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An efficient hybrid multi-objective particle swarm optimization with a multi-objective dichotomy line search

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ABSTRACT

Recently more research works are focused on multi-objective particle swarm optimization algorithm (MOPSO) due to its ability of global and local search for solving multi-objective optimization problems (MOOPs); however, most of existing MOPSOs cannot achieve satisfactory results in solution quality. This paper proposes an efficient hybrid multi-objective particle swarm optimization with a multi-objective dichotomy line search (MOLS), named MOLS-MOPSO, to deal with such problem. MOLS-MOPSO combines an effective particle updating strategy with the local search of MOLS. The effective particle updating strategy is used for global search to deal with premature convergence and diversity maintenance within the swarm; the MOLS is periodically activated for fast local search to converge toward the Pareto front. The exploratory capabilities are enhanced more efficiently by keeping a desirable balance between global search and local search, so as to ensure sufficient diversity and well distribution amongst the solutions of the non-dominated fronts, while retaining at the same time the convergence to the Pareto-optimal front. Comparing MOLS-MOPSO with various state-of-the-art multi-objective optimization algorithms developed recently, the comparative study shows the effectiveness of MOLS-MOPSO, which not only assures a better convergence to the Pareto frontier but also illustrates a good diversity and distribution of solutions.

1. Introduction

Most real-world optimization problems that exist in practical engineering and scientific applications can be formulated as MOOPs, aiming to optimize all the objective functions simultaneously. This group of optimization problems has a rather different perspective compared to single objective problems. In the single objective optimization there is only one global optimum, but in MOOPs there is a set of solutions, called the Pareto-optimal set, which is considered to be equally important, all of them constitute global optimum solutions.

Traditional MOOP methods attempt to find the set of non-dominated solutions using mathematical programming. In the case of nonlinear problems, the weighting method and the ε-constraint method are the most commonly used techniques [1]. Both methods transform the MOOPs into a single objective problem which can be solved using nonlinear optimization. With the weighting method, non-dominated solutions are obtained if all weights are positive but not all Pareto-optimal solutions can be found unless all objective functions as well as the feasible region are convex. Another disadvantage of this method is that many different sets of weights may produce the same solution, compromising the efficiency of the method.

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Evolutionary Algorithms (EAs) are good candidates for MOOPs due to their abilities, to search simultaneously for multiple Pareto-optimal solutions and perform better global search [2]. Ever since the pioneering effort of Schaffer [3], many evolutionary techniques for multi-objective optimization have been proposed and have shown great progress and success [4–6]. A few of these algorithms include the non-dominated sorting genetic algorithm II (NSGAII) [4], the strength Pareto evolutionary algorithm 2 (SPEA2) [5], etc. Recently, a lot of emphasis has been laid on enhancing evolutionary algorithms to yield a computationally efficient and convergent procedure [7–9]. However, the well-known drawbacks of EAs are their slow convergence near the optimum solution and premature convergence. These behaviors are still true for evolutionary multi-objective evolutionary algorithms (EMOAs). To cope with the convergence issue, hybrid methods incorporating local search into EMOAs have been suggested [10–12]. Lara et al. [11] presented a novel iterative search procedure, known as the hill climber with sidestep (HCS), which is designed for the treatment of MOOPs, and show further two possible ways to integrate the HCS into a given evolutionary strategy leading to new hybrid algorithms. The results of NSGA-II-HCS show that the combination is advantageous in many cases. Kim et al. [12] developed a novel adaptive local search method for hybrid EMOA to improve convergence to the Pareto front in multi-objective optimization. The hybrid EMOA can provide significant convergence enhancement from the baseline EMOA by dynamic adjustment of adaptation parameters monitoring the properties of multi-objective problems on the fly.

More recently, based upon the interaction of individual entities called particles, Eberhart and Kennedy proposed particle swarm optimization algorithm (PSO) [13] which is inspired by social behaviors of bird flocking or fish schooling. PSO has been extensively applied in various optimization problems due to its unique searching mechanism, excellent convergence and simple implementation, moreover, PSO is particularly suitable for multi-objective optimization mainly because of the high speed convergence that the algorithm presents for single-objective optimization [14–17]. In recent years, various studies have been published on MOPSO in different fashion [14,15,18]. In MOPSO, in contrast to single-objective optimization, it is essential to obtain a well-distributed and diverse solution set for finding the final tradeoff in MOOP optimization. However, the high speed of convergence in PSO often implies a rapid loss of diversity during the optimization process, which inevitably leads to undesirable premature convergence [19]. Due to the drawback of PSO mentioned above, though MOPSO has good global optimization performance, the optimization efficiency of MOPSO sometimes obviously decreases near Pareto solutions. To cope with the premature convergence issue, many effective particle updating strategies are incorporated into MOPSO to improve the diversity in the Pareto-optimal solutions, such as the hyper-grid approach [15], σ-method with clustering [20] and Sigma method [21]. On the other hand, it is known that hybridizing PSOs and local search heuristics can be implemented to maintain a balance between exploration and exploitation, which is often crucial to the success of the search and optimization processes [22,23]. To overcome the disadvantage of MOPSO, hybrid MOPSOs combining MOPSO with local search method are highly effective to improve the performance of MOPSO [24–30]. Chen et al. [25] developed a hybrid immune multi-objective optimization algorithm (HIMO) based on clonal selection principle. In HIMO, a hybrid mutation operator is proposed with the combination of Gaussian and polynomial mutations, the exploratory capabilities are enhanced by keeping a desirable balance between global search and local search, so as to accelerate the convergence speed to the true Pareto-optimal front in the global space with many local Pareto-optimal fronts. A new memetic algorithm for multi-objective optimization [26] is proposed, which combines the global search ability of particle swarm optimization with a synchronous local search heuristic for directed local fine-tuning. Kaveh et al. [27] proposed a new hybrid method for multi-objective optimization problem. In the new hybrid MOPSO, to improve the convergence and maintain diversity of solutions, charged system search method is incorporated into the search process of PSO to select the global best particle for each particle of the population from a set of Pareto-optimal solutions. Izuia et al. [28] proposed a new multi-objective optimization method for structural problems based on MOPSO. A gradient-based optimization method is combined with MOPSO to alleviate constraint-handling difficulties. This is done in order to obtain an algorithm that offers on one hand the globality and robustness of the evolutionary approach, but on the other also an improved overall performance by the inclusion of well directed local search.

Although a number of works can help to improve the search ability and enhance convergence of MOPSO, there still remains research room to improve the performance of MOPSO. With respect to hybrid MOPSOs, many hybrid MOPSOs incorporating general-purpose local search heuristic algorithm still show low convergence precision and undesirable diversity and distribution of solutions. In this study, an efficient hybrid multi-objective particle swarm optimization with a multi-objective dichotomy line search is proposed, called MOLS-MOPSO, which aims to enable the MOPSO to gain the better convergence to the Pareto frontier and good diversity and distribution of solutions at the same time. In MOLS-MOPSO, the MOLS is used for a fast local search as a neighborhood search engine to improve the solution quality. Apart from hybridizing MOLS and PSO, an effective particle updating strategy combining adaptive hyper-grid approach [15] and Sigma method [21] in PSO is used to account for the requirements in MOOP optimization. The MOLS periodically utilizes non-dominance information to perform a local search operation, while the particle updating strategy for the updating of a particle trajectory is to deal with the problem of maintaining diversity within the swarm as well as to promote exploration in the search.

The implementation results show that by using the proposed methods in a MOPSO, we can achieve better convergence to the Pareto frontier, good diversity and distribution of solutions. Rest of this paper is organized as follows: some background information is provided in Section 2; the details of MOLS are introduced in Section 3; the proposed method is given in Section 4; experimental results used to illustrate the efficiency of the proposed algorithm are given in Section 5; finally, Section 6 concludes this paper.