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The Whale Optimization Algorithm

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ABSTRACT

This paper proposes a novel nature-inspired meta-heuristic optimization algorithm, called Whale Optimization Algorithm (WOA), which mimics the social behavior of humpback whales. The algorithm is inspired by the bubble-net hunting strategy. WOA is tested with 29 mathematical optimization problems and 6 structural design problems. Optimization results prove that the WOA algorithm is very competitive compared to the state-of-art meta-heuristic algorithms as well as conventional methods. The source codes of the WOA algorithm are publicly available at http://www.alimirjalili.com/WOA.html

1. Introduction

Meta-heuristic optimization algorithms are becoming more and more popular in engineering applications because they: (i) rely on rather simple concepts and are easy to implement; (ii) do not require gradient information; (iii) can bypass local optima; (iv) can be utilized in a wide range of problems covering different disciplines.

Nature-inspired meta-heuristic algorithms solve optimization problems by mimicking biological or physical phenomena. They can be grouped in three main categories (see Fig. 1): evolution-based, physics-based, and swarm-based methods. Evolution-based methods are inspired by the laws of natural evolution. The search process starts with a randomly generated population which is evolved over subsequent generations. The strength point of these methods is that the best individuals are always combined together to form the next generation of individuals. This allows the population to be optimized over the course of generations. The most popular evolution-inspired technique is Genetic Algorithms (GA) [1] that simulates the Darwinian evolution. Other popular algorithms are Evolution Strategy (ES) [110], Probability-Based Incremental Learning (PBIL) [111], Genetic Programming (GP) [2], and Biogeography-Based Optimizer (BBO) [3].

Physics-based methods imitate the physical rules in the universe. The most popular algorithms are Simulated Annealing (SA) [4,5], Gravitational Local Search (GLSA) [6], Big-Bang Big-Crunch (BBBC) [7], Gravitational Search Algorithm (GSA) [8], Charged System Search (CSS) [9], Central Force Optimization (CFO) [10], Artificial Chemical Reaction Optimization Algorithm (ACROA) [11], Black Hole (BH) [12] algorithm, Ray Optimization (RO) [13] algorithm, Small-World Optimization Algorithm (SWOA) [14], Galaxy-based Search Algorithm (GbSA) [15], and Curved Space Optimization (CSO) [16].

The third group of nature-inspired methods includes swarm-based techniques that mimic the social behavior of groups of animals. The most popular algorithm is Particle Swarm Optimization, originally developed by Kennedy and Eberhart [17]. PSO is inspired by the social behavior of bird flocking. It uses a number of particles (candidate solutions) which fly around in the search space to find the best solution (*i.e.* the optimal position). Meanwhile, they all trace the best location (best solution) in their paths. In other words, particles consider their own best solutions as well as the best solution the swarm has obtained so far. Another popular swarm-based algorithm is Ant Colony Optimization, first proposed by Dorigo et al. [18]. This algorithm is inspired by the social behavior of ants in an ant colony. In fact, the social intelligence of ants in finding the closest path from the nest and a source of food is the main inspiration of this algorithm. A pheromone matrix is evolved over the course of iteration by the candidate solutions.

Other swarm-based techniques are listed in Table 1. This class of meta-heuristic methods started to be attractive since PSO was

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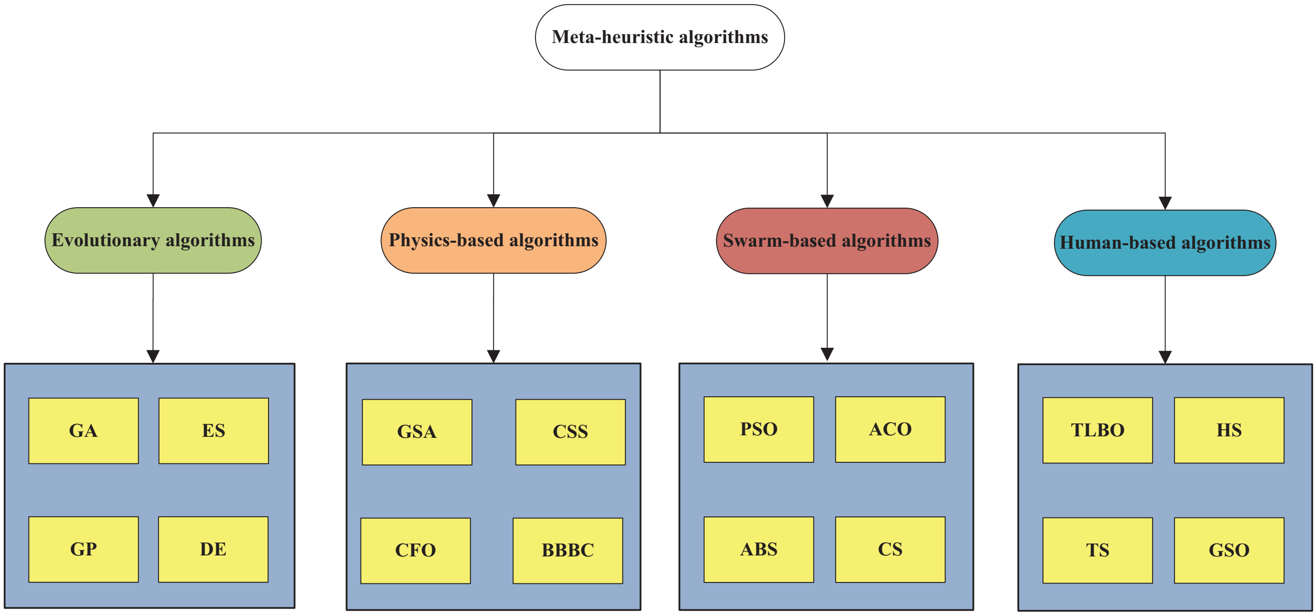

Fig. 1. Classification of meta-heuristic algorithms.

Table 1
Swarm-based optimization algorithms developed in literature.

Algorithm	Inspiration	Year of proposal
PSO [17]	Bird flock	1995
Marriage in Honey Bees Optimization Algorithm (MBO) [19]	Honey Bees	2001
Artificial Fish-Swarm Algorithm (AFSA) [20]	Fish swarm	2003
Termite Algorithm [21]	Termite colony	2005
ACO [18]	Ant colony	2006
ABC [22]	Honey Bee	2006
Wasp Swarm Algorithm [23]	Parasitic wasp	2007
Monkey Search [24]	Monkey	2007
Wolf pack search algorithm [25]	Wolf herd	2007
Bee Collecting Pollen Algorithm (BCPA) [26]	Bees	2008
Cuckoo Search (CS) [27]	Cuckoo	2009
Dolphin Partner Optimization (DPO) [28]	Dolphin	2009
Bat-inspired Algorithm (BA) [29]	Bat herd	2010
Firefly Algorithm (FA) [30]	Firefly	2010
Hunting Search (HS) [31]	Group of animals	2010
Bird Mating Optimizer (BMO) [32]	Bird mating	2012
Krill Herd (KH) [33]	Krill herd	2012
Fruit fly Optimization Algorithm (FOA) [34]	Fruit fly	2012
Dolphin Echolocation (DE) [35]	Dolphin	2013

proven to be very competitive with evolution-based and physical-based algorithms. Generally speaking, swarm-based algorithms have some advantages over evolution-based algorithms. For example, swarm-based algorithms preserve search space information over subsequent iterations while evolution-based algorithms discard any information as soon as a new population is formed. They usually include less operators compared to evolutionary approaches (selection, crossover, mutation, elitism, *etc.*) and hence are easier to implement.

It is worth mentioning here that there are also other meta-heuristic methods inspired by human behaviors in the literature. Some of the most popular algorithms are Teaching Learning Based Optimization(TLBO) [36,37], Harmony Search (HS) [38], Tabu (Taboo) Search (TS) [39–41], Group Search Optimizer (GSO) [42,43], Imperialist Competitive Algorithm (ICA) [44], League Championship Algorithm (LCA) [45,46], Firework Algorithm [47], Colliding Bodies Optimization (CBO) [48,49], Interior Search Algorithm (ISA) [50], Mine Blast Algorithm (MBA) [51], Soccer League Competition (SLC) algorithm [52,53], Seeker Optimization Algorithm (SOA) [54], Social-Based Algorithm (SBA) [55], Exchange Market Algorithm (EMA) [56], and Group Counseling Optimization (GCO) algorithm [57,58].

Population-based meta-heuristic optimization algorithms share a common feature regardless of their nature. The search process is divided into two phases: exploration and exploitation [59–61]. The optimizer must include operators to globally explore the search space: in this phase, movements (*i.e.* perturbation of design variables) should be randomized as most as possible. The exploitation phase follows the exploration phase and can be defined as the process of investigating in detail the promising area(s) of the search space. Exploitation hence pertains to the local search capability in the promising regions of design space found in the exploration phase. Finding a proper balance between exploration and exploitation is the most challenging task in the development of any meta-heuristic algorithm due to the stochastic nature of the optimization process.

This study describes a new meta-heuristic optimization algorithm (namely, Whale Optimization Algorithm, WOA) mimicking the hunting behavior of humpback whales. To the knowledge of the present authors, there is no previous study on this subject in the optimization literature. The main difference between the current work and the recently published papers by the authors (particularly GWO [62]) is the simulated hunting behavior with random or the best search agent to chase the prey and the use of a spiral to simulate bubble-net attacking mechanism of humpback whales. The efficiency of the WOA algorithm developed in this research is evaluated by solving 29 mathematical optimization problems and six structural optimization problems. Optimization results demonstrate that WOA is very competitive compared to the state-of-the-art optimization methods.

The rest of the paper is structured as follows. Section 2 describes the Whale Optimization Algorithm developed in this study. Test problems and optimization results are presented and discussed in Sections 3 and 4, respectively, for mathematical functions and structural optimization problems. Section 5 summarizes the main findings of this study and suggests directions for future research.