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Artificial bee colony algorithm with multiple search strategies

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ABSTRACT

Considering that the solution search equation of artificial bee colony (ABC) algorithm does well in exploration but badly in exploitation which results in slow convergence, this paper studies whether the performance of ABC can be improved by combining different search strategies, which have distinct advantages. Based on this consideration, we develop a novel ABC with multiple search strategies, named MuABC. MuABC uses three search strategies to constitute a strategy candidate pool. In order to further improve the performance of the algorithm, an adaptive selection mechanism is used to choose suitable search strategies to generate candidate solutions based on the previous search experience. In addition, a candidate solution is generated based on a Gaussian distribution to exploit the search ability. MuABC is tested on a set of 22 benchmark functions, and is compared with some other ABCs and several state-of-the-art algorithms. The comparison results show that the proposed algorithm offers the highest solution quality, the fastest global convergence, and the strongest robustness among all the contenders on almost all the cases.

1. Introduction

Since various science and engineering fields involve the complex optimization problems, optimization techniques are very important for researchers and have always been a hot spot. General speaking, a minimization problem can be expressed by the following form

$$Minimize\ f(X), \quad subject \quad to \quad X \in \Omega, \tag{1.1}$$

where $X = [x_1, x_2, \ldots, x_D]$ is a D-dimensional vector of decision variables in the feasible region Ω. Traditional optimization algorithms such as steepest decent, conjugate gradient method, Newton method, etc., generally fail to handle the multimodal, non-convex, non-differentiable or discontinuous optimization problems. For instance, most of traditional methods require gradient information and hence it is impossible for them to deal with the non-differentiable functions. Furthermore, they often easily fall into local optima when dealing with complex multimodal functions. Therefore, it is essential to develop more practical optimization techniques.

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In the past few decades, evolutionary algorithms (EAs) have achieved considerable success in handling these complex problems as they do not depend on the differentiability, continuity, and convexity of the objective function. And they have attracted more and more attention. In the family of EAs, the most popular methods are genetic algorithms (GA) [1], differential evolution (DE) [2], particle swarm optimization (PSO) [3], biogeography-based optimization (BBO) [4], ant colony optimization (ACO) [5], and artificial bee colony (ABC) algorithm [6].

Concretely speaking, this paper focuses on ABC, developed by Karaboga [6] based on simulating the intelligent foraging behavior of honey bees. The simulation results indicate that ABC is superior to or at least comparable to GA, DE, and PSO [7–10]. Due to its simple structure, easy implementation and outstanding performance, ABC has received growing interest and has been successfully applied to solve many real-world optimization problems [11–13] since its invention.

However, similar with other EAs, ABC also faces slow convergence. It is because the search equation of ABC does well in exploration but badly in exploitation [25]. For the sake of an exquisite balance between the exploration and the exploitation, many ABC variants have been proposed to improve the performance of ABC by hybrid ABC with other operations [14–24]. For example, Karaboga and Basturk [14] developed a modified version of ABC which employs the frequency of perturbation and the ratio of the variance operation. Kang et al. [15] integrated Nelder–Mead simplex method into ABC and proposed a hybrid ABC. Alatas [17] proposed a chaotic ABC by introducing the chaotic map into the initialization and the scouts phase. Xiang and An [22] reported an improved ABC by employing a chaotic search technique, a reverse selection and a combinatorial solution search. Gao et al. [24] suggested a general framework to improve the search ability of ABC by using the orthogonal learning strategy.

Many attempts have also been developed to improve the search ability of ABC by the modified search equations [24–30]. For example, motivated by PSO, Zhu and Kwong [25] proposed a gbest-guided ABC (GABC) which makes use of the information of global best solution to improve the exploitation. Li et al. [27] introduced an inertia weight and two acceleration coefficients, and developed a modified ABC. Drawing inspiration from DE, Gao et al. [30] designed two modified solution search equations, named ABCbest. Gao et al. [24] proposed a novel solution search equation like the crossover operation of GA, named CABC. The experimental results show the modified search equation performs effectively. The study is not limited to the above two aspects and more work can be seen in [10].

It has been clear that some search strategies suit the global exploration and some other strategies can speed up the convergence. Without question, these experiences are very useful for improving the performance of ABC. However, it has been observed that these experiences have not been systematically utilized to design a new ABC variant. This motivates us to research whether the performance of ABC can be improved by combining several different search strategies, which have different advantages identified by other researchers' works. Our work along this line develops a novel ABC with multiple search strategies, named MuABC. This presented approach combines three search strategies by an adaptive selection mechanism to produce candidate solutions. In addition, a Gaussian distribution is introduced to the three search strategies to improve the search ability. MuABC also preserves the good characteristics of the original ABC, such as simple structure, easy implementation, and so on. The comparison results, on a set of benchmark functions, denote that MuABC performs competitively and effectively when compared to the selected state-of-the-art algorithms.

The rest of this paper is organized as follows. Section 2 reviews ABC. The presented approach is introduced in Section 3. The comparison results are presented and discussed in Section 4. Finally, the conclusion is drawn in Section 5.

2. The original ABC

ABC, proposed by Karaboga [6], is a newly proposed optimization algorithm which simulates the intelligent foraging behavior of honey bee swarms. In ABC, a colony involves three different classes of bees: employed bees, onlookers, and scouts. The framework of ABC is shown in Fig. 1.

The population of ABC consists of SN D-dimensional vectors of decision variables

$$X_i = \{x_{i,1}, x_{i,2}, \ldots, x_{i,D}\}, \quad i = 1, 2, \ldots, SN. \tag{2.1}$$

In the beginning, each X_i which is defined by lower and upper bounds X_{min} and X_{max}, is generated by Eq. (2.2).

$$x_{i,j} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j}), \tag{2.2}$$

where $i = 1, 2, \ldots, SN$, $j = 1, 2, \ldots, D$.

In the employed bee phase, with respect to each individual X_i, a candidate V_i is produced by adding the scaling difference of two population members to the base individual, i.e.

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}), \tag{2.3}$$

where $k \in \{1, 2, \ldots, SN\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes; k has to be different from i, and ϕ_{ij} is a random number in the range $[-1, 1]$. The selection operation is performed to select the better one from the old individual X_i and the candidate V_i.

After all employed bees finish their search, they will share the information with onlookers. Each onlooker chooses a solution depending on the probability value p_i of the corresponding solution as follows

$$p_i = fit_i \Big/ \sum_{j=1}^{SN} fit_j, \tag{2.4}$$