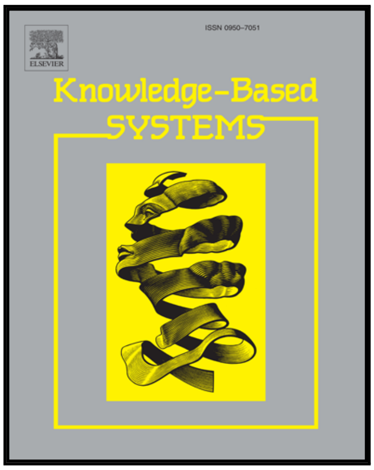

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Multi-objective differential evolution with dynamic covariance matrix learning for multi-objective optimization problems with variable linkages

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Abstract

Recently, many multi-objective differential evolution versions (MODEs) have been developed by incorporating the search engine of differential evolution (DE) and multi-objective processing mechanisms. However, most existing MODEs perform poorly in solving multi-objective optimization problems (MOPs) with variable linkages. The cause of this poor performance is the rotational variability of binomial crossover operator (BCO), which is not conducive to making simultaneous progress across all variables within a solution vector in the search for such MOPs. To alleviate the limitation, dynamic covariance matrix learning (DCML) based on the information distribution of the entire or a portion of the population is proposed to establish a proper coordinate system for the BCO by eigen decomposition. In this method, the rotational invariance of DE can be enhanced to a certain extent by releasing the interactions among the variables; thus, it is useful for MODEs to better balance their exploration and exploitation abilities. By integrating the DCML into existing MODEs, a class of new MODEs, which are called MODEs+DCML for short, are presented in this study. For comparison purposes, the proposed DCML strategy is applied to four commonly used MODEs. Twenty-nine benchmark problems with variable linkages are selected as the test suite to evaluate the performance of the proposed MODEs+DCML. The experimental results show that the proposed DCML can significantly improve the performance of the state-of-the-art MODEs in most test functions.

Keywords: Multi-objective optimization; Variable linkages; Differential evolution; Rotational invariance; Dynamic covariance matrix learning

1. Introduction

Many real-world multi-objective optimization problems (MOPs) have explicit linkages among variables in nature, whose decision variables cannot be optimized independently. Due to the presence of variable linkages, MOPs pose big challenges to evolutionary algorithms (EAs) since a tiny change on the decision variables may cause significant change of the objective vector. How to effectively solve this type of MOP has become a challenge in research, and is of great significance to gain better insight into the working principle of methodologies [1]. This paper considers the following MOPs with variable linkages:

$$\begin{aligned} \min \quad & \mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \cdots, f_m(\mathbf{x})), \\ \text{s.t.} \quad & \mathbf{x} = (x_1, x_2, \cdots, x_D) \in \Omega \end{aligned} \tag{1}$$

where $\Omega = \prod_{i=1}^{D} [L_i, U_i] \subseteq \Re^D$ defines a search space, $\mathbf{x} = (x_1, x_2, \cdots, x_D)$ is the decision vector with variable linkages, D is the dimension of decision vector, and L_i and U_i are the lower and upper bounds of the ith variable x_i, respectively. $\mathbf{F} : \Omega \to \Re^m$ consists of m real-valued objective functions, and $\Re^m$ is called the objective space.

The objectives in Eq. (1) usually conflict with one another, and no single solution can simultaneously optimize them. Instead, the optimal trade-off solutions among different objectives are of practical interest to decision

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