L-SHADE with an Adaptive Penalty Method of Balancing the Objective Value and the Constraint Violation

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ABSTRACT

In the constraint-handling techniques, the penalty approaches (especially the adaptive penalty methods) are simple and flexible, and have been combined with various Evolutionary Algorithms so far. In this paper, we propose a new adaptive penalty method combined with L-SHADE as a method to optimize the 28 benchmark problems provided for the GECCO 2019 Competition on constrained single-objective numerical optimization effectively. The penalty factor is adjusted based on the trade-off information between the objective function value and the constraint violation that can be taken by individuals, the ranges of the objective function value and the constraint violation that can be taken by individuals and the proportion of feasible individuals in the current population. By doing this, the proposed method balances the objective function value and the constraint violation, and population is not converged in the only direction in which one improves and the other becomes worse. In addition, we use a few parameters that are easy to set up.

CCS CONCEPTS

• Mathematics of computing → Evolutionary algorithms; Bio-inspired optimization; • Theory of computation→ Continuous optimization; • Computing methodologies → Continuous space search;

KEYWORDS

Penalty approach, Adaptive penalty, Constraint Handling, Constrained optimization, Differential Evolution

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1 INTRODUCTION

Many real-parameter optimization problems in the real world are constrained, i.e. constrained optimization problems (COPs). The 28 benchmark problems provided for the GECCO 2019 Competition on constrained single-objective numerical optimization [1] is the COPs. In this paper, we propose a method to optimize these problems effectively. Specifically, we added a new penalty method to L-SHADE [2] which is proposed as an unconstrained optimization method. L-SHADE [2] is an improved method of SHADE [3], adjusts the parameter F_i and CR_i based on historical memories of successful parameters settings that were previously used during the run. L-SHADE uses DE/current-to-pbest/1/bin as a mutation strategy and crossover operator.

The rest of the paper is organized as follows. The proposed method is described in Section II. In Section III, the parameter settings are summarized. Finally, the paper is concluded in Section IV.

2 PROPOSED METHOD

L-SHADE is an unconstrained optimization method. Therefore, in this paper, we added a new penalty method to L-SHADE in order to optimize COPs.

In COPs, it is importance to discover feasible individuals. However, if searching with a larger penalty factor to prioritize finding feasible individuals, the population may favor constraint violation minimization and converge to the local optimum.

Moreover, if searching with a smaller penalty factor from the beginning, the population converges towards smaller objective function values. If the objective function value and the constraint violation are in trade-off, it may not be possible to find feasible individuals. Therefore, a suitable penalty factor does not guide only in the direction in which only one improves and the other becomes worse.

The proposed penalty method calculate the new fitness $\phi(x)$ addeing the objective function value $f(x)$ and the constrained violation $\bar{v}(x)$ as the follow:

$$\phi(x) = f(x) + PF \times \bar{v}(x)$$

where is the penalty factor which is a coefficient for adjusting the importance of the constraint violation. The method of determining the penalty factor proposed in this paper is described in Section 2.1, 2.2 and 2.3.

2.1 Penalty Factor Candidate Calculation

First of all, a penalty factor candidate (PFC) is calculated to recognize the penalty factor of larger and smaller as a follow:

$$PFC_{i,j} = \frac{f(x_j) - f(x_i)}{\bar{v}(x_i) - \bar{v}(x_j)} \tag{1}$$

Eq.(1) calculates a penalty factor that equalizes the fitness of any two individuals x_i, x_j ($i \neq j$). By calculating Eq.(1) many times with different individuals i and j, it is possible to calculate a larger penalty factor (dotted line), a smaller penalty factor (thick line) and other penalty factors as shown in Figure.1. An average penalty factor probably not lead population in the only direction in which the one improves and the other worse. If the objective function value and the constraint violation are in a trade-off relationship, the value of the Eq.(1) takes a non-positive value. A suitable penalty factor that takes these into consideration is calculated in Section 2.2.

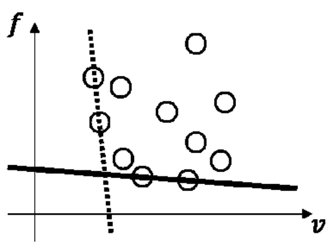

Figure.1: Example of PFC

2.2 Derivation of Penalty Factor from $PFCs$

In Eq.(1), by taking many x_i, x_j from within the region being searched, information on the region being searched can be extracted. At this time, if calculate $PFCs$ with more combinations of x_i and x_j, this method probably recognize the information of the region being searched more accurately. Therefore, in the proposed method, we calculate all combinations of the group $P \cup C$ which is added current population P and generated children C, as x_i, x_j. If the objective function value and the constraint violation are not in a trade-off relationship in the region being searched, most of the $PFCs$ are not a positive value. Therefore, if the number of positive $PFCs$ is lower than the number of other values, there is no trade-off relationship, and the penalty factor of the previous generation is used. Otherwise, the average value of the positive $PFCs$ is used as an actual penalty factor.

2.3 Proportion of Feasible Individuals in Population

Suitable penalty factor is calculated in Section 2.1 and 2.2. However, if the most individuals in the $P \cup C$ become feasible, the penalty factor of the previous generation PF_{G-1} certainly is used again. If the optimal solution exists at the edge of the feasible region, it is better to allow a slight constraint violation. Therefore, in the proposed method, if the proportion r_{feas} of feasible individuals in the population exceeds the threshold value p_{feas}, the penalty factor is decreased, and an increase in the constraint violation is allowed. If the r_{feas} exceeds p_{feas}, don't update the penalty factor described in Section 2.1 to 2.2 and calculate the new penalty PF_G using Eq.(2).

$$PF_{G+1} = p_{rate} * PF_G \tag{2}$$

where $p_{rate} \in [0,1)$ is a parameter.

3 PARAMETER SETTING

The settings of the parameters in L-SHADE are as follows:

1) Population size: initial population size $N^{init} = 12 \times D$, minimal population size $N^{min} = 4$
2) Memory size: $H = 6$, Archive size: $|A| = 2.6 \times N_G$, where N_G is the population size in the current generation G.
3) DE/current-to-pbest parameter: $p = 0.11$

The settings of the parameters in the proposed adaptive penalty method are as follows: $p_{feas} = 0.5$, $p_{rate} = 0.95$

4 CONCLUSIONS

In this paper, we proposed a method which is added a new adaptive penalty method to L-SHADE to optimize the benchmark problems [1] effectively. It uses three pieces of information, trade-off information, the ranges of the objective function values and the constraint violation that can be taken by individuals, and the proportion of feasible individuals in the current population. It balances the objective function value and the constraint violation, and population is not converged in the only direction in which one improves and the other becomes worse.

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