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A Novel Multiobjective Optimization Method Based on Improved Artificial Bee Colony Algorithm

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Abstract

In order to improve the convergence and diversity of multiobjective optimization algorithms, the harmonic average distance is employed to improve the aggregating function combined L-rank value. Selection model and searching scheme of artificial bee colony algorithm and diversity maintaining scheme are improved in this paper. This novel many objectives optimization method based on improved artificial bee colony algorithm (ABC) in this paper is compared with other three many objectives optimization methods on 3 to 8 objectives DTLZ. Simulation results show that the proposed algorithm is superior to other algorithms in the diversity and convergence of solutions.

Keywords: *artificial bee colony algorithm, many objectives optimization, aggregating function combined L-rank value*

1. Introduction

Many real world optimization problems involve multiple conflicting objectives. Therefore, multiobjective optimization (MOO) has attracted much attention of researchers and many algorithms have been developed for solving multiobjective optimization problems in the last decade. Preference rank immune memory clone algorithm (PISA) [1], light beam search based multiobjective optimization using evolutionary algorithm (LbsNSGA-II) [2] and non-dominated sorting genetic algorithm II (NSGA-II) [3] are three of the most popular multiobjective algorithms. They have been successfully applied to solve a number of real world multiobjective optimization problems. However, when the number of objects increases, the optimization performance of all these algorithms will be poor. For example, the calculation will be complex, the approximate Pareto front points will be not enough and the coverage will be incomplete.

The ABC algorithm proposed by Karaboga D in 2005 is a kind of swarm intelligence optimization algorithm. Its operation is simple without setting a lot of parameters and has powerful search ability. It has been widely applied in numerous fields, such as function optimization problem, artificial neural network training, filter design and network optimization. However, there are a few strategies based on foraging behaviors of honey bees for optimizing multiobjective problems [4]. Therefore, this paper proposes a method based on improved ABC algorithm to deal with many objectives, which is called as DMABC. In the new algorithm, the selection mode of onlooker and the behavior of scout are changed. Furthermore, an improved fitness evaluation method based on dynamical

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multiobjective evolutionary algorithm using L-optimality (MDMOEA) and a novel diversity maintaining scheme are proposed according to the characteristics of multiobjective optimization problem.

The remainder of this paper is organized as follows. In Section 2, we improve some methods used in the ABC algorithm. In Section 3, we describe the DMABC algorithm in detail. Experimental results are presented in Section 4. Finally, some conclusions are made in Section 5.

2. Improved Methods in ABC

If we use the ABC algorithm to solve multiobjective problem directly, it is easy to fall into local optimum and the convergence speed is not fast enough. So this paper proposes some improvements based on the characteristics of multiobjective optimization problem.

2.1. Improved Fitness Evaluation Method

The MDMOEA, a method based on the principle of the minimal free energy in thermodynamics, was described in [5]. It adopted an aggregating function that combined L-rank value with entropy and density. The fitness of individual *i* in MDMOEA is represented by expression (1).

$$fitness(i) = LR(i) - T \times LS(i) - Ld(i) \tag{1}$$

Where, fitness(i) denotes the fitness of individual i; LR(i) is the L-rank value of individual i; Ld(i) indicates the crowding distance; T is the analog of temperature; LS(i) is defined as follows:

$$LS(i) = -PT(i)\log PT(i)$$

$$PT(i) = {}^{1}\!/_{Z}\exp(-LR(i)/T)$$

$$Z = \sum_{i=1}^{N}\exp(-LR(i)/T)$$

In the formula (1), which is computed by using a density estimation technique that is described in [3] can get an estimated crowding distance. However, it can’t assess crowding distance very well when dealing with multiobjective problem. Literature [6] pointed out that the harmonic average distance can get accurate assessment of crowding distance in the case of multiobjective problem. So we substitute crowding distance with the harmonic average distance which is calculated by expression (2).

$$d_i = \frac{k}{\frac{1}{d_{i1}} + \frac{1}{d_{i2}} + \cdots + \frac{1}{d_{ik}}} \tag{2}$$

Where, k is the number of nearest neighbors around individual i, d_{ik} is the distance between individual i and the kth neighbor.

2.2. Improved Selection Mode of Onlookers

Through many simulation experiments, we found that onlookers use roulette way to select food source is so greedy that the diversity of population is decreased. In the free search algorithm [7], an important model called sensitivity and pheromone cooperation model is put forward. Individuals choose an area to search according to the steps as follows:

Step 1. Compute the pheromone nf(i) of individual i according to the formula (3).

$$nf(i)=\begin{cases}\dfrac{f(i)-f_{\min}}{f_{\max}-f_{\min}} & if \quad f_{\max}\neq f_{\min}\\ 0 & else\end{cases} \tag{3}$$

Where, $f(i)$ is the fitness value of individual i, f_{max} and f_{min} are the maximum and minimum fitness values respectively.

Step II. Sensitivity and pheromone cooperation model is represented by expression (4).

$$nf(j)\leq S(j) \tag{4}$$

Where, $S(j)$ is the sensitivity of individual j .

According to this model, each individual can search any area, which avoids falling into local optimum. The pheromone of searching area must adapt to the sensitivity, which makes the algorithm have evolution direction. Onlookers can use the pheromone and sensitivity coordination model to select food source. The steps are as follows: Firstly, compute the pheromone of each food source according to the formula (3). Secondly, generate a random number as the sensitivity of an onlooker. Finally, onlookers choose food source satisfying formula (4).

2.3. Forced Mutation Operation of the Employed Bee

The scout in ABC algorithm is used to avoid falling into local optimum. However, an individual position change will lead to a change in each individual harmonic average distance, which makes the fitness value of food source change in every generation. It will be hard to start the scout. To solve this problem, we substitute the behavior of scout with a forced mutation operation of the employed bee. When onlookers have determined a new position, they will be converted to the employed bees and explore a new food source according to formula (5).

$$V_{i,k'}=V_{i,k}+V_{i,k}\times randn(0,1) \tag{5}$$

Where, k' is a random variation index; $V_{i,k}$ and $V_{i,k'}$ are the positions before and after mutation respectively.

2.4. Diversity Maintaining Scheme

In order to make the multiobjective optimization solution set wide coverage and uniform distribute, the diversity maintaining scheme in the later stage of the DMABC algorithm is put forward. Its expression is shown by formula (6).

$$f(i)=PX(i)-L(i) \tag{6}$$

Where, $f(i)$ is the fitness value of individual i; $L(i)$ is the harmonic distance; $PX(i)$ is the Pareto rank value of individual i.

From formula (6), we know that the individual with lower Pareto rank and greater harmonic distance is better. This will prompt evolution, increase population diversity and make the population evenly distribute throughout the whole Pareto front.

3. Steps of the Proposed Algorithm

The main steps of the DMABC algorithm are described as follows.

Step 1. Initialize. Set the algorithm parameters including the maximum number of earlier stage iteration N_{max1}, the maximum number of later stage iteration N_{max2} and the analog of temperature T. Generate N individuals from a uniform distribution on the interval [0, 1]. Choose the improved fitness evaluation method described in section 2.1 as individual evaluation method.

Step 2. Evaluate each individual and select N/2 individuals whose fitness values are better as the position of employed bees. Each employed bee searches for the food source and produces a modified position given by formula (7), and then evaluates the new position. If the fitness value is better than the previous one, the employed bee will remember it and forget the old one.

$$V_{ij} = x_{ij} + R_{ij}(x_{ij} - x_{kj}),\ j \in \{1,2,\ldots,d\}\ ,\ \ k \in \{1,2,\ldots,N\} \tag{7}$$

Where, i denotes the bee index of an employed bee; k is a random bee index that must be different from i; N is the number of employed bees; j is a random dimension index in d; d is the problem dimension; R_{ij} is a random number in the range of [-1, 1].

Step 3. Calculate the pheromone of food source using formula (3) and start onlookers. Firstly, onlookers select food source according to the formula (4). Secondly, they start searching for the new food source and produce modified positions given by formula (7). Finally, they evaluate the new position fitness values and remember N/2 individuals whose fitness values are better.

Step 4. N/2 individuals produce forced mutation according to the formula (5) and evaluate the new position. If the fitness value is better than the previous one, the employed bee will remember it and forget the old one.

Step 5. Combine the individuals produced by steps 2 and 4 into a new population.

Step 6. Check the number of earlier stage iteration. If the number of earlier stage iteration is equal to Nmax1, then the algorithm selects formula (7) as individual evaluation method and executes the next step; otherwise, add 1 to the number of earlier stage iteration and go to step 2.

Step 7. Check the number of later stage iteration. If the number of later stage iteration is equal to Nmax2, then the algorithm is finished; otherwise, it adds 1 and goes to step 2.

4. Experimental Results

A lot of scalable test problems were proposed to test the efficacy of a new proposed algorithm in handling problems with more than two objectives. Here, two scalable test problems DTLZ2 and DTLZ3 [8] are considered. There are n = M + k−1 decision variables in these problems, where M is the number of objectives and k specifies the distance to the Pareto front. In our experiment, k = 10 is used in DTLZ2, whereas k = 7 is used in DTLZ3. For various algorithm performance evaluation and comparison, we choose generation distance (GD) and spacing (S) as standard [1].

To verify the effectiveness of the DMABC algorithm, we compare it with other three current popular algorithms, such as PISA algorithm, LbsNSGA-II algorithm and NSGA-II algorithm. All algorithms have been implemented on a PC with a Pentium IV processor, running at 1.6 GHz and with 256-MB RAM. All parameters in the PISA, LbsNSGA-II, and NSGA-II are on the basis of the studies of X. F. Zou et al [5]. In our experiment, the population size N = 200 is chosen; the number of earlier and later stage iteration are 480 and 20 respectively; the specific parameters p and T are set to 1 and 10000 respectively; the number of objectives is 3~ 8. For each algorithm on each test problem, ten rounds are performed and the mean and variance of GD and S to four algorithms are calculated. Results of four algorithms on DTLZ2 and DTLZ3 are listed in Tables 1 and 2 respectively.

Table 1. Results of Four Algorithms on DTLZ2

Obj	SP	The mean and variance values of GD				The mean and variance values of S			
		DMABC	PISA	LbsNSGA-II	NSGA-II	DMABC	PISA	LbsNSGA-II	NSGA-II
3	Average	**2.0641e-8**	2.7e-4	7.7e-04	6.1e-04	**1.1e-3**	4.6e-3	6.3e-3	0.04
	Std.Dev	**1.1488e-8**	1.1e-4	2.6e-04	1.8e-04	**1.0711e-4**	6.4e-4	6.7e-4	0.003
4	Average	**2.1063e-7**	1.1e-3	3.05e-03	6.07e-02	**7.6203e-4**	9.1e-3	1.1e-2	0.12
	Std.Dev	**1.8352e-7**	4.1e-4	8.3e-04	3.4e-02	**6.097e-5**	2.3e-3	1.5e-3	0.016
5	Average	**1.1925e-6**	1.78e-3	4.6e-03	1.85	**1.2e-3**	9.5e-3	1.4e-2	0.33
	Std.Dev	**8.3519e-7**	8.22e-4	1.6e-03	0.19	**2.7417e-4**	1.2e-3	2.8e-3	0.016
6	Average	**2.3169e-7**	1.65e-3	4.554e-03	4.5	3.96e-2	**1.6e-2**	2.6e-3	0.59
	Std.Dev	**4.1108e-7**	3.9e-4	1.7e-03	0.88	9.1e-3	**6.5e-3**	6.1e-3	0.05
7	Average	**3.3342e-6**	2.1e-3	5.2e-03	4.99	**2.0e-3**	1.57e-2	1.7e-2	0.67
	Std.Dev	**6.6684e-6**	1e-3	1.7e-03	0.34	**4.0694e-4**	5.4e-3	5.2e-3	0.02
8	Average	**2.048e-7**	1.56e-3	5.6e-03	5.45	**4.51e-3**	1.84e-2	1.85e-2	0.84
	Std.Dev	**4.096e-7**	6.4e-4	1.6e-03	0.14	**1.8e-4**	9.1e-3	3.4e-3	0.01

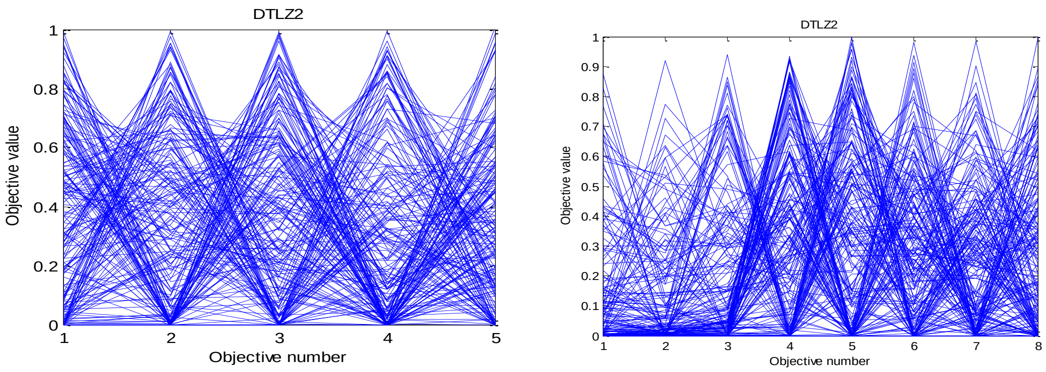
Table 2. Results of Four Algorithms on DTLZ3

Obj	SP	The mean and variance values of GD				The mean and variance values of S			
		DMABC	PISA	LbsNSGA-II	NSGA-II	DMABC	PISA	LbsNSGA-II	NSGA-II
3	Average	**1.3375e-4**	1.7e-3	0.017	2.32e-02	**1.2e-2**	2.32e-2	2.42e-2	0.132
	Std.Dev	**2.5468e-5**	1.5e-3	0.01	6.4e-04	**7.7717e-5**	6.4e-4	1.4e-2	8.6e-2
4	Average	**2.4651e-5**	3.4e-3	1.39e-02	4.03e-02	**6.4096e-4**	2.5e-02	2.88e-2	30.95
	Std.Dev	**2.9546e-6**	1.8e-3	1.11e-02	44	**8.2249e-6**	6.56e-03	1.2e-2	8.26
5	Average	**1.15e-5**	5.5e-3	8.37e-03	6.97e-02	**1.3e-3**	3.6e-2	3.8e-2	84.3
	Std.Dev	**7.5329e-6**	2.8e-3	5.26e-03	86.4	**1.833e-4**	2.7e-2	1.2e-2	11.8
6	Average	**1.2961e-5**	2.5e-3	2.1e-02	1.09e-03	**4.35e-2**	0.128	6.9e-2	1.74e-2
	Std.Dev	**2.33e-5**	2.6e-3	1.54e-02	57.1	**3e-3**	0.103	2.1e-2	22.8
7	Average	**6.244e-6**	5.49e-	2.3e-02	1.36e-	**2.1e-3**	0.088	8.62e-2	2.91e-2

			3		03				
	Std.Dev	**1.2488e-5**	5.39e-3	1.8e-02	77.2	**4.8415e-4**	0.027e-3	2.54e-2	28
8	Average	**3.8594e-6**	5.44e-3	2.79e-02	1.54e-03	3.84e-1	**1.84e-2**	9.8e-2	9.8e-2
	Std.Dev	**4.7659e-5**	5.64e-3	1.65e-02	54.2	4.5e-3	**9.1e-3**	2.5e-2	2.5e-2

From Tables 1 and 2, we can observe that the mean and variance of GD of the DMABC algorithm proposed in this paper is less than that of the other three algorithms for 3 ~ 8 objects on DTLZ2 and DTLZ3 problems. In other words, the convergence and stability of the DMABC algorithm are better than other three algorithms. We also see that the mean and variance of S of the DMABC algorithm is less than that of other three algorithms in addition to six objects on DTLZ2 problem and eight objects on DTLZ3 problem. Results show that the new algorithm can get the better distribution in most cases.

Distribution index S can only reflect the distribution of solution set, but cannot intuitively reflect the solution set whether cover the entire Pareto front or not. Therefore, we give distribution of the optimized result for five objects and eight objects on DTLZ2 problem, which is shown in Figure 1.



(a) Results on DTLZ2 with five target **(b) Results on DTLZ2 with eight target**

Figure1. Results of DMABC on DTLZ2 with Five Objectives and Eight Objectives

Because the convergence and distribution of PISA algorithm are better than LbsNSGA-II and NSGA-II [1], we only compare the DMABC algorithm with PISA algorithm. For five objects on DTLZ2 problem, the coverage of PISA algorithm on the first four objects are 0.3 ~ 0.5, on the fifth object is 0.2 ~ 0.5; On the other hand, the coverage of the DMABC algorithm on the all five objects can reach the theoretical value 0 ~ 1. For eight objects on DTLZ2 problem, the coverage of PISA algorithm on the all objects is 0 ~ 0.5, and that of the DMABC algorithm on the all objects is also the theoretical value 0 ~ 1. The simulation results show that the coverage of solution set solved by the DMABC algorithm is better than that solved by the PISA algorithm.

5. Conclusions

This paper proposed a novel multiobjective optimization method based on improved ABC algorithm. Simulation results prove that the proposed method can successfully solve multiobjective problems and the diversity and convergence of solution set are better than other three popular algorithms including PISA, LbsNSGA-II and NSGA-II. The DMABC algorithm proposed in this paper need set a few parameters which directly affect its performance, so how to choose the suitable parameters will be the direction of further research.

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