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Robotic Path Planning Based on Episodic-cognitive Map

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Abstract: Inspired by mammal's spatial awareness and navigation capabilities, a new episodic-cognitive map building and path planning method was proposed, used for navigation tasks of mobile robot under the unstructured environment. Combined with characteristic of cognitive map and simulated the formation mechanism of episodic memory in the hippocampus, a novel episodic-cognitive map encapsulated the information of scene perception, state neuron and pose perception was built, realized the real-time, incremental accumulative and updating cognition of the robot to the environment. Based on the episodic-cognitive map, using the minimum distance between events, an algorithm of the event sequence planning was put forward for preferred trajectory choosing. Experimental results showed that the proposed algorithms realized the mobile robot choose the preferred planning path, and using the SIFT-based visual navigation method, the mobile robot can reach the target very well. The method in this paper extended the application of biological cognition theory in the field of robotic planning.

Keywords: Episodic-cognitive map, episodic memory, mobile robot, path planning, state neurons.

1. INTRODUCTION

As the robotic technologies keep advancing and start interweaving into our lifestyle, it is inevitable that some robots will be required to make intelligent decisions, for example, in an unfamiliar environment, the robot needs to assess the current location, predict the future trajectories, and execute a series of actions to arrive at the target location. However, animals and humans can accomplish various navigation tasks very well, so some researchers seek clues from the mammal brains, particularly the hippocampus and its surround areas. O'Keefe and Dostrovsky first found a type of pyramidal neuron within the hippocampus which becomes active when an animal enters a particular place in its environment, they defined this kind of neurons as place cells [1] which were considered as the main components of the cognitive map [2]. Grid cells were an unique spatial awareness brain cells within the entorhinal cortex and were discovered in 2005 by Hafting *et al*, they suggested that grid cell firing signaled the rat's changing position representing a "neural odometry" for navigation [3]. The grid cells are regarded as the core of the path integration system and play a vital role in ensuring stable spatial representation during mammals navigation [4, 5]. Tolman suggested that the cognitive map is an essential module responsible for estimating the animal's position during navigation in the environment [6].

Based on cognitive map some researchers are focusing on the study of the mobile robot's navigation. Endo proposed a model of cognitive map that allows robot to anticipate future path and the simulation experiment showed that the cognitive map contributes to a robot's ability for navigation, however, the method has not been tested on a real robot [7]. Tian used the RatSLAM [8], a brain-inspired SLAM algorithm, for building a cognitive map and proposed a navigation system using an RGB-D sensor for mobile robots [9]. Shim [10] imitated a human-like behavior when travelling to a target destination by following the directional guidance from someone else, proposed a direction-driven navigation system, in which a mobile robot was instructed to follow the given directions instead of a global path. The experimental results show that the robot can efficiently navigate to a location at a passageway except for a specific location of a place, but it can not detect a junction. Cheng [11] proposed a topological map and loop closing method to build the cognitive map, they used the derived map and the Markov localization method for navigation in the indoor environment. Pandu proposed a D* Lite algorithm for path planning in partially known environment based on a grid map and laser scanner data

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[12].

For humans, they can adapt to the complex environment by recalling previous experiences, similarly, for robots. Episodic memory, a form of memory that contains information associated with a particular episode of experience, and it is stored in a way that episode can be traced back and recalled in later time [13]. Endo [14] explained a biologically inspired episodic memory based approach for computing anticipatory robot behavior, he extended the episodic memory into a framework to solve partially observable Markov decision process problems efficienty, i.e., find the best action for the current situation. Kleinmann [15] proposed a cognitive architecture which is substantiated by biologically inspired multiple memory systems, including episodic memory and other units, and showed the realized applications of it with a simulated mobile robot. Stachowicz and Kruijff [16] utilized index data simulation storing episodic memroy to provide knowledge for the robotic cognitive model and carried out the long-time simulation experiments. Kelley [17] implemented a memory store to allow a robot to retain knowledge from previous experiences based on image to construct events. Leconte [18] presented an episodic memory system consisting of a cascade of two Adaptive Resonance Theory (ART) networks, based on artificial emotions learning and episode recalling, a robot can deliver objects to people within an office area, however, different complex tasks need to be tested extensively with a higher number. Liu [19] presented a robotic global planning method based on the episodic memory for efficient behaviors sequence prediction using bottom-up attention.

Neuroscientist found that the hippocampus plays a major role in the storage of episodic memory [20, 21]. Considering the close relation between cognitive map and hippocampus, we are dedicated in the researching of robotic episodic-cognitive map based navigation. The contribution of this paper is to present how to model an episodic memory and based on which build an episodic-cognitive map, then describe the autonomous global path planning and motion controlling methods detailedly. For episodic memory modelling, different from that most episodic memory based robotic navigation are focused on episode-like memory which is a kind of memory structure, we simulate the organization of episodic memory by introducing neuron stimulation mechanism for environmental cognitive learning. For the autonomous path planning, we choose next situation based on neurons transition weights and minimum events distance. Based on [22], we use the SIFT-based visual navigation method to control robot to reach the target. The experiments will be presented at last to validate the methods.

2. EPISODIC-COGNITIVE MAP BUILDING

The episodic memory and concerned biological basis of hippocampus described above are the foundation of episodic memory model built in this paper. The episodic memory is expressed by interconnected events sequence, and the event consists of some knowledge which can be recalled, such as the observation perception of environment and pose perception of mobile robot. Based on the episodic memory model, a mobile robot can achieve the cognitive learning of spatial environment and build an episodic-cognitive map for target navigation. The crucial problem to build this model is how to constitute episodic memory by a kind of information and how to describe current environment information of mobile robot.

2.1. Episodic memory model building

In the hippocampus there are some connected neurons, called place cells, which activate depending on the perceived location of the mammals, and the changing of activation patterns of these neurons is related to the episodic events' characteristic and the occurrence of environment. By imitating the mechanism, we adopt the stimulation mechanism of state neurons to build the episodic memory model and realize the cognitive learning to the environment.

Episodic memory model in this paper comprises of a temporal sequence of events (e) and a goal (g), as shown in (1).

$$E = \{(e_1, e_2, \cdots, e_m), g\}, \tag{1}$$

where m is the number of events in the episode. The goal is the robotic target observation at the end of an episode. Note that the episodes depend on goals, i.e., a new episode starts from the robot starts pursuing a new target and ends when the robot reaches the target.

More specifically, an event comprises of a set of observation perception (o), state neuron (s) and pose perception (p), as shown in (2).

$$e = (o, s, p). \tag{2}$$

Observation perception is a feature vector of the environmental scene captured by vision sensor. Its observability plays an important role as landmarks for the environmental cognitive learning and closed-loop detection phase during the episodic-cognitive map building process, and it's also used for robot relocation phase during autonomous navigation process.

State neuron is abstracted to imitate the place cell for estimating the robotic state. It's a one-dimensional scalar and its role is to organize the episodic memory neural network, as shown in Fig. 1. Yellow circle represents the current activated state neuron, while the blue circle represents its context state neurons. The activation and connection of the state neurons contribute to the events connection in episodic memory model and own the ability of global

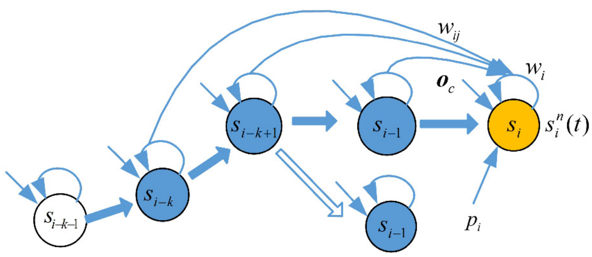

Fig. 1. Episode organization by the state neurons.

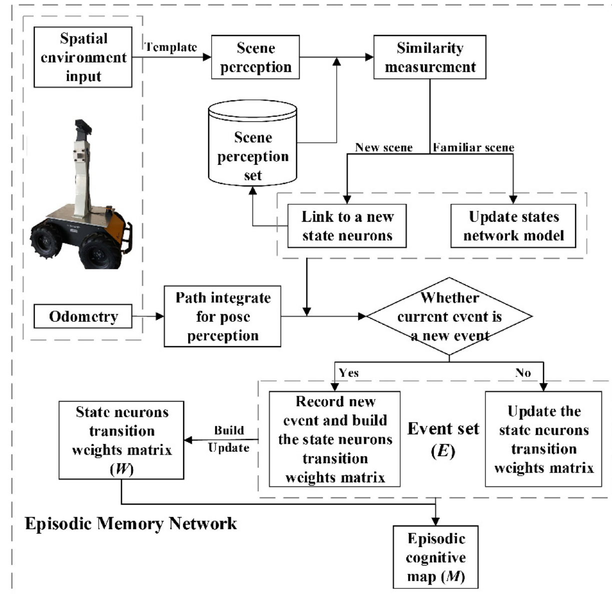

Fig. 2. Episodic-cognitive map building process.

planning. Assumed that the mechanism of robots' representation of environmental cognitive learning is similar to the mechanism of hippocampal neurons sequence in memory, a many-to-one mapping projection $f: o \rightarrow s$ is defined, which means that there is always a unique corresponding state neuron for any observation.

Pose represents the state's location (x,y) and its corresponding orientation (θ) of the mobile robot. Pose perception is calculated based on path integrating the odometer data (linear velocity and angular velocity), and it allocates the specific location information for an event, so the episodic-cognitive map has the geometric description of the environment.

In this paper, by simplifying the firing patterns of hippocampus place cells to simulate the organization process of episodic memory, we use tritupl e (o,s,p) to build the episodic memory model, and abstract state neurons to imitate place cells to map the high-dimensional observation perception for reducing the computational complexity and improving the planning efficiency. The proposed model can realize the robotic cognitive learning, real-time storage, incremental accumulation and integration to the unkown environment. Robot can evaluate the past events sequence, predict the current state and plan a desired trajectory.

2.2. Robotic episodic-cognitive map building

Based on the proposed episodic memory model, we introduced the state neurons to imitate the hippocampal CA1 place cells, and assumed that an episodic-cognitive map is represented by a discrete finite event space$e$and a set of events transition weights. The process of map building is shown in Fig. 2.

During the episodic-cognitive map building process, the inputs are the robotic cognition to spatial environment(scene images) and robotic odometry information(linear and angular velocity). The output is an episodic-cognitive map$M$which consists of a vertex set$E$and edge set$W$. The detailed process is described as follows:

First template the current spatial environment inputs, compute the similarity degrees between the current scene perception and the existing scene perceptions respectively, and meanwhile path integrate the linear velocity and angular velocity to form pose perception (x,y,θ); Then based on the similarity degrees to estimate whether it is a new scene, if an unfamiliar scene, link it with a new state neuron, and record the current pose pereption; otherwise update the state neuron network model and the current pose perception. According to the similarity measurement, we can modulate the accumulative error which occurred in the path integration process and solve the problem of loop closure during map building process; Finally based on the state neurons' activation, new events and familiar events are divided for learning respectively. If no state neurons are activated, record the event and build the state neurons transition weights matrix W, otherwise update the state neurons transition weights matrix W for updating the events transition weights. Each pair of state neurons $(s_i,s_j) \in W$ which has a feasible transition is associated with a positive transition weight w_{ij}. Thus, we have an edge-weighted episodic trajectory graph with a vertex set E and edge set W as shown in (3).

$$M = \{E,W\}. \tag{3}$$

The robotic episodic-cognitve map building algorithm is described in Table 1.

The state neurons transition weights matrix$W$can be represented as the following form:

$$W = \begin{bmatrix} s_1(t) & w_{12} & \cdots & w_{1i} & \cdots & w_{1q} \\ w_{21} & s_2(t) & \cdots & w_{2i} & \cdots & w_{2q} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ w_{i1} & w_{i2} & \cdots & s_i(t) & \cdots & w_{iq} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{q1} & w_{q2} & \cdots & w_{qi} & \cdots & s_q(t) \end{bmatrix}. \tag{4}$$

Table 1. Episodic-cognitve map building algorithm.

Input: A series of observations, robot linear velocity v and angular velocity w
Output: Episodic-cognitive map M with a vertex set E and edge set W
while $t <$ num of input observations
  path integrate v and w to form pose perception
  if $t = 1$
    record e_1 consisting of the first scene perception o_1, state neuron and pose perception
  endif
  compute the similarity between o_t and any scene perception from scene perception set O
  if the similarity<a given threshold
    add o_t into O
    build a new corresponding state neuron
    record the pose perception
  elseif
    update the state neurons
    update the current pose perception
  endif
  if no activated state neurons
    build a new event
    add the event into$E$and build transition weights matrix W
  elseif
    Update state neurons transition weights matrix W
  endif
endwhile
return M

In (4), the rows and columns of matrix represent the serial number of state neurons. The activation of state neurons$s_i$in current time can be represented by $s_i(t) = 1$, then the output activity of state neuron is represented by (5).

$$s_i(t) = \begin{cases} w_i s_i(t-1), & s_i(t) > \theta_n, \\ 0, & s_i(t) \le \theta_n, \end{cases} \tag{5}$$

where decay weight $w_i = e^{-1/\tau}$, $\tau = 10$ simulates the decay of state neurons, threshold θ_n determines the depth of memory for state neurons.The transition weight can be represented by w_{iq} as shown in (6).

$$w_{iq} = s_i(t)\, s_q(t). \tag{6}$$

It denotes the connection strength of state neurons for constructing an episode. It remembers the context information of state neurons$s_q$relevant to the current activated neuronss_i. Based on the matrix (4), the maximum transition weight for row vector is computed by (7).

$$w_i^* = \max w_{ij}, \quad j = 1, 2, \cdots, q. \tag{7}$$

If the quantity of maximum transition weight in a row is more than 1, we define these neurons as similar state neurons, it means that there are a variety of driving choices from the current state neuron to the target state neuron, considering the activation status of the context neurons, the robot will choose the similar state neuron with larger number of active context neurons as the next active state neuron.

$$\tau_m = \sum \lambda_n, \tag{8}$$

$$\lambda_n = \begin{cases} 1, & active\_state(k-n) = state(j-n), \\ 0, & \text{otherwise}, \end{cases} \tag{9}$$

where $m \in (1, num)$, num represents the quantity of maximum transition weight in a row. τ_m represents the number of active neuron around the mth similar state neuron. k represents that already $k-1$ neurons have been activated during the path planning, and now activate the kth neuron. $n = \min\{k-1, 9\}$ denotes the number of context neurons, for the decay of state neurons, its maximum value is equal to 9.

3. MOBILE ROBOTIC PATH PLANNING AND MOTION CONTROLLING

Based on the episodic-cognitive map, we proposed a novel robotic global path planning method by imitating the mechanism of human memory and recall, and used a biologically based motion controlling method for mobile robot to reach the target. The global path planning phase represented by blue arrow only implements before motion controlling or sometime when robot lost itself in the global path, the system needs to relocate the robot and plan the global path again. After the global path planning phase, the system implements the motion controlling phase, which is represented by dark arrow and red dashed box, and controls the robot to reach the target. The overall architecture is shown in Fig. 3.

3.1. Global path planning

Given the current and target observations, the mobile robot needs to plan a global path which consists of some events extracted from the episodic-cognitive map. This process consists of state neuron location, event location and event sequence planning phases.

First it's the phase of state neuron location. Based on the current robotic observation o_{cur}, we built the observation similarity measurement set between the current observation o_{cur} and any observation o_i in the episodic memroy as shown in (10).

$$\varepsilon_i = \frac{1}{\|o_{cur} - o_i\|_2}, \tag{10}$$

where $i = 1, 2, \cdots, l$, l represents the number of observations in the episodic memory.

The similarity measurement can be directly translated into the robotic location's similarity degree, thus the system chooses the current optimal observation as shown

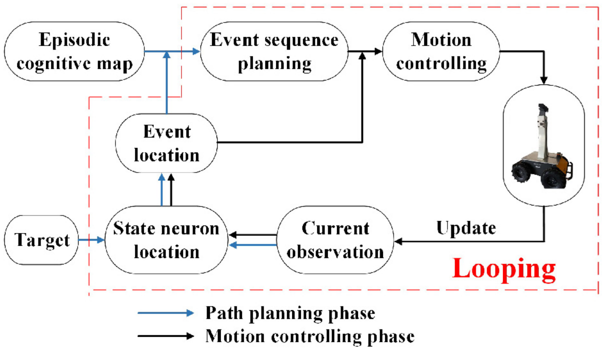

Fig. 3. Overall architecture of robotic autonomous navigation.

in (11).

$$o_{opt} = \arg\max_{o_i \in o} \varepsilon_i, \quad i = 1, 2, \cdots, l. \tag{11}$$

For the many-to-one mapping projection $f : o \to s$, the system locates the current state neuronss_{cur}in the episodic memroy, in the same way, the system locates the target state neuronss_{tar}.

Second it's the phase of event location. After locating the current and target state neurons, the system needs to locate the preferred current and target events. In the proposed episodic memory model, an event comprises of observation, state neuron and pose respectively. If any of the three factors is different from the factor of experienced events, a new event will be added. So one state neuron may corresponds to different events, we define this kind of state neuron as fuzzy state neuron. For the uncertain characteristic of state neuron, we proposed the following principles for event location in Fig. 4.

Considering the event characteristic of one-way growth, we define the serial number difference between the two events as the events distance. To reduce the planned trajectory's distance and improve the efficiency of robotic task executing , for the fuzzy state neuron, we adopt the principle of minimum events distance and choose the event which is nearest to target event as the located event.

Finally it's the phase of event sequence planning. The proposed algorithm shown in Table 2 describes how to reorganize a sequence of events for the global path. Based on the one-way linear transition character of events along with time in episodic memory, the planned event sequence is unidirectional too.

3.2. Motion controlling

Assumed that the robot knows its next event in an episode, however, it can not plan its behavior in real time. To solve this problem, in this paper we used the SIFT algorithm to complete the implemention of the robotic motion controlling. The process of motion controlling is shown in Fig. 5. Using the SIFT algorithm, the system first extracts the SIFT feature of current image, and makes a comparison with all the features which belong to local SIFT feature database to locate the best matched SIFT feature. Based on the continuity of image capturing in environment learning, the system could know the next SIFT feature. Then the system estimates the robot behavior by the SIFT-based navigation algorithm, which is about how to get the linear and angular velocity taking according to the

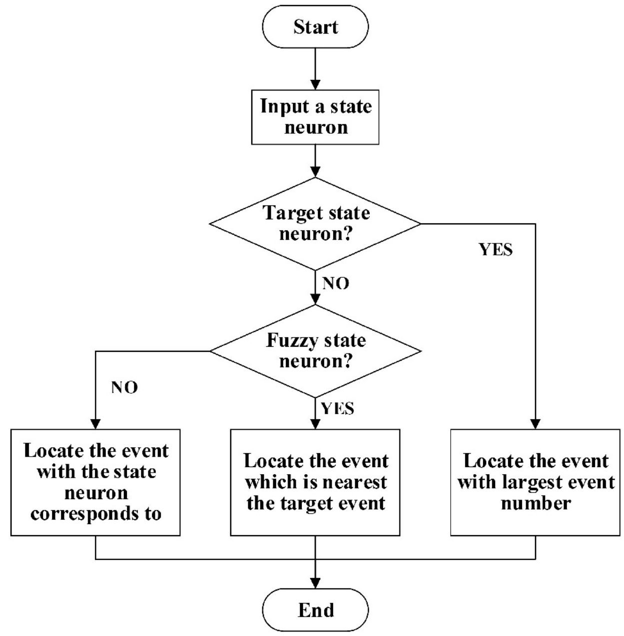

Fig. 4. The principles of event location.

Table 2. Robotic event sequence planning algorithm.

Input: M, e_{cur}, e_{tar}, $i = 1$
Output: ES (Event Sequence)
$ES(i) = e_{cur}$
while $cur < tar$
$e_{cur} \to s_{cur}$, $e_{tar} \to s_{tar}$
compute s_j with maximum transition weight as (7)
if $num > 1$
compute these similar nurons' τ_m as (8), (9)
find the j which maximizes τ_m
$s_{next} = s_j$
else
$s_{next} = s_j$
endif
locate e_{next} with s_{next}
$cur = next$
$e_{cur} = e_{next}$
$i{+}{+}$
$ES(i) = e_{next}$
endwhile
return ES

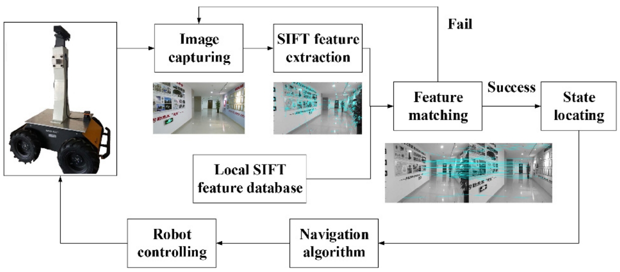

Fig. 5. Process of motion controlling.

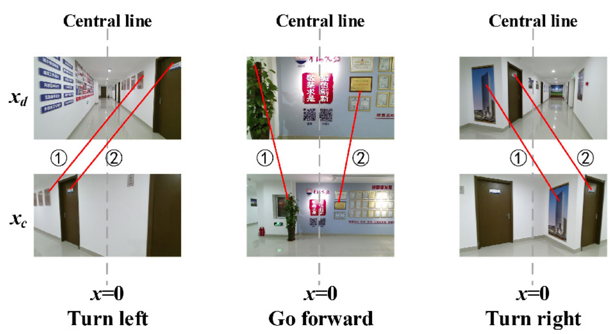

Fig. 6. Six matching forms for descriptors pairs.

position and horizontal coordinate relationship between the matched feature points. If the match similarity degree is larger than a threshold, the system considers the position of best match feature point as the robot current position. Loop through the above steps until the current best matched SIFT feature is the SIFT feature of next event, which means the system finishes the behavior control between two events.

We define that the robot has three kinds of behavior mode, go forward, turn right and turn left. For each behavior mode, it has two matching forms, so we can use six matching forms for local descriptor pairs to cover all the mobile robot navigation process, as shown in Fig. 6, where x_c represents the local SIFT descriptor's horizontal coordinate of robotic current scene image and x_d represents the horizontal coordinate of the desired scene image for robot. If $x_c < x_d \& x_c < 0$, then turn left, else if $x_c > x_d \& x_c > 0$, then turn right. If neither, then go straight. The navigation angle for robot is computed by (12).

$$\theta_r = \begin{cases} -\dfrac{r|x_c - x_d|}{t}, & x_c < x_d \& x_c < 0, \\ \dfrac{r|x_c - x_d|}{t}, & x_c > x_d \& x_c > 0, \\ 0, & \text{otherwise}, \end{cases} \tag{12}$$

where t is the time that navigation algorithm run for a cycle and r is the control gain of navigation angle θ_r. We set $r = 0.12$ and $t = 0.2$. After obtaining the navigation angle of the robot, considering that the frequency of image capturing is 5Hz, the angular velocity of the robot can be calculated by (13).

$$w = 5 \times \theta_r \times {}^{\pi}\!/_{180}. \tag{13}$$

During the robotic navigation without obstacles, the linear velocity should be larger in the forward direction when the robot needs to go forward and be smaller when the robot needs to turn left or right. To make the mobile robot move more smoothly, we computed the linear velocity as (14).

$$\begin{aligned} v = & v_{\min} + 0.5 \times (v_{\max} - v_{\min}) \\ & \times (1 + \tanh(\pi - k \times |w|)), \end{aligned} \tag{14}$$

where $v_{\min}$, $v_{\max}$ represent the minimal and maximal velocity of the robot, parameter k affects the change rate of linear and angular velocity. Comprehensively considered the environmental change, performance and flexibility of mobile robot, we set $v_{\min} = 0.01$ m/s, $v_{\max} = 0.2$ m/s, $k = 12$.

The mobile robot supports kinematic control mode in default, which uses a speed control feedback loop and allows specifying the desired linear and angular speed. After getting the linear and angular velocity of the mobile robot, the system publishes a standard ROS Twist message to the /'mobile robot'/cmd_vel topic to control the mobile robot directly. Loop through the SIFT feature extraction, feature matching, state locating, navigation algorithm and motion command sending phases until the best matched SIFT feature is the SIFT feature of next event, then the system completes the motion control between two events.

4. EXPERIMENTAL RESULTS

The experiments were implemented on a Husky A200 mobile robot in a dynamic environment shown in Fig. 7 to verify the effectiveness and robustness of the proposed cognitive map building and path planning algorithm. Husky is a rugged and easy-to-use [unmanned ground vehicle manufactured by Clearpath Robotics Inc, Canada. It can integrate with camera sensor, laser sensor and manipulator conveniently.

During the experiments, the Husky A200 mobile robot autonomously wandered along the grey solid line with arrows as shown in Fig. 7(b) in real life of corrider environment which include pedestrians and local environment changes. Through the Kinect2 camera sensor, we extracted the scene pictures as shown in Fig. 7(c). The relevant odometry information and scene perception are recorded as events.The mobile robot uses the events to build the episodic-cognitive map and then based on proposed event sequence planning and behavior controlling algorithm to realize autonomous navigation tasks. The related parameters is set in Table 3.

4.1. Performance for episodic-cognitive map building

Based on the proposed episodic memory network, the result of episodic-cognitive map building is shown in

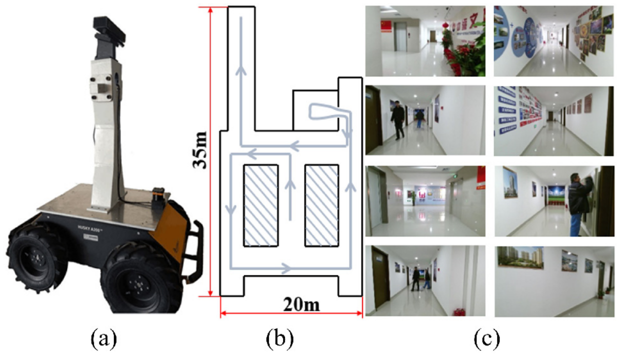

Fig. 7. (a) Husky A200 mobile robot, (b) experimental trajectory, and (c) environmental scene.

Table 3. The parameter setting in the experiments.

Description	Parameter	Value
Activation threshold	θ_o	0.91
Neuron memory depth	θ_n	0.4
Neuron decay coefficient	τ	10
Neuron transition weight	w_{ij}	[0,1]

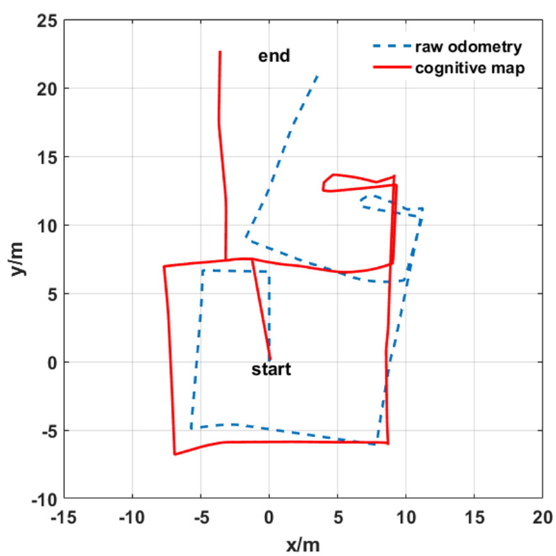

Fig. 8. Episodic-cognitive map building result.

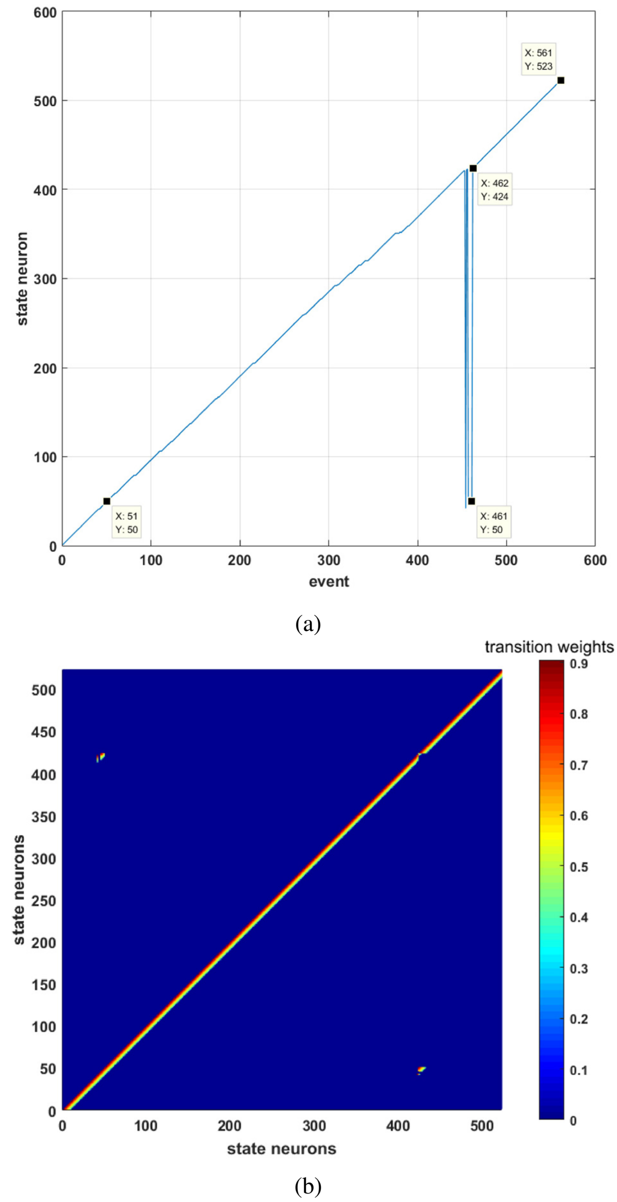

Fig. 9. (a) State neuron vs event and (b) state neurons transition weights.

Fig. 8. The blue dotted line describes the raw odometry information during the the robot wandered in corridor along the learning trajectory as shown in Fig. 7(a). The red solid line represents the built cognitive map based on the proposed episodic-cognitive map building algorithm, it is the graphical topology represention of episodic-cognitive map. The result shows that the proposed map building algorithm can solve the problem of accumulative error occured in the phase of path integration. And systems generates 561 events and 523 state neurons in total as shown in Fig. 9(a), thus based on the robotic cognition to the environment, the system generates events chain, and then forms experience map storing in episodic memroy. The experience map consists of 561 experience nodes, and each node records the corresponding observation, state neuron and pose perception respectively.

Fig. 9(a) shows the activation update process of state neurons in the incremental learning process of events sequence forming episodic memory. Before the robot wanders the same place again, subsequent state neurons are activated in successtion after the activation of current state neuron. However, one same observation is occurred, some state neurons are activated again. For state neuron 50, it was first activated at event 51, and at event 461, it is activated again, which indicates that the robot reminds a previous experience (same observation) in episodic memory. Transition weights which connect state neurons after learning is shown in Fig. 9(b). They are constantly updated in the learning process, and have decay process. The transition weights are used for the future robotic events sequence planning.

In the incremental process of state neurons, the current state neuron has max connection strength with the next state neuron. However, when the robot encounters a familiar observation, the state neuron may have max connection strength with multiple state neurons, for example, state neuron 50 has max connect strength not only with state neuron 51 but also with state neuron 424. We name this kind of state neurons as fuzzy state neurons.

By imitating the human's learning and cognition to environment, based on the episodic memory model and state neuron organization mechanism, the proposed robotic episodic-cognitive map building algorithm can built an episodic-cognitive map with a discret event vertex set and edge of events transition weights. Through the cognitive learning, the system updates the state neurons and transition weights constantly, realizes the accumulation, integration and updating of the episodic-cognitive map. Furthurmore, the state neuron set can be used for robotic anticipation and planning a optimal episodic trajectory.

4.2. Performance for global path planning and motion controlling

To verify the availability of the proposed robotic event sequence planning algorithm, we implemented two different target planning experiments based on the built episodic-cognitive map, the results are shown in Fig. 10.

Experiments 1 and 2 have the same initial event, but different target events, and experiment 2 has the longer events distance. Fig. 10(a) and (b) show these two experiments' planning path, (c) and (d) show the active state neuron id, (e) and (f) show the choosed event id respectively, for experiment 1, the robot do not reminds a previous experience in the episodic memory, so the state neuron is activated successfully, however, the robot reminds a previous experience, so the activated state neuron id is not sequential. From the results, we can see that the planning path is not the successive events sequence from initial event to target event, on the contrary, when encounter a fuzzy state neuron, i.e., the robot can choose multiple trajectory to the target, based on the proposed principle of minimum events distance, the system will choose the event which is much closer to the target event as the next active event. The performance analysis of robotic event sequence planning is shown in Table 4. It is much more apt to describes the robotic event sequence planning experiment.

The proposed event sequence planning algorithm is capable of choosing a much better trajectory for robot to reach the target in less time and shorter distance, improving the efficiency of robotic task executing.

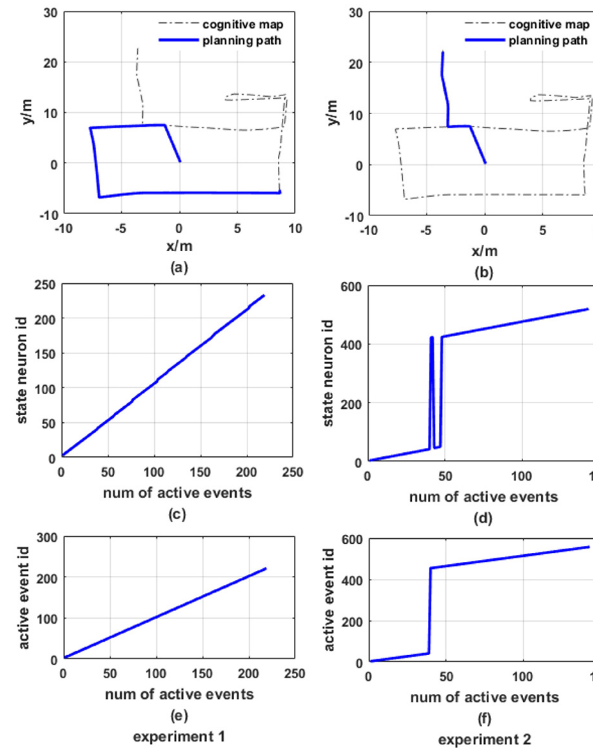

Fig. 10. Results of robotic event sequence planning.

Table 4. Performance analysis of robotic event sequence planning.

Experiment	1	2
Initial event id	3	3
Initial state neuron id	3	3
Target event id	233	557
Target state neuron id	221	519
Events distance	231	555
Active event number	219	143
Active state neuron number	219	143

Based on the mobile robot Husky A200 platform, we implemented a robotic motion controlling experiment, the result is shown in Fig. 11. It's clearly indication from the result, using the SIFT local feature descriptors of the image, we can do comparison and matching for the robot motion scene, through calculating the navigation angle, we can calculate the linear velocity and angular velocity of the mobile robot, then control the robot to complete the navigation task successfully.

4.3. Discusstion

Up to now, more researchers are studying the methods of robotic path planning based on cognitive map rather than episodic-cognitive map. For example, in [9], they proposed a global path planning method based on the cog-

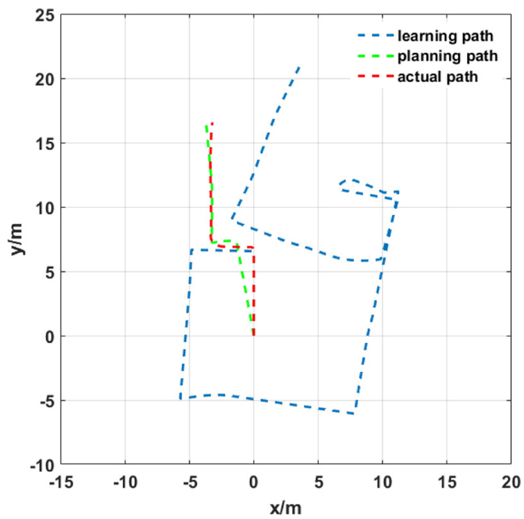

Fig. 11. Analysis of robotic motion control.

nitive map. Similar to this paper, the global path is a subset of the experienced path that the mobile robot has traveled during the map building process, however, the difference is that when several paths linking the current and the target locations and some paths are relatively close to each others, the global path in [9] is constructed by taking average of the coordinate points that are within a predetermined distance, the more the closely paths, the larger the computation. For adopting the episodic memory, we locate the event based on the principle of minimum events distance, which do not need to calculate the average of the coordinate points, and to some degree it can save the path planning time and improve the task executing efficiency.

In terms of motion controlling, traditional visual navigation mainly realizes the high precision location and path following, however, in this paper, we use the SIFT algorithm can also realize the high precision location, furthermore, based on our proposed path planning algorithm and SIFT-based navigation algorithm, the mobile robot can finish the navigation task more efficiency. The comparison result is shown in Fig. 12. These two subfigures describes the choosed navigation path (left subfigure) and events activation (right subfigure) respectively. It's obviously that our method actives 143 events and traditional visual navigation method actives 555 events, our method chooses a preferred path to the target which can reduce the task executing time and improve its efficiency very well.

5. CONCLUSION

Inspired by the spatial cognition of mammal animals, this paper proposed a new method of mobile robotic preferred path planning and motion controlling based on episodic-cognitive map. First, on the basis of episodic memory and cognitive map producing mechanism, we

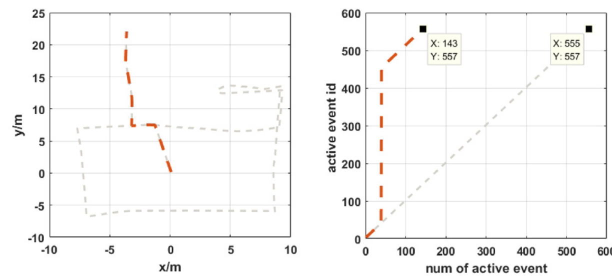

Fig. 12. Results of robotic path planning. Grey dashed line: traditional visual navigation method. Red dashed line: our method.

proposed a robotic episodic-cognitive map building algorithm, the built map saves these different states' observations, state neurons and pose perceptions respectively. Then a mobile robotic preferred path planning research was processing based on the episodic-cognitive map, this method can make a prediction about the future events sequence and choose a preferred trajectory from current place to the target place, improving the efficiency of task executing. At last, a motion controlling method is proposed for sending the robot motion commands to reach the target. These algorithms based on biological cognition extended the application of biological cognitive map on the mobile robotic behaviour planning fields. The future work will be devoted into decision making based on episodic memory and place cells.

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