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Discrete Optimization

A cooperative swarm intelligence algorithm for multi-objective discrete optimization with application to the knapsack problem

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ABSTRACT

We propose a novel cooperative swarm intelligence algorithm to solve multi-objective discrete optimization problems (MODP). Our algorithm combines a firefly algorithm (FA) and a particle swarm optimization (PSO). Basically, we address three main points: the effect of FA and PSO cooperation on the exploration of the search space, the discretization of the two algorithms using a transfer function, and finally, the use of the epsilon dominance relation to manage the size of the external archive and to guarantee the convergence and the diversity of Pareto optimal solutions.

We compared the results of our algorithm with the results of five well-known meta-heuristics on nine multi-objective knapsack problem benchmarks. The experiments show clearly the ability of our algorithm to provide a better spread of solutions with a better convergence behavior.

1. Introduction and literature review

Many exact methods are dedicated to solve small bi-objective problems, such as the two-phase method (Przybylski, Gandibleux, & Ehrgott, 2008; Raith & Ehrgott, 2009), the branch and bound (Sourd & Spanjaard, 2008; Visée, Teghem, Pirlot, & Ulungu, 1998) and methods based on dynamic programming (Rong & Figueira, 2014). These methods are effective for small sized problems. However, no exact method has been proven effective for large multi-objective problems with more than two objectives.

Unlike the exact methods, metaheuristics allow the approximations of the Pareto optimal solutions in a reasonable computational time. Most of the existing multi-objective metaheuristics are adaptations of metaheuristics originally proposed for single-objective optimization problems (Talbi, 2009). In the design of a multi-objective metaheuristic, one should take into account two important criteria (Zitzler & Thiele, 1998): the first criterion is how to prevent the diversity of the solutions population and the second criterion is how to ensure the convergence towards the true Pareto optimal front. These two criteria have been widely used to evaluate the performance of multi-objective metaheuristics. For instance, diversity evaluation metrics include spacing (Schott, 1995), maximum spread (Zitzler & Thiele, 1998) and diversity metric (Li, Zhang, Tsang, & Ford, 2004). The generational distance (Van Veldhuizen & Lamont, 1998) and the set coverage metric (Zitzler & Thiele, 1998) are generally used for the convergence metrics.

Basically, most of the existing multi-objective metaheuristics can be classified into three categories: the multi-objective evolutionary algorithms, the multi-objective swarm intelligence and the multi-objective hybrid metaheuristics. The NSGA-II algorithm that has been proposed by Deb, Pratap, Agarwal, and Meyarivan (2002) is among the most popular multi-objective evolutionary algorithms. This algorithm uses sorts based on the dominance relation (Fast Non dominated Sort) to obtain the convergence towards the Pareto optimal solutions. It also employs the crowding distance to maintain the diversity of the set of non-dominated solutions. Another common algorithm is the Strength Pareto Evolutionary Algorithm (SPEA-II), proposed by Zitzler, Laumanns, and Thiele (2001). SPEA-II algorithm represents a modified version of the SPEA algorithm. In contrast to the algorithm NSGA-II, SPEA-II is based on the use of an external population called archive. This external population contains a limited number of non-dominated solutions generated by the algorithm during the optimization phase. At any iteration, the new non-dominated solutions of the

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population are compared to members of the archive using the dominance criterion. To ensure a diversity of the obtained solutions with a lower computational cost, Deb, Mohan, and Mishra (2005) proposed ϵ-MOEA algorithm which uses a stationary evolution scheme and is based on the ϵ-dominance relation. To provide a better compromise to the 'exploration vs exploitation' criteria, indicator based evolutionary algorithm (IBEA) has been developed by Zitzler and Künzli (2004). In the last decade, several extensions and improvements have been proposed in the area of multi-objective evolutionary algorithms as the multi-objective evolutionary algorithm based on decomposition (MOEA/D) (Zhang & Li, 2007), the multi-objective evolutionary algorithm based on decision variable analysis (Ma et al., 2016) and the multi-objective evolutionary algorithm Based on the generational distance indicator (Rodríguez Villalobos & Coello Coello, 2012).

For multi-objective metaheuristics based on the swarm intelligence, we can cite the two most popular methods in swarm intelligence: multi-objective particle swarm optimization (Lin, Li, Du, Chen, & Ming, 2015; Reyes-Sierra & Coello, 2006) and multi-objective ant colony optimization (Rada-Vilela, Chica, Cordón, & Damas, 2013). Over the last few years, several swarm intelligence methods have been invented and extended to solve multi-objective optimization problems (MOP): multi-objective firefly algorithm (Yang, 2013), multi-objective cat swarm optimization (Bilgaiyan, Sagnika, & Das, 2015), multi-objective artificial bee colony algorithm (Xiang, Zhou, & Liu, 2015), multi-objective bat algorithm (Yang, 2011), multi-objective grey wolf optimizer 'MOGWO' (Mirjalili, Saremi, Mirjalili, & Coelho, 2016b), multi-objective ant lion optimizer (Mirjalili, Jangir, & Saremi, 2016a), multi-objective moth flame optimization (Vikas & Nanda, 2016) and multi-objective dragonfly algorithm (Mirjalili, 2016).

Several hybrid metaheuristics have been proposed to take advantage of using more than one metaheuristics at the same time. Various works have developed hybrid metaheuristics for solving MOP. Abdelaziz, Krichen, and Chaouachi (1999) proposed one of the first hybrid heuristic based on the combination of a tabu search algorithm and a genetic algorithm dedicated to the multi-objective knapsack problem. (Jaszkiewicz, 2002) has proposed the multi-objective genetic local search (MOGLS) which combines genetic algorithm with tabu search operator. Numerous evolutionary algorithms that integrate a hyper-volume indicator calculation have been also introduced in the literature (Auger, Bader, Brockhoff, & Zitzler, 2012; Jiang, Zhang, Ong, Zhang, & Tan, 2015).

In most cases, the discretization of the metaheuristics is performed in two ways: direct discretization and indirect discretization. The direct discretization is achieved by modifying the search space of the meta-heuristic to directly solve the discrete problems. The latter is using a mapping between the continuous search space and the discrete search space. In the literature, indirect discretization is generally achieved via transfer functions (sigmoid function, tanh function, etc.) or by the use of quantum computing concepts such as quantum superposition, quantum measurement, and quantum gates. Several discrete versions of swarm intelligence methods that use transfer functions have been proposed to solve single-objective optimization problems. Discrete binary particle swarm optimization (Bin, Qinke, Jing, & Xiao, 2012; Kennedy & Eberhart, 1997; Unler & Murat, 2010), binary harmony search algorithm (Kong, Gao, Ouyang, & Li, 2015) and discrete firefly algorithm (Sayadi, Hafezalkotob, & Naini, 2013) are among the most known methods. However, despite the common use of transfer functions in the discretization of swarm intelligence methods in the single-objective case, transfer functions are rarely used for the multi-objective discrete swarm intelligence methods. Among these work, we quote: multi-objective discrete particle swarm optimization (Wenzhong, Guolong, Min, & Shuili, 2007) and multi-objective discrete firefly algorithms (Karthikeyan, Asokan, Nickolas, & Page, 2015).

Recently, several discrete versions of swarm intelligence-based quantum computing concepts have been proposed to solve single-objective optimization problems: quantum-inspired evolutionary algorithm (Han & Kim, 2000), quantum-inspired particle swarm optimization (Wang et al., 2007), quantum-inspired differential evolution with PSO (Zouache & Moussaoui, 2015), quantum-inspired firefly algorithm with PSO (Zouache, Nouioua, & Moussaoui, 2016). There are also several quantum extensions of swarm intelligence methods to solve MODP: quantum-inspired multi-objective evolutionary algorithm (QMEA) (Kim, Kim, & Han, 2006), an adaptive population multi-objective quantum-inspired evolutionary algorithm (APMQEA) (Lu & Yu, 2013), quantum-inspired artificial immune system (MOQAIS) (Gao, He, Liang, & Feng, 2014).

We still think that many improvements can be achieved for the generation of Pareto optimal solutions in the case of MODP and that the use of different methods can be of great help. In this paper, we design a hybrid discrete metaheuristic called MOFPA 'Multi-objective Firefly algorithm with Particle swarm optimization' to solve MODP. For our algorithm, we use a tanh transfer function to map the continuous search space into a discrete search space. We utilize an external archive population to store Pareto optimal solutions; the ϵ-dominance relation is then used to avoid the explosion of the size of the external archive population, and to guarantee the convergence and the diversity of Pareto optimal solutions.

More explicitly those motivations can be presented as follows:

- Benefit from the cooperation of two intelligent swarm algorithms that provides an excellent balance between exploration and exploitation of the search space:
  1. FA efficiently explores the search space through automatic population subdivision and looks for local optima around each group while;
  2. The PSO uses the generated local optima to select the global optimal solution.
- Ensure more solutions diversity by:
  1. The use of the tanh discretization function that preserves the diversity of the solutions population;
  2. the use of the ϵ-dominance relation for the archive update to avoid the explosion of the archive and to provide diversity to the archived solutions.
- Avoid premature convergence of the solutions by:
  1. The use of the new discrete distance for the attractiveness allows more freedom in the fireflies movement and avoids a premature convergence;
  2. The use of the adaptive social coefficients for the PSO movement avoids premature convergence of solutions population.

The rest of the paper is organized as follows: a preliminary view of main concepts is provided in Section 2 including a brief overview of the multi-objective knapsack problem (Section 2.1), the main definitions of the Pareto dominance relation (Section 2.2), a short view of the firefly algorithm (Section 2.3) and the particle swarm optimization (Section 2.4). Section 3 is devoted to the description of the MOFPA algorithm. The results of our tests are presented in Section 4. The conclusion 5 suggests some directions for future research.

2. Background

2.1. Multi-objective knapsack problem

The multi-objective knapsack (0–1 MOKP) is a variant of the simple knapsack problem where several objectives are to be