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Improved seeker optimization algorithm hybridized with firefly algorithm for constrained optimization problems ☆

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A B S T R A C T

Seeker optimization algorithm is one of the recent swarm intelligence metaheuristics for hard optimization problems. It is based on the human group search behavior and it was successfully applied to various numerical optimization problems. While the seeker optimization algorithm was proven to be successful for different specific problems, it was not properly tested on a wide set of benchmark functions. Our testing on the standard well-known set of benchmark functions shows that the seeker optimization algorithm has serious problems with some types of functions. In this paper we introduced modifications to the seeker optimization algorithm to control exploitation/exploration balance and hybridized it with elements of the firefly algorithm that improved its exploitation capabilities. The firefly algorithm alone also exhibits deficiencies. Our proposed modified and hybridized seeker optimization algorithm not only overcame shortcomings of the original algorithms, but also outperformed other state-of-the-art swarm intelligence algorithms.

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1. Introduction

Optimization is the most widely used research area since almost any real life problem can be formulated as an optimization problem. Sometimes the problem is inherently a numerical optimization problem and sometimes elaborate adjustments to a mathematical model are necessary. During past centuries advances in mathematics facilitated solutions to almost all hard optimization problems. However, a class of very applicable problems remained that was not solvable by deterministic mathematical methods. Problems in this class, whose well-known representative is the traveling salesman problem, are simple to formulate and write an algorithm, however, they cannot be solved within reasonable time. There are many similar combinatorial problems, as well as some continuous optimization problems that include search for global optimum of highly irregular and non-linear functions with a huge number of local optima and possibly complicated constraints.

1.1. Continuous optimization problems

Unconstrained (or bound constrained) optimization can be defined as D-dimensional minimization or maximization problem:

$$\min\ (\text{or}\ \max)\, f(x), \quad x = (x_1, x_2, x_3, \ldots, x_D) \in S, \tag{1}$$

where x is a real vector with $D \geq 1$ components and $S \in R^D$ is an D-dimensional hyper-rectangular search space constrained by lower and upper bounds:

$$lb_i \leq x_i \leq ub_i, \quad i \in [1, D] \tag{2}$$

The nonlinear constrained optimization problem in the continuous space can be formulated as in Eq. (1), but in this case $x \in F \subseteq S$. S is again D-dimensional hyper-rectangular space as defined in Eq. (2) and $F \subseteq S$ is the feasible region defined by the set of m linear or non-linear constraints:

$$\begin{aligned} g_j(x) &\leq 0 \quad \text{for} \quad j \in [1, q] \\ h_j(x) &= 0 \quad \text{for} \quad j \in [q+1, m] \end{aligned} \tag{3}$$

where q is the number of inequality constraints and $m-q$ is the number of equality constraints.

Since most of the basic versions of search algorithms lack a mechanism to deal with the constraints of a numerical optimization problem, constraint handling techniques are usually incorporated in the algorithms in order to direct the search towards the feasible regions of the search space. The presence of equality constraints pose obstacle for optimization algorithms because they make the feasible space very small compared to the entire search space. To deal with such situation, equality constraints can be replaced by inequality constraints [1].

$$|h(x)| - \varepsilon \leq 0, \tag{4}$$

where $\varepsilon > 0$ is some small violation tolerance.

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1.2. Swarm intelligence

Since mentioned hard optimization problems cannot be solved by standard mathematical deterministic techniques, a new class of metaheuristics have evolved that try to find acceptable suboptimal solutions in a reasonable amount of computational time. They use iterative, population based, stochastic approach and do not make any assumptions about the fitness landscape.

Nature-inspired algorithms, that mimic the behavior of natural systems, represent an important subset of metaheuristic optimization methods. They start with initial (usually random) population of candidate problem solutions and iteratively improve them. Basic mechanisms of recombination and selection were introduced in older evolutionary and genetic algorithms which are still being improved [2,3]. Swarm intelligence is a newer category of bio-inspired metaheuristics which are based on the collective intelligent behavior of insects or animal groups like flocks of birds, schools of fish, colonies of ants or bees, etc. Complex interactions among simple individuals without centralized supervision mechanism facilitates remarkable collective intelligence. The most differentiating advantages of swarm intelligence over other approaches are scalability, speed, modularity, autonomy, adaptation, fault tolerance and parallelism.

Ant colony optimization (ACO) is among older representatives of the swarm algorithms [4]. The foundation of the ACO is the behavior of real ants and their ability to find the shortest path between food sources and their nests by deploying a substance called pheromone. Many combinatorial problems were successfully solved by different versions of the ACO algorithm [5–8]. The artificial bee colony (ABC) algorithm is one of the newer swarm intelligence algorithms which is based on the behavior of honey bee swarms. This algorithm was originally proposed by Karaboga for continuous optimization [9]. Testing results of various implementations show that this is the state-of-the-art algorithm for high dimensionality optimization [10–14]. The firefly algorithm (FA) is one of the latest swarm algorithms. It is inspired by flashing behavior of fireflies. The basic idea is that each firefly moves towards the position of the brighter firefly, where firefly brightness is proportional to the fitness value. FA was first proposed for unconstrained optimization [15], but was later successfully used for various problems [16–19].

In this paper we propose an improved seeker optimization algorithm (SOA) adapted for solving constrained numerical optimization problems. The SOA algorithm was recently proposed [20–22] and it has been adapted for various practical problems. It has been successful for particular cases, however, our testings show that for wider class of objective functions it has deficiencies.

Our main modifications refer to the search and inter-subpopulation learning processes. We modified the exploitation process of the original SOA approach by hybridizing it with the novel firefly algorithm. We named the new approach SOA with firefly search (SOA-FS) because it uses either SOA or firefly search when solution update is performed. Additionally, we decreased the frequency of inter-subpopulation learning and introduced new parameter for controlling that mechanism which prevents premature convergence of the subpopulations. This makes the algorithm more resistant to being stuck in local optima at early stages. The proposed algorithm is tested on well-known constraint benchmark functions and it showed favorable performance compared to other state-of-the-art algorithms.

The rest of the paper is organized as follows. Section 2 is the literature review, Section 3 presents the original SOA metaheuristic and its deficiencies. Section 4 describes our SOA-FS method. Parameter settings, test results and comparisons with other algorithms are given in Section 5.

2. Literature review

SOA is a relatively new population-based metaheuristic which models the cooperative behavior of human beings. This algorithm was introduced by Dai et al. [20,21]. It was applied to the real-parameter unconstrained optimization of complex functions and was compared with differential evolution (DE) and three modified PSO algorithms [22].

SOA mimics the human search process based on human memory, reasoning, past experience and human interactions. Each individual (potential problem solution) is called artificial agent, or seeker in this case. Seeker operates in the larger environment of candidate solutions called search population. The total population is divided into three equally sized subpopulations according to the sequence of the seekers. All the agents in the same population form a social unit called neighborhood. Each population performs search in its domain of the search space.

The SOA algorithm has mostly been tested on practical, real-life problems. Among few dozens of published papers on SOA most are about applications to power systems. It was applied to optimal reactive power dispatch (ORPD) optimization considering static voltage stability and voltage deviation [23]. A constrained economic load dispatch problem was encoded for the SOA method [24] and the proposed algorithm was found to be robust, fast converging and more proficient than other techniques for such a kind of problems. Economic dispatch (ED) of thermal power units was modeled by this novel approach [25]. Load-tracking performance of autonomous power systems was also modeled for optimization by the SOA [26]. SOA has been applied to optimal placement of power quality (PQ) meters for harmonic state estimation and proved to be effective method for this problem [27].

Other applications of the SOA are fewer in the literature. Since the error surface of digital infinite-impulse-response (IIR) filters is generally nonlinear and multimodal, global optimization technique such as SOA can be applied. It was shown [28] that the SOA has superior performance over other algorithms for digital IIR filter design problem. The application of the SOA to tuning the structures and parameters of artificial neural networks (ANNs) is presented [29] as a new evolutionary method of ANN training. Also, a new multilevel maximum entropy thresholding method based on a modified seeker optimization (MSO) algorithm was developed [30]. MSO was tested against the PSO algorithm and the results showed that the MSO performs better than PSO with respect to the quality of the segmentation results, while in terms of execution time, the PSO proved to be more efficient. SOA was implemented for parameter estimation of time-delay chaotic systems which has characteristics of nonlinear, multivariable and multimodal optimization problem [31]. SOA was also hybridized with other algorithms. Hybridization with the well-known ABC algorithm was performed [32] for testing multimodal unconstrained optimization. Such an algorithm was tested on a set of 23 benchmark functions and outperformed six state-of-the-art algorithms in terms of the results quality and robustness.

The SOA algorithm has been recently renamed by its inventor Chaohua Dai to human group optimizer (HGO) [33]. It has also been improved by introducing a small world scheme in a complex network [34] and applied to train the parameters of neural networks to build a soft sensor model for inferring the outlet ammonia concentration in a fertilizer plant. Version of the group optimizer algorithm hybridized with PSO [35] has been successfully applied to find optimal location and capacity of distributed generations in distribution networks. An interesting example of triple hybridization of similar algorithms is [36] where co-evolutionary algorithm, cultural algorithm, and particle swarm optimization are combined and tested on 13 standard benchmark functions and three real-life optimization problems.

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