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A Biological Plausible Spatial Recognition Model in Robots Based on Error Back-Propagation Algorithm

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Abstract

This paper proposes a model based on rat's hippocampus which can be used in the process of navigation for robot. Both grid cells and place cells in hippocampus play important roles in the process. The firing of grid and place cells are formed from persistent spiking grid cell model by Hasselmo; while the firing of place cells are formed by linear summation of appropriately weighted inputs from entorhinal grid cells through error back-propagation (BP) neural network. Every single confined place field could be formed by summing inputs from a modest number of grid cells with relatively similar grid phases, diverse grid orientations, and a biologically plausible range of grid spacings. As a result, spatial information is stored in robot in a way of place and grid cell firing.

Keywords: Spatial Representation; Hippocampus; BP Algorithm; Cognition Map

1 INTRODUCTION

Questions about how the environment has engaged cognitive science for decades [1] [2]. With the birth of experimental psychology and neuroscience, the mechanism of spatial behavior and spatial cognition could be analyzed experimentally. We review some evidences about the presence of a brain system for representation and storage of the environment from the past four decades. Here place cells and grid cells in the hippocampal and entorhinal cortices are key components about how we perceive and remember our position in the environment. This paper describes a kind of model based on the mechanism of hippocampus concerning how to represent or store the spatial information in robot. The model also has been tested in the paper according to the data recorded by Hafting in 2005[3].

2 BACKGROUND

2.1 Grid Cells and Entorhinal Map

Grid cells are becoming a hot topic due to their simultaneously simple behavioral firing correlate and complex spatial activity since they were discovered. Located in the medial entorhinal cortex (MEC), they code an animal's location in that each cell is characterized by multiple firing fields arranged in a strikingly regular, triangular, grid-like pattern that tessellates any two-dimensional environment explored by the animal [3]. The firing pattern of each 'grid cell' can be characterized by its spacing (the distance between neighboring vertices of the grid), orientation relative to the environment, and spatial phase (the offset relative to a fixed position in the environment). The spacing of the grid increases from the dorsal to the ventral end of MEC.

Regardless of external cues, these cells are suggested to be part of a universally applicable, internally generated map of the spatial environment. This neural map is activated whenever the animal's position coincides with any vertex of a regular grid of equilateral triangles spanning the surface of the environment. The map is anchored to extorhinal landmarks, but persists in their absence, demonstrating that grid cells may be part of a generalized, path-integration based map of the spatial environment [4] [5].

Many models have been suggested to explain the hexagonally arrayed spatial firing. Existing grid cell models use a

variety of different mechanisms. They are separate into groups of continuous attractor network (CAN) models and of interference models. However, some models use both CANs as well as the mechanism of interference. Proposed by Burgess, encoded positional information as the phase difference between oscillators, updated that position by modulating the oscillator frequencies, and used temporal interference to read that code out into the grid pattern. CANs are mechanisms for encoding and maintaining positional information, whereas interference is a read-out mechanism, so strictly the two are independent properties of a model [6].

Proposed by Hasselmo in 2008, a new model of grid cells based on the mechanism of intrinsic persistent spiking shown in entorhinal neurons is used in this paper [7]. This model provides an alternate implementation of the oscillatory interference model that is compared with the implementation using membrane potential oscillations. Evidences show that most cortical neurons generate spikes during depolarizing input, but will not continue firing after stimulation ends. Pyramidal cells in media entorhinal cortex commonly show persistent firing even when all synaptic input is blocked. Pyramidal neurons of medial entorhinal cortex continue firing at stable frequencies for an extended period after termination of current injection or synaptic stimulation.

2.2 Place Cells and Hippocampus Map

A principal cell type of this network is the hippocampal place cell .Which fires only if the rat is within a confined region of the environment, called the 'place field' of the neuron cell [8]. Neighboring place cells fired at different locations. At present Place cells are suggested to provide the animal a dynamic, continuously updated representation of allocentric space and animal's own position in that space. Most, but not all, place cells have a single firing field in a standard sized experimental environment. Grid cells recorded at the same dorsoventral level have similar spacings and orientations but, as for place cells in the hippocampus, the actual firing locations (spatial phase) of neighboring neurons are distributed, all locations in the environment are represented within a local ensemble of grid cells. Grid cells are active in all environments. It's a main difference between grid cells and place cells in the hippocampus.

The study on hippocampus spatial representation starts with the discovery of place cells 35 years ago. O'kefee and Nadel proposed that place cells are the basic elements of place representation in hippocampus in 1978.There are plenty of evidences demonstrated that hippocampus plays a key role in spatial representation and spatial memory. However, the entire environment was represented in the activity of the local population of cells. The spatial representation of hippocampal place cells is non-topographical, neighboring cells fire in different regions of the environment and the location of the animal can thus be represented accurately by the collective activity of any local ensemble of place cells .In open environments place fields can be approximated by a Gaussian function[9][10].

2.3 Connection from Grid Cells to Place Cells

Anatomical connectivity and recent neurophysiological results imply that Pace field are extracted from grid fields. Several studies show that hippocampal pyramidal neurons perform linear summation of synaptic inputs. Because grid cells are only one synapse upstream of the hippocampus, direct dendritic summation of grid-cell input appears as an attractive model for the emergence of hippocampal place fields [11].

The earliest model of the grids-to-places transformation views grid cells as the basis functions of a Fourier transformation and synaptic weights from MEC to hippocampus as the coefficients. Other models are based on competition in the hippocampal layer: the summed input to a hippocampal cell from grid cells is only weakly spatially selective, but competition allows only the hippocampal cells with the strongest excitation at any given location to become active, thus increasing the spatial selectivity suggest that maximizing sparseness in periodic grid inputs leads to punctate place fields in the output of independent components analysis [12].

Here is a basic model for place field formation (Fig.1). Assume anatomical connectivity between grid cells in the medial EC (MEC) and place cells in the hippocampus. Grid cells (blue) are illustrated with small grid spacings in the dorsal pole of MEC and with larger grid spacings at more ventral levels. All place cells with a place field receive input from grid cells of similar spatial phase (a common central peak) but with a diversity of spacings and orientations. Hippocampal place cells with a small firing field (green) are innervated by grid cells from more dorsal parts of the EC than place cells with a larger field (yellow). Connection weights are indicated by the thickness of the

arrows. Other neurons (red) provide nonspecific inhibition to keep overall firing rates at physiological levels. The color code for the rate maps ranges from blue (0 Hz) to red (peak rate) [12].

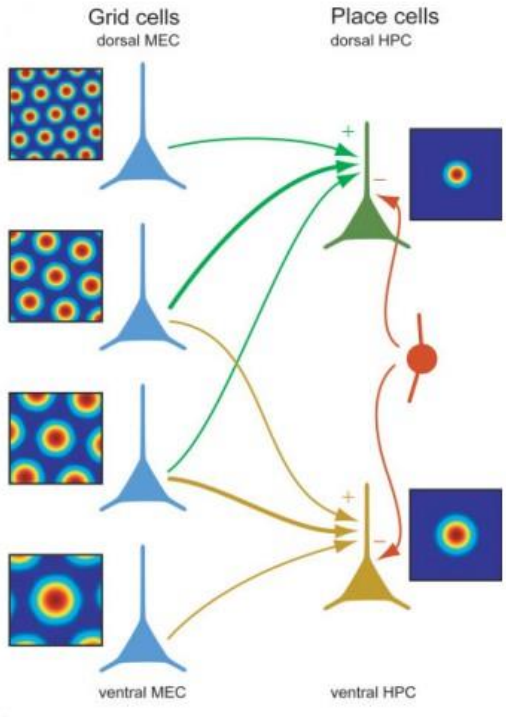


FIG. 1 ANATOMICAL CONNECTIVITY BETWEEN GRID CELLS AND PLACE CELLS

2.4 An Example- RatSLAM System

The RatSLAM system has a successfully spatial recognition method. It was developed to determine whether it is possible to create a biologically inspired SLAM system that can perform as well as, if not better than conventional techniques for SLAM. It has demonstrated to be capable of performing real-time, online SLAM in indoor or outdoor environments [13].

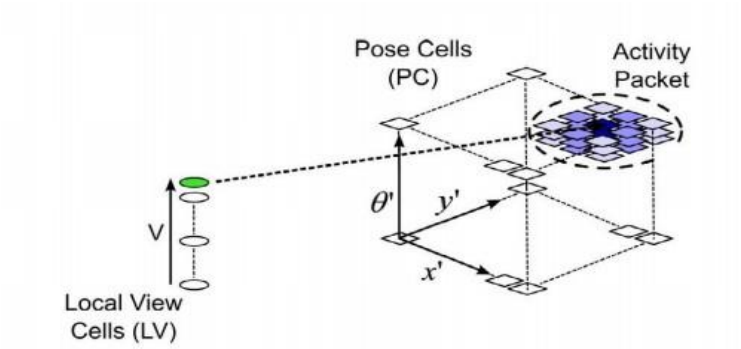


FIG. 2 CORE STRUCTURE OF THE RATSLAM SYSTEM

Its spatial representation called the pose cells. Fig.2 shows the core structure of the RatSLAM system. The pose cells represent a robot's pose by the activity in a competitive attractor neural network. Wheel encoder information is used to perform path integration by appropriately shifting the current pose cell activity. Activity can wrap in all three directions in the pose cell matrix. Vision information is converted in to a local view (LV) representation that is associated with the currently active pose cells. If familiar, the current visual scene also causes activity to be injected into the particular pose cells associated with the currently active local view cells [14].

The experience map produces a representation of the Cartesian space without collisions and discontinuities based on the temporal patterns of the pose cells combined with external sensor information. Using this representation space it is possible to perform effective goal recall in the presence of a large number of collisions and discontinuities in the

pose cells. The premise of the experience mapping algorithm is the creation and maintenance of a collection of experiences and inter-experience links. The algorithm creates experiences to represent certain states of activity in the pose cell and local view networks. The algorithm also learns behavioral, temporal, and spatial information in the form of inter-experience links. Fig.3 shows the structure of experience map.

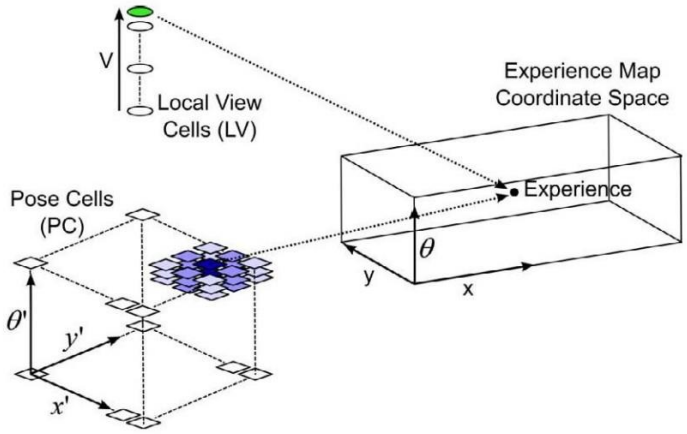


FIG. 3 STRUCTURE OF THE EXPERIENCE MAP OF THE RATSLAM

3 MATERIALS AND EXPERIMENTS

The goal of this study is to design a model which can generate the grids-to-places transformation and represent the environment. The firing of grid cell is based on persistent firing model proposed by Hasselmo in 2008[7]. It requires separate populations of neurons showing persistent firing at the same stable baseline frequency that remains constant in the absence of input.

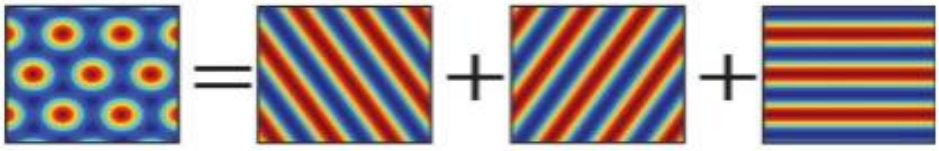


FIG. 4 MECHANISM OF GRID FUNCTIONS

As is shown in Fig.4 grid functions are constructed from, for example, a sum of three cosinusoidal grating functions with 60 and 120 degrees angular difference, and can take any specified orientation, spatial phase, and spacing. In the model, different persistent firing cells all send convergent synaptic input to individual grid cells. An individual grid cell will be brought over threshold and will spike when there is near simultaneous spiking across the persistent firing cell populations. In the model, the phase of the persistent firing cells is influenced by synaptic input coding speed and head direction, as in the oscillatory interference model. The speed-modulated head direction signal could come from head direction cells in the post-subiculum or in deep layers of the medial entorhinal cortex. The velocity-dependent depolarization causes a temporary and transient change in frequency. In the model, the phase of persistent spiking depends on the integration of velocity, due to transient shifts in the frequency of persistent spiking. For each persistent firing population, firing frequency is transiently increased by synaptic input from a population of head direction cells with a particular preference angle, and decreased by synaptic input from a population of head direction cells with the opposite angle of preference.

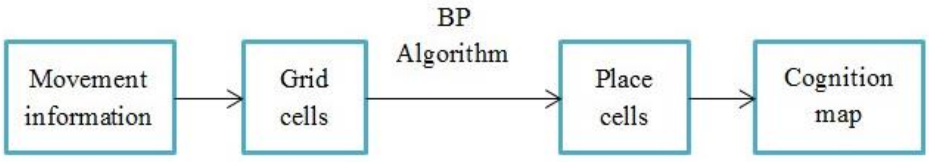


FIG. 5 STRUCTURE OF SPATIAL RECOGNITION MODEL

We assume $h(i)$ as speed-modulated head direction input.

$$h_i = H_i v = \begin{bmatrix} \cos(\theta_b + \theta_i)\sin(\theta_b + \theta_i) \\ \cos(\theta_b + \theta_i)\sin(\theta_b + \theta_i) \\ \cos(\theta_b + \theta_i)\sin(\theta_b + \theta_i) \\ \cos(\theta_b + \theta_i)\sin(\theta_b + \theta_i) \end{bmatrix} \begin{bmatrix} \Delta x(t) \\ \Delta y(t) \end{bmatrix} \tag{1}$$

It is obtained by multiplying the rat velocity vector $v(t) = [\Delta x(t), \Delta y(t)]$. Each row i of the head direction transformation matrix H .It consists of unit vectors corresponding to each preferred head direction. Where θ_b is the baseline head direction preference angle (set to zero in most simulations) and θ_i represents the relative preference angle of other head direction cells (at multiples of $2\pi / 3$).The phase of the spiking across each population of persistent spiking cells (indexed by i) changes at each time step according to the input from speed-modulated head direction input plus the baseline frequency.

Suppose $g(t)$ is the firing of the grid cell over time. The persistent spiking model of grid cells can be summarized as follows:

$$g(t) = \prod[\cos(2\pi(f_t + P(z)\int_0^t h_i(\tau)d\tau) + \varphi_i(0))]_H \tag{2}$$

The equation takes the product P of input to a single modeled grid cell from multiple persistent firing neurons i characterized by a single stable baseline frequency f .The repetitive spiking of individual persistent firing neurons is represented by a Heaviside step function $[]_H$ of a cosine function. The persistent spiking neurons have different initial phases represented by the initial phase vector $\varphi_i(0)$ and they receive input from different speed-modulated head direction cells h_i with different preference angles indexed by i . The frequency of each persistent firing neuron is transiently perturbed from baseline by depolarization in proportion to speed-modulated head direction, scaled by the parameter $P(z)$.

Currently back-propagation neural network is the most widely applied neural network architecture. Recently, Savelli and Knierim proposed a Hebbian learning rule that could learn the weights in a feed-forward network to generate the grids-to-places transformation. This popularity primarily revolves around the ability of back-propagation networks to learn complicated multidimensional modeling. Here we build the connection between grid fields and place fields by the method of back-propagation neural network.

As the robot gets the confined area, the pose correlated to the area is activated. The connection weights from grid cells to place cells can be obtained by BP neural network algorithm. Here we build a neural network with three layers named input layer, hidden layer and output layer as shown. Inputs of the network are grid cell activity $g(t)$ that we got previously.

Outputs of hidden layer in the network can be calculated as follows.

$$x_h^{\ l} = f_h(\sum_{i=1}^{m1} w_i g(i) + \theta_i) \tag{3}$$

Outputs of output layer in the network can be calculated as follows.

$$x_o^{\ k} = f_o(\sum_{1}^{m2} w_l x_h^l + \theta_o) \tag{4}$$

In the training process component of the BP algorithm, the gradient descent algorithm is applied. The error function is defined below. The parameter t_k represents target output from neuron k.

$$E = \frac{1}{2}\sum(t_k - x_o^k)^2 \tag{5}$$

The connection weights modified as follows. The parameter γ represents learning rate.

$$\Delta w_l = -\gamma \frac{\partial E}{\partial w_l} = -\gamma \frac{\partial E}{\partial x_o^k} * \frac{\partial x_o^k}{\partial w_l} = \gamma * (t_k - x_o^k) * f_o^{'} * x_h^l \tag{6}$$

$$\Delta w_i = -\gamma \frac{\partial E}{\partial w_i} = \gamma \sum (t_k - x_o^k) * f_o^{'} * w_l * f_h^{'} * g(i) \tag{7}$$

Suppose ε as the demand accuracy that we need. If $E < \varepsilon$, that means the error is small enough to meet the demand. Then the training is finished. Otherwise the training will continue. The connection weights will keep modifying until the error is small enough.

4 RESULTS

To simulate the behavior of the model, we let a virtual animal randomly explore square enclosures of size $1*1m^2$. We wanted the behavior to be somewhat realistic so we test the model with the experiment data from Hafting et al. 2005[3]. This contains trajectory of a rat running around an open field for about 591 seconds. The trajectory is shown as Fig .6.

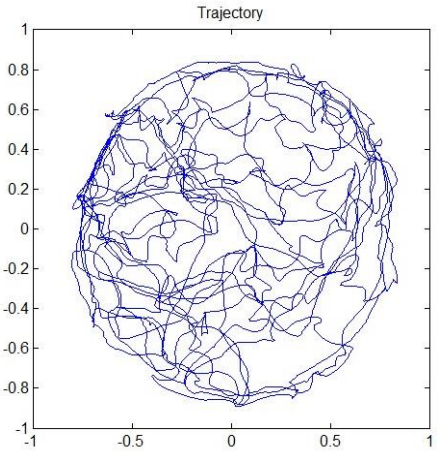


FIG. 6 TRAJECTORY OF A RAT IN HAFTING ET AL.2005

4.1 Grid Cells Performance

Here we choose 3 grid cells with different spacings and orientations. The first line represents the trajectory and spikes during the movement. The Second line contains 3 diagrams which show spike phases versus time.

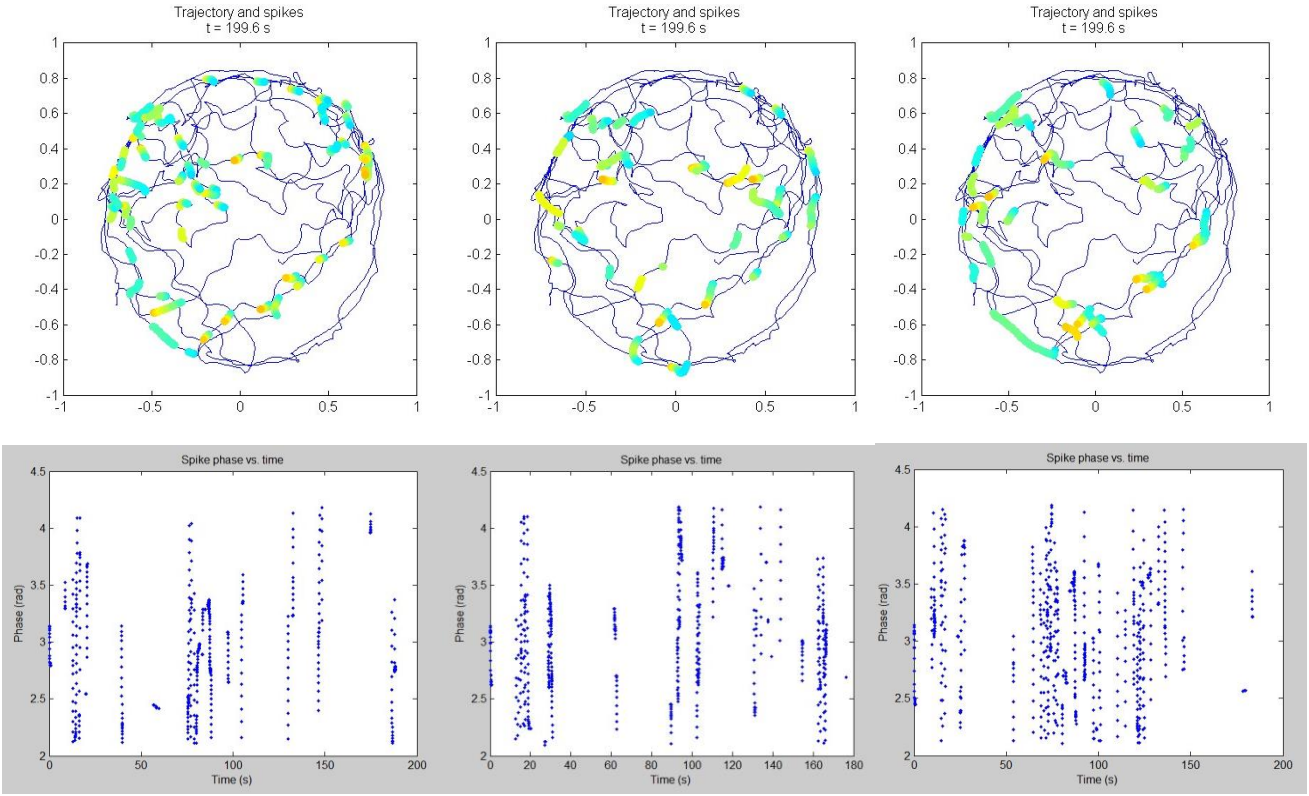


FIG. 7 FIRING FROM THREE GRID CELLS

We can see this three grid cells perform similar grid phases, diverse grid orientations, and a biologically plausible range of grid spacings. Their firing field perform hexagonal structure as described by Hafting [3]. This proved grid cell is feasible.

4.2 From Grid Cells to Place Cells

Here we take the first 20.4s of the exploration into consideration. The trajectory is shown follows.

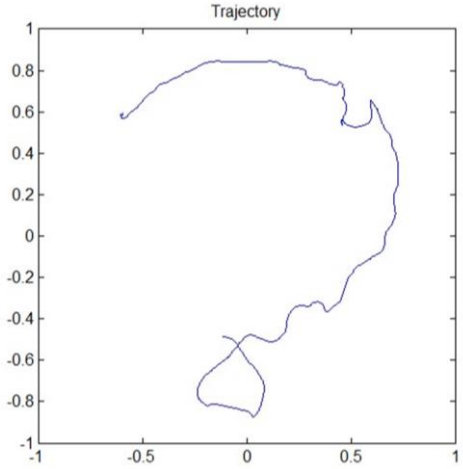


FIG. 8 TRAJECTORY OF THE FIRST 20.4S IN THE EXPERIENCE

Here 6 grid cells with different spacings and orientations are assumed here. Each grid cell is performed in the experience.

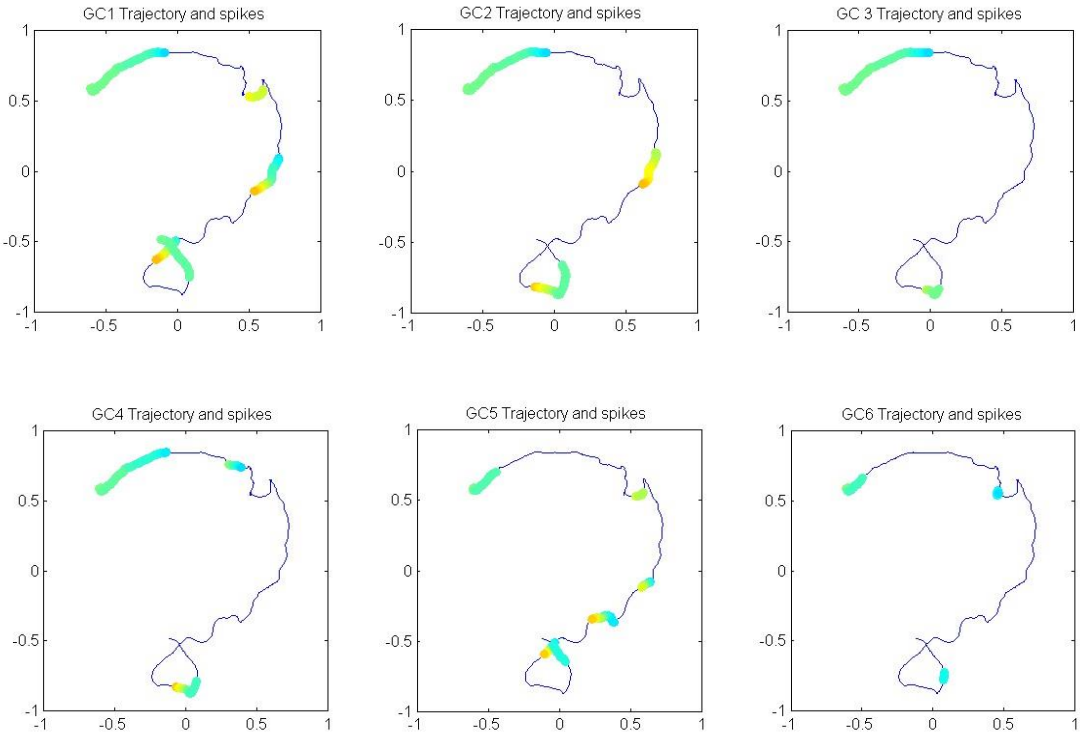


FIG. 9 TRAJECTORY AND FIRING IN THE FIRST 20.4S FROM THE SIX GEID CELLS

At the beginning, we choose a spot to be the firing spot of the place cell. When the robot first reaches this spot, the place cell fires (as is shown in the Fig10). The connection between place cell and grid cells is built according to the model described previously. The left figure shows the spike and trajectory .The right figure shows the activity of the place cell versus time.

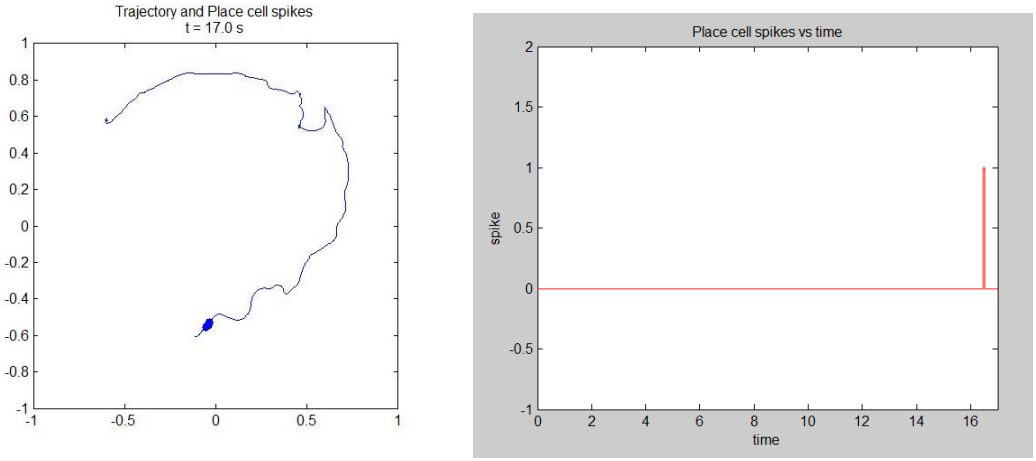


FIG. 10 PLACE CELL TRAJECTORY AND FIRING DURING THE FIRST 17S

Then the robot continues moving. About 4 seconds after the robot reaches this position again according to the relationship between grid cells and place cells in the spatial recognition model. The place cell should be activated by the model. As is shown in the Fig.11, the right figure proved the place cell is activated in the same spot during the exploring. Which demonstrated this spot is successful represented by the place cell.

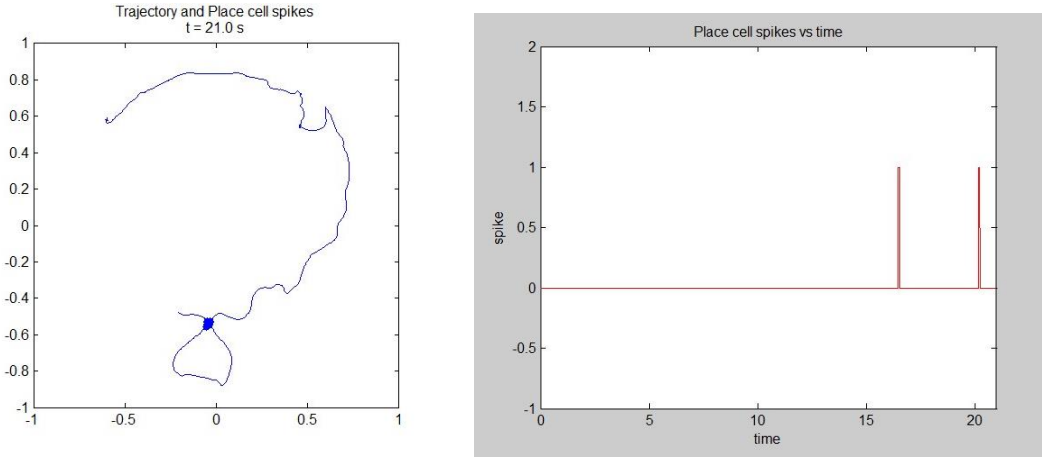


FIG. 11 PLACE CELL TRAJECTORY AND FIRING DURING THE FIRST 21S

5 DISCUSSION

A movement trajectory recorded from a real rat has been used in the experience. We extract speed and direction information from the trajectory. Here the spatial recognition model has successfully learned the grids-to-places transformation. The spatial will be represented more precisely as more place cells are summed here. We can see the grid cells and place cells in our model got the same performance comparing with the same parts in rat's hippocampus. This spatial recognition model has been demonstrated feasible.

6 CONCLUSION

This model has shown some advantages, such as the ability to use low-cost sensor to perform spatial recognition. Compared with RatSLAM and other traditional models, this kind of spatial recognition model can be less independent on hardware facilities and combined with the latest biological discoveries. This model can work successfully in the absence of external self-induced motion cues such as visual flow.

Future work: How to understand the output is a crucial outstanding question. These outputs are thought to have a vital role in providing a contextual tag for consolidation of episodic memories stored in distributed neocortical modules. In terms of understanding the role of the hippocampus in either navigation or memory, concerns the form of the output code of the hippocampal formation and how to use it.

In mammals' navigation process, external environmental and internal movement-related information are combined.

How big is the contribution of vision information? This is still partly unclear by now [15]. In the future work, neural representation between external information like vision and internal information like movement should be simulated.

Some researchers are focusing on the process of development of hippocampus [16]. The mechanism and performance of hippocampus are becoming clear. Future work can focus on modelling this process and apply the process in studies about robot development.

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