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Self Adaptive Artificial Bee Colony for Global Numerical Optimization

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Abstract

The ABC algorithm has been used in many practical cases and has demonstrated good convergence rate. It produces the new solution according to the stochastic variance process. In this process, the magnitudes of the perturbation are important since it can affect the new solution. In this paper, we propose a self adaptive artificial bee colony, called self adaptive ABC, for the global numerical optimization. A new self adaptive perturbation is introduced in the basic ABC algorithm, in order to improve the convergence rates. 23 benchmark functions are employed in verifying the performance of self adaptive ABC. Experimental results indicate our approach is effective and efficient. Compared with other algorithms, self adaptive ABC performs better than, or at least comparable to the basic ABC algorithm and other state-of-the-art approaches from literature when considering the quality of the solution obtained.

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Keywords*: artificial bee colony; self adaptive; global numerical optimization; exploitation;*

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1. Introduction

Optimization problems play an important role in both industrial application fields and the scientific research world. During the past decade, we have viewed different kinds of meta-heursitic algorithms advanced to handle optimization problems. Among them, Meta-heuristic based methods, such as simulated annealing (SA), genetic algorithm (GA), particle swarm optimization algorithm (PSO), artificial bee colony (ABC), and differential evolution [1-4], may be one of the most popular methods.

Particularly, artificial bee colony algorithm [5] is a population-based heuristic evolutionary algorithm inspired by the intelligent foraging behavior of the honeybee swarm. B. Akay and D. Karaboga [6] proposed a modify versions of the artificial bee colony. The modified artificial bee colony applied for efficiently solving real parameter optimization problem. The modified ABC algorithm employs a control parameter that determines how many parameters to be modified for the production of a neighboring solution. A scaling factor that tunes the step size adaptively was introduced. However, this field of study is still in its early days, a large number of future researches are necessary in order to develop the new version artificial bee colony algorithm for optimization problems.

Since ABC is a particular instance of EA, it is interesting to investigate how self adaptive can be applied to it. Until now, there is no paper to focus on self-adaptive in ABC has been reported. In our paper, the parameter control technique is based on the self adaptive of the magnitudes of the perturbation, associated with the evolutionary process. The main goal here produces a flexible ABC, in terms of control parameter. We propose a self adaptive ABC which the variant of control parameter is changed according to the iteration. The low value of control parameter allows the search to find the optimal search in small step. However, it makes the convergence slower. A high value of control parameter speed up the search but it reduces the exploitation capability of the perturbation process. Therefore, we use this method which can balance the exploration and the exploitation of ABC.

2. Self Adaptive ABC

Artificial Bee colony is an evolutionary algorithm first introduced by Karaboga in 2005. This algorithm simulates the foraging behavior of the bee colony. In this algorithm, the model of the ABC algorithm consists of three groups of bees: employed bees, onlooker bees, and scout bees. For each food source, there is only one employed bee. In other words, the number of bees is equal to the number of food sources. Employed bees are responsible for exploiting the nectar sources explored before, sharing their information with onlookers within the hive. After that, the onlookers will select one of the food sources within the neighborhood of the food source. An employed bee becomes a scout if the food source is abandoned, and then starts to search a new food source randomly [4].

In basic ABC, employed bees are responsible for exploiting the nectar sources explored before and giving information to the waiting bee in the hive about the quality of the food source sites which they are exploiting. Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. Scouts either randomly search the environment in order to find a new food source depending on an internal motivate or based on possible external clues. The ABC produces the new solution according to the stochastic variance process. In this process, the magnitudes of the perturbation are important since it can affect the new solution. In order to improve the convergence rates, a new self adaptive perturbation will be introduced in the basic ABC algorithm.

The self adaptive artificial bee colony algorithm is proposed based on the structure of basic ABC algorithm. By employing the self adaptive iteration according the relative maximum iterations, the employed bee and onlooker bee can be exploited. In the basic ABC, a random perturbation which avoids getting stuck at local minima is added to the current solution in order to produce the new solution. This random perturbation