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Robotic Episodic Cognitive Learning Inspired by Hippocampal Spatial Cells

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***Abstract*—This paper presents a robotic episodic cognitive learning framework based on the biological cognitive mechanism of hippocampal spatial cells. By emphasizing the cognition process and episodic memory in brain, the framework adopts the velocity modulated grid cells and place cells to afford the robot position cognition, abstracts the state neurons to represent the robotic state, and uses state neurons' activity and connection to simulate the episodic memory construction process. The episodic memory is formed by a sequence of particular events consisting of visual features, state neuron, phase, and pose information. Besides an episodic-cognitive map building approach based on this framework is proposed, which performs closed-loop correction by resetting the spatial cells phase to keep the map accurate. The episodic-cognitive map built in this paper is a topological metric map to describe the topological relations of the particular events coordinates in the unknown environment. The framework is applied on a mobile robot platform, the robotic episodic cognitive learning and episodic-cognitive map building approach are investigated. The robotic experiments demonstrate that the framework can effectively achieve the robotic incremental accumulative learning, update the spatial cognition to the environment and construct the episodic-cognitive map.**

I. INTRODUCTION

One of main objectives of recent robotics research is the development of robots which can be capable of realizing cognition to the unknown environment. The ability of spatial cognition is fundamental to robotic intelligent control, including environment exploration, map building, localization, and navigation [1]. The spatial cognition is also crucial for humans and animals to survive in the world. The three-maze navigation experiments revealed that the animal's navigation depended on the cognitive maps in brain, and clarified that cognitive maps were not solely for mapping physical space but for a broad range of "cognitive space" [2,3].

Reviewing the literature on hippocampal function and physiology, a large body of evidences show that hippocampus is selectively involved in spatial cognition and memory. The hippocampus damage experimental research also shows that hippocampus is the main region for representation of the space and episodic memory, and mice without hippocampus could not complete the Morris water maze navigation [4]. The 2014 Nobel Prize in Physiology or Medicine is awarded to John O'Keefe, May-Britt and Edvard Moser for their discoveries of hippocampal place cells [5] and medial entorhinal cortex grid cells [6]. Place cells, grid cells, together with other cells [7, 8] constitute a comprehensive global positioning system (GPS) in brain. Based on the biological cognitive mechanism, grid cells and place cells have been gradually applied in the field of spatial cognition and map building for mobile robot.

Humans and animals have large hippocampal-entorhinal brain structures which have been implicated in spatial learning and episodic memory long before. In this work, we aim to apply this biological cognitive mechanism into robot system and achieve the robotic cognition to the unknown environment. An episodic cognitive learning framework is proposed, which introduced spatial cells, visual cues, kinesthetic cues, and state neurons for realizing robotic cognition, constructing episodic memory and building a cognitive map. To the best of our knowledge, kinesthetic cues are used to maintain and update the activity of grid cells, and sequentially used to update the activity of place cells. Our strategy is based on that neuronal activity in the hippocampus reflects memory processing [9]. By studying the episodic memory storage mechanism and establishing the connection between neurons, the mobile robot can perceive its current position in the environment, and effectively retain the particular events of experiences to construct episodic memory [10]. The proposed framework can provide ideas for subsequent path planning and behavior controlling of mobile robot.

In summary, this paper makes the important progress in the following two aspects:

1) The proposed episodic cognitive learning framework emphasizes the process of cognition and memory, especially, it adopts the velocity modulated spatial cells to afford the robot spatial position information, abstracts the state neurons' activity and connection to simulate the memory construction process. The framework possesses high cognitive intelligence. Based on the framework, the robot can achieve spatial cognition to the unknown environment by accumulative learning, and retain the learned experiences to construct episodic memory.

2) The framework based map building method tracks the neural activities to encode locations and orientations with regard to the robot, and creatively performs the closed-loop correction by resetting the spatial cells phase. It can build an episodic-cognitive map with higher efficiency and accuracy. The final episodic-cognitive map is a topological metric map in the unknown environment, including environmental visual cues, state neurons, phase, and particular coordinates of topological relationships, which affords the robot high cognitive ability.

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II. RELATED WORK

Place cells are located in the hippocampus, they are activated respectively when an animal enters different particular locations in the environment, and these ensembles of place cells represent not only the animal's current location but also locations that the animal had visited earlier, they can build an inner map of the environment in the brain [11]. Grid cells are located in the entorhinal cortex which is the neighborhood of the hippocampus, they are activated when an animal passes specific locations, they are regarded as the core of path integration system, and they can form a coordinate system that allows for spatial navigation [12]. Inspired by the spatial cells' position cognition mechanism, many research models have been proposed for realizing the robotic cognition to the environment and building cognitive maps.

Among these models, some models [13-15] actually just built maps using place cells, they simplified the physiological basis and lacked of localization accuracy. To improve the spatial localization accuracy, Tejera presented a bio-inspired model for spatial cognition, which can create a World Graph topology map for robot navigation [16]. Milford presents a new SLAM system, RatSLAM, that has been derived from models of the hippocampal complex in rodents. It uses pose cells to integrate odometric information with landmark sensing to form a consistent representation of the environment [17]. Using both grid cells and place cells, Yuan proposed a computational model to build cognitive maps, they adopted a competitive hebbian learning method for selecting grid cells activity to compute place cells activity [18], whereas the high computational complexity has a high requirement on storage and run time. Chen applied boarder cells, view cells, grid cells, and speed cells to simultaneous localization and mapping to construct a computational GVGSP-SLAM model [19], but this model has not been implemented in simulation or a real robot. Yu proposed a unified spatial cells attractor model for self-motion trajectory path integration to build the environmental cognitive map [20]. However these models never consider the function of episodic memory formed in the hippocampus. The robot system with memory function could improve the robot capability and intelligence [21].

A few studies developed episodic memory models for cognitive robots in the field of mapping and navigation. EPIROME model was proposed to improve robot action planning based on the past experiences [22]. Stachowicz adopted index data structure to store episodic memory to provide knowledge for robot [23]. Kelley implemented a memory model to allow a robot to retain knowledge from previous experiences [24]. Liu created a framework of episodic memory driving Markov decision process for episodic memory construction and navigation [25]. In [26], an unsupervised learning model enhanced episodic memory adaptive resonance theory was proposed. The model can categorize and encode experiences of a robot to the environment and generate a cognitive map. However, the models [22-24] actually focused on data structure to simulate the functionality of episodic memory, which paid less attention on biological basis. The models [25, 26] elaborated how cognitive map is interfering with episodic memory, but they did not clarify how the neuronal activity in the hippocampus affects the memory construction. Thus, there remains a need to explore the interactive relationship among spatial cells, episodic memory and cognitive map for the mobile robotic application.

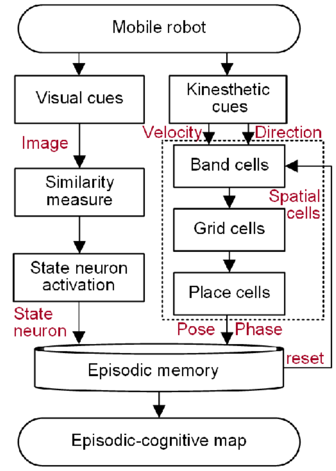

Fig. 1. Episodic cognitive learning framework.

III. EPISODIC COGNITIVE LEARNING FRAMEWORK

The proposed episodic cognitive learning framework is shown in Fig. 1. The robot system extracts the velocity and direction information to modulate the activity of spatial cells, and then combines with scene image information, activates state neurons and forms episodic memory. At last, the robot system generates an episodic-cognitive map as a result. The detailed description of these modules in this framework will be provided in the following sections.

A. Spatial Cells Model

1) Path integration model

Both grid cells and place cells are modulated by the theta rhythm that oscillates at between 4 and 12 Hz [27]. As the foundation neuron of grid cell [28], the band cell's membrane voltage (mv) can be computed as (1). It is the total of cosine function of soma oscillation at frequency f_s and dendrite oscillation at frequency f_d . And the simulation result of oscillation interference between soma and dendrite is shown in Fig. 2. It creates the phase precession phenomenon [29].

$$bc(t) = \cos(2\pi f_d t) + \cos(2\pi f_s t) \tag{1}$$

According to (1), the beat frequency f_b is obtained from the difference of f_s and f_d , i.e., $f_b = f_d - f_s$. Moreover, the beat frequency f_b is influenced by the velocity and direction of the animal's movement according to (2)

$$f_b = Bs\cos\left(\varphi - \varphi_d\right), \tag{2}$$

where s is the movement velocity, φ is the movement direction, φ_d is the preferred direction, and constant B is used for keeping band cell's firing pattern stable. The resulting interference pattern of (1) resembles parallel bands across a 2D environment, as shown in Fig. 3. They fire periodically whenever an animal moves a fixed distance in the cell's preferred direction. And the fixed distance is called spatial wavelength, which is related with the spacing of grid cell.

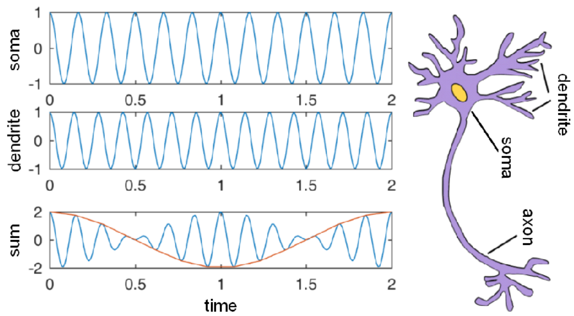

Fig. 2. Simulation result of oscillation interference.

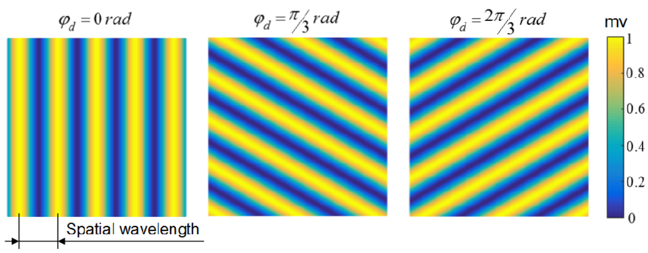

Fig. 3. Interference pattern along different preferred directions.

As we know, the change in spatial position can be represented by the velocity, which is the change in spatial coordinates for a given change in time $(\Delta x/\Delta t, \Delta y/\Delta t)$. So the velocity can be computed as $s = \sqrt{(\Delta x/\Delta t)^2 + (\Delta y/\Delta t)^2}$, and the animal's movement direction can be calculated as $\varphi = \arctan((\Delta y/\Delta t)/(\Delta x/\Delta t))$. For the movement relative to the preferred direction $\varphi_d = 0$, f_b can be rewritten as $f_b = Bs\cos(\varphi - \varphi_d) = B\,\Delta x/\Delta t$. The phase is the time integral of its frequency, and the change in phase of the beat oscillation with frequency f_b over time can be transformed into the change in phase with position as (3)

$$\Delta\phi_b(\varphi_d = 0) = 2\pi f_b \Delta t = 2\pi B \Delta x. \qquad (3)$$

Summing (3) from the start point shows that phase depends directly on position relative to the start position x_0, i.e., $\phi_b(\varphi_d = 0) - \phi_0(\varphi_d = 0) = 2\pi B(x - x_0)$. $\phi_0(\varphi_d = 0)$ is the initial phase relative to the preferred direction $\varphi_d = 0$. In this way, the relationship between phase difference and position difference is built, which is the basis for path integration.

2) Grid cell and place cell model

Grid cells fire periodically to form a hexagonal firing field to cover the whole environment when the animal is exploring the environment. The hexagonal firing pattern of grid cell may be simplified as overlay of three spatial patterns of band cells, which have preferred directions differing by multiples of pi/3 rad, as shown in Fig. 4, it is obtained by summing of three band cells shown in Fig. 3. The activity of grid cell over time can be obtained according to (4) and (5)

$$\begin{aligned} gc(t) &= \prod_{i=1}^{3}\left\{\cos\left(2\pi f_d t + \phi_i\right) + \cos\left(2\pi f_s t\right)\right\} \\ &= \prod_{i=1}^{3}\left\{\begin{matrix}\cos\left(2\pi\left(f_s + Bs\cos(\varphi - \varphi_{di})\right)t + \phi_i\right) \\ +\cos\left(2\pi f_s t\right)\end{matrix}\right\} \end{aligned} \qquad (4)$$

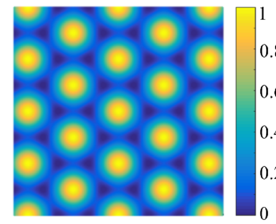

Fig. 4. Hexagonal firing pattern of grid cell.

$$gc(t) = \begin{cases} gc(t) & if\ gc(t) > \theta_{gc} \\ 0 & otherwise \end{cases}, \qquad (5)$$

where φ_{di}, ϕ_i are the preferred direction and phase offset of the ith dendrite input respectively, and θ_{gc} is the activity threshold of grid cell.

The fact that grids are reliably located from trial to trial implies that the grids become associated to the environmental landmarks within a familiar environment. For the reason that the movement velocity and direction are subject to error, these dendrite oscillations would have a cumulative effect on the grid location in space. The cumulative error can be optimized by resetting all dendrite oscillators to the same phase at the familiar location.

In this paper, to avoid the high computational complexity, we simplified the physiological basis, and modeled the place cell as an AND gate for receiving inputs from several presynaptic grid cells with similar spatial phase but different spacings and directions. The output activity of place cell can be computed as (6)

$$pc(t) = \left[\prod_{i=1}^{3}(gc_i(t))\right]_+. \qquad (6)$$

The activity of place cell is abstracted to describe the particular positions, which can afford the robot position cognition in the environment.

B. Spatial Episodic Memory Model

For the fact that neuronal activity in the hippocampus reflects memory forming process, this work abstracts the state neurons to imitate place cells to represent the robotic states, and uses the state neurons' activity and connection to simulate the episodic memory construction process.

1) Event model

The episodic memory stores a series of particular events representing experience. More specifically, as (7), one event e is modeled as a tuple of observation o, state neuron s, pose p, and phase ϕ_b.

$$e = \langle o, s, p, \phi_b \rangle \qquad (7)$$

Observation is used for place recognition. The SIFT features of current scene image is extracted, and the descriptors are used to describe the robotic current observation.

State neuron is used to estimate the robotic current state. We use the state neurons' activity and connection to construct the episodic memory. The sequence of state neurons allows the mobile robot to remember temporally ordered representations of events.

Pose is calculated by the path integration, it represents the robotic current position (x, y) and heading direction φ, and affords the topological description of the particular events in the environment.

Phase describes the phase of beat oscillation at frequency f_b at the robotic current state. The phase can be transformed to location and used to afford the spatial coordinates for map building.

2) State neuron activation

When the robot first enters a new place, the robot system would capture the current scene image and extract the SIFT features to represent the current observation. This work defines a unidirectional mapping projection from high dimensional observation to low dimensional state neuron, which means that there is always a unique state neuron for any observation. To estimate whether to activate a new state neuron or a previous activated state neuron, the maximum observation similarity measurement between current observation and the previous observation is specified as (8)

$$\varepsilon = \arg\max_{i=1,2,\cdots,n} \frac{\mathrm{match}\left(o_{cur}, o_i\right)}{\max\left(\mathrm{length}(o_{cur}{}^T), \mathrm{length}(o_i{}^T)\right)}, \tag{8}$$

where n denotes the number of previous activated state neurons, $\mathrm{match}\left(o_{cur}, o_i\right)$ returns the number of matched SIFT feature points, $\mathrm{length}(o_{cur}{}^T)$ returns the number of current observation's feature points.

If the maximum observation similarity measurement ε is larger than a similarity threshold θ_s, the robot system would assume it encounters a familiar place. And then the Euclidean distance between the current estimated positon and previous position is calculated. If the distance is less than the preset distance threshold, the robot system would consider that it encounters a familiar place, and activate the corresponding state neuron. Otherwise, the robot system would think it enters a new place that it never reaches before, and it activates a new state neuron for current place. In this case, the previous activated state neurons become the context state neurons of current activated state neuron. In different places, the robot system would activate different state neurons to represent its different states for place recognition.

3) *Episodic memory construction*

The process of episodic memory construction is shown in Fig. 5. Along with the time, the robot wanders into different places, the robot system combines the observation with the pose and phase information through the velocity modulated spatial cells to activate different state neurons, builds events, and forms the episodic memory. As shown in Fig. 5, the red circle represents the current activated state neuron s_i, and the blue circles represent the context state neurons $s_j, j \in [i-k, i-1]$. This work uses the state neurons' activity and connection to simulate the episodic memory construction process. When one state neuron is activated, it would build the connection with its context state neurons. We define $w_{i,j}$ as

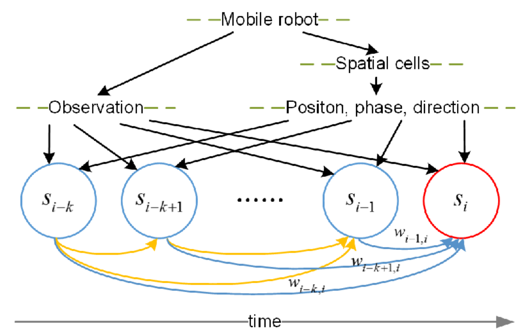

Fig. 5. Memory construction by state neurons' activity and connection.

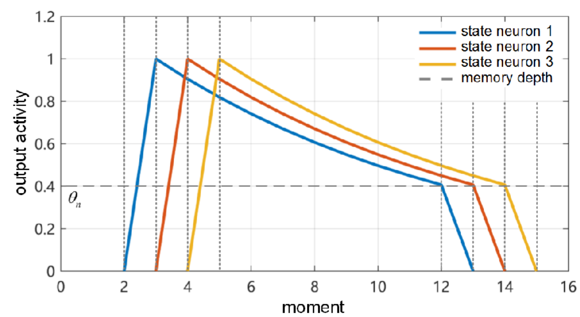

Fig. 6. State neurons activation and decay characteristic.

the connection weight, and compute it as (9). It represents the connection relationship between the current activated state neuron s_i and the context state neuron s_j (the blue arrows in Fig. 5). Similarly, the yellow arrows are used to describe the connection relationship between the previous activated state neuron and its context state neurons. These state neurons connect with each other to form the episodic memory.

$$w_{i,j} = s_i(t) \cdot s_j(t) \tag{9}$$

In this paper, the output activity of current activated state neuron s_i at current moment t can be represented by $s_i(t) = 1$. For the reason of decay characteristic of state neurons along with time, the output activity of the state neuron can be calculated as (10)

$$s_i(t) = \begin{cases} s_i(t-1) \cdot \exp(-1/\tau) & s_i(t-1) > \theta_n \\ 0 & otherwise \end{cases}, \tag{10}$$

where τ is a decay coefficient, memory depth θ_n determines the maximum quantity of the context state neurons. The schematic of state neurons activation and decay characteristic is shown in Fig. 6. The curve shapes of the output activity of the state neuron would be changed if it is reactivated again.

Along the robotic exploration process, the robot system activates a series of state neurons, meanwhile it builds sequence of events. In this work, there are two premise elements that determine whether to build a new event. If the activity of place cell $pc(t)$ is larger than the activity threshold of place cell θ_{pc}, and the distance between the self-estimated position and the latest event's position is larger than a distance threshold θ_l, the robot system would build a new event. The event's position can be computed as (11)

$$\begin{cases} x = x_0 + \left[\phi_b(\varphi_d = 0) - \phi_0(\varphi_d = 0)\right] / 2\pi B \\ y = y_0 + \left[\phi_b(\varphi_d = \pi/2) - \phi_0(\varphi_d = \pi/2)\right] / 2\pi B \end{cases}. \tag{11}$$

Through connecting these state neurons to build the connection strength between these events, which can be used to perceive the order of events in the memory space for robot. And we abstract the connection strength to describe the topological relations between events. These events are stored to form the episodic memory, which can realize the robotic incremental cognition to the environment.

IV. Episodic-cognitive Map Building Approach

Based on the episodic cognitive learning framework, this work proposed an episodic-cognitive map building algorithm as follows.

Episodic-cognitive map building algorithm

Input: current scene image, velocity, and direction
Output: an episodic-cognitive map
  Compute the activity of grid cell $gc(t)$ and place cell $pc(t)$
  If $pc(t) > \theta_{pc}$
    Extract the SIFT feature of current scene image
    Compute the current phase and pose
    If $n = 1$
      Activate the first state neuron s_1, build the first event e_1
      $n = n + 1$
    Elseif
      Compute the similarity measurement as (8)
      If $\varepsilon > \theta_s$
        Activate a previous activated state neuron
        Update the current phase and position
      Elseif
        Activate a new state neuron
      Endif
      Update the state neuron connection weights
      Build a new event e_n
      $n = n + 1$
    Endif
    Store the event into episodic memory
  Endif
  Return the episodic-cognitive map

When the mobile robot first enters into an unknown environment, it has no knowledge about the environment. It gets the knowledge by wandering about and interaction with the environment. During the exploration, the mobile robot system extracts its self-motion information to modulate the activity of grid cell and place cell. Given an activity threshold, if the current place cell's activity is larger than the threshold, the robot system would capture the scene image and extracts the SIFT features. According to the observation's similarity measurement, a new state neuron or a previous activated state neuron is activated, and the corresponding event is built and stored into episodic memory at the same time. Based on the formed episodic memory, the robot system can extract a topological metric map to describe the topological relations of the particular events' coordinates in the unknown environment.

If a previous activated state neuron is reactivated, the robot system would consider it encounters a familiar place where it has reached before. However, due to the path integration

Fig. 7. Robot system and corridor environment.

TABLE I. The Predefined Parameters

Symbol	Value	Symbol	Value
f_s	6	θ_s	0.3
θ_{gc}	0.15	θ_l	0.5
θ_{pc}	0.4	τ	10
B	[2.96, 2.17, 1.72]	θ_n	0.4

deviation, the robot estimated current position is not the same as the previous position, so it needs to correct the corresponding position. In this work, we correct the position information by resetting the phase as (12)

$$\phi_b'(t) = \phi_b(t) - \frac{\alpha\left(\phi_b(t_{loc})\text{-}\phi_b(t_{pre})\right) \cdot \left|\phi_b(t) - \phi_b(t\text{-}1)\right|}{\sum_{t_0 = t_{pre}+1}^{t_{loc}} \left|\phi_b(t_0) - \phi_b(t_0\text{-}1)\right|}, \tag{12}$$

where $\phi_b'(t)$ is the new phase after resetting, $t, t_0 \in \left[t_{pre}, t_{loc} - 1\right]$, t_{loc} and t_{pre} represent the current and previous time when the robot reaches to the current place respectively, α is a reset factor.

V. Implementations and Results

To evaluate the proposed episodic cognitive learning and map building method, we implemented it in a real corridor environment, as shown in Fig. 7. The robot system contains a Husky mobile robot with a Kinect vision and Hokuyo laser sensor mounted on it. Two computers with 2.40GHz CPU speed construct the whole episodic cognitive learning and map building platform. Laptop 1 connects directly to the robot and sensors for robot control and data extraction. Laptop 2 is responsible for running the algorithm, and it communicates with laptop 1 through TCP/IP. The predefined parameters utilized in this experiment are specified in Table I. The experimental results are discussed in the following sections.

A. Performance of Episodic Cognitive Learning

During the experiment, the mobile robot wanders along the predefined trajectory in the corridor environment. The results of robotic episodic cognitive learning are shown in Fig.8.

During the mobile robotic exploration process, the dendrite oscillation frequency is modulated by the kinesthetic cues, and it varies over time as shown in Fig. 8(a). Fig. 8(b) shows the phase of beat oscillation changes over time. The blue dashed line depicts the phase relative to the preferred

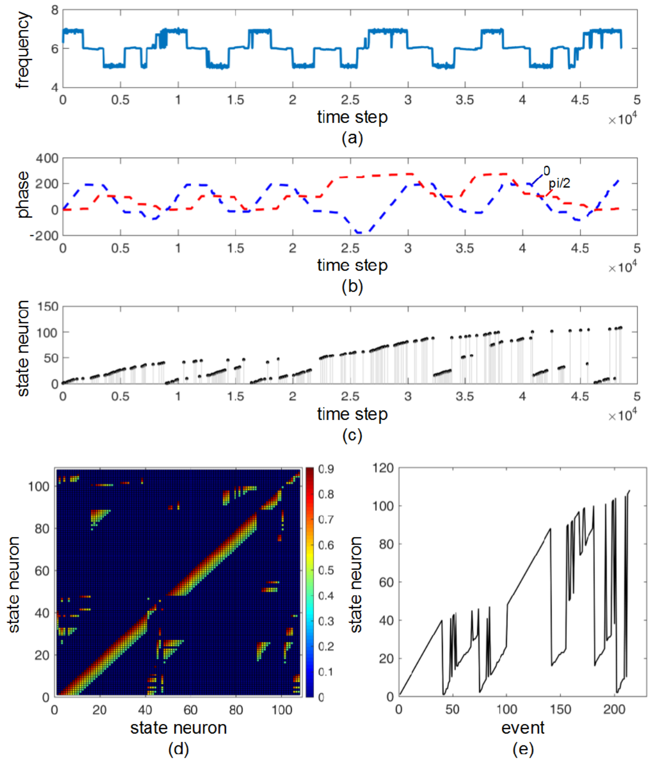

Fig. 8. Results of robotic episodic cognitive learning. (a) Frequency of dendrite oscillation (b) Phase of beat oscillation relative to different preferred directions (c) State neurons activation sequence (d) State neurons connection weights (e) Relationship between state neurons and events.

direction $0\,rad$, and the red dashed line depicts the phase relative to the preferred direction $\pi/2\,rad$. They are proportional to the robot's movement distance in the preferred direction, and provide the robot position cognition in the environment.

State neuron is abstracted to represent the robotic state and construct the episodic memory. Fig. 8(c) describes the state neurons activation sequence along the robotic exploration. Initially, the environment surroundings are new to the robot, therefore the robot activates different state neurons to represent its different states and forms experiences. When the robot revisits the environment, some previous activated state neurons are reactivated because the robot recognized the explored environment based on previously learned experiences. This experiment totally has activated 108 state neurons. These state neurons connect with each other to construct the episodic memory, and the connection weights is shown in Fig. 8(d). Each square corresponds to the connection weight from state neuron i (y direction) to state neuron j (x direction). The larger the connection weight between two state neurons is, the more adjacent of them store in the episodic memory. The robot system uses the events to represent its learned experiences. According to the principle of event building, this experiment has totally built 214 events. Fig. 8(e) shows the relationship between state neurons and events, one state neuron may correspond to different events. These state neurons establish the relationship among events to form the episodic memory.

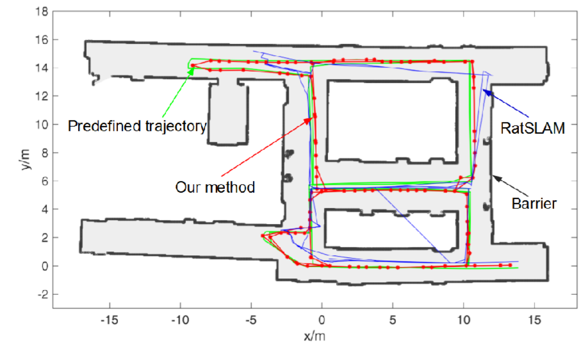

Fig. 9. Results of episodic-cognitive map building.

From the above results, the proposed method can afford the robot ability of acquisition, storage, and retrieval of knowledge about spatial scene and position. It can achieve the spatial cognition to the unknown environment in the following three parts. First, the method can path integrate the kinesthetic cues to afford the robot position cognition. Second, the method can adapt to the environment changes by updating the state neurons and building events to form the episodic memory, which is important for long term operation. Third, the method can retrieve the previous learned experiences to recognize the environment, which is the process of cognitive learning and memory retrieval, and the process does not require any human intervention, therefore it can work in the natural environment.

B. Performance of Episodic-Cognitive Map Building

The result of the proposed episodic-cognitive map building method is shown in Fig. 9. The green line is the predefined trajectory for the mobile robot, it traverses the entire corridor environment. The grey area surrounded by black dots is the grid map built by implementing the Gmapping algorithm, and it is used to display the layout of the actual corridor environment. The red dots marked line is the final constructed episodic-cognitive map, and the red dots represent these particular events built in the exploration process. The result shows that our method can better path integrate the kinesthetic cues and perform the closed-loop correction by resetting the spatial cells phase.

In this work, each event consists of observation, state neuron, phase, and pose information. After the robotic exploration, the robot system can build sequence of events to represent the particular learned experiences. Through connecting the events coordinates according to the generation sequence of events, the robot system can build the episodic-cognitive map with a set of vertices representing the discrete events, and a set of edges representing the connection strength between two adjacent events. The generated episodic-cognitive map is not solely a topological metric map for mapping the physical environment, but a broad range of spatial cognition to the environment, which can afford the robot high cognitive ability. Based on the episodic-cognitive map, the robot system can get the spatial position relationship among different particular scenes in the environment, and the sequence of these learned experiences.

B. Discussion

Similar to this work, RatSLAM is a novel SLAM approach inspired by computational model of the hippocampus. We

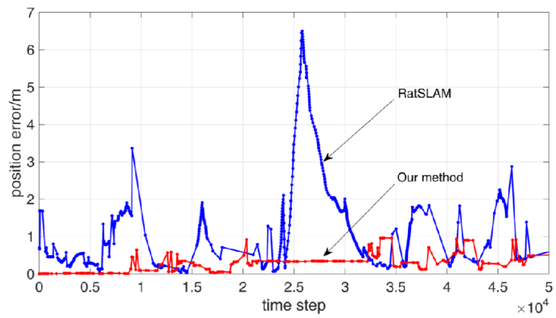

Fig. 10. Comparison result of position error.

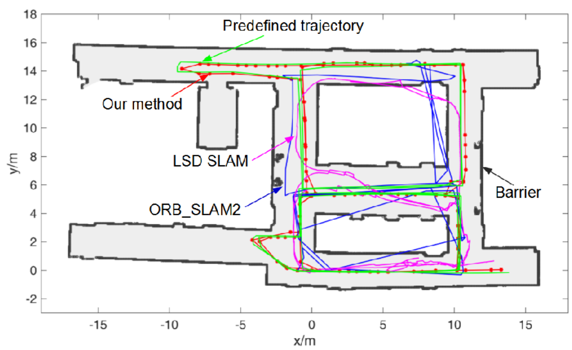

Fig. 11. Results of ORB_SLAM2 and LSD-SLAM.

implemented the RatSLAM algorithm to run the same experiment, and the comparison result is shown in Fig. 9. The blue line is the map built by RatSLAM. The detailed discussions are provided in the following two aspects.

1) Our method has higher efficiency than RatSLAM. RatSLAM uses a competitive attractor network to integrate odometry information with local image for modelling the pose cells, and uses the pose cells to represent the belief about the location and orientation of the robot. Therefore, RatSLAM needs to compare every step image, which will result in large amount of computation. In this experiment, running RatSLAM for single instance takes 7988s. However, our method only compares the image if place cell at current positon is activated and its activity is larger than a given threshold. In this case, it only takes 2069s to run a single instance with our method. The efficiency of our method is nearly four times higher than RatSLAM.

2) The map built by our method has higher precision than RatSLAM. Our method creatively performs the closed-loop correction by resetting the spatial cells phase, which is much more aligned with biological mechanism. It can improve the accuracy of cognitive map. To evaluate the accuracy of map building, we use the Euclidean distance between the position of experience node and the position of corresponding point in the predefined trajectory as the positon error. Fig. 10 shows the comparison result of position error. The position error of our method is within 1m, whereas RatSLAM has larger error than our method. Therefore, our method has higher precision than RatSLAM.

In addition, we compared our method with ORB_SLAM2 [30] and LSD-SLAM [31]. The former is a feature based method that composed of three main parallel threads: tracking, local mapping, and loop closing. The latter is a direct monocular SLAM technique, it directly operates on image intensities both for tracking and mapping. We implemented ORB_SLAM2 and LSD-SLAM with loop detection module turned to run the same experiment. Fig. 11 shows the results, it can be seen that the map built by our method is better matched with the predefined trajectory. In this experiment, ORB_SLAM2 occurs multiple tracking failures, which may be caused by this simple or plain corridor scene. Similar to ORB_SLAM2, LSD-SLAM has drawback in tracking in the corridor environment, and it is not qualified for the rotational movement in the corners. So we ignored the corner trajectory in this experiment. Compared to these traditional SLAM methods, our method tracks the neural activities, which encode locations and orientations with regard to the robot in a cognitive map. It can build a high accuracy cognitive map, which is necessary for the robot to perform tasks.

VI. Conclusion

To achieve the robotic spatial cognition to the unknown environment, a novel framework of robotic episodic cognitive learning inspired by the biological cognitive mechanism of hippocampal spatial cells is proposed. This paper creatively introduces spatial cells and state neurons to achieve robotic incremental accumulative learning, and update robotic spatial cognition to the environment, as well as construct the episodic memory to retain these learned experiences. Furthermore, the robot system can build an episodic-cognitive map to describe the topological relations of the particular events coordinates in the unknown environment with higher efficiency and accuracy. The method in this paper extends the application of biological cognition mechanism in the field of robotic learning and map building. It can be used as a foundation for further study on the efficient robot bionic navigation and localization. Future work is to devote this method into much more intelligent control of mobile robot.

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