Vision enhanced neuro-cognitive structure for robotic spatial cognition

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ABSTRACT

This paper presents a brain inspired neural architecture with spatial cognition and navigation capability. The brain inspired system is mainly composed of two parts: a bio-inspired hierarchical vision architecture (HMAX) and a hippocampal-like circuitry. The HMAX encodes vision inputs as neural activities and maps to hippocampal-like circuitry which stores this information. Sensing a similar neural activity pattern this information can be recalled. The system is tested on a mobile robot which is placed in a spatial memory task. Among the regions in hippocampus, CA1 has place dependance response. With this property, the hippocampal-like circuitry stores the goal location according to the vision pattern, and recalls it when a similar vision pattern is seen again. The place dependent pattern of CA1 guides the motor neuronal area which then dictates the robot move to the goal location. The result of our current study indicates a possible way of connection between hippocampus and vision system, which will help robots perform a rodent-like behavior in the end.

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1. Introduction

Animals such as rat and primates have a strong capability to navigate in a complex environment. Comparing to current SLAM algorithms [1], biological system continuously builds, maintains, and uses its spatial representations throughout its lifetime. In the meanwhile, without accurate geometric information, the biological system can effectively maintain a spatial representation suitable for path planning. Neurophysiological studies suggest that hippocampus, a major component of brain, plays an important role in memory and spatial navigation [2,3]. The studies of neural activities in hippocampus in rat navigation experiments led to a theory that the hippocampus might act as a cognitive map: a neural representation of layout of the environment [4]. These findings arouse a great interest to incorporate the rat’s navigation model in mobile robots navigation. Barrera et al. [5] proposed a neural structure to mimic “place field” property of hippocampus and guide a robot to search for the goal. The proposed system shows a similar learning pattern as rat experiments in the goal hunting [6]. Arleo and Gerstner used a joined CA1 and CA3 model to analyze the place cell property [7]. Reward-based learning is applied to map place cell activity into action cell activity to drive the motion. Wyeth and Milford [1] proposed a more biological based spatial cognition model which includes two parts: pose cells which function as grid cells in entorhinal cortex (EC) and experience map which functions as place cells in CA1 and CA3. In these research works, the focuses are the place cell property and how it contributes to the spatial navigation. The neural models are based on some sub-regions of hippocampus, without considering the hippocampus as a whole system.

Hippocampus has been studied for many years based on an approximate mammalian neuroanatomy. At a macroscopic level, highly processed neocortical information from all sensory inputs converges onto the medial temporal lobe where the hippocampus resides [8]. These processed signals enter the hippocampus via EC. Within the hippocampus [9–11], there are connections from the EC to all fields of the hippocampal formation, including dentate gyrus (DG), CA3 and CA1 through perforant pathway, from DG to CA3 through mossy fibers, from CA3 to CA1 through schaffer collateral, and then from CA1 back to EC. There are also strong recurrent connections within the CA3 region. Based on these connection properties of sub-regions, Edelman and his team [12,13] developed a general brain-like model, namely brain-based device (BBD) to understand the hypotheses about how the mechanisms of the vertebrate nervous system give rise to cognition and behavior. Many interesting properties such as “place cells” and “episodic memory” in hippocampus have been realized with this model.

Inspired from the Edelman’s BBD model, we target to develop a hippocampal-like cognitive system for the robot spatial navigation. In the BBD model, the vision inputs are only filtered by color and edge. As human, we can process very complicated vision information with various types of shapes. To improve the neural system’s performance, we combine the HMAX model which is a bio-inspired vision
process model and hippocampus circuitry together. HMAX model has a unique feature when processes complicated shape information and it has scale invariance property. These properties help the neural system apply to a more complicated environment. The system also can help to understand how vision system and hippocampus work together in the spatial navigation.

The proposed system is mainly composed of two parts: hierarchical vision system and hippocampal-like circuitry. To explore the relationship between vision system and hippocampus, we implement the model in a mobile robot which is placed in a spatial memory task. The experiment environment is a plus maze where the robot is commanded to search for a hidden goal according to the vision. This maze environment has been used in rodent studies of spatial memory [14]. In the test, vision information is input to the HMAX model and its corresponding neural activities are mapped to the hippocampus. The region of CA1 shows a place-dependent response according to the vision inputs. This place-dependent pattern of CA1 guides the motor neuronal area which dictates the robot move to the goal location.

2. Brain-inspired cognitive system

The schematic of the neural structure is shown in Fig. 1, which includes sensory cortical regions, motor cortical regions and hippocampal circuitry. The sensory cortical regions include head direction cells, color filters, HMAX model, anterior thalamic nuclei (ATN) and inferotemporal cortex (IT). The motor cortical regions include motor cortical area (Mhdg) and value system (S). The hippocampal circuitry is inspired from Darwin series’ [15] hippocampus model which includes EC, DG CA3 and CA1. EC is composed of two layers: input and output. Detailed neural parameters for these regions are given in Appendix A.

Fig. 1. Schematic of the regional and functional neuroanatomy of brain-inspired structure. (A) Ellipses denote different neural area; boxes denote different device; triangle denotes a decoding process; arrows denote projections from one area to another. Inputs to the neural system come from a camera, compass and IR sensors for award given. The neural structure contains neural areas such as simulated visual cortex (V1 color and V1 shape); inferotemporal cortex (IT); head direction system (HD); anterior thalamic nuclei (ATN); motor cortical area (Mhdg); value system (S). Inside the hippocampus, there are neural areas including entorhinal cortex (ECin, ECout); dentate gyrus (DG); CA3 and CA1 subfields. In hippocampus, a theta rhythm (TR) signal is used to inhibit all hippocampus area to keep activity level stable. (B) HMAX model for object recognition [17]; the circuitry is composed of four hierarchical visual process layers with two different types of pooling methods: weighted sum (WSUM) and maximum (MAX). The first layer S1 performs a linear oriented filter and normalization to the input image. In the next layer C1, outputs of S1 with same orientation and close location are selected by a maximum operation. In the stage S2, outputs from C1 with close location are combined to form more complex features. The C2 layer is similar to C1 layer; by pooling together outputs of S2 with same type and close location by the maximum operation. The output of the C2 layer is mapped to the IT in a ventral cortical pathway.

Fig. 2. The responses of HMAX to different input of character images.
2.1. Vision input

Visual information in cortex is considered to be processed through ventral visual pathway [16] running from primary visual cortex V1 over extrastriate visual area V2 and V4 to IT. It is classically modeled as a hierarchical-layer structure. In this paper, HMAX [17] hierarchical vision architecture is adopted to mimic object recognition computation in cortex. It consists of four layers with linear and non-linear operations (shown in Fig. 1B). The first layer, namely S1, performs as both linear oriented filter and normalizer to the input image. In the next layer (C1), outputs from S1 with same orientation and close location are selected by a maximum operation. In the next stage (S2), outputs from C1 layer with close location are combined to form more complex features. The C2 layer is similar to C1 layer: by pooling outputs from S2 with same orientation and close location by a maximum operation together. The information in C2 becomes less sensitive to position shifting and size scaling, while the key features preserve. This property corresponds roughly to V4 area in visual cortex [17]. Fig. 2 shows neuronal responses of HMAX model with different inputs of character image (A, B and C). The response of HMAX shows a unique pattern for each character with strong robustness to noise and scaling factors.

The output of the C2 layer is mapped to the IT in a ventral cortical pathway (V1shape→IT). Another visual input is the color information where four different colors: red, green, blue and yellow, are filtered from camera input. The filtered outputs are mapped to IT in a ventral cortical pathway (V1color→IT). Then, the neuronal states of IT are projected to the hippocampus via EC.

2.2. Heard direction input

Head direction cells are modeled based on rodent neurons that respond selectively to the animal’s heading [18]. These neurons are often called head direction cells. The head direction cells are found in various brain regions around hippocampus, particularly in postsubiculum, retrosplenial cortex, and some regions of thalamus. The head direction cells help to maintain the estimation of orientation. In this paper, instead of maintaining the estimation, we directly use the compass value as the stimulus to the head direction cell. Same approach has been used by BBD model [13]. In this design, HD cells are composed of 360 neurons which correspond to animal heading from 0° to 359°. Each neuron has a preferred heading by a cosine tuning curve. The tuning curve is described as

\[ HD_i = \cos \left( \frac{i}{360} \cdot 2\pi - HD_c \right) \]

where \( HD_i \) is the i-th neuron with a preferred direction of \( i \) in degree, and \( HD_c \) is the compass input in radians. The head direction neurons are mapped to both anterior thalamic nucleus (ANT) and motor neuron area. The neural states of ANT are projected to hippocampus via EC (HD→ANT→EC).

2.3. Neural dynamics

In our neural system, all the neuronal units are simulated by a mean firing rate model. The mean firing range of each neuron is from 0 (no firing) to 1 (maximal firing). The state of a neuron is calculated based on its current state and contributions from other neurons. The postsynaptic influence on unit \( i \) is calculated based on equation:

\[ Post_i(t) = \sum_{j=1}^{M} \left[ w_{ij} \cdot s_j(t) \right] \]

where \( s_j(t) \) is activity of neuron \( j \), \( w_{ij} \) is connection strength from neuron \( j \) to neuron \( i \). \( Post_i(t) \) is postsynaptic influence on neuron \( i \), and \( M \) is the number of connection to neuron \( i \).

The new neuronal activity is determined by the following activation function:

\[ s_i(t+1) = \Phi(\tanh(Post_i(t) + \epsilon s_i(t))) \]

where \( \epsilon \) controls the persistence of unit activity from previous state, and \( \delta_i^{fire} \) is firing threshold.

2.4. Neural connections

Generally, the ways of connection between neural regions are divided into three types. The first type is “rectangular”, with particular height and width “\( h \times w \)” as shown in Fig. 3A. The second type is “doughnut” with inner and outer radians “\( \Theta 1 \times r2 \)” except the center as shown in Fig. 3B. The third type is “nontopo” in which any pair of presynaptic and postsynaptic neurons have an equal probability of being connected.

![Fig. 3. Receptive field of the neuron connections. (A) "rectangular", with particular height and width “\( h \times w \)”; (B) “doughnut”, with inner and outer radians “\( \Theta 1 \times r2 \)” except the center; (C) “nontopo”, any pair of presynaptic and postsynaptic neurons have an equal probability of being connected.](image-url)
2.5. Hippocampus circuitry

In hippocampus, neuronal states from both sensory regions are mapped to ECin. The ECin connects with all sub-regions of hippocampus, including dentate gyrus (DG), CA3 and CA1 through perforant pathway (ECin→DG, ECin→CA3, ECin→CA1). DG connects with CA3 through mossy fibers (DG→CA3). CA3 connects with CA1 through schaffer collaterals (CA3→CA1), and CA1 connects back to ECout (CA1→Ecout). There are also strong recurrent connections within the DG and CA3 regions (DG→DG, DG→CA3).

In hippocampus, a theta rhythm signal is used to inhibit all hippocampus neurons to maintain activity level stable (TR→ECin, ECout, DG, CA3, CA1). The TR activity follows a half cycle of sinusoidal wave:

\[ TR(n) = \sin\left(\frac{n\pi}{13}\right) \]  

where \( n \) is the running cycle number. Given sensory inputs (vision and orientation), the neuron network runs for 13 cycles, until the pattern in CA1 remains stable [15].

2.6. Neural plastics

In learning and memory, synaptic plasticity is one of the key issues for neural network to learn and store memory. Experimental data from visual cortex led to a synaptic modification. In this paper, the synaptic plastic among hippocampus is based on a modified BCM learning rule [15]:

\[ \Delta w_{ij}(t+1) = \eta \cdot s_i(t) s_j(t) BCM(s_i(t)) \]  

(6)

\[ BCM(s) = \begin{cases} 
-\frac{s}{2} & s \leq \theta \\
\frac{s}{2} & \frac{s}{2} > s \leq \theta \\
\tanh(s - \theta) & \text{otherwise} 
\end{cases} \]  

(7)

where \( s_i(t) \) and \( s_j(t) \) are activities of postsynaptic and presynaptic units, respectively, and \( \eta \) is the learning rate. The threshold \( \theta \) is adjusted based on the postsynaptic activity \( \Delta \theta = 0.25(s^2 - \theta) \). The parameters of learning rules are selected to have a fast and stable response in hippocampus. The values are given in Appendix A.

The synaptic strengths between CA1 and motor cortical area (Mhdg) are modified by a temporal difference reinforcement learning rule based on the reward system [15]:

\[ \Delta w_{ij}(t+1) = \eta \cdot s_i(t) s_j(t) T(t) D(t) \]  

(8)

\[ T(t) = \begin{cases} 
1 & \text{positive reward} \\
0 & \text{negative reward} \\
\frac{s(t) - s(t-1)}{s(t)} & \text{otherwise} 
\end{cases} \]  

(9)

where \( s(t) \) is the average activity of value system \( S \) at time \( t \). The number 13 is the cycle number to stabilize the neural activities. A similar reward-based learning rule is also used by Arleo and Gerkster [7] to drive the motor neural area.

2.7. Motor neuronal area

Motor cortical area dictates the moving direction of robot. To estimate the optimal moving direction from the motor cortical area, we adopt a maximum likelihood (ML) estimator method. Deneve et al. [19] have shown that ML estimation can be done with a biologically plausible neural network. In this paper, we use a recurrent neural network to read the neuronal activities in motor cortical area. The recurrent neural network is composed of a population of neurons with bell-shaped tuning curves. Neurons in the network communicate through symmetric lateral connections. The input of the network is the neuronal activities of Mhdg which are multi-modal noisy hill. By tuning the parameters of the network, the activity of the network should converge over time to a smooth hill which is unimodal. Once the smooth hill is obtained, its peak position is an optimal direction of motion.

2.8. Learning of an input image

In our cognitive neural system, an important feature is combining HMAX model in the visual cortex. For different types of shape information, HMAX returns a good feature property. Fig. 4 shows an example of learning two character image ‘A’ and ‘C’. As shown in Fig. 2, characters ‘A’ and ‘C’ have different features after the HMAX operator. These features result unique patterns in CA1 area. With two rounds of training, the neural system can recall the input character and show it in the output neuron area. In the recalling test, there are some remaining neuron activities due to the previous pattern. However, the overall output pattern is recalled correctly.

3. Device, task and environment in the simulation

Analyzing the hippocampus function in brain is challenging due to the difficulty of recording neuronal activities simultaneously from many neuronal areas and multiple neuronal layers. A possible solution is to build an artificial hippocampus model and simulate the hippocampus function [15,20–23]. In this paper, we implement our hippocampal-like structure in a simulated environment. The task is to navigate inside a plus–maze as shown in Fig. 5. The simulated environment is developed in Webots which is a dynamic simulation software based on open dynamic engine (ODE). All the real world sensors such as camera, compass, distance sensor and DC motors can be modeled in this environment.

The maze is similar to the experiment of Darwin XI [15] which has been used in study of rodent hippocampal place activity [14]. Robot explores the maze autonomously and chooses a direction to go at the intersection. At each trial, robot starts from any arm as indicated by the ‘**’ in Fig. 5. At intersection, it chooses a direction indicated by the Mhdg and continue moving to the end. A hidden goal platform is placed randomly at the end of four different arms. Visible signs with different shapes and colors are placed on the wall to provide the clue for the robot. In the simulation, camera and compass are mounted on the head; IR sensors are mounted on the body to detect the intersection; and one additional IR sensor is mounted at the bottom of the robot to detect the hidden goal platform. Positive reward is given to the value system once hidden goal has been founded. Otherwise, negative reward is given to the value system.

Generally, the neuron states of the whole system are updated based on Eqs. (2)–(4). The values are related with the neuron’s mutual connection weights. BCM learning rule described by Eqs. (6)–(7) is used to update the connection weights among neural areas in hippocampus. Temporal difference reinforcement learning rule described by Eqs. (8)–(9) is used to update the connection weights between CA1 and Mhdg. The detailed pseudocode is presented in Algorithm 1. The ‘for’ loop after the function MoveToGoalLocation( ) is the learning process.
Algorithm 1. Pseudocode for goal hunting experiment.

Parameter Description: Compass: $C_o$, Image $I_m$, Neuron A state $S_A$, Connection weights from A to B $C_{A \rightarrow B}$.

Initialization: ()
MoveToIntersection: ()
for location = 1 to 3 (front, left and right) do
    GetInput ($I_m$, $C_o$);
    StateUpdate ($S_{HD}$, $S_{color}$, $C_o$, $I_m$);
    HMAX ($S_{shape}$, $I_m$);
    for cycle = 1 to max_cycle do
        StateUpdate ($S_{ATN}$, $S_T$, $S_{ECin}$, $S_{ECout}$, $S_{DG}$, $S_{CA3}$, $S_{CA1}$, $S_{Mhdg}$);
        WeightsUpdateBCM ($C_{ECin}$ $-$ $DG$, $C_{ECin}$ $-$ $CA3$, $C_{ECin}$ $-$ $CA1$, $C_{CA1}$ $-$ $ECout$);
        WeightsUpdateBCM ($C_{DG}$ $-$ $CA3$, $C_{CA3}$ $-$ $CA3$, $C_{CA3}$ $-$ $CA1$);
        WeightsUpdateTem ($C_{CA1}$ $-$ $Mhdg$);
    end
    $S_{Mhdg}$ += $S_{Mhdg}$;
end

EstimateGoalLocation = Decoding($S_{Mhdg}$);
MoveToGoalLocation();
RewardUpdate ($S_t$, reward);
for cycle = 1 to max_cycle do
    StateUpdate ($S_{ATN}$, $S_T$, $S_{ECin}$, $S_{ECout}$, $S_{DG}$, $S_{CA3}$, $S_{CA1}$, $S_{Mhdg}$);
    WeightsUpdateBCM ($C_{ECin}$ $-$ $DG$, $C_{ECin}$ $-$ $CA3$, $C_{ECin}$ $-$ $CA1$, $C_{CA1}$ $-$ $ECout$);
    WeightsUpdateBCM ($C_{DG}$ $-$ $CA3$, $C_{CA3}$ $-$ $CA3$, $C_{CA3}$ $-$ $CA1$);
    WeightsUpdateTem ($C_{CA1}$ $-$ $Mhdg$);
end

Fig. 4. Auto-associative property. First two cycles are training for input 'A', the next two cycles are training for input 'C', in the testing stage images 'A' and 'C' are input to the system alternatively. Top to bottom: input image, neuron activity of IT, EC, DG, CA3, CA1 and Output.
The scenario of the simulation is designed as follows: robot starts from a starting point as marked by the red "⋆" in Fig. 5; moves to the intersection; check around with forward, left and right directions; chooses a direction which has highest possibility where goal may locate; moves to the end of the maze arm, check the reward and update the value system and hippocampus connection. Once the experiment has completed, the robot will be randomly placed in another maze arm for a new test. In total, the simulated nervous system contains 19 neural areas, 9084 neuronal units, and approx 0.2 million synaptic connections. The computation time is around 0.2 s to learn a reward, running in Matlab with a Core 2, 2.4 GHz 4 GB RAM laptop in Windows XP. Specific parameters of each area and detailed patterns of connectivity are given in Appendix A.

4. Simulation results

In the proposed neural system, the HMAX returns the key information of the input image. EC processes this vision information and maps to the hippocampus regions including DG, CA3 and CA1. In the DG area, self-inhibition is very strong which inhibits surrounding neurons. Due to the competitive learning process, the key information from EC will be maintained in DG area. The CA3 stores the memory information in hippocampus. In the design, a strong recurrent connection is included in the CA3 model to form a stable pattern for a given input. The stabilized response of CA3 will then activate the corresponding pattern in CA1. The detailed parameters of the hippocampus are given in Appendix A.

In the experiment, CA1 area in hippocampus shows place dependent response, when the robot navigates in the maze. The neuron activities in CA1 area show different pattern for each maze arm. This place related pattern is shown in Fig. 6. This property helps the robot associate the location to the neural activities of CA1. In the place dependent response, about 57 neurons out of 400 neurons in total in CA1 area are red when the robot navigates inside the maze. Although the size of CA1 is different, the ratio is similar to the value used in the experiment of Darwin XI [15], which was close to the observation in the experiments on rats [14].

During the environment exploration, hippocampus recognizes the location based on the unique neuron activities in CA1 area. This CA1 pattern is trained when the robot is close to the visual wall. When robot makes decision at intersection, the visual input is different from the closed view. In this case, HMAX model helps the system recognize the visual clue due to its scale invariance property. Comparing the neural activities in Fig. 6 which are closed views and the ones in Fig. 7 which are intersection views, the CA1 activities patterns are similar when their orientations are the same. We have compared their similarity based on their correlation results. As shown in Fig. 8, the correlation value between intersection view and closed view with same orientation is much higher than the one with different orientation. For the same orientation, all the similarity values are more than 60%. In this case, we think the CA1 pattern has been recalled.

In motor cortical area, Mhdg consists of 60 neurons. Each neuron covers 6° in range which maps a range of 0–359° in total. When there is no reward given to the system, all neuron activities in Mhdg are low. There is no preferred direction. During the exploration, if the hidden goal is founded in a location, the corresponding CA1 pattern will be associated to the goal location by increasing the connection weights between active CA1 neurons and goal location neurons in Mhdg by temporal difference reinforcement learning rule in Eqs. (8) and (9). In the beginning of experiment, all the locations have randomly low possibility of hidden goal (as shown in Fig. 7C upper sub-figure). The fastest case is that the robot chooses correct location at first trial. Once it has founded the hidden goal, the reward learning will increase the

![Neuro-Cognitive Robotics Platform](image)

Fig. 5. Simulation environment. The maze has four cue walls with different shapes and colors; a hidden platform is placed randomly at the end of a maze arm; camera and compass are mounted on the robot head to provide vision and orientation inputs for the robot; IR sensors are only used to detect the interception; robot can start the journey from any starting points marked by red "⋆" in the maze. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

![Fig. 6. Place dependent pattern of CA1 in different location. (A) Robot reaches the end of each arm; 1, 2, 3 and 4 correspond to east, north, west and south. (B) The response of CA1 at each arm. The arrow indicates the facing direction.](image)
connection weights between CA1 and goal location to make the robot remember the goal location. Since other locations still have low possibility of hidden goal, the robot will choose the correct location again in the next trial. If the first try fails, the reward learning will decrease the connection weights between active CA1 neurons and this location, which shows no goal here. In the second trial, the robot will explore other two possible locations.

In the first round, the robot goes to the north side, which is wrong. A negative reward is given which results decreased activities in Mhdg neurons in this direction. In the second trial, the robot goes to the west side, which is correct. A positive reward is given which results increased activities in Mhdg neurons in this direction. In the worst case, the robot needs three trials to find the hidden goal location in this plus maze experiment. Once the hidden goal has been founded, the robot can remember its location and make a correction choice in the next trial.

It is noted that, from these experiments, the connection weights between CA1 and Mhdg store the information of hidden goal location. Fig. 9 shows the change of weight when positive reward is given to the direction of $90^\circ$ . Based on the reinforcement learning rule in Eqs. (8) and (9), connection weights between fired neurons in CA1 and neurons around $90^\circ$ in Mhdg will be strengthened. It enables the system to associate the CA1 pattern of $90^\circ$ to the hidden goal location.

Fig. 10 shows connection weight changes in a sequence of trials where goal location can be changed. Yellow dot denotes starting location. Red dot denotes ending location. In the first four trials, the goal locates at west. In the rest six trials, the goal is changed to east. Since the robot only moves to east, west, north and south side, the connection weights from CA1 to these four neurons in Mhdg are presented. In the beginning, all the connection weights are initialized with a low value. There is no preferred direction. In the trial 1, the robot starts from south and ends at east. Since no goal has been founded at east, the connection weight from CA1 to east neuron has been even decreased. In the trial 3, the goal location has been founded at west side. The connection weights from CA1 to west neuron have been increased. The robot remembers the goal location and it founds the goal in the trial 4. After trial 4, we changed goal location to east side. Due to the effect of previous memory, the robot will still prefer go to the west side as trials 5 and 7. Trial 6 is an exception as robot start from west side.
Fig. 10. Connection weight modifications with different goal locations. Four sets of connection weight from CA1 to south, east, north and west are shown in this example. Yellow dot denotes starting location. When it reaches intersection, it checks left, forward and right directions and choose a preferred one. Red dot denotes ending location. Connection weights decrease when no goal has been founded such as trial 1. Connection weights increase when goal has been founded such as trial 3. Trial 5 to trial 7 between yellow dash line and blue dash line is ‘forget’ process. After that, it starts to search the new goal location again such as tests 8 to 10. The system is able to handle tasks with dynamic changed goal locations. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)
### Table A1
Information about the neural areas in simulated nervous system. The number of neuronal units and topology is shown in the size column. The other columns are physiological parameters for each neural area as defined in the simulation equations above. Roughly described, the parameters are scaling factor, $g$, firing rate thresholds, $\phi^{\text{pre}}$ and $\phi^{\text{post}}$, and persistence factor, $\omega$. This table includes inhibitory areas not described previously.

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<th>Size</th>
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<th>$\phi^{\text{pre}}$</th>
<th>$\phi^{\text{post}}$</th>
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<td>0.5</td>
</tr>
<tr>
<td>CA3i</td>
<td>15 x 15</td>
<td>1</td>
<td>0.02</td>
<td>0.1</td>
<td>0</td>
</tr>
<tr>
<td>CA1</td>
<td>30 x 30</td>
<td>0.75</td>
<td>0.1</td>
<td>0.1</td>
<td>0.5</td>
</tr>
<tr>
<td>CA1i</td>
<td>30 x 30</td>
<td>1</td>
<td>0.02</td>
<td>0.1</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table A2
Non-plastic connections between neural areas in the simulated nervous system. A presynaptic neuronal unit connects to a postsynaptic neuronal unit with a given probability ($P$) and a given projection topology. This receptive field can be rectangular with a particular height and width $\lceil h \times w \rceil$; doughnut-shaped with inner and outer radii $\lceil r1 \times r2 \rceil$ except the center; nontopological “nontopo” in which any pair of presynaptic and postsynaptic neurons have an equal probability of being connected. The initial connection strengths are set with a basic strength and a variation range. A negative value of connection strength denotes inhibitory connections. $\phi$ denotes the persistence of the synapse.

<table>
<thead>
<tr>
<th>Projection direction</th>
<th>Projection topology</th>
<th>$P$</th>
<th>Basic strength</th>
<th>Variation</th>
<th>$\phi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1color → IT</td>
<td>Nontopo</td>
<td>0.05</td>
<td>0.05</td>
<td>0.02</td>
<td>1</td>
</tr>
<tr>
<td>V1shape → IT</td>
<td>[0.5 x 0.5]</td>
<td>0.5</td>
<td>0.6</td>
<td>0.2</td>
<td>1</td>
</tr>
<tr>
<td>HD → ANT</td>
<td>[1 x 6]</td>
<td>1</td>
<td>0.04</td>
<td>0.02</td>
<td>1</td>
</tr>
<tr>
<td>IT → ECI&amp;II&amp;III</td>
<td>[1 x 1]</td>
<td>1</td>
<td>0.2</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>ITi → ITi</td>
<td>$\Theta1 \times 2$</td>
<td>1</td>
<td>0.06</td>
<td>0.02</td>
<td>1</td>
</tr>
<tr>
<td>ITi → IT</td>
<td>[1 x 1]</td>
<td>1</td>
<td>0.5</td>
<td>0.14</td>
<td>1</td>
</tr>
<tr>
<td>ANT → ECI&amp;II&amp;III</td>
<td>$\Theta1 \times 1$</td>
<td>1</td>
<td>0.3</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>ANTi → ANTi</td>
<td>$\Theta1 \times 2$</td>
<td>0.25</td>
<td>0.01</td>
<td>0.01</td>
<td>1</td>
</tr>
<tr>
<td>ANTi + ANTi</td>
<td>[1 x 1]</td>
<td>1</td>
<td>0.05</td>
<td>0.14</td>
<td>1</td>
</tr>
<tr>
<td>ECI&amp;II&amp;III → ECV</td>
<td>Nontopo</td>
<td>0.001</td>
<td>0.04</td>
<td>0.04</td>
<td>1</td>
</tr>
<tr>
<td>ECI&amp;II&amp;III + ECI&amp;II&amp;III</td>
<td>$\Theta1 \times 2$</td>
<td>0.45</td>
<td>0.15</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>ECV → ECI&amp;II&amp;III</td>
<td>Nontopo</td>
<td>0.001</td>
<td>0.04</td>
<td>0.04</td>
<td>1</td>
</tr>
<tr>
<td>ECV + Mhdg</td>
<td>Nontopo</td>
<td>1</td>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>ECV + ECVI</td>
<td>$\Theta1 \times 2$</td>
<td>1</td>
<td>0.45</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>ECVI + ECV</td>
<td>[1 x 1]</td>
<td>1</td>
<td>1.2</td>
<td>0.3</td>
<td>1</td>
</tr>
<tr>
<td>Mhdg + Mhdgi</td>
<td>$\Theta1 \times 2$</td>
<td>1</td>
<td>0.45</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>Mhdgi + Mhdg</td>
<td>[1 x 1]</td>
<td>1</td>
<td>1.2</td>
<td>0.3</td>
<td>1</td>
</tr>
<tr>
<td>DG → DGi</td>
<td>$\Theta1 \times 4$</td>
<td>0.3</td>
<td>0.45</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>DGi + DGi</td>
<td>[1 x 1]</td>
<td>1</td>
<td>1.2</td>
<td>0.3</td>
<td>1</td>
</tr>
<tr>
<td>CA3 → CA3i</td>
<td>$\Theta1 \times 2$</td>
<td>0.1</td>
<td>0.45</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>CA3i → CA3</td>
<td>[1 x 1]</td>
<td>1</td>
<td>1.2</td>
<td>0.3</td>
<td>1</td>
</tr>
<tr>
<td>CA1 → CA1i</td>
<td>$\Theta1 \times 4$</td>
<td>0.3</td>
<td>0.45</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>CA1i → CA1</td>
<td>[1 x 1]</td>
<td>1</td>
<td>1.2</td>
<td>0.3</td>
<td>1</td>
</tr>
<tr>
<td>TR → ECI&amp;II&amp;III</td>
<td>Nontopo</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>1</td>
</tr>
<tr>
<td>TR + DG</td>
<td>Nontopo</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>1</td>
</tr>
<tr>
<td>TR + CA3</td>
<td>Nontopo</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>1</td>
</tr>
<tr>
<td>TR + CA1</td>
<td>Nontopo</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>1</td>
</tr>
<tr>
<td>TR + ECV</td>
<td>Nontopo</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
<td>1</td>
</tr>
</tbody>
</table>

### Table A3
Plastic connections between neural areas in the simulated nervous system. A nonzero value of $\eta$, the learning rate parameter, signals a plastic connection that changes according to a modified BCM rule with parameters $k_1$ and $k_2$.

<table>
<thead>
<tr>
<th>Projection direction</th>
<th>Projection type</th>
<th>$P$</th>
<th>Basic strength</th>
<th>Variation</th>
<th>$\phi$</th>
<th>$\eta$</th>
<th>$k_1$</th>
<th>$k_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECI&amp;II&amp;III → DG</td>
<td>[3 x 3]</td>
<td>0.2</td>
<td>0.45</td>
<td>0.15</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>ECI&amp;II&amp;III → CA3</td>
<td>[3 x 3]</td>
<td>0.04</td>
<td>0.15</td>
<td>0.05</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>ECI&amp;II&amp;III → CA1</td>
<td>[3 x 3]</td>
<td>0.04</td>
<td>0.3</td>
<td>0.15</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>DG → CA3</td>
<td>[3 x 3]</td>
<td>0.06</td>
<td>0.45</td>
<td>0.15</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>CA3 → CA3</td>
<td>Nontopo</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>CA3 → CA1</td>
<td>[3 x 3]</td>
<td>0.1</td>
<td>0.45</td>
<td>0.15</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
<tr>
<td>CA1 → ECV</td>
<td>Nontopo</td>
<td>0.1</td>
<td>0.1</td>
<td>0.05</td>
<td>0.25</td>
<td>0.05</td>
<td>0.9</td>
<td>0.45</td>
</tr>
</tbody>
</table>
In our experiment, the robot is assigned to not go backward. Therefore, it will not go to the west side, but choose another direction. The period from trial 5 to trial 7 can be considered as a ‘forget’ period, as the connection weight between CA1 and west neuron has been decreased. Since trial 8, the robot searches for the new hidden goal location again. In the trial 9, it founds the goal location and do the correct thing in the trial 10. The system shows the ability to handle tasks with dynamic changed goal locations.

5. Conclusion

Hippocampus is one of the major components of the brain, which plays an important role in the spatial navigation. In this paper, we have presented our brain-inspired neural architecture for spatial navigation. The model includes a hippocampal circuitry, hierarchical vision architecture, sensory cortical regions and motor cortical regions. This is the first brain-inspired model which combines a biological vision system and hippocampus together. In the experiments, the place-dependent response is observed in CA1 area according to the vision inputs. The proposed structure may indicate a possible way of connection between vision system and hippocampus, which will help to explore the function of hippocampus in spatial navigation. Due to great complexity, we implemented the neural structure in a simple plus maze environment. To further implement the proposed neural system in a more complicated environment, computation complexity is an important factor to be considered. This analysis will be considered in our future works.

Appendix A. Neural parameters

The simulated nervous system is modeled on the anatomy and physiology of the mammalian nervous system but, obviously, with far fewer neurons and a much less complex architecture. It consists of a number of areas labeled according to the analogous neocortical, hippocampus, and subcortical brain regions. Each area contains neuronal units that can be either excitatory or inhibitory. In total, the simulated nervous system contained 19 neural areas, 9084 neuronal units, and approx 0.2 million synaptic connections (Table A1). Specific parameters relating to the patterns of connectivity are given in Tables A2 and A3.

References


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