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TSA: Tree-seed algorithm for continuous optimization

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ABSTRACT

This paper presents a new intelligent optimizer based on the relation between trees and their seeds for continuous optimization. The new method is in the field of heuristic and population-based search. The location of trees and seeds on *n*-dimensional search space corresponds with the possible solution of an optimization problem. One or more seeds are produced from the trees and the better seed locations are replaced with the locations of trees. While the new locations for seeds are produced, either the best solution or another tree location is considered with the tree location. This consideration is performed by using a control parameter named as search tendency (ST), and this process is executed for a pre-defined number of iterations. These mechanisms provide to balance exploitation and exploration capabilities of the proposed approach. In the experimental studies, the effects of control parameters on the performance of the method are firstly examined on 5 well-known basic numeric functions. The performance of the proposed method is also investigated on the 24 benchmark functions with 2, 3, 4, 5 dimensions and multilevel thresholding problems. The obtained results are also compared with the results of state-of-art methods such as artificial bee colony (ABC) algorithm, particle swarm optimization (PSO), harmony search (HS) algorithm, firefly algorithm (FA) and the bat algorithm (BA). Experimental results show that the proposed method named as TSA is better than the state-of-art methods in most cases on numeric function optimization and is an alternative optimization method for solving multilevel thresholding problem.

1. Introduction

Optimization is a task performed to find the best solution amongst the possible solutions for an optimization problem with regard to some criteria. Optimization deals with optimization problems, and can contain maximization or minimization processes. If S is a search space, F, $F \subseteq S$, is a set of acceptable solutions of S and f is an objective function, minimization or maximization is to find $\vec{x} \in F$ in Eqs. (1) and (2), those define minimization and maximization processes, respectively.

$$f(\vec{x}) \leqslant f(\vec{y}) \quad \forall \vec{y} \in F \tag{1}$$

$$f(\vec{x}) \geqslant f(\vec{y}) \quad \forall \vec{y} \in F \tag{2}$$

If the function to be optimized is non-continuous or non-differentiable, or optimizing the function is computationally expensive for high dimensional search space, heuristic search methods can be applied to optimize it.

The expert or intelligent systems aim to present a solution methodology to solve this type of problems (nonlinear or non-differentiable optimization problems). Over the last decades, a growing popularity of population-based intelligent search methods has been occurred due to their successes in solving the optimization problems, which are easy adaptation and implem entation for the optimization problem and low computation costs. These techniques use biological or physical phenomena in local interactions amongst the agents while solving the optimization problem. Genetic algorithm (GA) (Goldberg, 1989;Holland, 1992) has been developed by considering Darwinian evolutionary theory. In GA, crossover and mutation mechanisms are used to produce a new generation. Ant colony optimization (ACO) (Dorigo, Maniezzo, & Colorni, 1996) mimics the behavior of real ants between the nest and food source. Basically, ACO is proposed to solve discrete optimization problems and the main concept is based on pheromone mechanism to construct the solutions. Particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) has been inspired by cognitive and social behaviors of fish or birds. The solution update rule in PSO uses subtraction operation between the current solution and the best (the best of population and the best solution obtained so far by the particle) solutions to produce a new possible solution. Harmony search (HS) (Geem, Kim, & Loganathan, 2001) algorithm simulates the improvisation process of musicians. Bat algorithm (BA) (Yang, 2010b) imitates the echolocation behavior of bats.

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Firefly algorithm (FA) (Yang, 2010a) has been inspired by the flashing behavior of fireflies. Artificial bee colony algorithm (ABC) (Karaboga & Basturk, 2007) simulates foraging and information sharing behaviors of bees in a hive. In ABC, the same subtraction-based update rule is used in both employed bee phase and onlooker bee phase of the algorithm, and the best solution obtained so far is not used in this algorithm. As well as organisms' behaviors, some methods modeled physical laws for solving optimization problems. Simulated Annealing (SA) (Kirkpatrick, Gelatt, & Vecchi, 1983) has been inspired by thermodynamic effects, and gravitational search algorithm (GSA) (Rashedi, Nezamabadi-Pour, & Saryazdi, 2009) is based on the Newtonian laws of gravity. In GSA, all the solutions are used to produce a new solution by using the Newtonian laws of gravity.

In the present study, it aims to establish a new optimizer named as tree–seed algorithm (TSA) to solve continuous optimization problems. In the new proposed method, two aspects, exploration and exploitation, are considered to overcome the characteristics of the optimization problems. For exploration, the method is designed as population-based, the search starts from multiple-points on the search space of the problem, and randomness is included in local interactions amongst the agents. These agents in the proposed method are called as *trees*. In order to compensate exploitation, *seeds* are used. The number of seeds produced from a tree is randomly obtained. The locations of trees and seeds on *n*-dimensional search space correspond to the possible solutions of the optimization problem, and while a new seed is produced from a tree, either another tree location or the best tree (the best solution obtained so far) location is considered with its own location. The search tendency to the best or randomly selected tree is handled with a control parameter named as *search tendency* (*ST*) and this control in the TSA provides a local intensification and convergence to the optimum or near optimum for the problem.

The paper is organized as follows: the study is introduced in Section 1, and the main contribution of the study is presented in this section. TSA method is detailed in Section 2, experimental studies and comparisons are conducted in Section 3, the obtained results are reported and discussed in Section 4 and finally, the study is concluded and future directions are given in Section 5.

1.1. Main contribution

In this study, a novel population-based iterative search algorithm is developed for solving continuous optimization problems. In the present study, two mechanisms are merged to balance exploration and exploitation capabilities of the method. First mechanism aims to improve exploration capability of the method by using search tendency parameter. The new solutions are produced by considering the current solution and the best or randomly selected solution with this parameter. The second mechanism focuses on improving the exploitation of the method. In this mechanism, more than one solution is created around a solution. Therefore, the search around the found solutions is improved by using the second search mechanism. Based on the literature review of the study, these mechanisms show the novelty and differences from the approaches exist in the literature.

2. TSA: Tree–seed algorithm

The natural phenomena in TSA is the relationship between trees and their seeds. In nature, trees spread to the surface through their seeds. These seeds grow over time and new trees become from these seeds. If we assume that the surface of these trees as a search space for the optimization problem, the location of trees and seeds can be considered as possible solutions for the optimization problem. To obtain a location of a seed that will be produced from a tree is important for the optimization problem because this process constitutes the core of search. We propose two search equations for this process. The first equation (Eq. (1)) considers the tree location that the seed will be produced for this tree and the best location of the tree population. This search equation also improves the local search or intensification capability of the proposed algorithm. The second update rule (Eq. (2)) uses two different tree locations for producing a new seed for the tree.

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (B_j - T_{r,j}) \quad (3)$$

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (T_{i,j} - T_{r,j}) \quad (4)$$

where, $S_{i,j}$ is jth dimension of ith seed that will be produced ith tree, $T_{i,j}$ is the jth dimension of ith tree, B_j is the jth dimension of best tree location obtained so far, $T_{r,j}$ is the jth dimension of rth tree randomly selected from the population, α is the scaling factor randomly produced in range of $[-1, 1]$ and i and r are different indices.

The most important point is which equation will be selected to produce a new seed location. This selection is controlled by a control parameter of the method named as search tendency (ST) in range of [0, 1]. The higher value of ST provides a powerful local search and speed convergence, the lower value of ST causes slow convergence but powerful global search. In other words, the exploration and exploitation capabilities of the TSA are controlled by ST parameter.

In the beginning of search with TSA, the initial tree locations which are possible solutions for the optimization problem are produced by using Eq. (5).

$$T_{i,j} = L_{j,\min} + r_{i,j}(H_{j,\max} - L_{j,\min}) \quad (5)$$

where, $L_{j,\min}$ is the lower bound of the search space, $H_{j,\max}$ is the higher bound of the search space and $r_{i,j}$ is a random number produced for each dimension and location, in range of [0, 1].

For minimization, the best solution is selected from the population using Eq. (6).

$$B = \min\{f(\vec{T}_i)\} i = 1, 2, \ldots, N \quad (6)$$

where, N is the number of trees in the population.

While the new seed locations are generated for a tree, the number of seeds can be more than one and this number depends on the population size. In the analysis of effects of control parameters to the performance of TSA, 10% of population size is the minimum number of seeds produced for a tree and 25% of the population size is the maximum number of seeds produced from a tree. The number of seed production is completely random in TSA.

The detailed algorithmic framework of the TSA is given in Fig. 1. In the algorithm, it is seen how to use the control parameter ST in TSA. If randomly produced number (rand in Fig. 1) in range of [0, 1] is less than ST, Eq. (3) is used for updating the dimension, otherwise Eq. (4) is used.

3. Experimental studies

3.1. Performance analysis and comparisons on the benchmark functions

In the experiments, the effects of control parameters to the performance of TSA are analyzed and then the performance of TSA with the selected control parameters is compared with the results of PSO, ABC, HS, FA, BA methods. In the analyses, TSA is applied to solve five basic benchmark functions (F1, F10, F11, F13, F15 in the Table 1) to obtain the best control parameters. The methods are run on the 2,3,4,5 dimensional 24 numeric functions given in Table 1 to compare with the other methods. For all experiments, the termination condition is selected as the maximum number of