The Effectiveness of Multiobjective Optimizer in Single-objective Optimization Environment

Shinya Watanabe
College of Information Science & Engineering,
Ritsumeikan University, Japan
1-1-1 Nojihigashi, Kusatsu
Shiga 525-8577, Japan
sin@sys.ci.ritsumei.ac.jp

Kazutoshi Sakakibara
College of Information Science & Engineering,
Ritsumeikan University, Japan
1-1-1 Nojihigashi, Kusatsu
Shiga 525-8577, Japan
sakaki@sys.ci.ritsumei.ac.jp

ABSTRACT
This paper presents two new approaches for transforming a single-objective problem into a multi-objective problem. The first approach is based on relaxation of the constraints of the problem and the other is based on the addition of noise to the objective value or decision variable. Intuitively, these approaches provide more freedom to explore and a reduced likelihood of becoming trapped in local optima.

Through numerical examples, we showed that the multi-objective versions produced by relaxing constraints can provide good results and that using the addition of noise can obtain better solutions when the function is multimodal and separable.

Categories and Subject Descriptors
G.1.6 [Global optimization]: Multi-objective optimization—multi-objectivizing

General Terms
ALGORITHMS

Keywords
Multiobjectivizing, Genetic Algorithms, Multi-objective optimization

1. DESCRIPTION OF THE NEW MULTI-OBJECTIVIZATION APPROACH
In this paper, we propose two new multi-objectivization approaches based on the addition of new objectives as follows:

- Relaxing the constraints of the problem.
- Adding noise to the objective value or decision variables.

The multi-objectivization approach translates single-objective optimization problems (SOOP) into multi-objective optimization problems (MOOP) and then applies EMO to the translated problem. The aims of these approaches are to increase paths to the global optimum that are difficult to obtain under the original SOOP and to maintain the diversity of the population.

These approaches have a low risk of providing solutions far from the optimal solutions as these approaches always deal with the original SOOP objective. In addition, these approaches can treat many types of problems and hardly produce new tasks such as decomposition of a problem into sub-problems.

The first approach is based on the concept of constraint relaxation. In this approach, a trade-off between the original and the relaxed objectives can be brought by differences in two constrains. Therefore, a search of EMO can be concentrated around the constrains of a problem. This approach can be expected to search effectively for the global optimum along the boundary of the feasible regions settled by the original constraints.

The another approach takes advantage of escaping from local optima. In this approach, the trade-off relation is introduced by the difference between the original objective and the new objective with noise. This approach will be useful for escaping from local optima using trade-off regions.

2. NUMERICAL EXAMPLES
In this paper, we describe application of the proposed approaches to two types of numerical experiment: the 0/1 knapsack problem with 750 items and typical test functions (Rastrigin, Schwefel, etc.). In implementing our proposed approach, we used two types of GA:

- "ga2k" [2] as a single-objective GA.
- "NSGA-II" [3] as a multi-objective GA.

2.1 Implementation of GA
In these experiments, GAs applied to the two types of experiment used bit coding. Similarly, two-point crossover and bit flip were implemented as for crossover and mutation. We performed 30 trials and all results are shown as averages of 30 trials. In addition, the terminal condition of all experiments was 200 generations.

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2.2 Multi-objectivization with relaxation of constraints

We used the 0/1 knapsack problem with 750 items and multi-objectivized the problem. This multi-objectivization was a maximization problem.

As many codings lead to infeasible solutions, we should implement a repair method as a constraint handling technique. We used the repair method proposed by Zitzler et al.[4]. We used the repair method when the codings violated the relaxed capacity. In addition, we used $\alpha = 3.0$ based on the results of our pilot study.

2.2.1 Results

The results are shown in Fig. 1. The horizontal axis in Fig. 1 (a) indicates the value of the weight parameter $\omega$ and that in Fig. 1 (b) indicates the magnitude of relaxation of the constraints settled by the difference between the original capacity and relaxed. Fig. 1 (b) shows the results of 4 experiments based on the implementation of objectives ($f_1$ and $f_2$).

The grey bands in Fig. 1 indicate the results of the original SOOP obtained by ga2k and NSGA-II. Therefore, by investigating whether the results of multi-objectivization were higher or lower than the grey band, it was possible to determine the useful of multi-objectivization for this problem.

The experimental results confirmed that this multi-objectivization approach using a multi-objective GA is effective for the 0/1 knapsack problem. In addition, we found that there is an optimum magnitude of relaxation for an additional objective.

2.3 Multi-objectivization with addition of noise

We examined the effectiveness of multi-objectivization by adding noise according using typical test functions (Rastrigin, Schwefel, etc.). In these experiments, all problems were minimization problems.

2.3.1 Test functions

In this example, we used functions from the perspective of the modality (unimodal or multimodal) of function and epistasis among decision variables (separable or non-separable). We used 5 types of function: Rastrigin, Schwefel, Ridge, Rotated Rastrigin and Rotated Schwefel functions. We treated all functions as having 10 decision variables in this example.

In this example, the grey coding is used and the length of the chromosome is 20 bits per decision variable. The simulation of all functions is terminated when the generation reaches over 200.

2.3.2 Results

Because space is very limited, the performances of 2 functions are shown in Fig. 2 and 3.