Ordered Incremental Multi-Objective Problem Solving Based on Genetic Algorithms

Wenting Mo, IBM, China
Sheng-Uei Guan, Xian Jiaotong-Liverpool University, China
Sadasivan Puthusserypady, Technical University of Denmark, Denmark

ABSTRACT

Many Multiple Objective Genetic Algorithms (MOGAs) have been designed to solve problems with multiple conflicting objectives. Incremental approach can be used to enhance the performance of various MOGAs, which was developed to evolve each objective incrementally. For example, by applying the incremental approach to normal MOGA, the obtained Incremental Multiple Objective Genetic Algorithm (IMOGA) outperforms state-of-the-art MOGAs, including Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Strength Pareto Evolutionary Algorithm (SPEA) and Pareto Archived Evolution Strategy (PAES). However, there is still an open question: how to decide the order of the objectives handled by incremental algorithms? Due to their incremental nature, it is found that the ordering of objectives would influence the performance of these algorithms. In this paper, the ordering issue is investigated based on IMOGA, resulting in a novel objective ordering approach. The experimental results on benchmark problems showed that the proposed approach can help IMOGA reach its potential best performance.

Keywords: Conflicting Objectives, Incremental, MOGAs, Multi-Objective, Objective Ordering

INTRODUCTION

Background

In the real world, there are many optimization problems which have more than one objective. They are called multi-objective optimization problems (MOPs). In MOPs, the presence of multiple objectives results in a set of optimal solutions (named the Pareto-optimal set), instead of one optimal solution. Without further information, one Pareto-optimal solution cannot be declared as better than another. Given the Pareto-optimal set, users can get a clear idea on how one objective will benefit from the deterioration of one or more other objectives. In that case, they could evaluate the cost and choose the Pareto-optimal solution which most satisfies their requirements. That is why MOGAs are increasingly used (Tamaki et al., 1996). MOGAs
maintain a population of solutions and thus can find a number of solutions which are uniformly distributed in the Pareto-optimal set in a single run. This distinguishes it with classical methods such as weighted sum approach or ε-constraint method and goal programming (Taha, 2003), which can only find one Pareto-optimum in a single run. The aims of MOGAs are to find as many Pareto-optimal solutions as possible, and to ensure a good spread of the solutions. No prior knowledge about the objectives is assumed. In contrast, the goal programming method converts the original multiple objectives into one single goal and obtains only one compromised solution in a single run. Preemptive method (Taha, 2003) is one of the goal programming methods, which assigns different priorities to the objectives according to prior knowledge. It is different from the objective ordering discussed in this paper.

So far, a number of MOGAs (Deb et al., 2002; Fonseca & Fleming, 1993; Fonseca & Fleming, 1995; Fonseca & Fleming, 1998; Knowles & Corne, 2000; Kursawe, 1991; Laumanns et al., 1998; Schaffer, 1985; Srinivas & Deb, 1994; Zitzler & Thiele, 1998; Zitzler & Thiele, 1999) have been suggested. However, almost all of them treat the objectives of an MOP as a whole and evolve them together. Only in VEGA (Schaffer, 1985), appropriate fractions of the next generation are selected from the whole of the old generation according to each of the objectives separately. But the objective space is still explored as a whole, as the overall fitness corresponded to a linear function of the objectives. Because of the weighted-sum fitness, VEGA can only solve the MOPs with convex Pareto fronts (Schaffer, 1985).

In order to explore the objective space in a more powerful manner, IMOGA was designed to evolve the objectives one-by-one and it benefits from inheritance. The superiority of IMOGA over other MOGAs has been shown in (Chen & Guan, 2004), where IMOGA outperformed three well known MOGAs, NSGA-II (Deb et al., 2002), SPEA (Zitzler & Thiele, 1999) and PAES (Knowles & Corne, 2000), on all the problems tested. The development of IMOGA arose from an idea that performance of a certain tool will improve as its task gets easier. It is assumed that the performance of a MOGA will improve, or at least would not degrade as the objective set gets smaller, and the Pareto-optimal points are likely to remain Pareto-optimal after objective increment. Applying this rationale, if the initial solutions from the first few objectives contain better candidates, upon subsequent objective increment, they are most likely to stay, and also improve the accuracy and quality of the solutions. Thus an incremental approach can be more efficient. This incremental approach can also be applied to the mentioned state-of-art MOGAs, NSGA-II, SPEA and PAES, resulting in INSGA-II, ISPEA and IPAES. Performance of the obtained incremental algorithms has been shown better than the original ones (Chen, 2003). In fact, the concept of incremental evolution has been also successfully applied in supervised learning, which works both in the input and output spaces (Guan & Li, 2001; Guan & Li, 2002; Guan & Li, 2004; Guan & Liu, 2002; Guan & Liu, 2004; Guan & Zhu, 2003). However, the objective ordering problem still remains. With regard to the IMOGA, the objectives were handled according to the original order they were given. Whether this is a good choice is questionable. This issue is discussed in this paper.

Challenges and Proposed Solution

According to our subsequent study, the performance of IMOGA fluctuates a lot as the objective order changes. Generally the original objective order does not result in the best performance. This can be seen from the following example, which is a 4-objective problem solved by IMOGA.

As shown in Figure 1, the performance of IMOGA varied as the objective order changes, which is measured by the distance between the found solutions and the true Pareto front. When the objective functions of this problem were evolved in their original order, the distance was 2.065759. If the positions of the last two objective functions were exchanged, the distance was increased to 2.837251, i.e. the performance
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