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Behavioral Match Evaluation of Spatial Cognition in Rats and Robots

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Abstract— **In this paper we present a comparative behavioral analysis of spatial cognition in rats and robots by contrasting a similar goal-oriented task in a cyclical maze, where a computational system-level model of rat spatial cognition is used integrating kinesthetic and visual information to produce a cognitive map of the environment and drive robot experimentation. A discussion of experiments in rats and robots is presented contrasting learning latency while characterizing behavioral procedures such as body rotations during navigation and election of routes to the goal.**

I. INTRODUCTION

OVER the past months we have been identifying the neural mechanisms underlying rats' spatial cognition system in order to computationally model abilities such as the generation of the cognitive map, learning and unlearning of goal locations, and map exploitation during navigation to goal locations from any given point of departure. Taking inspiration from rat's hippocampus function, several computational models implemented on robots have been proposed such as [1]–[5]. The main distinctive aspects of our approach include: (i) generation of a holistic topological-metric map, (ii) modeling of the rat's unlearning ability, (iii) modeling of the interaction between the hippocampus and the striatum, (iv) map exploitation process to enable goal-directed navigation, and (v) validation of our robotic architecture not limited to test well-known spatial tasks performed with rats, but also by designing and implementing new experiments with rats. Refer to [6] for further detail on the comparative analysis between our model and the abovementioned approaches.

To evaluate the model we have developed both computer simulations and mobile robot experimentations. Tasks previously evaluated include learning and unlearning of classical spatial reversal behaviors with normal and hippocampus-lesioned rats in a T-maze and in an 8-arm radial maze as carried out by O'Keefe [7]. We describe corresponding results showing a behavioral similarity between robots and rats in [6]. We also experimented with robots using a classical goal-oriented navigation experiment inspired in Morris [8], where we employed multiple non-cyclical T-mazes surrounded by landmarks. We describe corresponding experiments and results in [9] including modification to landmark configurations after having trained the robot to find the goal. The current paper extends this work by evaluating the robot's behavior while solving a spatial task within a cyclical maze in terms of place recognition and goal-oriented navigation against the results derived from our experiments with rats solving the same spatial task in a similar maze.

The following sections present the bio-inspired spatial cognition model, as well as the experiments with animals and robots solving the spatial task in the cyclical maze, and a comparative behavioral analysis of the results obtained.

II. A ROBOTIC MODEL OF RAT SPATIAL COGNITION

The model comprises distinct functional modules shown in Fig. 1 that capture some properties of rat brain structures involved in the spatial cognition system. A detailed mathematical depiction of each module is presented in [6].

Motivation module, related to the rat's lateral hypothalamus [10], computes the immediate reward the robot gets by the presence of goals (r).

Kinesthetic Processing module, involving the participation of the posterior parietal cortex (PPC) [11] and the retrosplenial cortex (RC) [12], represents the updated position of the robot's point of departure each time the robot moves in relation to its current position through a dynamic remapping perceptual schema (*DR*), and produces groups of neurons that respond to specific kinesthetic information patterns (*PI*) due to the use of Hebbian learning [13].

Landmarks Processing module, associated with the entorhinal cortex (EC) [2], encodes landmark-related spatial positioning in landmark perceptual schemes (*LPS*), generates landmarks information patterns, and integrates them into a single pattern representing the egocentric view from the robot (*LP*).

Affordances Processing module attributes to PPC [14] the generation of the affordances perceptual schema (*APS*) encoding possible turns the robot can perform at any given time being at a specific location and orientation.

Place Representation module corresponds to the rat's hippocampus. It comprises a place cell layer (PCL) with neurons resembling pyramidal cells (*place cells*) found in hippocampal substructures CA3 and CA1 [15] responding to the combination of kinesthetic (*PI*) and visual cues (*LP*) information [16], and a world graph layer (WGL) corresponding to the prelimbic cortex [17], which associates activation fields (*place fields*) [15] of neurons in PCL with a

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physical area in the environment that is identified directionally by the ensemble activity pattern (*PC*) and whose extension is determined by affordances (*APS*) changes sensed by the robot during exploration. WGL stores those associations in a spatial representation referred to as cognitive map [18], and performs place recognition. The activation patterns generated by PCL when the robot is oriented to diverse directions are stored in Actor units. Thus, every node in the map (a place) can be connected to several Actor units (different views), one for each direction, and every connection is associated with a weight (representing the expectation of getting a reward when orienting to the particular Actor unit direction at the current location), and an eligibility trace (marking the connection as eligible to be reinforced later in time). In this way, Actor units compete to select the next moving direction from the current location that allows the robot to get the greatest reward, thus WGL analyzes Actor weights to obtain the biggest ones (*EX*) and their corresponding directions (*DX*).

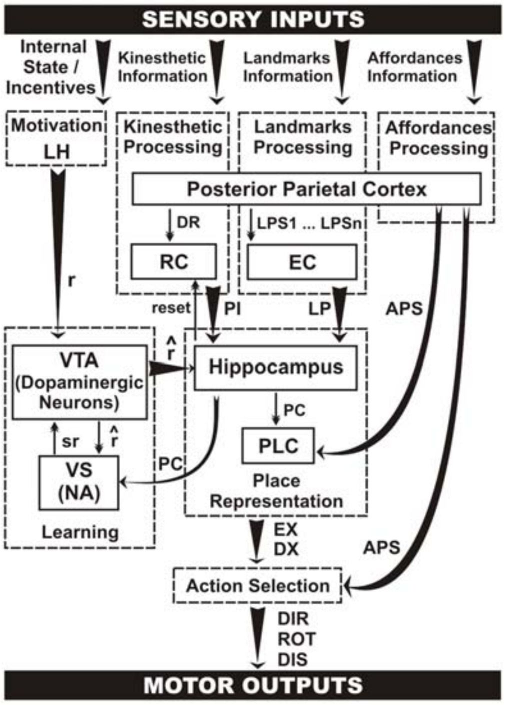

Fig. 1. The modules of the rat spatial cognition model and their interaction. Glossary: LH – Lateral Hypothalamus; RC – Retrosplenial Cortex; EC – Entorhinal Cortex; VTA – Ventral Tegmental Area; VS – Ventral Striatum; NA – Nucleus Accumbens; PLC – Prelimbic Cortex. Inputs/Outputs: r= primary reinforcement; sr= secondary reinforcement; $\hat{r}$ = effective reinforcement; DR= dynamic remapping perceptual schema; LPS= landmark perceptual schema; APS= affordances perceptual schema; PI= kinesthetic information pattern; LP= landmarks information pattern; PC= place information pattern; EX= expectations of maximum reward and their corresponding directions (DX); DIR= next robot direction; ROT= robot rotation; DIS= next robot moving displacement.

Learning module is related to dopaminergic neurons in the ventral tegmental area and to ventral striatum processing reward information [19]. Houk et al. [20] proposed that the striatum implements an Actor-Critic architecture [21]. In our model, an Adaptive Critic predicts reward values of any given place in the environment and produces the error signal ($\hat{r}$) that allows to adapt reward expectations associated to robot different motor actions represented by means of a number of Actor units. Additionally, to enable goal-directed navigation, a backward reinforcement method is implemented, where the eligibility traces of Actor units are updated in the direction of the arcs connecting the nodes in the path followed by the robot. This strategy is based on the goal gradient hypothesis [22], according to which the reinforcement effect is the most at the goal location and diminishes progressively as the animal moves backward through any given maze.

Action Selection module computes the motor outputs of the model (*DIR*, *ROT, DIS*). Motion is determined by considering the current *APS*, the selection of a random rotation between possible affordances, the curiosity to execute rotations not yet explored, and the expectations of maximum reward (*EX*, *DX*).

III. RAT AND ROBOT EXPERIMENTATION

We used two groups composed of three male rats and three robots respectively to carry out spatial tasks in mazes surrounded by four geometrical figures representing allocentric cues or landmarks as shown in Fig. 2.

In order to motivate the animals to learn the task, the consumption of water was prohibited during the prior 24 hours. The tip of a water dispenser was placed at the goal location to provide sweet water to rats as reward. During the experiment, rats and robots pass through three phases: habituation, training, and testing.

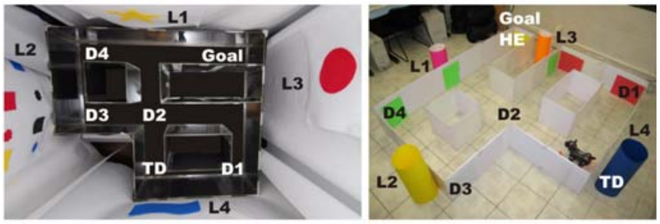

Fig. 2. Top view of cyclical mazes employed in the experiment with rats (left) and robots (right). Landmarks L1, L2, L3 and L4 are illustrated, as well as locations TD, D1, D2, D3, D4, and the goal location.

A. *Habituation Procedure*

The task begins with a habituation session, where the animal and the robot are independently placed in the maze and allowed to explore it freely from location TD (Fig. 2) until reaching the goal location. No reward is provided during this phase, thus rat and robot actions are determined by curiosity and randomness. As a result of habituation, the robot builds a cognitive map of the maze including nodes to represent the explored locations, and Actor units associated with different directions in which they were explored.

B. *Training Procedure*

During training, reward is provided to rats and robots at the goal location of the maze. At the beginning of every training trial, the subject is placed at location TD being oriented north, and the trial consists on exploring the maze until reaching the target. The subject is then removed from the maze. Robot exploration is interrupted if it spends more than 600 sec without reaching the goal.

The robot training begins from the cognitive map previously generated, where it recognizes all locations explored in same directions during habituation, and adds new nodes when it visits unexplored locations and experiments new orientations at explored locations.

Each rat daily training session included 9 trials, with each trial ending with the rat reaching the target for a total of 17 sessions, whereas robot training phase consisted of one session including 20 trials. Latencies and routes followed by animals and robots in locating the target were registered. Fig. 3 contrasts the average latency of arrival to the goal considering the average performance of all three rats and three robots.

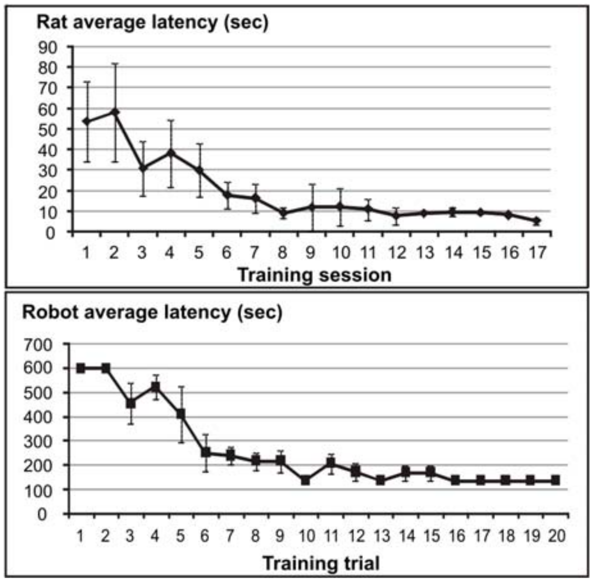

Fig. 3. Average latency of arrival to the goal per training session/trial during the spatial task in the cyclical maze, considering the average performance of all rats/robots and indicating the corresponding dispersion level.

C. Testing Procedure

In order to evaluate rat and robot ability to reach the target after having concluded the training procedure, we tested trajectories during 12 trials with subjects liberated three times from four different locations in the maze: D1, D2, D3, D4 (Fig. 2), pointing to four different orientations: north, north, east, and south, respectively.

In every testing trial, the subject is placed at the corresponding location and orientation, and the trial consists on exploring the maze freely until reaching the goal. The subject is then removed from the maze. Latencies and routes followed by subjects in locating the target were registered as exemplifying by Fig. 4 and 5. Each robot exploited the cognitive map built during habituation and maintained during training in order to reach the target successfully. During some of the testing trials, robots still modified their spatial maps by adding new nodes to represent unexplored locations. Fig. 6 illustrates nodes recognized by one of the robots within its spatial map during tests, and new nodes derived from additions.

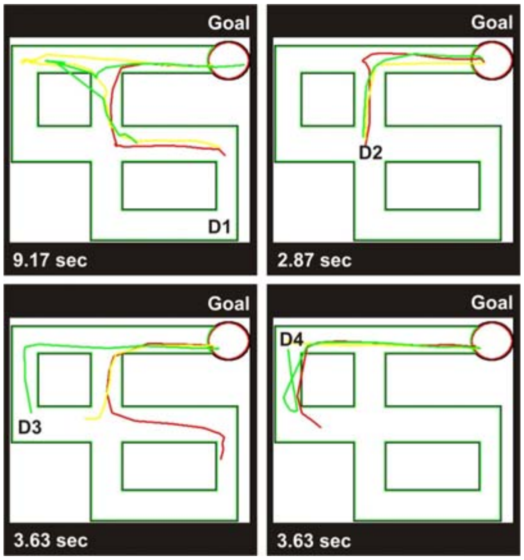

Fig. 4. Examples of routes followed by rats in locating the water during tests from different departure locations (D1, D2, D3, D4). Lines inside each maze illustrate three different routes and the average latency is shown below it.

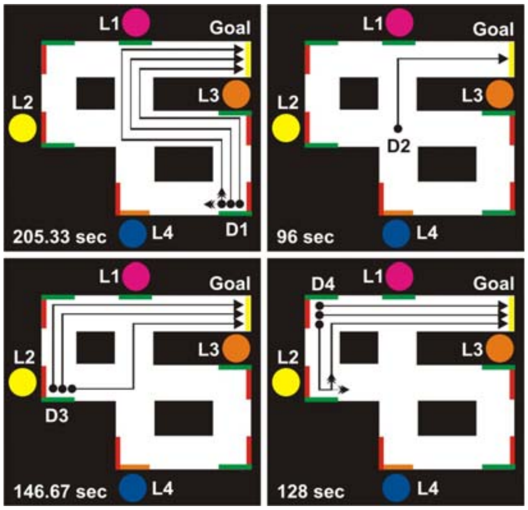

Fig. 5. Routes followed by robot #2 while locating the goal during tests departing from locations D1, D2, D3, D4. Lines inside each maze illustrate routes recorded from three trials and the average latency of arrival is shown below it. When the robot followed the same route in those three trails, the corresponding maze shows only one line. Small arrows over the routes represent hesitations executed by the robot in deciding its next motor action.

IV. COMPARATIVE ANALYSIS OF EXPERIMENTAL RESULTS

As a result of training, the latency of arrival to the target location decreases progressively until stabilizing in both rats and robots (Fig. 3), and both subjects were able to learn the shortest route to the goal from the initial fixed location.

It is possible to characterize comparatively the performance of rats and robots during tests by analyzing behavioral procedures such as errors associated with the election of a non-optimal route to the goal, and the number of body rotations during navigation. As depicted by Fig. 7(a), the average number of errors is less than one. All robots followed optimal routes to the goal from locations D1 and D2. Some of the robots selected non-optimal paths when departing from D3 and D4, since these locations were unexplored or barely explored during training. Therefore, those robots navigated randomly until recognizing a place previously learned, typically belonging to the shortest path to the goal, and followed the rest of that route. On the other hand, as shown in Fig. 7(b), the average number of body rotations in rats when departing from any given test location exceeds slightly the number of robot body rotations, partially indicating that rats took longer to reach the target in contrast to robots.

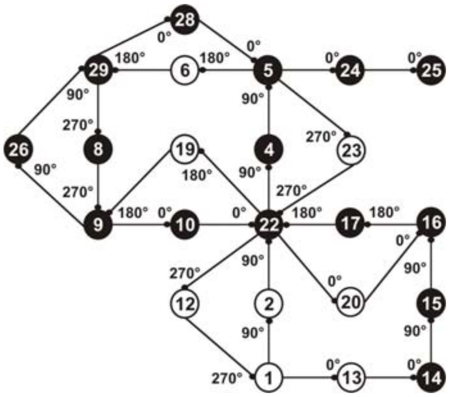

Fig. 6. Spatial map produced by robot #2 as a result of tests carried out in the spatial task within the cyclical maze. Black nodes indicate existing nodes recognized by the robot or new nodes created by it. White nodes are existing nodes not employed by the robot during tests. Nodes are numbered in order of creation, and arcs between nodes are labeled with the robot allocentric direction when it moved from one node to the next one.

V. Conclusions and Discussion

The aim of the work presented in this paper is to provide our model and robotic architecture to neurobiologists and neuroethologists as an alternative platform to study, analyze and predict rat spatial cognition based behaviors.

Results derived from the comparative experimental study with rats and robots discussed throughout the paper allow us to validate our robotic model in terms of performance match. Both, rats and robots, reached successfully the learning criterion during the training process of the spatial task within the cyclical maze. When rats were tested to find the goal location in this relatively complex maze departing from different locations, they did not always show an optimal performance following the shortest route, and this behavior was also exhibited by robots during tests.

We plan to extend our robotic model in the following directions: (i) the function of head-direction cells providing information on the rats' rotation magnitude and movement direction and supplying to the hippocampal module; (ii) the adaptation of place fields distribution by increasing their density in the presence of relevant elements in a given navigational task; and (iii) the functional differences between hippocampal substructures CA1, CA3 and DG relative to their capabilities of pattern completion and pattern separation in conditions where environmental changes promote new navigational behaviors.

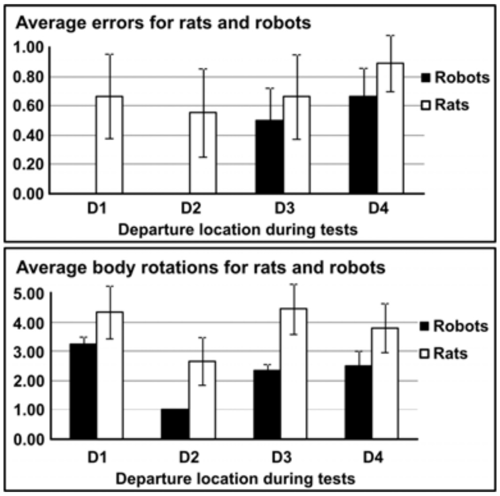

Fig. 7. Graphical comparison between behavioral procedures monitored from rats and robots during tests. Above: Average number of errors associated with following non-optimal paths to the goal location. Below: Average body rotations during navigation within the maze.

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