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QUasi-Affine TRansformation Evolution with External ARchive (QUATRE-EAR): An enhanced structure for Differential Evolution

Zhenyu Meng[*,a], Jeng-Shyang Pan[a,b]

[a] Department of Computer Science and Technology, Harbin Institute of Technology Shenzhen Graduate School, Shenzhen, China
[b] College of Information Science and Engineering, Fujian University of Technology, Fuzhou, China

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ABSTRACT

Optimization demands are ubiquitous in science and engineering. The key point is that the approach to tackle a complex optimization problem should not itself be difficult. Differential Evolution (DE) is such a simple method, and it is arguably a very powerful stochastic real-parameter algorithm for single-objective optimization. However, the performance of DE is highly dependent on control parameters and mutation strategies. Both tuning the control parameters and selecting the proper mutation strategy are still tedious but important tasks for users. In this paper, we proposed an enhanced structure for DE algorithm with less control parameters to be tuned. The crossover rate control parameter *Cr* is replaced by an automatically generated evolution matrix and the control parameter *F* can be renewed in an adaptive manner during the whole evolution. Moreover, an enhanced mutation strategy with time stamp mechanism is advanced as well in this paper. CEC2013 test suite for real-parameter single objective optimization is employed in the verification of the proposed algorithm. Experiment results show that our proposed algorithm is competitive with several well-known DE variants.

1. Introduction

Optimization exists all over the world, as one basic principle in our world is to find an optimal state [1,2]. In the macrocosm, biological evolution always keeps the species with the best adaption to the current environment survived, survival of the fittest as the principle [3]. In the microcosm, atoms always try to form bonds in minimization of their electrons energy [4]. Human-beings have always been striving for the perfection in all areas ever since the emergence in the world. This perfection, from certain point of view, can be considered as optimization problems studied and tackled in the end. Today, many optimization approaches have been learned and employed as an important tool in decision science and engineering, and the basic principle is that the tool tackling complex optimization problem should not itself be complicated. Differential Evolution (DE), proposed in 1995 [5–7], was such a simple but powerful method for optimization problems.

DE was originated with Genetic Annealing Algorithm (GAA) [8], which was a hybrid algorithm of Genetic Algorithm (GA) [9] and Simulated Annealing (SA) [10]. Therefore the operations such as mutation, crossover and selection in GA were also inherited into DE algorithm though the sequences of these operations are different [8,11] from one to the other. The discovered differential mutation operator in DE algorithm was arguably one of the most powerful operators for optimization, and many researchers as well as engineers had learnt about this technique and proposed many variants to enhance the performance of it. All those enhancements can mainly be classified into two categories, one mainly focused on tuning of control parameters and the other on enhancing the generating strategies of trial vectors. There are three control parameters in DE, the scale factor *F*, the crossover probability *Cr*, and the population size *ps*, and there are also 5 mutation strategies and 2 crossover schemes which constitutes a total 10 generating schemes of trial vector in the earlier researches of DE [5–8]. A general convention DE/x/y/z was given to define these different schemes, x denoted the base vector of the donor/mutant vector, y denoted the number of difference vectors, and z denoted a certain crossover scheme. Then the five mutation strategies can be written like DE/rand/1/z, DE/best/1/z, DE/target-to-best/1/z, DE/best/2/z, and DE/rand/2/z, and the two crossover schemes can be written like DE/x/y/exp (exponential crossover) and DE/x/y/bin (binomial crossover).

Control parameters played important roles in the optimization performance of DE. As perceived from the literature, many claims and counter-claims were reported concerning the rules of choosing proper parameters of DE [7,8,12,13]. Researchers started to consider some adaptive/self-adaptive approaches for parameter control techniques. Liu and Lampinen [14] introduced a fuzzy adaptive differential evolution using fuzzy logic controllers to adapt the parameters for the

* Corresponding author.
E-mail addresses: mzy1314@gmail.com, mzy_1314@126.com (Z. Meng).

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mutation and crossover operation. Brest et al. [15] introduced an adaptive parameter control scheme with changing F and Cr values in the evolutionary process. Qin et al. [16] proposed another adaptive DE algorithm, the control parameter Cr was adaptively renewed by the knowledge learnt from previous generations. Zhang and Sanderson [17] proposed a new adaption scheme of control parameters, control parameters F and Cr were updated according to their current-generation values and the means of success values. Peng et al. [18] proposed a fitness value based control parameter adaptive approach for DE algorithm, the associated fitness values were employed in the renewing process of control parameters. Tanabe and Fukunaga extended this parameter adaptive approach and made a big improvement in [19]. However, these proposed DE variants still existed some weaknesses, such as the exploration preference in a certain solution space (e.g., DE variants with small and fixed Cr settings were usually associated with exploration alongside the coordinate directions) and the mis-interaction within different control parameters (e.g., for DE variants, JADE [17], SHADE [19], and LSHADE [20] et al., with adaptive F and Cr schemes, a better fitness value can be calculated by a better Cr value and a worse F value or a worse Cr value and a better F value, then the worse value of F or Cr would be considered as the right one which was employed to propagate next generation values. This phenomenon was the mis-interaction within different control parameters.). Meng et al. [1,11,21–23] gave some hints to tackle one of the above mentioned weakness, biased exploration preference, of DE variants by proposing a new QUATRE structure for evolution, and an auto-generated evolution matrix instead of control parameter Cr was employed in the evolution structure. Moreover, when the renewing schemes of the evolution matrix and scale factor F were separated and conducted in independent ways, the mis-interaction weakness can also be tackled, and this is what we mainly focused on in this paper.

Trial vector generating strategy also played an important role in the performance of DE variants. There are two crucial components in generating trial vector, one is mutation strategy and the other is crossover scheme. DE variants [5–8,14,15] proposed earlier in literature mainly employed the canonical trial vector generating strategy, DE/rand/1/bin, to generate trial vectors. Besides the above mentioned two commonly used crossover schemes, there was also a third crossover scheme, disabled crossover, mentioned in literature. Price et al. [8] proposed a new DE/rand/1/either-or strategy for trial vector generation, crossover operation was disabled and therefore the trial vectors equaled to the mutant vectors in this strategy. Feoktistov and Janaqi [12] proposed a new DE/rand/dir mutation strategy, and fitness values were taken into consideration when generating donor vectors. Unlike these above mentioned single mutation strategy DE variants, Qin et al. proposed a mutation pool containing 4 strategies in SaDE [16], and individuals can adaptively choose a certain mutation strategy for evolution. Zhang [17] proposed an external archive based mutation strategy, DE/target-to-pbest/bin, and the external archive was employed in storing inferior solution during the evolution which could diversify the difference vector in the mutation strategy. Tanabe et al. [19] enhanced the mutation strategy DE/target-to-pbest/1/bin and obtained a higher level better performance by employing a new fitness value based adaptive scheme for control parameters, and these variants, called SHADE variants [19,20] secured the first ranks of Conference on Evolutionary Computation (CEC) on real-parameter single objective optimization competitions recently. Therefore, we employed the DE/target-to-pbest/1/bin mutation strategy as well in our paper and some advancements were also presented to enhance the optimization performance of it.

The QUATRE thought of evolution is first proposed by Meng et al. in [1], and that paper only discussed a single variant, the default QUATRE algorithm, of the QUATRE structure. Paper [11] gave some other variants of the QUATRE structure and paper [21] made a simple discussion of the relation between QUATRE algorithm and DE algorithm. In this paper, the main differences and highlights of this manuscript with regards to the former articles are listed below:

- A complete QUATRE structure is proposed in this paper, and it can be considered as an enhancement of DE algorithm.
- In the QUATRE structure, evolution matrix M is employed in the generation of trial vectors, and it can be considered as an alternative of crossover rate parameter Cr in DE algorithm implementing crossover operation, and the employment of M tackles the exploration bias in DE variants with fixed Cr values.
- Adaptive renewing schemes both for evolution matrix M and for control parameter F are given in independent manners and these avoid the mis-interaction between control parameters in some well-known DE variants.
- A time-stamp mechanism is employed in the enhancement of a former mutation strategy with external archive, QUATRE/pbest/1, and this avoids too old inferior individuals being archive-residents during the whole evolution, and this implements a good optimization performance on CEC2013 test suites.
- Several well-known DE variants with fixed population size and single mutation strategy is contrasted with our QUATRE-EAR algorithm under CEC2013 real-parameter single objective benchmark functions, and experiment results show that our algorithm is competitive with these excellent DE variants.

The rest of the paper is organized as follows. Section 2 gives a brief introduction of DE algorithm. Section 3 discusses the detailed QUATRE-EAR algorithm. Section 4 presents the experiment analysis conducted under CEC2013 test suite for real-parameter single objective optimization. Experiment comparisons between the proposed QUATRE-EAR algorithm and several well-known DE variants are also given in this section. Finally, conclusion is given in Section 5.

2. Differential evolution algorithm

Differential Evolution (DE) is arguably a simple but powerful evolution algorithm for optimization problems, and it utilizes ps-parameter vectors to find the global optimum for a complex problem. These vectors, i.e., the ith vector $X_{i,G} = (x_{i1,G}, x_{i2,G}, ..., x_{iD,G})$, $i = 1, ..., ps$, D denotes the dimensional number, G denotes the number of generations, were also called candidate solutions in the solution space. For generality, the optimization problem that minimizing an objective function $f = f(X)$ can be formally represented as finding the set:

$$\Omega^* \equiv \arg\min_{X\in\Omega} f(X) = \{X^* \in \Omega: f(X^*) \le f(X), \forall\ X \in \Omega\} \tag{1}$$

where X is the D-dimensional vector of parameters, and $\Omega \subseteq \mathbb{R}^D$ is the solution space.

DE algorithm often begins with vectors initialization of all the individuals when tackling such an optimization problem. All the individuals in the population should statistically cover the whole search domain Ω. Usually, parameter in these vectors may be restricted in a predefined bounds with the lower bound $X_{min} = (x_{min,1}, x_{min,2}, ..., x_{min,D})$ and the upper bound $X_{max} = (x_{max,1}, x_{max,2}, ..., x_{max,D})$. The stochastic cover of individuals can be implemented by uniformly randomizing ps vectors in the restricted bounds, shown in Eq. (2), $x_{ij,\ 0}$ denotes the jth parameter of the ith vector in 0th generation.

$$x_{ij,0} = x_{min,j} + rand_{ij}(0,\ 1)\cdot(x_{max,j} - x_{min,j}) \tag{2}$$

After initialization, DE utilizes base vector and difference vector to generate donor vector, i.e., $V_{i,\ G}$, and utilizes crossover operator to generate trial vector, i.e., $U_{i,\ G}$, for each target vector, i.e., $X_{i,\ G}$, $i = 1, 2, ..., ps$, in each generation.

2.1. Mutation

Mutation scheme is one of the most amazing parts in DE algorithm,