HHcMOEA: A Hyper-heuristic collaborative Multi-objective Evolutionary Algorithm

IEEE CEC'2018 Competition on Many-Objective Optimization

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May 2018

1 Introduction

This report presents a hyper-heuristic collaborative multi-objective evolutionary algorithm (HHcMOEA). This algorithm is composed by a pool of seven MOEAs and a selection hyper-heuristic. The hyper-heuristic selects an MOEA to be executed at every iteration. Then, the solutions are shared with the other MOEAs. The pool of algorithms is characterized by its heterogeneity and includes MOEAs based on Pareto, decomposition, and indicators.

2 Background

This work is inspired by the research of Ishibuchi [2]. That research evaluates different MOEAs in several many objective problems. As expected, no algorithm obtained the best results for all problems. Besides, MOEAs considered inefficient for many-objective problems (such as NSGA-II) achieved better results than the state-of-art MOEAs, in some problems. Those observations are compatible with the No Free Lunch theorem [3]: for a given problem, different search based algorithms will achieve a different quality of the output. However, if we consider all problems, those algorithms will become equivalents. Besides, when an algorithm obtains solutions of good quality in a given problem, its quality will deteriorate in another problem. Thus, there is no single algorithm which is capable of achieving the best result in all problem instances.

Therefore, the algorithm proposed here takes advantage of different MOEAs, and its varieties of features, to create a searchability that can dynamically adapt to different aspects of the landscape of a Many-Objective Problem (MaOP). In the HHcMOEA, the selection is performed online, i.e. during the search process. Currently, the pool of MOEAs is composed by NSGA-III, ThetaDEA, MOMBI-II, SPEA2, NSGA-II, MOEA/DD and MOEA/D. The aim is that every MOEA introduces different characteristics to the search process. Thus, each one of them may collaborate to the search at a given moment, for a given problem instance. The proposed algorithm also includes a migration strategy. The objective of the migration is to exchange information among the MOEAs. Every MOEA filters the received solutions and incorporates them into their search process. The migration may be important for example to escape from local optima or to improve diversity.

3 Proposed Algorithm

The proposed HHcMOEA is presented at Algorithm 1. First, the MOEAs are initialized, each one with its own population and parameter values. The hyper-heuristic parameters are also initialized. Then, the following steps are executed until the stop criterion is met. First, one MOEA is selected, using a heuristic selection method. Next, the current population of this MOEA is copied (*oldpop*). Then, the selected MOEA is executed for a given number of iterations. The reward of the selected heuristic is given comparing the quality of the population before and after the execution of the MOEA. Finally, the new population is shared with the neighborhood of the executed MOEA.

Algorithm 1: Proposed algorithm for the collaboration of MOEAs guided by hyper-heuristic

```
Data: pool of MOEAS
initialization;
while the stop criterion is not met do
    selected ← heuristic_selection(MOEAS);
    oldpop ← copy_population_from(selected);
    newpop ← execute(selected, maxit);
    metrics ← extract_metrics(oldpop, newpop);
    set_reward(selected, metrics);
    foreach moea ∈ get_neighborhood(selected) do
        migration(moea, newpop);
    end
end
```

We used the roulette based hyper-heuristic proposed by [1]. In this method, all heuristics have the same initial probabilities of being selected. The heuristic selection method randomly selects a heuristic based on those probabilities. The R2 metric is then used to compare the quality of the current and previous population. If the quality of the population is improved, the probability of the selected heuristic is incremented by a fixed amount. Otherwise, its probability is decremented. A minimal probability value is kept to avoid any heuristic of having zero probability of being selected.

The proposed algorithm incorporates a migration phase. This migration step is not present in traditional hyper-heuristic approaches. The goal is exchanging information among the MOEAs, to improve the overall searchability. In the migration step, the population generated by the executed MOEA is sent to the MOEAs in its neighborhood. Currently, the HHcMOEA uses a broadcast neighborhood, i.e. every MOEA is neighbor of all others. The solutions are then filtered and injected into the population of the neighbor MOEAs. This filter and injection are performed using the environmental selection method of the MOEA.

References

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