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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 such as 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.

Key words : Distributed Multiobjective Evolutionary Algorithm(DMEA), Inherited Age(IA), Objective Classification Sharing Algorithm(OCSA)

1. Introduction

Many real-world problems involve multiple performance measures or objectives 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 MultiObjective GA(MOGA) by Fonseca and Fleming, Niched Pareto GA(NPGA) by Horn, Nafpliotis, and Goldberg, and Nondominated Sorting GA(NSGA) by Srinivas and Deb([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 envelopebased 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 the 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 termi-

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nologies and notations in ref([7,8]).

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 $\vec{v}=(v_1,\cdots,v_m)\in Y$ if and only if $\forall i\in\{1,\cdots,m\}$: $u_i\le v_i$ 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([6]) by introducing a novel notion, called "inherited age". We first show briefly the new offspring generation scheme and then, explain the IAC.

Based on the fractal concept([6]), 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. 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.

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 effectively 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.

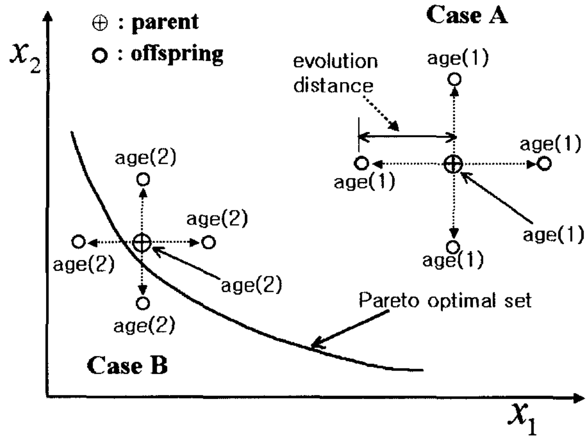

Fig 1. New offspring generation scheme

Definition (Inherited Age)

The age of a solution is defined as the number of its being nondominated regarding its offspring as the solution experiences during the evolution process starting from the initial solution. The inherited age has the following two properties:

1. Offspring succeed to the inherited age of their parent when they are generated.
2. A parent remains alive and grows old by one if and only if the parent is nondominated regarding its offspring.

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 regarding 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 of a solution means physically how far or near the solution exists from the Pareto optimal set.

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.

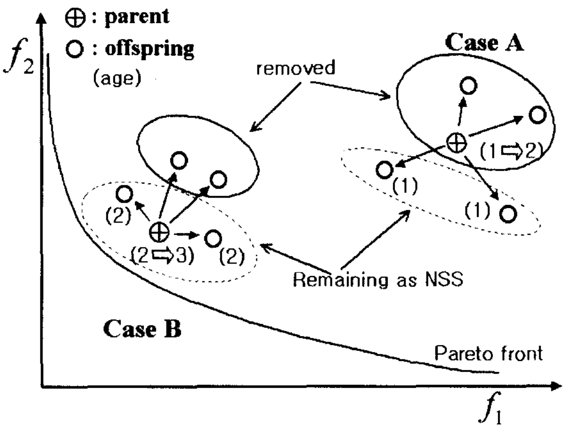

Fig 2. Comparison of parent with its own offspring

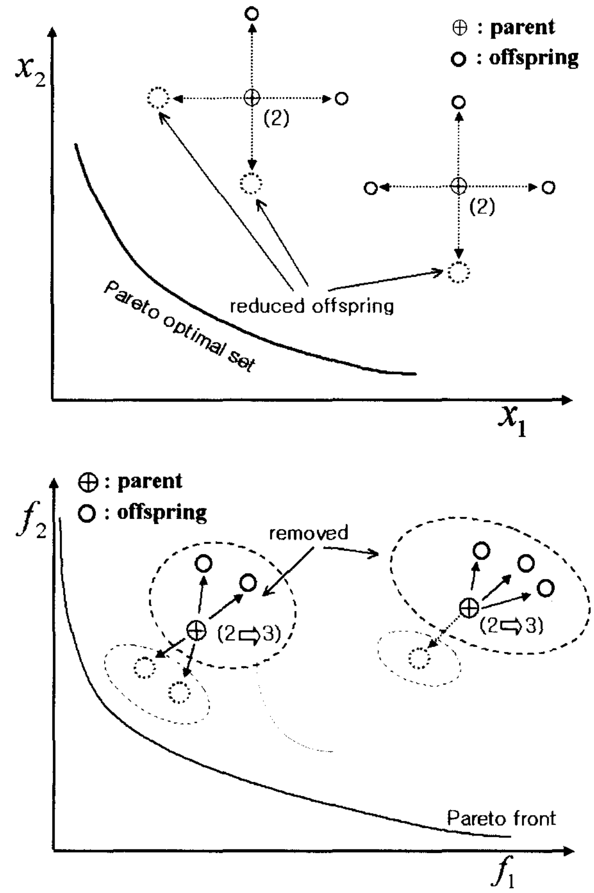

Fig 3. Reduced offspring case

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 exponentially decreasing according to its inherited age as follow; $d_a = d_0(r_a)^a$, where d_0 is the initial evolution distance and r_a $(0 < r_a < 1)$ 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 due to the characteristics of the new offspring generation scheme. 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 as shown in Fig. 3. To compensate for this wrong age increase, we increase the aging rate r_a. For the ideal case that all offspring are generated, we select the aging rate r_a as 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. 4.

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.

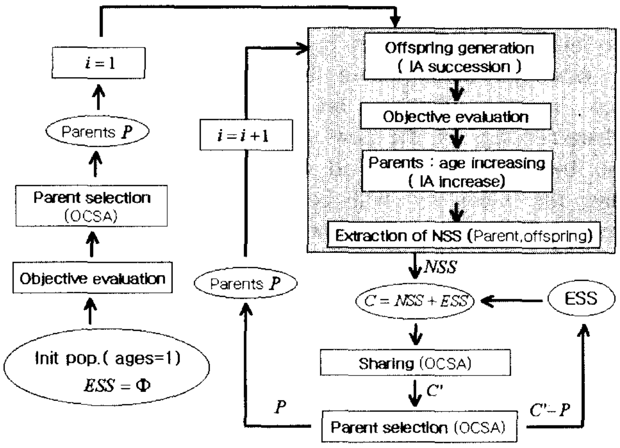

Fig 4. Total flow diagram of DMEA

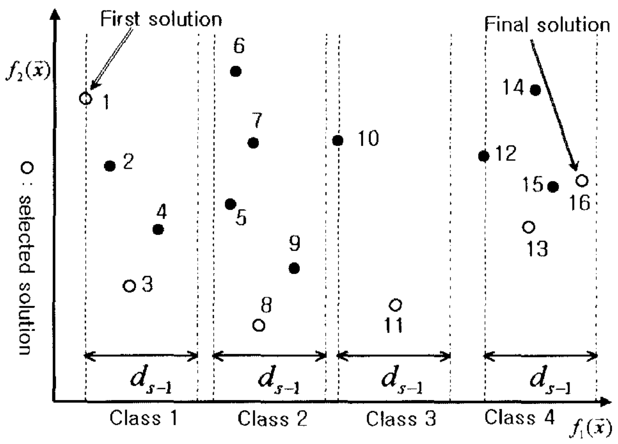

Fig 5. Example of the OCSA

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. 5, 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.

4. Simulation

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

$$\text{IC(Ideal Case)}: \begin{aligned} f_1(\vec{x}) &= 1-\exp(-(x_1-1)^2-(x_2-1)^2) \\ f_2(\vec{x}) &= 1-\exp(-(x_1+1)^2-(x_2+1)^2) \end{aligned}$$

$$(n=2,\ -10 \le \vec{x} \le 10)$$

$$\text{RC(Reduced Case)}: \begin{aligned} f_1(\vec{x}) &= 1-\exp(-4x_1)\sin^6(6\pi x_1) \\ f_2(\vec{x}) &= g(\vec{x})[1-(f_1(\vec{x})/g(\vec{x}))^2] \\ g(\vec{x}) &= 1+9((\sum_{i=2}^{n} x_i)/(n-1))^{0.25} \end{aligned}$$

$$(n=10, 100,\quad 0 \le \vec{x} \le 1)$$

a) Ideal offspring generation Case

For test functions IC, four offspring are generated for each parent as the dimension of the parameter space is two. The simulation results are compared with those of the PAES as shown in Fig. 6. In that figure, it can be known that we can find the good nondominated solutions even at a small number of generations in the DMEA, compared with the PAES. And we said that the inherited age can represent the distance from the Pareto optimal set. Fig. 7 shows the distance difference between the evolution distance of a solution and its distance to the Pareto optimal set in the parameter space. When the distance difference of a solution is positive, the solution exists within the evolution distance from the Pareto optimal set. As shown in Fig. 7, the distance differences are positive for most of the solutions, which verifies that solu-tionsexist within its evolution distance from the Pareto

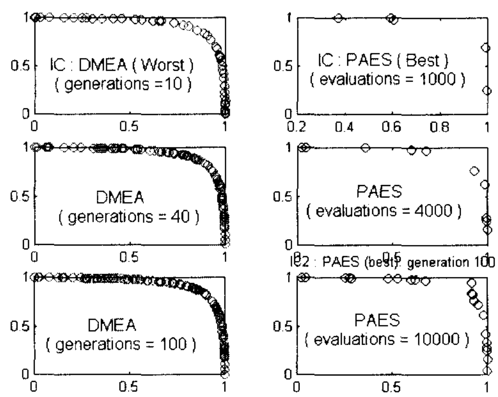

Fig 6. IC : Nondominated solutions

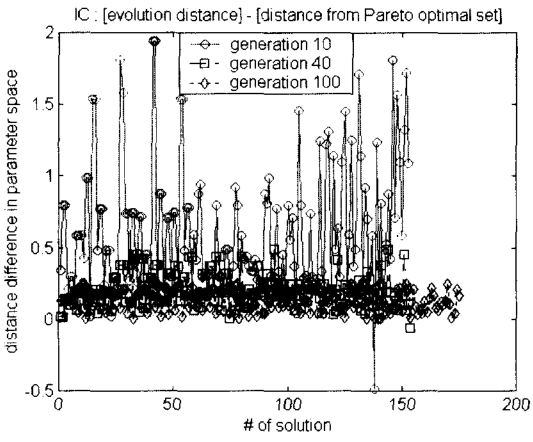

Fig 7. Distance difference between evolution distance and distance from the Pareto optimal set in the parameter space

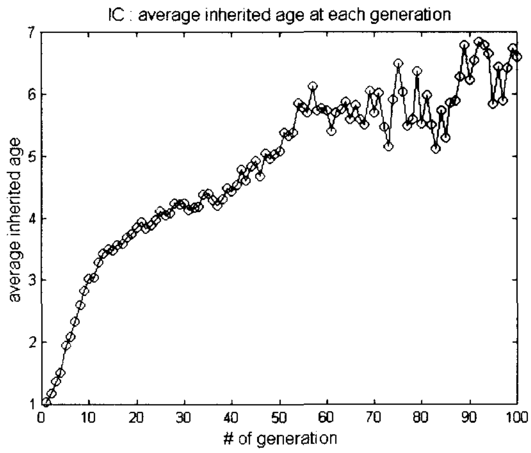

Fig 8. Average inherited age at each generation

optimal set. Fig. 8 shows the average inherited age at each generation. As solutions approach the Pareto optimal set, the average age gets increased.

b) Reduced offspring generation case

As mentioned before, we reduce the number of offspring generated for each parent when the dimension of the parameter space is large. In this simulation, three offspring ate generated for each parent to reduce the computational load, although 20 and 200 offspring should be generated ideally for each parent respectively for the test functions RC of dimension of 10 and 100. The other parameter values of the DMEA 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.
n=10	30(100)	100	3/4	150(250)
n=100	30(200)	200	19/20	950(1000)

The proposed algorithm is compared with SPEA, NSGA, NPGA, and SOEA in Fig. 9. 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 10. For large dimension of decision vector, proposed algorithm is much better than the other MEAs.

5. Conclusion

In this paper, we propose a new distributed multi-objective 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 convergence accuracy, convergence speed (number of generations), quantity, and uniform 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.

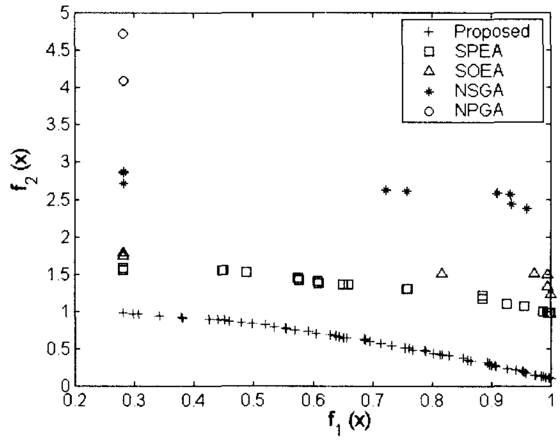

Fig 9. RC :Nondominated solutions(n=10)

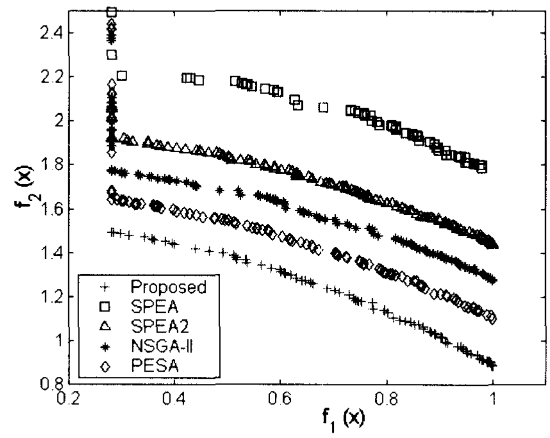

Fig 10. RC:Nondominatedsolutions(n=100)

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