Artif Life Robotics (2000) 4:42–45

ORIGINAL ARTICLE

Akira Sano

Generating novel memories by integration of chaotic neural network modules

Received: August 3, 1999 / Accepted: August 22, 1999

Abstract A principle of integrating neural network modules based on chaotic dynamics was studied on our two-moduled Nozawa model. Chaotic neural networks represent each embedded pattern as a low-dimensional periodic orbit, and the others are shown as high-dimensional chaotic attractors. This is equivalent to W. Freeman's "*I don't know*" and "*I know*" states. In particular, we noted that the combination of two-way inputs to each neural network module conflicted with embedded Hebbian correspondence. It was found that the interaction between the modules generated a novel "*I know*" state in addition to the embedded representation. Chaotic neural network modules can autonomously generate novel memories or functions by this interaction. The result suggests a functional integration in neural networks as it ought to be, e.g., feature binding and gestalt.

Key words Modularity · Chaotic neural network · Autonomous integration · Hebbian learning

Introduction

Functional localization with a module structure exists in the brain as the cortical columns or areas, and a large number of studies have been made on each individual function. Such functional modularity is effective in several types of internal representation, e.g., parallelization, specialization, and combination. On the other hand, these modules should integrate functionally in order to make the brain work as an information system. What seems to be lacking is *how to integrate the functional modules* into an information processing system.

Several attempts have been made to develop information processing by combining such multiple functional neural network (NN) modules.[1–4] These models have been applied as algorithms or controllers to integrate NN modules. However, the brain autonomously integrates the modules without external controls.

We have considered chaotic dynamics in NNs for integrating network modules. This provides an element of chaos in artificial and real NNs, and is different from the usual programs, e.g., *deterministic noise source, interactive searcher, novelty filter*, and so on.[5–10] Chaotic NN modules are able to both interact and preserve their module structure because they are destabilized by weak perturbations. This interaction between NN modules does not always lead to functional integration, however, although it is known that coupling between chaotic NN modules does not hinder their pattern recall with Hebbian learning.[11,12]

In this article, a two-module chaotic NN model is analyzed for the case where the relation between the modules is inconsistent with the embedded relationship.

Model

Two-module Nozawa model

A chaotic NN model was prepared in order to study the interaction between NN modules. The Nozawa model,[13] which is an artificial NN model having chaotic behavior, is expanded from a Hopfield-type[14] nonchaotic NN model by adding a negative self-feedback connection at each neural element. This was proved to be equivalent to a chaos neural network model.[15]

A modular neural network model is defined based on the Nozawa model to our specifications. A two-module Nozawa model is now described based on the Nozawa model with an external coupling term.[16]

A. Sano[1] (✉)
Graduate School of Informatics, Kyoto University, Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8501, Japan

Present address:
[1]Department of Applied Mathematics and Informatics, Ryukoku University, 1-5 Yokotani, Seta, Ohe-machi, Otsu 520-2194, Japan
Tel. +81-77-543-7528; Fax +81-77-543-7524
e-mail: sano@i.kyoto-u.ac.jp

This work was presented, in part, at the Fourth International Symposium on Artificial Life and Robotics, Oita, Japan, January 19–22, 1999

$$p_i(n+1) = F_{q_i(n)}\{p_i(n)\} \tag{1}$$

$$q_i(n) = \frac{1}{T}\left\{(1-\varepsilon)\sum_{j\neq i}^{N} T_{ij}p_j(n) + \varepsilon\sum_{k=1}^{M} T'_{ik}p'_k(n) + I_i\right\} \tag{2}$$

$$\text{with } F_q(p) = rp + (1-r)\left[1 - \frac{1}{2}\left\{1 + \tanh\left(\frac{p-q}{2\beta}\right)\right\}\right] \tag{3}$$

where $p_i(n)$ is an internal buffer of the i-th neuron at discrete time n, and $q_i(n)$ is the control parameter of the neuron i at n. T_{ij} denotes the connecting weight between the j-th and i-th neurons, and I_i is the threshold value of neuron i.

In eq. 2, $p'_k(n)$ is the k-th internal buffer of the external module, and T'_{ik} is a connection weight from the k-th element of the external module. The parameters ε and M denote the *coupling ratio and the number of coupled elements*, respectively, from the external module.

The constant values $r(0 < r < 1)$ and $\beta(>0)$ are given as

$$r = \left(1 - \frac{1}{R}\right), \qquad \beta = \frac{\alpha}{RT} \tag{4}$$

where R corresponds to the damping constant of Hopfield's model, and T is the connecting weight for the negative self-feedback ($T_{ii} = -T < 0$). So these constants have the values $r = 0.7$, $\beta = 0.006$, $T = 15$ in our computational experiments.

The conceptual diagram of the two-module NN model is shown in Fig. 1 ($N = 2$). In this paper, the intermodule coupling is restricted to one-way (flow-typed) projection, as in Fig. 1, because of previous observations of the influences of intermodule couplings.

Embedded memories

The NN modules of the two-module Nozawa model are called modules I and II (see Fig. 1). Two sets of three vector patterns were prepared for each NN module, $\{C,F,4\}$ and $\{C',F',4'\}$.

The prepared sets of vector patterns were embedded into each module using Hebbian learning.[17] Hebbian learning gives the following relation with the embedding vector patterns, which determines the value of the coupling weight T_{ij} between the neural elements within a module.

$$T_{ij} = \sum_{s=1}^{3}(2V_{si} - 1)(2V_{sj} - 1) \tag{5}$$

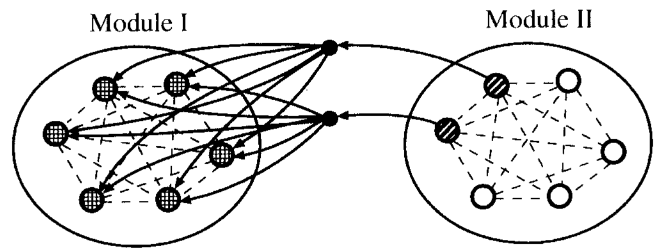


Fig. 1. Two-module (flow-type) neural network model

where $\mathbf{V}_s(= \{V_{s1}, \ldots, V_{s16}\}, s = 1, 2, 3)$ is the vector pattern.

Similarly, the coupling weights between the modules, T'_{ik}, are also given as

$$T'_{ik} = \sum_{s=1}^{3}(2V_{si} - 1)(2V'_{sk} - 1) \tag{6}$$

The vector patterns for modules I and II are written as $\mathbf{V}_s = \{V_{s1}, \ldots, V_{s16}\}$ and $\mathbf{V}'_s = \{V'_{s1}, \ldots, V'_{s16}\}$, respectively. Hence, the intermodule coupling weight T'_{ik} gives the pattern correspondence between modules I and II ($C \Leftrightarrow C'$; $F \Leftrightarrow F'$; $4 \Leftrightarrow 4'$). However, these are restricted unidirectionally from module II to module I.

External inputs

The pattern-recalling characteristics of chaotic NN models are well known from previous studies.[6–8,13]

Without external input, a chaotic NN model recalls wandering embedded patterns. Steady pattern recall is shown with an external input which is an embedded pattern. The Nozawa model also has the same features of pattern recall.

The external input to the two-module Nozawa model is given in eq. 7 to the threshold I_i of eq. 2 according to the simple Nozawa model.[13]

$$I_i = \begin{cases} 0.08T & \text{for } k_i = 0 \\ 0.09T & \text{for } k_i = \text{“nothing”} \\ 0.10T & \text{for } k_i = 1 \end{cases} \tag{7}$$

Let the 16-dimensional input vector pattern be $\mathbf{K} = \{k_1, k_2, \ldots, k_{16}\}$. These constants ($\approx 0.09$) indicate the control parameter $q_i(n)$ where $T_{ij} = T'_{ik} = 0$ in eq. 7. The external input I_i is given so that $q_i(n)$ stays near the chaotic parameter region.

Inconsistent condition

In the two-module Nozawa model, this intermodule coupling does not hinder the pattern recall process of the NN modules as long as the embedded Hebbian correspondence is kept between each NN module.[11,12]

We now focus attention on the more interesting case of the intermodule coupling condition where the two-module Nozawa model does not have embedded Hebbian correspondence with an external input pair, e.g., module I has an external input C and module II has F'. Such cases have an *inconsistent condition* as regards embedded Hebbian correspondences. The inconsistent condition shown in Fig. 2 will now be examined.

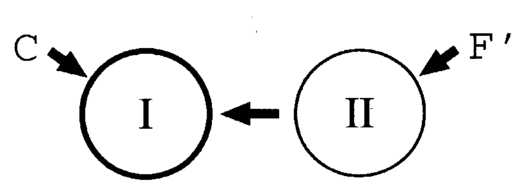
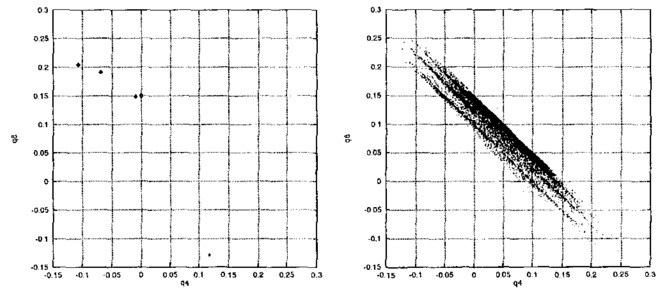


Fig. 2. Inconsistent condition (C–F')



a b

Fig. 3. Internal states of the NN module (q_4–q_8). **a** External input *C*. **b** No external inputs

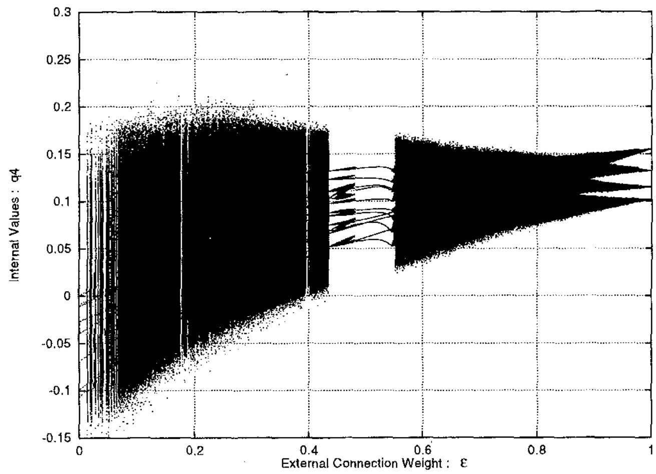


Fig. 4. Bifurcation map of q_4 with external connection weight ε; $M = 3$

Internal dynamics

"I know", "I don't know" states

Figure 3 shows a projection of the internal dynamics with the variables q_4 and q_8 at module I. The internal dynamics of a chaotic NN module are broadly divided into two types. Each embedded pattern is represented as *low-dimensional periodic orbit* (Fig. 3a), and the other cases are shown as *high-dimensional chaotic orbits* (Fig. 3b). The periodic orbits that indicate each embedded pattern are rather unstable, and change to chaotic behavior, as in Fig. 3b, owing to external or intermodule input in the absence of Hebbian correspondences.

These two types of internal dynamics in the chaotic NN module agree well with the role of "*novelty filter*" which is claimed by W. Freeman, based on the rabbit's olfactory EEGs. The low-dimensional attractor (Fig. 3a) means the "*I know*" state for the embedded memories, and the chaotic attractor (Fig. 3b) indicates the "*I don't know*" internal state.

The influence of intermodule coupling

In the inconsistent condition (Fig. 2), the two-module Nozawa model also shows "*I know*" states for the embedded patterns *C* and *F* on module I with extreme intermodule coupling parameters.

The two-module Nozawa model has two parameters, *M* and ε, for the strength of intermodule coupling (in eq. 2). *M* is the number of intermodule coupling elements, and ε is the intermodule coupling ratio. When there are no intermodule couplings ($M = 0$, $\varepsilon = 0.0$), a NN module is equivalent to a one-module Nozawa model. Then, the internal dynamics of module I obey an external input, i.e., they indicate an embedded pattern *C*. In the other extreme case when the modules connect with the strongest parameters ($M = 16$, $\varepsilon = 1.0$), module I has exactly the same intermodule inputs as module II, i.e., they indicate an embedded pattern *F*. Both extreme cases show the low-dimensional "*I know*" states.

However, these will be destroyed in spite of their weak intermodule coupling because these embedded limit cycles are unstable, as mentioned before. Hence, intermodule couplings having no Hebbian correspondence give a chaotic "*I don't know*" state in almost all the *M*–ε parameter space. The NN modules cannot recognize the input pairs which do not satisfy the embedded Hebbian correspondences. Generally, only embedded internal states with Hebbian learning (eq. 5) are recognized by way of their low-dimensional "*I know*" states in chaotic NN modules, and others are classified as "*I don't know*" high-dimension chaotic attractors.

Generating novel memories by intermodule couplings

In the two-module Nozawa model, it was found that intermodule couplings not only gave chaotic "*I don't know*" states, but also generated a few novel low-dimensional "*I know*" states. These novel "*I know*" states were observed in inconsistent conditions.

Figure 4 shows a bifurcation map of the internal buffer q_4 with the parameter ε. Low-dimensional internal states (novel "*I know*" states) appear as the windows over the bifurcation structure, and innumerable windows are shown. However, almost all the windows are limited to a very narrow region of intermodule connection weight ε, and cannot stably exist in opposition to the fluctuation of ε. In Fig. 4, a low-dimensional "*I know*" state whose parameter region ε is near 0.5 is the only stable state.

The low-dimensional periodic orbit which appears over the bifurcation structure can be regarded as an novel internal representation that means "*I know*" in the same sense as embedded patterns in Hebbian learning. However, these novel "*I know*" states do not have any correspondence to external patterns, i.e., the novel representations are generated based only on the relation between the embedded patterns, whose combinations do not have embedded Hebbian correspondences, e.g., *C*–*F* in the inconsistent condition.

The novel "*I know*" representation that is generated by the interaction between chaotic NN modules can be considered as a mechanism to process various combinations between the local representations on each NN module, including nonexperienced ones. This result from the two-module Nozawa model suggests how the brain recognizes an object which it has not memorized. Thus, how the brain accepts inconsistent combinations between functional modules can be explained.

Conclusion

The chaotic NN model shows two types of internal representation, the low-dimensional "*I know*" states and the chaotic "*I don't know*" states. This categorization plays the role of a novelty filter for external inputs, as in Freeman's biological experiment.

The internal representations of our chaotic model are dynamic and interact with external inputs. Hence, the "memories" of the chaotic NN model also seem to be dynamic and interactive, i.e., the memory of a chaotic NN is interpreted as a dynamic process that is generated, destroyed, and modified, and is different from computational memory that is memorized, maintained, and retrieved.

We also found that other "*I know*" states were generated by the interaction between chaotic NN modules. These can be interpreted as novel memories, and furthermore as novel functions in the NNs. This result suggests that the chaotic dynamics of the NNs play the role of an internal mechanism to recognize unknown relations between each module, i.e., an *autonomous integrator*.

To date the two-module Nozawa model is too abstract to represent realistic NNs in the brain. However, our model has not made any assumptions, and is thus sufficiently simple to represent NNs in general.

Even if the functional modules each have individual representation, their interaction is not always represented by their combination. In particular, the internal representation of the NN module which is given by the nonlinear (chaotic) dynamics itself varies with the modular interaction. Therefore, he feature which is binding on the brain is not considered to be merely a process of combining each basic feature if chaotic dynamics exist universally in the NNs of the brain. The brain has multiple functional modules and sensory modalities, and recognizes the world by integrating these features. However, the brain cannot experience and can not learn all their infinite combinations, and we know we will be able to recognize some things which we are seeing for the very first time, e.g., a blue rose. Our results give an explanation, based on chaotic dynamics, of how the brain constructs an internal state by integrating many functional modules.

These multimodule NN models will be useful to examine the internal representations of the brain with nonlinear chaotic dynamics, and may also provide a framework by which to explain how the interaction-based brain works, e.g., the binding problem, multimodal cognition, gestalt, and common sense.

Acknowledgments I wish to thank the Japan Society for the Promotion of Science (JSPS), Research for the Future Program (RFTF), for their generous financial assistance. My special tanks are due to Prof. Osamu Katai and members of the Theory Group of Bio-Informatics for valuable advice.

References

1. Jacobs RA, Jordan MI (1991) Task decomposition through competition in a modular connectionist architecture: the what and where vision tasks. Cognitive Sci 15:219–250
2. Kobayashi N, Iwata A (1993) Multi-module neural network model for higher order association. In: Proceedings IJCNN-93, vol I, pp 233–236
3. Happel BLM, Murre JMJ (1994) The design and evolution of modular neural network architectures. Neural Networks 7:985–1004
4. Gallinari P (1995) Modular neural net systems: training of. In: Arbib MA (ed) The handbook of brain theory and neural networks. MIT Press, Cambridge, pp 582–583
5. Freeman WJ, Skarda CA (1985) Spatial EEG patterns, nonlinear dynamics and perception: the neo-Sherringtonian view. Brain Res Rev 10:147
6. Tsuda I (1992) Dynamic link of memory – chaotic memory map in nonequilibrium neural networks. Neural Networks 5:313–326
7. Adachi M, Aihara K, Kotani M (1992) Nonlinear associative dynamics in a chaotic neural network. In: Proceedings of the 2nd International Conference on Fuzzy Logic and Neural Networks, pp 947–950
8. Nara S, Davis P, Totsuji H (1993) Memory search using complex dynamics in a recurrent neural network model. Neural Networks 6:963
9. Freeman WJ (1994) Neural mechanisms underlying destabilization of cortex by sensory input. Physica D 75:151
10. Ishii S, Sato M (1998) Associative memory based on parametrically coupled chaotic elements. Physica D 121:344–366
11. Sano A (1998) Integrating neural network modules based on chaos, and its pattern recalling and internal dynamics (in Japanese). IEICE Technical Report, NC98–63
12. Sano A, Kunifuji S (1998) Integration of chaotic behavior modules into a flow-typed two-body neural network model. Electron Commun Jpn, Part III, 81(5):41–50
13. Nozawa H (1992) A neural network model as a globally coupled map and applications based on chaos. Chaos 2:377–386
14. Hopfield JJ (1982) Neural networks and physical systems with emergent collective computational abilities. In: Proceedings of National Academy of Sciences USA, vol 79, pp 2554–2558
15. Aihara K, Takabe T, Toyoda M (1990) Chaotic neural networks. Phys Lett A 144:333
16. Sano A (1995) The role of intersubsystem coupling density and chaotic dynamics in multi-body neural network model. In: Proceedings of IIW95, RWC Technical Report TR-95010, RWCP, pp 41–53
17. Hebb DO (1949) Organization of behavior. Wiley, New York