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1. 注目の研究紹介　(J. Tani and S. Nolfi)

● Self-Organization of Modules and Their Hierarchy in Robot Learning Problems: A Dynamical Systems Approach

(Sony CSL Technical Report: SCSL-TR-97-03)
Jun Tani
谷　淳（ソニーコンピュータサイエンス研究所）
Stefano Nolfi (Institute of Psychology, National Research Council 15, Viale Marx　00187, Rome, Italy)

ABSTRACT
This paper describes how the internal representation of the world can be self-organized in modular and hierarchical ways in a neural network architecture for sensory-motor systems. We develop an on-line learning scheme -- the so-called mixture of recurrent neural net (RNN) experts in which a set of RNN modules becomes self-organized as experts in order to account for the different categories of sensory-motor flow which the robot experiences. Autonomous switching between winning expert modules, responding to structural changes in the sensory-motor flow, actually corresponds to the temporal segmentation of behavior. In the meanwhile, another mixture of RNNs at a higher level learns the sequences of module switching occurring in the lower level, by which articulation at a further more abstract level is achieved. The proposed scheme was examined through simulation experiments involving the navigation learning problem. The simulated robot equipped with range sensors traveled around rooms of different shape. It was shown that representative building blocks or ``concepts'' corresponding to turning right and left at corners, going straight along corridors and encountering junctions are self-organized in respective modules in the lower level network. In the higher level network, the ``concepts'' corresponding to traveling in different rooms are self-organized by combining the ones obtained in the lower level into sequences. The robot succeeded in learning to perceive the world as articulated at multiple levels through its recursive interactions.

1. Introduction
How can sensory-motor systems attain the internal representations of the world in structurally organized ways? A consensus in cognitive science and artificial intelligence is that complex worlds would be represented efficiently utilizing modular and hierarchical structures of symbol systems [Newell76, Newell80]. However, it is still not well understood that how such modular and hierarchical representation, if they existed, could be self-organized in analog neural systems from their iterative sensory-motor

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interactions.

The difficulty lies in the question that how the continuous sensory-motor flow can be perceived as articulated into sequences of meaningful representative modules. Kuniyoshi [Kuniyoshi94] addressed this articulation problems in the robot learning context. In his experiment with an assembling robot, the robot recognizes the various task performances by decomposing them into sequences of modular representations. Subsequently, the robot is able to learn various tasks in terms of compositions of the reusable modular representations obtained. For attaining such modular representation, the task performance was temporally segmented by means of detecting ``meaningful changes" in the observed sensory flow. The problem, however, is that the definitions of these ``meaningful changes" were predetermined by designers. Our investigation is of how a robot can define ``meaningful changes" by itself, the use of which allows a task performance to be segmented into reusable modules.

Robot navigation learning, which has a quite long research history, faces the same type of problem. There are basically two types of approach. One is the neural network learning approach. Krose [Krose94], Zimmer [Zimmer95] and Nehmzou [Nehmzou96] showed that for relatively simple workspaces, localization problems for robots can be solved using the topological preserving map scheme [Kohonen82]. It is, however, difficult to scale-up using this scheme since the very plain representation by a single neural network hardly organizes the modular and hierarchical structure of the learned contents at all. The other approach is the machine learning approach, which is used in landmark-based navigation [Kuipers87, Mataric92]. In this approach, the travel of the robot is temporally segmented by means of landmarks such as turning at corners, encountering junctions, or going straight along corridors. This temporal segmentation enables the abstraction of robot experiences into a simple chain representation of these landmark types.The scheme can be scaled-up much more readily than the neural network learning approach since the landmarks play the roles of the representative modules. However, the problem is that the landmark types, which are defined by designers, are not necessarily intrinsic to the perceptions of a robot. The representative modules such as corners, junctions, or corridors, if necessary to the problem's solution, ought to be generated from the robot's experiences.

In this paper, we introduce a novel scheme based on the dynamical systems approach [Beer95, Thelen94] whereby the problems of articulation and structural formation of modules and hierarchy are explained solely by the dynamical systems terms such as self-organization, coherence and phase transition. The scheme has been developed as inspired by a modular and hierarchical learning method using neural nets, namely the mixture of experts proposed by Jacobs and Jordan [Jacobs91]. We have extended this original architecture dramatically such that it can cope with learning of not only spatial patterns but also spatio-temporal patterns which sensory-motor systems are inevitably involved with. The readers will see that the sensory-motor flow are articulated in autonomous manners as modules and their hierarchy are self-organized in our proposed architecture.

The paper introduces the robot navigation learning as a prototype problem; our simulation experiments will illustrate how a set of primitive representative building blocks or ``concepts" emerge and how they construct the ones in the higher level dynamically. Our hierarchical learning is developed as combined with the prediction learning scheme which is described in the next section.

2. Prediction Learning Using Sensory-Motor Flow

Learning to predict next sensation means that the system acquires some analogical models of the target observed. Elman [Elman90] was the first to show that a recurrent neural network (RNN) can learn to predict word sequences by extracting regularity hidden in example sentences. Tani [Tani96] applied the RNN prediction learning to the navigation learning problem. In this scheme, a robot learns to predict encountering sensory sequences according to its action sequences taken in a given workspace. Actually, it was shown that a real mobile robot with a range sensor learned structure hidden in an obstacle workspace from the sensory-motor flow experienced. The structure of the environment was embedded in an attractor self-organized in the RNN by means of the prediction learning. However, a crucial critics in this scheme is that the prediction of sensory input is made in reality in a discrete temporal manner by means of the predefined branching mechanism. Branching plays the role of landmarks and invokes the temporal segmentation of the sensory-motor flow. Our new experiment is to attempt to eliminate these types of predefined mechanisms for temporal segmentation in the hope that the robot itself will find them.

One possible way to implement temporal segmentation of the sensory-motor flow is to focus on the magnitude of its change with time [Billard96]. For example, while a robot travels by following a straight wall using the range image, the image will be almost invariant. However, the sensory-motor state will change dramatically when the robot encounters a corner and starts turning left or right. This rapid change could be used as a signal for the segmentation between the two behaviors of following straight walls and turning at corners. However, the difficulty in this scheme is that the cornering behavior can be segmented several times since the sensory-motor state probably changes rapidly all through the cornering process. It is clear that the change of the sensory-motor state at a single moment provides only partial information about the on-going behavioral process. A specific mechanism is required by which a meaningful time interval of the behavioral process, such as a cornering behavior, can be recognized as a unique event through extracting its specific spatio-temporal structure from the sensory-motor flow.

3. New Scheme

Our new proposal in this paper is to use multiple module RNNs, each of which competes to become an expert at predicting the sensory-motor flow for a specific behavior. The experts achieve their status through learning processes. For example, one module RNN would win in predicting the sensory-motor flow while traveling around a corner; another would win while following a straight wall. The switching between the winning RNN modules actually corresponds to the temporal segmentation of the sensory-motor flow. The essential point in this scenario is that the segmentations take place by means of pronounced changes in the observed dynamical structure in the sensory-motor flow, rather than just temporal differences in the sensory-motor state. These highly pronounced changes correspond to switching between the dynamical functions each of which is embedded in an RNN through having learned the specific sensory-motor flow. One might ask how each RNN can choose to learn its corresponding sensory-motor flow. The speciality of each module is determined during the processes of on-line learning. The competition between the modules during the simultaneous processes of recognition and learning result in generating their specialties. The next section will introduce a new architecture called the mixture of RNN experts which has been extended from the original idea of the mixture of experts first expounded by Jacobs and Jordan [Jacobs91].

3.1 Architecture

Figure 1 shows the proposed architecture for the mixture of RNN experts (MRE) which is used for the prediction-learning of the sensory-motor flow.

Fig. 1(a) shows a hierarchical architecture consisting of two levels; more levels are possible in general.

Each RNN module in the lower level receives the sensory-motor inputs, $X_t : (s_t, m_t)$, and outputs the prediction of the sensory-motor inputs at a time Δt afterwards in the form $X_{t+1} : (s_{t+1}, m_{t+1})$, as shown in Fig. 1(b). The total output of the network is obtained from the weighted average of each output with its associated gate opening at the time g^i_t for all modules. The gate opening is computed dynamically with time using the prediction errors of each module, which are obtained from the difference between the prediction (s_{t+1}, m_{t+1}) and the outcome (s^*_{t+1}, m^*_{t+1}). The gate opens more if its module produces a relatively lower prediction error than the other modules. The module with the lowest error over a suitable time interval becomes the winner. The original work on the mixture of experts [Jacobs91] used a gating network which selected the module with the closest correspondence to the inputs. In our architecture, the module is activated autonomously without the gating network as the result of dynamical competition between all modules over time steps, utilizing on-line monitoring of the prediction errors. The winning module changes from one module to another as the profile of the sensory-motor flow changes with time.

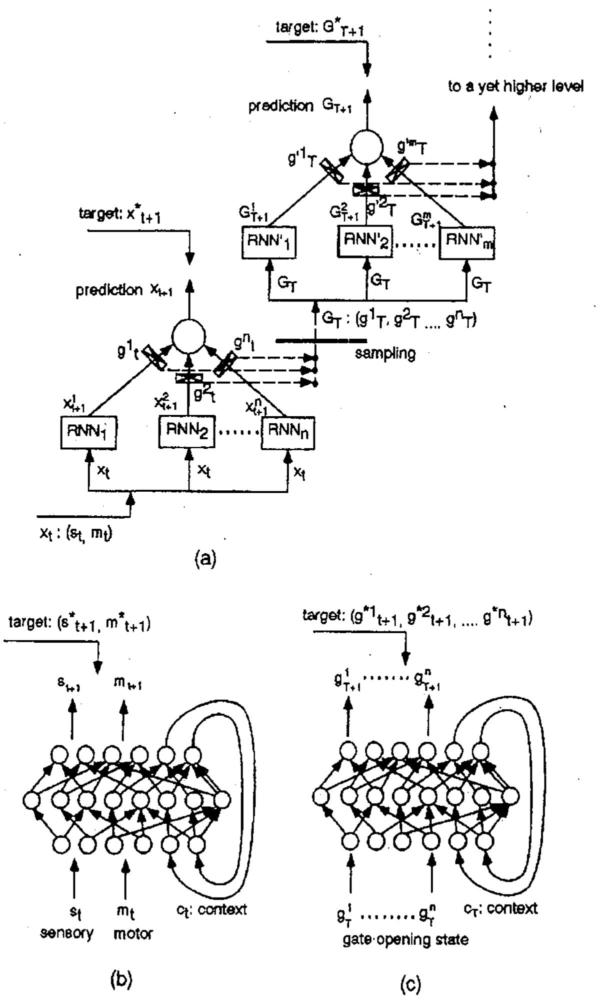

Figure 1: The complete architecture of the mixture of RNN experts for prediction learning. (a) hierarchical learning architecture, (b) details of each RNN module for learning sensory-motor flow in the lower level, and (c) RNN module for learning gate opening dynamics in the higher level.

The higher level network learns the gate opening dynamics of the lower level network. More specificly, each RNN module in the higher level samples the gate opening state of the lower level in the current time step $G_T : (g_T^1, g_T^2 .... g_T^n)$and makes a prediction for the next time step G_{T+1}, as shown in Fig. 1(c). T denotes the time step in the higher level; the higher level sampling interval ΔT is much larger than that in the lower level. The modules in the higher level compete for gate opening g'^i_T, in the same way as shown for the lower level, and the resultant gate opening can be sent to yet higher levels in a recursive manner. The higher level network observes the lower level activities by means of perceiving its gate opening dynamics while the lower level network perceives the sensory-motor flow. In this manner, the signal is ``bottom-up" as abstracted from one level to the next.

3.2 Algorithm

This subsection describes the mathematical formulae for the proposed scheme of the MRE. Suppose a single level network consists of n RNN modules for in general, where x^i_t, y^i_{t+1}, y^{*i}_{t+1}, and g^i_t are the inputs, the outputs, the target outputs for teaching and the gate opening of the i-th module RNN, respectively. x_t and y_{t+1} correspond to the sensory-motor state or the gate opening state depending on the levels of the network.

The ``soft-max" activation function is used to represent the i-th gate opening g^i_t given by:

$$g^i_t = e^{s^i_t} / \Sigma^n_{j=1} e^{s^j_t} \qquad (1)$$

where s^i_t is the current internal value of the i-th gate opening. The total output of the network is y_{t+1}, given by:

$$y_{t+1} = \sum_{j=1}^{n} g^i_t \cdot -y^i_{t+1} \qquad (2)$$

We define the following likelihood function which is maximized for prediction learning; it has been obtained by modifying the original definition of Jacobs and Jordan [3].

$$\ln L \;=\; \ln \sum_{j=1}^{n} g^i_t \cdot - e^{-1/2\sigma^2} \,||\, y^*_{t+1} - y^i_{t+1} \,||^2 \qquad (3)$$

σ denotes a scaling parameter.

Both the weight of each RNN and the gate opening are updated simultaneously such that the likelihood function is maximized. This point is essential for the on-line learning scheme. In order to obtain the update rules for these two processes, we consider the partial derivatives of the logarithm of the likelihood function with respect to the internal value s^i and with respect to the output of the i-th RNN y^i given by:

$$\partial lnL / \partial s^i = g(i/x_t, y^*_{t+1}) - g^i_t \qquad (4)$$

$$\partial lnL / \partial y^i = g(i/x_t, y^*_{t+1}) - (y^*_{t+1} - y^i_{t+1}) / \sigma^2 \qquad (5)$$

where $g(i/x_t, y^*_{t+1})$ is the *a posteriori* probability that the i-th module RNN generated the target vector y^*_{t+1}, in terms of x_t.

$$g(i/x_t, y^*_{t+1}) = \left(g^i_t \cdot e^{-1/2\sigma^2 \| y^*_{t+1} - y^i_{t+1} \|^2}\right) \Big/ \left(\sum_{j=1}^{n} g^j_t \cdot e^{-1/2\sigma^2 \| y^*_{t+1} - y^j_{t+1} \|^2}\right) \qquad (6)$$

where $\| y^*_{t+1} - y^i_{t+1} \|^2$ represents the square of the error of the current prediction. Eq. (4) denotes the direction of update for the internal gate opening value s^i_t. The s^i_t can be obtained dynamically by means of the steepest descent, which consequently determines the current gate opening. The differentiation of lnL with respect to y^i_{t+1} involves the error term $y^*_{t+1} - y^i_{t+1}$ weighted by the *a posteriori* probability associated with the i-th module RNN as shown in Eq. (5). Thus the connective weights of the RNN is adjusted to correct the error between the output of the i-th RNN and the global target vector, but only in proportion to the *a posteriori* probability. By this means, the individual expert RNN which is the expert for the on-going input sequence tends to learn exclusively. The error distributed to each module RNN is:

$$error^i_{t+1} = g(i/x_t, y^*_{t+1}) \cdot (y^*_{t+1} - y^i_{t+1}) \qquad (7)$$

The details of derivations of these equations from Eq. (4) to Eq. (7) should be referred to [Jacobs91].

Upon obtaining the mathematical formulae, the actual update of the gate opening and the connective weights for each RNN are computed incorporating with the back-propagation through time (BPTT) algorithm [Rumelhart86]. In this computation, the sequence of the sensory-motor inputs as well as the gate internal states for last l steps are temporally stored in the window memory. When new sensory-motor inputs are received, the window memory is shifted one step to the forward; the forward and backward computation by means of BPTT are iterated for *nepochs*; finally the l steps sequence of the gate internal states as well as the connective weights for each RNN module are updated. The update for s^i_k, which is the ith gate internal state in the kth step in the window memory, is obtained as:

$$\Delta s^i_k = \varepsilon_g \cdot \partial lnL / \partial s^i_k - \eta_g \cdot (s^i_k - s^i_{k-1}) \qquad (8)$$

The first term in the right-hand side in the equation represents the direction of the update obtained in Eq. (4); the second term represents the dumping term in order to suppress abrupt changes in the gate opening; ε_g and η_g are parameters. This update is computed in the forward direction in the window memory from k=1 to k=l. The error obtained from Eq. (7) is back-propagated [Rumelhart86] through the window memory for each RNN; the update of connective weights are obtained by means of the steepest descent method with parameters of learning rate ε and momentum α.

4 Experiments

4.1 The environment

The scheme proposed above was investigated in the context of the navigation learning problem by simulation. We assumed a mobile robot with a sensor belt on its forward side holding 20 laser range sensors. The robot, upon perceiving the range image of its surrounding environment, maneuvers in a collision-free manner using a variant of the potential method [Khatib86]. (For further details of this maneuvering scheme, see Ref. [Tani96].)

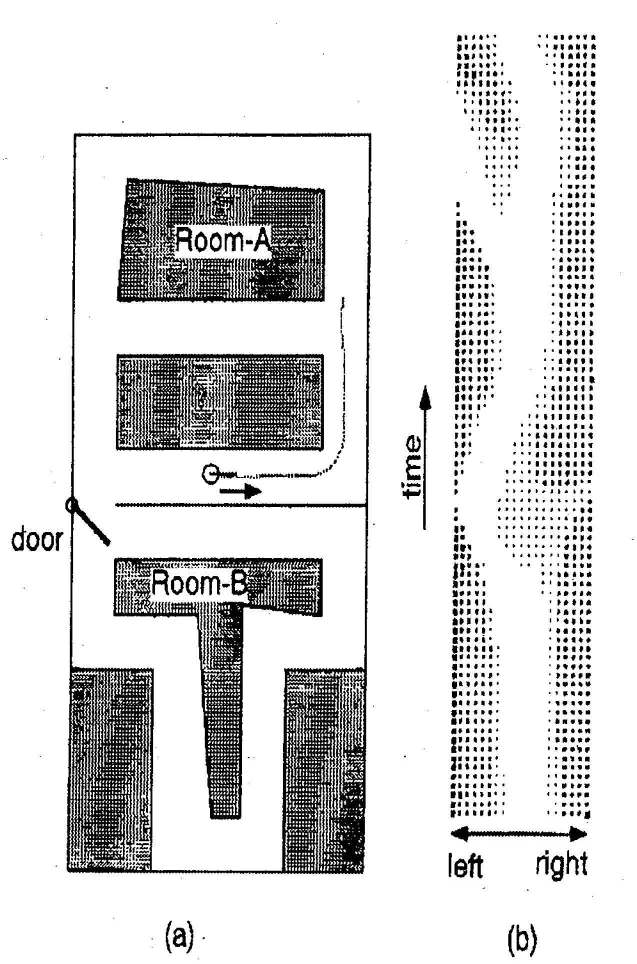

Figure 2: (a) Simulation workspace consisting of two rooms connected by a door. (b) the time development of the simulated range image while the robot traveled.

For our simulations, we adopted two different rooms, namely Room A and Room B connected by a door, as shown in Fig. 2 (a).

Fig. 2(b) shows an example of the sensory-motor flow which corresponds to the robot travel indicated by the dotted line in Fig. 2(a). In this workspace, the robot travels around one room three times, then enters the other room going through the opened door and again travels around the room three times. The on-line learning experiment was conducted while the robot moved between rooms for a total of 5 room encounters. The entire travel of the robot in this simulation took about 2100 Δt steps. The lower level network, which consists of 5 RNN modules each of which has 6 inputs, 6 outputs, 4 hidden units and 2 context units, learns to predict the sensory-motor state in the next step. The higher level network, which consists of 5 RNN modules each of which has 5 inputs, 5 outputs, 4 hidden units and 2 context units, learns to predict the gate opening state in the lower level network in the next step. Other parameter settings for the networks are $\varepsilon = 0.002$, $\alpha = 0.9$, $\varepsilon_g = 0.007$, $\eta_g = 0.02$. These settings are the same for the both levels. The sampling interval in the higher level is 10 times longer than that in the lower level ($\Delta T = 10 \cdot \Delta t$). We observed how modules become self-organized in a hierarchical manner by looking at the gate opening dynamics taking place during the prediction learning of these two levels.

4.2 Results

We recorded gate opening dynamics both in the lower and the higher levels during the entire learning process. Figure 3 shows the time development of each gate opening and of the motor input in the lower level for three different periods.

Fig. 3(a) shows the profiles for the period from step 130 to step 300 while the robot traveled around Room A for the first time. It can be seen that gate4 and gate3 open in turn as the profile of the motor command changes. It was found that the opening of gate4 corresponds to following a straight wall, while the opening of gate3 corresponds to both a left turn at a corner and passing a T-junction. Fig. 3(b) shows the profiles for the period from step 380 to step 550, when the

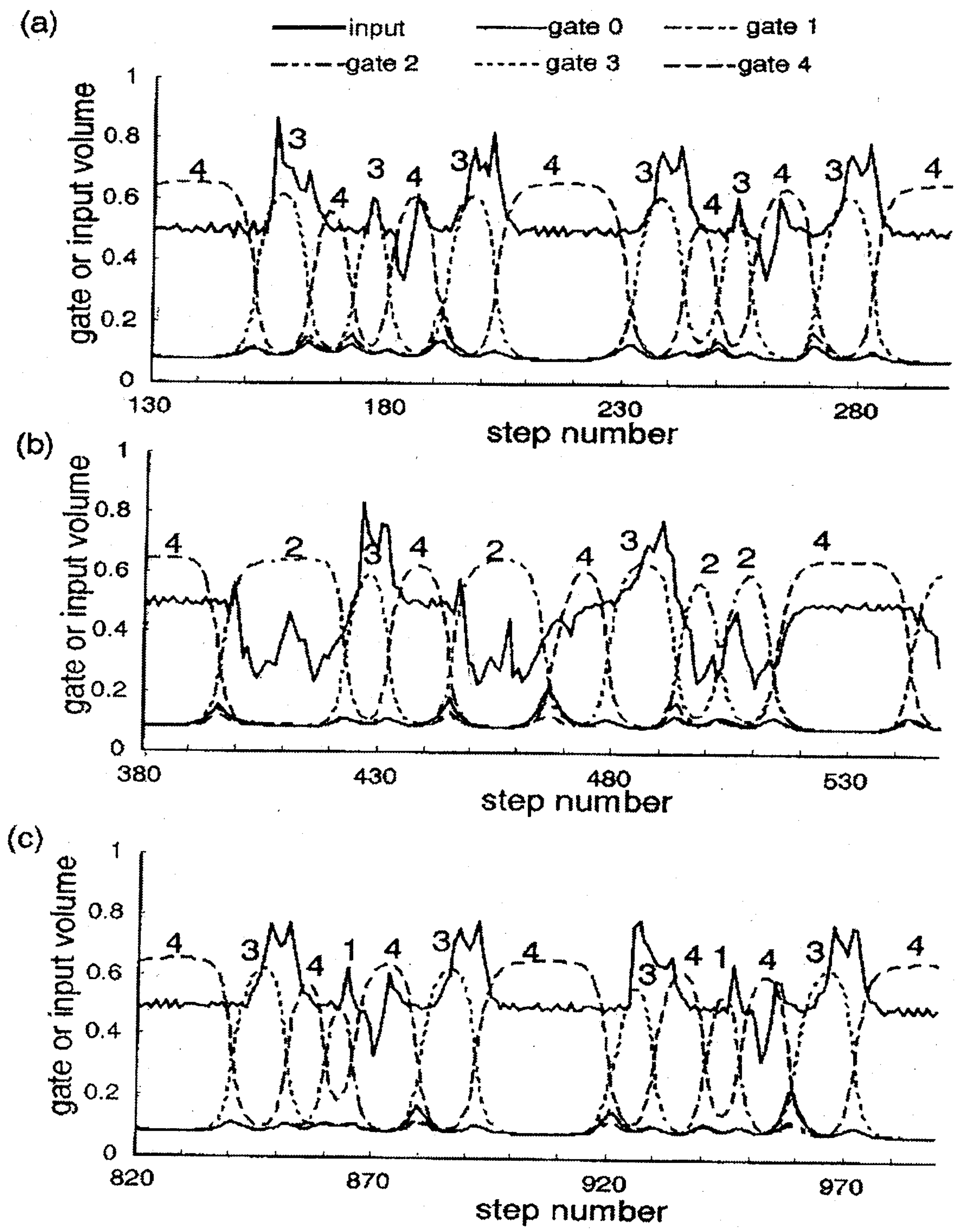

Figure 3: Time development of the opening of 5 gates and of a motor input in the lower level network for three different periods. The number near the data denotes the current winning gate.

robot experienced Room B for the first time. One can see that gate4, gate2 and gate3 open in turn. The opening events corresponded to following a straight wall, making a right turn at a corner and making a left turn at a corner, respectively. Fig. 3(c) shows the profiles for the period from step 820 to step 990, when the robot traveled around Room A for the second time. A remarkable finding is that the gate opening dynamics for this period differ from those observed during the first encounter with Room A. One can see that the opening of gate3, which corresponded to both making a left turn at a corner and passing a T-junction in the previous encounter, now corresponds only to making a left turn at a corner, and that the opening of gate1 now corresponds to passing a T-junction. After this period, the learning processes in the network appear to have stabilized and no further dramatic changes in the correspondence of the gate opening were found. By the end of the simulation, four types of meaningful concepts were generated using 4 RNN modules out of the 5 modules available in the lower level network. An important observation is that the process of generating concepts is totally dynamic in the sense that the correspondence between the RNN modules and their associated behavior is not static during the on-line learning process.

Next, we describe the gate opening dynamics in the higher level network. Figure 4 shows the opening of the 5 gates and the mean square prediction error for the whole period of on-line learning. (The step number in this graph denotes the sensory-motor step number of the lower level, for clarity.)

One can see that the error in the initial period is relatively high. The error becomes smaller on average after step 800. During this period the stable switching of the gate opening between gate4 and gate1 is observed. This switching actually corresponds to the movement between rooms during the travel, where the open state of gate4 and gate1 correspond to travel in Room A and in Room B, respectively. We observe that gate0 opened only in the beginning while the robot traveled in Room A for the first time. The dynamic replacement of module0 by module4, for representing Room A took place because the module representation in the lower level network also changed, as we have seen. It is readily understood that the dynamics in higher level network can be stabilized only after stabilization occurs in the lower level network.

From these results, we conclude that the proposed MRE architecture was successful in learning about the environment in a hierarchical way through the sensory-motor interactions of the robot. The lower level network learned to predict the row profile of the sensory-motor flow by organizing the modular representation of specific

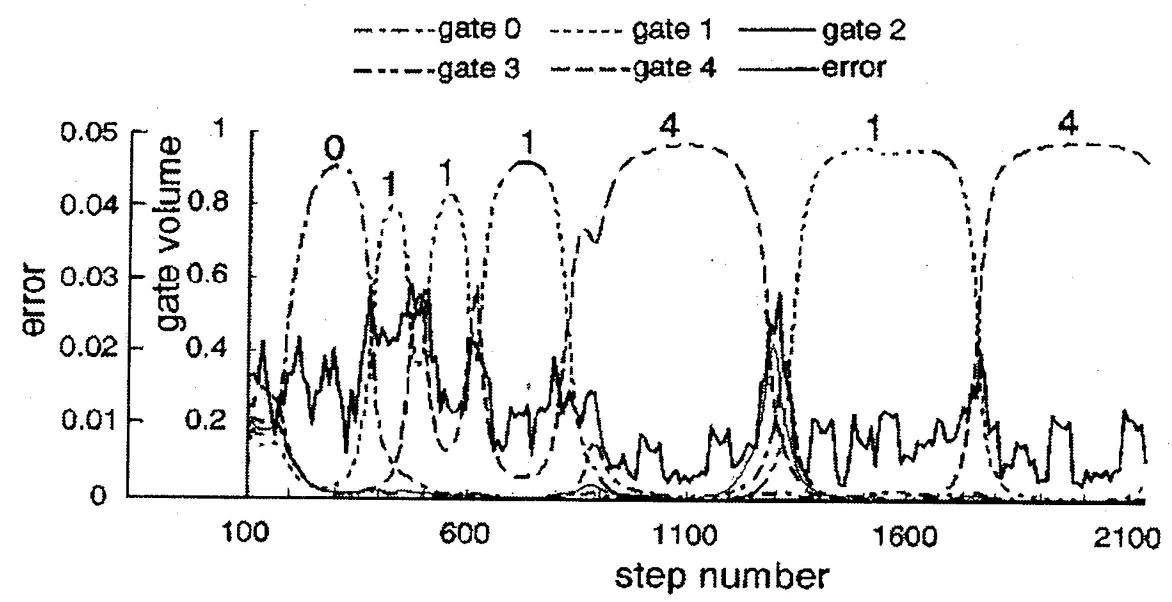

Figure 4:Gate opening dynamics and mean square prediction error in the higher level network during the whole process of learning.

behavior. The higher level network did likewise for the sequences of segmented behavior by creating the higher concept of a room. Therefore, it can be said that the robot is not just perceiving the current sensory-motor flow but it is also recognizing its background context of its behavior and situation.

We repeated this learning experiment for five times with varying initial conditions including the starting position of the robot in Room A and Room B and randomly set initial connective weights of the networks. First, by looking at structures self-organized in the higher level network in these five experiments, equivalent module structures to that in the previous results, representing Room A and Room B, were found in three cases out of five. Then, we observed the lower level structures for these three cases and found that the equivalent module structures to the previous result appeared in two cases and different ones did in one case. In the two cases where we could not see clear module structure corresponding to two separated rooms in the higher level, it was observed the lower level structures continued to change gradually by which the higher level structures could not be stabilized globally by the end of the simulations. The stability in the higher level substantially depends on that in the lower level. These results revealed that the self-organization processes are not always promised to reach one optimal solution. They could generate unstable and non-optimal structures with diversity by chances. We will analyze further this ``stability and diversity" problems in this hierarchical learning scheme in future.

5 Discussion

We have seen that building blocks for representing specific sensory-motor structures are self-organized in the lower level; then the building blocks in the higher level do as combining those in the lower level. The results may be interpreted as being the emergence of internal ``symbols". However, the definition of our ``symbols" is quite different to that used in traditional AI studies. The ``symbols" in our scheme are articulated not by the external designer's views but by the view intrinsic to the robot through its own experiences. In fact, the articulation emerges through the interactions between the system and its environment. Here, the mechanism for this articulation is best explained by dynamical systems language. In our previous work [Tani96], we have studied how the RNN prediction process can be *situated* in the environment through its sensory-motor experiences. Our analysis showed that the prediction process goes well when a coherence is achieved between the internal RNN dynamics and the environmental dynamics. The entrainment [Endo78] of the RNN dynamics by the sensory-motor flow can take places when the RNN learns to share the same dynamical structure with that of the environment. The same mechanism can explain the autonomous selections of modules shown in the current study; one module is activated in a mutually inhibitory manner by achieving its coherence with a specific dynamical structure hidden in sensory-motor flow. When the essential dynamical structure in the sensory-motor flow changes, the current activated module loses its coherence with the flow while another module is activated gaining its coherence with the one. This activation switching takes places in a rather quick move by means of the winner-take-all dynamics defined on the gate opening dynamics. This quick state changes in terms of phase transitions actually result in the articulation which the system internally perceives for the structural changes in the sensory-motor flow.

Another important aspect which should be discussed is the relationship between state and function in the hierarchical learning. The direct observation of the sensory-motor state provides only non-robust information about its present process since the state can evolve in many ways. What should be focussed on is rather the spatio-temporal structure hidden in the time development of the state, since such structures could be consistent in many cases even when the state changes quantitatively. The RNN, which is basically an adaptive type dynamical function, is used for capturing such consistent structure from the observed time development of the state. This time development of the state is, eventually, represented by one of the RNN functions. The higher level observes that which RNN function is currently activated in the lower level in terms of its gate opening state. This gate opening state can vary as the result of structural change in the lower level. The resultant time development of the gate opening state is again captured by the RNN functions in the higher level. Here, we see that the aim of the hierarchical learning is to organize such recursive chains from the state to the function, and from the function to the state, through the level of abstraction.

Some previous researches are related to our study. Gomi and Kawato [Gomi93] showed that modular representation are self-organized for manipulated objects in the mixture of expert networks with a gating network through the sensory-motor interactions. The study, however, was not extended further to the problems of articulation and hierarchy in our ways. Jordan and Jacobs [Jordan94] developed further the original architecture of the mixture of experts in order to cope with some hierarchical structures. The hierarchy in this study refers to the structure of recursive function approximation in multiple layers, of which formations are not directly related to our problems that how articulation along time take places across multiple levels.

The proposed approach can be developed in many ways in the future. Our example shown in this paper was limited in the prediction learning of the sensory-motor flow. One missing point is that the scheme does not include motor or action-learning mechanisms. The scheme should be extended to cover both prediction-learning and reinforcement-learning to ensure that ``concepts" can also be self-organized for the purpose of action generation. Another missing point is that all the interactive processes were undertaken only through the bottom-up pathway in this architecture. More plausible model is that the top-down processes interact with the bottom-up ones such that a module is activated by manas of bi-directional interactive dynamics between the top-down prediction from the higher level network and the bottom-up signals from the lower one. In future research, we will study how goal-directed behavior can be generated in the extention of the proposed scheme by investigating these missing points.

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2．第２回シンポジウム「脳の適応的変化：記憶の形成制御」印象記

泰羅雅登（日本大学・医学部・第一生理）

１月最終週は、未来開拓研究のシンポジウムに始まり、重点研究の班会議、重点研究シンポジウムと、忙しい、しかし、知的にも身体的にもリフレッシュできた１週間であった。シンポジウム会場で木村先生から「印象記を書いてください」とにこやかに依頼された時には、内心、前日の班会議後の気の置けない連中とのアフターミーティングを悔やんだ。また、すぐに書けばいいものを、将来の怠け癖で、時間がたってから講演のメモをもとにまとめたので、ひとまず、言い訳をしておきます。

シンポジウムは、前半３題は神経生理系の先生がお話をされ、後半２題は工学系の先生がお話されたが、前半後半で結構、聴衆に入れ替わりがあるように思われた。

最初は東北大学の山鳥先生の講演で、前頭葉が記憶に果たす役割を人での前頭葉障害例から考察された。前頭葉障害は基本的には記憶そのものを障害しないと考えられている。講演では前脳基底部健忘、重複記憶錯誤、習慣性行動の突出、自伝記憶障害、喚語困難の症例を示され、これらの症状が、前頭葉の障害による、アクセスして再生した記憶の時間、空間的再構成、照合、評価の障害、アクセスのストラテジーの障害として解釈できることを示唆された。酒田先生も質問されたように、近年、PET、fMRIの研究で左右の前頭葉が記憶の形成と、読み出しに特異的に機能しているとの報告があり、トピックスになっている。しかし、ヒトの症例から同じ結果を見いだすのは難しいように思われる。山鳥先生も述べられたが、機能が回復する症例も多くヒトの障害例から責任病巣を決めるのは慎重でなければならないであろう。

とはいうものの、高次脳機能、特に連合野を研究している研究者にとって、ヒトの障害症状はきわめて有用な情報で、研究テーマを考え、サルのタスクを考えるとき、まずヒトでの症状をもとに考える（以前に東大の宮下先生がRolls先生と海馬の研究を始められるに当たって、海馬の障害症状を詳しく検討されて、課題を組んだという話を伺ったことがある）。われわれも優れた歴史的なneurologyの教科書は手放せないが、教科書に記載されている症例は典型例だけであり、普段患者に接してみえる先生方とのディスカッションはきわめて示唆に富んで有用である。日本でも、PET、fMRIの仕事が盛んになりつつあるが、この領域で優れた仕事をするためには、ヒトを対象として研究しているneurologist、psychologistの参加がぜひ必要であり、日本ではこの点がまだ立ち後れているように思う。今後、この方面での研究ネットワークの設定が是非望まれる。

酒田先生はオリバーサックスの「火星の人類学者」に登場する記憶から実景と違わぬ絵を描く画家のお話からはじめられ、最近の我々の研究室のデータを紹介された。最近の我々の教室のデータは頭頂間溝外側壁の後方部分でLIP野とV3A野との中間の領域（cIPS領域）が視覚対象の三次元的特徴の情報処理を行っている可能性を示している。視覚刺激をＣＧで作成し、立体視ディスプレイに呈示する方法で、細長い物体の三次元的な軸方向、三次元的な面の傾きに選択性をもつニューロンを詳しく調べている。面の傾きの識別にはいろいろな手掛かりがあるが、この領域のニューロンは透視画法に従った輪郭の情報や、視差信号でも傾き視差、幅視差、視差勾配など、種々の手掛かりを統合して面の傾きをコードしていことがわかってきた。これらの結果は三次元視覚情報の階層的な処理システムが頭頂連合野にある可能性を示している。MarrがVisionで提唱した３次元モデル表現形成の理論で軸と面の傾きの認識が重要であると述べており、我々のデータは彼の理論を支持していると考えている。外山先生、小松先生からは今後の研究に大変参考になるコメントを頂いた。

次の講演は京都府立医大の外山先生であった。最近の先生の興味は発生、神経回路の構成に移っておられるようで、今回の講演も発生・発達に関するものであった。特に、層状構造の形成が神経活動に依存しない、先天的な物であることを、外側膝状体の移植や外側膝状体と皮質視覚野との共培養標本のデータから示された。また、柱状構造は神経活動に基づく学習課程により形成される後天的な構造であり、発達期タイプのＬＴＰとの関連をお話された。

成長発育に関しては津本先生を代表者とする別の重点領域研究が走っている関係で、以前の重点研究でよくお目にかかった先生方とお話をする機会が少なくなり、勉強不足になりがちである。神経回路網の形成はその機能を語る上で欠かすことので

きない要因であり、合同の研究会があってもいいのではないと思われる。

東海大学の深井先生は大脳基底核をモデルとされて、一度ため込まれたデータが時間的な順序で読み出されるモデルのお話をされた。

運動のプログラムという言葉がよく使われるが、実際の脳内でプログラムがどう表現されているかまだわかっていない。最近、操作運動に関してRizzolattiのグループは腹側運動前野に基本的な運動パターンをコードする細胞を見つけvocabularyと呼んでいる。異論を挟まれる方は多いとは思うが、仮にこの細胞がある運動パターンを指令するなら、その指令によって運動パターンに関係した個々の筋肉の適切な発火パターンがどこかにプリセットされ、それが適宜読み出されていくというのはありそうな話である。深井先生のお話はこのような状況を想定されているのだと解釈し、大変興味深く聞かせて頂いた。

ただ、そうであったとしても、個々の筋肉の活動パターンがセットされる場所の候補は大脳基底核だろうか。筆者は一次運動野の局所回路にもまだその可能性はあるような気がする。

あと、一つ気になったのは、（間違っていたらごめんなさい）蓄えられているパターンが、一定のペースメーカーで作られたトリガー信号で読み出される仕組みになっていたように記憶しているが、むしろ、トリガーは任意の時間に入って来て、たとえば、あるフェーズの終わりに視覚、深部感覚、体性感覚など末梢からのフィードバックの信号が入力し、次のパターンを起動すると考えたほうがより魅力的に思えるのだが。

東大の金子先生はカオス振動をする要素が相互作用しながら集団を形成し、その集団が動的に変化していく現象をお話しされた。すなわち個々の要素がカオス振動しながら相互に作用している系を作ると、はじめ同じ振動をしていた各要素がそのうちに違った振動を始め、振動が同期しているもので集団を作る。そしてしばらくするとまた別な要素同士で集団を作り、時間ともに集団がどんどん変化して行く。この現象が生物の多様性、進化のモデルとして扱えるのではないかというお話は、聞いていて大変興味深かった。

先生ご自身も話しておられたが、この現象と脳の話がどう結びつくのか、まだ不明な点が多いように思う。最近の研究によれば海馬のCA3の細胞の膜電位がバースト時にカオス的な振る舞いをすることが確認されているようなので、意味のある局所回路の形成（自己組織化）において、何らかの関連づけが出てくるかもしれない。

最後に、シンポジウムの印象記とは話がそれるかもしれないが、最近ではモデル（理論）を研究されている先生方の間では、脳での情報表現の基本は集団表現であるという考え方が一般的になっていると思われる。ただ、「集団を形成する個々のニューロンは均質」とは考えてほしくない。確かに最近Vaadia達が示した例はその可能性を示してはいるが、ほとんどの神経生理学者はいろいろな領野で個性のあるニューロンを探して、記録し、その性質を調べている。個々のニューロンがある性質を表現するにあたって、何らかの個性を持っているということに反対する研究者はいないであろう。セルアッセンブリーを強調されている櫻井先生も「単一ではなく、何らかのニューロン集団が協調的に働くことによって情報を表現するという、集団的表現（集団的符号化）をどうしても考えざるをえなくなる。ただし、ここでの集団という言葉は、個々のニューロンが無個性で均質であり集団となってはじめて意味を持つ、ということではない。<u>ニューロンが個性的であることは十分わかっている。それら個性が集まり協調することで、特定の情報が表現されるということである</u>」（岩波「科学」66:784-792より抜粋、下線は筆者）と述べている。個々のニューロンの持つ個性を無視したようなモデル、理論に、納得しがたいものを感じるのは僕だけだろうか。（手助けしてくれた友人諸氏、AN、AMT、AMI、AKNに感謝します）。

岡田真人（科学技術振興事業団・川人学習動態脳プロジェクト）

80年代初期に連想記憶モデルが再評価され、多くの理論物理学者が神経回路モデルの研究に参入してから約15年がたった。そのうち多くの研究者は人工神経回路モデルの汎化特性等の学習理論へ研究分野を移したが、そこで先駆的な役割をはたした研究者の一人であるD.J. Amit (Roma大、Hebrew大)は、宮下先生(東大医)の仕事に多いに影響を受け、最近では自身の研究室でサルを飼い実験までしているという話を聞く。この事が直接そうさせたとい

うわけではないが、今回の－記憶の形成制御－というタイトルにひかれて、シンポジウムに参加した。ここでは、その日行われた5題の講演を要約する。

東北大の山鳥先生は「前頭葉と記憶」というタイトルで、具体的な臨床のデータをもとに前頭葉による記憶の制御について解説された。前脳基底部健忘症候群では再認の成績は良い事から個々の記憶事象は破壊されていないが、強い作話が起こる事から記憶事象間の時空間構造が破壊されていると推測される。その他、重複記憶錯誤や自伝的記憶障害等の臨床例の知見から、前頭葉は、把持されている記憶へのアクセスと、アクセスして再生したものの評価、特に再生したものと環境情報の照合や再生したものの時間・空間的な構造化に役割をはたすという結論を出された。京大の船橋先生の質問にもあったように、ストアされている記憶に前頭葉がアクセスする場所や経路がはっきりしてくれば、新たな進展が期待されるように思えた。

日本大の酒田先生は「視覚的世界の認知と記憶」というタイトルで、頭頂葉における短期記憶について解説された。まず視覚的運動失調や半側空間無視の例から、頭頂葉が立体感の認知に重要である事を示された。次に種々のステレオグラムについて遅延見本照合課題を用いた頭頂葉に関する実験結果を紹介された。遅延期間中に発火を持続する細胞が約1/3存在する事から、
頭頂葉においても短期記憶に関する細胞が存在すると結論された。またこれはGoldman-RakicらやNakamuraらの前頭葉での短期記憶保持に関する細胞の応答特性と似ていることから、頭頂葉と前頭葉との相互結合の重要性を指摘された。座長の理研の仁木先生の質問にもあったように、これら異なった領野で挙動が似ている細胞を同時測定し、その相違点を明確にする事が重要であろう。またそのための実験技術にも目処がついているようで、これから理論家にとって目の離せない状況になっていくように感じた。

京都府立医大の外山先生は「記憶のシナプス機構」というタイトルで、大脳皮質の発達における層状構造と柱状構造の形成の形成ついて解説された。まず脳のシナプス数と遺伝子の情報量を比較して、大脳皮質の発達に学習が必要なことを示された。大脳皮質の層状構造はの形成は遺伝情報に依存しており、柱状構造は学習に依存していること指摘された。LGBからIV層への結合とV層からのLGBへの結合の形成が視覚野だけによらないことを共培養の方法を用いて示された実験には感動を憶えた。学習のメカニズムに関して、Slow LTPとfast LTPが存在し、それぞれの分子メカニズムも異なり、slow LTPは発達期に、fast LTPはアダルトでの学習課程に主要な働きを持つ事を示された。

東海大の深井先生は「時間パターンによる記憶情報表現」というタイトルで、先生の提案された大脳基底核のモデルについて解説された。このモデルは大きく分けて二つのモジュールからなる。一つは運動系列に対応する時系列を記憶する部分で、この時系列は前頭葉を想定した皮質に、Lismanの海馬のモデルの二重振動モデルを用いてストアされている。この回路の想起過程は数10msecであるので、これを実際の運動の時間スケールに変換する為に視床でのウィナーテイクオール(WTA)回路とそれに付加された線条体→淡蒼球→視床のループを持つ回路を提案された。このループにより運動終了まで前段の回路で想起された事象を保持する事が出来る。運動終了時にはリセット信号によりこの閉ループは解除され、WTA過程を経て次の運動に移る。GABAの時定数等も考慮されており、出来るかぎり現実に即した構成論的なモデルである。先生の物理学者としてのバックグラウンドが感じられ好感を持った。

東大の金子先生は「分化、内部表現、集団安定性:相互内部ダイナミクス系アプローチ」というタイトルで、先生が提案された大域結合写像モデル(GCM)について解説された。まず先生の御自身の立場を総¥成論的アプローチによる普遍的論理の抽出窒ニ名づけられた。このような立場から提案されるモデルは、少なくとも神経科学においては、モデルをもとに実験する計画する程には具体性がないと評価されているように思える。その点から考えて、私は金子先生の立場でどの程度生物学なり神経科学に寄与が可能であるかに大変興味がある。

昨年末にモデル系の国際会議であるNIPSのComputational models of episodic memory and hippocampal functionというワークショップに参加した。そこで、臨床データや非侵襲計測等の実験データが豊富に得られているわりには、モデルは相関型連想記憶モデルの枠組から出ていないように感じた。しかし今回このシンポジウムに出席して、若干停滞気味に思われる記憶系の神経回路モデルにも新たな進展が期待されるように思えた。

3．お知らせ

(1): 重点領域研究班の活動も２年目を終えます。前号でお知らせしましたように、昨年１０月に行われた文部省ヒアリングではこれまでの成果に高い評価を得たものの、今後の活動に幾つかの課題点も指摘されました。班構成員の皆様のご研究の今後のますますのご発展を期待します。

(2): 研究成果の発表の際には、Acknowledgmentに研究課題番号を忘れずに。計画班員は各班の研究代表者からお知らせのあった課題番号を、公募班員はご自身の課題番号をおつけ下さい。ちなみに重点領域による助成はGrant-in-Aid for Scientific Research on Priority Areas、文部省は The Ministry of Education, Science, Sports and Cultureです。

(3): 所属・連絡先の変更は実行委員会（委員長、大阪大学 健康体育部　木村　實、e-mail: h63429@center.osaka-u.ac.jp、FAX: 06-850-6030)までお知らせ下さい。