Examination of multi-objective genetic algorithm using the concept of a Peer-to-Peer network

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***Abstract*—The characteristics of a network of Peer-to-Peer Evolutionary Algorithms (P2P EA), which are parallel genetic algorithms, are discussed. We applied the concept of P2P EA, which is a single-objective optimization method, to a multi-objective Genetic Algorithm. To verify the performance of the solution set in the proposed method, we compared the proposed method to the generational multi-objective genetic algorithm NSGA-II. Moreover, to verify the influence of network topology and cache size, we performed the proposed method with three types of network topologies and three cache sizes. Numerical examinations indicated that the difference in network structure has no influence on the solution set, while the cache size affects the solution set.**

I. Introduction

There are several types of parallel Genetic Algorithm (GA). Typical examples are the island model[1], [2], [3], master/slave model, and diffusion model. In the diffusion model, one or several individuals are allocated to each processor. Multiple processors form a neighborhood and evolutionary operations (e.g., crossover and mutation) are executed between the neighborhood individuals. Cellular GA[4], [5] and Peer-to-Peer Evolutionary Algorithm (P2P EA)[6] are examples of diffusion model GAs. The P2P EA is a search technique using the concept of the Evolvable Agents model and the Newscast protocol used in P2P networks. P2P EA can search for the optimum solution and maintains diversity of individuals.

In previous studies, the island[7], [8], master/slave[9], [10], and cellular GA[11] -all examples of diffusion models - have already been applied to multi-objective GAs[12]. However, the concept of P2P EA has not been applied to multi-objective GAs. In this study, we applied the concept of P2P EA to a multi-objective GA, and the characteristics and search capabilities were examined through numerical experiments.

II. Multi-objective optimization

A. Multi-objective optimization problem

Multi-objective optimization problems have a number of objective functions and there are tradeoffs between these objective functions. Multi-objective optimization problems are defined as problems involving minimizing (or maximizing) multiple objective functions that are in conflict with each other with a given limitation condition. Generally, because of the tradeoff in objective functions, a unique solution cannot be determined but a set of solutions may be derived. For the set of solutions, the concept of the Pareto-optimal solution is used.

1) Dominance relation
If $f_k(x_1) < f_k(x_2)(\forall k = 1, ..., p)$ and $f_k(x_1) < f_k(x_2)(\exists k = 1, ..., p)$ under the condition $x_1, x_2 \in F$, it is said that "x_1 dominates x_2" (where x:decision variable; p:number of objective function; $f_k(x)$i: objective function).
2) Pareto optimum solution
If $x \in F$ hat dominates a certain x_0 does not exit ,x_0 is called a Pareto-optimal solution (or noninferior solution).

A good Pareto-optimal solution means a set of solutions with high quality with regard to accuracy, uniform distribution, and broadness. Accuracy indicates how close the obtained solutions are to the true Pareto front, and uniform distribution indicates how evenly located solutions are without concentrating in certain areas. Broadness indicates the spread of the solutions and is decided by the solutions located at the edge of the Pareto front, which are optimal solutions for each objective.

B. Multi objective Genetic Algorithm

In the field of the multi-objective optimization, there have been many studies of multi-objective GA[13], [14], [15], [16], [17], [18] using Genetic Algorithms that is a multi-point search technique. NSGA-II[16] and SPEA2[17] are typical multi-objective GA techniques, and these algorithms treat Pareto solutions explicitly. In addition, It has some important mechanisms (e.g., selection of excellent solutions in diversity and the other mechanism) in the multi-objective optimization. These mechanisms enable good search performance.

III. Peer to peer Evolutionary Algorithm

The P2P EA is a single optimization method, which uses the concept of the Evolvable Agents model and the Newscast protocol used in P2P networks. P2P EA maintains diversity of individuals while searching for the optimum solution[6].

A. Evolvable Agents model

The Evolvable Agents model carries out the main steps of evolutionary computation, i.e., selection, variation, and evaluation of individuals. The Evolvable Agents model has its own operations using information regarding the neighborhood.

Each Evolvable Agent evolves within its neighborhood, which is locally maintained by the P2P protocol Newscast.

B. Newscast

Newscast is a system to share the newest information with every node on an unstructured P2P network[19]. At every fixed time interval, every node chooses one node from the neighborhood list at random and the nodes exchange information. With this technique, information spreads through the total node slowly. Repeating these operations, information spreads gradually through the total nodes.

IV. Proposal method

To perform P2P EA, the neighborhood of each individual should be defined. Crossover is performed only among individuals within the neighborhood. Moreover, each individual is able to evolve by themselves.

A. Cache

In our proposal method, cache mechanism is used. We defined that the cash holds individual information such as individual ID number, a chromosome and the fitness value. The individual exchanges his cash for one of neighborhood by the generation. As a result, the individual can maintain information of individuals in the surrounding it. It enables the comparison between neighbor individuals and the own individual at the time of selection to maintain the information of neighboring individuals.

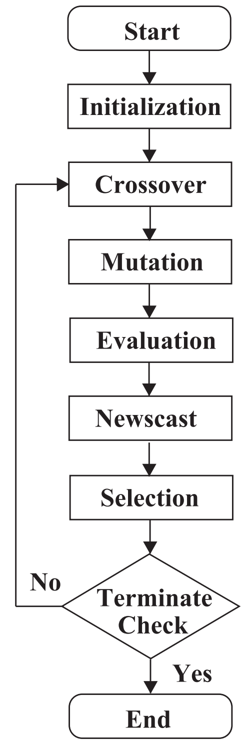

Figure 1. algorithm of proposed method

B. Algorithm

Here, we propose a method for adding the Evolvable Agents model and Newscast to a multi-objective GA. The flow of the algorithm is shown in Figure 1.

The proposed algorithm is composed of initialization, crossover, mutation, evaluation, Newscast, and selection.

- Initialization
  In the initialization process, the neighborhood is defined for all individuals. Neighborhood information (e.g., chromosome and fitness value) is stored in the used with Newscast.
- Crossover, Mutation
  Crossover is performed between the neighboring individuals. Mutation is performed after crossover.
- Evaluation
  In the evaluation process, the fitness value of offspring is calculated. The offspring information is stored in the cache.
- Newscast
  Each $individual_i$ conducts a cache exchange. It selects neighbor $individual_j$ randomly. Then $individual_i$ and $individual_j$ exchange and merge their caches according to $Cache_i \bigcup Cache_j$. The maximum cache size is given as a parameter. If cache size increases more than the max cache size, the cash size is kept constant by selecting individuals randomly from the cache.

- Selection
  $Cache_i$ is merged with the information (e.g., chromosome, fitness value) of $individual_i$. Then, non-dominated sorting is performed with the cache.If $individual_i$ is not rank 1, It selects one from the individuals of rank 1 at random. Otherwise, the crowded distance is calculated in the individuals of rank 1. Then, it selects the individual from among those with crowded distance greater than $individual_i$ at random.

V. Numerical experiment

A. Experimental overview

A numerical experiment was performed to verify the influence of differences in the network and in cache size on the solution set. The proposed method was compared with NSGA-II, which is a general multi-objective GA technique, to verify the performance of the search result. ZDT2, ZDT4 and ZDT6 were used in this experiment as test problems. ZDT2 is a two-objective continuous problem with a single peak and nonconvex-type Pareto front. ZDT4 is a two-objective continuous problem with multiple peaks and a convex-type Pareto front. ZDT6 is a two-objective continuous problem and has a deflection between an objective function and a design variable. To make the evaluation frequency of NSGA-II equivalent to that the proposed technique, max generation of NSGA-II was set as 800 and that of the proposed method was set as 400.

Table I shows the parameters used in this experiment. The topology of the population structure used in the experiment was as follows.

1) Grid network
   The population structure in multi-objective GA was set as a two-dimensional grid network structure. In the grid network structure, the number of edges of each individual is uniquely decided.
2) Random network
   The population structure in multi-objective GA was set as a random network structure. In a random network structure, the number of edges of each individual is given as a parameter.
3) Scale free network
   The population structure in multi-objective GA was set as a scale-free network structure. We used a Barabási-Albert model[20] as a scale-free network.

Many metrics are available to evaluate the obtained solutions. Generational distance (GD) and cover rate were adopted for discussion of derived results. GD is the average distance from each solution of the Pareto-optimal front to the closest obtained solution, and is a metric of accuracy. Cover rate shows how much the divided area between maximum and minimum values of each objective within the obtained Pareto front can be covered and is a metric of uniformity.

B. Result

Search results of ZDT2, ZDT4 and ZDT6 by the proposed method and NSGA-II in 30 trials are shown in Figure 2, 3 and Figure 4. For Figure 2, 3 and 4, max cache size was set to 100 and the method described above was applied to each of the three networks.

The mean values and averages of GD and cover rate values are shown in Table II, III and IV. Table II, III and IV show that the cover rate increased as the cache size increased. The differences in network structure had no influence on the performance of the solution set. Finally, Table II, III and IV show that the proposed method is inferior to NSGA-II in ZDT2, ZDT4 and ZDT6.

VI. Conclusions

Here, we applied the Evolvable Agent model and Newscast, which are concepts of P2P EA, to a multi-objective Genetic Algorithm. To verify the performance of solution set in the proposed method, we compared the proposed method with NSGA-II, which is a generational multi-objective Genetic Algorithm. Moreover, to verify the influence of network topology and cache size, we performed the proposed method with three types of network topologies and three cache sizes.

The results indicated that differences in network structure have no influence on the solution set, but the cache size affects the solution set. Moreover, the proposed method was inferior to NSGA-II in ZDT2, ZDT4 and ZDT6.

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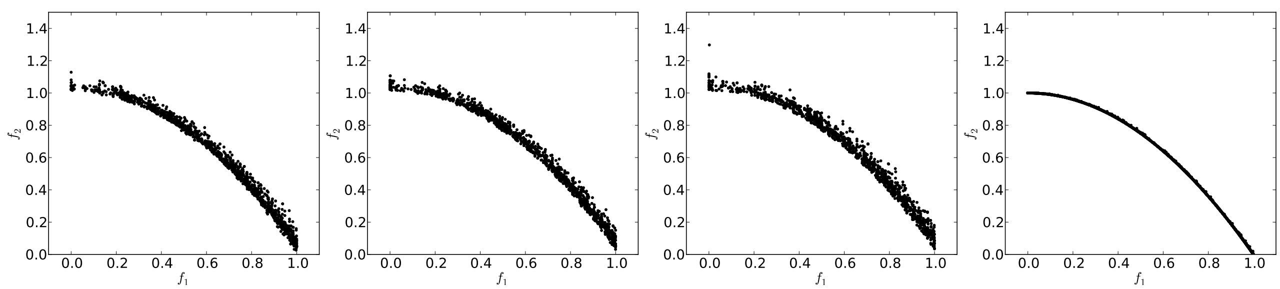
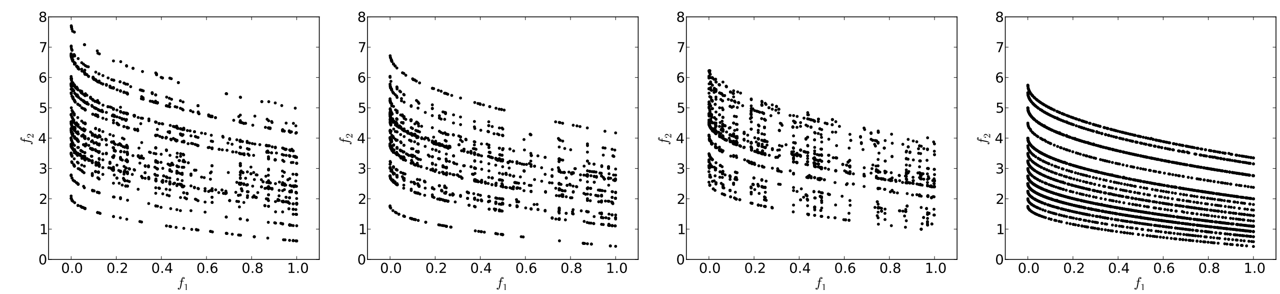
Table I
PARAMETERS

	NSGA-II	Proposed method
Population size	100	100
Design variable length	20	20
Crossover	2 point crossover	2 point crossover
Crossover rate	1.0	1.0
Mutation rate	1 / chromosome length	1 / chromosome length
Max generations	800	400
Selection	Crowded tournament selection	
Tournament size	2	
Cache size		10, 40, 100



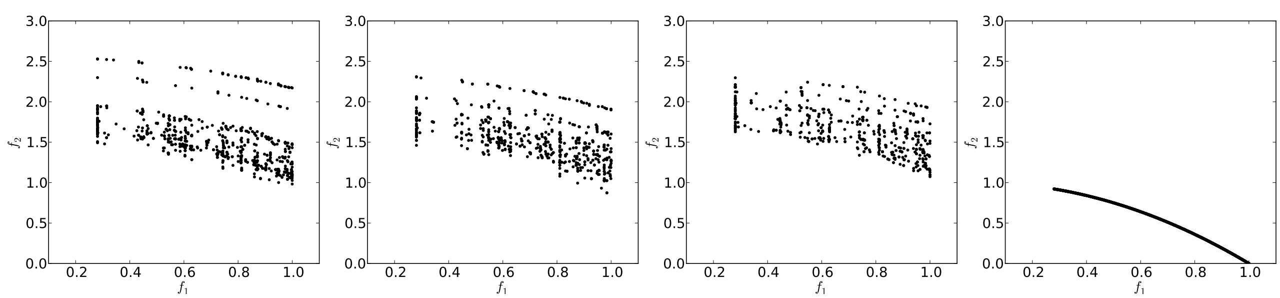
(a) (b) (c) (d)

Figure 2. Solution set of optimization in ZDT2. (a)grid network;(b)random network;(c)scale-free network;(d)NSGA-II



(a) (b) (c) (d)

Figure 3. Solution set of optimization in ZDT4. (a)grid network;(b)random network;(c)scale-free network;(d)NSGA-II



(a) (b) (c) (d)

Figure 4. Solution set of optimization in ZDT6. (a)grid network;(b)random network;(c)scale-free network;(d)NSGA-II

Table II
COVER RATE AND GD OF SOLUTION SET IN ZDT2

	Proposed method									NSGA-II
network	grid network			random network			scale-free network			
cache size	10	40	100	10	40	100	10	40	100	
cover rate(median)	0.1725	0.3300	0.3600	0.1550	0.2825	0.3250	0.1350	0.2700	0.3250	0.7475
cover rate(average)	0.1745	0.3175	0.3608	0.1533	0.2863	0.3262	0.1356	0.2723	0.3283	0.7483
GD(median)	0.0137	0.0301	0.0339	0.0100	0.0373	0.0417	0.0259	0.0501	0.0435	0.0003
GD(average)	0.0146	0.0340	0.0350	0.0100	0.0450	0.0454	0.0309	0.0510	0.0549	0.0003

Table III
COVER RATE AND GD OF SOLUTION SET IN ZDT4

	Proposed method									NSGA-II
network	grid network			random network			scale-free network			
cache size	10	40	100	10	40	100	10	40	100	
cover rate(median)	0.1700	0.3100	0.3550	0.1800	0.3150	0.3650	0.1425	0.2450	0.3050	0.7450
cover rate(average)	0.1733	0.3702	0.3493	0.1828	0.3165	0.3603	0.1421	0.2528	0.2928	0.7403
GD(median)	3.0987	3.2343	2.7381	2.6311	2.6334	2.7354	2.7147	2.8980	2.6093	1.4490
GD(average)	2.9604	2.9290	2.9367	2.7120	2.8100	2.8050	2.6337	2.8763	2.5806	1.7022

Table IV
COVER RATE AND GD OF SOLUTION SET IN ZDT6

	Proposed method									NSGA-II
network	grid network			random network			scale-free network			
cache size	10	40	100	10	40	100	10	40	100	
cover rate(median)	0.0850	0.1100	0.1475	0.0800	0.1150	0.1400	0.0750	0.1050	0.1300	0.7950
cover rate(average)	0.0910	0.1162	0.1590	0.0798	0.1105	0.1417	0.0757	0.1023	0.1228	0.7975
GD(median)	0.6861	0.6656	0.6942	0.7576	0.7567	0.7376	0.9128	0.9341	0.8312	0.0004
GD(average)	0.6622	0.6704	0.7558	0.7861	0.7777	0.7539	0.9147	0.9456	0.8813	0.0003

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