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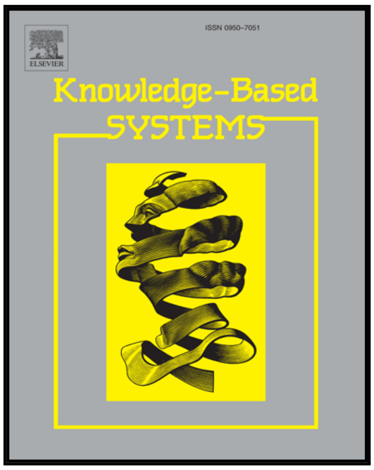

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MOEA/D-ARA+SBX: A new multi-objective evolutionary algorithm based on decomposition with artificial raindrop algorithm and simulated binary crossover

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Abstract

In the field of optimization computation, there has been a growing interest in applying intelligent algorithms to solve multi-objective optimization problems (MOPs). This paper focuses mainly on the multi-objective evolutionary algorithm based on decomposition, MOEA/D for short, which offers a practical general algorithmic framework of evolutionary multi-objective optimization, and has been achieved great success for a wide range of MOPs. Like most other algorithms, however, MOEA/D has its limitations, which are reflected in three aspects: the problem of balancing diversity and convergence, non-uniform distribution of the Pareto front (PF), and weak convergence of the algorithm. To alleviate these limitations, a new combination of the artificial raindrop algorithm (ARA) and a simulated binary crossover (SBX) operator is first integrated into the framework of MOEA/D to balance the convergence and diversity. Thus, our proposed approach is called MOEA/D with ARA and SBX (MOEA/D-ARA+SBX). On the other hand, the raindrop pool in ARA is further extended to an external elitist archive, which retains only non-dominated solutions and discards all others. In addition, the k-nearest neighbors approach is introduced to prune away redundant non-dominated solutions. In such a way, a Pareto approximate subset with good distribution to the true PF may be achieved. Based on the relevant mathematical theory and some assumptions, it is proven that MOEA/D-ARA+SBX can converge to the true PF with probability one. For performance evaluation and comparison purposes, the proposed approach was applied to 44 multi-objective test problems with all types of Pareto set shape, and compared with 16 other versions of MOEA/D. The experimental results indicate its advantages over other approaches.

Keywords: Multi-objective optimization; Artificial raindrop algorithm; Decomposition; k-nearest neighbors; External elitist archive; Convergence analysis

1. Introduction

Many optimization problems encountered in the real-world frequently involve multiple conflicting objectives that should be optimized synchronously [1, 2]. Such optimization problems are considered multi-objective optimization problems (MOPs), which can be defined as

$$\min_{\mathbf{x}\in\Omega} \mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \cdots, f_k(\mathbf{x}))^{\mathrm{T}}, \tag{1}$$

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

Because of the conflicting nature of the objectives, i.e., the amelioration of one objective gives rise to the deterioration in another, there is no single solution to optimize all objectives. Instead, the best trade-off solutions between different objectives are introduced in MOPs. In MOPs, a solution $\mathbf{x}_1$ is said to dominate $\mathbf{x}_2$ (denoted by $\mathbf{x}_1 \prec \mathbf{x}_2$) if and only if $\forall i \in \{1, 2, \cdots, k\}$, $f_i(\mathbf{x}_1) \leq f_i(\mathbf{x}_2)$ and $\exists\, i_0 \in \{1, 2, \cdots, k\}$, and $f_{i_0}(\mathbf{x}_1) < f_{i_0}(\mathbf{x}_2)$. $\mathbf{x}^* \in \Omega$ is said to be *Pareto optimal* if no other feasible solution $\mathbf{x} \prec \mathbf{x}^*$ exists. The union of all $\mathbf{x}^*$ is termed a *Pareto set* (PS) and its image in the objective space is called *Pareto front* (PF). In addition, $\mathbf{x}^* \in \Omega$ is said to be a weakly

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