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Cognitive behavior optimization algorithm for solving optimization problems

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Nature-based algorithms have become popular in recent fifteen years and have been widely applied in various fields of science and engineering, such as robot control, cluster analysis, controller design, dynamic optimization and image processing. In this paper, a new swarm intelligence algorithm named cognitive behavior optimization algorithm (COA) is introduced, which is used to solve the real-valued numerical optimization problems. COA has a detailed cognitive behavior model. In the model of COA, the common phenomenon of foraging food source for population is summarized as the process of exploration–communication–adjustment. Matching with the process, three main behaviors and two groups in COA are introduced. Firstly, cognitive population uses Gaussian and Levy flight random walk methods to explore the search space in the rough search behavior. Secondly, the improved crossover and mutation operator are used in the information exchange and share behavior between the two groups: cognitive population and memory population. Finally, the intelligent adjustment behavior is used to enhance the exploitation of the population for cognitive population. To verify the performance of our approach, both the classic and modern complex benchmark functions considered as the unconstrained functions are employed. Meanwhile, some well-known engineering design optimization problems are used as the constrained functions in the literature. The experimental results, considering both convergence and accuracy simultaneously, demonstrate the effectiveness of COA for global numerical and engineering optimization problems.

1. Introduction

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Global optimization which can be defined as the process of searching for the global optimum in an optimization problem is a hotspot in applied mathematics [1,2]. However, the classical methods are difficult to find the global optimum for the problems as the dimension size of search space increased [3]. How to solve such complex problems becomes a key issue for global optimization.

The behaviors observed in creatures such as reproduction, foraging food, defending oneself, communication and information exchange are very promising and complex. It is because of the behaviors that the problem-solving skills of super organisms are highly developed. As a result, the nature-based algorithms (NAs) come next, enabling non-linear and non-differentiable optimization problems to be solved effectively [4–6]. In addition, such optimization algorithms have been applied to various fields such as dynamic optimization [7], inverse geophysical problems [8], twin-screw configuration problem [9], IIR filter design [10], image processing [11], distribution transformer design problem [12], mechanical design optimization problems [13], sensor deployment problems [14], task scheduling [15], data mining applications [16], chemical processes [17] and many other engineering problems.

Generally speaking, NAs can be divided into three main classes: swarm intelligence algorithms (SIAs), evolutionary algorithms (EAs), and physical phenomenon algorithms (PPAs) [18]. EAs are inspired by the genetic or evolution behaviors of creatures. Genetic algorithm (GA) [19] and differential evolution (DE) [20] algorithm can be described as representative algorithms in EAs. Firstly, the EAs evolve an initial random population for optimization. Then the combination and mutation strategies are used to generate the new population. Finally, greedy selection method is usually used to select a better solution between the new population and original population. In contrast, DE has a relative simpler structure and is more efficient for optimization. Many researchers have proposed a number of advanced variants of DE to improve its optimization performance, such as self-adapting control parameters in differential evolution (jDE) [21], the strategy adaption self-adaptive differential evolution algorithm (SADE) [22], the parameter adaptive

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differential evolution algorithm (JADE) [5], the DE based on covariance matrix learning and bimodal distribution parameter setting (CoBiDE) [23], and differential search algorithm (DSA) [24].

The second main class of NAs is swarm intelligence algorithms. The SIAs as well as EAs are usually inspired by the behaviors of intelligent nature creatures. But most of SIAs use genetic rules only, which are different from the EAs. On the other hand, SIAs always take fully advantages of each solution in search space to provide better solutions to the problem. Some of the popular SIAs are particle swarm optimization (PSO) inspired by the social behavior of bird flocking [25], symbiosis organisms search (SOS) that simulates the interactive behavior seen among organisms in nature [26], artificial bee colony (ABC) that mimics the honey-bees food searching behavior [27], cuckoo search (CS) inspired by parasitic bio-interactions in living creatures [28], animal migration optimization (AMO) algorithm that gets the idea from the behavior of the animal migration [29], gray wolf optimizer (GWO) inspired by hunting mechanism of gray wolves [30].

Physical phenomenon algorithms are the third class of nature-based algorithms. Different from the other two nature-inspired algorithms EAs and SIAs, the PPAs are mostly inspired by physical rules in the nature. There are some popular PPAs such as central force optimization (CFO) [31], big-bang big-crunch (BBBC) [32], charged system search (CSS) [33] and gravitational search algorithm (GSA) algorithm [34]. These algorithms in the three classes of the nature-based algorithms have been used to solve complex computational optimization problems. However, fast convergence along with accuracy is still a challenge need to be solved for the NAs.

As a result, we develop a new nature-inspired algorithm named cognitive behavior optimization (COA) in this paper. Firstly, according to analyzing the classic behavior model of ABC and DE, the common phenomenon of finding food source is summarized as the process of exploration–communication–adjustment. Secondly, combining with social behaviors of human, a relative detailed cognitive behavioral model of swarm intelligence is proposed. Finally, based on the developed model, which contains three main behaviors: rough search, information exchange and share, and intelligent adjustment, COA is proposed which satisfy both fast convergence and accuracy for the selected global optimization problems in this paper.

Preliminary studies show that the NAs such as ABC, DE, GSA, CoBiDE, DSA, GWO, AMO, CMA-ES [35] and other well-known optimization algorithms are very promising and could be used as the compared algorithms for evaluating COA's performance in solving global optimization problems.

The rest of this paper is organized as follows. Section 2 reviews the two typical behavior models of NAs. Then the COA is presented in Section 3. The experiment sets and experimental analysis for different tests are presented in Section 4. Finally, Section 5 concludes the work and suggests some directions for the future.

2. Typical behavior model in NAs

Many researchers are looking forward to a perfect way to model the intelligence of nature creatures' behaviors so as to solve real world complex problems. Herein DE is a kind of evolutionary algorithm which has the ability of information exchange. Besides, ABC is typical bionic algorithm based on the self-organized model and swarm intelligence of bee colony in nature.

Based on optimization technique that models the foraging behavior of the honey bees in the nature, Karaboga proposed the ABC algorithm [4]. The model of artificial bees in ABC contains three groups namely employed bees, onlookers and scouts. It can be concluded from the behavior model of ABC algorithm that based on the division of the swarm. The model is composed of three kinds of behavior for three kinds of bees: preliminary search, accurate search and abandoning a food source. ABC algorithm finds the global optimal value through various individuals of local optimization behavior. Compared with other nature-based algorithms, the detailed behaviors of foraging food and cooperation in ABC are emphasized so as to make it have faster convergence rate. However, it is simplified by using selected individuals' information as the whole population's information to exchange. It may result in loss of useful information. Meanwhile, the primary search stage for employed bees and the accuracy search stage for onlooker bees have the same search equation. It unfits the demand of different search behavior in ABC model.

On the other hand, DE, proposed by Storn and Price [20], is a simple, yet powerful, evolutionary algorithm with the generate-and-test feature for global optimization. It can be summarized that the behavior model of DE is mainly composed of the mutation and crossover operation, which is a process of information exchange. In DE, each individual in the population is called a target vector. DE produces a mutant vector by making use of the mutation operator, which perturbs a target vector using the difference vector of other individuals in the population. Then, the crossover operator is applied to the target vector and the mutant vector to generate a trial vector. Finally, the trial vector competes with its target vector for survival according to their objective function values. In a word, the function of information exchange in DE, which is explained by the mutant and crossover operator, is emphasized and it plays a very important role in the DE model.

3. Cognitive behavior optimization algorithm (COA)

In this section, we propose a novel swarm intelligence algorithm named cognitive behavior optimization algorithm (COA) inspired by ABC and DE. Based on the behavior model of ABC and DE, cognitive behavior model is proposed and it contains three main behaviors: rough search, information exchange and share and intelligent adjustment.

3.1. Cognitive behavior model of COA

As we have known, the exploration refers to the ability to investigate the various unknown regions in the solution space to discover the global optimum, while the exploitation refers to the ability to apply the knowledge of the previous good solutions to find better solutions [36]. From the perspective of balancing the performance of exploration and exploitation, based on the biological behavior model of ABC and DE, the common process of finding food source for social insects is summarized as exploration–communication–adjustment. Meanwhile, combining with social behaviors of human, the cognitive behavior model is generalized as Fig. 1 shown. The model contains three main behaviors: rough search, information exchange and share, and intelligent adjustment, which compose the main parts of COA. As ABC designed, the population of COA is also divided into two important groups namely cognitive population (*Cpop*) and memory population (*Mpop*) in this model, which play different roles in the COA algorithm. The abstract behavior model of foraging food source is introduced as follows:

1) Rough search. For cognitive population *Cpop*, the individuals use the Levy flight and Gaussian random walk method to explore the search space randomly (RS and RS_1 in Fig. 1). Gaussian random walk method used in the optimization algorithm has a promising performance in finding global minima, while Levy flight converges faster than that of Gaussian random walk. As a result, the two random walk methods are used in this search behavior.

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