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A novel real-coded population-based extremal optimization algorithm with polynomial mutation: A non-parametric statistical study on continuous optimization problems

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ABSTRACT

As a recently developed optimization method inspired by far-from-equilibrium dynamics of self-organized criticality, extremal optimization (EO) has been successfully applied to a variety of combinatorial optimization problems while its applications in continuous optimization problems are relatively rare. Additionally, there are only few studies concerning the effects of mutation operation on EO algorithms although mutation operation plays a crucial role in controlling the optimization dynamics and consequently affecting the performance of EO-based algorithms. This paper proposes a novel real-coded population-based EO algorithm with polynomial mutation (RPEO-PLM) for continuous optimization problems. The basic idea behind RPEO-PLM is the population-based iterated optimization consisting of generation of a real-coded random initial population, evaluation of individual and population fitness, generation of a new population based on polynomial mutation, and updating the population by accepting the new population unconditionally. One of the most attractive advantages is its relative simplicity compared with other popular evolutionary algorithms due to its fewer adjustable parameters needing to be tuned and only selection and mutation operations. Furthermore, the experimental results on a large number of benchmark functions with the different dimensions by using non-parametric statistical tests including Friedman and Quade tests have shown that the proposed RPEO-PLM algorithm outperforms other popular population-based evolutionary algorithms, e.g., real-coded genetic algorithm (RCGA) with adaptive directed mutation (RCGA-ADM), RCGA with polynomial mutation (RCGA-PLM), intelligent evolutionary algorithm (IEA), a hybrid particle swarm optimization and EO algorithm (PSO–EO), the original population-based EO (PEO), and an improved RPEO algorithm with random mutation (IRPEO-RM) in terms of accuracy.

1. Introduction

As a novel meta-heuristics optimization algorithm originally inspired by far-from-equilibrium dynamics of self-organized criticality (SOC) [1,2], extremal optimization (EO) [3,4] provides a novel insight into optimization domain because it merely selects against the bad instead of favoring the good randomly or according to a power-law probability distribution. The mechanism of EO can be characterized from the perspectives of statistical physics, biological co-evolution and ecosystem [5,6]. So far, the basic EO algorithm and its modified versions have been successfully applied to a variety of benchmark and real-world engineering optimization problems, such as graph partitioning [7], graph coloring [8], traveling salesman problem [9,10], maximum satisfiability (MAX-SAT) problem [11,12], community detection in complex network [13], and steel production scheduling [14]. The more comprehensive introduction concerning EO is referred to the surveys [15,16].

To the best of our knowledge, the applications of EO to continuous optimization problems are relatively rare [17]. Sousa et al. [18,19] presented generalized EO (GEO) based on individual-based iterated mechanism for numerical and engineering optimization problems, where each continuous or discrete variable is encoded as a binary string. In [20], a modified algorithm called population-based EO (PEO) has been proposed for solving constrained optimization problems. The main advantage of PEO is the iterated optimization based on the basic EO algorithm starting from an initial population that consists of a set of individuals. Additionally, Chen et al. [21] proposed a hybrid algorithm called PSO–EO by combining the exploration ability of particle swarm optimization (PSO) with the exploitation ability of EO. The effectiveness of

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PSO–EO has been demonstrated by the experimental results on 6 benchmark test functions. Another similar hybrid algorithm for continuous optimization problems is based on the combination of improved shuffled frog-leaping algorithm and EO [22]. However, not following the line of these reported hybrid algorithms combining EO and other evolutionary algorithms, this paper focuses on a novel real-coded population-based EO algorithms with polynomial mutation (RPEO-PLM) for continuous optimization problems.

It should be emphasized that mutation operation plays a crucial role in controlling the optimization dynamics and consequently affecting the performance of EO-based algorithms especially real-coded EO algorithms, but there are only few studies concerning the effects of mutation operation on EO algorithms. In our recent research work [23], random mutation is adopted in an improved real-coded population-based EO algorithm called IRPEO-RM. Moreover, we have proposed a real-coded population-based EO algorithm with multi-non-uniform mutation to optimize multi-variable PID and PI controller [24]. Nevertheless, these reported experimental results are still for small size continuous optimization problems. In order to further study on the effects of mutation operations on the performance of EO algorithms for large continuous optimization problems, we introduce polynomial mutation in real-coded population-based EO algorithm in this work. To the best of our knowledge, polynomial mutation is firstly used in EO algorithm to further enhance its performance although it has been used in other heuristic and meta-heuristic algorithms [25]. Moreover, much more experimental results on benchmark continuous optimization problems have been provided in this paper. The basic idea behind the proposed RPEO-PLM in this work is the population-based iterated optimization consisting of generation of a real-coded random initial population, evaluation of individual and population fitness, generation of a new population based on polynomial mutation (PLM) [26], and updating the population by accepting the new population unconditionally. Compared with other popular population-based evolutionary algorithms, such as real-coded genetic algorithm (RCGA) with adaptive directed mutation (RCGA-ADM) [25], RCGA with polynomial mutation (RCGA-PLM) [25], intelligent evolutionary algorithm (IEA) [27], the hybrid particle swarm optimization and EO algorithm (PSO–EO) [21], original population-based EO (PEO) [20], RPEO-PLM has fewer adjustable parameters needing to be tuned and only selection and mutation operations. Furthermore, the superiority of RPEO-PLM to these recently reported successful evolutionary algorithms is demonstrated by the experimental results based on non-parametric statistical tests including Friedman and Quade tests [28,29] for a large number of benchmark functions with different dimensions chosen from the reported literature. Due to the fact that non-parametric statistics do not need prior assumptions related to the sample of data for being analyzed, it is more appropriate to analyze and compare the performance of the proposed RPEO-PLM algorithm and other popular population-based evolutionary algorithms.

The rest of this paper is organized as follows. The preliminaries on continuous optimization problems and the basic EO algorithm are introduced in Section 2. Then, Section 3 presents the proposed RPEO-PLM algorithm. Furthermore, the experimental results on a large number of benchmark test functions are given to demonstrate the superiority of RPEO-PLM in Section 4. Finally, the conclusion and the open issues of this paper are given in Section 5.

2. Continuous optimization problems and extremal optimization

2.1. Continuous optimization problems

It is widely known that a variety of real-world engineering problems can be formulated as continuous optimization problems [30–34]. An unconstrained continuous optimization problem [35] is generally defined as the following form:

$$\min \text{ (or max)} f(X), X=(x_1,x_2,\ldots,x_n)$$

$$\text{st. } L \le X \le U \tag{1}$$

where $f(\boldsymbol{X})$ is the objective function under the decision variables $\boldsymbol{X}$, $\boldsymbol{L}=(l_1, l_2, \ldots, l_n)$ and $\boldsymbol{U}=(u_1, u_2, \ldots, u_n)$ are the vector of minimum and maximum of decision variables, respectively, and l_i and u_i are the minimum and maximum of the decision variable x_i respectively. In other words, $l_i \le x_i \le u_i$, $i=1,2,\ldots,n$.

2.2. Extremal optimization

In general, the τ-EO [3,4] algorithm and its modified versions consist of the following basic operations, such as initialization of a random solution, evaluation of global fitness and local fitness, selection of some bad local variables based on power-law probability distribution, mutation for the selected variables and generation a new solution, updating the solution by accepting the new solution unconditionally. The τ-EO algorithm for a minimization optimization problem is described as follows:

(1) Initialize a configuration S randomly and set $S_{\text{best}}=S$ and $C(S_{\text{best}})=C(S)$, where S_{best} is the best solution so far and $C(S_{\text{best}})$ is the global fitness of S_{best}.
(2) For the current configuration S,
 (a) Evaluate the local fitness λ_i for each variable x_i and rank all the variables according to λ_i, i.e., find a permutation Π_1 of the labels i such that $\lambda_{\Pi_1(1)} \ge \lambda_{\Pi_1(2)} \ge \ldots \ge \lambda_{\Pi_1(n)}$.
 (b) Select a rank $\Pi_1(k)$ according to a probability distribution $P(k) \propto k^{-\tau}, 1 \le k \le n$, where τ is a positive parameter, and denote the corresponding variable as x_j.
 (c) Generate the new solution S_{new} so that x_j must be changed according to some mutation rules.
 (d) If $C(S_{\text{new}}) < C(S_{\text{best}})$ then $S_{\text{best}}=S_{\text{new}}$.
 (e) Accept $S=S_{\text{new}}$ unconditionally.
(3) Repeat at step (2) as long as desired.
(4) Return S_{best} and $C(S_{\text{best}})$.

According to the seminal works [3,4], the global fitness $C(S)$ of a solution S for an optimization problem with n optimized variables should be decomposed into n equivalent degrees of freedom, i.e., the local fitness λ_i. Furthermore, Liu et al. [10] give consistency and equivalence conditions between global fitness and local fitness.

3. The proposed algorithm

In this selection, we propose a novel real-coded population-based EO algorithm with polynomial mutation (RPEO-PLM). The basic idea behind the RPEO-PLM is population-based iterated optimization consisting of generation of a real-coded random initial population, evaluation of individual and population fitness, generation of a new population based on polynomial mutation (PLM), and updating the population by accepting the new population unconditionally. Fig. 1 presents the flowchart of RPEO-PLM for unconstrained continuous optimization problems. The proposed algorithm is described as following steps:

Input: A continuous optimization problem and the control parameters of the RCEO-PM, including the size of population (NP), maximum number of iteration $I_{\max}$ and the parameter q used in polynomial mutation.