Minimum Requirements for an Artificial Rat

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Abstract. Neuroscience experiments have shown that rats separate a navigation task into blocks of knowledge, which are likely to be recombined and reused to solve these tasks. Being able to replicate this ability in an artificial system is hypothesised to enable flexibility and robustness to a variety of navigation tasks. This work aims to determine what a minimal system needs in order to accomplish a given task. Spike Timing Dependent Plasticity models are constructed that successfully navigate a series of more complex maze simulations. This identifies the need for boundary cells and grid cells, including place cells and ultimately time cells, to construct and reuse blocks of learnt knowledge.

Keywords: Animat, Spike Timing Dependent Plasticity, Autonomous Navigation

1 Introduction

Recently, in-vivo neuroscience experiments have shown that rats separate a navigation task into blocks of knowledge, which are likely to be recombined and reused to solve these tasks. The hypothesis is to use Spike Timing Dependent Plasticity (STDP) models of brain functionality to replicate useful behaviours. Hence the following research question was adopted: 'what are the minimum components of learning, including the use of building blocks, that would enable an artificial rat to achieve navigation tasks of varying complexity?' This model is to be tested with sequential decision making in simulated mazes, in order to mimic the in-vivo tests that inspired the design.

2 Background

The study of the neuron systems for navigation in rats has been a rapidly developing area since the applications of the techniques to record single neuron activities in freely-moving rats [1]. Place cells in the hippocampus fire at specific locations [2]. Then head direction cells [3], grid cells [4], boundary cells [5] and speed cells [6] were found in the entorhinal cortex and other regions. However, the neuron basis for navigation is a highly complex system, such that the mechanistic details of spatial mapping is still not totally understood ([1] 2017). Hence, we will not try to simulate the entire rat brain. Instead we will draw analogies from the areas in a rat brain considered important for navigation.

Analogues of rat neuron systems for navigation, e.g. place cells, grid cells, have been used in artificial systems to assist spatial cognition [7, 8]. However, these works were not based on spiking neuron networks or spike timing–dependent plasticity (STDP) [9], and did not include the design of building blocks of information.

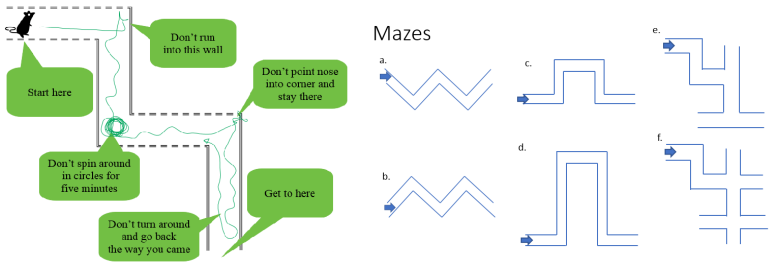

Fig. 1. Maze navigation tasks. The arrows show the direction of navigation. (a) W (b) M (c) The hat (d) The high hat (e) Double T junction (f) X junction mazes.

All the models are spiking neuron networks created in CARLsim 3.1.3. CARLsim is a C/C++ spiking neuron network library where Izhikevich spiking neurons and realistic synaptic dynamics such as STDP are employed [10]. CARLsim has been used in robotics [11], but has not to test the building-block mechanism.

3 Methods

Different mazes as shown in Figure 1 are developed to train our agent and test its performance. The first maze (the W maze) is a corridor with left and right turns. This is to train and test the agent on the response to the boundaries. M maze and the hat maze are successively applied to test whether the agent can apply the boundary response (one type of the building blocks in maze solving) learned from W maze on a mirror (rotated) or a turn order altered version. Then a high hat maze is tested for the scalability of the boundary building blocks. Mazes with double T junctions and/or X junctions are used to train the agent on developing specific response according to locations (another type of building block).

The connections between different neurons are strengthened/weakened by the STDP mechanism during each training run. Training is set to run 50 times in our models by applying sensor readings plus a 'current' to the rat to supervise its navigation, i.e. fire motor cells to make appropriate decisions. Then, the agent is tested on the same and rotated/scaled mazes without the input current, where the agent must rely on what it has learned, that is, the synaptic weights among neurons that have been built up during training. All excitatory neurons are regular spiking neurons (class 1 excitable): a=0.02, b=0.2, c=-65, d=8, while all inhibitory neurons are Fast spiking neurons (class 2 excitable) : a=0.1, b=0.2, c=-65, d=2. For the simple model there are 4 motor neurons: one excitatory and one inhibitory for each direction (left or right), 360 neurons for each degree in the Boundary cells and 100 cells in each of the one layer Grid, Gaussian receptive place and Memory Recording Place cells.

Figure 2 shows a simplified view of its structure, which is split into three regions: dentate gyrus (DG), cornu ammonis 3 (CA3) and cornu ammonis 1 (CA1). This is inspired by the observations in a real rat brain, which possesses different scales of spatial representations from dorsal to ventral hippocampus [12]. Furthermore, this structure is replicated in two hemispheres, for a total of 3x3x2 = 18 cell groups. The output layer consists of two groups of motor cells

to steer the agent right and left respectively, noting this functionality is more complicated in a real brain.

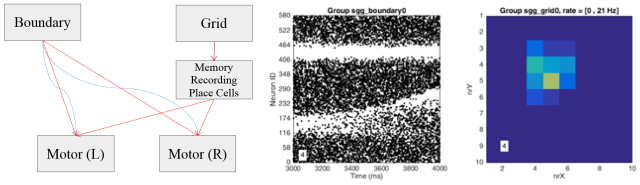

Fig. 2. Left: the model; red lines excitatory, blue inhibitory connections. Middle: firing rate of the boundary neurons changes when the rat movez forward and the surrounding boundary changes. Right: the firing field of one grid cell.

4 Results and Analysis

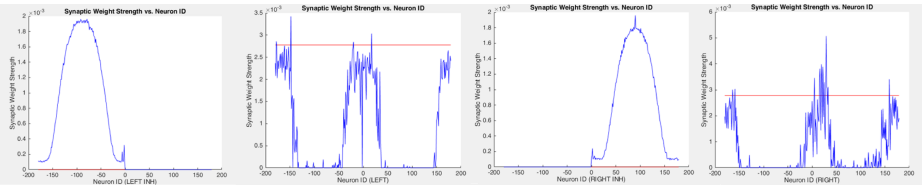

Fig. 3. A synaptic weight developed between boundary cells and motor neurons. Neuron ID is the number of the boundary cell: 0 front, 180 back. INH inhibitory.

An example of the synaptic weights developed is shown in Figure 3. It illustrates that both motor neurons will be excited when there is a wall in front of the agent, or corners diagonally behind, and the left (right) motor neuron will be inhibited when there is a wall to the left (right) of the agent. This means the agent can learn to avoid turning to boundaries, turn left (right) at a left (right) bend, and apply these rules on a different maze (rotated, mirrored, the order of turns re-arranged, scaled).

When the model is trained in the W maze, it can navigate successfully in M maze, the hat maze and the tall hat maze as well. If it is trained in the maze e or d in Figure 1 with different steering direction in the successive T or X junctions, it can navigate by itself in the same maze afterwards, and navigate successfully through a maze without decision points (e.g. T or X junction) such as W maze or the hat maze. However, its performance is still not ideal as sequences of different decisions at one location cannot be made.

5 Conclusion

The work successfully achieved its aim of building a Spike Timing Dependent Plasticity model for agent navigation in a series of complex mazes. Experimental results demonstrated that for simple corridor mazes, boundary cells are sufficient

to enable navigation that is invariant to the pose and scale of the maze once it has been learnt. However, when the agent has to make decisions based on specific locations, the grid cells and place cells need to be included in the system. Finally, if a sequence of decisions is needed in a given location, then the grid cell infrastructure needs to be extended to time cells. Analysis of the learnt agents show that important building blocks, e.g. location in the west of a maze, are reused in the navigation tasks to facilitate flexible and robust learning.

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