A Dimensional-level Adaptive Differential Evolutionary Algorithm for Continuous Optimization

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ABSTRACT

In differential evolution (DE), the optimal value of the control parameters are problem-dependent. Many improved DE algorithms have been proposed with the aim of improving the exploration ability by adaptively adjusting the values of F. In those algorithms, although the value of F is adaptive at the individual level or at the population level, the value is the same for all dimensions of each individual. Individuals are close to the global optimum at some dimensions, but they may be far away from the global optimum at other dimensions. This indicated that different values of F may be needed for different dimensions. This paper proposed an adaptive scheme for the parameter F at the dimensional level. The scheme was incorporated into the jDE algorithm and tested on a set of 25 scalable benchmark functions. The results showed that the scheme improved the performance of the jDE algorithm, particularly in comparisons with several other peer algorithms on high-dimensional functions.

Categories and Subject Descriptors

G.1.6 [**NUMERICAL ANALYSIS**]: Optimization—*global optimization, unconstrained optimization*

Keywords

Differential evolution, self-adaptation, dimensional-level adaptation

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1. INTRODUCTION

Differential evolution (DE), introduced by Price and Storn [4], is a simple yet powerful evolutionary algorithm (EA) for global optimization problems. DE creates a new candidate solution by combining the information of a parent individual and several other individuals of the population. There are many different trial vector generation strategies for DE, each of which seems to be suitable for some particular tasks or for solving a certain type of problems [2, 3]. There are three control parameters in DE: the amplification factor of the difference vector—F, the crossover control parameter—CR, and the population size—NP. Although several adaptive DE algorithms have been proposed, they are all at the population level or at the individual level, i.e. for an individual, the values of F are the same for all dimensions. Individuals are close to the global optimum at some dimensions, but they may be far away from the global optimum at other dimensions. In general, in the case that population converges to the global optimum, the distance between an individual and the global optimum gradually decreases to zero for all dimensions but in a chaotic way. This suggests that using an adaptive F for each dimension for an individual may improve the performance of DE algorithms. This paper aims to address this issue based on a case study of the jDE algorithm [1].

2. DIMENSIONAL-LEVEL ADAPTATION OF F

In this section, we propose an adaptive scheme of F for jDE at the dimensional level. To adjust the values of F at different dimensions, the encoding for each individual in the population is extended with a value of F at each dimension parameter (see Fig. 1). The mutation in the improved algorithm Dim-jDE is changed as follows:

$$\mathbf{v}_{i,G} = \mathbf{x}_{r_1,G} + \mathbf{F}_{i,G} \cdot (\mathbf{x}_{r_2,G} - \mathbf{x}_{r_3,G}), \qquad (1)$$

where $\mathbf{F}_{i,G} = \{F_{i,1,G}, F_{i,2,G}, \ldots, F_{i,D,G}\}$. In Eq. (1), for an individual, the value of F of each dimension is independent. For the mutant vector $\mathbf{v}_{i,G}$ generated by Eq. (1), the range

Table 1: $b/n/w$ summarizes the statistical results: b, n, and w denote the number of functions for which Dim-jDE performs significantly better, no significantly different and significantly worse than its peer, respectively.

	D=50			D=100		
	jDE(NP=30)	jDE(NP=100)	DE/rand/1/bin	jDE(NP=30)	jDE(NP=200)	DE/rand/1/bin
Dim-jDE	10/6/9	13/10/2	10/8/7	12/6/7	16/5/4	18/2/5

of $v_{i,j,G}$ is $\left[x_{r_1,j,G} - F_{i,j,G} \cdot |x_{r_2,j,G} - x_{r_3,j,G}|, x_{r_1,j,G} + F_{i,j,G} \cdot |x_{r_2,j,G} - x_{r_3,j,G}|\right]$, $j = 1, 2, \ldots, D$. Therefore, if the values of $F_{i,j,G}$, $j = 1, 2, \ldots, D$, are different, the magnitude change of $x_{r_1,j,G}$ will be different with dimensions.

$x_{1,1,G}$	$x_{1,2,G}$	…	$x_{1,D,G}$	$F_{1,1,G}$	…	$F_{1,D,G}$	$CR_{1,G}$
$x_{2,1,G}$	$x_{2,2,G}$	…	$x_{2,D,G}$	$F_{2,1,G}$	…	$F_{2,D,G}$	$CR_{2,G}$
…	…	…	…	…	…	…	…
$x_{NP,1,G}$	$x_{NP,2,G}$	…	$x_{NP,D,G}$	$F_{NP,1,G}$	…	$F_{NP,D,G}$	$CR_{NP,G}$

Figure 1: The new individual encoding.

The new control parameter $\mathbf{F}_{i,G+1}$ is adapted as follows:

$$\mathbf{F}_{i,G+1} = \begin{cases} \mathbf{F}'_{i,G+1} & \text{if } rand_1 < \tau_1 \quad (2a) \\ \{0.5, \ldots, 0.5\} & \text{otherwise} \quad (2b) \end{cases}$$

where

$$\mathbf{F}'_{i,G+1} = \left\{\theta_j | \theta_j = F_l + rand_2 \cdot F_u, j = 1, 2, \ldots, D\right\}, \quad (3)$$

The methods of generating θ in Eq. (3) is the same as jDE [1]. $rand_1, rand_2 \in [0, 1]$, which are uniformly distributed random numbers. τ_1 represents probabilities. F_l=0.1, F_u=0.9 and τ_1=0.1, which are the same values used as the original jDE algorithm [1]. Eq. (3) improves the diversity of F, which makes a DE algorithm too explorative. It will slow down the convergence speed. To alleviate this issue, in Eq. (2a), the values of F are adapted at the dimensional level with a small probability.

3. EXPERIMENTAL STUDY

A set of 25 scalable benchmark functions for the competition on IEEE CEC05, are used with dimensionality of D=30 and D=50. For the 30-dimensional problems, there are 7 functions for which Dim-jDE archives the best error; while there are 11 functions for which DE/rand/1/bin archives the smallest error. From the statistical significant results (see Table 1), we can see that Dim-jDE performs slightly better than DE/rand/1/bin. Dim-jDE performs much better than jDE with NP=100. Compared with jDE with NP=30, although the initial population of Dim-jDE is the same as its, Dim-jDE performs a little significantly better because of the improved adaptation of F. For the 50-dimensions problems, there are 10 functions for which Dim-jDE can get the best results. And Dim-jDE performs much significantly better than DE/rand/1/bin and jDE with NP=200. This is because an enlargement in population size causes an increase in the set of potential ineffective moves [2]. For these high-dimensional functions, compared with jDE with NP=30, Dim-jDE performs significantly better. From the above results, we can see that although the population size of Dim-jDE is small, its performance is good, and we can conclude that the improved adaptation of F can improve the performance of jDE algorithm, especially for high-dimensional problems.

4. CONCLUSIONS

In this paper, we has studied the adaptation of F at the dimension level, and proposed an improved scheme of adapting F. In the improved adaptation of F, each individual in the population is extended with parameter values of F, and the values of F are applied not only at the individual level but also at the dimensional level. So the mutation operation improves the explorative capability of an algorithm. The improved adaptation is incorporated into the jDE algorithm and is tested on a set of 25 scalable benchmark functions. The results show that the improved adaptation of F can significantly improve the performance of the jDE algorithm. Even if the population size of jDE is small, the improved jDE algorithm also has a superior performance in comparisons with several other peer algorithms for high-dimensional function optimization.

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