계승적 나이개념을 가진 다목적 진화알고리즘 개발

The Development of a New Distributed Multiobjective Evolutionary Algorithm with an Inherited Age Concept

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ABSTRACT

Recently, several promising multiobjective evolutionary algorithms, e.g., SPEA, NSGA-II, PESA, and SPEA2, have been developed. In this paper, we also propose a new multiobjective evolutionary algorithm that compares to them. In the algorithm proposed in this paper, we introduce a novel concept, "inherited age" and total algorithm is executed based on the inherited age concept. Also, we propose a new sharing algorithm, called objective classication sharing algorithm(OCSA) that can preserve the diversity of the population. We will show the superior performance of the proposed algorithm by comparing the proposed algorithm with other promising algorithms for the test functions.

Keywords : Distributed multiobjective evolutionary algorithm(DMEA), Inherited Age(IA), Objective classification sharing algorithm(OCSA)

1. Introduction

Many real-world problems involves multiple performance measures or objective that need to be optimized simultaneously. The multiobjective optimization problem(MOP) is no doubt a very practical and challenging topic in the optimization field. Unlike a single-objective optimization problem, the MOP seldom admits a single perfect solution. Instead, the MOP may render a family of alternative solutions, all of which should be treated to be equally important with no preference information about the multiple objectives.

There have been proposed various methods of solving the MOP. Among them, the evolutionary algorithm(EA) seems particularly suitable to solve the MOP, noting that EA is population-to-populat-on based search method.

It was during 1980's when the EA was first applied to the MOP. In the early 1990's, many Pareto-based approaches were reported such as Fonseca and Fleming's MOGA, Horn, Nafpliotis, and Goldberg's NPGA, and Srinivas and Deb's NSGA([3,5]). Those multiobjective evolutionary algorithms(MEAs) showed the potential of the EA on the MOP. However, they did not incorporate the elitism explicitly so that their performances seem somewhat low in various complex test problems. Therefore, elitist MEAs such as strength Pareto EA(SPEA), Pareto archived evolutionary strategy(PAES), NSGA-II, Pareto envelope-based Selection Algorithm(PESA), and SPEA2, which are shown to outperform many non-elitist MEAs([1,2,4,7,8,9]).

In this paper, we also propose a new distributed MEA(DMEA) which is comparable well to above elitist MEAs in its performances. In the proposed algorithm, an inherited age(IA) concept will be introduced and utilized as a very important concept. Also a new sharing algorithm, called objective classification sharing algorithm(OCSA) will be introduced and utilized as a sharing technique and as a parent selection method. It will be shown that the performance of the proposed algorithm is better or at least equal to SPEA, PESA, NSGA-II, and SPEA2 for the test problems.

2. Problem formulation

Without loss of generality, we consider a multiobjective minimization problem. We shall use the terminologies and notations in ref([7,8]).
Problem statement on the multiobjective minimization problem: Given n decision variables and m objectives, the problem to consider is:
Minimize

$$\vec{y}=f(\vec{x})=(f_1(\vec{x}),f_2(\vec{x}),\cdots,f_n(\vec{x})),$$

where $\vec{x}=(x_1,x_2,\cdots,x_n)\in X$, $\vec{y}=(y_1,y_2,\cdots,y_m)\in Y$.
Here, $\vec{x}$ is called a decision vector, X the parameter space, $\vec{y}$ an objective vector, Y the objective space([7]).
An objective vector $\vec{u}=(u_1,\cdots,u_m)\in Y$ is said to dominate an objective vector $\vec{v}=(v_1,\cdots,v_m)\in Y$ iff $\forall i\in\{1,\cdots,m\}$: $u_i\le v_i$ and $\exists j\in\{1,\cdots,m\}$: $u_j < v_j$. The objective vector $\vec{u}\in Y$ is said to be nondominated regarding a set $Y'\subseteq Y$ if and only if there is no vector in Y' which dominates $\vec{u}$. A decision vector $\vec{x}_u$ is said to be Pareto-optimal if and only if there exists no $\vec{x}_v\in X$ for which $f(\vec{x}_u)$ is nondominated regarding the set $Y\ni f(\vec{x}_v)$. The detailed definitions and notions can be shown in ([7,8]).

3. A new distributed multiobjective evolutionary algorithm(DMEA)

The procedure of the proposed algorithm is almost equal to some known MEAs but the concrete selection method and offspring generation scheme are different. In particular, a novel notion, inherited age concept is newly introduced. In this section, we elaborate the inherited age concept and present the proposed algorithm in detail.

3.1 Inherited age concept(IAC)

In the search algorithm, it would be desirable that exploration and exploitation capabilities are properly adjusted to the various situations. However, in many EAs, offspring generation operators, crossover and mutation, have the same exploration and exploitation capabilities for all the generations. To compensate for this weak point and thus to improve the searching effectiveness, we devise a new offspring generation scheme based on the fractal geometry by introducing a novel notion, called "inherited age"([6]). we first show briefly the new offspring generation scheme then, explain the IAC.

Based on the fractal concept, the position structure of offspring, called fractal frame from now, is fixed and only its size or evolution distance is scaled down according to the IA of the parent as shown in Fig. 1([6]). The fractal frame consists of all the positions distant from the parent by the evolution distance along all parameter axes. When offspring are generated, they inherit the IA from their parents as shown in Fig. 1.

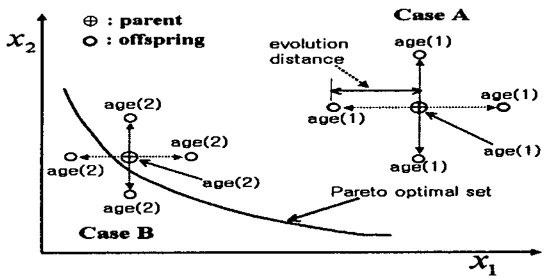

Fig. 1 New offspring generation scheme

Now, Let's consider the IAC based on the new offspring generation scheme. As shown in Fig. 1, solutions can approach fast the Pareto optimal set if the evolution distance is large in case A and, in case B, the solutions can converge more accurately to the Pareto optimal set if the evolution distance is small. To do so, it is needed to measure how near or far a solution exists from the Pareto optimal set in the parameter space.

To measure the distance information, all the solutions are endowed with the inherited age(IA). The IA of the parent is increased by one when the parent solution is nondominated to its own offspring as shown in case B of Fig. 2. That is, the IA of the parent is increased by one when it exists within its evolution distance from the Pareto optimal set as shown in case B of Fig. 1. Therefore, it can be said to a certain extent that the IA means physically how far or near a solution exists from the Pareto optimal set.

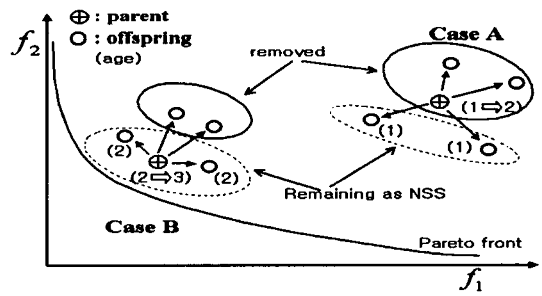

Fig. 2 Comparison of parent with its own offspring

When offspring are generated, they inherit the ages from their parents as shown in Fig. 1. In a human being, newly born baby grows old from one year because he does not inherit anything from his parents. Note that the age in this paper contains the information about the growing history and exploration experience. Offspring grow old not from one year but from the ages of their parents because they inherit the exploration experience by succeeding the IA of their parents.

So, solutions can converge to the Pareto optimal set more effectively if the evolution distance becomes smaller whenever their IAs are increased. Therefore, under the assumption that the range of each decision variable is normalized to constant value, the evolution distance d_a of a parent with inherited age a is determined to be inversely proportional to its inherited age as follow;

$d_a = d_0(r_a)^a$, where d_0 is the initial evolution distance and $r_a\,(0.5 \le r_a \le 1)$ is the aging rate. In this paper, d_0 is a third of total range of each variable in the parameter space.

When the dimension of the parameter space is large, too many offspring are generated. So, the computational load will be increased very much and the efficiency will be decreased. Therefore, we reduce the number of offspring for each parent, instead of generating offspring at all the positions of the fractal frame. If the number of offspring is decreased, the probability of the wrong age increase is also increased. To compensate for this wrong age increase, we increase the aging rate r_a. For the ideal case, the aging rate r_a is 1/2. Note that the probability of the wrong age increase gets higher as the number of offspring gets smaller compared with the ideal case. Therefore, the aging rate should be increased as the number of offspring is reduced. If the aging rate r_a is greater than one, the evolution distance becomes larger as the age is increased, which is undesirable effect in search algorithm. Therefore,, we confine the maximum value of r_a to be one.

3.2 A new distributed multiobjective EA

In previous many EAs, the promising solutions to be evolved to the Pareto solutions may have a high probability to be removed by the superior solutions, noting that parents are selected by comparing simultaneously all the solutions. To solve this problem, each parent generates its own offspring with no relation to other parents and is also compared with its own offspring in the proposed algorithm. Therefore, each parent can perform independently the searching task so that the MEA proposed is called distributed *multiobjective* EA(DMEA).

The procedure of the proposed algorithm can be represented as shown in Fig. 3. As explained before, offspring are generated and then, they are compared with their parents and the nondominated solutions are extracted. It is kept in mind that each parent is compared with its own offspring. All the resulting nondominated solutions are collected to be one solution set, called the nondominated solution set(NSS).

Then, NSS is combined with the external solution set(ESS). For the combined solution set, the OCSA is executed to reduce its size. Among the resulting solutions after the sharing, parent solutions are selected using the OCSA and offspring are generated from the selected parents. And the remaining solutions are stored to be the ESS and they are combined with the NSS at the next generation. So, ESS plays an important role in preserving the diversity of the population. All the procedure is repeated until the final generation.

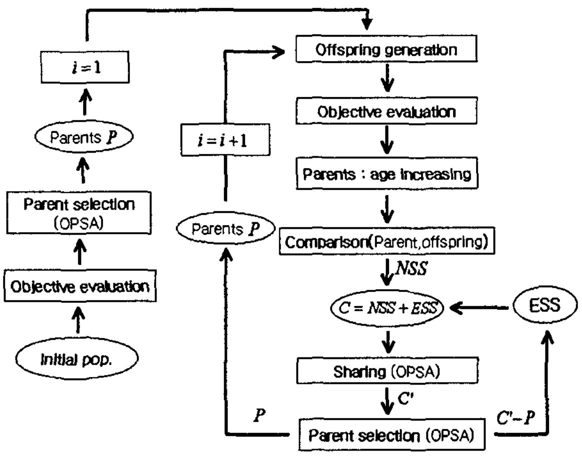

Fig. 3 Total flow diagram of the DMEA

In the OCSA, we select solutions in terms of their distribution such that selected solutions are distributed evenly into the entire objective space. As shown in Fig. 4, solutions are classified into several classes based on the distribution of one objective value. In each class, the best solution is selected in terms of the other objective.

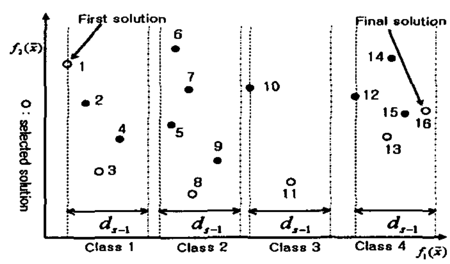

Fig. 4 Example of the OPSA

4. Simulation

To compare the proposed algorithm with other MEAs, simulation will be performed for the test functions as follows([8,9]).

$$f_1(\vec{x}) = 1 - \exp(-4x_1)\sin^6(6\pi x_1)$$
$$f_2(\vec{x}) = g(\vec{x})[1-(f_1(\vec{x})/g(\vec{x}))^2]$$
$$g(\vec{x}) = 1 + 9((\sum_{i=2}^{n} x_i)/(n-1))^{0.25}$$

where $n=10,100$ and $x_i \in [0,1]$. For each parent, three offspring are generated. The other parameter values are represented in Table 1(the numbers in the blank represent the parameter values in other MEAs). As mentioned before, the aging rate is much larger in case of large decision vector. The parameter values for other algorithms are the same in ref([8,9]).

Table. 1 The parameter values

	parent	sharing	r_a	gen.	eval.
n=10	30	100(100)	3/4	150(250)	19611(25000)
n=100	30	200(200)	19/20	950(1000)	97293(100000)

The proposed algorithm is compared with SPEA, NSGA, NPGA, and SOEA in Fig. 5. In that figure, the performance is much better than the other MEAs in terms of the quality and quantity of the nondominated solutions found even at a small generation and objective evaluation. Also, the proposed algorithm is compared with SPEA, SPEA2, NSGA2, and PESA in Fig. 6. For large dimension of decision vector, proposed algorithm is much better than the other MEAs.

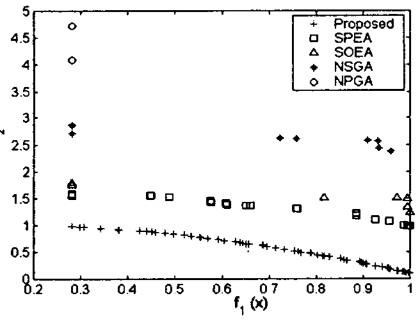

Fig. 5 The case of n=10

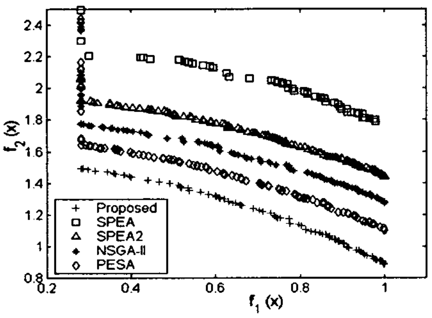

Fig. 6 The case of n=100

5. Conclusion

In this paper, we propose a new distributed multiobjective evolutionary algorithm based on the inherited age concept. As shown in the simulation, the proposed DMEA is much better than other MEAs in terms of quality, quantity, and distribution. Therefore, it can be guaranteed that the inherited age concept plays an important role in the proposed algorithm. Therefore, the inherited age concept can be utilized in various search algorithms.

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