



Neurogenesis performs the formation of the cognitive space in rat's navigation

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Abstract

It is known that a rat can take a shortcut even if it is an inexperienced path for the rat. Recently, the relation between the neurogenesis and learning mechanism has attracted attention. In this paper, we present a neural network model for the memory formation by introducing the neurogenesis in order to achieve successful navigation. We discuss two types of neurogeneses. Both types of neurogeneses play an important role in acquiring a universal rule in the navigation and avoiding incorrect learnings. It is considered that real animals use either type or both types of the neurogeneses presented here.

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1. Introduction

Recently, the study on the neurogenesis of adult animals has developed rapidly [3]. Neurogenesis means the generation of neurons in the brain, and its obvious relation with learning has been pointed out [12,16]. In the case of an adult rat, the hippocampus is known as the field where the neurogenesis takes place [1]. It takes place especially in a novel environment enriched with many attractive materials for the rat [4]. But, its concrete learning mechanism has not yet been understood.

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On the other hand, we, as higher animals, use abstract information to solve complicated problems. For example, it is known that a rat is able to solve navigation problems. The rat chooses a shorter way in an unfamiliar environment, even if it is an inexperienced way for the rat [19]. In case the information about the environment is incomplete for the rat, it is considered that the rat infers the goal direction by utilization of characters of the space that the rat has acquired through experiencing various environments, i.e. with the help of the cognitive map [18], and then chooses a proper passage. The cognitive map is the internal map of the rat for navigation. In this paper, a “map” is defined as a system which makes the shortcut navigation possible.

To suggest one plausible functional role of the neurogenesis, we present a neural network model for the formation of memory by introducing neurogenesis in the rat’s navigation. In our model, neurogenesis plays a crucial role in acquiring a map. Below we show that our model equipped with the neurogenesis can carry out shortcut well, and introduce two types of the neurogeneses. Then, we compare this model with a model that is not equipped with the neurogenesis but with highly decaying connections that are expected to be comparable to the performance of our model.

2. Model

2.1. Overall structure of the model

For planning the route to the goal, there is the graph search, and some biomimetic navigation models using the graph search are proposed (e.g., [5,8,15]). However, since each node corresponds to a specific location, these models cannot cope with environmental changes. They cannot choose unknown paths and can only take a path from already known places. Thus, those models do not realize the shortcut navigation in a newly encountered environment. A fundamental idea which overcomes this problem is to make the meaning of each node abstract type. As described later, this becomes possible by introducing the neurogeneses into the graph search.

Our model is composed of four layers and one reward (RW) cell (Fig. 1). The layers are called V-, F-, M-, and W-layers, respectively. Each layer consists of cells that are combined into forms suitable for functions of each layer. The V-layer detects changes of the visual information and stores the model’s views. The V-layer connects with the F-layer. When the model meets with a novel environment, connections between the V-layer and the F-layer are reset.

The F-layer is considered to be the hippocampus. That is, the F-layer has recurrent connections as a circulatory network, connections with other layers vary abruptly, and they perform the neurogenesis.

More precisely, recurrent connections are made between activated cells to memorize the time evolution of activities of cells in the F-layer. Moreover, when the total input to the F-layer from the V- and the F-layer is below a threshold, that is, when the model cannot position or predict the input from the outside, the F-layer causes the neurogenesis. As the neurogenesis process model, we make the model generate a new

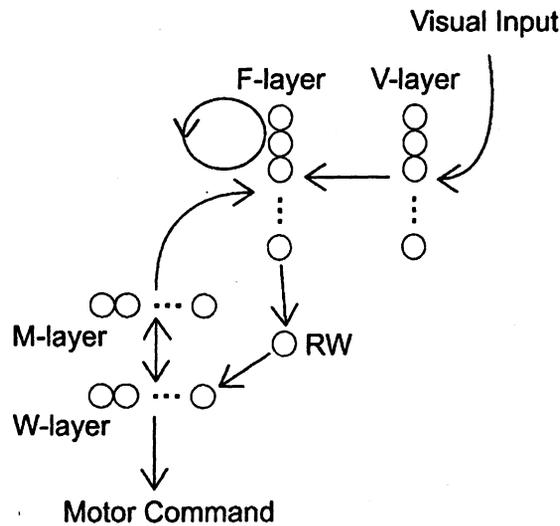


Fig. 1. Structure of the model.

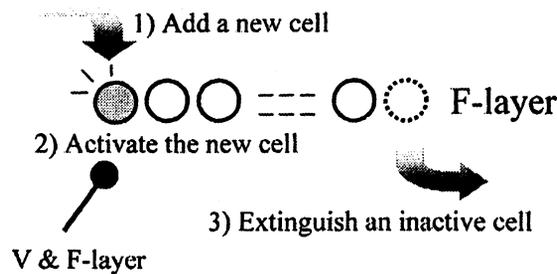


Fig. 2. Flow of the neurogenesis: the model (1) generates a new cell in the F-layer, (2) connects it with activated cells between the V-layer and the F-layer, and (3) extinguishes an inactive cell in the F-layer.

cell in the F-layer, connect it with activated cells between the V-layer and the F-layer, and extinguish one of the inactive cells in the F-layer (Fig. 2).

The M-layer is constructed with motor neurons. Each motor neuron encodes an egocentric direction (i.e. a movement to the forward, the left, etc). In our simulation, the model can move in eight directions. Therefore, the M-layer has eight neurons. In addition, activities at the M-layer provide constraints for selecting recurrent connections between cells in the F-layer.

For simplicity, we divide the model into two modes. (However, it can be explained as nervous dynamics like in Schmajuk and Thieme [15] with a difference in the time scale.) One is the Learning mode, which relates a previous view to a current view with a recurrent connection in the F-layer. If the model arrives at the goal, a cell, which is active on the F-layer, will make connection with the RW cell. The other mode is the Reflection mode, which generates an adequate prediction of the goal through a closed loop in the F-layer and activates the W-layer by the F-layer through the RW cell. In the Reflection mode, the model searches for the pathway from the current position to

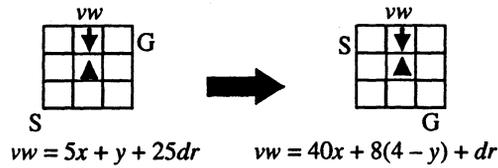


Fig. 3. Example of environments: each environment has a set of views. Each view vw is decided by a linear combination of the model's position (x, y) and allocentric direction dr . Its coefficients are different for different environments.

the goal for every direction. When the RW cell is activated through connections from the F-layer, the RW cell activates the W-layer.

Each cell of the W-layer memorizes an activity of the RW cell for each direction. Since the activity of the RW cell becomes lower with the distance to the goal, the direction of the cell which shows the highest activity on the W-layer is the closest to the goal direction.

2.2. Environments and views

An "environment" consists of a 3×3 or 4×4 matrix as illustrated in Fig. 3. In Fig. 3, "S" means the start position and "G" means the assigned goal. Each environment has a set of views. At each position and direction of the model in the environment, the corresponding view is input into the V-layer of the model. Each view vw is decided by an equation that is composed of the model's position (x, y) and allocentric direction dr . The view vw is a linear combination of x , y and dr , but its coefficients are different for different environments (Fig. 3).

If the position or direction of the model is changed, so is the view. Then the corresponding cell of the V-layer, which has the same number as vw , becomes active. The one-to-one correspondence is found between each cell of the V-layer and views in each environment, although the cell happens to match some views over all environments. The relationship between views is different for different environments, so that, which cell becomes active the next time depends on environments. Note that the model cannot distinguish the model's direction or position from the vw itself.

2.3. Simulation protocol and formal description of the model

The initial conditions are as follows:

- $N_F = 300$, $N_V = 250$, where N_F and N_V are the number of neurons of the F-layer and the V-layer. The M-layer and the W-layer have eight neurons each.
- The output of the i th neuron of the F-layer, Y_F^i , is 1 if $i = i_0$, and 0 otherwise. The index, $i_0 = N_F$.
- w_{FV}^{ij} is a random value between 0 and 0.1 ($\forall i, j$), where w_{FV}^{ij} is the connection weight from the j th neuron of the V-layer to the i th neuron of the F-layer.

- w_{FFM}^{ijk} is 0 ($\forall i, j, k$), where w_{FFM}^{ijk} is the connection weight from the j th neuron of the F-layer and the k th neuron of the M-layer to the i th neuron of the F-layer.
- w_{RF}^i is 0 ($\forall i$), where w_{RF}^i is the connection weight from the i th neuron of the F-layer to the RW cell.
- $dr=0$, where dr is the model's allocentric (geometric) direction. The value dr takes from 0 to 7. $dr=1$ means 45° clockwise direction compared with $dr=0$. In the same way, $dr=n$ means 45° clockwise direction compared with $dr=n-1$ ($n: \{0, 1, \dots, 7\}$). So, the model can select one out of the eight directions.
- $m=0$, where m is the model's egocentric direction which means forward, left, right, and so on. "0" means forward and the relationships between "0" and other values are the same with as in the case of dr .

The model attempts some trials at each environment. During each trial, the model carries out the following steps.

Step 1. Learning mode: Turn the model's head towards the m th egocentric direction. The output of the i th neuron of the M-layer, Y_M^i , is 1 if $i = m$, and 0 otherwise.

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

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

$$i_a = \arg \max_{i \neq i_0} (U_F^i), \quad (2)$$

$$Y_F^i = \begin{cases} 1, & i = i_a, \\ 0 & \text{others,} \end{cases} \quad (3)$$

where U_F^i is the membrane potential of the i th neuron of the F-layer. Y_F^i is the output of the i th neuron of the F-layer. Y_V^j is the output of the j th neuron of the V-layer, and $Y_V^j = 1$ if the model looks at the j th view, $j = vw$, and $Y_V^j = 0$ otherwise (for the definition of "vw", see the Section 2.2), while α is a positive constant which is fixed to be 0.7 in our model.

If $U_F^{i_a}$ is below the threshold value $\Upsilon (=0.2$ in our model and the definition of i_a is written in Eq. (2)), the F-layer causes neurogenesis as follows:

$$i_a = \arg \min_i \sum_{l,m} w_{FFM}^{ilm}, \quad (4)$$

$$w_{FFM}^{i_a j k} = 0 \quad \forall j, \forall k, \quad (5)$$

$$w_{FV}^{i_a j} = 0 \quad \forall j, \quad (6)$$

$$Y_F^i = \begin{cases} 1, & i = i_a, \\ 0 & \text{others.} \end{cases} \quad (7)$$

Eqs. (5) and (6) show the extinction of connection weights of the i_a th neuron of the F-layer. It can be interpreted as the death of that cell. Eq. (7) shows the spontaneous

activation of that cell. It means the generation of a new cell. Because the newborn cell is active, it makes a new connection by the next Eqs. (8) and (9).

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

$$dw_{FV}^{ij}/dt = k1 Y_F^i (Y_V^j - w_{FV}^{ij}), \quad (8)$$

$$dw_{FFM}^{ijk}/dt = k2 Y_F^i Y_M^k (Y_F^j - w_{FFM}^{ijk}) + k3(0 - w_{FFM}^{ijk}), \quad (9)$$

where $k1$, $k2$ and $k3$ are positive constants.

The time in the next Reflection mode, t , sets 0. The strength of the activity of the RW cell, Y_{RW}^t , is given by the following equation:

$$Y_{RW}^t = \max_i (w_{RF}^i Y_F^i), \quad (10)$$

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

Step 2. Reflection mode:

1. $t = 1$.
2. Calculation of Y_F^i :

$$U_F^i = \sum_{j,k} w_{FFM}^{ijk} f(dY_F^j/dt), \quad (11)$$

$$Y_F^i = \begin{cases} 1 - 0.01t, & U_F^i > 0.3, \\ 0 & \text{otherwise,} \end{cases} \quad (12)$$

where $f(x) = 1$ if $x > 0$, and $f(x) = 0$ otherwise. Calculate Eq. (10).

$$t = t + 1, \quad (13)$$

3. If $t < 10$, go back to 2.
4. Calculation of the output of the m th neuron of the W-layer, Y_W^m :

$$Y_W^m = \max_i (Y_{RW}^i), \quad (14)$$

$$m = \begin{cases} m + 1, & m + 1 < 8, \\ 0 & \text{otherwise.} \end{cases} \quad (15)$$

5. If $m \neq 0$, go to Step 1.

Step 3. Movement: Pick up the egocentric direction mr (the definition is the same as m) which has the highest value of Y_W^i .

$$Y_W^{mr} = \max_i (Y_W^i). \quad (16)$$

Reset mr to a random direction if $Y_W^{mr} < \theta$ or if it is impossible for the model to move towards the mr th direction.

$$Y_M^i = \begin{cases} 1, & i = mr, \\ 0 & \text{otherwise,} \end{cases} \quad (17)$$

$$Y_F^i = \begin{cases} 1, & i = i_0, \\ 0 & \text{otherwise.} \end{cases} \quad (18)$$

Calculate Eqs. (1)–(3) once again and move the model towards the mr th egocentric direction.

$$mr = \begin{cases} mr + dr, & mr + dr < 8, \\ mr + dr - 8 & \text{otherwise.} \end{cases} \quad (19)$$

$$i_0 = i_a. \quad (20)$$

Go back to Step 1 until the model reaches the goal or 10 times maximum iteration.

If the model has acquired the map (for the definition of “map”, see Introduction), it can successfully activate the RW cell and cells of the W-layer. The value of Y_W^{mr} is inversely proportional to the distance from the current position of the model to the goal and the direction mr implies the goal direction.

In a similar manner as Schmajuk and Thieme’s model [15], our model turns its head towards each direction, and looks at the corresponding view. Then, the model is reminded of the goal by the recurrent network of the F-layer and concludes as to which direction activates the RW cell most strongly. However, we add a new function as the neurogenesis into the model, whereas Schmajuk and Thieme’s model assumes place cells. Since the emergence of the map from egocentric information is our current interest, we cannot prepare place cells a priori. Moreover, since the information flowing in the model becomes more abstract, the model can apply the same network to various environments and locate the goal even if the environment is novel for the model. If the concluded direction is a possible direction to move to, the model takes a shortcut.

2.4. Neurogenesis avoids incorrect learnings

To avoid incorrect learnings, we introduce the neurogenesis into the model. The neurogenesis brings two kinds of new connections when the maximum of the total input of each cell in the F-layer is below the threshold. One is a connection between the V-layer and the F-layer, and the other is a recurrent connection in the F-layer by introducing a new cell in the F-layer (and extinguishing an inactive cell). In other words, the neurogenesis takes place when the model meets the inexperienced situation or a scenario which cannot be predicted.

Most of the incorrect learnings occur when the model faces a new environment in succession after experience of some other environments. For example, when the model runs a path with a sequence of activated cells of the M-layer, $mr = \{0, 0, 0\}$ (means that the model moves forward three times), in the environment C (Fig. 4a), the connections w_{FV}^{ij} and w_{FFM}^{ijk} are formed like in Fig. 5a. Then, the model is put into the environment D (Fig. 4b), resets w_{FV}^{ij} to 0, and runs a path with a sequence of activated cells of the M-layer, $mr = \{0, 6, 3, 7\}$. The first activated cell of the F-layer at each starting point is the same through environments and its activity is conveyed to the F-layer through $w_{FFM}^{i,j,mr}$, along the model’s movement. However, when there is a movement into an inexperienced direction whose corresponding $w_{FFM}^{i,j,mr}$ is low, an incorrect learning, that

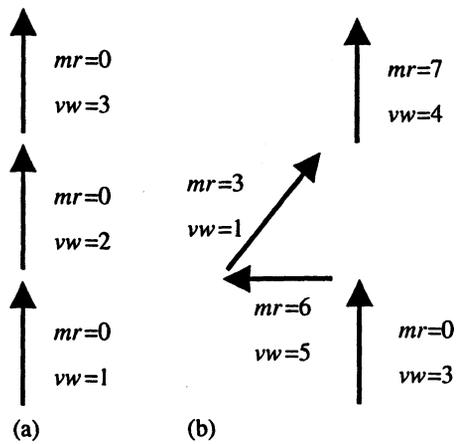


Fig. 4. Examples of paths for explaining incorrect learning: (a) Environment C: the model runs a path with a sequence of activated cells of the M-layer, $mr = \{0, 0, 0\}$. See Section 2.3 for the definition of mr . (b) Environment D: the model is put into Environment D, and runs a path with a sequence $mr = \{0, 6, 3, 7\}$.

is a contradicting connection as shown in Fig. 5b, may occur in the F-layer unless neurogenesis is performed. In Fig. 5b, the third cell of the F-layer developed duplicated meanings, namely “2 steps forward from the start” and “1 step left from the start”. We call this contradicting connection between the previous environment and the new environment “error connection”.

Since the neurogenesis forms a new connection which is temporarily separated from the already formed network of w_{FFM}^{ijk} , it can avoid contradicting connections. Fig. 5c shows an ideal formation process of the network of w_{FFM}^{ijk} . In Fig. 5c, cells a and b of the F-layer are generated and activated in order to make new connections. Then cells a and b form correct connections with other cells of the F-layer. Such a network formation enables the model to predict the direction of a goal. Although the new cell (the cell b of the F-layer in Fig. 5c) does not necessarily connect with the already formed network quickly (the third cell of the F-layer in Fig. 5c), connections fit for given environments are integrated into one network by selection and all others disappear through experiencing various environments.

2.5. Two types of neurogeneses

Neurogenesis is theoretically classified into two types. One is the temporal type (T-type), in which a newborn neuron memorizes new information, and then is extinguished by losing competition after transferring the information to the existing network. Another is the permanent type (P-type), in which a newborn neuron memorizes new information, and then is positioned in the existing network by connecting with that network. It is expected that real animals use either or both types of the neurogenesis presented here.

For example, when the model moves in order, $mr = \{0, 0, 2, 0\}$ and then $\{1, 7, 2\}$, in Environment A (Fig. 6a), the connections w_{FV}^{ij} and w_{FFM}^{ijk} are formed like in

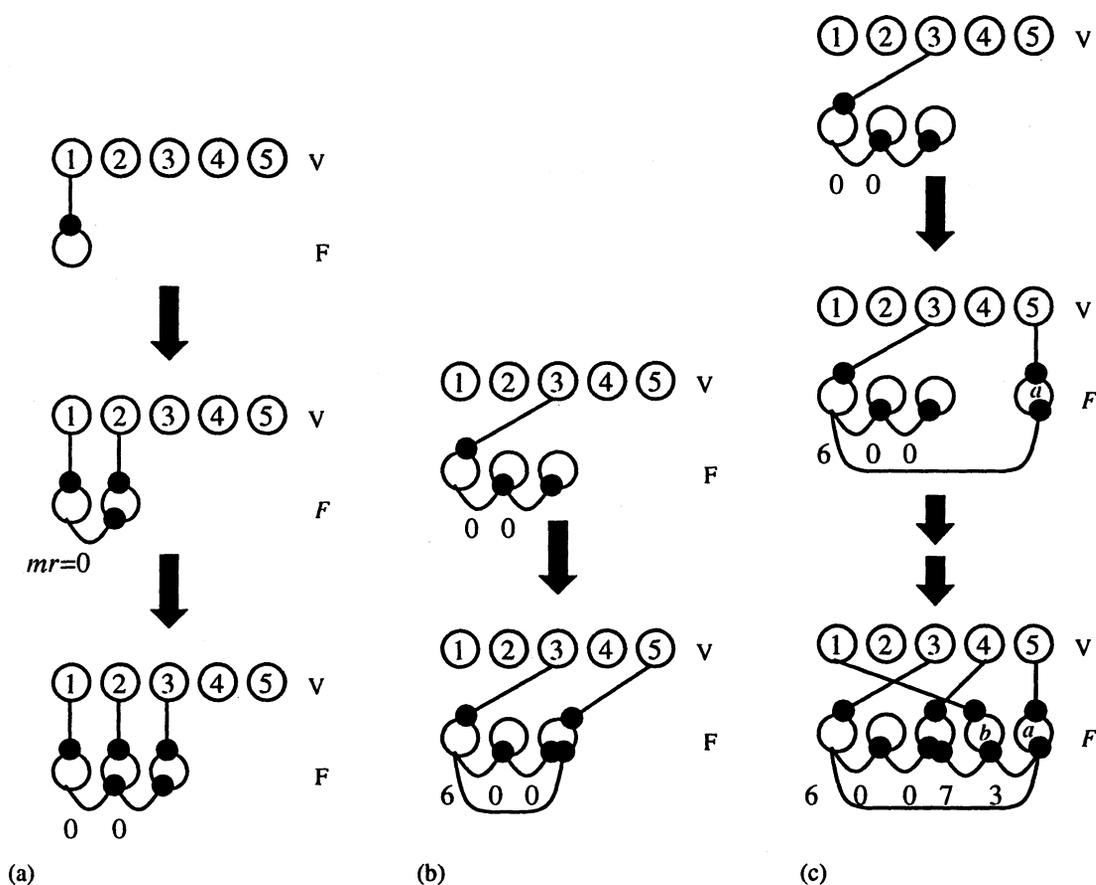


Fig. 5. Examples of connections for explaining incorrect learning: the model runs a path (a) in Environment C, then (b) in Environment D (incorrect learning) or (c) in Environment D (correct learning).

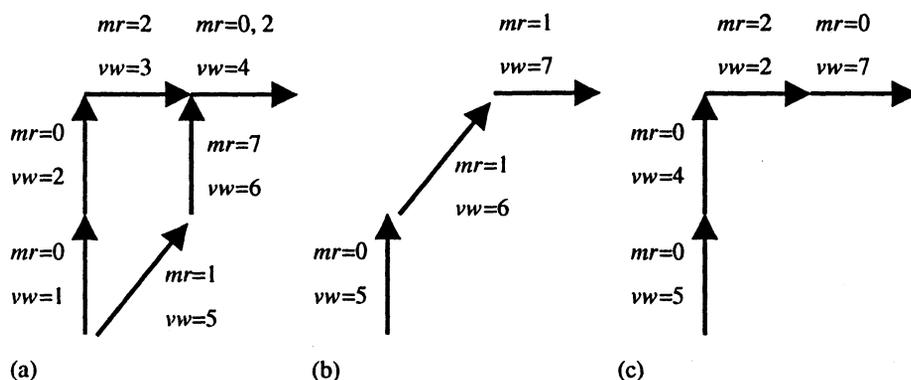


Fig. 6. Examples of paths for explaining two types of the neurogenesis. (a) The model runs on paths with sequences $mr = \{0, 0, 2, 0\}$ and $mr = \{1, 7, 2\}$ in Environment A. (b) The model is put into Environment B, runs on a path with a sequence $mr = \{0, 1, 1\}$. (c) Runs on a path with a sequence $mr = \{0, 0, 2, 0\}$.

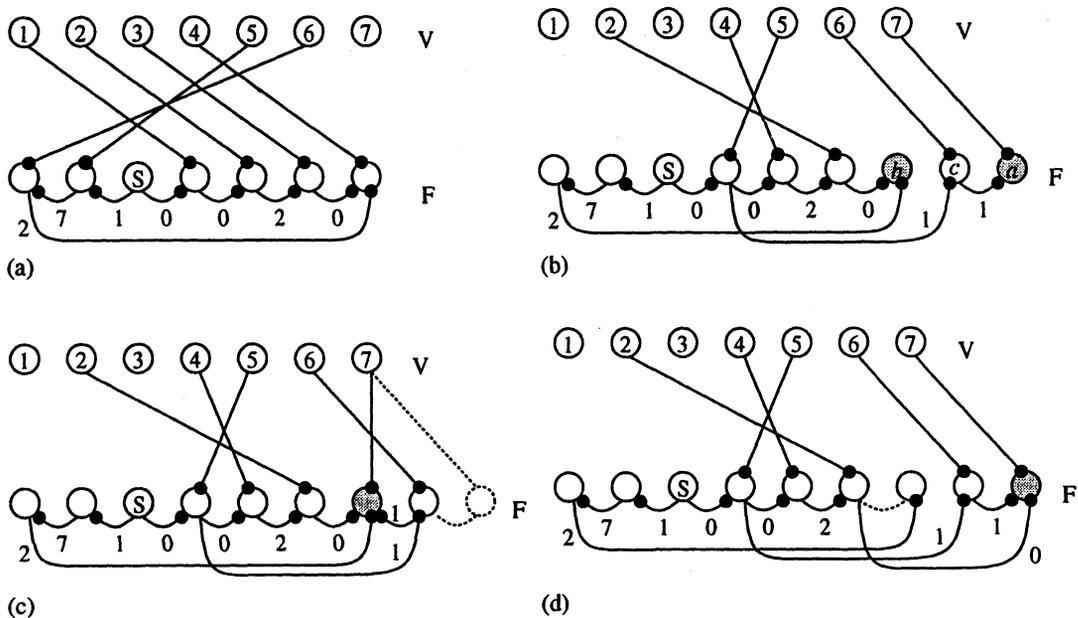


Fig. 7. Examples of connections for explaining two types of the neurogenesis: (a) After the model runs on paths in Environment *A* (Fig. 6a). (b) The competition when the model runs on a path with a sequence, $mr = \{0, 0, 2, 0\}$, in Environment *B*. (c) In the case of T-type. (d) In the case of P-type.

Fig. 7a. Then, the model is put into Environment *B* (Fig. 6b), and runs in order, $mr = \{0, 1, 1\}$. Because this order is different from both orders experienced in Environment *A*, neurogenesis occurs and new connections are created in the second and third steps of this order (Cells *a* and *c* in Fig. 7b). Then, when the model runs on a path, $mr = \{0, 0, 2, 0\}$, in Environment *B* (Fig. 6c), competition occurs between cells *a* and *b* of the F-layer. As shown in Fig. 7b, cell *a* is activated by the V-layer and cell *b* is activated by another cell of the F-layer through $w_{FFM}^{i,j,mr}$. The winner cell will be different according to the type of neurogenesis. In the case of the T-type, cell *b* wins and cell *a* disappears (Fig. 7c). In the case of the P-type, cell *a* wins and in many cases, since there are other connections from the F-layer, cell *b* also survives (Fig. 7d).

If we set k_1 and k_2 in Eqs. (8) and (9) lower, the speed of making connections from the neuron created by the neurogenesis becomes slow. This corresponds to the T-type, and high values for k_1 and k_2 correspond to the P-type. It makes the neuron from the neurogenesis the winner at the competition. We set up $(k_1, k_2) = (0.2, 0.1)$ for the T-type, and $(k_1, k_2) = (0.6, 0.4)$ for the P-type. In Section 3.2, we compare the T- and P-type with the case where there is no neurogenesis.

3. Computer experiments

3.1. Prediction of a shortcut in a novel environment

In this section, we demonstrate that our model can predict a shortcut in novel environments (Environment II and III) after learning various routes in a previous environment (Environment I). Environment II has the same 3×3 matrix with Environment

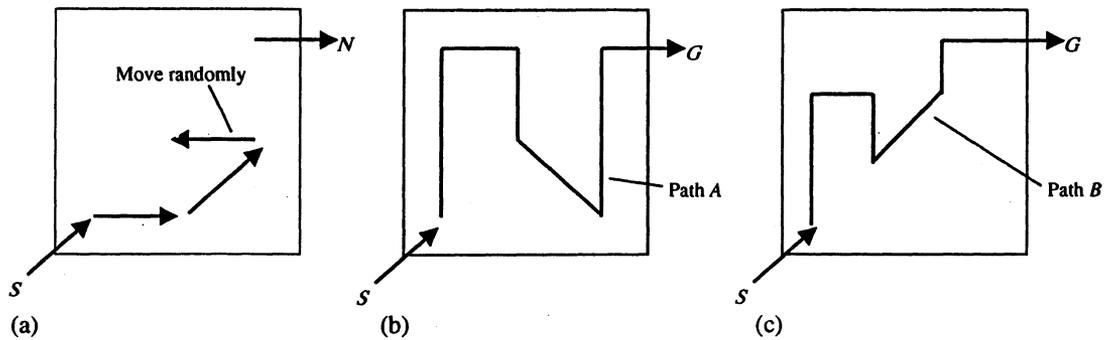


Fig. 8. Schematic representation of (a) Environment I, (b) Environment II and (c) Environment III.

I, but showing different views. Environment III has a 4×4 matrix, which is a larger field than Environment I, and shows different views. Especially, in Environment II and III, our model follows one route with a fixed sequence which has not experienced Environment I. Then we test whether the model takes a shorter way or not.

First, the model moves randomly in Environment I, but does not follow a way for which the movement pattern is identical to the Path A in Environment II (Fig. 8b) and the Path B in Environment III (Fig. 8c), and establishes an interconnection of views in the F-layer. Then the model applies the obtained relationships of views to Environment II or III to predict the goal.

Fig. 8a shows Environment I. The model starts from S and moves around randomly in Environment I. At every step, the vw th neuron of the V-layer becomes active, where vw is given by the following equation:

$$vw = 5x + y + 25 dr, \quad (21)$$

where (x, y) shows position of the model, and dr is the model's head direction (for the definition of dr , see Section 2.3). We chose coefficients so that the maximum of vw took under $N_V (=250)$. When the model reaches N in Environment I or takes 10 steps, the model moves to the next trial and starts again from S in Environment I. Four hundred and twenty models were tested. Each model used different random values and performed the task of Environment I for total 0, 5, 10, 15, 20, 25 or 30 trials. Sixty models for each total trials (0, 5, ..., 30 trials) were tested. Parameters were $(k_1, k_2, k_3) = (0.6, 0.2, 0.0001)$ and $\theta = 0.6$.

Before testing at Environment II or III, we ensured that the model did not follow the same route with Path A or Path B in Environment I. After learning Environment I, the model moved into Environment II or III, and was forced to run Path A in the case of Environment II or Path B in the case of Environment III 10 times. Like Tolman et al.'s experiment [18], each model learned only such restricted route in the new environment and it was tested whether the model chose a shorter path or not after learning that route. In Environment II and III, vw is given by

$$vw = 40x + 8(4 - y) + dr, \quad (22)$$

where coefficients were chosen so that those were different from Eq. (21) and the maximum value of vw took under N_V .

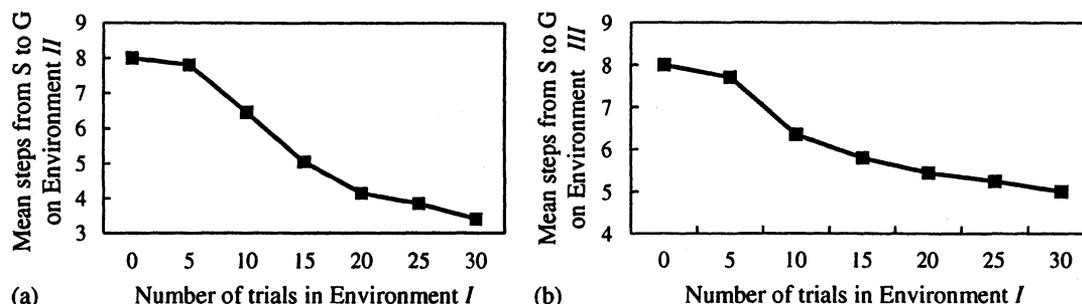


Fig. 9. The average of the step frequency from S to G per one trial in Environment II (a) and Environment III (b) in each experimental condition.

When the model reaches G in Environment II or III (Fig. 8b and c), the RW cell becomes active. After 10 times running on Path A in Environment II or Path B in Environment III, the model is placed in the starting point S again and tested whether the model would take a shortcut.

As a result, the model chose a closer way from S to G in the new environments as the total trials in Environment I increased. Fig. 9a shows the average of the step frequency from S to G per one trial in Environment II at each experimental condition. When the model had performed no trial in Environment I, all the models merely followed Path A. As the total trials increased, the model was able to take a shorter path and almost all models took the shortest path in Environment II after 30 trials in Environment I. Notice that after the model fully learned various routes in Environment I, the model could generate an appropriate sequence of path while the same sequence with Path A was inexperienced, and could take a shortcut which was never experienced before. It means that the model acquired the map properly.

In the case of Environment III, the model chose a shorter path but did not choose the shortest one (Fig. 9b). This is because the model had not learned large size environment. Environment III (4×4 matrix) is larger than Environment I (3×3 matrix). The model passed along the shortcut within the limits of the 3×3 matrix. But in the last two steps, the model followed Path B. It may be needed to add some kind of scaling mechanism which zooms in and zooms out the map in order to fit the environment.

3.2. Comparison between the model with neurogenesis and the model with highly decaying connections

Because error connections are detected when the model meets a new environment, the model with highly decaying connections might be expected to show good performance as well as the model with neurogenesis. In this section, we compare the model equipped with neurogenesis with the case where the model is not equipped with neurogenesis but with highly decaying connections, and then, compare T-type of the neurogenesis with P-type. In our model, highly decaying connections are realized by making the parameter $k3$ in Eq. (7) high, and non-neurogenesis is realized by the parameter $\gamma < 0$ (see Step 1 of the Section 2.3).

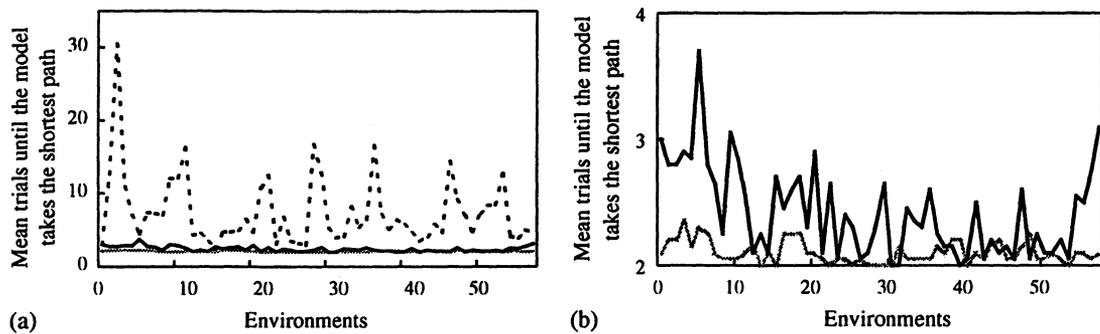


Fig. 10. Mean trials until the model takes the shortest path: (a) Without the neurogenesis (dotted line), the T-type (black line), and the P-type (gray line). (b) The T-type (black line), and the P-type (gray line).

We gave 58 environments to the model in succession. The size of each environment is a 3×3 matrix. Each environment has a set of views defined by an equation similar to Eq. (21) or Eq. (22). Those equations have different coefficients for different environments.

The model explores environments successively. Firstly, the model moves randomly in the environment (at this time, the parameter $\theta > 1$ which corresponds to the random search). When the model reaches the goal, the model is placed into S in the environment again and it is tested whether or not the model can take a shortcut (at this time, the parameter $\theta = 0.6$). If the model cannot take a shortcut, the random search ($\theta > 1$) 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 in the next environment. For the T-type neurogenesis, we set up parameters, $(k_1, k_2, k_3) = (0.2, 0.1, 0.0001)$, and for the P-type, $(k_1, k_2, k_3) = (0.6, 0.4, 0.0001)$. For the model with highly decaying connections, we set up the parameter $\gamma < 0$ and $k_3 = 0.01$ (100 times as high as the decaying rate of the T- and P-types). Twenty models were tested at each experimental condition.

As a result, the model without neurogenesis was not able to take a shortcut (Fig. 10a). The model with highly decaying connections showed the same result with the neurogenesis-based model at the first environment. But, the interference of learning was seen after the second environment. It means that decaying connections is not an adequate method for creating the map.

It might seem that the value of k_3 was not optimized. So, we tested other values of k_3 , that is $k_3 = 0.1$ and 0.001 . In all cases, the mean trial per one environment was higher than the case of the neurogenesis. The best value of k_3 in the case of highly decaying connections was $k_3 = 0.01$, the middle one between three (0.1, 0.01 and 0.001). It showed average $7.4 (\pm 20.9)$ trials per one environment, although the model with the neurogenesis showed average $2.4 (\pm 1.0)$ trials in the T-type and $2.1 (\pm 0.4)$ trials in the P-type.

The model with the neurogeneses was able to take a shortcut in novel environments after the first trial with a random search for the goal (Fig. 10a and b). Although the P-type was better than the T-type in Fig. 10b, both types acquired the ability of taking a shortcut.

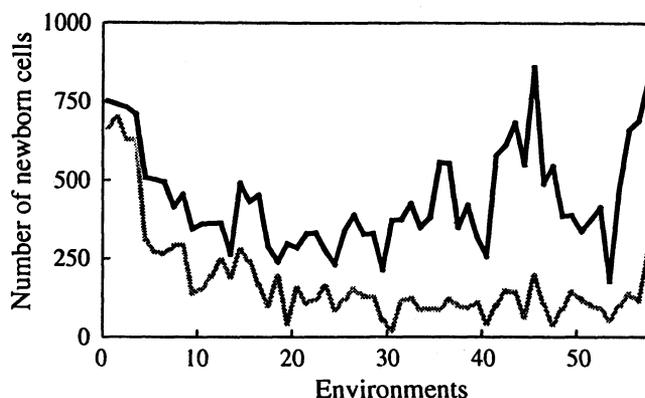


Fig. 11. Average of newborn cells by neurogenesis in each environment: The T-type (black line), and the P-type (gray line).

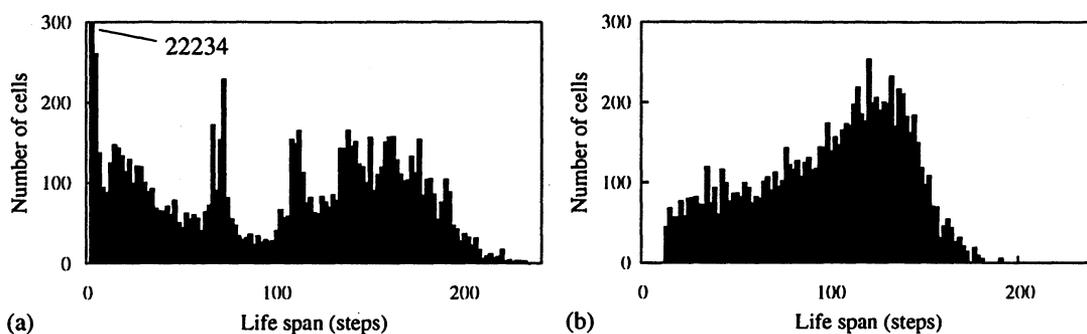


Fig. 12. Life span of cells at each type of the neurogenesis: (a) The T-type. (b) The P-type.

In this experiment, we can express the difference of two types of the neurogenesis well. Fig. 11 shows the average of newborn cells by the neurogenesis in each environment. Although the P-type made many cells in the first 20 environments of the learning, it decreased as the learning progressed. The T-type always made more cells than the P-type, and even when the learning progressed, the number of cells did not become fewer. Fig. 12 shows the life span of each cell of the F-layer. In the T-type (Fig. 12a), the numbers of cells with a long life and cells with a short life are larger than those of the P-type (Fig. 12b). As described before, this is because a newborn neuron of the T-type memorizes a new view, which cannot be positioned in the network built up so far, temporally and then be extinguished after consolidation of the view into the network.

Fig. 13a shows the increase and saturation of the sum of w_{FFM}^{ijk} in both types of neurogeneses. However, in the T-type, the number of cells relating to the network with high $w_{FFM}^{ijk} (> 0.3)$ has decreased in the last 40 environments (Fig. 13b). It shows that, although the connections w_{FFM}^{ijk} had dispersed in the beginning by the neurogenesis, it was integrated to cells which survived through learning several environments.

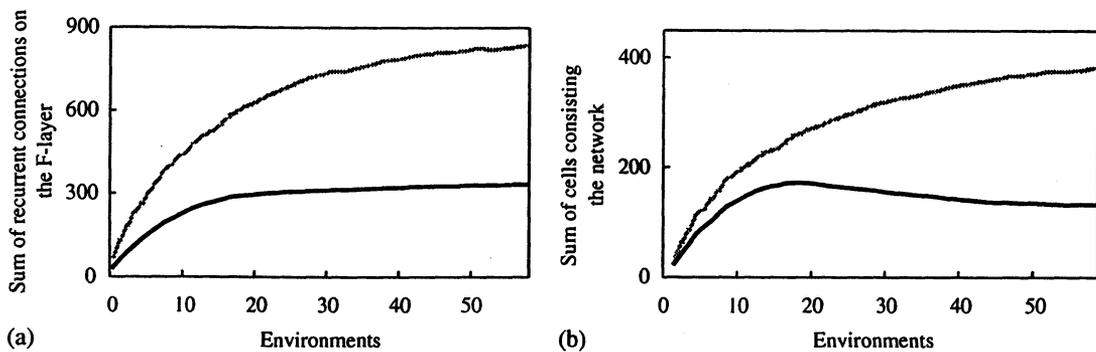


Fig. 13. Relationship between the sum of recurrent connections on the network and the number of cells, which are constructing the network: (a) Sum of w_{FFM}^{ijk} in each environment. (b) Total number of cell $_i$ of which $\sum_{j,k} w_{FFM}^{ijk}$ is above 0.3. The T-type (black line), and the P-type (gray line).

4. Discussion

4.1. Model with the neurogenesis

Our model started from a low ability to merely follow the path to the goal experienced just before. Then, the model acquired an internal map (about “map”, see Introduction) for the shortcut navigation by relating views of each environment to the network and avoiding contradicting connections by the neurogenesis.

Two types of neurogeneses were introduced, that is, the temporal type (T-type) and the permanent type (P-type). In Section 3.2, the P-type acquired the shortcut ability more quickly than the T-type. This is because connections are hard to be lost since the network is formed not by competitions but by integrations through the P-type of the neurogenesis. But the P-type needed more neurons to construct the network than the T-type. It is interesting as to which type of neurogenesis is realized in the real animal brain.

Moreover, we compared the neurogenesis with the highly decaying connections in Section 3.2. The highly decaying connections were expected to show the same ability with the neurogenesis. But, the results showed a lower performance of the highly decaying connections than those of the neurogenesis. Thus, it can be said that the neurogenesis plays an important role that avoids incorrect learnings and acquires the map, in the integration process of memory. (When the neurogenesis occurs is described in Step 1 of Section 2.3, and why it avoids incorrect learning is explained in Section 2.4.)

4.2. Navigation and allocentric information

According to the reviews on biomimetic navigation models by Trullier et al. [20,21], the rat’s performance of the shortcut navigation is called “metric navigation”. Since the metric navigation needs some allocentric information on distances and angles between

places, almost all models rely on coordinate frames that are implemented a priori in those models, for example, assuming place cells [10,11].

But, do real rats have place cells and maps by nature (a priori)? In the case of the place cell, visual landmarks can control the location of the place fields (e.g., [7,9]). It is often thought that visual information plays an important role in the localization process (e.g., [6]). Moreover, although Save et al. [14] discovered that blind rats developed place cells, it came out only within the case when rats could acquire some visual-like information, such as some objects different from each other in texture, instead of visual informations. Therefore, we think that the map is formed as a result of learning, and the biomimetic navigation model for explaining the metric navigation should be based on egocentric inputs.

Recently, Foster et al. proposed the navigation model which learns a coordinate system [2]. The model consists of two components. One is the actor-critic system, which learns actions to the goal using temporal difference (TD) learning [17], and the other is the dead-reckoning system, which learns coordinate system. When these two systems combine, the model could cope with goal shifts in a circular watermaze.

However, if the environment itself changes, for example, sufficient shifts of visual cues around the watermaze for changing a chart (a set of place cells [6]), the model cannot use the coordinate system built up until then, but must relearn it from the start. Moreover, the model assumes allocentric information with place cells as inputs. The problem is at the point that each cell showing the status of the model and the coordinate showing the location of the model are connected directly to the previous environment. In order to realize the metric navigation, a model needs to have the robust structure for environmental shifts. From this point, it can be said that our model with the neurogenesis performed the metric navigation by no utilization of any allocentric informations a priori.

But, as a navigation model, this model has some problems. For example, the model cannot perform a detour of an obstruction. It needs to give the information not only on the goal but the obstruction to the network. Maybe, such a model should be constructed to a unified system of several modules as suggested by Trullier et al. [21]. For constructing such a unified system to deal with dynamic environments, a problem will be how to implement emergent processes in a highly hierarchical structure.

4.3. *Path integration*

It is suggested that the path integration system also plays an important role in the localization process [6,13]. Even if there is no visual information, we can specify the original position. As stated previously, it is thought that real animals acquire this ability by learning. Therefore, the next step is to consider the acquisition process of the path integration ability.

The model predicts a shortcut by calculating the F-layer and the W-layer (and not calculating the V-layer) at the Reflection mode (Step 2 of the Section 2.3). This means that the model hardly needs the visual information after the model acquires the map. Therefore, we think that results in this paper show not only the performance of the neurogenesis but also the emergent process of the path integration ability. Although

there are many models which assumed the path integration (e.g. [13]), there are few models which treat the formation process of the path integration system as a problem.

4.4. Future problem

The neurogenesis may play an important role for the transfer of memories to long-term memory from short-term memory. However, the neurogenesis is not observed in the neocortex [3], although it is thought that a long-term memory is stored in the neocortex. Therefore, it is a problem how new information, which is formed by the neurogenesis in the hippocampus, is included in the existing network of the neocortex without neurogenesis.

Moreover, our model does not memorize individual rules, but it memorizes a universal rule for avoiding incorrect learning. Such a system—organizing a global rule to achieve its goal—may help to realize other biological processes like the acquisition of language.

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