Benchmarking the region learning-based JADE on Noiseless Functions

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ABSTRACT

This paper proposes a region-learning based JADE algorithm, namely RL-JADE, to solve numerical optimization problems. To exploit as much as possible the most promising areas known by the current population, the worst parts of population are eliminated, and some new individuals are regenerated in the area where the best parts of population locate. RL-JADE is tested based on COCO benchmarks, and compared with other DE-variants. Experimental results show that RL-JADE has a better performance than JADE on the tested 5-D problems.

CCS CONCEPTS

• **Numerical Analysis**; • **Optimization**; • **Analysis of Algorithms and Problem Complexity**; • **Numerical Algorithms and Problems**;

KEYWORDS

Benchmarking, Black-box optimization

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1 INTRODUCTION

In some classic mutation operators of DE algorithm, such as $DE/current-to-best$ and $DE/current-to-pbest$, the population moves to the best one or several individuals. The method proposed in this paper concentrates on the guidance of population to a region, not several best individuals. This operation tends to improve the possibility of finding the global optimumcan by providing more samples for the promising regions. The distribution characteristics of the global optimal solution introduced in paper [5] illustrate the necessity of sampling around the current optimal solution. The proposed method is devoted to the exploitation of the current known most promising area. In each generation, all the individuals are ranked in terms of fitness value, and the distribution range of top $p\%$ individuals are regarded as the promising region. To exploit the promising area, $p\% \times NP$ new individuals are randomly sampled, where NP is the population size. To keep the fixed population size, the worst $p\%$ population are eliminated.

To test this method, it is embedded into JADE [4] to become a new algorithm RL-JADE. JADE algorithm is an improved version of Differential evolution with adaptive parameter setting. It has good performance on the optimization benchmarks, so is a suitable and convincing comparison with RL-JADE.

The rest of this paper is organized as follows: Section 2 introduces the proposed region learning in details. The experimental procedure is presented in section 3. Section 4 is devoted to the result analysis of experiment. The paper is concluded in section 5 with a future outlook.

2 ALGORITHM PRESENTATION

In each generation of RL-JADE, the learned promising range is denoted by lower boundaries R^L and upper boundaries R^U. Among them,

$$R^L = \{R_1^L, \ldots, R_j^L, \ldots, R_{DIM}^L\}, R^U = \{R_1^U, \ldots, R_j^U, \ldots, R_{DIM}^U\},$$

where DIM is the problem dimension. A matrix $rank$ is set to store the ranking information of population $\{x_{1,G}, \ldots, x_{i,G}, \ldots, x_{NP,G}\}$. Assuming that in generation G, the area those current best $p\%$ population $\{x_{m,G}|rank(m) < floor(p\% \times NP)\}$ locate at is the learning target, the promising range can be learned by

$$\begin{cases} R_j^L = min(\{x_{j,m,G}|rank(m) < floor(p\% \times NP)\}) \\ R_j^U = max(\{x_{j,m,G}|rank(m) < floor(p\% \times NP)\}) \end{cases}$$

where $1 <= j <= DIM$ and NP is population size. $x_{j,m,G}$ is the $j-th$ dimension of individual $x_{m,G}$. Then, the samples are generated in

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the learned range by $x_{j,n,G+1} = rand(R_j^L, R_j^U)$, where $rank(n) > floor(p\% \times NP)$.

The implementation of JADE-RL, is shown in algorithm 1. The introductions of parameters ($\mu_{CR}, \mu_F, A, S_F, S_{CR}, mean_A(\Delta), mean_L(\Delta), c$) related to JADE algorithm can be found in paper [4].

Algorithm 1: RL-JADE

Input: Population size NP; Problem dimension DIM;
  Maximum generation G_{max};
Output: Best solution: $x_{a,G}$
$G \leftarrow 0$, $\mu_{CR} \leftarrow 0.5$, $\mu_F \leftarrow 0.5$, $A = \varnothing$;
for *Each* $i < NP$ **do**
  Produce individual $x_{i,G}$ randomly;
end
for *Each generation* G **do**
  Rank the population, and store the ranking index of individuals in matrix $rank$;
  $S_F \leftarrow \varnothing$, $S_{CR} \leftarrow \varnothing$;
  for *Each individual* $x_{i,G}$ **do**
    Generate $CR_i \leftarrow randn_i(\mu_{CR}, 0.1)$, $F_i \leftarrow randc_i(\mu_F, 0.1)$;
    Perform **Mutation** on $x_{i,G}$ to generate $v_{i,G}$;
    Perform **Crossover** on $v_{i,G}$ to generate $u_{i,G}$;
    Perform **Selection** on $u_{i,G}$ to generate $x_{i,G+1}$;
    if $f(x_{i,G+1}) < f(x_{i,G})$ **then**
      $x_{i,G} \rightarrow \mathbf{A}$;
    end
  end
  Perform **Region Learning** to produce new individuals;
  $\mu_{CR} \leftarrow (1-c) \cdot \mu_{CR} + c \cdot mean_A(S_{CR})$;
  $\mu_F \leftarrow (1-c) \cdot \mu_F + c \cdot mean_L(S_F)$;
  Print $x_{a,G}$, where $rank(a) = 1$;
end

3 EXPERIMENTAL PROCEDURE

The performance of RL-JADE on COCO benchmark functions is compared with JADEctpb, DEctpb, DE-ttb, BBDE, BBDE-N, BBDE-best, and DE-PSO. The test code is written in MATLAB based on work in paper [3], and the CPU of computation machine is Intel(R) Core(TM) i5-7200U with 2.50GHz. The RAM is 8.00GB, and the operation system is 64-bit WIN10. The test data of compared algorithms are obtained from the webpage of COCO [1]. The configuration for RL-JADE is as follows: the max function evaluation times = $5e4 \times D$, $\mu_F = 0.5$, $\mu_{CR} = 0.5$, learning rate for $\mu_C R = 0.1$, and learning rate for $\mu_F = 0.1$. The population size is $5 \times D$. P is set to be 10%, and the dimension of tested problems is 5.

4 RESULTS

Results from experiments according to [1] [2] on the benchmark functions are presented in figure 1. Algorithms are tested with the rank-sum test for a given target Δf_t (10^{-8}) for each trial. Figure 1 shows the bootstrapped empirical cumulative distribution

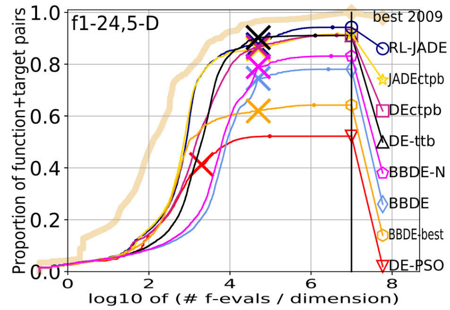

Figure 1: The performances of all the compared algorithms

of the number of objective function evaluations divided by dimension ($\#f - evals/dimension$) for 50 targets in $10^{[-8..2]}$ for all functions and subgroups in 5-D. The **best 2009** line corresponds to the best ERT observed during BBOB 2009 for each single target. Among all the compared algorithms, RL-JADE performs best, and has significantly improved the performance of JADE. The superiority is obvious after $\log(\#f - evals/dimension) > 4$, while $\log(\#f - evals/dimension) < 4$, RL-JADE and JADE have the similar performances.

5 CONCLUSIONS AND FUTURE WORK

This paper proposes a partial population regeneration method to produce samples in the current known promising region. Experimental result shows that this operation can provide effect detailed search in the target area. According to the complexity of a specific optimization problem, the proportion p of regenerated individuals can be slightly changed.

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