

Evolutionary Computation Using Interaction among Genetic Evolution, Individual Learning and Social Learning

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Abstract. This paper studies the characteristics of interaction among genetic evolution, individual learning and social learning using an evolutionary computation system with NK fitness landscape, both under static and dynamic environments. We show conditions for effective social learning: at least 1.5 times lighter cost of social learning than that of individual learning, beneficial teaching action, low epistasis and dynamic environment.

Key words: Evolutionary computation, Genetic evolution, Individual learning, Social learning, NK fitness landscape

1 Introduction

Biologically inspired computation algorithms, such as neural networks mimicking the brains and genetic algorithm simply implementing genetic evolution, are often utilized in many adaptive and intelligent systems, optimization and system designing. Recently, adaptive algorithms using interaction between evolution and learning have been studied [1–4]. In this paper, we also study such adaptive algorithm, especially we pay attention to the interaction among genetic evolution, individual and social learnings.

Learning is classified into individual and social. The former is change of individual characters through individual experiences, such as enhancement of muscles through exercises and gain of knowledge and skills by trial and error. The latter is transmission of knowledge and skills through direct and indirect interactions between individuals. The social learning is mediated by imitation or teaching. While the individual learning is often seen in many organisms, the social learning is found in only some animals with sociality.

The representative of such social animals is some primates including humans. We claims that the ability of social learning is one of the key features enabling the humans to adapt to various environments. Thanks to this ability, the humans can discovers new knowledge accumulatively and utilize the knowledge of predecessors [5]. Such knowledge accumulated forms “culture”. The ability of social

learning works effectively when the ability of individual learning is adequately combined with it. The both abilities had evolved through genetic evolutionary processes. That is, the humans had acquired the characters realizing fruitful cultures and the culture itself is thought to have been evolved through interaction among genetic evolution, individual learning and social learning. We may be able to utilize such adaptive strategy for intelligent systems and optimization.

In this paper, we study the characteristic of evolutionary algorithm in which genetic evolution, individual learning and social learning interact with each other. Especially, we focus on conditions that enable effective social learning. Social learning is useful, as we have said, but not ubiquitous in biological species. This may be because that obtaining the ability of social learning is difficult. This fact lead us a prediction that the condition realizing the social learning is stern.

We adopt NK fitness landscape [6] as a model of environment for individuals to fit. The NK landscape models originally fitness function taking the interaction among genes, called epistasis, into consideration. Many combinatorial optimization problems can be reduced to the NK landscape. Actually, the NP-completeness had been proven [7]. This model has also been used as important test beds for search and optimisation techniques, especially, evolutionary computation algorithms. We investigate the characteristic of the present algorithm under static and dynamic environments, in the latter, the NK fitness landscape changes with generations.

This paper is structured as follows. We introduce the model to incorporate genetic evolution, individual and social learnings in section 2. The simulation results in static and dynamic NK landscapes are described in section 3. We discuss the results in section 4 from the viewpoint of the difficulty of social learning. The paper is concluded by section 5 to deliver conditions favorable to the social learning.

2 Model

We model a population of agents which are engaged in genetic evolution, individual learning and social learning on a NK fitness landscape. The structure of the model is schematically shown in Fig. 1. One generation consists of three phases, the individual learning, the social learning and the genetic evolution (reproduction), in turn.

2.1 Structure of Agent

Each agent has three types of genetic elements: a genotype G which is a bit string with length N , the maximum time of individual learning operations, $IL_{MAX} = 0 \sim L_{MAX}$, and the social learning factor, $SLFactor = \{t, s, i\}$. The genotype determines the agent's innate fitness, denoted by F_{gt} , on the predefined NK fitness landscape. This string has a circular structure with a head in order for all genes to have the same number of neighbors. The capacity of learning operations is limited by L_{MAX} , given as a common parameter to all agents. The capacity

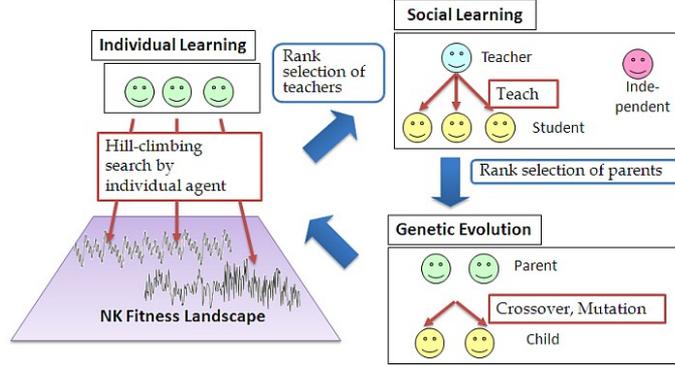


Fig. 1. The structure of the model, consisting of three phases corresponding to the three adaptive algorithms.

is apportioned to the individual and social learning operations, IL_{MAX} and SL_{MAX} ($L_{MAX} = IL_{MAX} + SL_{MAX}$). Each agent is doomed to be a teacher, a student or none of each genetically at the social learning phase. This role is represented by $SLFactor = \{t, s, i\}$, respectively.

Each agent has the other characters that change through learning: a phenotype P , which is the same as the genotype G at the moment of birth, counters for the individual learning, social learning and teaching operations, IL , SL and TL , respectively. The SL and TL are, respectively, used only by student agents having the student factor, $SLFactor = s$, and by teacher agents having the teacher factor, $SLFactor = t$.

The initial population is generated by the following procedure.

1. Generate agents having the same genotype which is randomly determined. The number of agents is Num .
2. Flip the genotype of each agent with a provability $1/N$ per each bit.
3. Determine IL_{MAX} between 0 and L_{MAX} and $SLFactor$ from $\{t, s, i\}$ using uniform random numbers.

2.2 Individual Learning

The individual learning of each agent proceeds as the following process:

1. Copy genotype G of the agent to a phenotype bit string P and set the individual learning counter IL to 0.
2. If any one bit flip of P does not increase the NK fitness of P , $F_{NK}(P)$, go to the 4th procedure; otherwise, make a bit string P' in which one random bit of P is flipped.
3. When $IL < IL_{MAX}$ and $F_{NK}(P') > F_{NK}(P)$, copy P' to P , increment IL and go to the 1st procedure; otherwise go to the 4th procedure.
4. Stop the individual learning phase of the agent and set the fitness after individual learning to $F_{indi} = F_{NK}(P)$.

2.3 Social Learning

In the social learning phase, the teacher agents transmit their phenotypes, that is, the learning results, to the student agents. At first, all teachers are ranked according to their fitness after individual learning, $F_{indi}(P^t)$, and their teaching counters TL are set to 0. The following two procedures are repeated for all the student agents.

1. Each student agent selects one teacher agent using the rank selection, that is, in terms of the probability proportional to the teacher ranking. If the teacher has higher fitness after individual learning than the student, $F_{indi}(P^t) > F_{indi}(P^s)$, then the teacher is adopted, otherwise the student does not learn socially, $F_{social} = F_{indi}(P^s)$.
2. Set the social learning counter SL of the student agent to 0. The student compares each bit of its phenotype P^s with the teacher's P^t . If the bit has different value, the student copies the teacher's bit and increments its social learning counter, SL . At the same time, the teacher increments its teaching counter, TL . When $SL = SL_{MAX}$ or $P^s = P^t$ during this copy process, the student stops copying and sets its fitness after social learning to $F_{social} = F_{NK}(P^s)$. Note that the teacher's phenotype may be partially copied to the student's due to the limitation of SL_{MAX} .

2.4 Fitness and NK Landscape

By means of the learned results, the lifetime fitness of the agent is calculated by

$$F_{lt} = F_b - C_{lt} \quad , \quad (1)$$

$$F_b = \begin{cases} F_{indi} & \text{for } SLFactor = t \text{ or } i \quad , \\ F_{social} & \text{for } SLFactor = s \quad , \end{cases} \quad (2)$$

$$C_{lt} = C_{indi} \cdot IL + C_{student} \cdot SL + C_{teacher} \cdot TL \quad , \quad (3)$$

where C_{indi} , $C_{student}$ and $C_{teacher}$ are the costs of the individual learning, social learning and teaching, respectively, given as parameters common to all agents.

The environment is modeled by Kauffman's NK fitness landscape [6]. An NK fitness landscape is specified by the length of genotype, N , and the strength of epistatic interactions among genes, K . The parameter K controls the ruggedness of the fitness landscape. Larger K brings the more number of local optima.

A landscape is defined by the N number of tables with 2^{K+1} uniform random numbers between 0.0 and 1.0. An example table is shown in Fig. 2. The i -th table determines the fitness of the i -th gene, $f_{NK}(i)$, by making correspondence between the $K+1$ bits patterns to the random numbers. The NK fitness of a genotype G is the average of the fitness of all genes, $F_{NK}(G) = (1/N) \sum_{i=1}^N f_{NK}(i)$. The same method and the same tables are used to calculate the fitness of phenotype.

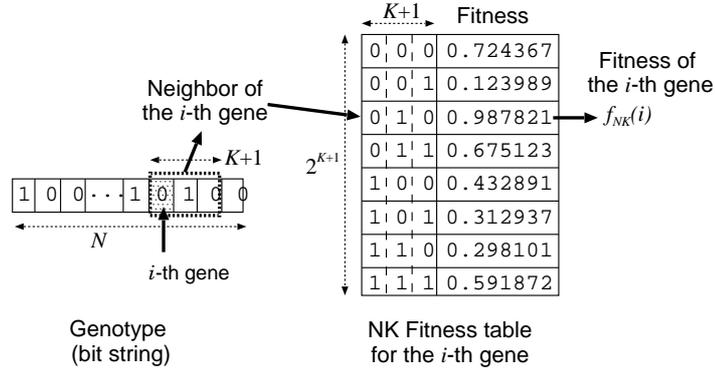


Fig. 2. An example of the NK fitness table for $K = 2$

2.5 Reproduction

The next generation consisting the same number of agents is produced through crossover and mutation.

At first, two parental agents are selected using rank selection according to the lifetime fitness, F_{lt} . Two genotypes from those of the parental agents are made with one-point crossover. Note that we use the genotypes of the parental agents, not their phenotypes, to prevent the inheritance of acquired characters. One of the new genotypes is randomly adopted as the genotype of an offspring agent. This agent inherits the maximum time of individual learning, IL_{MAX} , and the social learning factor, $SLFactor$, from one of the parental agents randomly determined.

Mutation of the genotypic structure consists of bit flips of the genotype, increment/decrement of IL_{MAX} , and change of $SLFactor$ with the mutation rate μ . If the result of mutation on IL_{MAX} exceeds the maximum value, L_{MAX} , or the minimum, 0, the increment/decrement operation is canceled. The result of mutation on $SLFactor$ may coincide with that before mutation, since one value from $\{t, s, i\}$ is adopted with equal probabilities.

3 Simulation Results

We conducted computational experiments under static and dynamic environments. In static environment, the NK fitness landscape is fixed at initially defined. In dynamic environment, the landscape changes with generations. We investigated from the viewpoint that under which conditions the social learning is effectively used or is superior to the individual learning.

The fixed parameters used in the experiments are, the number of agents, $Num = 100$, the length of genotype/phenotype bit strings, $N = 20$, the total capacity of learning operations, $L_{MAX} = 5$. All graphs shows the average data of 10 runs, unless specially indicated.

3.1 Static Environment

We show the dynamics of various fitness achievement rates averaged over all agents in Fig. 3. The achievement rate is the ratio of the fitness value to the optimal value in the landscape, indicated by bars on F 's. The parameter setting is the following: the individual learning cost $C_{indi} = 0.01$, the social learning cost, $C_{student} = 0.001$, the teaching cost, $C_{teacher} = -0.001$, the mutation rate, $\mu = 0.02$, the epistasis, $K = 2$. We use a moderate value of the mutation rate smaller than the error threshold ($\mu = 1/N = 0.05$), since some information should be passed over generations to estimate the effect of three evolutionary algorithms. Until around the 20th generation, the individual learning has much larger effectiveness than the social learning. After this generation, fitness raised by the social learning is larger than by the individual learning.

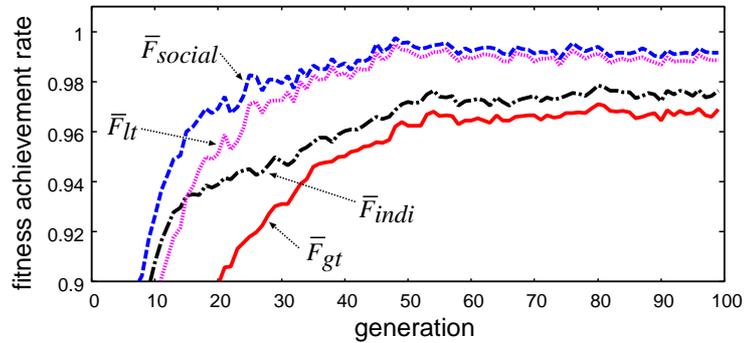


Fig. 3. The transition of fitness achievement rate averaged over all agents with generations in a static environment. The solid line is the achievement rate of the innate fitness \bar{F}_{gt} , the chain line is that after individual learning, \bar{F}_{indi} , the dashed line is that after social learning, \bar{F}_{social} , and the broken line is of the lifetime fitness achievement rate, \bar{F}_{lt} .

Figure 4 represents the dynamics of the average learning operations. While the individual learning is used at the initial stage, it comes to be unused. The acquired results through the individual learning seems to be genetically assimilated, since the individual learning is costly when $C_{indi} = 0.01$. Actually, as seen in Fig. 3, the innate fitness catches up with that after individual learning until the 55th generation. In contrast, the social learning operations less decreases relatively than the individual learning, as the social learning cost is ten times smaller than the individual learning cost. The value of IL and SL at the stable point depends on the parameter settings as shown in the following paragraphs.

The individual and social learning operations vary with the individual and social learning costs as shown in Fig. 5. This graph uses the average values of IL and SL at the 20th generations. Rightfully, the social learning is used than the individual learning at the region of larger individual learning cost and smaller

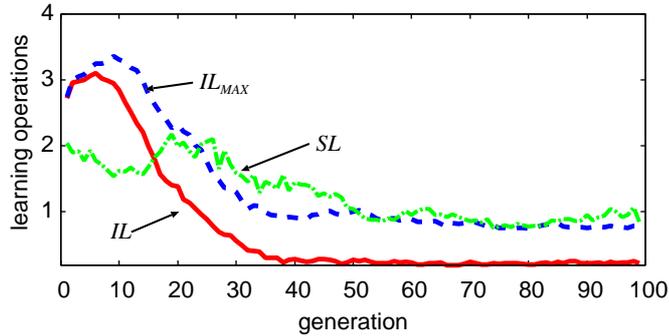


Fig. 4. The transition of the times of learning operations with generations in a static environment. The solid line is the times of individual learning, IL , and the dashed line is the maximum times of individual learning, IL_{MAX} . These are averaged over all agents. The chain line is the times of social learning, SL , averaged over all the student agents at each generation.

social learning cost. The cross section of the IL and SL planes forms roughly a straight line, $C_{indi} \approx 1.5C_{social} + 0.0055$. This implies that both types of learning are used comparably when the cost of individual learning exceeds 1.5 times than that of social learning under the present parameter setting. We confirmed that if the individual learning cost is larger than 0.02, IL_{MAX} comes to nearly 0. This means that the individual learning is avoided under such large cost.

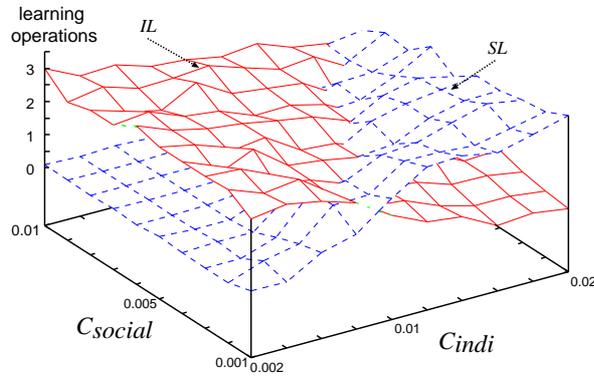


Fig. 5. The times of individual (IL) and social (SL) learning operations v.s. the individual (C_{indi}) and social (C_{social}) learning costs. The plane with solid and dashed lines represent IL and SL , respectively.

We investigated how the other important parameters, epistasis K and mutation rate μ , affect the learning operations. The times of learning operations

changes with the both parameters as shown in Fig. 6. The individual and social learning costs are $C_{indi} = 0.01$, and $C_{social} = 0.001$. Larger K and μ , as overall effect, increase IL and decrease SL . The IL plane is roughly symmetrical with respect to the diagonal line of $K - \mu$ space. This implies that the epistasis and the mutation affect similarly the individual learning. As for the social learning, their effects are different. The change of SL with μ is smaller than that with K . SL takes the highest at $0.02 \lesssim \mu \lesssim 0.04$ in small K region.

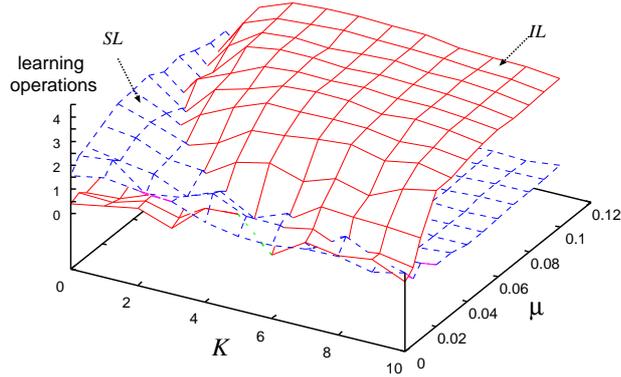


Fig. 6. The times of individual (IL) and social (SL) learning operations v.s. the epistasis (K) and the mutation rate (μ). The plane with solid and dashed lines represent IL and SL , respectively.

The IL and SL planes are nearly flat at $IL = 4 \sim 4.4$ and at $SL = 0$, respectively, in the region $K \gtrsim 4$ and $\mu \gtrsim 0.05$ (coincide with the error threshold). In such rugged (complex) fitness landscape and unstable genetic circumstance, the agents use most of their learning capacity for the individual learning and the social learning does not work. Actually, we confirmed that, in such region, the difference between the innate fitness and the fitness after individual learning, $F_{indi} - F_{gt}$, is larger than in the region of smaller K and μ , and the fitness after social learning F_{social} virtually the same as F_{indi} . These two planes cross at the small K and μ . The cross section is approximately described by $\mu \cdot K \approx 0.04$.

In the above results, we used a negative teaching cost ($C_{teacher} = -0.001$). Namely, teaching behavior is not costly but beneficial, which is favorable for social learning. When the teaching cost is set at positive value, the social learning is very unstable (Fig. 7). The teacher only momentary lives, since selective pressure affects to exclude the teacher factors. The social learning operations sharply rises and falls stochastically.

3.2 Dynamic Environment

While organisms adapt genetically to stable environments, learnable organisms can adapt to changing environments. For changes with an intermediate time

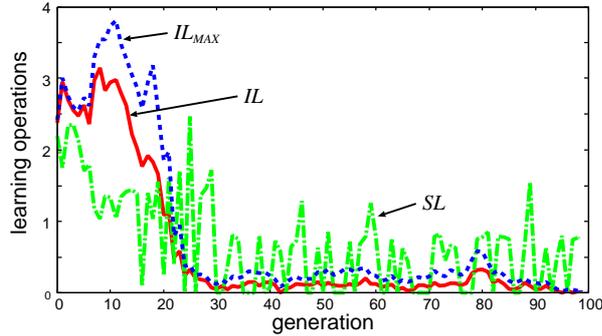


Fig. 7. The transition of the times of learning operations with generations in a static environment. The teaching cost is $C_{teacher} = 0.001$. The solid line is the times of individual learning, IL , and the dashed line is the maximum times of individual learning, IL_{MAX} . These are averaged over all agents. The chain line is the times of social learning, SL , averaged over all the student agents at each generation. This graph shows the result of one typical run.

scale, cultural evolution through social learning may work well. In this section, we study how our hybrid evolutionary algorithm works in dynamic environments, since good adaptive algorithms for dynamic environments have not been invented so much. We are interested in the division of roles corresponding to time scales.

The way to change the environment is to remake one NK fitness table corresponding to one bit randomly selected. This models environmental change that affects the fitness of one gene. The fittest gene varies by this change, therefore the surrounding genes are also indirectly affected, if $K > 0$. In our experiments, the environment changes every 5 generations. The parameter values are, $C_{indi} = 0.01$, $C_{social} = 0.001$ and $C_{teacher} = -0.001$ and $K = 2$, which are the same as the case in the static environment shown in Fig. 3 and 4.

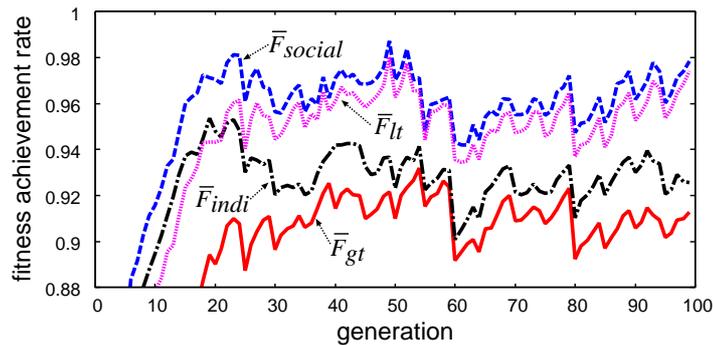


Fig. 8. The transition of the times of learning operations with generations both in static and dynamic environments. The legends of lines are the same as Fig. 3

In contrast to the static environment (Fig. 3), the innate fitness F_{gt} stays, as shown in Fig. 8, at lower value and does not increase substantially after the 25th generation. The rapid environmental changes brings this result, since the rapid change make genetic assimilation of learning result impossible. On the other hand, the social learning promotes the average fitness relatively than in the case of static environment.

Figure 9 compares the average times of individual and social learning operations in the static and dynamic environments. The social learning remains until later generations at around 2.0 operations per each student agent when the environment is dynamic, while it decreases in the static environment with generations. The individual learning decays in the both environmental conditions.

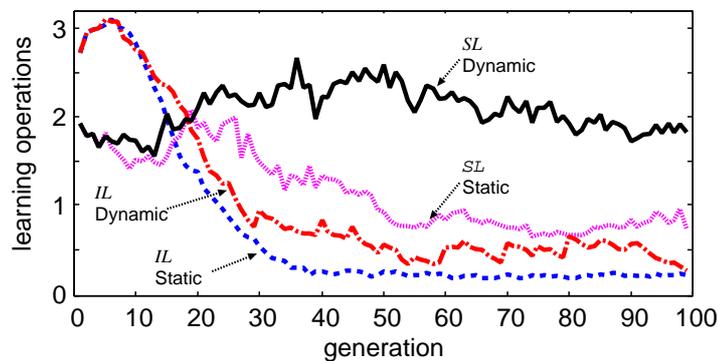


Fig. 9. The transition of the times of learning operations with generations both in static and dynamic environments. The dashed and chain lines are the times of individual learning, IL , for the static and dynamic environments, respectively. The broken and solid lines are the times of social learning, SL , for the static and dynamic environments, respectively.

4 Discussion

In our model, although one operation in both the individual and social learnings are one bit flip, the individual learning operation outnumbers that of social learning under the same cost level. In order to make the social learning superior, there must be cost difference of 1.5 times at least and the teaching must not be cost but benefit.

These severe conditions are brought by the several constraints for social learning in the present model. The individual learning always precedes the social learning. Unless the individual learning rises the fitness of some individuals, the only way for the social learning to improve the fitness of population is to propagate the innate superiority. Low diversity in the population prevents the social

learning, since it is difficult for students to find good teacher. Further, the students cannot always copy the whole phenotypes of the teachers, since the times of social learning operation is limited by $SL_{MAX}(= L_{MAX} - IL_{MAX})$. In epistatic landscapes, incomplete copy of teacher phenotype often degrades the students' fitness, no matter how high the teacher's fitness is. Namely, the diversity in the population is indispensable but large diversity becomes harmful for the social learning to be effective. Such difficulties of social learning is not limited to our present model but essential feature of social leaning.

The social learning operations is the highest at the range of mutation rate $0.02 \lesssim \mu \lesssim 0.04$ in the low epistasis region. As we mentioned, on the one hand, the mutation rate must not be too small in order to supply diversity for effectual social learning. On the other hand, too high mutation rate makes the genetic assimilation impossible. Actually, in the region of high mutation rate, the innate fitness, F_{gt} , hardly grows with generations, despite that individual learning rises the fitness, F_{indi} . Therefore, the maximum times of individual learning IL_{MAX} stays nearly at L_{MAX} . Namely, the learning capacity is devoted mostly to the individual learning, and the agents cannot reserve the capacity for social learning, even though the teacher and student agents exist.

We show that the learning capacity is used only for the individual learning also in strong epistasis $K \gtrsim 4$. Mayley suggests that individual learning does not work well when epistasis is too strong [2]. Based on Mayley's suggestion, how the individual learning works under strong epistasis in our model should be studied in more detail.

We indicate that in a dynamic environment the social learning is used continually than the individual learning and can contribute to rise the fitness, while the times and the effectiveness of individual learning are the same as in the case of static environment. However, the experiments and analysis of the dynamic environment are considerably insufficient, although the observation shown in section 3.2 is typical in that setting. We need intensive investigation about the phenomena concerning the way of environmental change, the degree of epistasis and costs.

5 Conclusion

We study a new type of evolutionary computation in which three adaptive algorithms, genetic evolution, individual learning and social learning, interact with each other. In this model, the three adaptive algorithms interact as follows. A population of individuals search higher fitness in a rugged landscape as hill-climbing using the individual learning. Then, the results of the learning are transmitted to the population from teachers to students using the social learning. Finally, the results of individual and social learnings are genetically assimilated due to the selective pressure posed by learning costs.

We investigated the conditions which favor the social learning. The conditions are qualitatively as follows: The individual learning cost is larger than the social learning cost. Teaching is beneficial for teachers. Mutation rate is low. Epistasis

is low (The fitness landscape is not so complex). Environmental change occurs. In the present model, the individual learning cost should be at least 1.5 times than the social one; the mutation rate should be less than 0.04 per each gene; more than 3 genes should not interact.

As we discussed, the social learning in the present model has many constraints. The social learning is really so constrained that it is hard to establish biologically. Therefore, it is difficult to study the essential interaction of social learning with genetic evolution and individual learning. One of the most missing points concerning the social learning in our model is generation overlapping which is important to realize accumulative knowledge creation and transmission. We show only phenomenological findings in this paper. Although some conditions are reasonable and some are discussed, we should pursue the understandable mechanism and causal relationship between the model and the conditions in order to understand the interaction among the three adaptive algorithms and to utilize their interaction. In order to discuss our algorithm from the view point of computational complexity, it would be interesting to analyze the time of evaluations required to verify if some changes on genotypes and phenotypes improve the fitness of agents or not.

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