Information Sciences 320 (2015) 244–287

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Differential evolution with hybrid linkage crossover

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ARTICLE INFO

Article history:
Received 2 March 2014
Received in revised form 5 February 2015
Accepted 15 May 2015
Available online 27 May 2015

Keywords:
Differential evolution
Linkage learning
Crossover
Grouping
Numerical optimization

ABSTRACT

In the field of evolutionary algorithms (EAs), differential evolution (DE) has been the subject of much attention due to its strong global optimization capability and simple implementation. However, in most DE algorithms, crossover operator often ignores the consideration of interactions between pairs of variables. That is, DE is linkage-blind, and the problem-specific linkages are not utilized effectively to guide the search process. Furthermore, linkage learning techniques have been verified to play an important role in EA optimization. Therefore, to alleviate the drawback of linkage-blind in DE and enhance its performance, a novel linkage utilization technique, called hybrid linkage crossover (HLX), is proposed in this study. HLX utilizes the perturbation-based method to automatically extract the linkage information of a specific problem and then uses the linkage information to guide the crossover process. By incorporating HLX into DE, the resulting algorithm, named HLXDE, is presented. In order to evaluate the effectiveness of HLXDE, HLX is incorporated into six original DE algorithms, as well as several advanced DE variants. Experimental results demonstrate the high performance of HLX for the DE algorithms studied.

1. Introduction

Differential evolution (DE), proposed by Storn and Price [55], is a simple and powerful evolutionary algorithm (EA) for global optimization over continuous space. In the field of EA, DE has been the subject of much attention due to its attractive characteristics, such as its compact structure, ease of use, speediness and robustness. In the last few years, DE has been extended for handling multiobjective, constrained, large scale, dynamic and uncertain optimization problems [11,40] and is now successfully used in various scientific and engineering fields [47,66,19,85], such as chemical engineering, engineering design, and pattern recognition.

When DE is applied to a given optimization problem, there are two main factors which significantly affect the behavior of DE: control parameters (i.e., population size *NP*, mutation scaling factor *F* and crossover rate *Cr*) and evolutionary operators (i.e., mutation, crossover and selection). During the last decade, many researchers have worked to improve DE by adopting self-adaptive strategies for the control parameters [48,30,13], devising new mutation operators [23,5,67], developing ensemble strategies [68,25,6], and proposing a hybrid DE with other optimization algorithms [73,46,64], etc. Many studies related to the evolutionary operators of DE have focused on the mutation operator [48,30,23,5,68,25]. In contrast, there have been few studies on the crossover operator of DE [43,24,69].

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http://dx.doi.org/10.1016/j.ins.2015.05.026
0020-0255/

Linkages or inter-dependencies between pairs of variables have been studied and utilized in genetic algorithm (GA) and EAs to improve performance on difficult problems [8,65]. From the perspective of GA, tight linkage refers to the identified building blocks (BBs) on a chromosome, and the genes belonging to the same BB should be inherited together by the offspring at a higher probability. According to the existing work, linkage identification or recognition of BBs plays an important role in GA optimization [8,65]. Many linkage learning techniques have been proposed for combinatorial optimization [8,65,17], while techniques for global numerical optimization have been rarely discussed [84,7]. In addition, to the best of our knowledge, studies explicitly using linkage information to enhance the performance of DE are scarce. Therefore, most DE algorithms are not able to effectively utilize problem-specific linkages for guiding the search.

Based on these considerations, we present a novel linkage utilization technique, called hybrid linkage crossover (HLX), to utilize the problem-specific linkages to guide the crossover process of DE. First, HLX uses a perturbation-based method, an improved differential grouping (DG) method [44], to adaptively extract the linkage information between pairs of variables. The linkage information is stored in a linkage matrix (*LM*). In *LM*, each element stands for "linkage strength" which measures the likelihood of a pair of variables being tightly linked. Then, with *LM*, the BBs are identified by automatically decomposing the problem variables into different groups without overlaps. Here, BB is a group of tightly interactive variables. Finally, two group-wise crossover operators are designed to explicitly use the identified BBs for guiding the crossover process. One is named group-wise binomial crossover (GbinX). Different from the conventional binomial crossover of DE, GbinX exchanges the variables based on the detected groups. The second one is referred to as group-wise orthogonal crossover (GorthX), which combines the orthogonal design [27,38] and the identified BBs to make a systematic search in a region defined by a pair of the target and mutant vectors. In this way, both GbinX and GorthX can avoid the disruption of BBs during crossover. By incorporating HLX into DE, the resulting algorithm, named HLXDE, is proposed. In HLXDE, the conventional binomial crossover operator and the two group-wise crossover operators are implemented together in a cooperative manner.

In order to evaluate the effectiveness of HLXDE, HLX is incorporated into six original DE algorithms, as well as several advanced DE variants. Experimental studies are carried out on a suite of benchmark problems, including the classical functions [74], the functions from the IEEE congress on evolutionary computation (CEC) 2005 special session on real-parameter optimization [56] and the functions from the IEEE CEC 2012 special session on large-scale global optimization [60]. The results indicate that HLX can effectively enhance the performance of most DE algorithms studied.

The major contributions of this study include the following:

- An improved differential grouping technique is presented to address the linkage learning problem for global numerical optimization. It provides some insights on how the idea of grouping variables can be extended beyond the cooperative coevolution framework.
- Two group-wise crossover operators, GbinX and GorthX, are designed to explicitly utilize the identified BBs to guide the crossover process of DE.
- HLXDE effectively combines two group-wise crossover operators with the binomial crossover in a cooperative manner, which effectively maintains the advantages of the binomial crossover and utilizes the BBs of good or promising individuals.
- HLX can be easily applied to other advanced DE variants and cooperated with different kinds of modifications in the advanced DE variants. It provides a new promising approach for optimization.

The rest of this paper is organized as follows. Section 2 briefly describes the original DE algorithm, the related work to the crossover operator of DE and the linkage learning techniques. Then, HLX and HLXDE are presented in detail in Section 3. In Section 4, the experimental results for a suite of benchmark functions are reported and analyzed. Finally, the conclusions are drawn in Section 5.

2. Related work

In this section, the original DE algorithm is introduced first. Then, the related work to the crossover operator of DE and the linkage learning techniques are reviewed.

2.1. DE

DE is for solving the numerical optimization problem. Without loss of generality, we consider the following optimization problem: *Minimize* $f(X), X \in S$, where $S \subseteq R^D$ and D is the dimension of the decision variables. DE evolves a population of vectors, and each vector is denoted as $X_{i,G} = (x_{1,i,G}, x_{2,i,G}, \ldots, x_{D,i,G})$, where $i = 1, 2, \ldots, NP$, NP is the size of the population and G is the number of current iteration. Here, the initial value of the jth parameter of $X_{i,G}$ can be generated by:

$$x_{j,i,G} = L_j + rndreal(0,1) \cdot (U_j - L_j) \tag{1}$$

where $rndreal(0,1)$ represents a uniformly distributed random variable within the range [0, 1] and L_j (U_j) represents the lower (upper) bound of the jth variable.

During each generation, DE uses three main operators for population reproduction: mutation, crossover and selection.