Brain-inspired neural network navigation system with hippocampus, prefrontal cortex, and amygdala functions

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***Abstract*—We propose a brain-inspired neural network model consisting of the hippocampus, prefrontal cortex, and amygdala models for a navigation system that acquires specific knowledge in home environments from few experiences. The proposed model was evaluated in a home environment using a robot simulator. In the experiment, the robot determines a path for navigation based on the knowledge acquired by the brain-inspired model.**

***Keywords*—brain-inspired neural network, reservoir computing, service robot, navigation**

I. INTRODUCTION

Service robots that can support daily lives in home environments are attracting attention because of the falling birth rate and shrinking population in Japan. Service robots require two types of knowledge to work in home environments. One of them is common knowledge, which can be shared in any environment and is required for object recognition and voice recognition. The other is environment-specific knowledge, such as family preferences and room layouts. We can share a large amount of training data to acquire such common knowledge using current artificial intelligence (AI) models, such as deep learning, but environment-specific knowledge must be acquired from the robot's experiences, which comprise very little data. Acquiring environment-specific knowledge using a small amount of training data is difficult for current AIs.

Navigation is a typical task for service robots in which specific knowledge is required. Although the navigation systems currently implemented in robots can generate paths to avoid obstacles using temporary information obtained from sensors, introducing specific knowledge acquisition can improve the navigation performance of the system.

In this study, we propose a novel system that can acquire episodic memories from experiences and generate actions based on those memories and their emotional values. We focused on three areas of the brain: the hippocampus, prefrontal cortex, and amygdala. The hippocampus is concerned with episodic memories. The prefrontal cortex predicts future behavior to plan actions. The amygdala is concerned with emotions. We integrated the functions of the three brain areas into a neural network, including reservoir-computing and a self-organizing map (SOM) for the navigation system of robots.

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II. PROPOSED METHOD

Figure 1 illustrates the proposed model comprising the hippocampus, prefrontal cortex, and amygdala models. The model has two execution phases: training and inference. The blue arrows indicate the flow of the training phase, and the red arrows indicate the flow of the inference phase.

A. Hippocampus model

We use a model inspired by the place cell found in the hippocampus that represents self-positions [1]. The model receives the self-position obtained by a robot through simultaneous localization and mapping and output location information $\boldsymbol{x}_t$, where t indicates a time step, that represents the location of the robot. The self-position of the robot in a room in Fig. 2(a) is converted to the location information represented as a 2-dimensional Gaussian function by the model, as shown in Fig. 2(b).

B. Prefrontal cortex model

A prefrontal cortex model consisting of an echo state network (ESN) is concerned with the navigation path generation [2]. This model learns the time evolution of location information and generates a sequence of location information, $\boldsymbol{y}_t$ (Fig. 1), without external input signals.

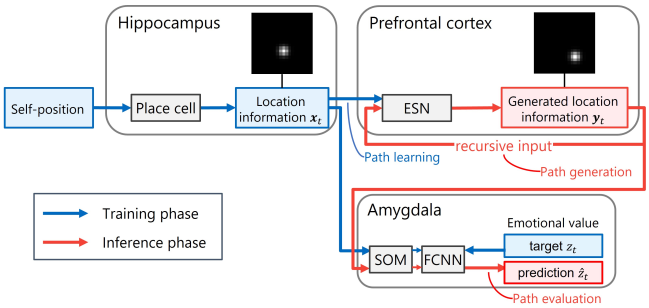

Fig. 1. Proposed model

(a) Robot in the simulator (b) Location in the hippocampus model

Fig. 2. Experiment environment

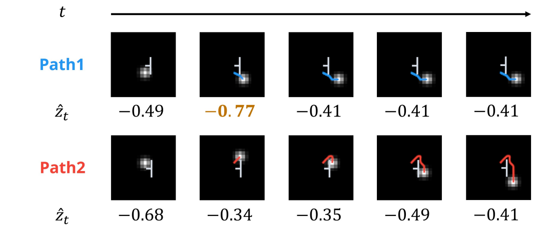

Fig. 3. Generated place information and the estimated emotional values

C. *Amygdala model*

An amygdala model [3] obtains location information $\boldsymbol{x}_t$ from the hippocampus model and estimates the emotional value $\hat{z}_t$ of the location. The amygdala model is composed of a SOM and a fully connected neural network (FCNN). The location information is classified at the SOM, and the FCNN outputs an emotional value using the SOM output.

D. *Integrated model*

1) *Training phase*

In the training phase, the location information from the hippocampus model $\boldsymbol{x}_t$ is given to the prefrontal cortex and amygdala models. The prefrontal cortex model is trained to output the time evolution of the location information that corresponds to the navigation path. The location information $\boldsymbol{x}_t$ as an input, and $\boldsymbol{x}_{t+1}$as a target from the hippocampus model is given. Since $\boldsymbol{x}_t$ is represented as a Gaussian function, a small difference of the place information does not affect the navigation path generation.

When the robot experiences a predefined event that affects task accomplishment, the target emotional value z_t is given to the amygdala model shown in Fig. 1 (for example, when the robot arrives in front of a closed door and cannot pass through there, the negative target emotional value is given because the robot cannot accomplish the task). The amygdala model is trained to output the emotional value z_t when a predefined event occurs.

2) *Inference phase*

During the inference phase, the next-location information $\boldsymbol{y}_t$ is generated by the prefrontal cortex model. Next, location information is fed to the prefrontal cortex model recursively to generate the path acquired during the training phase. Here, in the first time step, $t = 0$, we must provide an initial input to the prefrontal cortex model, which is the output of the hippocampus model $\boldsymbol{x}_0$. The generated location information $\boldsymbol{y}_t$ is also provided to the amygdala model. The amygdala model estimates the emotional value $\hat{z}_t$ of each location information. In this manner, the model can generate the path and evaluate its emotional value to determine the next action.

III. Experiment

In the experiment, we provided a map of a room with two open doors to the robot. We provide a goal position G to the robot in a room where only Door B was closed, as shown in Fig. 2(a). Without the proposed model, the robot missed the closed door when the robot rotated or moved because the door was outside the sensor range. The robot could not reach this goal because the navigation system processed only temporary sensor information. We evaluated whether the robot—with the proposed model—could avoid choosing Path 1 with a closed door in the room, as shown in Fig. 2(a).

A. *Training of the models*

First, we moved the robot from the start position S to the goal position G through Path 1 (Door B was open), and Path 2 so that the robot can learn both paths. The robot acquires self-position at constant intervals. We trained the prefrontal cortex model with the location information generated by the hippocampus model at $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t+1}$.

Next, we trained the amygdala model. We set a predefined event for the amygdala model as the robot was located in front of Door B, and we set its target emotional value as negative because the robot could not arrive at the goal through Door B. We provided an emulated output of the hippocampus model at Door B and provided $z_t = -1.0$ as the target emotional value. After training, the amygdala model output $\hat{z}_t \leq -0.70$, which was close to the target value, when the robot was near Door B. We considered the emotional value of location to be low if the output emotional value $\hat{z}_t$ was less than or equal to a predetermined threshold, -0.70.

B. *Result*

The prefrontal cortex model generated a path using the previously acquired memory. The generated location information and estimated emotional values are shown in Fig. 3. The trajectory of the location corresponding to the path is shown as a colored line. The prefrontal cortex model recursively generated Path 1 and Path 2, respectively, by providing the initial input of each path. In Path 1, the amygdala model outputs a low emotional value when the location information at Door B is given. Because the emotional value of Path 1 was low, the robot chose Path 2, which was not the shortest path.

IV. Conclusion

We proposed a brain-inspired neural network for the navigation system and evaluated it using a robot simulator. In this study, we must set a threshold to determine whether the emotional value of the path was low. In a future study, we aim to introduce a determination system that does not rely on the threshold. By combining various information such as the distance to the goal and the time required to move in addition to the emotional value, the model would be able to determine the path without a predetermined threshold.

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