Dynamic Pareto Optimum GA against the changing environments

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Abstract

The purpose of this study is to show the two new views on the studies under dynamic environment and to propose new method "Dynamic Pareto Optimum GA".

The former is that "In the static environment, the adaptation is done for the optimum solutions, but in the case of dynamic environment, the adaptation should be done toward the characteristics of environmental changes that can be adapted."

The latter is "When the environmental changes are faster than the velocity of adaptation, we have to choose how we adapt." If the velocity of the environmental changes approaches the fastest limit, the situation is the same as multi-objective-optimization problem. The choice of how to adapt becomes important, in the environment including trade-off along the time axis, in which , for example, the high fitness peaks disappear quickly, and the low fitness peaks remain for long time.

In this new method, genes, schemas and chromosomes are not conserved, but the past fitness values are retained as internal time series of each agent. And by pareto-optimum, this method decides which agent should be conserved.

1 INTRODUCTION

1.1 The first view: the target of adaptation is how the environment changes

The initial researches under dynamic environments were done in the periodically changing environments on the binary phenotype space. But recently many studies have been done on some test functions in which the peaks are moving continuously on the phenotype space. References are in [1],[2],[4]. The reasons of this trend are that the adaptation is hopeless if the optimum point flies here and there at every moment, and that the periodically changing environments do not seem to have so many varieties. But I think that immediate result of this kind of hopelessness in adaptation is that the target of adaptation is not a peak but how the environment changes. In the case of dynamic environments, adaptation should not be done for optimum solutions and should be done toward the characteristics of changes that can be adapted, like examples below. Each adaptation method should be developed toward each characteristic. The previous studies have been often classified into the memory base and the diversity base. I review them from the point of some typical characteristics that can be adapted.

1. **Reappearance**
   Reappearance means that optimum solution appears in the neighborhood of the optimum solutions that appeared before $n(>1)$ steps.
   The useful algorithm against these environments obviously contains memory.

2. **Continuity**
   Continuity means that optimum solution appears in the neighborhood of the optimum solutions that appeared before 1 step.
   One of the useful algorithms against these environments is the neighborhood search operators on the phenotype space(the adaptation space).

3. **Rarity**
   Rarity means that the environments can be adapted even if the optimum point flies here and there if the frequency of the environments change is small.
   The useful algorithm against catastrophes is such algorithm that keeps diversity or produces diversity at a moment.

I am sorry that I cannot discuss other possibility of characteristics that can be adapted, because of space limitation. According to above discussions, for the adaptation against the environment which changes continuously, we need strong local search. Then in my proposed method, local search is separated from GA selection and the selection for local search is done deterministically. The cause of high performance of Experiment 1 is this.

1.2 The latter view: we have an option of how we adapt

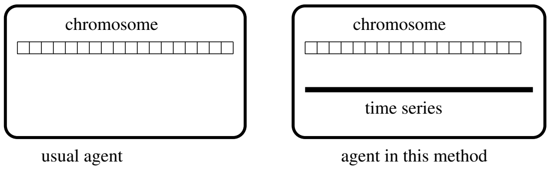
In our daily life, there are many situations in which the environments change faster than our adaptation. And there are many environments that include trade-off along the time axis. Such situations are important, because the following words are very familiar to us.
⟨ conservative or progressive ⟩
⟨ long-term insight or short-term insight ⟩
⟨ stable or high-risk instead of high-return ⟩
⟨ riding on the flow or going against the flow ⟩
To make the agents adapt in one of such manners, some mechanisms are necessary, because usually selection is done by temporary fitness values of agents. On the problem in the dynamic environments, the objective functions $G = \{g_\tau, g_{2\tau}, g_{3\tau}, ...\}$ appear one after another at the interval of τ. On the problem of multi-objective optimization, the multiple objective functions appear at the same time. But as τ becomes smaller, $g_{n\tau}$s can be regarded as appearing almost at the same time. I pay attention to this similarity, I propose the new method "Dynamic Pareto Optimum GA".

2 Dynamic Pareto Optimum GA

This method has following two features which correspond to two views described above .

1. After n times local search, each agent deterministically takes the chromosome whose fitness value is the best. An agent does not lose own identity by local search.

2. By pareto-optimum, this method decides which agent should be conserved. In this new method, genes, schemas and chromosomes are not conserved, but the past fitness values are retained as internal time series of each agent.



Selection is done by multi-objective-ranking method by regarding the changing objective functions as multi-objective functions. As this result, the agent who recorded the high fitness value in the past is conserved, because such agent is not dominated by any other agent.

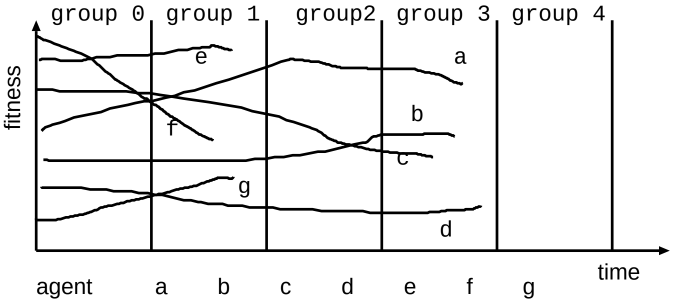
The flow of this method is as follows. t=0

1. **Do local search and fitness evaluations.**
A chromosome is made by real number series and mutation is done by normal distribution.
Each agent mutates and evaluates n times, and takes the chromosome whose fitness value is the best.

2. **if $t = n\tau$, memorize the current fitness value of each agent in each time series.**

3. **Probe current fitness of agents of the type you want.**
Because population keeps various kinds of agents, we can easily extract the agent we want, by examining agents' time series f_{it}. ("i" is the agent number). In this study we probe four types of agent.
⟨ The current best ⟩ $max_i(f_{it})$
⟨ The average best ⟩ $max_i average_t(f_{it})$
⟨ The maximum best ⟩ $max_i max_t(f_{it})$
⟨ The minimum best ⟩ $max_i min_t(f_{it})$

4. **Parato Optimum**
g_t is the fitness landscape at step t. τ is the interval of memory. We take $G = \{g_\tau, g_{2\tau}, g_{3\tau}, ...\}$ as the objective functions in multi-objective-optimization problem. Different from ordinary pareto optimum, the length of time series of each agent is not equal. Then we divide the agents into groups by the length of time series. The agents in the same group are compared to decide dominant relationship. The dominant-relationship of two agents is decided as follows.
If following both conditions are satisfied, say that agent A dominates agent B:
all n steps fitness of A >= fitness of B
more than 1 step fitness of A > fitness of B
Here n is the shorter length of two time series of A agent's and B agent's. C_{ig} is the number of



agent	a	b	c	d	e	f	g
group	3	3	3	3	1	1	1
C	0	1	0	3	0	0	2
ScaildC	1	0.33	1	0	1	1	0

Figure 1: how to decide the dominance

agents which dominate an agent "i" in the group "g". C_{ig} is scaled from 0 to 1 within the same group.
$ScaledC_{ig} =$
$1 - (C_{ig} - min_i(C_{ig}))/(max_i(C_{ig}) - min_i(C_{ig}))$
See Fig.1. If no agent dominates other agents in a group, $ScaledC_{ig}$s are all set to 1.

5. **Share by distance on the genotype space.** Sharing is done by following functions.
$d_{ij}^2 = \sum_{k=1}^{5}(x_k(i) - x_k(j))^2$
$s_{ij} = 1.0 - (d_{ij}/30)^{0.2}$
$rank_i = ScaledC_i / \sum_j s_{ij}$
Here, $x_k(i)$ is the value of k th gene of agent i, and $ScaledC_i$ is $ScaledC_{i,g}$ renumbered.

6. **Using $rank_i$, ranking is done.**

7. **Select 20% of the population and reproduce and mate.**

8. **Initialize randomly 1% of the population.**

9. **t=t+1 Return 1**

3 EXPERIMENT

I use the test function for the dynamic environments, which has been proposed in Branke,J.[3]. I do three experiments. Parameters are shown in Table1. In all experiments, we show the result that has been averaged over 20 run of different seed of random number. We use the multi-agent simulator SWARM that has been developed in Santafe Institute.

EXPERIMENT 1: High fitness value
This experiment is done under all the parameters being

population size	100
mating rate	0.5
mutation rate	1.0
standard deviation of mutation	10.0
the times of localsearch	5
time interval of memorization	5
maximum size of time series	50
number of groups	5
mimimum length of time series	2
	Scenario 2
variable range	$0 < x < 100$
no of peaks	50
peak function	cone
minheight	30
maxheight	70.0
minwidth	1.0
maxwidth	12.0
standardwidth	0.0
standardheight	50.0
lambda	0
vlength	1.0
height severity	7.0
width severity	1.0
change every x evaluatuins	5000
change every x steps	10

Table 1: Parameters of Test Function

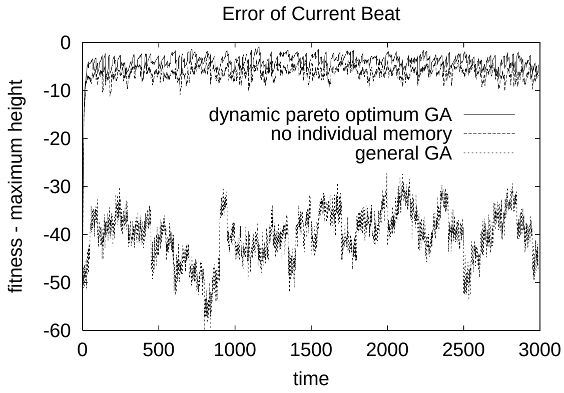


Figure 2: Fitness - the maximum height of peaks

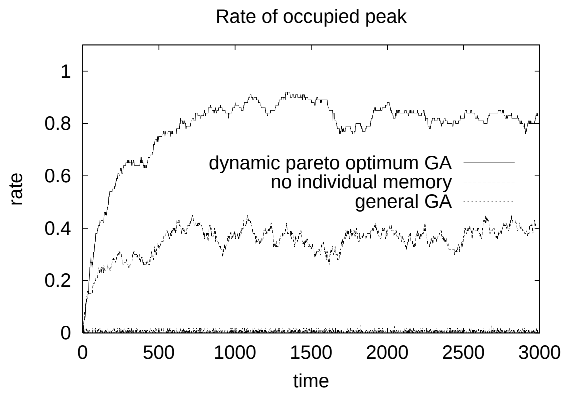


Figure 3: the proportion of the occupied main peaks

equal to Branke's scenario 2. The purpose of this experiment is to show "Dynamic Pareto Optimum GA" can record high fitness values in ordinary environment. We compare following three populations.

◇ The population of "Dynamic Pareto Optimum GA"

◇ The population which does not have the individual memory and of which other things are the same as "Dynamic Pareto Optimum GA"

◇ The population of ordinary GA with ranking selection

Fig.2 shows errors of the current best agent. (Here, error = fitness - maximum height of the peak) The average error from 500 step to 3000 step are as follow.

the times of local search	5 times	1 times
change every x steps	10 steps	50 steps
change every x evaluations	5000	5000
Dynamic Pareto Optimum GA	**-3.78**	-18.42
No individual memory	-6.22	-21.66
Ordinary GA	-40.29	

In both experiments the environments are changed every 5000 evaluations, so the one-local-search experiment (with GA type local search) is far inferior to original experiment (with deterministic local search). As I mentioned in $1 , the main cause of high fitness value is due to deterministic local search.

EXPERIMENT 2: Capability of keeping peaks

The purpose of this experiment is to show "Dynamic Pareto Optimum GA" can keep peaks of fitness functions very well without using multi-population methods, even if the vertical movements of the peaks are quite severe. Furthermore even if the optimum is not a peak but a line or other areas, this method can also keep these areas.

In this experiment, the 5 main peaks do vertical movement in the height of from 30 to 100 as moving horizontally. I use the other 45 peaks as basis functions and they also do vertical movement in the height of from 0 to 50 as moving horizontally. Often, some of the main peaks become lower than basis peaks. The environment is severe to keep the 5 main peaks, nevertheless, the population of "Dynamic Pareto Optimum GA" keeps well about 80% of the 5 main peaks. (To keep the peak means that one agent at least is within the circle of radius 5 around the peak.) Fig.3 shows the proportion of the occupied main peaks. The average percentage of peak occupation and the average error are as follows.

	peak	error
Dynamic Pareto Optimum GA	**0.83**	**-6.59**
No individual memory	0.37	-15.39
Ordinary GA	0.00	-78.43

EXPERIMENT 3 :Extraction of the solutions of how we adapt

The purpose of this experiment is to show "Dynamic Pareto Optimum GA" can extract the various solutions of how we adapt. In this study, we extract four types of agents, the current best, the average best, the maximum best and the minimum best. The environments of this experiment include trade-off relation along the time axis. The high fitness peaks disappear quickly, and the low fitness peaks remain for long time. In this model, 50 peaks have random initial height = h_0 from 50 to 100. The height of each peak is changed in the following probabilities.

height : $h_0 \rightarrow 0$ $\quad 1/(100 - 95 * (h_0 - 50)/50)$

height : $0 \rightarrow h_0$ $\quad 1/(95 * (h_0 - 50)/50)$

The following table shows the average, maximum and minimum fitness values over agent's time series of 4 types of agents. In the average, the average best agent is better than the current best agent . The maximum best agent is more useful if getting high fitness value only once is important (like option in finance). The minimum best agent is more suitable when too low fitness destroys the system.

	average	maximum	minimum
	over agent's time series		
average best	**48.12**	58.57	7.03
maximum best	36.50	**70.25**	1.00
minimum best	38.73	46.38	**26.7**
current best	43.72	62.75	8.17

4 CONCLUSION

The purpose of this study is to show the two new views on the studies under dynamic environment($1) and to propose new method($2). And I show the usefulness of this new method in 3 experiments ($3). This work was supported by Academic Frontier Project and Joint Research Fee of Tokyo University of Information Sciences. I thank members of Tokyo University of Information Sciences for useful discussion.

References

[1] De Jong,K. Evolving in a Changing World:Springer. 1609 Lecture Note In Artificial Intelligence pp.512-519

[2] Branke,J. Evolutionary Approaches to Dynamic Optimization Problems:A survay. In Evolutionary algorithms for dynamic optimization problems(pp.134-137)

[3] Branke,J. Memory Enhanced Evolutionary Algorithms for Changing OptimizationProblem: CEC 1999,pp.1875-1882

[4] Grefenstette,J.J. Evolvability in Dynamic Landscapes: A Genetic Algorithm Approach:CEC 1999,pp.2031-2037

[5] Yamasaki,K: The problems under the dynamic environments need the consideration of the evaluation standard between the environments that are changing. The Proceedings of 6th International Symposium on Artificial life and Robotics: 2001, Vol.2, pp577-580