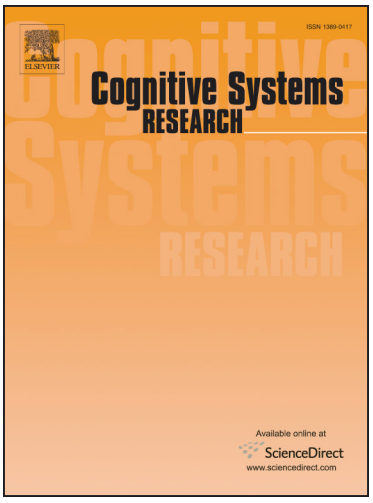

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A Bare Bones Bacterial Foraging Optimization Algorithm

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Abstract: Bacterial foraging optimization (BFO), based on the social foraging behaviors of bacteria, is a new intelligent optimizer. It has been widely accepted as an optimization algorithm of current interest for a variety of fields. However, compared with other optimizers, the BFO possesses a poor convergence performance over complex optimization problems. To improve the optimization capability of the BFO, in this paper a bare bones bacterial foraging optimization (BBBFO) algorithm is developed. First, a chemotactic strategy based on Gaussian distribution is incorporated into this method through making use of both the historical information of individual and the share information of group. Then the swarm diversity is introduced in the reproduction strategy to promote the exploration ability of the algorithm. The performance of BBBFO is verified on various benchmark functions, the comparative results reveal that the proposed approach is more superior to its counterparts.

Keywords: Intelligent computing; Global optimization; Particle swarm optimization; Metaheuristic; Bare bones; Chemotactic; Reproduction

1. Introduction

Over the past decades, many researchers seek different approaches to handle various real-world engineering optimization problems, the majority of them are numerical methods that usually adopt simple and ideal mathematical models. These numerical methods usually require some gradient information to search better solutions revolving around a special point in a local region. However, they are very sensitive to the initial point and the finial solutions are not always the best. As many real-world optimization problems are involving complex nonlinear functions and constraints as well as a large number of decision variables, which enable these traditional methods helpless in solving these optimization problems.

Recently, a wide range of nature-inspired metaheuristics have been developed and applied to different practice problems with varying degrees of success [1-5], Compared with the numerical methods, these metaheuristics show some distinct advantages. First, they do not need to meet the requirement of derivative in the variable space; second, they are insensitive to the initial points and are not easy to trap into local optima. There are the three most popular optimization algorithms: genetic algorithm (GA), particle swarm optimization (PSO) and ant colony optimization (ACO). GA, as one of the most representative search algorithm, is motivated from the survival of the fittest of Darwinism theory, it well adopts three operators including mutation, crossover and selection that make GA easy to avoid the local optimum and to search high-quality solutions. PSO, inspired from the behaviors of bird flocking in the sky, is a swarm-based metaheuristic, this method updates the solution of each individual by the globally best solution and its locally best solution, resulting in a fast convergence rate. ACO, based on the collective behaviors of ants, searches the shortest path from nest to food sources by pheromone trails. With their emergency, many other metaheuristic algorithms such as cuckoo search [6], social spider optimization (SSO) [7], invasive weed optimization (IWO) [8], electromagnetism-like mechanism (EM) algorithm [9], artificial bee colony (ABC) [10], gravitational search algorithm (GSA) [11], bacterial foraging optimization (BFO) [12], backtracking search optimization (BSA) [13], differential evolution (DE) [14], fireworks algorithm [15], bat algorithm (BA) [16], biogeography-based optimization (BBO) [17], atom search optimization [18], and so on, are proposed and have received much attention in last years [19-23].

BFO, as a new methheuristic algorithm, mimics the bacterial foraging behaviors, its key success generally depends on its heuristic components. The chemotaxis, reproduction, and elimination-dispersal have all evident stochastic characteristics that encourage BFO to search the global optimum more efficiently than the traditional numerical methods. Since its emergence, the application of BFO can be seen in a variety of fields, such as image processing [24,25], industry control [26,27], vehicle routing [28], and machine learning [29,30]. The increasing interest for BFO has revealed that it is a promising, swarm-based optimization algorithm. However, the basic BFO still has some limits in tackling nonlinear, high-dimensional and multimodal functions, which can result in a delay in approximating the global solution and a poor convergence rate.

To improve the global convergence of BFO and make it more suitable for handling the practical optimization problems, a bare bones bacterial foraging optimization (BBBFO) is proposed. First, a chemotactic