EMERGENCE OF RECOGNIZED SPACE IN RAT NAVIGATION —A NEURAL NETWORK MODEL OF THE SHORTCUT PROBLEM

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ABSTRACT

It is known that rat can take a shortcut even if it was an inexperience path for the rat. In this paper, we present a neural network model that associates a goal and selects a shorter path in a given maze even if the model has only experience of a roundabout route. The model learns relationships of egocentric views on one or more environments by the recurrent network, which equipped with the neurogenesis. When the model meets with a novel environment, this relationship is utilized for placing the self in the space and associating a goal through a shortcut.

Key words: navigation, neural network, shortcut, neurogenesis.

1. INTRODUCTION

It is known that rat is able to solve navigation problem. For example, a rat can choose a shorter way in an unfamiliar environment, even if it is inexperienced way for the rat (Tolman *et al.*, 1946). In case the information on the environment is incomplete for the rat, it is considered that the rat infers goal direction from utilization of the character of the space that was acquired by the rat through experiencing various environments, i.e. cognitive map (Tolman, 1948), and chooses a proper passage.

According to Trullier *et al*'s reviews about biomimetic navigation models (Trullier *et al*, 1997; Trullier and Meyer, 1997), such performance on spatial tasks of rats is called "metric navigation". Because metric navigation needs some allocentric information on distances and angles between places, almost all models use vector manipulations and coordinate frames that are implemented *a priori* in those models. In this paper, we define "coordinate system" (or "map") as some system by which the metric navigation (shortcut) is possible.

But, do real rats have 2D maps by nature? Although rats have their eyes opened and began exploratory behavior in 14 days after birth (Bolles, R.C. and Woods, P.J., 1964), it is estimated to be 21st day after which spatial learning has began (Raunch, S.L. and Raskin, L.A., 1984).

On the other hand, recently the study of neurogenesis of adult animals has developed rapidly (Kempermann, G. and Gage, F.H., 1999). Neurogenesis means the generation of neurons in brains. In case of rats, the hippocampus is known as the field where the neurogenesis happens (Altman, J. and Das, G.D., 1965). It would be especially happened in a novel environment enriched with many attracting materials for rats (Kempermann, G., Kuhn, H.G. and Gage, F.H., 1997). Moreover, it is widely noted that the hippocampus forms the cognitive map (O'Keef, J. and Nadel, L., 1978).

So, we present a neural network model that forms a coordinate system through experiencing some environments by introducing the neurogenesis and predicts a goal direction. The emergent process of the coordinate system is interesting for understanding the principle of information processing of the brain. Moreover, wide application of such global optimality system is expected.

2. MODEL

2.1 Global Structure, Information Flow, and Shortcut Strategy of the Model

As illustrated in Figure 1, the model is composed of 4 layers and one reward cell. Each layer consists of cells, which are modified into forms suitable for functions of each layer. The V-layer represents view from the model

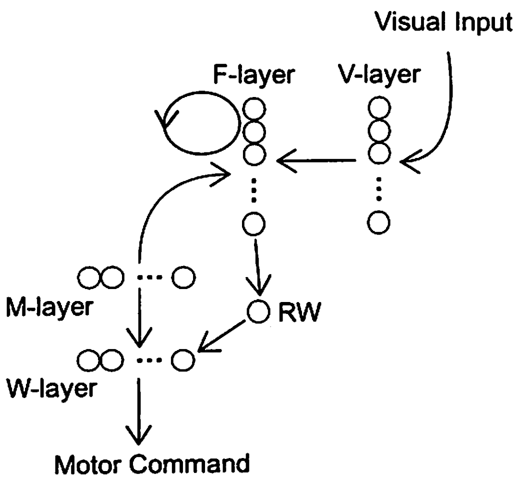


Fig. 1. Structure of the model

(visual information). The V-layer connects to the F-layer. When the model meets with a novel environment, connections between the V -layer and the F-layer are reseted. The F-layer makes recurrent connections between activated cells to memorize time evolution of activities of cells in the F-layer. Moreover, when the total input from the V-layer and the F-layer to the F-layer is under the threshold, the F-layer causes neurogenesis. As neurogenesis, we make the model generate a new cell in the F-layer, connect with activated cells between the V-layer and the F-layer, and extinguish not very used cell in the F-layer.

The M-layer is constructed from motor neurons. Each motor neuron is encoding egocentric direction (i.e. a movement to the forward, the left etc). In addition to that, activities at the M -layer provide constraints for selecting recurrent connections between cells in the F -layer. Because
the model has recurrent structure, it can have two modes. First is a learning mode, which constructs a coordinate system and establishes a relationship between a given environment and the coordinate system. Second is a reflection mode, which generates an adequate prediction of the goal through a closed loop in the F -layer. At the learning mode, the model relates a view of a previous position to a current view with a recurrent connecti on in the F-layer. Then, the model propagates activities in the F-layer from a current view at the reflection mode and associates a goal by activating the RW cell, if there are connections with activated cells of the F -layer. After propagation of activity, the model returns to the learning mode, turns its head and relates the view of the previous position to the current view. This relating is continued until the model finishes all views of the current position.

At the reflection mode, the W-layer receives activities from the M-layer and the RW cell. Each neuron in this layer memorizes activity of the RW cell at individual egocentric direction. Then the model moves in a direction that has highest value of cells in the W-layer. If the value is under threshold, the model selects a direction at random. After one step movement into the selected direction, the model changes the mode into the learning mode and repeats relating and propagating of activity.

In this way, the F-layer successfully memorizes topological r elationships between views. Since recurrent connections in the F -layer remain as it is throughout environmental changes, although connections from the V-layer to the F-layer are reseted at each environmental change, time evolution of activities of cells in the F-layer converges to a certain pattern. That pattern is stable to environmental change. So, the topological representation on the F-layer becomes more abstract, and it enables metric navigation. So, this abstract representation corresponds to the coor dinate system.

In a similar manner as Schmajuk and Thieme's model (1992), our model turns its head towards each direction, looks corresponding views, associates the goal by the recurrent network of the F-layer and concludes which direction activated the R W cell most strongly. However, we add a new function as neurogenesis to the model, and Schmajuk and Thieme's model assumes place cells. Because emergence of coordinate system from egocentric information is our current interest, it cannot prepare place cells *a priori*. Moreover, since information flowing in the model becomes more abstract, the model can apply the same network to various environments and orient towards the goal even if the environment is novel for the model. If the concluded direction is possi ble to move to, the model steps into the corresponding path.

2.2 Simulation Protocol and Formal Description of the Model

Step 0. Initial condition

Decide the total number N_F (=300) of neurons of the F-layer and N_V (=250) of the V-layer. The total number of neurons of the M-layer and the W-layer is 8, equal to the total directions. The output of the i-th neuron of the F-layer, Y_F^i, is 1 if $i=i_0=N_F$, and 0 otherwise. As initial values, connections from the neuron j of the V-layer to the neuron i of the F-layer, w_{FV}^{ij}, are random values between 0 and 0.1 ($\forall i, j$). Connections from the neuron j of the F-layer and the neuron k of the M-layer to the neuron i of the F-layer, w_{FFM}^{ijk}, are 0 ($\forall i, j, k$), and connections from the neu ron i of the R-layer to the RW cell, w_{RF}^i, are 0 ($\forall i$).

Place the model into the start position, decide the model's allocentric direction, dr, and the egocentric direction, m.

Simulations consist of a number of trials. During each trial, the model carries out following steps.

Step 1. Learning mode (Exploratory behavior)

Turn the model's head towards the m-th egocentric direction. The output of the i-th neuron of the M-layer, Y_F^j, is 1 if i=m, and 0 otherwise.

The i-th neuron of the F-layer is given by following equations:

$$U_F^i = \sum_j w_{FV}^{ij} \cdot Y_V^j + \alpha \cdot \sum_{j,k} w_{FFM}^{ijk} \cdot Y_F^j \cdot Y_M^k, \quad (1)$$

$$Y_F^i = \begin{cases} 1, & i = i_a, U_F^{i_a} = \max_{i \neq i_0}\left(U_F^i\right) \\ 0, & others, \end{cases} \quad (2)$$

where Y_M^k is the membrane potential of the neuron i of the F-layer. Y_F^i is the output of the neuron i of the F-layer. Y_V^j is the output of the neuron j of the V-layer, Y_V^j = 1 if the model looks the j-th view, View j, and Y_V^j = 0 otherwise, and α is a positive constant (= 0.7).

The second term of the right-hand side of the eq. 1 is the multiplication of Y_F^j and Y_M^k. It does not necessarily need the multiplication instead of the addition, essentially. The multiplication of Y_F^j and Y_M^k guarantees that the cell that will be active next is also different, if the movement direction is different.

If $U_F^{i_0}$ is under the threshold (< 0.2), the F -layer causes neurogenesis as follows:

$$w_{FFM}^{ijk} = 0, \qquad i = i_a, \sum_{j,k} w_{FFM}^{i_a jk} = \min_i \sum_{j,k} w_{FFM}^{ijk}, \forall j, \forall k, \quad (3)$$

$$w_{FV}^{ij} = 0, \qquad i = i_a, \sum_{j,k} w_{FFM}^{i_a jk} = \min_i \sum_{j,k} w_{FFM}^{ijk}, \forall j, \quad (4)$$

$$Y_F^i = \begin{cases} 1, & i = i_a, \\ 0, & others. \end{cases} \quad (5)$$

The eq. 3 and the eq. 4 shows the extinction of connections. It can interpret as death of the cell. The eq. 5 shows the spontaneous activation of the cell having no connection with other cells. It means the g eneration of a new cell.

Changes in connections w_{FV}^{ij}, w_{FFM}^{ijk} are given by following equations:

$$\mathrm{d}\, w_{FV}^{ij} / \mathrm{d}t = k1 \cdot Y_F^i \cdot \left(Y_V^j - w_{FV}^{ij}\right), \quad (6)$$

$$\mathrm{d}\, w_{FFM}^{ijk} / \mathrm{d}t = k2 \cdot Y_F^i \cdot Y_M^k \cdot \left(Y_F^j - w_{FFM}^{ijk}\right) + k3 \cdot (0 - w_{FFM}^{ijk}), \quad (7)$$

where $k1$, $k2$ and $k3$ are positive constants where ($k1$, $k2$, $k3$) = (0.6, 0.2, 0.0001). Activity of the RW cell at time t=0, Y_{RW}^0, is given by the following equation:

$$Y_{RW}^0 = \max_i\left(w_{RF}^i \cdot Y_F^i\right), \quad (8)$$

where w_{RF}^i is the connection from the neuron i of the R-layer to the RW cell.

Step 2. Reflection mode (Association of a goal)

1. Time t=1.
2. The i-th neuron of the F-layer is given by following equations:

$$U_F^i = \sum_{j,k} w_{FFM}^{ijk} \cdot f\left(\mathrm{d}\, Y_F^j / \mathrm{d}t\right), \quad (9)$$

$$Y_F^i = \begin{cases} 1 - 0.01 \cdot t, & U_F^i > 0.3, \\ 0, & others, \end{cases} \quad (10)$$

where f(x)=1 if x>0, and f(x)=0 otherwise.

Activity of the RW cell at time t, Y_{RW}^t, is given by the following equation:

$$Y_{RW}^t = \max_i(w_{RF}^i \cdot Y_F^i). \quad (11)$$

3. Add 1 to t. Repeat 2 of Step 2 while t<10.
4. Activity of the m-th neuron of the W -layer is given by following equation:

$$Y_W^m = \max_t\left(Y_{RW}^t\right). \quad (12)$$

Add 1 to m and repeat Step 1 and Step 2 until the model finishes looking around all views from the present position. When finished, reset m to 0.

Step 3. Movement

Obtain the egocentric direction mr which have the highest value of Y_W^i. If the model has acquired the coordinate system, it can successfully activate the RW cell and cells of the W-layer. The value of Y_W^{mr} is in inverse

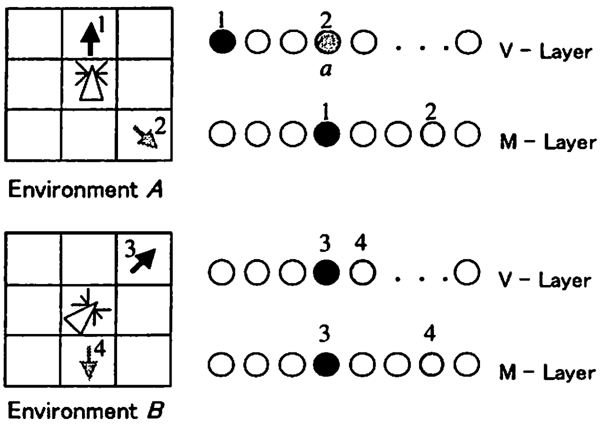


Fig. 2. Examples of activity on the V-layer and the M-layer at each different environment.

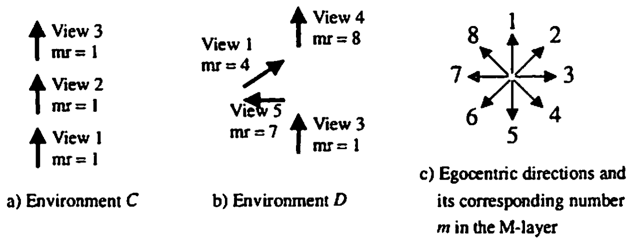


Fig. 3. Examples of paths for explaining erred learning.

proportion to the distance from model's present position to the goal and the direction mr means the goal direction.

Change mr to a random direction if $Y_W^{mr}<0.6$ or impossible to move towards the mr-th direction. $w^i_{RF}=1$ if $i=mr$, and $Y^i_M=0$ otherwise. $Y^i_F=1$ if $i=i_0$, and $U^i_F=0$ otherwise.

Repeat the eq.1 and the eq.2 once again and move towards the mr-th egocentric direction. Substitute i_a for i_0. Add mr to dr if $mr+dr<8$, add mr-8 to dr otherwise. Go back to Step 1 until the model reaching a goal or a maximum 10 times.

When the model reaches the goal, finish the trial and change w^i_{RF} by the following equation:

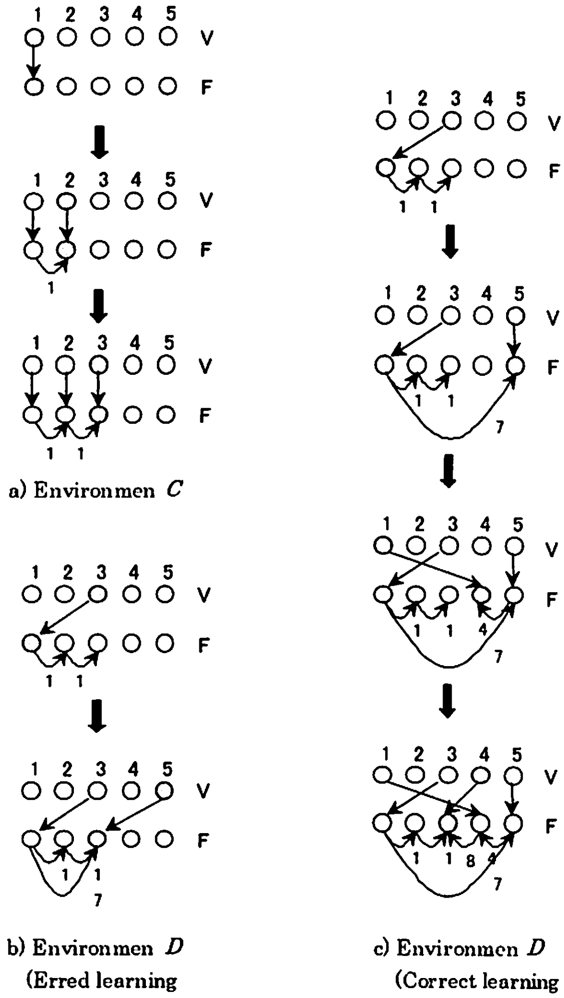


Fig. 4. Examples of connections for explaining erred learning.

$$dw^i_{RF}/dt = k4 \cdot Y^i_F \cdot \left(1 - w^i_{RF}\right), \tag{13}$$

where $k4$ is a positive constant (=1). If the model is placed into a novel environment, w^{ij}_{FV} are reseted to 0.

2.3 Environments and Views

Each environment has a set of Views. Each View is corresponding to visual information represented by the model at each place and direction. The model represents a View as an activated cell in the V -layer. If place or direction of the model is changed, View is changed too. The one - to - one correspondence is found between each cell of the V -layer and Views in each environment, although these cell matches some Views over all environments. Relationship between Views is different at each environment. So, if the environment is different, it is also different that which cell becomes active at next time.

Fig.2 shows examples of activity selection pattern on the V-layer and the M-layer at each different environment. Numbers in Fig.2 is time at which the model behaves. When the model changes its direction from 1 to 2 by activating the corresponding cell of the M -layer and inactivating previous one, View is changed and corresponding cell of the V -layer is activated. In Fig.2, the model is putted into environment *B* after the time 2. The cell *a* of the V-layer matches the different view with environment *A*'s at time 3 in the environment *B*. And same behavior causes activation of the different cell in the V-layer. As a consequence, it is understood that the cell *a* is correspondent to two views through two environments and relationship of cells of the V -layer is different between environments.

2.4 Neurogenesis

To avoid erred learning, we introduce neurogenesis to the model. Neurogenesis brings a new connection between the V-layer and the F-layer and a new recurrent connection in the F-layer by introducing a new cell in the F-layer (and extinguishing not very used cell), when the eq.1 is under the threshold.

Mostly, erred learning happens when the model learns a new environment in succession after experience of some environments. For example, when the model runs a path with a sequence of activated cells of the M -layer, $mr=\{1,1,1\}$ (of which corresponding egocentric directions are shown in Fig.3*c*), in the environment *C* (Fig.3*a*), connections w_{FV}^{ij} and w_{FFM}^{ijk} are formed like Fig.4*a*. Then, the model is putted into the environment *D* (Fig.3*b*), and resets w_{FV}^{ij} to 0. The first activated cell of the F-layer at each starting point is constant through environments and its activity is conveyed in the F -layer through $w_{FFM}^{i,j,mr}$, along the model's movement. But, when

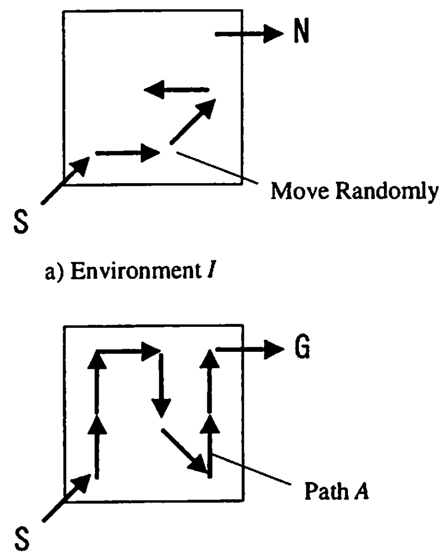


Fig. 5. Schematic representation of the Environment *I* and the Environment *II*.

there is a movement into an inexperienced direction of which corresponding $w_{FFM}^{i,j,mr}$ is low, erred learning, that is contradicting connection as shown in Fig.4 *b*, may happen in the F-layer unless neurogenesis be performed.

Because neurogenesis forms a new connection where is temporarily separated from already formed network of w_{FFM}^{ijk}, it can avoid contradicting connections. Fig.4 *c* shows an ideal forming process of the network of w_{FFM}^{ijk}. In Fig.4*c*, the cell 4 and the cell 5 of the F -layer are generated and activated for creating new connections. Then the cell 4 forms a correct connection with the cell 3. Such network enables the model to predict the direction of a goal. Although the new cell (the cell 4 in Fig.4 *c*) does not necessarily connect to the already formed

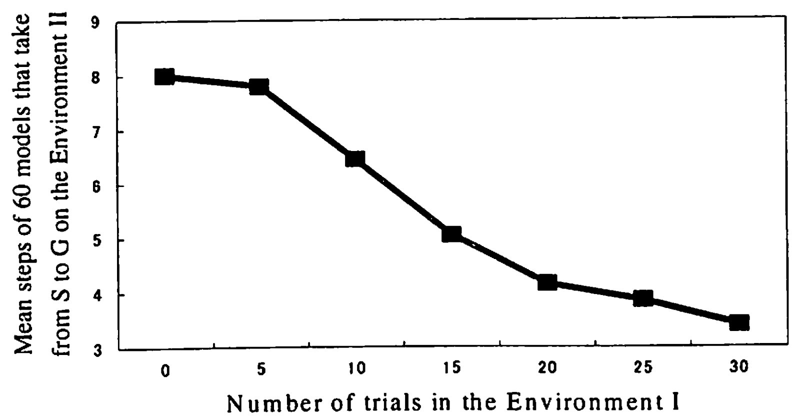


Fig. 6. Mean steps of 60 models from S to G that the model had taken.

network (the cell 3 in Fig.4c) quickly, connections that fit given environments are integrated as one network by selection with all others that are recessive in the network dying out, through experiencing various environments. Further details will be described later.

3. COMPUTER EXPERIMENTS

3.1 Prediction of a shortcut in a novel environment

In this section, we demonstrate that the model can predict a shortcut in a novel environment after learning various routs in a previous environment except for a rout that has a same sequence with a tested pa th in the novel environment. First, the model moves randomly in the Environment *I* shown in Fig.5*a*, but not follows a way of which movement pattern is identical with the Path *A*'s on the Environment *II*, and constructs interconnection of Views in the F -layer. Then the model utilizes obtained relationships of Views to the Environment *II* (Fig.5*b*) to predict the goal.

Fig.5*a* shows the Environment *I* that the model is placed during the first half of the experiment. The model starts from S in the Environment *I* and moves around randomly in the Environment *I*. At every step, the neuron *mv* of the V-layer is activated, where *mv* is given by the following equation:

$$mv = 5 \cdot x + y + 25 \cdot dr , \qquad (14)$$

where (x,y) are pointing to a position of the model, and *dr* is an allocentric direction that the model is looking to. When the model reaches N in the Environment *I* or moves for 10 steps, activation of neurons in the F -layer is resetted to the initial values and the model starts again from S in the Environment *I* as a next trial. We prepared 7 experimental conditions as total trials in the Environment *I*, 0, 5, 10, 15, 20, 25 and 30 trials. At each condition, 20 model rats, given different initial values, were tested.

Before rewarded learning in the Environment *II*, we checked that the model did not have passed the same way with the Path *A*, in the Environment *I*. After nonrewarded learning in the Environment *I*, the model is moved into the Environment *II* and forced to run Path *A* at 10 times. In the Environment *II*, *mv* is given by the following equation:

$$mv = 40 \cdot x + 8 \cdot (4 - y) + dr , \qquad (15)$$

When the model reaches G in the Environment *II*, reward is given to the model. Then the model is placed in the starting point S of the Environment *II* and tested which rout the model selects. For this experiment, 60 models are tested.

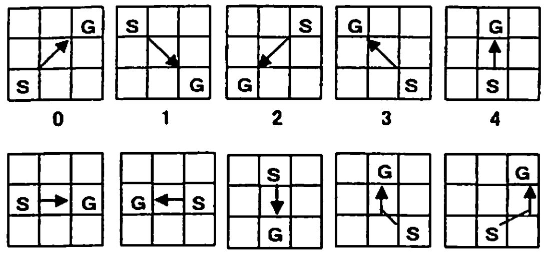


Fig. 7. Examples of environments that the model experiences in succession.

As a result, the model would choose the closer way from S to G on the Environment *II*, as the trial frequency on the Environment *I* was increased. Fig.6 shows the average of the step frequency from S to G per one trial in the Environment *II* at each experimental condition. When no trial in the Environment *I* had been given to the model, all models merely followed the Path *A*. As the trial frequency was increased, the model became possible to take a shorter path and almost all models took the shortest path in the Environment *II* after 30 trials in the Environment *I*.

Notice that after the model fully learned various routs in the Environment *I*, the model could generate the appropriate sequence while the same sequence with the Path *A* was inexperience, and could take a shortcut never experienced before. It means that the model acquired the coordinate system properly.

3.2 Emergence of the coordinate system

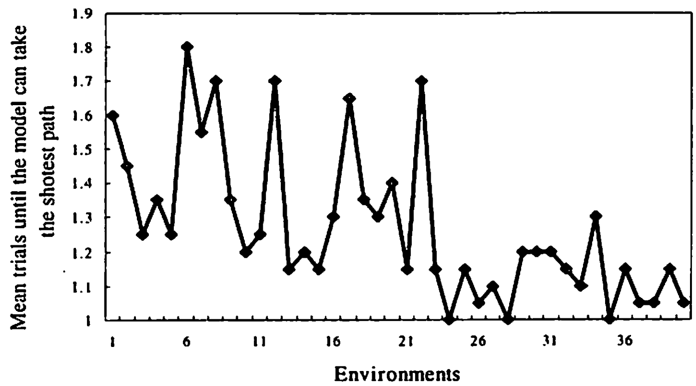
Probably, real rats acquire the coordinate systems through experiencing various environments. In this section, we gave 40 environments to the model in succession. Fig.7 shows examples of environments. Each environment is composed of 9 squares, "S" means starting position, "G" means goal position, and an arrow shows shortest path on each environment. Each environment has a set of Views defined by an equation like the eq.14 or the eq.15. Those equations are different with each environment.

The model explores environments successively. First, the model moves randomly on an environment. When the model reaches the goal, the model is placed into S on the environment again and tested that whether the model can take a shortcut at the next trial. If the model can not take a shortcut, random search is repeated in the same environment. If it can take a shortest way, total trials taken in the environment are counted and the model is placed into S on the next environment.

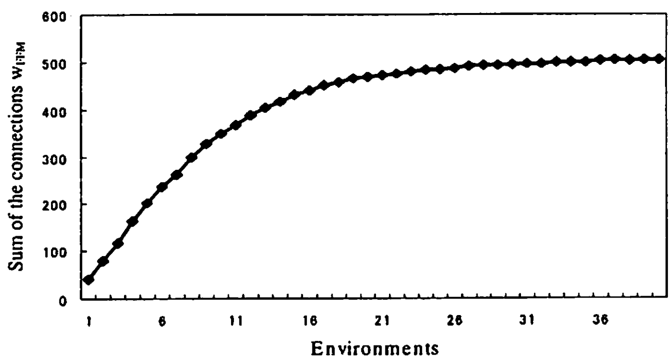
As a result of 20 models examined, each model was able to gradually take a shortcut in novel environments after one trial (Fig.8*a*). Although Fig.8*b* shows increase and saturation of the sum of w_{FFM}^{ijk}, number of cells relating to the network with high w_{FFM}^{ijk} (>0.3) has decreased in the last 20 environments (Fig.8*c*). It means that, though the connections w_{FFM}^{ijk} had dispersed in the beginning by the neu rogenesis, it was integrated to cells those survived through learning several environments.

4. FURTHER RESEARCH

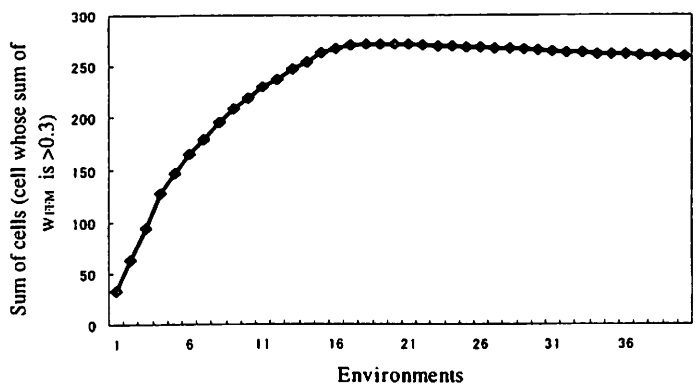
Because the F -layer has recurrent connections and performs the neurogenesis, it resembles to the hippocampus. But our model does not explain f acts that *a*) if the environment is changed, the relationship of cells in the hippocampus is also changed and *b*) it is place cells to compose the map in the hippocampus. If the V -layer, instead of the F -layer, provide constraints for selecting recurrent connections between cells in the F -layer, it may solve the problem *a*). We presented the emergent model of place cells (Aota et al., 1999). It may solve the



a) Mean trials until the model can take the shortest path



b) Sum of w_{FFM}^{ijk} at each environment.



c) Total number of cell , of which $\sum_{j,k} w_{FFM}^{ijk}$ is

Fig. 8. 20 models were examined for the formation of the coordinate system.

problem *b*) by incorporating that model into the present model.

This model could take a shorter path on the novel environment by forming and utilizing the coordinate system. Although our model can orient towards the location of the goal, it cannot deal with detour problems. Maybe, it needs to construct a unifie d system of several modules as suggested by Trullier *et al* (1997). For constructing such unified system to deal with dynamic environments, it will be problem that how do we implement emergent process in the high hierarchical structure.

On the other hand, t he presented model started from low ability to merely follow the path to the goal experienced just before. Then, the model acquired the algorithm for metric navigation by relating Views of each environment to the network and avoiding contradicting connections with the neurogenesis. Such system — organizing universal rule to achieve its goal — would help to realize other biological process like acquisition of language.

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