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The performance comparison of a new version of artificial raindrop algorithm on global numerical optimization

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ABSTRACT

Very recently, a new metaheuristic called artificial raindrop algorithm (ARA) was proposed. This search algorithm inspired from the phenomenon of natural rainfall, including the generation of raindrop, the descent of raindrop, the collision of raindrop, the flowing of raindrop and the updating of vapor. However, the original ARA only focused on the changing process of a raindrop. In this paper, we present an extension of ARA (ARA_E) to more raindrops without any major conceptual change to its structure. In the proposed ARA_E, all vapors are dynamically divided into several small-sized groups according to the relative distance of vapors in each generation. Each vapor has an associated weight proportion to the fitness value. The raindrop in the corresponding group is then generated based on weighted mean of the current vapors positions. But beyond that, some operators of ARA are further modified to enhance its exploration/exploitation capabilities. In order to thoroughly evaluate the performance of ARA_E, a comprehensive comparative study has been carried on the CEC2005 contest benchmark functions. The obtained results indicate that ARA_E has overall better performance than ARA, and is very competitive with respect to other twenty-four state-of-the-art original intelligent optimization algorithms and twenty-four improved metaheuristic algorithms. Finally, the proposed ARA_E is also applied to artificial neural networks and the promising results on the nonlinear function approximation show the applicability of ARA_E for problem solving.

1. Introduction

Global numerical optimization is very universal in our real life, and has delivered many applications in the areas of scientific and engineering. For instance, classification of unbalanced data [1], data clustering [2], sensor scheduling in wireless sensor networks [3], etc. According to the No Free Lunch theorem [4], however, there is no explicit approach to be optimized for all optimization problems. As a result, how to design efficient optimization techniques to solve them has become a hot and challenging research topic whether in the mathematical programming or evolutionary computation area.

Over the past decade, various optimization techniques have been proposed to deal with diverse global optimization problems. They can be widely divided into two categories: gradient-based approaches and gradient-free approaches [5]. For relative simple and ideal models, gradient-based methods can offer some useful descent strategies to locate a global minimum of the objective function. However, they always face great difficulties and challenges in many complex real world problems since the gradient information is usually unreliable or unavailable.

The potential computational limitations of existing gradient-based approaches have forced more and more researchers to rely on metaheuristic algorithms for highly complex global optimization problems characterized as nonconvex, nondifferentiable or discontinuous, etc. [6]. Compared with the gradient-based approaches, metaheuristic algorithms have an advantage that they do not need any gradient information, which can be very suitable for solving complex optimization problems. It is generally known that the metaheuristic algorithms usually combine some rules and randomness to simulate natural phenomena [7]. These natural phenomena could be broadly classified into three aspects as follows.

- *Biological evolutionary process*: Evolutionary algorithms (EAs) are a subset of evolutionary computation, and they are usually designed to simulate mechanisms inspired by biological evolution process, such as recombination, mutation, and selection [8]. Examples of evolutionary algorithms include: Genetic algorithm (GA) [8], Evolutionary Strategies (ES) [9], Evolutionary Programming (EP) [10], Differential Evolution (DE) [11], Backtracking

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Search Algorithm (BSA) [12], Biogeography-Based Optimization (BBO) [13], Differential Search Algorithm (DSA) [14], Symbiotic Organisms Search (SOS) [15], etc.

● *Swarm behavior process*: Swarm intelligence algorithms (SIA_S) are inspired by all kind of behaviors which collective animals have driven. These behaviors usually involve many aspects: searching behavior, mating behavior, foraging behavior, etc. In recent years, SIA, as a relatively new branch of metaheuristic algorithms, has been rapidly developed. At the same time, more and more SIAs based on various behaviors of animals have been proposed by researchers. Representatively, Particle Swarm Optimization (PSO) [16], Artificial Bee Colony (ABC) [17], Group Search Optimizer (GSO) [18], Seeker Optimization Algorithm (SOA) [19], Cuckoo Search (CS) [20], Bird Mating Optimizer (BMO) [21], Social Spider Optimization (SSO) [22], Competition Over Resources (COR) [23], etc.

● *Other nature-based optimization process*: In addition to the above two kinds of metaheuristic algorithms, there exists many other metaheuristic optimization algorithms. In comparison with EAs and SIAs, these algorithms are not straightforwardly inspired from biological evolutionary process or swarm behavior process. Instead, they are usually based on alternative processes or concepts [24], including physical phenomena or rules, chemical reaction process, social activities process, etc. For instance, Simulated Annealing (SA) inspired by the process of annealing in metallic materials [25], Gravitational Search Algorithm (GSA) based on the law of gravity and mass interactions [26], Water Cycle Algorithm (WCA) inspired from the observation of water cycle process and how rivers and streams flow to the sea in real world [27], Mine Blast Algorithm (MBA) derived from the explosion of mine bombs in real world [28], Stochastic Fractal Search (SFS) inspired by the natural phenomenon of growth [29], States of Matter Search (SMS) which draws inspiration from the simulation of the states of matter phenomenon [30], interior search algorithm (ISA) which is inspired by interior design and decoration [31], Electromagnetism Like Optimization (ELO) which mimics the attraction repulsion mechanism among charges to evolve the members of a population [32], artificial raindrop algorithm (ARA) which approximately simulates the changing process of a raindrop [33], etc.

In this paper, we concentrate on ARA which is a newly developed meta-heuristic method inspired from the phenomenon of natural rainfall and has already been applied to identify the unknown parameters of chaotic system [34]. The main parts of ARA include the generation of raindrop, the descent of raindrop, the collision of raindrop, the flowing of raindrop and the updating of vapor. However, the original ARA only focused on the changing process of a raindrop. Besides that, similar to other metaheuristic algorithms, ARA also faces up to the premature convergence. The above-mentioned two reasons have motivated researchers to develop an extension of artificial raindrop algorithm (ARA_E) to more raindrops without any major conceptual change to its structure, which seems to more closely simulate the phenomenon of natural rainfall. For purpose of achieving better performances on global optimization problems, some operators are further modified for keeping a good balance in exploration and exploitation of ARA.

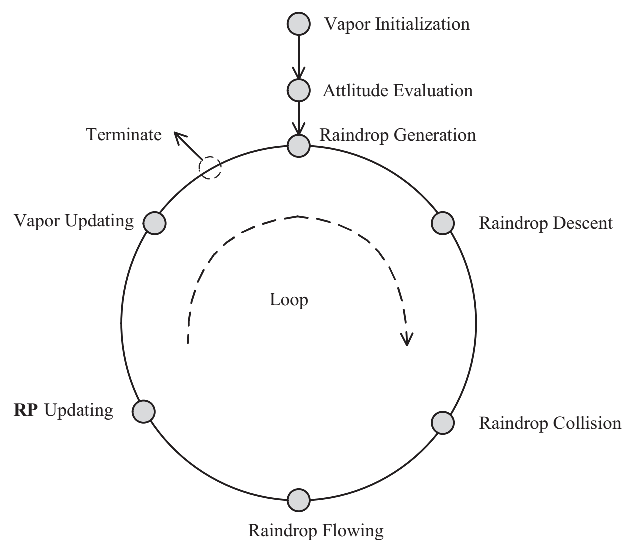

Fig. 2. The algorithm framework of ARA.

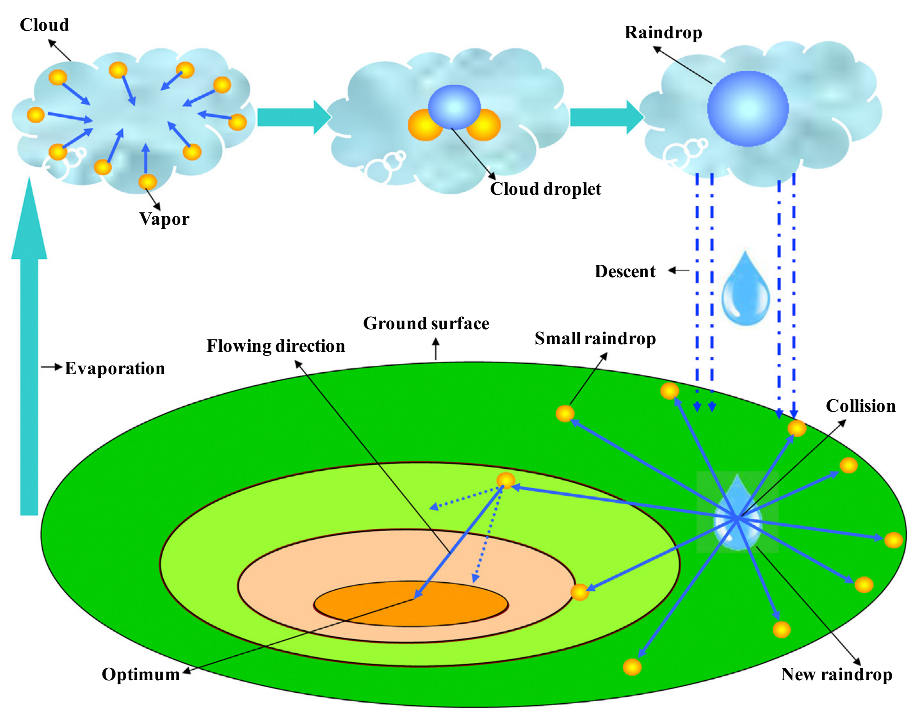

Fig. 1. The scene graph of ARA [34].