Symbiotic Evolutional Models in Multiagent Systems

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Abstract- Multiagent Systems with Symbiotic Learning and Evolution (Masbiole) has been proposed as a new learning and evolutionary method for Multiagent Systems (MAS) recently, which is based on symbiotic phenomena among creatures. In this paper, a symbiotic evolutional model of Masbiole is proposed using Genetic Network Programming (GNP), which has been also proposed as one of the evolutionary computations. In the simulations, the proposal Masbiole is applied to the tile-world model and various characteristics of Masbiole have been clarified.

1 Introduction

Various studies applying Artificial Intelligence (AI) to control complex systems have been done. These studies are based on the idea that autonomous decentralized control systems are basically superior to centralization control systems.

Accordingly, Multiagent Systems (MAS) have been proposed and studied [weis00, woold02], which deal with the systems with a plural number of agents. In MAS, agents having their own objects make interactions each other, and the solutions for the problem are usually obtained without designer's instructions. Various kinds of studies related to MAS have been done and applied to various fields utilizing these characteristics.

An expansion of MAS, i.e. Multiagent Systems with Symbiotic Learning and Evolution: Masbiole [egu02] has been proposed based on the symbiotic phenomena among creatures. In Masbiole, the concept of symbiotic learning and evolution is used for agents, which considers the benefit or loss of the agent itself and opponent agent in stead of the benefit of the agent itself only, using symbiotic phenomena such as Mutualism, Competition, Predation and Altruism. Therefore, compared with conventional MAS considering its own benefit only, Masbiole is expected to have more flexible and better solutions.

In this paper, a symbiotic evolutional method is focused on, which is one of the two methods of Masbiole (Symbiotic Learning and Symbiotic Evolution), and the symbiotic evolutional models for multiagent systems are constructed and their various properties are examined. To study them, Genetic Network Programming (GNP) [kata01, mabu02] is used to construct agents, which has been proposed recently as one of the evolutionary computations, and evolutional Masbiole is applied to tile-world models [poll90] for simulations, which is a test bed of conventional MAS.

This paper is organized as follows. In the next section, Masbiole is briefly described. Section 3 describes the simulation model and shows the results of the simulations. Finally, conclusions are devoted in section 4.

2 Multiagent Systems with Symbiotic Learning and Evolution (Masbiole)

2.1 Basic Concepts

In conventional MAS, an agent adapts to the systems by changing its "Strategy" based on its "Evaluation" showing the achievement of its own. At that time, as a whole MAS realizes the solutions for the problem by the interactions among agents. However, in MAS, agents consider only their own benefit, so there are some cases where the collision of benefits among agents arises and conventional MAS drops into a competitive solution. This competitive solution is called "Nash Equilibrium Point" and it evokes the disadvantage of conventional MAS, where the flexibility and diversity of the solutions of MAS are lost.

The proposed method, Masbiole employs the symbiotic learning and evolution hinted from symbiotic phenomena among creatures "considering the benefit or loss of not only itself but also the opponent". Here, a minimal unit which has its own strategy and evaluation is defined as an individual, therefore learning means the changing of the strategy of an agent which consists of an individual, while evolution means the changing of the strategies of an agent consisting of several individuals (population). Hence Masbiole is divided into learning Masbiole and evolutionary Masbiole by the construction of agents. In this paper, evolutionary Masbiole is dealt with.

In Masbiole, "Symbiotic Relations" are set among agents and agents learn and evolve considering them. Consequently, solutions of Masbiole can escape from Nash Equilibrium Point by the complex interactions based on various symbiotic relations, as a result flexible and diversified solutions are obtained. Therefore, fundamentally Masbiole is not the methodology for optimization problem but the model for examining the rise and falls of the agents based on symbiotic relations. For instance, Masbiole can be applied to the "Company's Competition Model" where several companies take various strategies toward others by regard-

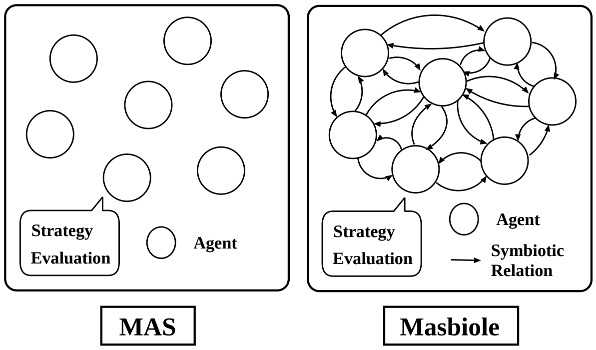


Figure 1: Basic structures of Masbiole and MAS

ing the companies as agents and symbiotic relations toward others as their strategies. Of course, by focusing that every agent considers the benefits of it and its opponent, it is also possible to apply Masbiole to the optimization problems. Fig.1 shows the basic structures of Masbiole and conventional MAS based on the above.

Symbiotic relations are defined as “Mutualism”, “Competition”, “Predation”, “Altruism”, “Self Improvement” and “Self Deterioration” according to the combination of improvement/deterioration of an agent and its opponent. The outline of symbiotic relations is shown in Table 1. The symbiotic relation is set between two agents and symbiotic learning and evolution are implemented sequentially for every pair of agent. For instance, in the case of Predation learning of an agent, the agent changes its strategy so that the evaluation of its own improves and that of its opponent agent deteriorates. On the other hand, Self Improvement and Self Deterioration are defined as those considering its evaluation only. Especially Self Improvement corresponds to the learning and evolution of conventional MAS. Hence it can be said that Masbiole includes conventional MAS in a broad sense.

In Masbiole, symbiotic learning and evolution are implemented for a symbiotic relation between specific agents. Hence the specific two agents (self agent and opponent agent) and the symbiotic relation between them need to be selected. When symbiotic learning and evolution are carried out, the strategies of other agents including an opponent agent are fixed except the self agent. By implementing this local learning and evolution, the proposed method can realize meticulous learning and evolution based on various symbiotic relations and be easily applied to systems even if they are complex.

Table 1: Symbiotic relations from an agent to its opponent

Symbiotic Relation	Self	Opponent
Mutualism	Improve	Improve
Competition	Deteriorate	Deteriorate
Predation	Improve	Deteriorate
Altruism	Deteriorate	Improve
Self Improvement	Improve	-
Self Deterioration	Deteriorate	-

2.2 Algorithms of Symbiotic Evolution

In this subsection, the algorithm of symbiotic evolution is explained. In evolutionary Masbiole, each individual of an agent has its own strategy and evaluation, and the evolution of its strategy is done utilizing Multiobjective Genetic Algorithms (MOGAs) [bag99]. The whole procedures of symbiotic evolution are described as follows.

Algorithms of symbiotic evolution

1 : Initial strategies and symbiotic relations between agents are set.

2 : The self agent which changes its strategies and its opponent agent are selected.

3 : The strategies of individuals of the self agent are changed by genetic operations, then offspring is generated.

4 : An individual is selected from each agent, and they are carried out in the problem space in order to calculate their evaluation points.

5 : The ranks of the individuals of the self agent are calculated according to the multiobjective ranking method of MOGAs considering the symbiotic relation from the self agent toward its opponent agent.

6 : New individuals of the self agent are selected from the individuals having better rank for the next generation according to $\mu + \lambda$ selection method.

7 : The process is returned to procedure **2** until the final generation.

Next, the procedure **4**, **5** and **6** are explained concretely. Here, for the simplicity, the self agent is denoted as s, its opponent agent as o, and other agents are $other$. For each agent, some definitions are described as follows.

λ_i : The strategy of an individual of agent i
E_i : The evaluation of an individual of agent i

Under these definitions, the evaluation of a pair of individuals from agent s and o is calculated by Eq.(1),

$$\begin{cases} E_s = E_s(\lambda_s, \lambda_o, \lambda_{other}) \\ E_o = E_o(\lambda_s, \lambda_o, \lambda_{other}), \end{cases} \quad (1)$$

where, λ_{other} denotes the strategies of selected individuals from other agents.

The pair of evaluations in Eq.(1) (E_s, E_o) is called "Evaluation Point". Fig.2 shows the image of pairing individuals selected from a self agent and its opponent agent and calculating evaluation points in the (E_s, E_o) space.

The ranks of the evaluation points in Fig.2, to be more concrete, the ranks of the individuals of agent s are calculated considering the symbiotic relation from agent s toward agent o. The rank of each evaluation point is calculated according to the following rule utilizing MOGAs.

Rule of calculating rank

The rank of an evaluation point is determined to be $R+1$ when it is dominated by other R evaluation points under the symbiotic relation from agent s toward o.

Fig.3 shows examples of calculating ranks in cases of Mutualism, Competition, Predation and Altruism. In Fig.3, the symbols of A,B,C,$\cdots$ show evaluation points and the numbers in () show the ranks of them. Here, the increase of evaluation is regarded as the improvement of it. For example, in the case of Mutualism+, the ranks of evaluation point C, F and G become 1 because they do not dominated by any other evaluation points in a sense that both E_s and E_o are improved. In the same way, the rank of other evaluation points are calculated as follows; A: 3 (dominated by C and F), B: 5 (dominated by C, D, F and G), D:2 (dominated by F), E: 3 (dominated by F and G). In the cases of Self Improvement and Self Deterioration, the rank is calculated considering E_s only.

New individuals of agent s for the next generation are selected from the individuals of agent s with higher rank according to $\mu + \lambda$ selection method. This method described next has been used in conventional evolutionary computations such as Evolutionary Strategy (ES) [bey01] and Genetic Programming (GP) [koza92].

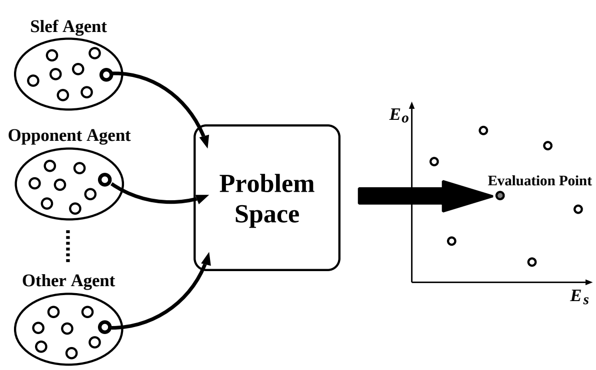


Figure 2: The structure of calculating evaluation points

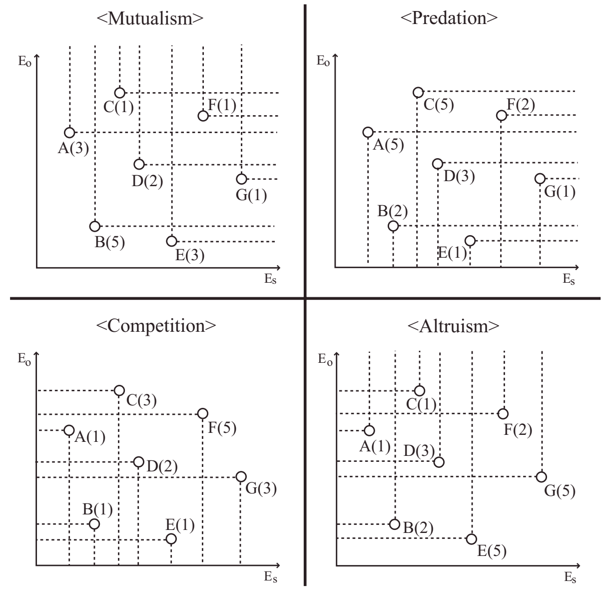


Figure 3: Examples of ranking for various symbiotic relations

Algorithms of $\mu + \lambda$ selection method

1 : Parent population which consists of μ individuals is selected.

2 : Offspring population which consists of λ individuals is generated.

3 : Parent population with the size of μ is selected again from the individuals of offspring having better rank.

where, $\lambda \geq \mu \geq 1$. The image of $\mu + \lambda$ selection method is shown in Fig.4.

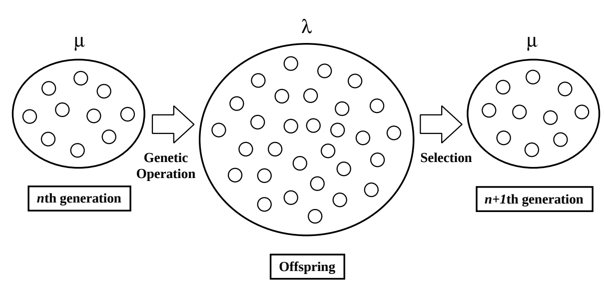


Figure 4: Images of $\mu + \lambda$ selection method

2.3 Symbiotic Pareto Solutions

The solutions obtained by symbiotic evolution satisfy the Pareto optimality because evaluations of agent s and agent o are considered. These solutions are called as "Symbiotic Pareto Solutions" and defined as follows.

Symbiotic Pareto Solutions

For the set Λ_s of strategies of agent s and the strategy λ_o, λ_{other} of agent s and other agents, if and only if there is no $\lambda_s \in \Lambda_s$ which satisfies the following conditions, $\lambda_s^* \in \Lambda_s$ is called symbiotic Pareto solution of agent s toward agent o under λ_o and λ_{other}.

$\langle Conditions \rangle$

$$E_s = E_s(\lambda_s, \lambda_o, \lambda_{other}) \sim E_s(\lambda_s^*, \lambda_o, \lambda_{other}) \quad (2)$$

$$and$$

$$E_o = E_o(\lambda_s, \lambda_o, \lambda_{other}) \approx E_o(\lambda_s^*, \lambda_o, \lambda_{other}) \quad (3)$$

The symbols of $\sim$ and $\approx$ in Eq.(2) and Eq.(3) are as follows according to the symbiotic relation from agent s to agent o.

$$\begin{array}{lcl} \langle Mutualism \rangle & \Longrightarrow & \sim \ : \ > \ , \ \approx \ : \ > \\ \langle Competition \rangle & \Longrightarrow & \sim \ : \ < \ , \ \approx \ : \ < \\ \langle Predation \rangle & \Longrightarrow & \sim \ : \ > \ , \ \approx \ : \ < \\ \langle Altruism \rangle & \Longrightarrow & \sim \ : \ < \ , \ \approx \ : \ > \end{array}$$

The images of symbiotic Pareto solutions in (E_s, E_o) space for various symbiotic relations are shown in Fig.5.

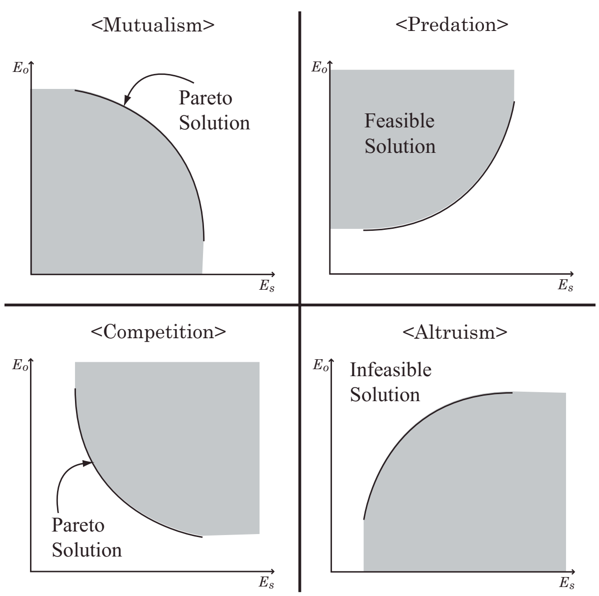


Figure 5: Symbiotic Pareto solutions for various symbiotic relations

3 Simulation

In this section, the simulations of evolutionary Masbiole using tile-world models are done in order to study the complex phenomena by symbiotic evolution and to compare evolutionary Masbiole and conventional MAS.

3.1 Simulation Models

The tile-world model used in the simulations is a virtual environment which has a 2-dimensional grid world and is known as the typical test bed for dynamical environments. A tile-world consists of dynamic units, tiles, obstacles and holes, and each component occupies one grid (cell). The dynamic unit is called "agent" generally, but the name "agent" in the tile-world models and the name of "agent" in Masbiole could be misunderstood. Therefore, we call this dynamic unit just "unit" for distinction.

Especially, in this paper, a "Match Type Tile-world Model (MTTM)" is proposed for simulations, where agents compete each other for the benefit or loss of itself and its opponent. An example of MTTM among 3 agents used in the simulations is shown in Fig.6. In Fig.6, there exist 3 units for each agent (agent 1,2,3), and the action sequences of the units of an agent are generated by one of the individuals (GNP) belonging to the agent. The subscript of holes indicates an agent to which the hole belongs, and there also exist two kind of tiles, i.e. the tile for score (Tile S) and the tile for disturbance (Tile D). Evaluation of individuals of an agent are calculated mainly by the number of Tile S dropped into the hole belonging to the agent. Tile D is not related directly to the evaluation, but the improvement of evaluation is disturbed by dropping Tile D into the hole belonging to the agent. By this model, it is possible to realize various evolutions based on symbiotic relations such as Mutualism, Competition, and so on. For instance, agent

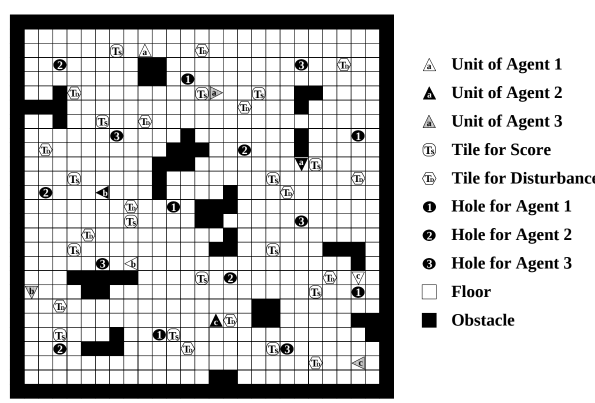


Figure 6: An example of Match Type Tile-world Model (MTTM)

1 executing Mutualism toward agent 2 intends to evolve in such a way that the units belonging to agent 1 drop Tile S into not only Hole 1 but also Hole 2 (however, by the interactions from other agents, the evolution like this is not necessarily obtained).

3.2 Construction of Agents by GNP

In this paper, individuals of an agent are constructed by Genetic Network Programming (GNP), which has been proposed recently as one of the evolutionary computations. Each individual of GNP has the network structure where "Judgment Nodes" and "Processing Nodes" are connected by directed branches each other. Judgment nodes judge the information on the environments, while processing nodes determine an action/processing for the agent. In GNP, the program starts from the initial boot node and transfers from node to node according to the connections and judgment results of the nodes. At judgment nodes, GNP selects an appropriate branch depending on the judgment result and moves to the corresponding next node, while at processing nodes, the action/processing is done and moves to the next node automatically, because the processing node has only one branch. GNP has no terminal node and node transitions are iterated until the program arrives in the terminal condition. GNP is superior to PADO which has graph structures [tell95] in a sense that there is no need for explicit memories in GNP, i.e. GNP has more general structure possible to realize dynamical systems than PADO. The action sequences of units in MTTM are generated by these procedures.

Fig.7 shows the construction of units by GNP and the mechanism of introducing GNP into MTTM. In Fig.7, each unit has its own view and can obtain the information on the location and direction of the objects in its view and so on.

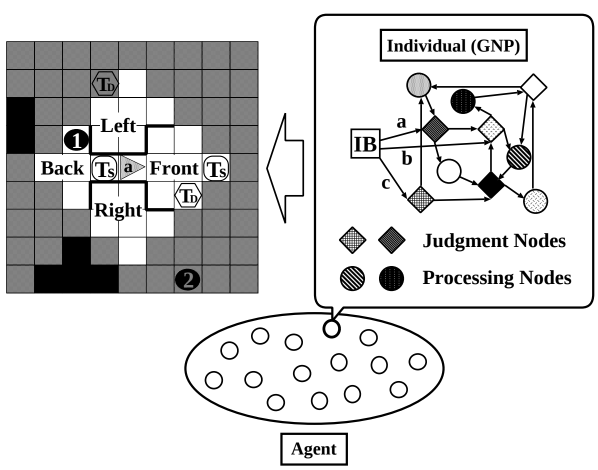


Figure 7: The mechanism for introducing GNP into MTTM

Table 2: Node function sets

Node type	Node functions	Branch
Judgment node	**SF**, **SB**, **SL**, **SR**	10
	NTS, **NTD**, **NH1**, **NH2** **NH3**, **NU1**, **NU2**, **NU3**	6
Processing node	**MF**, **MB**, **ML**, **MR**, **SH**	1
Initial boot node	**IB**	1

As mentioned in the previous section, action sequences of units belonging to the same agent are generated by the same GNP program (an individual). Each unit acts sequentially, and "1 Step" means that a unit carries out judgments and at least one processing, while "1 Episode" means that given steps are carried out. After an episode ends, evaluations of individuals are calculated.

In the simulations, each unit can move to forward (**MF**), backward (**MB**), left (**ML**) and right (**MR**) or stay here (**SH**). Besides, each unit can know what exists in front of (**SF**), backward (**SB**), left (**SL**) and right (**SR**) of the unit and also the direction of the tile (**NTS**, **NTD**), hole (**NH1**, **NH2**, **NH3**) and unit (**NU1**, **NU2**, **NU3**), which is closest to the unit. Therefore, judgment/processing nodes of GNP in this paper are prepared as shown in Table 2. In Table 2, **SF**, **SB**, **SL** and **SR** have 10 judgment results (Tile S, Tile D, Unit 1∼3, Hole 1∼3, Floor, Obstacle), and **NTS**, **NTD**, **NH1**∼**NH3** and **NU1**∼**NU3** have 6 judgment results (Forward, Backward, Left, Right, Several, None).

In addition, the change of strategies of agents is implemented by the genetic operators of GNP such as crossover[1], mutation[2], elite preservation[3] and tournament selection[4].

3.3 Evaluation Function

The evaluation of each individual (GNP) of agent i: E_i $(i = 1, 2, 3)$ is calculated by Eq.(4).

$$\begin{aligned} E_i = \; & k_T \times T_i + \sum_{l=1}^{L} (k_{TN}^l \times TN_i^l) \\ & + k_C \times C_i + k_N \times N_i \\ & + k_{RS} \times RS_i \end{aligned} \tag{4}$$

[1]Some nodes in parent GNP are selected by the probability P_c, then the branches from the corresponding nodes are exchanged and two new offspring GNPs are generated.

[2]Some branches in a GNP are selected by the probability P_m, then the connections of these branches are changed randomly.

[3]Some elite individuals having excellent rank are preserved to the next generation.

[4]An individual having the best rank is selected from two or three randomly selected individuals.

where,

- T_i : The number of Tile S dropped into Hole i
- TN_i^l : The number of Tile S located in the lth vicinity of Hole i ($l = 1, 2, 3, 4$)
- C_i : Average number of cells an individual of agent i moved
- N_i : Average number of node transitions of GNP of agent i per one step
- RS_i : The rest steps when all Hole is are buried by Tile S
- k_T, k_{TN}^l, k_C, k_N, k_{RS} : Weight coefficient

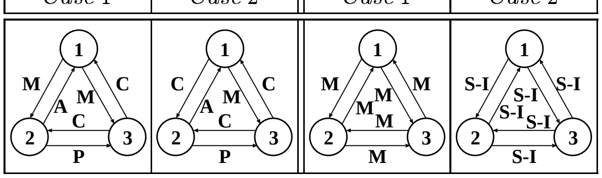
T_i, TN_i^l and RS_i indicate the performance of the task on how many Tile Ss are dropped into Hole i and to what degree Tile S is moved to Hole i, and C_i and N_i are used to avoid premature convergence of evolution by distributing evaluation points widely in (E_s, E_o) space. Each weight coefficient is set to k_T : 200, k_{TN}^1 : 80, k_{TN}^2 : 60, k_{TN}^3 : 40, k_{TN}^4 : 20, k_C : 1, k_N : 1 and k_{RS} : 1. In Fig.6 there exist some Tile Ss in the $1st \sim 4th$ vicinity of each hole at an initial condition, therefore individuals can obtain some amount of evaluations even though their units do nothing. This is set so that the evaluation could be deteriorated by the symbiotic relations such as Competition and Altruism.

3.4 Simulation Conditions

In the simulations, there exist 3 agents (agent 1, 2, 3) and 6 symbiotic relations (each agent has symbiotic relations toward other two agents). Evolution is implemented in the order of agent $1 \rightarrow 2$, $2 \rightarrow 3$, $3 \rightarrow 1$, $1 \rightarrow 3$, $2 \rightarrow 1$, $3 \rightarrow 2$. The symbiotic relation of each agent is set like Table 3. There are 2 patterns of simulations, and each pattern has 2 cases. $Pattern\ A$ is the complex symbiotic evolution model where symbiotic relations of agents are set variously, and $Pattern\ B$ is the comparison model of Masbiole and conventional MAS where each agent in Masbiole takes Mutualism and each agent in MAS takes Self Improvement.

Table 3: Symbiotic relation of each agent in the simulations

$Pattern\ A$		$Pattern\ B$	
$Case\ 1$	$Case\ 2$	$Case\ 1$	$Case\ 2$



M : Mutualism, **C** : Competition, **P** : Predation
A : Altruism, **S-I** : Self Improvement

Table 4: Conditions for symbiotic evolution and GNP

Generation $=$ 1500/Symbiotic relation
Population size of an agent $=$300
$\mu = 300$ (population size)
$\lambda = 900$
The number of maximum steps in 1 episode $= 40$
The maximum number of vicinities of views of a unit $= 4$
Crossover probability: $P_c = 0.1$
Mutation probability: $P_m = 0.01$
The number of elite individual $= 1$
Tournament size $= 2$
The ratio of crossover/mutation in offspring $= 2 : 3$
The number of nodes of a GNP $=$ 15/Kind + Initial node

The conditions for symbiotic evolution and GNP are shown in Table 4. As the simulation environments, 6 kinds of MTTMs are used for securing the reliability of the results, in such a way that the positions of units are changed in MTTM. In addition, simulations are implemented for different 5 kinds of random sequences.

3.5 Simulation Results

Simulation results of each case are shown in Fig.8. Fig.8 shows the average of evaluation curves of individuals of each agent (vertical axis: evaluation, horizontal axis: generation). All the results are the average over 30 independent simulations (6 kinds of environments $\times$ 5 kinds of random sequences).

In $Pattern\ A$, symbiotic relations among 3 agents are set variously and it is studied how the symbiotic evolution based on complex combinations of symbiotic relations is obtained. Besides, it is also studied what effects are obtained by changing a symbiotic relation (agent $1 \rightarrow$ agent 2). In $Case\ 1$, Fig.8 shows that agent 1 evolves to obtain the best evaluation followed by agent 2 and 3. This is because agent 1 takes Mutualism toward others and agent 2 takes Altruism toward agent 1. On the other hand, agent 2 can't evolve sufficiently because it obtains benefits by Mutualism and Predation, but loses them by Altruism and Competition at the same time. Agent 3 also loses benefits by taking Competition toward others, so its evaluation is the worst. In $Case\ 2$, a symbiotic relation (agent $1 \rightarrow$ agent 2) is changed from Mutualism to Competition. By this local change, it is expected that the evaluations of agent 1 and 2 are deteriorated, but in fact, Fig.8 shows that not only the expectation is proved to be right but also the evaluation of agent 3 is improved. In addition, it can't be anticipated easily that the evaluation of agent 3 is superior to that of agent 2 because of the Predation of agent 2 toward agent 3. It is thought

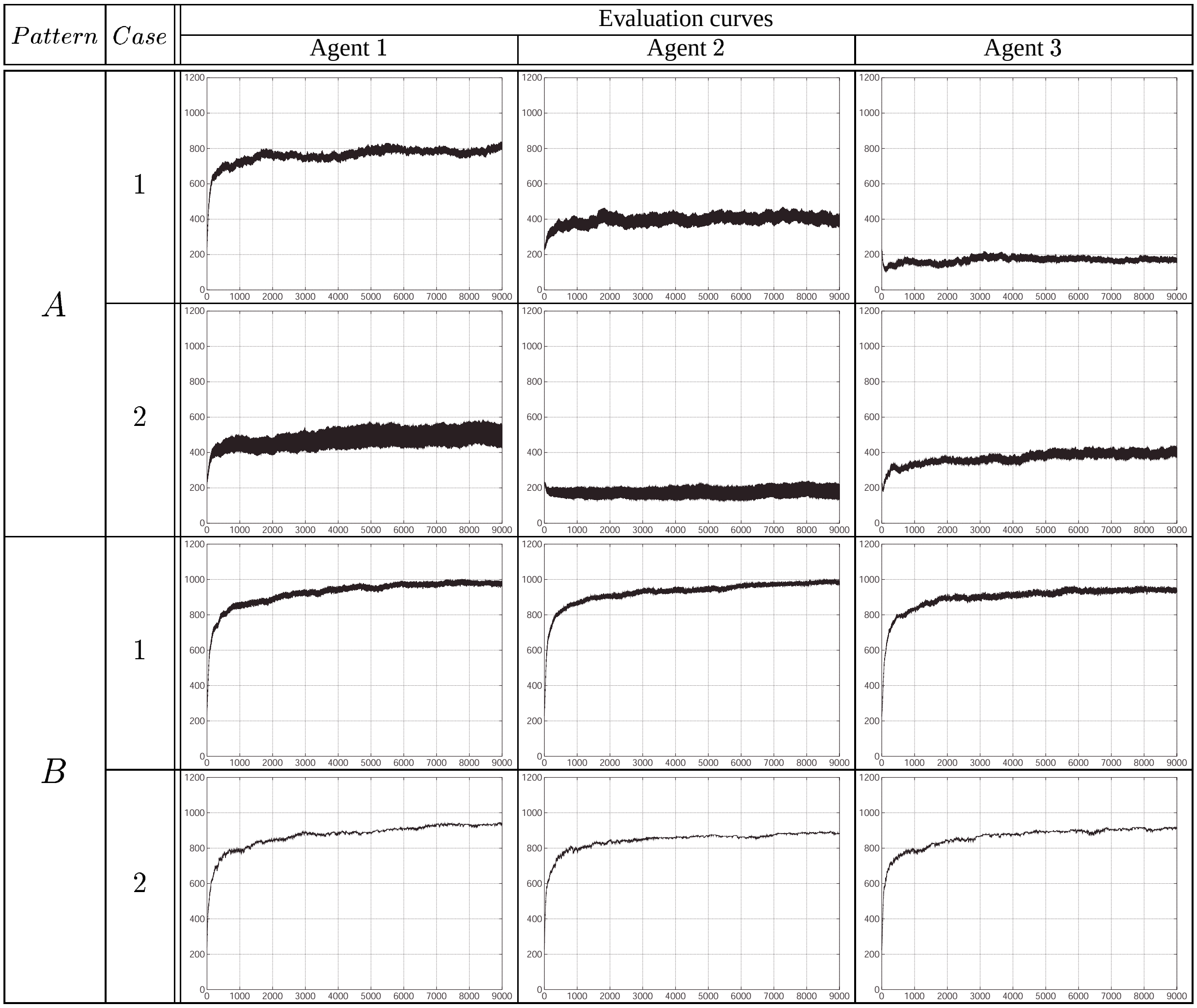


Figure 8: The evaluation curve of each agent for various symbiotic evolutions

that by this change, benefits shared between agent 1 and 2 in $Case$ 1 move to agent 3. It is a property of Masbiole that unpredictable evolution occurs by complex interactions based on symbiotic relations.

In $Pattern\ B$, the aim of simulations is to compare the performances of Masbiole where each agent takes Mutualism toward others ($Case$ 1) and conventional MAS where each agent takes Self Improvement ($Case$ 2). This is an optimization problem in a sense that the sum of the average evaluations each agent gets is compared between $Case$ 1 and $Case$ 2. It is found from Fig.8 that the evaluation of every agent in $Case$ 1 is superior to that in $Case$ 2. In addition, for more concrete comparison, the sum of evaluations of 3 agents ($E_1 + E_2 + E_3$) and the evaluation points in (E_1, E_2, E_3) space obtained by evolution are shown in Fig.9 for two cases. From the comparisons in Fig.9, it is also clarified that the sum of the evaluations in $Case$ 1 is superior to that in $Case$ 2 and many evaluation points of $Case$ 1 are superior to that of $Case$ 2 in each coordinate. In other words, Masbiole where agents take Mutualism can solve the problem of tile-world more optimally than conventional MAS. The reason for this is that in Masbiole individuals are selected depending on the ranks calculated by multiobjective ranking method, so more global search for solutions is possible (Symbiotic Pareto solutions) than MAS. In contrast, in conventional MAS, individuals are easy to converge into a local solution (Nash equilibrium point) without global search by high selection pressure ($\lambda = 900$). This has been clarified from Fig.9, i.e. the evaluation points of $Case$ 1 (Masbiole) disperse broadly, but those of $Case$ 2

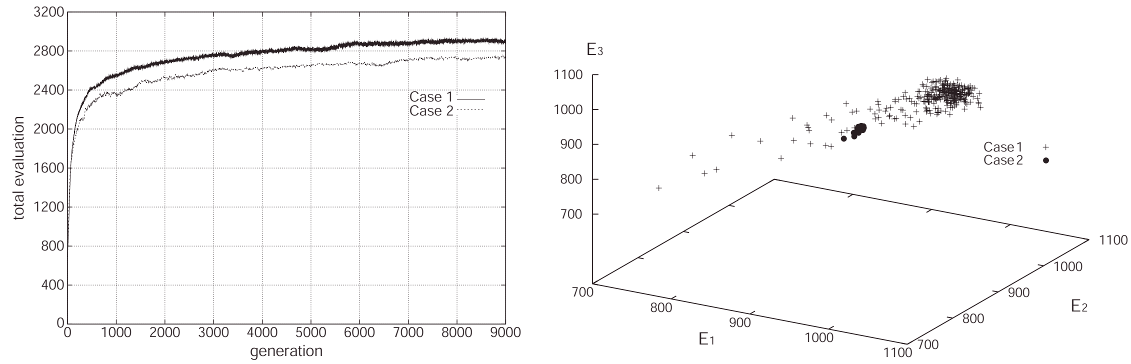


Figure 9: The comparisons on the sum of the evaluation curves and on the evaluation points of Masbiole and MAS

(MAS) converge in one point. Hence it could be mentioned that Masbiole is a more efficient methodology than conventional MAS even for optimization.

4 Conclusions

In this paper, Multiagent Systems with Symbiotic Learning and Evolution (Masbiole) based on symbiotic phenomena in the ecosystems is applied to tile-world models using Genetic Network Programming (GNP), which has been proposed recently as one of the evolutionary computations and various properties of the proposal symbiotic evolutionary model are studied. As a result, it is shown that various evolutions of agents, which are hard to predict, are obtained in Masbiole. In addition, it is also clarified that Masbiole with each agent taking Mutualism can solve a kind of optimization problem more efficiently and effectively than conventional MAS.

Henceforth, we will clarify various properties of Masbiole more concretely by applying it to other multiagent problems such as the maze problem, the chasing problem and the artificial ant system. Besides, we will also clarify the efficiency of Masbiole in more details for various optimization problems.

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