New composite evolutionary computation algorithm using interactions among genetic evolution, individual learning and social learning

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Abstract. This paper studies the characteristics of a new composite evolutionary computation algorithm in which genetic evolution, individual learning and social learning interact in NK fitness landscape. We derive conditions for effective social learning in static and dynamic environments using computer simulations of a model of the composite evolutionary algorithm. The conditions for static environments are: 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. These conditions qualitatively mean that: the individual learning cost is larger than the social learning cost; teaching is beneficial for teachers; mutation rate is not too high, must be smaller than error threshold; the fitness landscape is not so complex. We also show that this algorithm is effective in dynamic environments in which NK fitness landscape changes with time, if these conditions are satisfied. Frequent environmental change favors social learning, but under more severe conditions, such as high epistasis and higher mutation rate than the error threshold, individual learning is more useful in finding better solutions.

Keywords: Evolutionary computation, Genetic evolution, Individual learning, Social learning, NK fitness landscape, Dynamic environment

1. Introduction

Biologically-inspired computation algorithms, such as neural networks mimicking brains and genetic algorithms simply implementing genetic evolution, are often utilized in many adaptive and intelligent systems, in optimization and system design. Recently, adaptive algorithms using interaction between evolution and learning have been studied [1,4,7,9]. These studies usually presuppose Darwinian evolution as genetic evolution, in which acquired characters are not inherited to the next generation, in order to contrast between the roles of evolution and learning. It is also known that in changing environment...
Darwinian evolution is better than Lamarkian evolution [10] which is the inheritance of acquired characters. In this paper, we also study such adaptive algorithms, especially we pay attention to the interactions among genetic (Darwinian) evolution, individual learning and social learning.

Learning is, by contrast with Darwinian genetic evolution, acquired change of characters through lifetime, and is classified into individual and social. The former involves change of individual characters through individual experiences, such as enhancement of muscles through exercise 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. Social learning is mediated by imitation or teaching. While individual learning is often seen in many organisms, social learning is found in only some animals with social behavior.

The representatives of such social animals are some primates including human beings. We claim that the ability of social learning is one of the key features enabling humans to adapt to various environments. Thanks to this ability, the humans can discover and accumulate new knowledge and utilize the knowledge of predecessors [11]. Such accumulated knowledge forms “culture”. The ability of social learning works effectively when the ability of individual learning is adequately combined with it. Both abilities have evolved through genetic evolutionary processes. That is, humans have acquired these abilities to realize fruitful cultures, and culture itself is thought to have evolved through interactions among genetic evolution, individual learning and social learning. These interactions among genetic (biological) evolution, individual learning and cultural evolution form double-loop dynamics as illustrated in Fig. 1. This double-loop is important for the origin and the evolution of culture and language [6]. We may be able to utilize such an adaptive strategy for artificial intelligent systems and optimization.

In this paper, we study the characteristics of the composite 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 acquiring the ability of social learning is difficult. Further, problems in which social learning is indispensable are not ubiquitous in nature. These facts lead us to a prediction that the conditions for realizing social learning are stern. In order to properly make use of the adaptive strategy of such social animals as human beings, we need to understand the characteristics of the problems, not only those of the composite algorithm, to which social learning and its interactions with genetic evolution and individual learning are applied.
We adopt NK fitness landscape [8] as a model of an environment for individuals to fit. The NK landscape was created to model fitness function taking the interactions among genes, called epistasis, into consideration. Many combinatorial optimization problems can be reduced to the NK landscape. Actually, the NP-completeness has been proved [12]. This model has also been used as an important test bed for search and optimisation techniques, especially, for evolutionary computation algorithms.

We investigate the characteristics of the composite algorithm under static and dynamic environments; in the latter, the NK fitness landscape changes with time. The reason why we test the present algorithm under dynamic environments is that we think that the composite algorithm is likely to exert its effect in dynamic environments, for social animals adopting the composite adaptive strategy can fit to diverse environments in which the frequency of environmental changes is high relative to the length of individuals’ lifetime.

This paper is structured as follows. We introduce the model incorporating genetic evolution, individual learning and social learning 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 and utility of social learning. The paper concludes in Section 5 to explain conditions favorable to social learning.

2. Model

We model a population of agents which are engaged in individual learning, social learning and genetic evolution on an NK fitness landscape. The structure of the model is schematically shown in Fig. 2. One generation consists of three phases, individual learning, social learning and genetic evolution (reproduction), in turn.

2.1. Structure of agent

Each agent has three types of genetic elements:
- genotype $G$ which is a bit string with length $N$,
- maximum frequency of individual learning operations, $IL_{MAX} = 0 \sim L_{MAX}$,
- 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 is apportioned to the individual and social learning operations, $IL_{MAX}$ and $SL_{MAX}$, namely, $L_{MAX} = IL_{MAX} + SL_{MAX}$. Each agent is destined to be a teacher, a student or neither genetically in the social learning phase. This role is represented by $SLFactor = \{t, s, i\}$, respectively.

Each agent has other characteristics that change through learning:

- phenotype $P$,
  which is the same as the genotype $G$ at the moment of birth.
- counter for the individual learning operations, $IL$,
- counter for the social learning operations, $SL$,
  used only by student agent which has the student factor, $SLFactor = s$,
- counter for the teaching operations, $TL$,
  used only by teacher agent which has 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 probability $1/N$ per bit.
3. Determine $IL_{MAX}$ between 0 and $L_{MAX}$ and set $SLFactor$ to $t$ or $s$ using uniform random numbers.

2.2. Individual learning

The individual learning of each agent proceeds in 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 $IL = IL_{MAX}$ or any one bit flip of $P$ does not increase $F_{NK}(P)$, i.e., $P$ is at a local optimum, then go to step 5; otherwise go to step 3, where $F_{NK}(P)$ is the NK fitness of the phenotype $P$.
3. Make a bit string $P'$ in which one random bit of $P$ is flipped.
4. If $F_{NK}(P') > F_{NK}(P)$, then copy $P'$ to $P$, increment $IL$ and go to step 2; otherwise go to step 3.
5. Stop the individual learning phase of the agent and set the fitness after individual learning to $F_{indi} = F_{NK}(P)$.

The above steps 1 to 5 are repeated for all agents.

2.3. Social learning

In the social learning phase, the teacher agents transmit their phenotypes, that is, the learning results, to the student agents. The following is the social learning process

1. All teachers are ranked according to their fitness after individual learning, $F_{indi}(P^t) = F_{NK}(P^t)$, and their teaching counters $TL$ are set to 0, where $P^t$ is teacher’s phenotypes.
2. Each student agent selects one teacher agent using rank selection, that is, in terms of probability proportional to the teacher ranking.
3. 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, and the social learning counter $SL$ of the student agent is set to 0; otherwise the student does not learn socially, $F_{social} = F_{indi}(P^s)$, where $P^s$ is student’s phenotype.
4. The student compares each bit of its phenotype $P^s$ with the teacher’s $P^t$. If a bit has a 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, $TL$.

5. If $SL = SL_{MAX}$ or $P^s = P^t$ during this copy process, then the student stops copying and sets its fitness after social learning to $F_{social} = F_{NK}(P^s)$; otherwise go to step 4.

The above steps 2 to 5 are repeated for all the student agents. 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

\[ F_{lt} = F_b - C_{lt} , \]  

\[ F_b = \begin{cases} F_{indi} = F_{NK}(P^t) & \text{for SLFactor} = t, \\ F_{indi} = F_{NK}(P^i) & \text{for SLFactor} = i, \\ F_{social} = F_{NK}(P^s) & \text{for SLFactor} = s, \end{cases} \]  

\[ C_{lt} = C_{indi} \cdot IL + C_{student} \cdot SL + C_{teacher} \cdot TL , \]

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

We introduce the cost term in the fitness function to be optimized. If there is no cost for each learning, it is straightforwardly predictable that individual learning is fully used to consume all learning capacity, and social learning is not used. In such situation, no interactions of social learning with genetic evolution and individual learning occur. If individual learning is costly, learned character will be genetically assimilated, since agents which innately possess characters that are learned in the former generations can lower the cost term. This phenomenon, in which individual learning and genetic evolution interact and acquired characters are nativized, is called “the Baldwin effect” [3] and was proved computationally by Hinton and Nowlan [7] for individual learning. The genetic assimilation of the learned results can enhance the adaptability, since the limited capacity of learning is not consumed after the assimilation and is assigned to fit more. This possibility, in which the genetic assimilation prepares a basis for better fit, is called “assimilate stretch” [2] and was computationally shown in the model of language evolution [13]. We expect that the Baldwin effect and the assimilate stretch work also for social learning and are key mechanisms for social learning to be effectively used to find better solutions by introducing the interactions among genetic evolution, individual learning and social learning. Therefore, we introduce the cost for each learning as well as the limitation on the capacity of learning operations, $L_{MAX}$.

The environment is modeled by Kauffman’s NK fitness landscape [8]. 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 $K$ leads to more 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. 3. The $i$-th table determines the fitness of the $i$-th gene, $f_{NK}(i)$, by making a correspondence between the $K + 1$ bit patterns and the random number. 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.
2.5. Reproduction

The next generation consisting of the same number of agents is generated through crossover operations, and then the genotypic structures of all offspring agents may change through mutation operations.

In the crossover operation, 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 learned results, to prevent the inheritance of acquired characteristics, since we suppose Darwinian evolution. One of the new genotypes is randomly adopted as the genotype of an offspring agent. This agent inherits the maximum frequency of individual learning, \( IL_{MAX} \), and the social learning factor, \( SLFactor \), from one of the parental agents randomly determined.

Mutations of the genotypic structure consist of flipping of each bit one by one in the genotype, increment/decrement of \( IL_{MAX} \), and change of \( SLFactor \). The mutation rate per element is denoted by \( \mu \). The same rate is used for all elements. If the result of mutation on \( IL_{MAX} \) exceeds the maximum value, \( L_{MAX} \), or is less than the minimum, 0, the increment/decrement operation is discarded. The result of mutation on \( SLFactor \) may coincide with the state before mutation, since any one value from among \{t, s, i\} may be adopted with equal probability.

3. Simulation results

We conducted computational experiments under static and dynamic environments. In static environments, the NK fitness landscape is fixed as initially defined. In dynamic environments, the landscape changes with generations. We investigated the conditions in which social learning is effectively used or is superior to 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, \( L_{MAX} = 5 \).
3.1. Static environment

In this subsection, we show the results of computational experiments for static environments. All graphs in this subsection show the average data of 10 runs, unless specially indicated. The parameter setting is the following:

- the individual learning cost \( C_{\text{indi}} = 0.01 \),
- the social learning cost, \( C_{\text{student}} = 0.001 \),
- the teaching cost, \( C_{\text{teacher}} = -0.001 \),
- the mutation rate, \( \mu = 0.02 \),
- the epistasis \( K = 2 \).

We mainly use a moderate value of the mutation rate, smaller than the error threshold. The error threshold is the minimum threshold of accuracy of transmission of genetic information, which is the limitation on the mutation rate in order for population of individuals to accurately transmit genetic information over generations [5]. The error threshold is defined by the inverse of the total number of elements subject to mutation. In the present case, it is \( 1/(N+2) = 0.0455 \), where \( N+2 \) is the total number of genetic elements subject to mutation operations, including the length of gene, the maximum frequency of individual learning operations, and the social learning factor. Remember the description of the structure of agent (§2.1) and mutation (§2.5) and see the genotypic structure in Fig. 3. This mutation rate was chosen because some information should be passed to the next generations to estimate the effect of three evolutionary algorithms.

We show the dynamics of various fitness achievement rates averaged over all agents in Fig. 4. The achievement rate is the ratio of the fitness value to the optimal value in the landscape, indicated by bars on \( F' \)’s. This graph shows that until around the 20th generation, the individual learning has greater effectiveness than the social learning. Here we mean by “greater effectiveness” that the increase of fitness by individual learning is greater than the increase by social learning. After this generation, fitness raised by the social learning is larger than by the individual learning.

Figure 5 represents the dynamics of the average learning operations. While individual learning is used at the initial stage, its use decreases. The results acquired through individual learning seem to be
Fig. 5. The transitions of the frequency of learning operations with generations in static environments. The solid line is the frequency of individual learning, $IL$, and the dashed line is the maximum frequency of individual learning, $IL_{MAX}$. These are averaged over all agents. The chain line is the frequency of social learning, $SL$, averaged over all the student agents at each generation.

Fig. 6. The frequency of individual ($IL$) and social ($SL$) learning operations v.s. the individual ($C_{indi}$) and social ($C_{social}$) learning costs. The planes with solid and dashed lines represent $IL$ and $SL$, respectively.

genetically assimilated, since individual learning is costly when $C_{indi} = 0.01$. Actually, as seen in Fig. 4, the innate fitness catches up with that after individual learning by the 55th generation. In contrast, social learning operations decreases relatively less than individual learning, as the social learning cost is ten times less than the individual learning cost. The values of $IL$ and $SL$ at the stable point depend on the parameter settings, as shown in the following paragraphs.

The individual and social learning operations vary with individual and social learning costs, as shown in Fig. 6. This graph uses the average values of $IL$ and $SL$ at the 20th generation. The social learning is used more frequently than the individual learning at the region of larger individual learning cost and smaller 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 by 1.5 times that of social learning under the present parameter settings. We confirmed that if the individual learning cost is larger than 0.02, $IL_{MAX}$ comes to nearly 0. This means that individual learning is avoided with such a large cost.
We investigated how the other important parameters, epistasis $K$ and mutation rate $\mu$, affect the learning operations. The frequency of learning operations changes with both parameters, as shown in Fig. 7. The individual and social learning costs are $C_{indi} = 0.01$ and $C_{social} = 0.001$. Larger $K$ and $\mu$, as overall effect, increase $IL$ and decrease $SL$. Large $K$ and small $\mu$ decrease $IL$ and small $K$ and large $\mu$ decrease $IL$. This implies that the epistasis and the mutation similarly affect individual learning. As for social learning, their effects are different. The change of $SL$ with $\mu$ is smaller than that with $K$. $SL$ has the highest value at $0.02 \lesssim \mu \lesssim 0.04$ in small $K$ region.

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 $\mu \gtrsim 0.05$ (coincides roughly with the error threshold). In such a rugged (complex) fitness landscape and with unstable genetic circumstances, the agents use most of their learning capacity for individual learning and social learning does not operate. Actually, we confirmed that, in such region, the difference between the innate fitness and the fitness after individual learning, $F_{indi} - F_{gt}$, is greater than in the region of smaller $K$ and $\mu$, and the fitness after social learning $F_{social}$ virtually the same as $F_{indi}$. These two planes cross at the small $K$ and $\mu$. 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 a positive value, social learning is very unstable (Fig. 8). The teacher only lives temporarily, since selective pressure works to exclude the teacher factors. The social learning operations sharply rise and fall stochastically.

### 3.2. Dynamic environment

While organisms adapt genetically to stable environments, learning organisms can adapt to changing environments. For changes with an intermediate time scale, cultural evolution through social learning
may work well. In this section, we study how our composite evolutionary algorithm works in dynamic
environments, since no good adaptive algorithm for dynamic environment has yet been invented. 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 this paper, we test the environmental change at fixed intervals, denoted by $IEC$. The parameter values for the costs are $C_{\text{indi}} = 0.01$, $C_{\text{social}} = 0.001$ and $C_{\text{teacher}} = -0.001$, which are the same as in the case with the static environment, shown in Figs 4 and 5. The simulation results in this subsection are averaged over 20 runs with different random seeds, unless specially noted.

Figure 9 shows an example of the transition of the fitness achievement rates. The interval of environmental change ($IEC$) is 20 generations. The effects of environmental changes become salient after attaining an adapted state to some extent. Before that, since there still are diversified agents, the environmental changes are good for some agents and bad for others. After that, the environmental changes come to be detrimental to almost all agents, due to the loss of diversity. As shown in the inset of Fig. 9, the recovery seems to be a result of interactions among all three adaptive algorithms.

The effects of environmental changes are not uniform for each run, while the regular reductions of fitness at every environmental change are observed only in the averaged view over lots of different runs. We depict some examples of the transition of fitness achievement rates at each run in Fig. 10. The effect appears once in a while in some cases (Fig. 10B and F), and virtually does not appear in some runs. However, it is more frequent for other runs (Fig. 10A and E).

The scenario of recovery from reductions is also not simple, as we can see in Fig. 10. The three adaptive algorithms, individual learning, social learning and genetic evolution, do not always work collaboratively. We distinguish major four patterns in the route to recover:

1. Individual learning $\rightarrow$ Social learning $\rightarrow$ Genetic assimilation
2. Individual learning $\rightarrow$ Genetic assimilation
3. Social learning $\rightarrow$ Genetic assimilation
4. Genetic evolution
5. Other
Fig. 11. The dependencies of fitness on the interval of environmental change and the degree of epistasis in dynamic environment. The X-axis is the inverse of the interval of environmental change. The origin represents no environmental change. The Y-axis is the average fitness achievement rate. The mutation rate is $\mu = 0.005$. Upper four lines are for $K = 0$ and lower $K = 2$. The solid lines are the achievement rates of the innate fitness $\bar{F}_{gt}$, the chain lines are that after individual learning, $\bar{F}_{indi}$, the dashed lines are that after social learning, $\bar{F}_{social}$, and the broken lines are of the lifetime fitness, $\bar{F}_{lt}$. Upper four lines are for $K = 0$ and lower $K = 2$.

Each pattern is labeled in Fig. 10. In pattern 1, $\bar{F}_{indi}$ (chain line) is above $\bar{F}_{gt}$ (solid line) and $\bar{F}_{social}$ (dashed line) is above $\bar{F}_{indi}$. This means that all three algorithms function properly. In pattern 2, $\bar{F}_{social}$ is almost on $\bar{F}_{indi}$, for social learning does not work in this case. In pattern 3, $\bar{F}_{indi}$ is virtually on $\bar{F}_{gt}$, due to the inefficiency of the individual learning. In pattern 4, neither learning algorithms is used, thus three lines overlap. Even in this case the system recovers, through genetic evolution. Some recoveries, which are compound cases, have double labels. Different types are identified at an earlier and later periods of the recovery. Pattern 5 includes cases not classified in the four patterns listed above. In this case (Fig. 10F pattern 5), only the lifetime fitness, the broken line, decreases.

The diversity of recovery scenarios means that the interactions among the three adaptive algorithms is complex. Patterns 3 and 4 suggest that the individual learning is not always effective, and patterns 2 and 4 do for social learning. The compound cases imply that one algorithm prepares conditions for another algorithm to function.

We consider the dependencies of the system on the parameters. Figure 11 represents the fitness for different intervals of environmental change for $K = 0$ and 2. The Y-axis is the average of fitness achievement rate, which is averaged three times, for space, ensemble and time. The X-axis of Fig. 11 is the inverse of $IEC$, corresponding to the frequency of environmental change. The more frequent environmental changes occur, the smaller the fitness attained. Stronger epistasis reduces the fitness more, and the slope is greater. Figure 11 shows that individual learning and social learning recover from fitness deterioration caused by environmental changes, and that the recovery is more effective for more frequent changes. Comparing $K = 0$ and 2, we can understand that the recovery effect due to individual learning.
Fig. 12. The dependencies of fitness on the mutation rate. The X-axis is the mutation rate ($\mu$) and the Y-axis is the average fitness achievement rate. Four graphs are for $IEC = 20$, $K = 0$ (top left), $IEC = 5$, $K = 0$ (top right), $IEC = 20$, $K = 2$ (bottom left) and $IEC = 5$, $K = 2$ (bottom right).

and social learning is larger for stronger epistasis. The improvement of fitness by individual learning (the separation between the solid and the chain lines) is better in $K = 2$, while that due to social learning (the separation between the chain and the broken lines) is similar for both $K$. This is because the agents use individual learning more with stronger epistasis.

In order to show the dependency on the mutation rate, we show the same information (four kinds of fitness achievement rates) for different mutation rates, for different frequencies of change and different epistasis in Fig. 12. Although the innate fitness (the solid lines) decreases for larger mutation rate in all cases, the decrease is gentle in the fitness after social learning (the dashed lines). While genetic evolution with a greater mutation rate cannot produce a fitted agent, individual and social learning can recover the fitness. With each $K$ value, the dependency of fitness on mutation rates is similar for rare ($IEC = 20$) and frequent ($IEC = 5$) environmental change (compare two graphs horizontally). But the dependency is different for different epistasis (compare two graphs vertically). We pointed out that agents use individual learning more with strong epistasis. This inclination is intensified for greater mutation rate. Social learning is seldom used with greater mutation rate in stronger epistasis case. Most improvement of fitness from innate state is realized by individual learning.
Next, we analyze the frequency of learning operations. Figure 13 compares the average frequencies of individual and social learning operations in static and dynamic environments. The use of social learning continues until later generations when the environment is dynamic, while it decreases to nearly zero in the static environment. The individual learning decays rapidly in both environmental conditions, but is a little bit greater in the dynamic environment.

The parameter dependency of the learning operations is displayed in Fig. 14. For low mutation rate (Fig. 14 (top row)), both learning operations increase with the frequency of environmental change ($1/IEC$). The individual learning changes responding to epistatic conditions ($K$). The effect of environmental change is larger in the case of stronger epistasis. On the other hand, social learning does not change with $K$. For more frequent environmental change, social learning operations are used more, irrelevant to the degree of epistasis. These features are the same for lower mutation rate ($\mu = 0.005$).

For higher mutation rate (Fig. 14 (bottom row)), both learning operations show little response to the frequency of environmental change. The number of operations shows higher values than the low mutation rate case. Greater mutation rate is likely to destroy the innate fitness, even if a fitted agent appears. The learning operations are used to improve the fitness state. Thus, environmental change is not influential. The reaction of each learning method to the degree of epistasis is opposite. Larger $K$ leads to the frequent use of individual learning but rare use of social learning.

4. Discussion

In our model, although one operation in both the individual and social learning operations is one bit flip, the frequency of individual learning operations outnumber that of social learning operations under the same cost level. In order to increase the use of social learning than individual learning, there must be a cost difference of at least 1.5 times, and teaching must not be costly but beneficial.

These severe conditions are brought about by several constraints on social learning in the present model. The individual learning always precedes social learning. Unless the individual learning improves
Fig. 14. The parameter dependency of the frequency of learning operations. The X-axis is the inverse of $IEC$. The top row is $\mu = 0.01$ and the bottom $\mu = 0.05$. The left and right columns are the individual and the social learning operations, respectively. Four different degrees of epistasis are depicted in each graph.

the fitness of some individuals, the only way for social learning to improve the fitness of a population is for it to propagate the innate superiority. Low diversity in the population prevents the social learning, since it is difficult for students to find good teachers. Further, the students cannot always copy the whole phenotypes of the teachers, since the frequency of social learning operations 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 great diversity becomes harmful to the effectiveness of social learning. We think that such difficulties of social learning are not limited to our present model, but are an essential feature of
social learning.

The social learning operations are the highest in 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, a very high mutation rate makes genetic assimilation impossible. Actually, in the region of high mutation rate, the innate fitness, $F_{gt}$, hardly increases at all with successive generations, despite the fact that individual learning improves the fitness, $F_{indi}$. Therefore, the maximum frequency of individual learning $IL_{MAX}$ stays nearly at $L_{MAX}$. Namely, learning capacity is devoted mostly to individual learning, and agents cannot reserve capacity for social learning, even though teacher and student agents exist.

We show that the learning capacity is used only for individual learning also with strong epistasis $K \gtrsim 4$. Mayley suggests that individual learning does not work well when epistasis is too strong [9]. Based on Mayley's suggestion, how individual learning works under strong epistasis in our model should be studied in more detail.

In dynamic environments, social learning can be used more continuously than individual learning, and can contribute to improve the fitness, while the frequency and the effectiveness of individual learning are similar to the case of static environments. We summarize the conditions for social learning to be effectively utilized in dynamic environments: frequent environmental change ($IEC < 10$, probability of environmental change is 0.1 per generation); weak epistasis ($K \leqslant 2$); and moderate mutation rate ($\mu < 0.04$, nearly the error threshold). The second and third conditions are the same as in the case of static environments. These conditions indicate that the environment is severe but not too harsh. In a very severe environment, that is, strong epistasis or higher mutation rate than the error threshold, individual learning plays a useful role. As we discussed above, most learning ability is used for individual learning. In our model, individual learning is burdened larger cost than social learning, thus the lifetime fitness is reduced when individual learning is used a lot. During adaptation, the cost term is critical in order to evolve agents which can utilize the three adaptive algorithms properly. But from the viewpoint of optimization, the solution found by an agent with the highest $F_b$, i.e., the fitness before subtraction of the cost, is the best.

We found that the parameter dependency of both fitness and the frequency of learning operations is rather simple, when we look at data averaged over many runs. The interactions among biological evolution, individual learning and social learning seems, however, complex in close observations, as we suggested with diverse scenarios of recovery from deterioration caused by environmental change. The conditions for social learning to be effective are obtained in the average view. Further, NK fitness landscape is a kind of model of general complex problems such as combinatorial optimization, but not real problems. In order to apply the present algorithm to solving real optimization problems, we need to analyze the characteristics of the algorithm by applying it to real problems based on the analysis of results in this paper. In order to analyze our algorithm from the viewpoint of computational complexity, it would be interesting to analyze the time cost of calculation required to verify whether some changes of genotypes and phenotypes improve the fitness of agents or not.

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 searches higher fitness in a rugged landscape such as hill-climbing using individual learning. Then, the results of the learning are transmitted to the
population from teachers to students using social learning. Finally, the results of individual and social learning are genetically assimilated, according to the selective pressures posed by learning costs.

The conditions which favor social learning were investigated. 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 not too high, and must be smaller than the error threshold. Epistasis is low (the fitness landscape is not so complex). In the present model, the conditions are quantitatively described as follows: the individual learning cost should be at least 1.5 times the social one; the mutation rate should be less than 0.04 per gene; more than 3 genes should not interact.

We also showed that the present algorithm is useful in a dynamic problem, in which the fitness landscape changes with time. The algorithm can find better solutions, even when a genetic algorithm does not work well. Social learning is favored more in such a dynamic problem than in a static one. The more frequently change occurs, the more social learning is used.

As we discussed, social learning in the present model has many constraints. Social learning is really so constrained that it is hard to establish biologically. Therefore, it is difficult to study the essential interactions of social learning with genetic evolution and individual learning. One of the key missing points concerning social learning in our model is generation overlapping, which is important in realizing accumulative knowledge creation and transmission. We show only phenomenological findings in this paper. Although some conditions are reasonable, we should search for understandable mechanisms, in order to understand the interactions among the three adaptive algorithms, and to utilize their interactions.

Acknowledgements

The authors are grateful to Ms. Mary Ann Mooradian for English editing. We are grateful to reviewers for their valuable comments for improving our manuscript. This work is supported by Grant-in-Aid for Scientific Research (No. 17680021 and 20300082) of Japan Society for the Promotion of Science (JSPS).

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