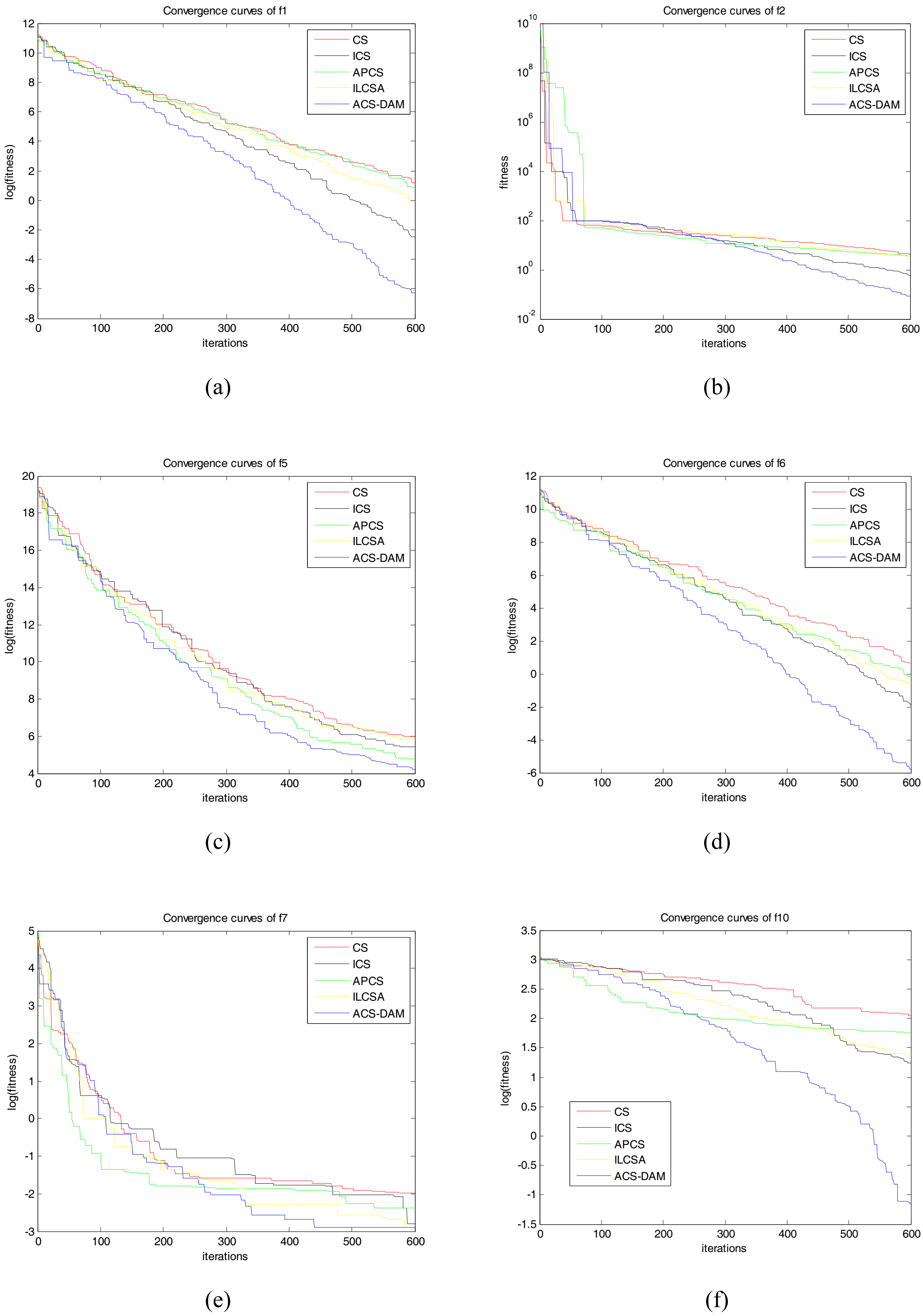


Fig. 2. Convergence curves of some functions

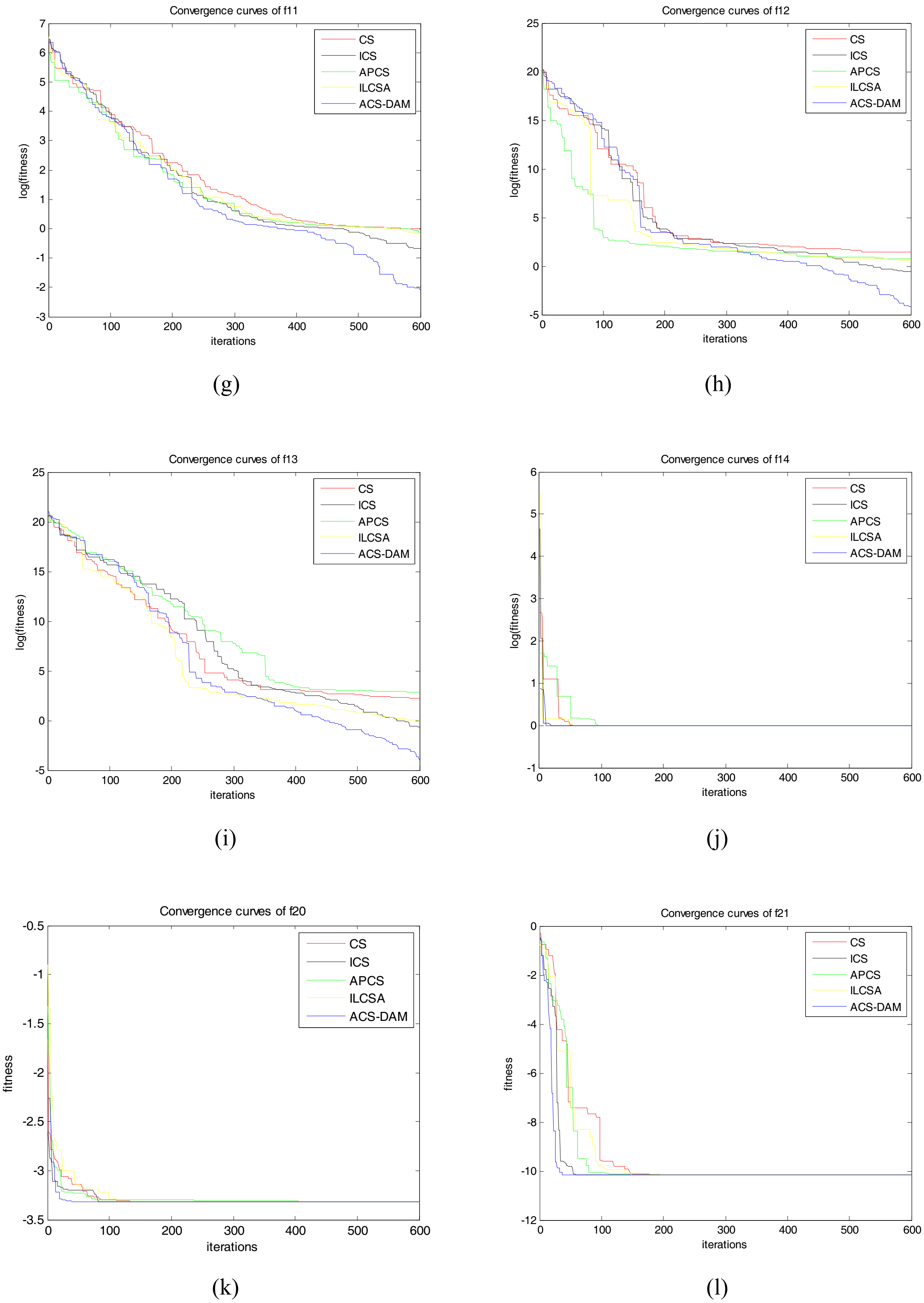
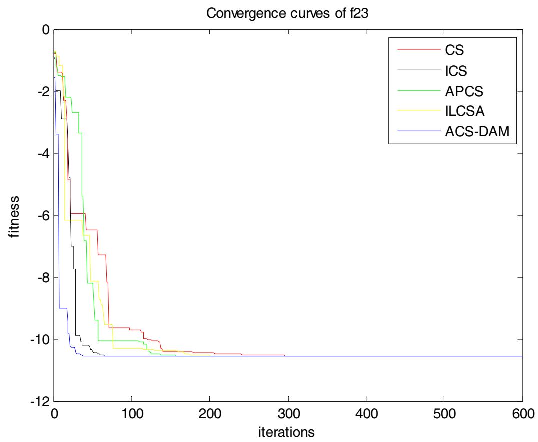


Fig. 2. Convergence curves of some functions (continued)



(m)

Fig. 2. Convergence curves of some functions (continued)

First of all, the ACS-DAM algorithm shows absolute superiority in the convergence rate from the beginning of the iteration, and it can maintain to the end of the iteration. This is due to the proposed adaptive mechanism, which helps it to continuously search the space during the whole iteration process and converge to the optimum more quickly after the middle of the iteration. This situation is clearly reflected in f1, f5 and f6.

Secondly, in f2, f7, f10, f11, f12 and f13, the rate of fourconvergences are the same at the early iteration. When the iteration is more than half (f11 is the late iteration), the convergence rate of ACS-DAM algorithm speeds up rapidly and the optimal solution is found. This may be because ACS-DAM falling into local optima, so it kept looking for good values and converged quickly.

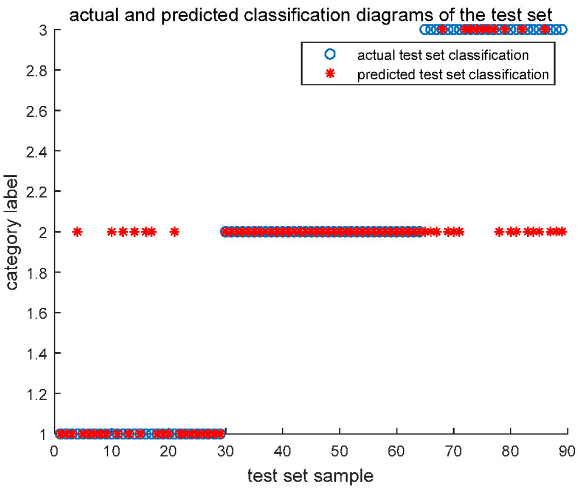
The results tell exploration and development of ACS-DAM are balanced, and the local optimal avoidance and convergence speed are all high. It is helpful for the algorithm to find the global optimal earlier.

5 Support Vector Machine Based on ACS-DAM

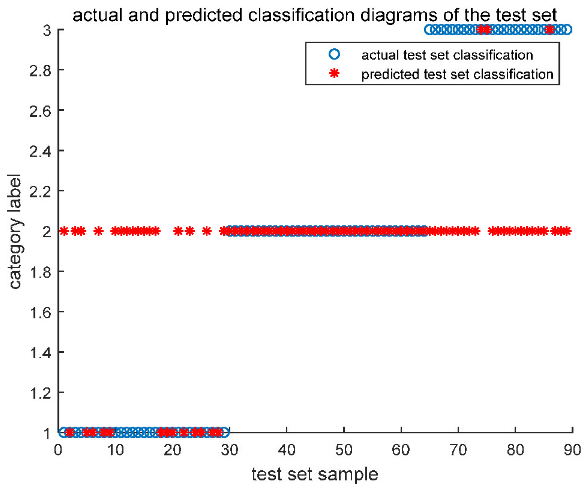
Cortes C et al. [22] proposed the current basic Support Vector Machine algorithm (SVM). In order to find two types of classification problems that meet the requirements of the optimal hyperplane, SVM can maximize the blank area (classification interval) on both sides of the hyperplane to guarantee the accuracy of the model [23]. Due to the classification performance of the selective shadow response SVM, the range of the two parameters C and G is large. It is usually necessary to optimize its parameters [24].

The matrix with test data of 178*13 imported in the experiment contains 3 categories, in which 1-30 of the first category, 60-95 of the second category and 131-153 of the third category are taken as training sets, and 1-30 of the first category, 96-130 of the second category and 154-178 of the third category are taken as training sets. When the random values 25 and 15 were selected for C and G, the classification accuracy was 75.2809%. When the random values 25 and 25 were selected, the accuracy set was 57.3034%. When random values 0.1 and 0.1 were selected, the accuracy was 39.3258%, as shown in Fig. 3.

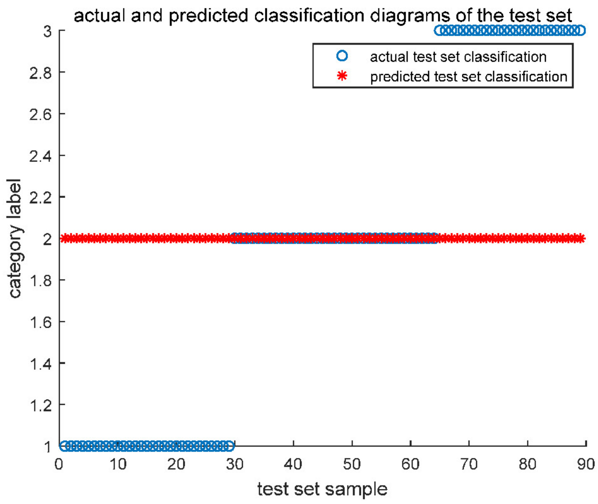
C and Gof SVM are optimized with ACS-DAM, compared with CS algorithm. As shown in Fig. 4, the classification accuracy of test set reached 100% after parameter optimization by the two algorithms. The accuracy is highest at 10^{th} iteration with CS, while the accuracy is highest only at 4^{th} iteration with ACS-DAM. It proves that the convergence rate with ACS-DAM is better than that with CS obviously. It can be seen that ACS-DAM has stronger optimization ability and higher efficiency than CS.



(a)

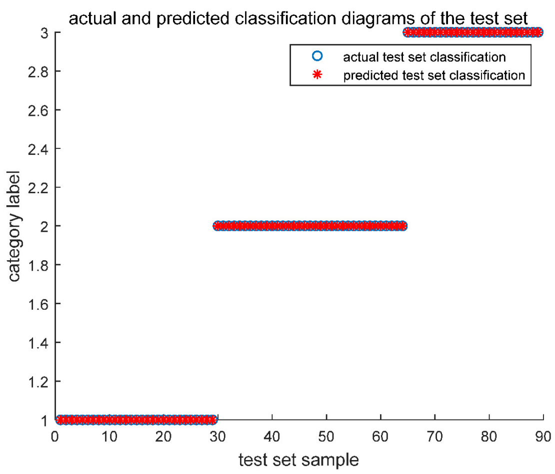


(b)

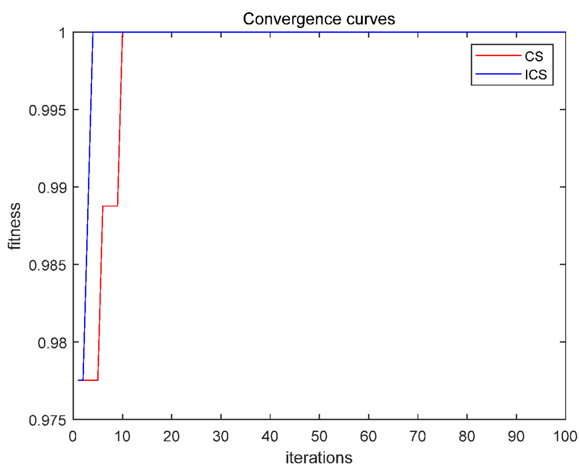


(c)

Fig. 3. Classification accuracy of test set when C and G selected random values



(a)



(b)

Fig. 4. Test set classification accuracy of optimized parameters of the algorithm

6 Conclusion

This paper proposes an adaptive searchalgorithmon the basis of dynamic adjustment mechanism (ACS-DAM). According to the constant iteration of each nest, dynamically adjusted parameters are selected, and the updating step size and discovery probability of each nest are adjusted adaptively, thus forming a mechanism to balance global exploration and local development. By comparing the fitness values and convergence curves of 23 standard test functions with those of standard CS and other improved algorithms, the ACS-DAM algorithm can effectively avoid local optimum, improve the optimization accuracy, and converge quickly and stably. The parameters of support vector machine (SVM) are optimized, and the experimental results show that ACS-DAM greatly improves the actual classification accuracy of SVM, reaching 100%. Compared with standard CS, ACS-DAM achieves 100% accuracy in earlier iterations and improves classification performance. In conclusion, ACS-DAM is a new cuckoo search algorithm with high efficiency and practical value because it increases the adaptive step size and the adaptive adjustment mechanism of discovery probability. In the future, I hope ACS-DAMcan be applied to more aspects, such as regression support vector machine. More research will also be carried out to make more effective improvements in new algorithms such as cuckoo algorithm.

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