Recombination of Similar Parents in EMO Algorithms

Hisao Ishibuchi and Kaname Narukawa

Department of Industrial Engineering, Osaka Prefecture University,
1-1 Gakuen-cho, Sakai, Osaka, 599-8531, Japan
{hisaoi, kaname}@ie.osakafu-u.ac.jp

Abstract. This paper examines the effect of crossover operations on the performance of EMO algorithms through computational experiments on knapsack problems and flowshop scheduling problems using the NSGA-II algorithm. We focus on the relation between the performance of the NSGA-II algorithm and the similarity of recombined parent solutions. First we show the necessity of crossover operations through computational experiments with various specifications of crossover and mutation probabilities. Next we examine the relation between the performance of the NSGA-II algorithm and the similarity of recombined parent solutions. It is shown that the quality of obtained solution sets is improved by recombining similar parents. Then we examine the effect of increasing the selection pressure (i.e., increasing the tournament size) on the similarity of recombined parent solutions. An interesting observation is that the increase in the tournament size leads to the recombination of dissimilar parents, improves the diversity of solutions, and degrades the convergence performance of the NSGA-II algorithm.

1 Introduction

Since Schaffer's study [21], various evolutionary multiobjective optimization (EMO) algorithms have been proposed to find well-distributed Pareto-optimal or near Pareto-optimal solutions of multiobjective optimization problems (Coello et al. [2] and Deb [4]). Recent EMO algorithms usually share some common ideas such as elitism, fitness sharing and Pareto ranking. While mating restriction has been often discussed in the literature, it has not been used in many EMO algorithms as pointed out in some reviews on EMO algorithms [7, 23, 26]. In this paper, we examine the effect of recombining similar parents on the performance of EMO algorithms to find well-distributed Pareto-optimal or near Pareto-optimal solutions.

Mating restriction was suggested by Goldberg [8] for single-objective genetic algorithms. Hajela & Lin [9] and Fonseca & Fleming [6] used it in their EMO algorithms. The basic idea of mating restriction is to ban the recombination of dissimilar parents from which good offspring are not likely to be generated. In the implementation of mating restriction, a user-definable parameter σ_{mating} called the mating radius is usually used for banning the recombination of two parents whose distance is larger than σ_{mating}. The distance between two parents is measured in the decision space or the objective space. The necessity of mating restriction in EMO

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algorithms was also stressed by Jaszkiewicz [17] and Kim et al. [18]. In the parallelization of EMO algorithms, mating restriction is implicitly realized since similar individuals are likely to be assigned to the same processor or the same island (e.g., see Branke et al. [1]). On the other hand, Zitzler & Thiele [25] reported that no improvement was achieved by mating restriction in their computational experiments. Van Veldhuizen & Lamont [23] mentioned that the empirical evidence presented in the literature could be interpreted as an argument either for or against the use of mating restriction. Moreover, there was also an argument for the selection of dissimilar parents. Horn et al. [10] argued that information from very different types of tradeoffs could be combined to yield other kinds of good tradeoffs. Schaffer [21] examined the selection of dissimilar parents but observed no improvement.

A similarity-based mating scheme was proposed in Ishibuchi & Shibata [13] to examine positive and negative effects of mating restriction on the performance of EMO algorithms. In their mating scheme, one parent (say Parent A) was chosen by the standard fitness-based binary tournament scheme while its mate (say Parent B) was chosen among a pre-specified number of candidates (say β candidates) based on their similarity or dissimilarity to Parent A. To find β candidates, the standard fitness-based binary tournament selection was iterated β times. Almost the same idea was independently proposed in Huang [11] where Parent B was chosen from two candidates (i.e., the value of β was fixed as $\beta = 2$). Ishibuchi & Shibata [14] extended their similarity-based mating scheme as shown in Fig. 1. That is, first a pre-specified number of candidates (say α candidates) were selected by iterating the standard fitness-based binary tournament selection α times. Next the average vector of those candidates was calculated in the objective space. The most dissimilar candidate to the average vector was chosen as Parent A. On the other hand, the most similar one to Parent A among β candidates was chosen as Parent B. Furthermore, it was demonstrated in [15] that the diversity-convergence balance can be dynamically adjusted by controlling the values of the two parameters α and β.

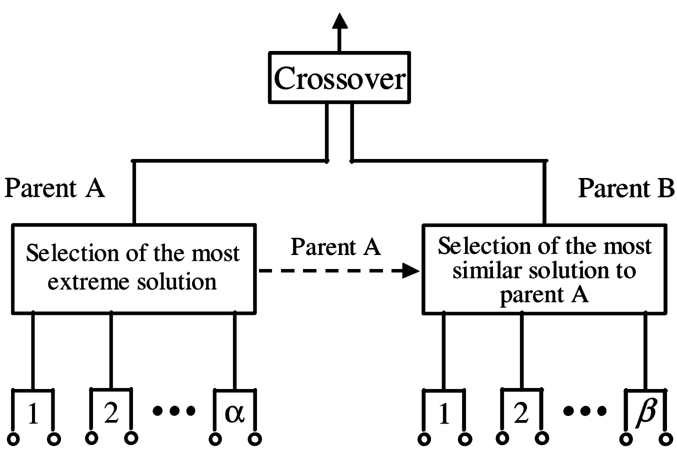

Fig. 1. Mating scheme in Ishibuchi & Shibata [14]