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Cooperative two-engine multi-objective bee foraging algorithm with reinforcement learning

Lianbo Ma [a], Shi Cheng [b], Xingwei Wang [a], Min Huang [c,*], Hai Shen [d], Xiaoxian He [e], Yuhui Shi [f]

[a] College of Software, Northeastern University, Shenyang, China
[b] College School of Computer Science, Shaanxi Normal University, Xi'an, China
[c] College of Information Science and Engineering, Northeastern University, Shenyang, China
[d] College of Information Science & Engineering, Central South University, Changsha, China
[e] College of Physics Science and Technology, Shenyang Normal University, Shenyang, 110034, China
[f] Department of Computer Science and Engineering, Southern University of Science and Technology, Shenzhen, China

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ABSTRACT

This paper proposes a novel multi-objective bee foraging algorithm (MOBFA) based on two-engine co-evolution mechanism for solving multi-objective optimization problems. The proposed MOBFA aims to handle the convergence and diversity separately via evolving two cooperative search engines with different evolution rules. Specifically, in the colony-level interaction, the primary concept is to first assign two different performance evaluation principles (i.e., Pareto-based measure and indicator-based measure) to the two engines for evolving each archive respectively, and then use the comprehensive learning mechanism over the two archives to boost the population diversity. In the individual-level foraging, the neighbor-discount-information (NDI) learning based on reinforcement learning (RL) is integrated into the single-objective searching to adjust the flight trajectories of foraging bee. By testing on a suit of benchmark functions, the proposed MOBFA is verified experimentally to be superior or at least comparable to its competitors in terms of two commonly used metrics IGD and SPREAD.

1. Introduction

In many real-world industrial applications, decision makers (DMs) have to tackle complex problems with simultaneous satisfaction of multiple objectives that are non-commensurable and normally conflicting to each other. These problems are also referred as multi-objective optimization (MO) problems. Generally, the solutions to these MO problems, known as the Pareto-optimal solutions (PS), represent a possible best trade-off to satisfy all conflicting objectives [1,2]. In virtue of the promising property of population-based stochastic searching, evolutionary algorithms (EAs) have been widely used to solve the MO problems. Accordingly, the primary goal of these multi-objective EAs (MOEAs) is to find a set of non-dominated solutions that have an accurate and well distributed approximation of the true Pareto-optimal front (PF). One representative paradigm to obtain this goal is Pareto optimality based algorithm, such as NSGAII [3] and SPEA2 [4]. Pareto-based MOEAs have been deeply developed to deal with the MO problems and have received a surge of attention. However, sometimes these algorithms would become ineffective to improve convergence when dealing with complex MO problems because estimating the similarity in a MO space is difficult and it inevitably causes the difficulty of identifying the differences between solutions. Accordingly, several attempts at diversity improvement have been developed but do not solve this issue completely [5–7]. As a response to resolve this issue, a considerable number of algorithms have been proposed recently.

The first type is the decomposition-based approach that utilizes aggregation functions to decompose a MO problem into a set of single-objective optimization problems. Among them, the representative algorithm is MOEA/D [8]. In MOEA/D, each solution vector is assigned with a specific weight vector for the sub-problem in a cooperative approach. Several contemporary variants have been proposed [9–12]. For instances, Li and Silva [9] develop a greedy randomized adaptive search procedure (GRASP) to optimize each sub-problem, Chen et al. [10] propose an framework of double-level archives for MOEA/D to retain fast convergence and even distribution along PF, and in [11] a new variant MOEA/D-EGO is developed for expensive MO problems, and it can yield a set of reasonable solutions within a given computational budget.

* Corresponding author.
E-mail address: submit_ieee_smc@hotmail.com (M. Huang).

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Another alternative to the Pareto-based approach is the quality indicator-based algorithm, within which the fitness of each solution is evaluated by the values of the quality indicator between individuals. The first indicator-based algorithm is the indicator-based evolutionary algorithm (IBEA) proposed in [13], which has a significant merit of boosting the convergence. However, it is proven that this indicator-based approach suffers from the lack of diversity maintenance in its indicator. Aiming at this issue, some improved variants have been proposed. In [14], the S-metric selection strategy is incorporated in the MOEA to enhance convergence and diversity simultaneously. Likewise, Gomez et al. proposes a $R2$ indicator based evolutionary algorithm called MOMBI [15]. Another interesting improvement is the incorporation of hypervolume-based metric in MOEAs, which can evaluate convergence and diversity simultaneously [16]. Recently, several novel MO bio-inspired algorithms i.e., MOGWO, MODA and MOALO are developed by Mirjalili based on social behaviors of grey wolf, dragonfly and ant lion and receive a surge of attention [17,18,19].

The third type of valuable improvements are to augment the selection pressure in MO space, such as the ε-dominance [20], the controlling dominance area [21], and the α-dominance [22]. These methods have been proven experimentally to be more effective than the original Pareto dominance. In addition, several other strategies are developed to improve dominance definitions, such as the fuzzy-Pareto dominance [23], L-optimality [24], and ranking method [25]. Especially, in [26], the crowding distance mechanism presented in NSGAII is replaced with the farthest-candidate method, which is more conductive to diversity preservation. In [27], a new grid dominance method is proposed to retain appropriate balance of convergence and distribution.

Besides above categories, there are other emerging approaches, including NSGAIII [28] and two-archive MOEA [29]. NSGAIII uses a set of reference points with even distribution to refine the diversity maintenance, and it has been validated experimentally [28]. In [29], an improved two-archive algorithm is developed by assigning indicator and Pareto metrics to the two archives respectively, which can enhance the convergence and diversity separately. Other approaches based on reference or objective space reduction have also been proposed and developed [30–35].

Inspired by pioneering effort of the above works, especial that in [29], by leveraging the specific advantages of Pareto-based and indicator-based measure approaches, our work in this paper aims to design a two-engine multi-objective bee foraging algorithm (MOBFA) to achieve excellent performance on convergence and diversity without requiring any reference information in advance. As mentioned previously, managing convergence and diversity is an essential task in the design of MO algorithms. That is, the two common but conflicting goals i.e., to minimize the distance to the true PS and to maximize the diversity within the approximation of the PS, have to be appropriately balanced [36]. In order to solve this issue, only employing the Pareto dominance approach is insufficient. It has been proven that the quality indicator measure proposed in IBEA [13] has great potential to boost the convergence and the Pareto dominance is able to improve the diversity [29]. By using these features, we can follow the idea of cooperative evolution by combining with these two dominance relations.

One of our main ideas is to cooperatively evolve two heterogeneous search engines (i.e., evolutionary populations) to promote convergence and diversity separately. Specifically, in the colony-level interaction, the Pareto-based engine (PE) that is to maintain diversity and the indicator-based engine (IE) that aims to boost convergence are evolved in parallel, and they update their archives independently, namely Pareto-based archive (PA) or indicator-based archive (IA). At each evolutionary step, each agent (or individual) of the engine is updated by indirectly learning from a random one selected from its counterpart's archive. In the individual-level searching, the artificial bee colony (ABC) paradigm [37] is selected as the basic search rule. Then the reinforcement learning (RL) is integrated into the ABC to adjust the flight trajectories of the foraging bee. By incorporating these mechanisms, the single population ABC has been extended to the interacting multi-hive and multi-objective model.

Intuitively, the novelties and characteristics of the proposed MOBFA for MO problems can be summarized as follows.

(1) The MOBFA uses two heterogeneous engines (or demes) with different evolutionary rules to deal with the convergence and the diversity separately. Obviously, this cooperative multi-engine framework is open-ended and extensible that various potential MO strategies can be easily incorporated and accordingly new search engines including evolutionary algorithm (EA) and swarm intelligence (SI) paradigms can be selected in the corresponding engine. This also means this framework can achieve an appropriate search trade-off in the MO optimization.
(2) Based on the proposed framework, the MOBFA provides a cooperative evolution mechanism of diversity preservation and distribution control and a mechanism for the communication of the two demes.
  - In the colony-level interaction, the Pareto-based engine (PE) and indicator-based engine (IE) are evolved through information exchanging to maintain a global archive. That is, each agent in the engine (PE or IE) is updated by indirectly learning from a random one selected from its counterpart's archive (IA or PA) all through the search process. This way, the explicit amalgamation of competitive advantages of Pareto dominance and indicator-based measure, show huge potential to address the task of balancing convergence and diversity.
  - In the individual-level searching, the reinforcement learning (RL) based on Q function is incorporated into the single-objective ABC engine to determine the flight trajectories of the foraging bee, in which each individual can learn from its neighbor through the neighbor-discount-information (NDI) mechanism, and use this information to update its position, which essentially enhances the efficiency of information exchange.

The rest of this paper is organized as follows. Section 2 presents the literature review. In Section 3 the proposed algorithm is presented in detail. In Section 4, the experimental study on a set of benchmarks is given. Finally, Section 5 outlines the conclusions.

2. Literature review

This section presents the principles of multi-objective optimization and the brief review of the multi-objective ABC algorithms.

2.1. Multi-objective optimization

The principle of a multi-objective optimization problem can be stated as below:

$$\begin{aligned} &\underset{x}{\text{Minimize}} \quad F(x) = (f_1(x), \ldots, f_m(x)) \\ &\text{s.t.} \quad \begin{cases} g_i(x) \geq 0, i = 1, 2, \cdots, k \\ h_j(x) = 0, j = 1, 2, \cdots, q \end{cases} \end{aligned} \tag{1}$$

In this definition, $x \subset R^n$, and $x = (x_1,\ldots,x_n)$ is decision vector consisting of n variables, R^n is the decision space, $F: x \to R^m$ consists of m real-valued objective functions that should be optimized simultaneously, R^m is the objective space, and k and q is the number of inequality and equality constraints respectively. Essentially, the goal is to find a set of solutions that yield a best trade-off among all m objective functions. The formal definition of Pareto dominance is given as follows.