Information Sciences 418–419 (2017) 383–404

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Landscape-based adaptive operator selection mechanism for differential evolution

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ARTICLE INFO

Article history:
Received 1 November 2016
Revised 14 July 2017
Accepted 6 August 2017
Available online 9 August 2017

Keywords:
Differential evolution
Fitness landscape
Adaptive operator selection

ABSTRACT

Over the last two decades, many different differential evolution algorithms for solving optimization problems have been introduced. Although most of these algorithms used a single mutation strategy, several with multiple mutation strategies have recently been proposed. Multiple-operator-based algorithms have been proven to be more effective and efficient than single-operator-based algorithms for solving a wide range of benchmark and practical problems. In these algorithms, adaptive operator selection mechanisms are generally applied to place greater emphasis on the best-performing evolutionary operators based on their performance histories for generating new offspring. In this paper, we investigate using problem landscape information in an adaptive operator selection mechanism. For this purpose, a new algorithm, which considers both this problem landscape information and the performance histories of the operators, for dynamically selecting the most suitable differential evolution operator during the evolutionary process, is proposed. The contributions of each component of the selection mechanism are analyzed and the performance of the proposed algorithm is evaluated by solving 45 unconstrained optimization problems. The results demonstrate the effectiveness and superiority of the proposed algorithm to state-of-the-art algorithms.

1. Introduction

Optimization plays an important role in many practical decision-making processes. Numerous optimization problems arise in the engineering domain, industry, and both the public and private sectors. In general, a global unconstrained single-objective optimization problem, which is considered in this paper, can be described as determining the appropriate decision vector $\vec{x} = (x_1, x_2, \ldots, x_D) \in \mathbb{R}^D$, that satisfies the variable bounds, $\vec{x}_{\min} \le x \le \vec{x}_{\max}$ and optimizes the objective function $f(\vec{x})$, where D is the problem's dimensions, $\vec{x}_{\min}$ and $\vec{x}_{\max}$ its lower and upper bounds, respectively. Such problems may contain different types of variables, such as integer, real, discrete or a combination of them [10] while the objective function can be linear or non-linear, convex or non-convex, continuous or discontinuous, and uni-modal or multi-modal.

Although researchers and practitioners have used both traditional and computational intelligence (CI) approaches, such as evolutionary algorithms (EAs) and swarm intelligence (SI) techniques [25], to solve these types of complex optimization problems. However, the former encounter many difficulties [19], such as: 1) their convergence to a near-optimal or optimal

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http://dx.doi.org/10.1016/j.ins.2017.08.028
0020-0255/

solution relies on the initial solution; 2) they require specific mathematical properties, like continuity, convexity and differentiability, to be satisfied; and 3) they may need to simplify a problem by making different assumptions for the convenience of mathematical modeling [41]. Therefore, researchers have begun to use CI approaches because of their many advantages, for example, as EAs are resilient to dynamic changes, have the capability of self-organization, do not need particular mathematical characteristics to be achieved, can evaluate several solutions in parallel, and are more widely used in practice [10], they have often been proven to work better than traditional methods [39]. However, there is no guarantee that EA-based methods can obtain exact solutions and the quality of their solutions relies on the settings of their parameter. In fact, as no single EA has been found to be the best for solving all types of optimization problems, generally, using more than one algorithm in a single framework may help to overcome this limitation [10].

Over the years, researchers and practitioners have used frameworks that contain more than one search operator or algorithm in a single algorithmic framework, such as ensemble-based (use a mix of operators) [29], hyper-heuristics (a heuristic to select among heuristics) [15], mutli-methods (use more than one optimization algorithm) [11,52], multi-operators (use more than a single search operator within a single optimization algorithm) [10,18], and heterogeneous (using different algorithms with different behaviors) [33] approaches. To clarify, they use a pool of different algorithms/operators and a selection procedure to determine the best-performing algorithm and/or operator through the evolutionary process. The selection procedures of these algorithms, which are usually called adaptive operator selections (AOSs), rely on different criteria, such as a re-enforcement learning mechanism [20], improvement in the solution quality and/or constraint violations and/or feasibility rate [10], convergence differences and progress ratios [14] and pheromone updates of the ant colony optimization meta-heuristic (ACO-MH) [33].

Landscape information is usually helpful for judging function complexity and, if carefully incorporated in the selection of operators, may boost the performance of an algorithm. While selection methods based on landscape analysis are very rare [2,7], they have the following limitations: (1) a landscape analysis is performed using an off-line mode, i.e., initial experiments are conducted to calculate the values of the landscape statistics independently of the evolutionary process for solving the problem; (2) calculations of landscape measures are computationally expensive; and (3) as a training and testing mechanism is used, the algorithm may be limited to the test problems considered and its performance deteriorate when solving another set of problems.

Of the EAs, differential evolution (DE) has gained popularity for solving continuous optimization problems [5,8,37,40]. In this paper, in order to select the best-performing operator during the evolutionary process without any prior knowledge of the problem's characteristics, a new DE algorithm, which utilizes the strengths of multiple DE mutation operators and has an adaptive operator selection process (DE algorithm with landscape-based Adaptive Operator Selection (LSAOS-DE)) based on both the (1) problem landscape and (2) performances of operators, is proposed. In the proposed algorithm, at each generation, m mutation strategies are considered, with each new solution able to be generated using any one of the m operators, and the landscape measure value and performance history of each operator calculated and recorded for a certain number (CS) of generations. Then, based on the normalized average value of both landscape and performance history measures of each operator, the best-performing operator is used to evolve the entire population for CS generations. However as the performance of one operator may change during the evolutionary process, all the operators are re-used to evolve all individuals in the entire population, and the landscape and performance history measures are then re-evaluated after CS generations. This process is continued up to a pre-defined number of fitness function evaluations and then the best-performing DE mutation strategy selected to evolve the current population until an overall stopping condition is met.

It is worth mentioning that this proposed algorithm has the same structure as multi-method/multi-operator, heterogeneous and ensemble-based algorithms with its pool consisting of several different DE mutation strategies. However, different from those in the literature, the selection mechanism relies on both landscape information and the performance history of each DE mutation strategy.

To judge the performance of LSAOS-DE, it is tested on 45 problems from benchmark sets with different mathematical properties (10, 30 and 50 dimensions) (introduced in the CEC2014 and CEC2015 competitions [21,22]) with its overall computational results better than those obtained from other state-of-the-art algorithms for most of the test problems.

The rest of this paper is organized as follows: in Section 2, a review of DE algorithms and operators as well as some landscape measures is provided; in Section 3, the proposed algorithm is described; in Section 4, the simulation results for benchmark problems and the effect of the parameters are discussed; and, finally, in Section 5, the conclusions drawn from this study and possible future research directions are presented.

2. Related work

In this section, a literature review of DE and the concept of landscape analysis are discussed.

2.1. Differential evolution algorithm

DE is an EA variant which was proposed by Storn and Price [44]. It is popular because it usually converges fast, is simple to implement and the same parameter values can be applied for various optimization problems. In the literature, it is shown to perform better than several other EAs for a wide range of problems [8,10]. It starts with an initial population and to