A Study on Effects of Migration in MOGA with Island Model by Visualization

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***Abstract*—In this paper, we propose a visualization method for the distribution of population in Multi-Objective Genetic Algorithm (MOGA) based on island model. In the proposed method, each island is regarded as a cluster, then, searching solutions belonging to each island are projected together onto a two-dimensional space formed by the axes acquired by Multiple Discriminant Analysis (MDA). The visualization result enables us to grasp the distribution of population in each island and the relationship of evolution among them. This paper investigates the effects of migration in island model with the influence to each island through the experiment by a benchmark function and effective migration can be done through the visualization result.**

I. Introduction

Genetic Algorithm (GA), which comes after the model of living evolution, is one of the strong optimization algorithm and a lot of studies has been reported. Recently, the application of GA to Multi-objective Optimization Problems (MOPs) has been focused[1]. One of the advantage in the application of GA to MOPs is that the search in GA is done with multi-point search. In MOPs, it is usually impossible to acquire the solutions which satisfy all objective functions because of their trade-off. Then it is required to search Pareto solutions which are superior to the others at least one objective function with their varieties. Then especially in the case that the objective functions are large in number, high calculation or evaluation cost is needed for searching Pareto solutions. GA also has a characteristic suitable for parallelization of calculation potentially. The studies to reduce calculation time with parallel computation have been carried out, and there are three representative methods of parallel computation[2] : global single-population master-slave model, single-population fire-grained model and multiple-population coarse-grained model.

Master-slave model uses parallelization to speed up the calculation. This model has one population or all solutions in one processor (master) and the evaluation of solutions is calculated on other processors (slaves). This parallel GA is applied to the problems which need high calculation cost to evaluate solutions. In fire-grained model, each processor has one or a few solutions. This model is suitable for the parallelization using a large number of computers. Multiple-population coarse-grained model is well-known as "island model", in which the solutions are divided into some sub-populations which are called islands. Each island and the evolution there is basically independent from the others, then some solutions in each island sometimes migrate to another island for the exchange of information. This operation is called "migration".

In single-objective optimization problems, some studies on island model has been reported. J. Tang et al. investigated the effects of migration topology, i.e. random migration or ring-type migration, based on the calculation time[3]. M. Miki et al. proposed the island model in which each island had different parameter set of genetic operations one another[4]. In GA, it is difficult to adjust the parameters of genetic operations appropriately because they strongly depend on the applied problems, population size and so on. This method has the advantage that it needs no preliminary experiment to find appropriate parameters. O. Hatanaka investigated the parameters on island model cyclopaedically, the number of islands / individuals, the number / frequency of migration and so on[5]. In single-objective optimization problems, the main advantage of an island model is to keep diversity of solutions. On the other hand, some studies on the application of island model to Multi-Objective Genetic Algorithm (MOGA) have been reported[6][7][8]. There are the studies on the division of solutions into islands or the role of them. In [6], MOGA is applied to whole population for some generations, then the acquired solutions are divided into islands based on the fitness value of the objective functions. In [7], the evolution in each island is done as single objective optimization with each objective function, and MOGA is parallelly done in one more island given all objective functions. [8] gives different weights of the objective functions to islands. The investigations of these studies are based on the comparison of the performance, and they have not mentioned the distribution of solutions in islands, the effects of migration and the application to the problems with large number of objective functions.

This paper proposes a visualization method for the distribution of population in MOGA with island model. In this method, each island is regarded as a cluster, then, searching solutions belonging to each island are projected together onto a two-dimensional space formed by the axes acquired by Multiple Discriminant Analysis (MDA)[9]. The visualization result enables us to grasp the distribution of solutions in each island and the relationship of evolution among them. This paper shows that we can grasp the effects of migration in island model with the influence to each island. It investigates the timing and the candidates of migration and the change of evolution in migrated island through the experiment by a benchmark function. It shows effective migration can be done through the visualization result.

II. Visualization Method

A. Multiple Discriminant Analysis: MDA

Projection axes are identified by MDA to reduce the dimensionality of evaluation space. The projection axes are obtained as linear combinations of objective functions and the number of projection axes is two in this paper. MDA can identify projection axes which maximize the distances among the clusters and minimize each cluster size, that is, it identifies the projection axes to maximize the criterion function $J(W)$ shown in eq.(1) which is the ratio of between-class scatter matrix S_B to within-class scatter matrix S_W in visible space.

$$max\{J(W)\} = \frac{|W^t S_B W|}{|W^t S_W W|} \tag{1}$$

$$S_B = \sum_{i=1}^{N_C} n_i(\boldsymbol{m}_i - \boldsymbol{m})(\boldsymbol{m}_i - \boldsymbol{m})^t \tag{2}$$

$$S_W = \sum_{i=1}^{N_C} \sum_{\boldsymbol{x} \in C_i} (\boldsymbol{x} - \boldsymbol{m}_i)(\boldsymbol{x} - \boldsymbol{m}_i)^t \tag{3}$$

W is the transformation matrix, N_C is the number of cluster, n_i is the number of data (solutions) in cluster i, $\boldsymbol{m}_i$ presents the average of cluster centers in multi-dimensional evolutional space, $\boldsymbol{m}$ is the average of all data and C_i is each cluster.

Using S_W and S_B, the discriminant is derived by solving a generalized eigenvalue problem expressed as

$$S_B \boldsymbol{w}_l = \lambda_l S_W \boldsymbol{w}_l, \tag{4}$$

where l is the number of dimension in visible space ($l = 1, 2$), λ_l is the l-th eigenvalue and $\boldsymbol{w}_l$ is the l-th coefficient vector. The projection axes ξ_l which generate visible space can be acquire by the obtained $\boldsymbol{w}$.

$$\xi_l = \boldsymbol{w}_l^t \boldsymbol{x} = w_{l1}x_1 + w_{l2}x_2 + \cdots + w_{lp}x_p \tag{5}$$

(p is the number of objective functions.)

B. Visualization by MDA

In MOPs, it is difficult for us to grasp the distribution of solutions or the relationship among islands in a high-dimensional evaluation space. The visualization by MDA can give them in the visible space. The visualization steps in the proposed method are described as follows :

(Step 1) MDA is applied to the solutions in MOGA and they are projected onto a two-dimensional space.
(Step 2) The Pareto rank information in whole solutions is added to each solution with color contrast.

First, MOGA with island model is done for a certain generations, then each island is regarded as a cluster and MDA is applied. Searching solutions belonging to each island are projected together onto a two-dimensional space formed by the first and second axes acquired by MDA. We can grasp the distribution of the solutions in each island and the relation among islands. MDA identifies most separable axes for the clusters, then non-separated clusters or the parts of them means that similar solutions are acquired there in the original evaluation space. The proposed method adds the Pareto rank information in whole solutions to each solution with color contrast. The first rank is the non-dominated solutions by any others in whole islands, and the second rank is the non-dominated solutions except for the first ones. In this paper, the deep color indicates high-ranked, i.e. better solutions, and the light one shows worse solutions. With this operation, the visualization result can show the degree of evolution of solutions and the difference of them among islands. The visualization enables us to pick up the solutions for migration and select the islands to be migrated based on the information of them.

III. Experiment

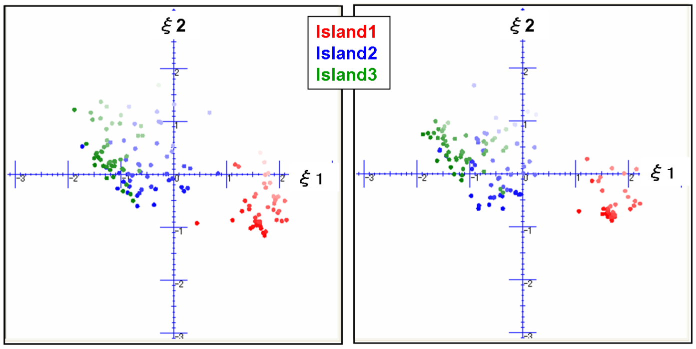
This paper investigated the effects of the migration in island model with the influence to each island through the experiment by a benchmark function. The benchmark function for the experiment is shown in eq.(6) and eq.(7)[10], and the genetic parameters for GA are shown in Table I. The island model in this experiment was based on [8], in which the evolution in each island was done as the single objective optimization with the different weights of objective functions and given different genetic parameter set. Here, the weights for objective functions in island 1, 2, 3 were $(f_1, f_2) = (1.0, 0.0), (0.5, 0.5), (0.0, 1.0)$, respectively, and the parameters of crossover and mutation rate were given randomly to each island in the range on Table I.

TABLE I
Genetic Parameters

Number of Islands	3
Individuals in Each Island	50
Migration Rate	0.3
Selection Rate	0.2
Crossover Rate	0.6〜0.8
Mutation Rate	0.001〜0.01

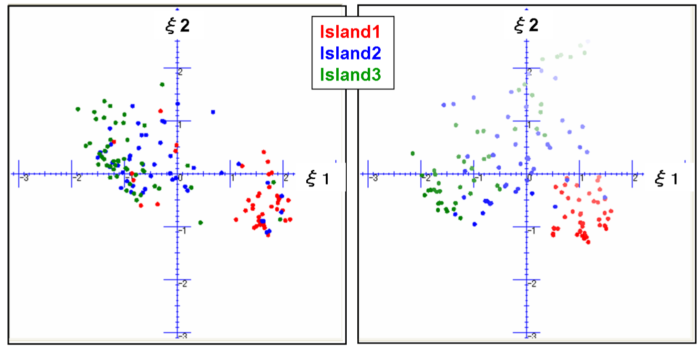
$$f_1(x) = \sum_{i=1}^{n-1}(-10exp(-0.2\sqrt{x_i^2 + x_{i+1}^2})) \tag{6}$$

$$f_2(x) = \sum_{i=1}^{n}(|x_i|^{0.8} + 5sin(x_i^3)) \tag{7}$$



(a) 30th generation (b) 33rd generation

Fig. 1. Distribution of solutions without migration



(a) 30th generation (b) 33rd generation

Fig. 2. Distribution of solutions with migration

The visualization results to the solutions acquired at 30th (Fig.1(a)) and 33rd (Fig.1(b)) generation are shown in Fig.1. The migration was not applied in these results. The solutions at 33rd generation were plotted onto the same axes with 30th one. The result gives some informations.

1. Almost equal Pareto solutions were acquired.

The evolution performance was nearly equal in three islands. The single objective optimization in each islands could give advancement well to the weighted direction. Because of only two objective functions, the migration might not be needed to acquired Pareto solutions with high fitness value.

2. Overlap of solutions can be seen in island 2 and island 3.

A part in island 2 and island 3 is overlapped each other. It means some of the solutions there were similar and continuous Pareto solutions were acquired from objective function f_2 to middle of f_1 and f_2. On the other hand, island 1 is separated and the gap of Pareto front will be in the middle of f_1 and center of f_1 and f_2.

3. Distribution of solutions was not much changed from 30th to 33rd generation.

Since single objective GA was being done in each island, they would converge in later generations. Migration would be effective for the evolution with diversity and various Pareto solutions. It will be effective for the diversity to pick up the solutions in island 1 as the migration to island 2 or island 3 and vise versa. The migration of the solutions in non-overlapping parts in island 2 and island 3 will also give new population each other.

Fig.2(a) shows the result of migration after the 30th generation shown in Fig.1(a). The solutions in Fig.2(b) were also plotted onto the same axes with Fig.2(a). In this result, 30% solutions in each island were migrated one another. We can see the solutions are widely spread in these three generations after the migration. The isolated island 1 went closer to island 2 and island 3 by this operation. The migration before the convergence of solutions at the 30th generation was effective for the diversity.

IV. Conclusion

This paper proposed a visualization method for the distribution of population in MOGA with island model. In this method, each island was regarded as a cluster, then, searching solutions belonging to each island were projected together onto a two-dimensional space formed by the axes acquired by MDA. The visualization result enabled us to grasp the distribution of solutions in each island and the relationship of evolution among them. This paper showed that we could grasp the effects of migration in island model with the influence to each island. It investigated the proposed method through the experiment by a benchmark function. It showed effective migration could be done through the visualization result. Future work is to carry out detail investigation of the effects of migration and the selection of solutions for migration based on the visualized information. We will also apply the proposed method to optimization problems with more objective functions and practical problems.

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