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Stud krill herd algorithm

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ABSTRACT

Recently, Gandomi and Alavi proposed a meta-heuristic optimization algorithm, called Krill Herd (KH), for global optimization [Gandomi AH, Alavi AH. Krill Herd: A New Bio-Inspired Optimization Algorithm. Communications in Nonlinear Science and Numerical Simulation, 17(12), 4831–4845, 2012.]. This paper represents an optimization method to global optimization using a novel variant of KH. This method is called the Stud Krill Herd (SKH). Similar to genetic reproduction mechanisms added to KH method, an updated genetic reproduction schemes, called stud selection and crossover (SSC) operator, is introduced into the KH during the krill updating process dealing with numerical optimization problems. The introduced SSC operator is originated from original Stud genetic algorithm. In SSC operator, the best krill, the Stud, provides its optimal information for all the other individuals in the population using general genetic operators instead of stochastic selection. This approach appears to be well capable of solving various functions. Several problems are used to test the SKH method. In addition, the influence of the different crossover types on convergence and performance is carefully studied. Experimental results indicate an instructive addition to the portfolio of swarm intelligence techniques.

1. Introduction

In management, computing science, and artificial intelligence area, in essence, optimization is a selection of a vector that can make an optimal solution for the objective function [1]. With the development of the science and technology, practical engineering optimization problems are becoming more and more complex. Usually, intelligent stochastic methods have been applied to deal with these complex problems. A familiar way for categorizing techniques is to explore the attribute of the methods, and these techniques can be primarily divided into two parts canonical methods, and stochastic methods. Canonical methods always follow the same optimization path. We can repeat the process of optimization and get the same final solutions if the optimization begins with the same initial condition [1]. Contrary to the canonical methods, for modern stochastic methods, their behavior has some randomness at all times, and they have no rigorous step to follow. The process of optimization cannot be repeatable, and they would always follow new different optimization path. Eventually, this randomness leads to different solutions regardless of the initial value. However, in most cases, both of them can find the optimal solutions though they have slight difference. Recently, meta-heuristic search approaches perform effectively in dealing with nonlinear problems. In all meta-heuristic search techniques, much effort has been devoted to make an appropriate trade-off between the exploration and exploitation in searching for the optimal solutions [2].

A great many robust meta-heuristic search approaches that are inspired by nature have been designed to solve complicated engineering problems [3], like parameter estimation [4], system identification [5], education [6], and engineering optimization [7,8]. A vast majority of meta-heuristic approaches can always find optimal or sub-optimal solutions from a population of solutions. In the last two decades, many famous optimization techniques have been developed, like artificial bee colony (ABC) [9], genetic programming (GP) [10], ant colony optimization (ACO) [11,12], differential evolution (DE) [13,14], evolutionary strategy (ES) [15], bat algorithm (BA) [16,17], charged system search (CSS) [18,19], biogeography-based optimization (BBO) [20], harmony search (HS) [21,22], cuckoo search (CS) [23,24], particle swarm optimization (PSO) [25–27], big bang-big crunch algorithm [28–31], population-based incremental learning (PBIL) [32] and

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more recently, the KH algorithm [33] that is based on the simulation of the swarm behavior of krill.

In 2012, a swarm intelligence approach, namely KH method [33], was firstly presented for the global optimization problem. The KH methodology draws its analogy from the herding behavior of krill individuals in nature. The objective function used in KH method is mostly decided by the least distances of the position of the food and the biggest swarm density. The position for each krill mostly covers three parts.

KH is an effective method in exploitation. However, on occasion, it may not escape some local best solutions in multimodal fitness landscape so that it cannot search globally well [3]. For regular KH approach, the search relies fully on randomness; therefore, it cannot always converge rapidly.

In standard GA (genetic algorithm) [34,35], three genetic operators (selection, crossover and mutation) repeat until a termination condition is satisfied. To improve the performance of GA, a variety of GAs has been developed. One of the well-famous methods is Stud GA (SGA) [36]. In SGA, instead of stochastic selection, the best individual, the Stud, provides its useful information for all the other individuals in the population by GA operators [36].

In this paper, an effective SKH method combining KH with SGA is proposed. The aim of SKH is to accelerate convergence speed. In the first stage of SKH, we utilize basic KH to choose an optimal promising solution set. Subsequently, for more accurate modeling of the krill behavior, inspired by SGA, an updated selection and crossover operation, called stud selection and crossover (SSC) operator, is added to the approach. The SSC operator is applied to fine-tune the chosen promising solution in order to enhance its reliability and robustness for global optimization. The added SSC operator updated the krill's position according to the roulette wheel selection. The crossover operation in SSC operator can help to avoid premature convergence in the early run phase, and refine the final solutions in the later. The proposed SKH method is verified on 22 benchmarks. Experimental results indicate that SKH performs more efficiently and robust than the KH, and other 11 optimization methods.

The mainframe of this paper is provided below. Section 2 and Section 3 describe the KH and SGA methods in brief, respectively. Our SKH approach is presented in Section 4. The superiority of the SKH method is verified by 22 benchmarks in Section 5. Finally, Section 6 summarizes all the work in the present work.

2. KH algorithm

KH [33] is a new generic stochastic optimization approach for the global optimization problem. It is inspired by the krill swarms when hunting for the food and communicating with each other. The KH approach repeats the implementation of the three movements and follows search directions that enhance the objective function value. The time-relied position is mostly determined by three movements

i. foraging action;
ii. movement influenced by other krill;
iii. physical diffusion.

Regular KH approach adopted the Lagrangian model [33] as shown in the following expression:

$$\frac{dX_i}{dt} = F_i + N_i + D_i \tag{1}$$

where F_i, N_i, and D_i denote the foraging motion, the motion influenced by other krill, and the physical diffusion of the krill i, respectively.

The first motion F_i covered two parts: the current food location and the information about the previous location. For the krill i, we formulated this motion below:

$$F_i = V_f \beta_i + \omega_f F_i^{old} \tag{2}$$

where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{3}$$

and V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in (0,1) F_i^{old} is the last foraging motion.

The direction led by the second movement N_i, α_i, is estimated by the three effects: target effect, local effect, and repulsive effect. For a krill i, it can be formulated below:

$$N_i^{new} = N^{max} \alpha_i + \omega_n N_i^{old} \tag{4}$$

and N^{max} is the maximum induced speed, ω_n is the inertia weight of the second motion in (0,1) N_i^{old} is the last motion influenced by other krill.

For the ith krill, as a matter of fact, the physical diffusion is a random process. This motion includes two components: a maximum diffusion speed and an oriented vector. The expression of physical diffusion can be given below

$$D_i = D^{max} \delta \tag{5}$$

where D^{max} is the maximum diffusion speed, and δ is the oriented vector whose values are random numbers between -1 and 1.

According to the three above-analyzed actions, the time-relied position from time t to $t+\Delta t$ can be formulated by the following equation:

$$X_i(t+\Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \tag{6}$$

Most importantly, note that Δt is an important parameter and should be regulated in terms of the special real-life problem. The reason is that, to some extent, this parameter can be treated as a scale factor of the speed and features the variations of the global best attraction, and its value is of vital importance in determining the speed of the convergence and how the KH works. More details about regular KH approach and the three main moves can be referred as [3,33].

3. Genetic algorithm and SGA

SGA is based on the simple genetic algorithm, therefore firstly a brief description of GA is provided in this section.

3.1. Genetic algorithm

Genetic algorithm (GA) is a canonical stochastic meta-heuristic search method for the global optimization in a large search space. The genetic information is encoded as genome that is implemented in an uncommon way that permits asexual reproduction that leads to the offspring that are genetically the same with the parent. While sexual reproduction can exchange and re-order chromosomes, giving birth to offspring which include a hybridization of genetic information from all parents. This operation is frequently called crossover because the chromosomes crossover when swapping genetic information. To evade premature convergence, mutation is applied to increase the diversity of the population. A general GA procedure has the following moves: randomly initializing a population of candidate solutions, generating new offspring by genetic operators. The fitness of the newly generated solutions is approximately calculated and well-fitted selection scheme is then utilized to decide which solutions will be held into the next generation. This process is then repeated until a fixed number of generations is reached or some stop criterion is satisfied.