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Elite-guided multi-objective artificial bee colony algorithm

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ABSTRACT

Multi-objective optimization has been a difficult problem and a research focus in the field of science and engineering. This paper presents a novel multi-objective optimization algorithm called elite-guided multi-objective artificial bee colony (EMOABC) algorithm. In our proposal, the fast non-dominated sorting and population selection strategy are applied to measure the quality of the solution and select the better ones. The elite-guided solution generation strategy is designed to exploit the neighborhood of the existing solutions based on the guidance of the elite. Furthermore, a novel fitness calculation method is presented to calculate the selecting probability for onlookers. The proposed algorithm is validated on benchmark functions in terms of four indicators: GD, ER, SPR, and TI. The experimental results show that the proposed approach can find solutions with competitive convergence and diversity within a shorter period of time, compared with the traditional multi-objective algorithms. Consequently, it can be considered as a viable alternative to solve the multi-objective optimization problems.

1. Introduction

Multi-objective optimization, which involves more than one objective function, has been applied in many fields such as manufacturing optimization [1,2], engineering design [3], and chemical engineering [4]. For example, while buying a car, minimizing cost and maximizing comfort are the two objectives needed to be optimized. Usually, there are conflicts among these objectives, for instance, the car with better comfort would cost more, which lead to the difficulty of optimizing the multiple objectives. Therefore, when dealing with multi-objective optimization, the trade-off analysis that needs to be taken between the conflicting objectives, and then the Pareto optimal solutions [5] can be obtained.

Evolutionary algorithms (EA) can explore the Pareto optimal solutions for the multi-objective optimization problems that are too complex to be solved by the exact methods within a reasonable computation time [6]. Due to their inherent parallelism and their capability to exploit the similarities of solutions by recombination, they are able to approximate the Pareto optimal solutions after several iterations. Over the past two decades, many biologically inspired algorithms have been proposed to solve the multi-objective optimization problems, such as Pareto-archived evolution strategy (PAES) [7], Pareto envelope-based selection algorithm II (PESA-II) [8], improved strength Pareto evolutionary algorithm (SPEA2) [9], non-dominated sorting genetic algorithm II (NSGA-II) [10], multi-objective particle swarm optimization (MOPSO) [11], indicator-based evolutionary algorithm (IBEA) [12], multi-objective evolutionary algorithm based on decomposition (MOEA/D) [13], archived multi-objective simulated annealing (AMOSA) [14], and preference-inspired co-evolutionary algorithm (PICEA) [15]. These algorithms search for the optimal solution set by iterative evolution. The quality of the solution has being improved as the study continues in depth.

By modeling the intelligent behavior of honey bee swarm, artificial bee colony (ABC) algorithm proposed by Karaboga [16] is a new swarm intelligence method. It has been found to be successful in a wide variety of optimization tasks [17], and has got the widespread concern of researchers [18–21]. For multi-objective optimization, some researches combine ABC with the fast non-dominated sorting method in NSGA-II and propose the MOABC algorithm [22–25]. The vector evaluated artificial bee colony (VEABC) [26] classifies the bee colonies based on the number of optimized objectives. Each colony separately evaluates one single goal and exchanges their information to obtain the optimal solution set. A Pareto-based discrete artificial bee colony algorithm was proposed for solving multi-objective flexible job shop scheduling problems [27]. In this algorithm, a crossover operator and an external Pareto archive set were designed, and several local search approaches were designed to balance the exploration and exploitation capability. Hybrid multi-objective artificial bee colony (HMOABC) algorithm [28] is proposed for solving the burdening process optimization. The mechanisms about the intelligent foraging behavior of bees and diversified selection were added. Recently, a new multi-objective artificial bee colony algorithm by dividing the searching space (dMOABC) was proposed [29]. In this algorithm, three colonies are used to search in different regions of the searching space and share information. The diversity of the archived solutions is controlled by a self-adaptive grid.

However, in the current multi-objective optimization algorithms based on ABC, any dimension of the feasible solution changes based on the information of the neighbor solutions. This relatively random change cannot ensure that the new candidate solution is superior to the previous one. In this paper, we present a novel multi-objective optimization algorithm called the "elite-guided multi-objective artificial bee colony" (EMOABC) algorithm. The elite-guided solution generation strategy is proposed to accelerate the convergence speed and improve the solution quality. In order to judge the quality of solution, the fast non-dominated sorting and population selection strategy from NSGA-II [10] are applied. A novel fitness calculation method is also presented, because the original single-objective fitness calculation method is not applicable for multi-objective optimization. In order to evaluate the performance of the EMOABC, we compared EMOABC algorithm with NSGA-II, MOPSO, and MOABC on a set of well-known benchmark functions in terms of four indicators: GD, ER, SPR, and TI. The experimental results show that EMOABC algorithm has the ability to provide competitive performance on most of the test problems.

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The remainder of this paper is organized as follows. An introduction to multi-objective optimization is presented in Section 2. The original ABC algorithm is described in Section 3. Section 4 specifies the details of the proposed EMOABC algorithm and the multi-objective optimization strategies. Section 5 presents a comparative study of the proposed EMOABC with other algorithms on a number of benchmark functions. Finally, the conclusion is given in Section 6.

2. Multi-objective optimization

Let x be a n-dimensional vector of decision variables, $x = (x_1, x_2, \ldots, x_n)$, and S be the search space. For the single objective optimization function $\min(f(x))$, which is just a scalar function, the optimal solution can be achieved by directly comparing the objective values. $f^*(x)$ is the global minimum solution if and only if:

$$\forall x \in S : f^*(x) \le f(x). \tag{1}$$

When there is more than one objective, the problem becomes a multi-objective optimization problem.

Definition 1 *(Multi-Objective Optimization problem).* A multi-objective optimization problem (MOP) can be stated as follows:

$$\begin{aligned} &\text{Minimize} \quad F(x) = [f_1(x), f_2(x), \ldots, f_u(x)], \\ &\text{Subject to} \quad x \in S. \end{aligned} \tag{2}$$

where u is the number of the objectives. The absolute optimal solution needs to make multiple targets optimal simultaneously. However, due to the mutual restriction of decision variables among multiple targets, it is difficult to obtain the absolute optimal solution. So that the solution of the multi-objective optimization problem is usually described by a Pareto optimal set [11], which is defined based on Pareto dominance. Assuming that $K = [1, 2, \ldots, u]$, the definition of Pareto set is given below.

Definition 2 *(Pareto Dominance).* A vector v is said to dominate w ($v \prec w$) if and only if:

$$\forall k \in K : f_k(v) \le f_k(w) \wedge \exists k \in K : f_k(v) < f_k(w). \tag{3}$$

Definition 3 *(Pareto Optimality).* In the feasible region S, a point $x^* \in S$ is Pareto optimal if and only if it satisfies one of the following two conditions:

(1) $\forall x \in S, \forall k \in K, f_k(x^*) = f_k(x)$,
(2) $\exists k \in K, f_k(x^*) < f_k(x)$.

All the Pareto optimal solutions constitute the Pareto optimal set P^*.

Definition 4 *(Pareto-front).* For Pareto optimal set P^*, the Pareto-front (PF^*) is defined as:

$$PF^* := \{[f_1(x), f_2(x), \ldots, f_u(x)] | x \in P^*\}. \tag{4}$$

3. Artificial bee colony algorithm

The artificial bee colony (ABC) algorithm is a new swarm intelligence method which simulates intelligent foraging behavior of honey bees. It searches the optimal solution by the random but targeted evolution of the candidate solution group.

In the original ABC algorithm, each food source represents a feasible solution of the problem to be solved, and the nectar quality of the food source denotes the fitness of this feasible solution, indicating the quality of this solution. The bees are classified into three groups:

(1) *Employed bees*. They are responsible for exploiting the neighborhood of the food source and sharing their information with bees waiting in the hive.
(2) *Onlookers*. They wait in the hive and choose a food source to exploit depending on the information. When they find a better food source, they will notify the appropriate employed bee to update its position.
(3) *Scouts*. When there is no update after several iterations, which means the algorithm has fallen into the local optimum, the employed bee will become a scout and randomly find a new food source to start a new search.

The ABC algorithm tends to converge gradually through collaboration of these three kinds of bees, and obtains the optimal or near-optimal solution in the feasible space. The main steps of the algorithm can be summarized as follows:

Step 1. Initialization
Generate the initial solution population randomly and then calculate the objective function value of each solution in the population.
Step 2. Employed bee phase
Each employed bee searches the neighbor of the food source to produce a new solution. Then calculate the objective function value and apply the greedy selection strategy to update the position.
Step 3. Onlooker phase
Each onlooker selects a food source in the population depending on the selecting probability associated with that food source, and searches its neighbor to produce a new solution. Then, calculate the objective function value and apply the greedy selection strategy to update the position.
Step 4. Scout phase
Send the scout to the search area for discovering a new food source.
Step 5. Memorize the best food source found so far.
Step 6. If a termination is not satisfied, go to step 2; otherwise stop the procedure and return the best food source found so far.

4. EMOABC algorithm

Currently, some studies have employed the ABC algorithm for solving multi-objective optimization problems, such as MOABC algorithm [1,22–25] combining ABC with the non-dominated sorting of NSGA-II [10]. However, in local searching strategy of MOABC, any one dimension of the feasible solution changes based on the information of neighbor solutions. This relatively random change cannot ensure that the new candidate solution is better than the previous one. In order to improve the quality of the solution, the Gbest-guided artificial bee colony (GABC) algorithm was proposed [30] for the single-objective optimization, which takes advantage of the information of current global best solution to guide the local searching in order to improve the exploitation. Based on this, we propose the elite-guided multi-objective artificial bee colony (EMOABC) algorithm for multi-objective optimization which guides the local searching by the elite set.

The flowchart of the EMOABC algorithm is given in Fig. 1. The EMOABC algorithm is constituted of four parts: Initialization, send employed bees, send onlookers and send scouts, which will be explained in the following Section 4.3. Besides, it also involves some multi-objective optimization strategies, like fast non-dominated sorting method and population selection strategy, which is described in Sections 4.2.1 and 4.2.2 respectively.