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The Ant Lion Optimizer

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ABSTRACT

This paper proposes a novel nature-inspired algorithm called Ant Lion Optimizer (ALO). The ALO algorithm mimics the hunting mechanism of antlions in nature. Five main steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented. The proposed algorithm is benchmarked in three phases. Firstly, a set of 19 mathematical functions is employed to test different characteristics of ALO. Secondly, three classical engineering problems (three-bar truss design, cantilever beam design, and gear train design) are solved by ALO. Finally, the shapes of two ship propellers are optimized by ALO as challenging constrained real problems. In the first two test phases, the ALO algorithm is compared with a variety of algorithms in the literature. The results of the test functions prove that the proposed algorithm is able to provide very competitive results in terms of improved exploration, local optima avoidance, exploitation, and convergence. The ALO algorithm also finds superior optimal designs for the majority of classical engineering problems swith unknown search spaces as well. Note that the source codes of the proposed algorithm in solving real problems with unknown search spaces as well. Note that the source codes of the proposed ALO algorithm are publicly available at http://www.alimirjalili.com/ALO.html.

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1. Introduction

In recent years metaheuristic algorithms have been used as primary techniques for obtaining the optimal solutions of real engineering design optimization problems [1–3]. Such algorithms mostly benefit from stochastic operators [4] that make them distinct from deterministic approaches. A deterministic algorithm [5–7] reliably determines the same answer for a given problem with a similar initial starting point. However, this behaviour results in local optima entrapment, which can be considered as a disadvantage for deterministic optimization techniques [8]. Local optima stagnation refers to the entrapment of an algorithm in local solutions and consequently failure in finding the true global optimum. Since real problems have extremely large numbers of local solutions, deterministic algorithms lose their reliability in finding the global optimum.

Stochastic optimization (metaheuristic) algorithms [9] refer to the family of algorithms with stochastic operators including evolutionary algorithms [10]. Randomness is the main characteristic of stochastic algorithms [11]. This means that they utilize random

E-mail address: seyedali.mirjalili@griffithuni.edu.au *URL:* http://www.alimirjalili.com operators when seeking for global optima in search spaces. Although the randomised nature of such techniques might make them unreliable in obtaining a similar solution in each run, they are able to avoid local solutions much easier than deterministic algorithms. The stochastic behaviour also results in obtaining different solutions for a given problem in each run [12].

Evolutionary algorithms search for the global optimum in a search space by creating one or more random solutions for a given problem [13]. This set is called the set of candidate solutions. The set of candidates is then improved iteratively until the satisfaction of a terminating condition. The improvement can be considered as finding a more accurate approximation of the global optimum than the initial random guesses. This mechanism brings evolutionary algorithms several intrinsic advantages: problem independency, derivation independency, local optima avoidance, and simplicity.

Problem and derivation independencies originate from the consideration of problems as a black box. Evolutionary algorithms only utilize the problem formulation for evaluating the set of candidate solutions. The main process of optimization is done completely independent from the problem and based on the provided inputs and received outputs. Therefore, the nature of the problem is not a concern, yet the representation is the key step when utilizing evolutionary algorithms. This is the same reason why evolutionary algorithms do not need to derivate the problem for obtaining its global optimum.





ENGINEEBING



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