Learning of Symbiotic Relations among Agents by Using Neural Networks

Hirasawa, Kotaro
Dept. of Electrical and Electronic Systems Engineering, Graduate School of Information Science and Electrical Engineering, Kyushu University

Yoshida, Hidemasa
Dept. of Electrical and Electronic Systems Engineering, Graduate School of Information Science and Electrical Engineering, Kyushu University : Graduate Student

Hu, Jinglu
Dept. of Electrical and Electronic Systems Engineering, Graduate School of Information Science and Electrical Engineering, Kyushu University

https://doi.org/10.15017/1515686

出版情報：九州大学大学院システム情報科学紀要. 5 (2), pp.215-222, 2000-09-26. 九州大学大学院システム情報科学研究院

九州大学大学院
システム情報科学紀要
第5巻 第2号 平成12年9月

Research Reports on Information Science and
Electrical Engineering of Kyushu University
Vol.5, No.2, September 2000

Learning of Symbiotic Relations among Agents by Using Neural Networks

Kotaro HIRASAWA* , Hidemasa YOSHIDA** and Jinglu HU*

(Received June 16, 2000)

Abstract: Symbiotic relation among the agents is regarded as one of the most basic relations in the complex systems. In this paper, a method for constructing the required symbiotic relations among the agents is proposed, where the agent is made up of a hierarchical neural network and its parameters are trained in order to realize the required symbiotic relations. From the simulations of the ecosystem, where the agent corresponds to the species, it has been cleared that the proposed method can give the ecosystem model with more flexible and more powerful representation abilities than the conventional Lotka-Volterra model.

Keywords: Symbiotic relation, Learning, Multi-agent, Neural networks, Complex systems, Fuzzy systems, Emergence, RasID learning

1. Introduction

Before 1970's, the fundamental way of research was to mainly decompose the large systems into small elements and to understand the phenomena of the elements microscopically. But, there has been a big trend since 1980's to regard the complex systems as they are, where the interaction among the elements of the systems becomes a key role to understand the complex systems. In addition, there have been done extensive research [1),2),3)] on the essence of the complex systems in order to construct the theoretical framework for understanding the complex systems.

In this paper, we studied the multi-agent system with symbiotic relations as an example of the study of complex systems, especially paying attention to the ecosystems. It has been known since Lotka and Volterra first developed the ecosystem's model that the Lotka-Volterra model is the most typical model for the study of the ecosystems [4)]. Furthermore, many kind of advanced Lotka-Volterra models have been studied [5),6)], for example, the model with time varying symbiotic parameters using fuzzy inference is introduced [7)].

In this paper, a very powerful general model of the multi-agent system is proposed [8)], which can easily construct many kind of symbiotic relations such as competition, exploitation, mutualism among the agents than the coventional Lotka-Volterra-like models by training neural networks. To be more specific, an agent is constructed by a hierarchical neural network, in other words, the output of each neural network corresponds to the output of each agent. In addition to that, the parameters of the neural network are trained so that the agent can have specific required symbiotic relations with other agents. By adopting the proposed network architecture and training algorithm for the model of the agents with symbiotic relations, the more generalized symbiotic model can be easily obtained.

But, generally speaking, as the symbiotic relations between agent i and agent j can be represented by the ordered derivative of the output of agent j to that of agent i and also the ordered derivative of the output of agent i to that of agent j, the second ordered derivatives are needed in order to train the parameters of the neural network corresponding to each agent when using the gradient method. Although Universal Learning Networks [9)] allows us to calculate the higher order derivatives systematically, RasID [10)] (Random Search Method with Intensification and Diversification) is used to train the parameters of the network considering that the required targets of the symbiotic relations are calculated by fuzzy inference with fairly complicated computation. Simulations are done in order to prove that the proposed method is more powerful than the conventional models in terms of the representation ability by using the model with three species corresponding to agents.

The paper is organized as follows. Section two describes the structure of the proposed modeling method, and in section three RasID training algorithm is briefly stated. Section four treats the sim-

* Department of Electrical and Electronic Systems Engineering

** Department of Electrical and Electronic Systems Engineering, Graduate Student

ulation results. Finally the last section is devoted to conclusions.

2. Structure of Symbiotic Relation

2.1 Mutual interaction between agents

In this paper, the population of each agent is described by the output of each neural network corresponding to the agent. In addition, the agents, that is the neural networks are connected with each other in order to materialize the symbiotic relations among the agents. Required symbiotic relations can be obtained by training the parameters of the neural networks, where the target values of the symbiotic relations, i.e., the teaching signals for the networks are given by fuzzy inference so that the target values can be time varying depending on the states of the agents. By adopting the above architecture, the more generalized symbiotic relations than the conventional models can be obtained in terms of representation ability, because time varying symbiotic relations between the agents are easily realized.

Now, let $h_i(t)$ and $h_j(t)$ be the population of agent i and agent j, respectively. Then, the symbiotic relations between agents such as exploitation, competition and mutualism are described as follows[2),11)].

$\ll$ In the case of exploitation $\gg$

Agent i exploits agents j, i.e., the ordered derivative of the output of agent j to that of agent i takes a negative value while the ordered derivative of the output of agent i to that of agent j has a positive value.

$$\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)} < 0 \ , \ \frac{\partial^\dagger h_i(t)}{\partial h_j(t-1)} > 0 \qquad (1)$$

In this paper, one sampling delay between agents is assumed when calculating $\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)}$ and $\frac{\partial^\dagger h_i(t)}{\partial h_j(t-1)}$.

$\ll$ In the case of competition $\gg$

Agent i and agent j compete with each other, in other words, the ordered derivative of the output of one agent to that of the other agent takes a negative value.

$$\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)} < 0 \ , \ \frac{\partial^\dagger h_i(t)}{\partial h_j(t-1)} < 0 \qquad (2)$$

$\ll$ In the case of mutualism $\gg$

Agent i and agent j cooperate with each other. Therefore, the ordered derivative of the output of one agent to that of the other agent takes a positive value.

$$\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)} > 0 \ , \ \frac{\partial^\dagger h_i(t)}{\partial h_j(t-1)} > 0 \qquad (3)$$

$\ll$ self regulation $\gg$

When the output of agent i at time t is influenced by the output of the identical agent i at $t-1$, then

$$\frac{\partial^\dagger h_i(t)}{\partial h_i(t-1)} < 0 \qquad (4)$$

is supposed.

It means that the increase of $h_i(t-1)$ causes the decrease of $h_i(t)$ and vice versa.

The above ordered derivative $\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)}$ can be easily calculated by the Back Propagation algorithm of Universal Learning Networks [9),12),13)].

2.2 Learning of agents

In this paper, learning of the agents, i.e., training of the parameters of the neural networks corresponding to the agents is carried out by calculating the target value $S_{ij}(t)$ of $\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)}$ by fuzzy inference and minimizing the squared errors between $S_{ij}(t)$ and $\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)}$.

In addition, as $S_{ij}(t)$ is inferred by $h_i(t-1)$ and $h_j(t)$, $S_{ij}(t)$, in other words, required symbiotic relation between agent i and agent j becomes time varying.

Therefore, for example, the ecosystem model with more flexible representation ability than the conventional methods can be realized by the proposed model. To be specific, the criterion function E for training parameters is defined as follows.

$$E = \sum_{t\in T}\sum_{j}\sum_{i\in J_F(j)} \left(\frac{\partial^\dagger h_j(t)}{\partial h_i(t-1)} - S_{ij}(t)\right)^2 \qquad (5)$$

where

T : set of sampling instants t

$J_F(j)$: set of suffixes of nodes connected to agent j

The parameters of all neural networks corresponding to the agents are adjusted by minimizing the above criterion function E.

As stated before, $S_{ij}(t)$ calculated by fuzzy inference is a fairly complicated function, therefore parameter's training is done by using RasID [10)] which is a kind of adaptive random search method with intensified and diversified search.

2.3 Calculation of $S_{ij}(t)$

The target value $S_{ij}(t)$ of symbiotic relation between agent i and agent j is calculated by the fuzzy inference network with its input being $x = (h_i(t-1), h_j(t))$.

The reason for using fuzzy inference is that time varying symbiotic relation depending on the population of the agents can be realized and a priori specific information on symbiotic relation can be easily introduced into the model.

The fuzzy inference of $S_{ij}(t)$ is carried out as follows.

$$\text{IF } (h_i(t-1), h_j(t)) \text{ is } H_{ijq} \text{ THEN } S_{ij}(t) \text{ is } S_{ijq} \qquad q \in Q \tag{6}$$

where

H_{ijq}	:	fuzzy set of $(h_i(t-1), h_j(t))$ defined by the *if* part membership function $f_{xq}(h_i, h_j)$
S_{ijq}	:	fuzzy set of $S_{ij}(t)$ defined by the *then* part membership function $f_{yq}(S_{ij})$
q	:	suffixes of fuzzy rules
Q	:	set of suffixes of fuzzy rules $\{q\}$

$$f_{xq}(h_i, h_j) = \exp\{-\frac{1}{2(1-r_{hijq}^2)}[\frac{(h_i-\mu_{hiq})^2}{\sigma_{hiq}^2} - 2r_{hijq}\frac{(h_i-\mu_{hiq})(h_j-\mu_{hjq})}{\sigma_{hiq}\sigma_{hjq}} + \frac{(h_j-\mu_{hjq})^2}{\sigma_{hjq}^2}]\} \tag{7}$$

$$f_{yq}(S_{ij}) = \exp\{\frac{(S_{ij}-\mu_{Sijq})^2}{2\sigma_{Sijq}^2}\} \tag{8}$$

It is seen from Eq.(7) and Eq.(8) that typical two and one dimensional Gaussian distribution functions are adopted as the *if* and *then* membership function, respectively.

μ_{hiq}, μ_{hjq}, σ_{hiq}, σ_{hjq} and r_{hijq} are parameters which describe the 'mean', 'variance' and 'correlation coefficient' of 2-D Gaussian membership function $f_{xq}(h_i, h_j)$, respectively, and μ_{Sijq} and σ_{Sijq} describe the 'mean' and 'variance' of the Gaussian membership function $f_{yq}(S_{ij})$. As the results of fuzzy inference depend on the mean values of the *then* part membership functions strongly required symbiotic relation can be realized by setting them appropriately.

3. RasID training

In this section, Random Search Method with Intensification and Diversification (RasID) is briefly stated, which is utilized for training the parameters of the neural networks corresponding to the agents. The reason for using RasID is that the criterion function expressed by Eq.(5) is more complicated than the conventional root squared errors used for neural network training, especially in terms that the criterion functon has the first order derivatives in it.

Neural networks have wide potential applications to pattern recognition, system modeling, and other tasks because they learn nonlinear mapping. Applications usually involve training networks. Neural network training is equivalent to multidimensional, nonlinear, underconstrained, multimodal optimization [14].

Although most neural network training uses gradient-based schemes such as well-known back-propagation (BP), pure BP is slow and is stuck easily at local minima, resulting in a poorly trained network. One way to increase BP reliability is to decrease its sensitivity to small details in the error surface by introducing a momentum term in the BP algorithm, enabling a network to respond to the local gradient and recent trends in the error surface (momentum BP). The role of recent trends in a BP algorithm is increased by using an adaptive training rate (fast BP with momentum) to greatly improves the speed and reliability of BP algorithm.

Nondeterministic methods such as random search[15),16)], simulated annealing [17),18)], and genetic algorithm [19),20),21)] do not use local gradient and have no local minimum problem. Most find the global minimum of error function but few are efficiently applicable to neural network training[16),17),18),19),20),21),22)]. Some have suggested using a hybrid scheme to increase search efficiency[23),24),25)]. Typical is to combine global search and local one. The hybrid scheme uses switching that may lower algorithm efficiency. A hybrid scheme cannot be applied to a network where the local criterion function gradient is incalculable or difficult to obtain.

In training of some neural network based application systems, an extra term often must be incorporated into the criterion function to improve system performance. Such an extra term often consists of first or higher order derivatives and complicates the criterion function and makes its gradient difficult to calculate. When the criterion function surface is very complicated, local gradient plays less role on the local search. It is preferable to use a pure nondeterministic search for complex cases. The efficiency of pure nondeterministic methods must be raised. A nondeterministic method may be more efficient if local information on the criterion function surface is used effectively. We introduce a novel random search scheme, random search with intensification and diversification (*RasID*), that does an intensified search where it is easy to find good solutions locally and a diversified search to escape from local minima under a pure random search scheme. A sophisticated probability density function (PDF) is introduced for generating search vectors. The PDF provides two adjustable parameters which to control the local search range and direction efficiently. Adjusting these parameters effectively based on past success-failure information yields intensified and diversified searches. The local gradient, if available, and trend information on the criterion function surface are used to improve search performance.

4. Simulations

In this section, simulations are done using the ecosystem as an example in order to study the effectiveness of the proposed method in terms of the representation ability of the model. The studies are carried out by varying symbiotic relations among species and fuzzy parameters in the membership functions to see how the populations of the species are influenced by these parameters.

4.1 Simulation conditions

The conditions of the simulation studies are described as follows. The number of agents, i.e., the number of species is set at a small number of three, because simulations are done to investigate the basic characteristic of the proposed method in this paper.

The symbiotic relations among three species are shown in **Fig.1**. In the figure, symbiotic relation between agent 1 and agent 2 is supposed to be mutualism, and the relation between agent 2 and agent 3 is exploitation, to be more specific, agent 2 exploits agent 3. Furthermore, agent 2 and agent 3 are in the competitive relation. In addition, all the time delay between agents is supposed to be one sampling time.

The agent is made up of a hierarchical neural network with three inputs, eight intermediate nodes and one output as shown in **Fig.2**. The sigmoidal function used belongs to the type of $f(x) = \frac{1}{1+exp(-\phi x)}$ and its weight parameters are set randomly between (-1, 1) at the initial time.

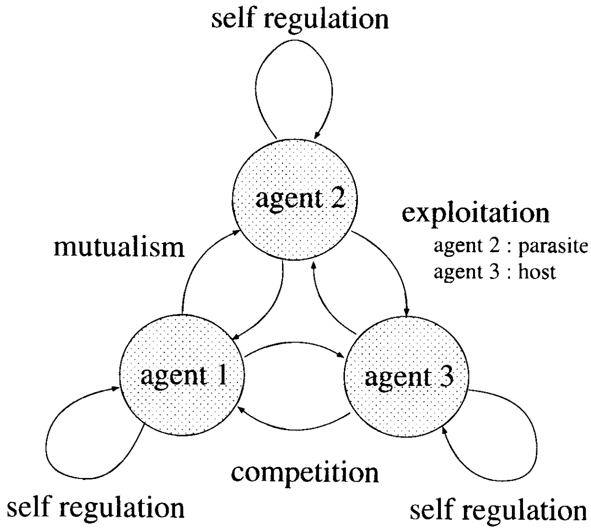


Fig.1 Symbiotic relation between agents

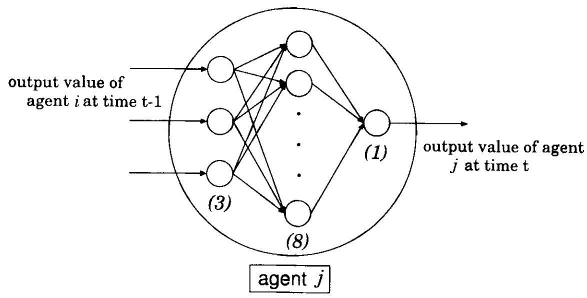


Fig.2 Structure of agent constructed by layered neural networks

Table 1 The mean and variance of if-rule

q	(μ_{hiq}, μ_{hjq})	q	$(\sigma_{hiq}, \sigma_{hjq})$
1	(0.25,0.25)	1	(0.10,0.10)
2	(0.75,0.25)	2	(0.10,0.10)
3	(0.25,0.75)	3	(0.10,0.10)
4	(0.75,0.75)	4	(0.10,0.10)
5	(0.50,0.50)	5	(0.12,0.12)

As for the fuzzy rules, five if part membership functions are allocated to the two dimensional $(h_i(t-1), h_j(t))$ space. The fuzzy parameters, i.e., means (μ_{hiq}, μ_{hjq}) and variances $(\sigma_{hiq}, \sigma_{hjq})$ of each five if part membership functions are listed in **Table 1**, while all correlation coefficients r_{hijq} are set at zero.

The three dimensional pictures of the above five if part membership functions are drawn in **Fig.3**. The reason for the variance of the 5th rule being a

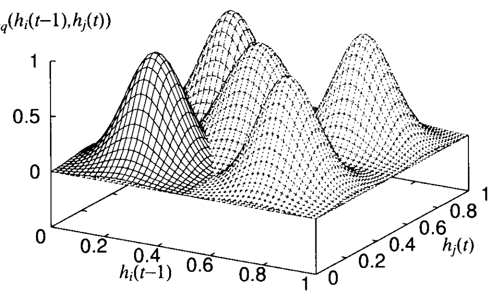


Fig.3 Form of the *if* rule membership function

little bit larger than the other rules is for h_i and h_j around 0.5 to have stronger influence on the populations of the species than the other values.

Furthermore, as for the *then* part membership functions, the mean μ_{Sijq} and variance σ_{Sijq} are set as shown in **Table 2** in order to realize the symbiotic relations between species shown in **Fig.1**.

The case of pattern 1 in **Table 2** emphasizes the exploitation compared to the other weak symbiotic relations, while mutualism is strongly stressed in pattern 2 with other symbiotic relations being increased as well. In pattern 3, symbiotic relations are set two times stronger than those of pattern 2 for the sake of increasing the symbiotic relations. Time T is set at 100 sampling instants.

Table 2 The mean and variance of *then*-rule

q	μ_{Sijq} : pattern 1			
q	exploitation (parasite/host)	competition	mutualism	self regulation
1	0.85/-0.85	-0.55	0.35	-0.70
2	1.00/-1.00	-0.70	0.55	-0.10
3	0.75/-0.75	-0.50	0.40	-0.10
4	0.95/-0.95	-0.65	0.60	-0.70
5	0.90/-0.90	-0.60	0.45	-0.40

q	μ_{Sijq} : pattern 2			
q	exploitation (parasite/host)	competition	mutualism	self regulation
1	0.70/-0.70	-1.10	1.60	-1.40
2	1.20/-1.20	-1.40	1.90	-0.20
3	0.80/-0.80	-1.00	1.50	-0.20
4	1.10/-1.10	-1.30	2.00	-1.40
5	0.90/-0.90	-1.20	1.70	-0.80

q	μ_{Sijq} : pattern 3			
q	exploitation (parasite/host)	competition	mutualism	self regulation
1	1.70/-1.70	-1.10	0.70	-1.40
2	2.00/-2.00	-1.40	1.10	-0.20
3	1.50/-1.50	-1.00	0.80	-0.20
4	1.90/-1.90	-1.30	1.20	-1.40
5	1.80/-1.80	-1.20	0.90	-0.80

q	σ_{Sijq}
1	0.50
2	0.50
3	0.50
4	0.50
5	0.50

4.2 Simulation results

Learning curve, β of RasID training and the outputs of three agents of pattern 1, pattern 2 and pattern 3 are shown in **Fig.4**, **5** and **6**, respectively assuming that the initial values of the agents are 0.3, 0.5 and 0.7. **Fig.7** shows the same kind of figures of pattern 3 when all the initial values of the agents are equal to 0.4.

Generally speaking, when β of RasID takes a large value, intensified search are carried out, on the contrary, diversified search is emphasized in the case of small β [10].

From **Fig.4(b)**, **5(b)**, **6(b)** and **7(b)**, it is clear that RasID is functioning well, because RasID carries out the intensified and diversified search adaptively.

From **Fig.4(a)**, **5(a)**, **6(a)** and **7(a)** which describe the learning curves also show the effectiveness of the RasID learning.

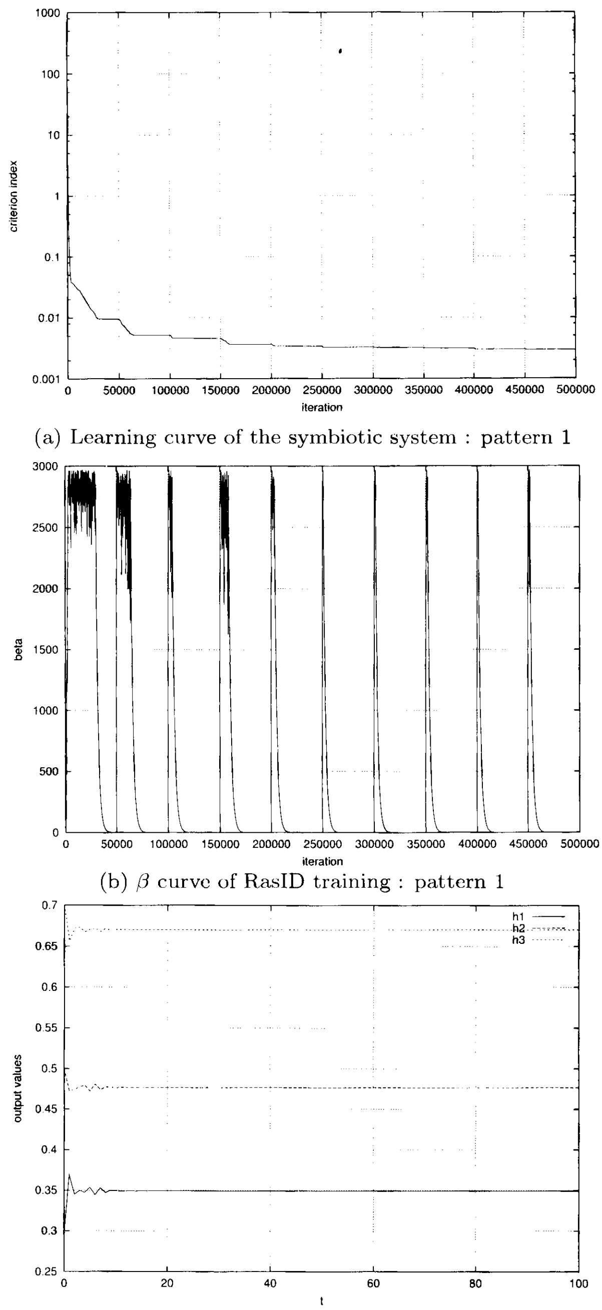
From **Fig.4(c)**, **5(c)**, **6(c)** and **7(c)** show the dynamics of the population of the species in the cases of various symbiotic relations.

In the case of pattern 1, relatively weak symbiotic relations are set, although exploitation is stressed among the symbiotic relations. In this case, the dynamics approach the stable points within ten sampling instants. On the contrary the dynamics of pattern 2 shows the totally different aspects from pattern 1 as shown in **Fig.5**.

In the case of pattern 2, where mutualism is strongly stressed with other symbiotic relations being increased as well, the dynamics are stable, but show the relatively complicated phenomena.

Although the dynamics seem to approach the stable points until 50 sampling instant, the strong mutual interactions between the species are found from 60 to 100 sampling instant in pattern 2. This is because in pattern 2 stronger symbiotic relations are assigned to the agents than pattern 1.

When we double the strength of all the symbiotic relations compared to the pattern 1, we can obtain another complicated dynamics shown in **Fig.6**. In

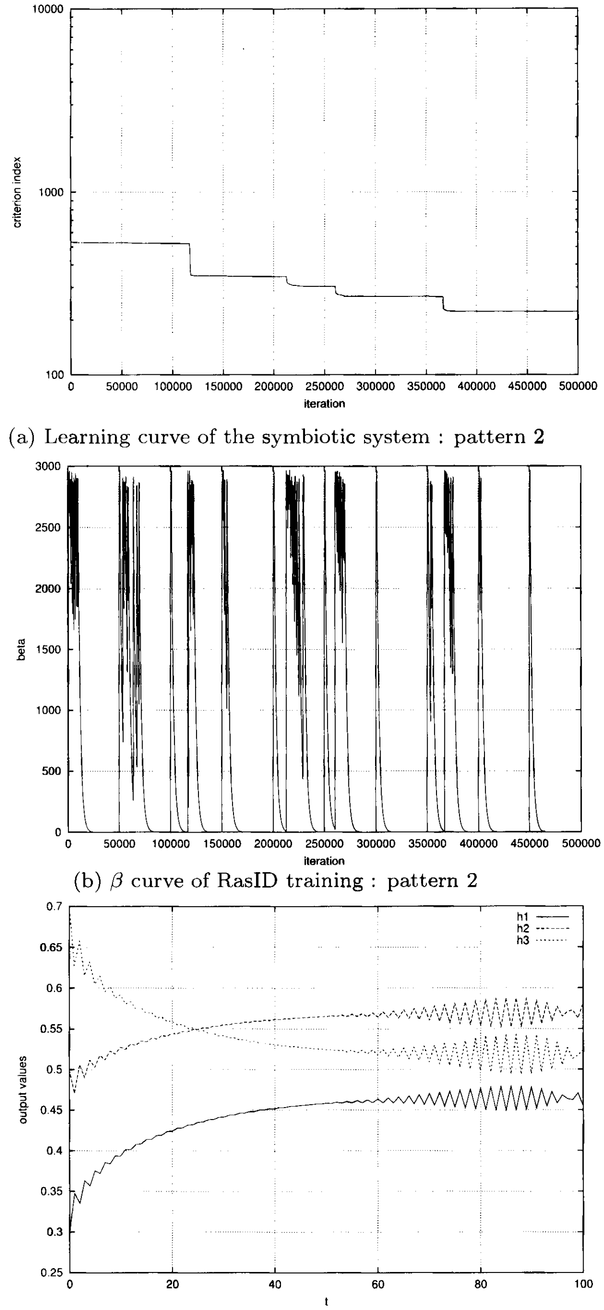


(a) Learning curve of the symbiotic system : pattern 1

(b) β curve of RasID training : pattern 1

(c) Output values of the agents : pattern 1

Fig.4 Result of Simulation in the case of pattern 1 (initial value of $h_j(t)$: 0.3, 0.5, 0.7)



(a) Learning curve of the symbiotic system : pattern 2

(b) β curve of RasID training : pattern 2

(c) Output values of the agents : pattern 2

Fig.5 Result of Simulation in the case of pattern 2 (initial value of $h_j(t)$: 0.3, 0.5, 0.7)

this case of pattern 3, relatively complicated mutual interactions among agents, i.e., fluctuating dynamics are found within 40 sampling instant.

Fig.7 shows the dynamics of the ecosystems with the same symbiotic relations to those of pattern 3 except the initial populations of the species.

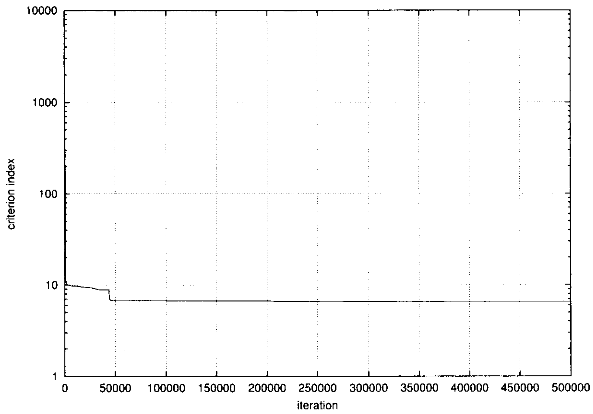
Comparing **Fig.6** and **Fig.7**, we can see that fairly different dynamics are obtained even if only the initial conditions are changed with other symbiotic relations being unchanged.

The dynamics of the populations of the species obtained by the proposed method are approximately described and studied by the following equation,

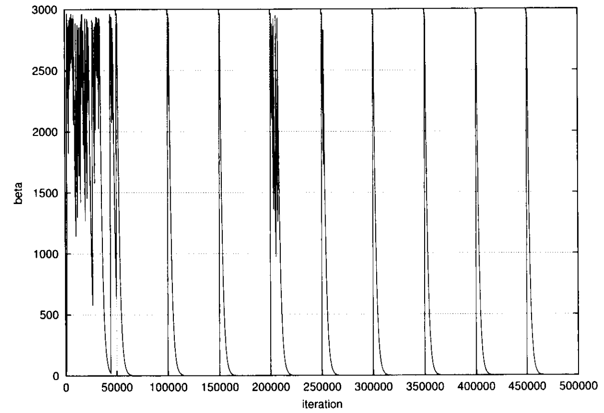
$$\Delta h_j(t) \simeq \sum_i \left(\frac{\partial^{\dagger} h_j(t)}{\partial h_i(t-1)} \Delta h_i(t-1) \right) \tag{9}$$

where

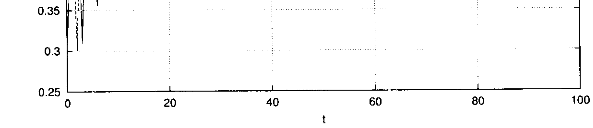
$\Delta h_j(t)$: the difference between $h_j(t)$ and $h_j(t-1)$ $(h_j(t) - h_j(t-1))$



(a) Learning curve of the symbiotic system : pattern 3

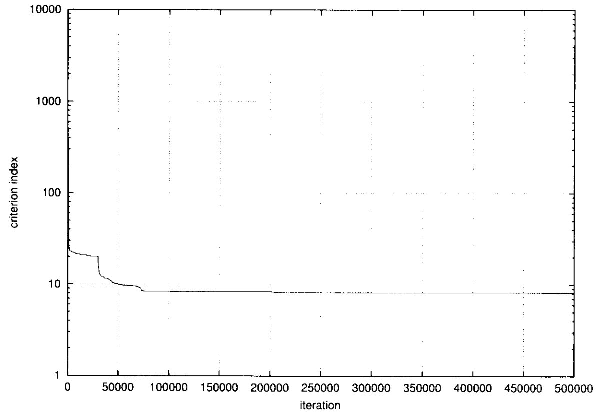


(b) β curve of RasID training : pattern 3

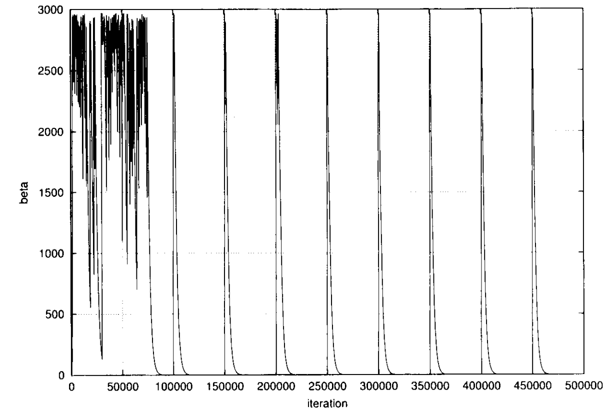


(c) Output values of the agents : pattern 3

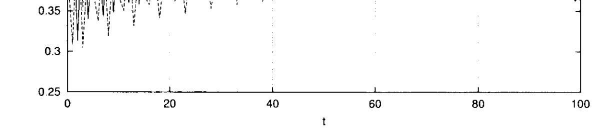
Fig.6 Result of Simulation in the case of pattern 3 (initial value of $h_j(t)$: 0.3, 0.5, 0.7)



(a) Learning curve of the symbiotic system : pattern 3



(b) β curve of RasID training : pattern 3



(c) Output values of the agents : pattern 3

Fig.7 Result of Simulation in the case of pattern 3 (initial value of $h_j(t)$: 0.4, 0.4, 0.4)

Therefore, the increase of the population of species j is determined by the symbiotic relations between species j and other species, and also by the increase of other species from one sampling ahead. It is clarified that all the dynamics of the population of the species described in **Fig.4(c)**, **5(c)**, **6(c)** and **7(c)** approximately follow the above equation. As a result, it becomes possible to investigate how the strength and the type of the symbiotic relations between the species influence the dynamics of the ecosystems quantitatively by using Eq.(9).

From simulation results, it has been proved that the proposed method can give the ecosystem model with more flexible and better representation ability than the conventional methods.

The reason for this is that many kind of symbiotic relations such as exploitation, competition and mutualism are easily introduced to the model, and time varying symbiotic relations are realized by fuzzy inference in the model [26].

5. Conclusion

In this paper a new model of the agents with symbiotic relations is proposed, where the agent is composed of a hierarchical neural network and it's parameters are trained in order to realize the required symbiotic relations.

The required symbiotic relations are described by fuzzy inference, therefore many kinds of and time varying symbiotic relations can be easily introduced into the model.

From the results of the simulations where three species are interacted with each other by symbiotic relations, it has been cleared that the proposed method can give the model with more flexible and more powerful representation abilities than the conventional Lotka-Volterra-like models.

References

1) K. Kaneko and T. Ikegami : Chaostic Scenario for Complex Systems, Asakura-Shoten, 1996
2) K. Kaneko and I. Tsuda : Evolutionary Scenario for Complex Systems, Asakura-Shoten, 1998
3) M. Mitchell Woldrop(translated by M. Tanaka and T. Toyama) : Complex Systems, Shinchou-Sha, 1996
4) A. J. Lotka : Growth of mixed populations, J. Wash. Acad. Sci., Vol. 22, pp. 461–469, 1932
5) Y. Iwasa : Introduction to mathematical biology — Study of the dynamics of biological society—, Kyoritu-Shuppan, 1990
6) H. Teramoto : Mathematical biology, Asakura-Shoten, 1997
7) M. Takesue, K. Hirasawa and J. Hu : Analysis of Lotka-Volterra Ecological System by Fuzzy Inference, Proc. of IEEJ Society Conference of Electric, Information and Systems, pp. 577–580, 1998
8) H. Yoshida, K. Hirasawa and J. Hu : Learning Symbiotic Phenomena between Agents, Proc. of SICE Annual Conference, pp. 819–820,1999
9) K. Hirasawa, X. Wang, J. Murata, J. Hu and C. Z. Jin : Universal Learning Network and It's Application to Chaos Control, Neural Networks, Vol. 13, No. 2, pp. 239–253, 2000
10) J. Hu, K. Hirasawa, J. Murata : RasID - Random Search for Neural Network Training, Journal of Advanced Computational Intelligence, Vol. 2, No. 4, pp. 134–141, 1998
11) H. Matsuda : What is Symbiosis—the third relation between species beyond exploitation and competition—, Gendai-Shokan, 1995
12) P. Werbos : Beyond regression:new tools for prediction and analysis in the behavior science, Unpublished doctoral dissertation, Harvard University, 1974
13) J. S. R. Jang, and C. T. Sum : Neuro-Fuzzy Modeling and Control, Proceedings of the IEEE, vol. 83, No. 3, pp. 378–406, 1995
14) R. L. Watrous : Learning algorithm for connectionist networks: Applied gradient methods of nonlinear optimization, Proc. of IEEE International Conference on Neural Networks, Vol. 2, pp. 619–628, 1987
15) J. Matyas : Random optimization, Automation and Remote Control, Vol. 28, pp. 244–251, 1965
16) E. B. Bartlett : A stochastic training algorithm for artificial neural networks, Neurocomputing, Vol. 6, No. 1, pp. 31–43, 1994
17) S. Kirkpatrick, C. D. Gelatt, and M. P. Uecchi : Optimization by simulated annealing, Science, Vol. 220, pp. 671–680, 1983
18) E. Aarts and J. Korst : Simulated Annealing and Bosltzman Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing, John Wiley and Sons, 1989
19) D. E. Goldberg : Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley Publishing Company, Inc., 1989
20) I. Rechenberg : Evolutions Strategie:Optimierung Technisher System Nach Prinzipieren der Biologischen Evolution, Stuttgart: Frommann–Holzbooz, 1973
21) D. B. Fogel : An analysis of evolutionary programming, Proc. of the 1st Annual Conference on Evolutionary Programming, pp. 43–51, 1992
22) D. Whitley and T. Hanson:Optimizing neural network using faster more accurate genetic search , Proc. of International Conference on Genetic Algorithm, 1989
23) N. Baba : A hybrid algorithm for finding a global minimum, Int. Journal of Control, Vol. 37, No. 5, pp. 929–943, 1983
24) N. Baba, Y. Mogami, M. A. Kohzaki, Y. Shiraishi, and Y. Yoshida : A hybrid algorithm for finding the global minimum of error function of neural networks and its applications, Neural Networks, Vol. 7, No. 8, pp. 1253–1265, 1994
25) C. T. Leung and T. W. S. Chow : A hybrid global learning algorithm based on global search and least squares techniques for backpropagation networks, Proc. of IEEE International Conference on Neural Networks, Vol. 3, pp. 1890–1893, 1997
26) M. Takesue, K. Hirasawa and J. Hu : Modeling for Symbiosis and Evolution, SICE Symposium on Decentralized Autonomous Systems, pp. 433–438, 2000