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ORIGINAL ARTICLE

A novel comprehensive learning artificial bee colony optimizer for dynamic optimization biological problems

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Abstract There are many dynamic optimization problems in the real world, whose convergence and searching ability is cautiously desired, obviously different from static optimization cases. This requires an optimization algorithm adaptively seek the changing optima over dynamic environments, instead of only finding the global optimal solution in the static environment. This paper proposes a novel comprehensive learning artificial bee colony optimizer (CLABC) for optimization in dynamic environments problems, which employs a pool of optimal foraging strategies to balance the exploration and exploitation tradeoff. The main motive of CLABC is to enrich artificial bee foraging behaviors in the ABC model by combining Powell's pattern search method, life-cycle, and crossover-based social learning strategy. The proposed CLABC is a more bee-colony-realistic model that the bee can reproduce and die dynamically throughout the foraging process and population size varies as the algorithm runs. The experiments for evaluating CLABC are conducted on the dynamic moving peak benchmarks. Furthermore, the proposed algorithm is applied to a real-world application of dynamic RFID network optimization. Statistical analysis of all these cases highlights the significant performance improvement due to the beneficial combination and demonstrates the performance superiority of the proposed algorithm.

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1. Introduction

Many real-world optimization problems are subject to changing conditions over time, which can be identified as dynamic optimization problems (DOP) (Ha, 2016). In the DOP cases, changes may affect the object function, the problem instance,

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or constraints, causing that the optimal solutions of such dynamic problem being considered may change over time (Branke, 2001). From this point of view, most of the real world problems have dynamic characteristics, where one or more elements of the under-lying model for a given problem may change over time. This requires optimization algorithms to not only find the global optimal solution under a specific environment but also to continuously track the changing optima over different dynamic environments.

In recent years, investigating swarm intelligence (SI) algorithms for DOPs has attracted a growing interest (Clerc and Kennedy, 2002), due to that SIs are intrinsically inspired from natural or biological evolution, which is always subject to an ever-changing environment, and hence SIs, with proper enhancements, have a potential to be good optimizers for DOPs. Artificial bee colony algorithm (ABC) is one of the most popular members of the family of swarm intelligence, which simulates the social foraging behavior of a honeybee swarm (Karaboga and Basturk, 2007a,b). Due to its simple arithmetic and good robustness, the ABC algorithm has been widely used in solving many numerical optimizations (Karaboga and Basturk, 2007a,b; Biswas et al., 2014) and engineering optimization problems (Karaboga et al., 2007). However, facing up complex dynamic problems, similar to other EAs, ABC algorithm suffers from the following drawbacks (Karaboga and Basturk, 2007a,b): (1) the solution search equation of ABC works well in global exploration but is poor in the exploitation process. (2) With the dimension increasing, the information exchange of each individual is limited in a random dimension, resulting in a slow convergence rate.

Several ABC variants have been developed to improve its optimization performance. One significant improvement is the introduction of PSO-based search equation (Zhu and Kwong, 2010), which allows a powerful global search in the early stage by incorporating the information of the *gbest* solution into ABC. Similarly, Banharnsakun et al. (2011) presented a modified search equation for the onlooker bees. In their method, the new candidate solutions are more likely to be close to the current best solution. Gao et al. (2013a, b) proposed an efficient and robust ABC variant based on modified search equation and orthogonal learning strategies, which demonstrated its high effectiveness and efficiency. Another interesting approach by (Gao et al., 2013a,b) is using the Powell's method as a local search tool to enhance the exploitation of the algorithm. In this method, ABC good at exploration ensures the search is less likely to be trapped in local optima while it enjoys the merits of fine local search by Powell's method. Hybridization of ABC with other operators has also been studied widely. For example, Kang et al. (2011) used the Rosenbrock's rotational direction method to implement the exploitation phase and proposed the Rosenbrock ABC algorithm. Coelho and Alotto (2011) developed a novel alternative search equation in which a parameter is responsible for the balance between the Gaussian and the uniform distribution.

Inspired by previous works, this paper presents a novel optimization algorithm called comprehensive learning artificial bee colony optimizer (CLABC), which synergizes the idea of extended life-cycle evolving model with a pool of local searching strategies (Liu, 2013). The main motive of CLABC is to enrich artificial bee foraging behaviors in ABC model by combining population initialization based on orthogonal Latin squares approach, Powell's pattern search method, life-cycle, and crossover-based social learning strategy, which contributes in the following aspects:

(1) The orthogonal Latin squares approach can be used for artificial bee colony initialization to cover the search space with balanced dispersion and neat comparability.
(2) The crossover operation, which helps bees exchange more information after the early stage of the algorithm. In this case, the neighbor bees with higher fitness can be chosen to crossover, which effectively enhances the global search ability.
(3) Powell's local search method enables the bee exploit around promising area while avoiding search stagnation.
(4) Life-cycle, which results in a dynamic population. This means that, the bee can reproduce and quit adaptively throughout the foraging process and the population size varies as the algorithm runs in the dynamic landscapes.

This work adopted the moving peaks benchmark (MPB) to illustrative the inherent adaptive mechanism in the proposed algorithm of surviving in a changing environment. The proposed CLABC has been compared with its classical counterpart, the classical ABC algorithm (Karaboga, 2005) over dynamic benchmarks with respect to the statistical performance measures of solution quality and convergence speed.

The rest of the paper is organized as follows. In Section 2, the proposed comprehensive learning artificial bee colony (CLABC) algorithm is given. Section 3 presents the experimental studies of the proposed CLABC and the other algorithms with descriptions of the involved benchmark functions, experimental settings, and experimental results. Finally, Section 4 outlines the conclusion.

2. Comprehensive learning artificial bee colony algorithm

The main procedures of CLABC, including orthogonal Latin squares population initialization, Powell's pattern search, life-cycle, and crossover-based social learning strategies, are details as follows.

2.1. Population initialization based on orthogonal Latin squares approach

The orthogonal Latin squares approach can be used for population initialization to cover the search space with balanced dispersion and neat comparability. Suppose a population consisting of N individuals (or food sources)