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A new multi-objective particle swarm optimization algorithm based on decomposition

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A B S T R A C T

The diversity of solutions is of great importance for multi-objective evolutionary algorithms. In this paper, a new multi-objective particle swarm optimization algorithm based on decomposition (MPSO/D) is proposed. Firstly, the objective space of a multi-objective problem is decomposed into a set of sub-regions based on a set of direction vectors. Then MPSO/D makes each sub-region have a solution to maintain the diversity. Secondly, considering the convergence of solutions, MPSO/D uses the crowding distance to calculate the fitness values of the reserved solutions for selection operator, and uses the neighboring particles of a particle to determine the global best historical position (*gbest*) of the particle. The proposed algorithm has been compared with NSGAII, MOEA/D and NNIA on sixteen test instances. The experimental results illustrate that the proposed algorithm outperforms NSGAII, MOEA/D and NNIA in terms of convergence and diversity.

1. Introduction

Since many real-world problems [38] that involve several optimization objectives or criteria are referred to as multi-objective optimization problems (MOPs). Unlike single-objective optimization problems, MOPs have a series of non-dominated solutions, also known as Pareto optimal solutions (the set of Pareto optimal solutions in the objective space is called Pareto front [6]). Therefore, multi-objective optimization algorithms for MOP should be able to: (1) discover solutions as approximated to the optimal solutions as possible; (2) find solutions as uniform as possible in the obtained non-dominated front; (3) determine solutions to cover the true Pareto Front (PF) as broad as possible. However, achieving these three goals simultaneously is still a challenge for multi-objective optimization algorithms.

Among various multi-objective optimization algorithms, multi-objective evolutionary algorithms (MOEAs), which make use of the strategy of the population evolution, are an effective method for solving MOPs. Nowadays, there exist many MOEAs, such as multi-objective genetic algorithms (GA) [11,29], multi-objective particle swarm optimization algorithms (MPSO) [25,47], multi-objective differential evolution algorithms [44,49], multi-objective immune clone algorithms [18,34], and group search optimizer [43]. The recent literature survey indicates PSO, which is inspired by the social behavior of bird flocking or fish schooling, is a potential competitor of GA which has been mostly used for solving MOPs [2,23,35,39]. Although it cannot draw the conclusion that PSO outperforms GA, PSO has many advantages, for example, easy implementation, effective memory, efficient maintenance of the solution diversity [25,47], etc.

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However, there are two particular issues to be addressed when applying PSO to solve MOPs. The first issue in multi-objective particle swarm optimization is archive maintenance to balance the convergence and the diversity. External elitist archive is used to store the non-dominated solutions obtained by an algorithm and these obtained solutions are filtered by a certain quality measure, such as density. There are several proposals for MPSO where the archive size is unconstrained [1,3], the pre-fixed maximum size of an archive is widely applied because the number of non-dominated solutions can grow very fast, which quickly increases the computation cost of updating the archive. Besides, the physical memory is always finite in size. Thus, an appropriate archiving is necessarily required to filter these non-dominated solutions with a lower quality measures. There are many strategies used to update the archive, for example, many MPSOs [4,5,17,20] adopt the crowding distance [11] to prune the archive, Kernel density is originally proposed in [9] and used in MPSO [33], the clustering mechanism for maintaining an archive is firstly applied in [24] and used in MPSOs [31] for keeping size of external archive constant. Another particular issue in MPSOs is the update of global best (*gbest*) and personal best (*pbest*), because there is no absolute best solution, but rather a set of non-dominated solutions. Several methods are proposed to select *gbest* and *pbest*. The crowding distance technique can be applied to select *gbest* [32]. Dynamic neighborhood strategy is proposed in [21] to update the *gbest* in MPSO. Decomposition approach [48] was applied to MPSOs [19,28,42] to select *gbest* and *pbest*. Ranking methods [12,16,41] are used to identify the best solutions to guide the search process.

An effective MPSO should well maintain population diversity. For this purpose, the external archive strategy is often used to maintain the diversity of the obtained solutions. An external elitist archive stores the non-dominated solutions found by an algorithm and uses a certain strategy to update the archive to maintain the diversity. However, if some Pareto optimal solutions are difficultly found by a MOEA (e.g., MPSO) and these Pareto optimal solutions play an important role in maintaining the diversity of the archive, the diversity of the archive can't be maintained. Recently, decomposition approach is also used to maintain the diversity. The representative algorithm called MOEA/D (multi-objective evolutionary algorithm based on decomposition) [48] has a good performance on searching a diversity of non-dominated solutions for various kinds of MOPs [14,26,45,50]. MOEA/D makes use of traditional aggregation methods to transform the task of approximating the Pareto front (PF) into a number of single objective optimization sub-problems. When evolving the solution set, MOEA/D replaces an old solution by a new solution based on their aggregation function values if the aggregation function value of the later is smaller than that of the former (i.e., the later is closer to the optimal solutions than the former). However, this replacement does not consider the location (and distribution) of the new solution in the solution set in the objective space, which may cause a severe loss of the diversity of the solution set.

To overcome these shortcomings, the solution location (or distribution) of the obtained non-dominated solution set in the objective space should be considered when the algorithm makes the solutions replacement. In this paper, a new multi-objective particle swarm optimization algorithm based on objective space decomposition (MPSO/D) is designed for solving MOPs. To be specific, the objective space of a MOP is firstly decomposed into a set of sub-regions based on a set of direction vectors. Then, MPSO/D maintains the diversity of solutions by making each sub-region have a solution to the maximum extent. In addition, MPSO/D adopts the following extra schemes to improve the convergence. The crowding distance [11] is used to calculate the fitness values of the reserved solutions for selection operator to improve the convergence of the obtained non-dominated solution set. A strategy that neighboring particles of a particle are used to determine its *gbest* and its *pbest* is designed to help the crossover operators to improve the search ability of the algorithm. Moreover, experimental results show that MPSO/D can significantly outperform MOEA/D, NSGAII and NNIA [18] on a set of test instances.

The rest of this paper is organized as follows: Section 2 introduces the main concepts of the multi-objective optimization and the multi-objective particle swarm optimization; Section 3 presents MPSO/D in detail; while Section 4 shows the experiment results of the proposed algorithm and the related analysis; finally, Section 5 draws the conclusions and proposes the future work.

2. Preliminaries

In this section, the main concepts of the multi-objective optimization and the standard particle swarm optimization algorithm are introduced.

2.1. Multi-objective optimization

A multi-objective optimization problem can be formulated as follows [40]:

$$\begin{cases} \min y = F(x) = (f_1(x), f_2(x), \ldots, f_m(x)) \\ \quad s.t.\, g_i(x) \le 0,\ i = 1, 2, \ldots, q \\ \quad\ h_j(\mathrm{x}) = 0,\ j = 1, 2, \ldots, p \end{cases} \tag{1}$$

where $x = (x_1, \ldots, x_n) \in X \subset R^n$ is called decision variable and X is n-dimensional decision space. $f_i(x)(i = 1, \ldots, m)$ is the ith objective to be minimized, $g_i(x)(i = 1, 2, \ldots, q)$ defines ith inequality constraint and $h_j(x)(j = 1, 2, \ldots, p)$ defines jth equality constraint. Furthermore, all the constraints determine the set of feasible solutions which are denoted by Ω, and $\mathrm{Y} = \{F(x) | x \in \Omega\}$ is denoted as the objective space. To be specific, we try to find a feasible solution $x \in \Omega$ minimizing each