A Novel Multi-Objective Optimization Algorithm Based on Artificial Bee Colony

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ABSTRACT

Multi-objective optimization has been a difficult problem and focus for research in fields of science and engineering. This paper presents a novel algorithm based on Artificial Bee Colony (ABC) to deal with multi-objective optimization problems. ABC is one of the most recently introduced algorithms based on the intelligent foraging behavior of a honey bee swarm. It uses less control parameters and it can be efficiently used for solving multimodal and multidimensional optimization problems. Our algorithm uses the concept of Pareto dominance to determine the flight direction of a bee and it maintains nondominated solution vectors which have been found in an external archive. The proposed algorithm is validated using the standard test problems ZDT1 to ZDT3 and ZDT6, and simulation results show that the proposed approach is highly competitive and that can be considered a viable alternative to solve multi-objective optimization problems.

Categories and Subject Descriptors

I.2.8 [Articial Intelligence]: Problem Solving, Control Methods, and Search – *Heuristic Methods*

General Terms: Algorithms

Keywords: Multi-objective Optimization; Evolutionary Algorithm; Artificial Bee Colony; Pareto Optimality; Pareto Front.

1. MULTI-OBJECTIVE ABC ALGORITHM

In our algorithm, we use an external archive to keep a historical record of the nondominated vectors found along the search process. This technique is used in many MOEAs [1] [2].

In the initialization phase, we evaluate the fitness of the initial food source positions and sort them based on nondomination. Then we select nondominated solutions and store them in the external archive EA. This is the initialization of the external archive.

In our algorithm, all solutions in the external archive are regarded as food source positions and all bees are regarded as onlooker

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bees. There does not exist employed bees and scouts. In the onlooker bees' phase, we use comprehensive learning strategy to produce new solutions v_i . For each bee x_i , it randomly chooses *m* dimensions and learns from a nondominated solution which is randomly selected from *EA*. And the other dimensions learn from the other nondominated solutions. The new solution is produced by using the following expression:

$$v_{i, f(m)} = x_{i, f(m)} + \phi(m)(EA_{k, f(m)} - x_{i, f(m)})$$

(1)

where $k \in (1, 2, ; p)$ is randomly chosen index, and p is the number of solutions in the *EA*. f(m) is the first m integers of a random permutation of the integers 1:n, and f(m) defines which x_i 's dimensions should learn from EA_k . As opposed to ϕ_{ij} in original ABC algorithm, $\phi(m)$ produce m random numbers which are all between [0, 2]. And the m random numbers correspond to the m dimensions above. This modification make the potential search space around EA_k . The remaining each dimension learns from the other nondominated solutions by using expression (6).

$$v_{ij} = x_{ij} + \phi_{ij} \left(EA_{lj} - x_{ij} \right) \tag{2}$$

where $l \neq k$, $j \in (1, 2, ..., p)$ and $j \notin f(m)$. After producing new solution, we compare two solutions to decide which solution enters *EA*. If the new solution dominates the original individual, then the new solution is allowed to enter the external archive *EA*. On the other hand, if the new solution is dominated by the original individual, then it is denied access to the external archive *EA*. If the new solution and the original individual do not dominate each other, then we randomly choose one of them to enter *EA*.

As the evolution progresses, more and more new solutions enter the external archive. The size of external archive must be limited. After each generation, we update external archive. The solutions in the EA are sorted based on nondomination and we keep the nondomination solutions of them staying in the EA. If the number of nondominated solutions exceeds the allocated the size of EA, then crowding distance [3] is applied to remove the crowded members and to maintain uniform distribution among the archive members.

2. EXPERIMENTS

In order to compare the performance of the proposed MOABC algorithm with MOCLPSO [4] [5], we used four well-known test problems ZDT1 to ZDT3 and ZDT6.

So as to facilitate the quantitative assessment of the performance of a multi-objective optimization algorithm, convergence metric Υ and diversity metric Δ are taken into consideration.

Table 1: Results of convergence metric

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		MOABC	MOCLPSO	NSGA-II
1	Median	2.2455e-002	2.4156e-003	1.4410e-001
	Std	2.6057e-003	4.9069e-004	2.3806e-001
2	Median	9.5537e-004	1.0350e-003	1.8105e-001
	Std	2.5380e-004	3.7382e-004	2.6288e-001
3	Median	1.5186e-003	2.4152e-003	1.5563e-001
	Std	2.2384e-004	5.3581e-004	1.7221e-001
6	Median	2.8035e-005	8.1531e-003	3.9688e+000
	Std	8.9540e-003	1.9448e-002	1.4822e+000

Table 2: Results of diversity metric

		MOABC	MOCLPSO	NSGA-II
1	Median	3.3108e-001	2.9207e-001	5.2694e-001
	Std	2.4324e-002	2.4574e-002	1.5649e-001
2	Median	2.9185e-001	3.1660e-001	7.2999e-001
	Std	2.2147e-002	2.6171e-002	2.3567e-001
3	Median	6.6325e-001	7.2578e-001	6.9255e-001
	Std	1.8462e-002	3.3709e-002	4.6110e-002
4	Median	4.7318e-001	7.5949e-001	1.1187e+000
	Std	2.7989e-001	4.2953e-001	8.8914e-002

3. CONCLUSION

In this paper, we present Multi-Objective Artificial Bee Colony (MOABC) algorithm to solving multi-objective optimization problems. In our algorithm, we use Pareto concept and external archive strategy to make the algorithm converge to the true Pareto-optimal front. We also use comprehensive learning strategy to ensure the diversity of population. In order to demonstrate the performance of the MOABC algorithm, we compared the performance of the MOABC with those of MOCLPSO and NSGA-II optimization algorithms on several benchmark functions. From the simulation results, it is concluded that the average performance of MOABC algorithm is good. Therefore MOABC can be considered a viable alternative to solve multi-objective optimization problems.



Figure.1. Optimal solutions for ZDT1, ZDT2, ZDT3 and ZDT6 using MOABC, MOCLPSO and NSGA-II;

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