An Extended SHADE and Its Evaluations

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Abstract. Differential Evolution (DE) is a population-based stochastic search method for real-valued function optimization. Similar to other meta-heuristic algorithms, DE searches for optimal or near-optimal solutions without a priori knowledge of the function being optimized. However, DE generally shows largely different performances on the basis of the DE parameters adopted. Therefore, many DE variants, including one called SHADE—one of the most highly efficient DEs so far, have been developed to obtain a more stable and better performance. SHADE introduces parameter archives for robust parameter adaptations. In this paper, an extended form of SHADE is proposed, in which parameter archives are managed by a novel strategy with three new operators. Computer simulations are conducted to examine the performance of the proposed DE on the basis of 28 benchmarks.

Keywords: Evolutionary Computation, Differential Evolution, Numerical Optimization.

1 Introduction

Differential evolution (DE) is a simple yet evolutionary algorithm for real-valued function optimization problems [6], [4], [1]. DE has fundamental control parameters, which are the population size (NP), crossover rate (CR), and scaling factor (F). Although DE variants are fixed in classical DE, many DE variants, such as [8], [5], [9], [3], and [7]—in which the control parameters are variables during calculations, have been proposed. The motivation behind this is that control parameter tuning is recognized as one of the key issues for obtaining better optimization performance.

In this paper, a new DE, inspired by JADE [9] and SHADE [7], is proposed, and its performance is examined on the basis of 28 test functions adopted by CEC2013. The remainder of this paper is organized as follows. In the next section, the basic DE algorithm is reviewed. In Section 3, JADE, which is our foundation, is briefly introduced. Section 4 introduces SHADE, which is a DE variant based on JADE. Section 5 presents the details of our proposed DE, RSHADE, which is inspired by SHADE. In Section 6, computer simulations are conducted using a set of 28 benchmarks to examine the performance of the proposed method. Finally, Section 7 shows the conclusions.
2 Differential Evolution

Similarly to conventional evolutionary computation techniques, DE is composed of three procedures: mutation, crossover, and selection. An individual component in DE is represented by a real-valued vector $x_i = \{x_0, x_1, \ldots, x_{D-1}\}$, $(i = 0, 1, 2, \ldots, NP - 1)$, where $D$ and $NP$ are the dimensions defined by a given problem and the population size, respectively. Each individual component is initialized before the evolutionary search.

2.1 Mutation

At each generation $G$, a mutation vector, $v_{i,G}$, is generated for each individual $x_{i,G}$. For example, three well-known mutation strategies with a mutation vector are described as follows:

“DE/rand/1”

$$v_{i,G} = x_{r1,G} + F \cdot (x_{r2,G} - x_{r3,G}),$$

“DE/best/1”

$$v_{i,G} = x_{\text{best},G} + F \cdot (x_{r1,G} - x_{r2,G}),$$

and

“DE/current to best/1”

$$v_{i,G} = x_{i,G} + F \cdot (x_{\text{best},G} - x_{i,G}) + F \cdot (x_{r1,G} - x_{r2,G}),$$

where $r1$, $r2$, $r3$, and $r4$ are uniformly and randomly chosen integers from the set $\{0, 1, 2, \ldots, NP - 1\} \setminus \{i\}$ and assumed to be different from each other. In addition, $x_{\text{best},G}$ represents the best individual component for the current generation $G$.

2.2 Crossover

After executing a mutation operation to generate a mutation vector $v_{i,G}$, a crossover operator is applied to generate a trial vector $u_{i,G}$. A common crossover method is a binomial crossover described by the following equation:

$$u_{j,i,G} = \begin{cases} v_{j,i,G} & \text{if } \text{rand} [0, 1) \leq CR \text{ or } j = j_{\text{rand}}, \\ x_{j,i,G} & \text{otherwise} \end{cases}$$

(1)

where rand $[a, b)$ is a uniform random number in the interval $[a, b)$, $CR$ is the crossover rate whose value is $\in [0, 1]$, $j$ is the $j$th dimension, and $j_{\text{rand}}$ is a random integer $\in [0, D - 1]$ generated for each $i$. 