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A novel bat algorithm with habitat selection and Doppler effect in echoes for optimization

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ABSTRACT

A novel bat algorithm (NBA) is proposed for optimization in this paper, which focuses on further mimicking the bats' behaviors and improving bat algorithm (BA) in view of biology. The proposed algorithm incorporates the bats' habitat selection and their self-adaptive compensation for Doppler effect in echoes into the basic BA. The bats' habitat selection is modeled as the selection between their quantum behaviors and mechanical behaviors. Having considered the bats' self-adaptive compensation for Doppler effect in echoes and the individual's difference in the compensation rate, the echolocation characteristics of bats can be further simulated in NBA. A self-adaptive local search strategy is also embedded into NBA. Simulations and comparisons based on twenty benchmark problems and four real-world engineering designs demonstrate the effectiveness, efficiency and stability of NBA compared with the basic BA and some well-known algorithms, and suggest that to improve algorithm based on biological basis should be very efficient. Further research topics are also discussed.

1. Introduction

Metaheuristic algorithms are stochastic algorithms with randomization and local search. They can provide certain tradeoff of randomization and local search. The metaheuristic algorithms mainly consist of two major components, which are selection of the fittest and randomization. The selection of the fittest ensures the solutions converge to the optimality, while randomization can provide a useful approach to move away from local search to the search on the global scale and increase the diversity of the solutions to avoid the solutions being trapped at local optima (Yang, 2010a). With their merits of obtaining acceptable solutions in a reasonably practical time and being tolerant of non-convex and non-differentiable, metaheuristic algorithms have attracted great research interest as an alternative to the traditional optimization methods (Gandomi, Yang, Talatahari, & Alavi, 2013a; Yang, Cui, Xiao, Gandomi, & Karamanoglu, 2013).

During the recent years, more and more metaheuristic algorithms have been proposed. To some extent, the diverse range of these algorithms may be classified as nature-inspired algorithms. Most metaheuristic algorithms have been developed based on some abstraction of nature, including the animals, plants, nature phenomena and laws, etc. For example, Genetic Algorithm (GA) (Bernardino, Barbosa, & Lemonge, 2007) is an abstraction of biological evolution based on Darwin's theory of natural selection. The quantum-inspired GA is based on the concepts of qubits and principles of quantum mechanics (Dey, Bhattacharyya, & Maulik, 2014). Differential Evolution (DE) (Das & Suganthan, 2011) is proposed by generalizing the biological evolution and nature selection. Cultural Algorithm (CA) (Reynolds & Ali, 2008), Harmony Search (HS) (Manjarres et al., 2013), Charged System Search (CSS) (Kaveh & Talatahari, 2010), Water Cycle Algorithm (WCA) (Eskandar, Sadollah, Bahreininejad, & Hamdi, 2012), Great Deluge Algorithm (GDA) (Baykasoglu, 2012) and Mine Blast Algorithm (MBA) (Sadollah, Bahreininejada, Eskandarb, & Hamdia, 2013) are the simulation of the natural phenomena and natural laws. Particle Swarm Optimization (PSO) (Jordehi & Jasni, 2013), Artificial Bee Colony (ABC) (Brajevic, Tuba, & Subotic, 2011), Firefly Algorithm (FA) (Gandomi, Yang, & Alavi, 2011), Bacterial Foraging Optimization (BFO) (Mezura & Hernandez, 2009), Cuckoo Search (CS) (Gandomi, Yang, & Alavi, 2013b), Flower Pollination Algorithm (FPA) (Yang, 2012), Krill Herd Algorithm (KHA) (Gandomi, Talatahari, Tadbiri, & Alavi, 2013c) and Social Spider Optimization (SSO) (Cuevas & Cienfuegos, 2014) are the

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simplification of the organisms in response to specific biology and environmental processes.

The essence of developing a nature-inspired algorithm is how to mimic the best features in nature and design effective mathematical operators to formulate those features. In general, the efficiency and performance of a nature-inspired algorithm depend on the balance between exploration and exploitation. Wherein, the exploration means to explore the search place globally, while the exploitation intends to search locally around the current best solutions. The good balance between these two components is in demand to achieve the global optimality (Yang, 2014). So far, how to extract the best merits of nature and design an efficient algorithm is still in progress.

The Bat Algorithm (BA), proposed by Yang (2010b), is such an attempt to further learn from the nature. It is inspired by the echolocation characteristics of bats with varying pulse rates of emission and loudness. It has been applied to a wide range of optimization applications (Yang, 2013), including image processing (Du & Liu, 2012), classifications (Mishra, Shaw, & Mishra, 2012), scheduling (Musikapun & Pongcharoen, 2012), electricity market (Niknam, Sharifinia, & Abaraghooee, 2013), Energy systems (Sambariya & Prasad, 2014) and various other problems. Experiments have shown its promising efficiency for global optimization. However, BA may also trap into local optima, and its convergence performance is still need to be further improved (Yang, 2014). Intuitively speaking, the imperfection of BA mainly depends on the two reasons. One is that BA is just the simplification of the social behavior of bats. The original algorithm does not reflect the self-adaptive ability of the bats with respect to the environment. Studies have shown that bats may discriminate targets by other insects' interference, such as the variations of the Doppler effect induced by the wing-flutter rates of the target insects (Altringham, 1996). The other is that the formulae of BA do not strike a best balance between exploration and exploitation.

Many studies focus on solving the imperfection of BA. For a systematic summary of these diverse variants of BA, there mainly exist two categories to improve BA.

The first category emphasizes the variants of BA mechanism itself, including the mathematics, parameter-tuning and auxiliary search strategies, etc. For example, Xie, Zhou, and Chen (2013) proposed an improved BA based on differential operator and Levy flights trajectory. Gandomi and Yang (2014) and Jordehi (2015) both introduced chaos into BA so as to increase its global search capability. Li and Zhou (2014) proposed a variant based on complex-valued encoding where the real part and the imaginary part will be updated separately. Bahman and Rasoul (2014) introduced four BA updating strategies of velocity to realize a new self-adaptive learning approach. Jaddi, Abdullah, and Hamdan (2015) proposed two new topologies for cooperation between subpopulations to maintain the diversity of bats in the populations.

The second one hybridizes other optimization techniques into BA. For example, Khan and Sahai (2012) incorporated a combination of PSO, HS and simulated annealing (SA) into BA using a certain combination of parameters. Wang and Guo (2013) hybridized HS as a mutation operator into BA. He, Ding, and Yang (2014) introduced SA and Gaussian perturbations into BA. Sadeghi, Mousavi, Niaki, and Sadeghi (2014) used Particle Swarm Optimization as a local searcher and incorporated it into BA. Yilmaz and Kucuksille (2015) improved BA by using Invasive Weed Optimization to enhance the local search capability of BA.

All these variants have proved to be very efficient on their specific cases. As we know, there is no universally better algorithms exist. Thus, how to further enhance the performance of BA is still on.

In this paper, a novel bat algorithm, namely NBA, is proposed to further mimic the bats' characteristics. This work falls into the first category with the focus on optimizing BA's biological basis. What the significant difference between the proposed algorithm and other variants is that the proposed algorithm enhances the performance of BA by further incorporating the bats' habitat selection and their self-adaptive compensation for Doppler effect in echoes into the basic BA. This proposed method focuses on further mimicking the bats' behaviors and improving BA in view of biology, while the aforementioned works mostly emphasize the variants of BA's mathematics. Different from the variants of BA's mathematics, Liu, Huang, Wang, and Chen (2012) mimicked the bats' behaviors by introducing the Doppler effect into BA. In that work, the new frequency equation with the Doppler effect was proposed. However, it did not consider the bats' self-adaptive compensation for Doppler effect in echoes, which is the fact that bats may face. This deficiency is totally solved in this work. Most importantly, the proposed algorithm creatively introduces the bats' habitat selection into the basic BA, creates a new search optimizer and proposes a self-adaptive local search strategy. Simulations and comparisons are conducted to verify the superiority of NBA over the basic BA and other well-known algorithms for solving many optimization problems and real-world engineering designs.

The rest of the paper is organized as follows. Section 2 briefly outlines the related works in this paper. The details about the NBA are provided in Section 3. Section 4 presents the simulations and comparative study. Several remarks and conclusions are given in Section 5.

2. Related works

2.1. Bat Algorithm

The BA was inspired by the echolocation behavior of bats. Based on some approximations and idealization (Yang, 2010b), the basic procedure of BA can be illustrated as follows.

Step 1: Initialization. The virtual N bats (solutions) described by the positions x_i and velocities v_i in a D-dimensional search space are randomly distributed in the feasible search space. The velocities of N bats may be set to zero (or other small value).

$$x_{i,j} = x_{jMin} + (x_{jMax} - x_{jMin}) * rand(0,1), \tag{1}$$

where $i \epsilon [1,\ldots,N]$, $j \epsilon [1,\ldots,D]$, here $rand(0,1)$ is a random vector drawn from a uniform distribution. Here the values of the x_{min} and x_{max} depend on the domain size of the problem of interest.

Step 2: Generate new solutions.

$$f_i = f_{min} + (f_{max} - f_{min}) \times \beta, \tag{2}$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*) \times f_i, \tag{3}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}, \tag{4}$$

where $\beta \in [0,1]$ is a random vector drawn from a uniform distribution. Here, x_* is the current global best solution. The values of the frequency f_{min} and f_{max} depend on the domain size of the problem of interest.

Step 3: Local search. If a random number is bigger enough than the rate of pulse emission r, then the local search is invoked. A new solution is generated around the current best solution.

$$\text{If } (rand(0,1) > r_i) \tag{5}$$

$$x_{new} = x_{old} + \varepsilon * A^t_{mean} \tag{6}$$