비지배 방향정보를 이용한 새로운 다목적 진화 알고리즘

A New Evolutionary Multiobjective Optimization Algorithm based on the Non-domination Direction Information

Young-Hoon Kang and Zeungnam Bien

Dept. of Electrical Engineering and Computer Science, KAIST
373-1, Kusong-dong, Yusong-gu, Taejon 305-701, Korea
Tel: +82-42-869-3419, Fax: +82-42-869-8019
E-mail: yhsteel@ctrsys.kaist.ac.kr

Abstract

In this paper, we introduce a new evolutionary multiobjective optimization algorithm based on the non-domination direction information, which can be an alternative among several multiobjective evolutionary algorithms. The new evolutionary multiobjective optimization algorithm proposed in this paper will not use the conventional recombination or mutation operators but use the non-domination directions, which are extracted from the non-domination relation among the population. And the problems of the modified sharing algorithms are pointed out and a new sharing algorithm will be proposed to overcome those problems.

1. Introduction

It is called multi-objective optimization problems(MOPs) to deal with multiple objective functions. In MOPs, it is one of the goals to derive Pareto-optimal solutions. Pareto optimal solutions are a set of optimum solutions that are in the relationship of trade-off. Multi-objective optimization is with no doubt a very important research topic both for scientists and engineers, not only because most real-world problems have multi-objective nature, but also because there are still many open problems in this area. The multi-objective optimization problems tend to be characterized by a family of alternatives that must be considered equivalent in the absence of information concerning the relevance of each objective relative to the others. There are many approaches in this multiobjective optimization problems. Why do the evolutionary multiobjective optimization preferred to other approaches? The reasons are as follows: Evolutionary algorithms(EAs) seem particularly suitable to solve multi-objective optimization problems because they deal simultaneously with a set of possible solutions(so-called population), that is, population-to-population based search method. Additionally, EAs are less susceptible to the shape or continuity of the Pareto frontier. Since the pioneering work of Rosenberg in the late 1960s regarding the possibility of using genetic-based search to deal with multiple objectives, this new area of research has grown considerably and many research results have been come out. For examples, there have been many research work in this evolutionary multiobjective optimization area, Syswerda and Palmucci's aggregating function methods in 1991([3]) using weights in objective evaluation, Schaffer's Vector Evaluated Genetic Algorithm(VEGA) in 1993 ([8]), Fonseca and Fleming's Multiobjective Optimization Genetic Algorithm(MOGA) in 1993([6]) using the rank concept in assignment of the fitness, Srinivas and Deb's Nondominated Sorting Genetic Algorithm(NSGA) in 1993([4]) using population classification where each sub-population is assigned the same fitness, dummy fitness, proportional to the size of it., and Horn and Nafpliotis's Niched Pareto Genetic Algorithm(NSGA) in 1993([9]) using a tournament selection scheme based on Pareto dominance. The classification process of the population in NSGA will be used in this paper. Those previous algorithms work well but have some problems. For examples, in VEGA, it is very difficult to obtain Pareto optimal solutions in presence of non-convex search space and in MOGA and NSGA, it is very difficult problem to determine the proper sharing distance. Therefore, in this paper, we propose a new evolutionary multiobjective optimization algorithm based on the non-domination direction information, called Kang's Multiobjective Evolutionary Algorithm(KMEA), which can solve above problems. This algorithm is a combination of the direct directional search of gradient search algorithms and the population-based search of evolutionary algorithms. And we will propose a new sharing algorithm which does not change the fitness function but reduces directly the size of population. A similar sharing algorithm was proposed in 1999([11]), which does not permit the existence of several different solutions with the same objective values. Therefore, we propose a new adaptive sharing algorithm which can overcome that problem, called Kang's Adaptive Sharing Algorithm(KASA).

2.Preliminary Work

In this section, some definitions and reduced nondominated sorting process will be explained.

2.1 Defintions in the multiobjective optimization

The concept of Pareto optimum was initially formulated in economics by Vilfredo Pareto([2]) in the 19_{th} century and constitutes by itself the origin of research in multiobjective optimization. The family of solutions of multiobjective optimization problem is composed of all those elements of the search space of which the corresponding objective vectors cannot be all simultaneously improved. This is known as the concept of Pareto optimality. The practical problems are often characterized by several non-commensurable and often conflicting measures of performance or objectives. Now, assuming a maximization problem, some basic concepts are defined as follows.

Definition 1 (Pareto dominance)
A given vector $u=(u_1\Lambda, u_n)$ is said to dominate $v=(v_1\Lambda, v_n)$ iff u is partially greater than v, i.e., in mathematically
$\forall i \in \{1,\Lambda\ n\},\ u_i \geq v_i$ and $\exists i \in \{1,\Lambda\ ,n\}$ s.t. $u_i > v_i$.

Definition 2 (Pareto Optimality)
A solution $x_u \in U$ is said to be Pareto optimal iff there is no $x_v \in U$ for which $v=f(x_v)=(v_1,\Lambda\ v_n)$ dominates $u=f(x_u)=(u_1,\Lambda\ u_n)$.

Definition 3 (Pareto frontier)
Pareto frontier is a set of nondominated solutions that represent the optimal tradeoff relationship between objectives such that the components of the corresponding objective vectors cannot be improved without sacrificing another objectives.

When Pareto optimality is mentioned in multiobjective optimization, solutions can be discriminated using the following four words, dominating, dominated, undominated, and nondominated. The meanings of them are described in Fig.1.

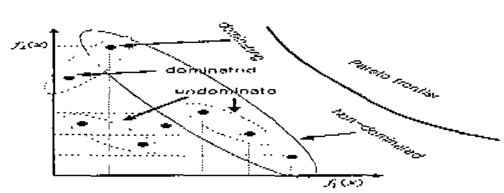


Fig. 1 Definitions of relation among solutions

2.2 Reduced Non-dominated Sorting Process(RNSP)

The non-dominated Sorting Genetic Algorithm(NSGA) was proposed by N. Srinivas and Kalyanmoy Deb([4]) and is based on several layers of classifications of the individuals. The NSGA is not directly applied to the proposed approach and only the classification process of population into the two layers of solution sets is used. For a given population, it can be firstly classified into the non-dominated solution set and the dominated solution set. The obtained non-dominated solution set is called as rank 1 solution set. Secondly, the dominated solution set can be again classified into the non-dominated solution set, which is called as rank 2 solution set, and the dominated solution set which is the remaining solution set. Rank 1 and rank 2 solution sets will be only utilized in this paper because it can be thought that the rank 2 solution set contains all the directional information of all the dominated solution set. From now on, dominated solutions will represent the rank 2 solution set of the population. As shown in Fig.?, RNSA can be considered as two cases, the case of one input population and two input population.

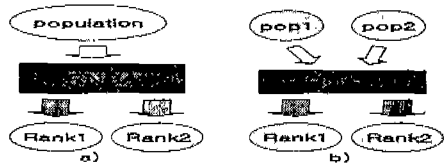


Fig.2 Reduced Nondominated Sorting Process(RNSP)

3 A New Evolutionary Multiobjective Optimization Algorithm based on the Non-domination direction Information

In this paper, the proposed algorithm, which is called Kang's Multibojective Evolutionary Algorithm(KMEA) from now, is almost the same as the Conventional Multiobjective Evolutionary Algorithms(CMEAs) except that fitness values are not used and offsprings are generated using nondomination direction information not using recombination, that is, crossover, or mutation operations.. In KMEA, we make only the nondominated solutions evolve and the dominated solutions provide them with the directional information of evolution. In this paper, a new sharing algorithm, Kang's Adaptive Sharing Algorithm(KASA), will be also introduced to prevent the explosion of the number of solutions by reducing directly the size of population in high density regions of solutions. In KASA, the sharing distances are automatically adjusted if the minimum number of Pareto solutions which we wish to find is determined. The concrete process will be explained in details in the following sections.

3.1 The general explanation for the Kang's multiobjective evolutionary algorithm

In the KMEA, fitness value system is never used and only non-domination information will be utilized. Unlike CMEAs where contribution of solutions to the generation of the next population is determined dependent on the fitness values, solutions of low objective values have the same equal importance as the solutions of high objective values in KMEA. In the proposed KMEA, objective values are only used in classifying the population into the non-dominated solutions and the dominated solutions so that the evolution direction information can be extracted from those classification for the generation of the offsprings. Although only the non-dominated solutions are allowed to generate offsprings, the dominated solutions also do the same important contributions as the non-dominated solutions in terms of providing the non-dominated solutions with the evolution direction information. In other words, offsprings are generated by pushing the non-dominated solutions along the non-domination directions which are the directions from the dominated solutions toward the non-dominated solutions.

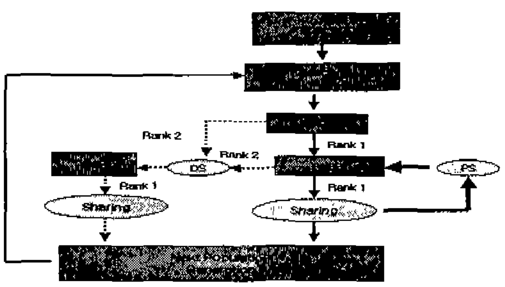


Fig. 3 Block Diagram of KMEA

Now, we will explain the general procedure of KMEA as shown in Fig.3. The initial population is generated randomly in the entire input parameter space and the generated population is evaluated by calculating the objective function values. As mentioned above, RNSA is firstly applied to the population and the population is classified into the first non-dominated and dominated solutions. Then, the first nondominated solutions are compared with Pareto solutions and the second non-dominated solutions and the second dominated solutions are extracted. We obtained two dominated solution sets. These dominated solutions contain the evolution direction information for the second nondominated solutions. However, because they have some redundancy in directional information. RNSP is again applied to them to simplify the computation by getting rid of the redundant solutions and we obtain the rank 1 solutions among them, which is third dominated solutions. Now, all the environment is prepared for the generation of the next population, but if all the second nondominated solutions and the third dominated solutions are used in generating offsprings, too many offsprings will be generated so that the computational load will be very large. We can think that the neighboring solutions to each other contain almost the same evolution direction information so that the redundant solutions can be removed. For this purpose, we consider a new sharing algorithm, called Kang's Adaptive Sharing Algorithm(KASA), for them. When KASA is applied to the them, the resulting solutions, Shared Leading Pareto Solutions(SLPS) and Shared Pushing Dominated Solutions(SPDS), can be obtained. Now, all the environment is really achieved for generating the next population. The offsprings are generated by making SLPS along the non-domination directions toward the actual Pareto frontier as shown in Fig.4. In other words, the evolution directions of SLPS are determined as the directions from the SPDS toward the SLPS so that offsprings are generated by making SLPS evolve along the evolution directions. However, all of the SLPS does not have dominated solutions. For SLPS without any dominated SPDS, we select the nearest one solution among SPDS to them and determine the directions from selected nearest solutions toward them as the evolution directions. Then, offsprings are generated along the evolution directions.

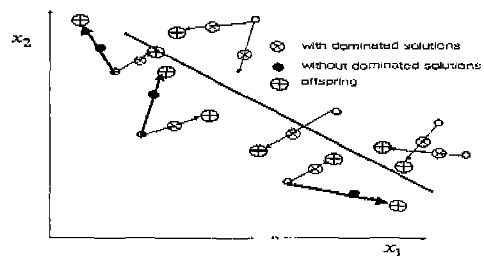


Fig. 4 The generation of the next population

3.2 Kang's Adaptive Sharing Algorithm

The conventional sharing techniques have the problem that the proper choice of sharing distance is very difficult and it does not permit the co-existence of different solutions with the same objective values. To overcome these problems, new sharing method, Kang's Adaptive Sharing Algorithm(KASA), will be proposed from now. In KASA, if the user only decide the minimum number of Pareto solutions, the sharing distances are automatically adjusted and the non-existence problem of solutions with the same objective values will be solved. At first, to overcome the choice of sharing distance, we select sharing variable at input space and objective space and determine the input sharing distance and objective sharing distance by dividing the largest input distance and objective distance by the minimum number of Pareto solutions which we want to find at least. The proper choice of the sharing distance will be solved by determining the sharing distances like above method. We combine the sharing technique of both in input parameter space and in the objective value space in the proposed Kang's sharing approach to overcome the disadvantages of each space as shown in Fig.5. At first, the population will be sorted for the objective variable of the largest standard deviation in the objective space. Then, for each solution, we find the solutions within the objective sharing distance from itself in objective space, which have possibility of being removed as the sharing solution candidates. To determine whether the sharing solution candidates are really removed, we calculate the distances between them in input space. We will remove the sharing solution candidates if it is within the input sharing distance. By doing this way, it can be protected to remove important Pareto solutions with similar objective values which are distributed in very different regions in the input parameter space.

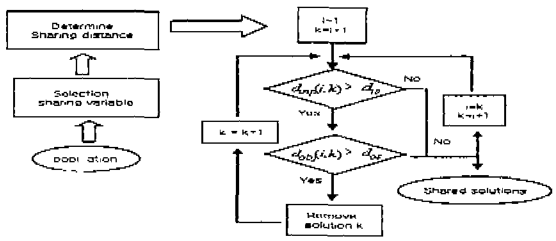
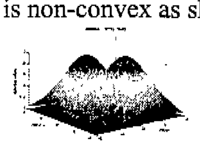


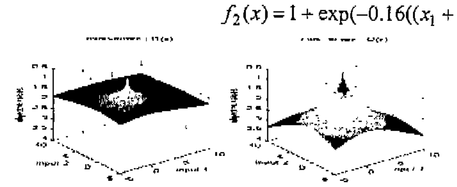
Fig. 5 Kang's Adaptive Sharing Algorithm

3.3 Simulations

In this section, the simulation will be performed for two kinds of objective functions. One is convex and the other is non-convex as shown in Fig.6



$$f_1(x) = 1 + \exp(-0.16((x_1 - 1)^2 + (x_2 + 1)^2))$$
$$f_2(x) = 1 + \exp(-0.16((x_1 + 1)^2 + (x_2 - 1)^2))$$



$$f_1(x) = -(x_1^2 - y^2)^{1/8}$$
$$f_2(x) = -((x_1 - 0.5)^2 + (x_2 - 0.5)^2)^{1/4}$$

Fig. 6 objective funtions: convex, non-convex

As shown in Fig.7, the performance is very good even at small number of iterations, 12 iterations.

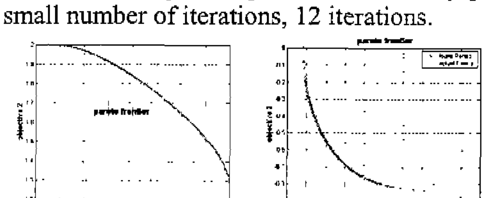


Fig.7 Found Pareto solutions for $f_1(x)$ and $f_2(x)$

The elapsed times for each kind of objective functions is 269 seconds and 25 seconds.

4. Conclusions

We proposed a new multiobjective evolutionary algorithm, which is a combination of direct directional search of gradient algorithm and population-based parallel search of evolutionary algorithm. As shown in simulations, the performance is very good for non-cnvex objective functions and the search speed is very fast, compared with other methods. And a new adaptive sharing algorithm was also proposed to overcome the problems of the conventional sharing algorithms. By this KASA, the problems of determining of sharing distances and non-existences of different solutions with the same objective values worked out.

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