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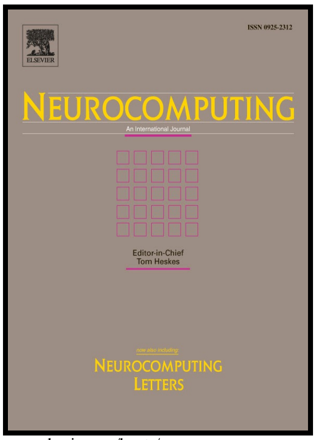

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An improved Multi-Objective Evolutionary Algorithm Based on Environmental and History Information

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Abstract

Proximity and diversity are two basic issues in multi-objective optimization problems. However, it is hard to optimize them simultaneously, especially when tackling problems with complicated Pareto fronts and Pareto sets. To make a better performance of multi-objective optimization evolutionary algorithm, the environmental information and history information are used to generate better offsprings. The conception of locality and reference front is introduced to improve the diversity. Adaptation mechanism of evolutionary operator is proposed to solve searching issue during different stages in evolutionary process. Based on these improvement, an improved multi-objective evolutionary algorithm based on environmental and history information(MOEA-EHI) is presented. The performance of our proposed method is validated based inverted generation distance(IGD) and compared with three state-of-the-art algorithms on a number of unconstrained benchmark problems. Empirical results fully demonstrate the superiority of our proposed method on complicated benchmarks.

Keywords: Evolutionary computation, Multi-objective optimization, Exploitation and exploration, Evolutionary algorithm

1. Introduction

Many real-world optimization problems are required to optimize several competing objectives simultaneously, which are so-called multi-objective optimization problems (MOPs). A variety of mathematical programming techniques currently exist to solve them, but MOPs from real world are too complex to solve by conventional optimization methods. So, evolutionary algorithms(EAs) have been introduced to solve these problems.

EAs are stochastic search techniques inspired on the ”survival of the fittest” principle from Darwins evolutionary theory and that have been used as an optimization technique in a wide variety of disciplines[1]. Unlike conventional optimization approaches, EAs are especially suitable for sophisticated optimization problems due to their population-based optimization techniques[1]. Since the birth of computers, EAs have been established as efficient approaches to solve diverse problems in applied mathematics, theoretical physics, engineering, mathematical modeling of real world problems and so on [2, 3, 4, 5, 6]. Recently, multi-objective evolutionary algorithms(MOEAs) have received much attention and have been proven to be highly successful across a wide range of computational tasks in modeling, optimization and engineering[7, 8, 9]. Non-dominated sorting genetic algorithm (NSGA)[10] and its improved version NSGA2[11] are noticeably more efficient than the previous genetic algorithm. Especially, NSGA2 is worthy to be researched for the reason that it is still used to compare with the newly proposed algorithm after its publication for many years. After computing the non-dominate ranks of each solution, NSGA2 estimates the density of solutions based on the crowding distance. So, NSGA2 enhances on the proximity. On the contrary, The Strength Pareto Evolutionary Algorithm (SPEA)[12] and its improved version SPEA2[13] pay more attention on diversity. SPEA2 employs an enhanced fitness assignment strategy compared to its predecessor SPEA as well as new techniques for archive truncation and density-based selection. These evolutionary strategies guarantee the preservation of diversity. A multi-objective evolutionary algorithm based on decomposition (MOEA/D)[14] is a recent multi-objective evolutionary algorithmic framework. It first uses a decomposition method to decompose MOPs into a number of scalar optimization problems. Then, an EA is employed for optimizing these sub-problems simultaneously. MOEA/D has been proven to be very successful in scalar optimization problems, and is good at finding a small number of uniformly distributed Pareto solutions at low computational cost.

Most of MOEAs can be categorized in two groups based on their approaches of fitness assignment: (I) algorithms based on Pareto–dominance relations, and, (II) algorithms based on decomposition–based approaches. Recent studies[15] have shown that the representatives of Pareto–based and decomposition–based approaches, i.e., NSGA2, SPEA2 and MOEA/D, respectively, are suitable for different problems. SPEA2 will perform well in the type of MOPs with continues global Pareto-optimal fronts and without local Pareto–optimal fronts. NSGA2 could be considered as a preferable choice of MOEAs to solve the problem with discrete Pareto-optimal front. MOEA/D exhibits a good performance when it encoun-

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