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Models of Neural Systems, WS 2014/15
Project 3: Learning of Grid Cells
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Background

Cells tuned to animal position have been found in the hippocampus and in the medial entorhinal cortex (mEC). In mEC, neurons are active at multiple spatial locations arranged in a strikingly regular hexagonal pattern [1]. These neurons have been named grid cells, and they are believed to underly self-location in an environment. Despite a growing body of literature on grid cells, the mechanisms underlying their formation are yet unclear. In this project we study a model by Kropff and Treves [2] who proposed that grid cells could emerge via learning with adaptation.

Problems

1. Literature Review. Study the papers by Kropff and Treves [2] and by Si, Kropff and Treves [3]. What are the main assumptions of the model? What are potential strengths or weaknesses of the model? How could it be experimentally falsified?

2. Simulate a virtual rat exploring a square environment (side-length: $L = 1.25$ m) at constant speed ($v = 0.4$ m/s). Choose the running direction randomly as described in [3] (page 487), and take care of the boundaries as described in [3]. Plot the trajectory over time in the environment.

3. Implement a layer of $N^{\text{in}} = 200$ input neurons with rates $\{r_j^{\text{in}}\}$ and randomly-centered Gaussian receptive fields in space (see Eq. 3 in [3]). Plot the receptive-field centers and the $1/e$ levels of the Gaussian functions in the environment.

4. Implement the adaptation mechanism of an output neuron by means of two coupled dynamical variables r^+ and r^-, reflecting the tendency of a neuron to activate and inactivate over time:

$$\tau^+ \frac{\mathrm{d}}{\mathrm{d}t} r^+ = h(t) - r^+(t) - r^-(t) \quad \text{and} \quad \tau^- \frac{\mathrm{d}}{\mathrm{d}t} r^-(t) = h(t) - r^-(t) \tag{1}$$

   where $h(t)$ is the total feed-forward input to the neuron, and $\tau^+ = 0.1$ s and $\tau^- = 0.3$ s set the time scales of activation and inactivation respectively. Study the effect of the adaptation dynamics when the neuron is fed with a sinusoidal linear chirp:

$$h(t) = \sin\left(\pi k t^2\right) \tag{2}$$

where h oscillates with frequency $f(t) = kt$ which increases linearly with time with speed $k = 0.1$ s^{-2}. Plot the input h and the activation variable r^+ as a function of frequency. What is the effect of adaptation in frequency domain?

5. Implement a layer of $N^{\text{out}} = 100$ output neurons receiving feed-forward input from the input layer. Output neuron i receives total feed-forward input $h_i(t) = \sum_j w_{ij} r_j^{\text{in}}(t)$, where w_{ij} is the synaptic weight between input neuron j and output neuron i. Initialize weights as random numbers: $w_{ij} = (1 - \xi) + \xi u$, where $\xi = 0.1$, and u is a random variable uniformly distributed in $[0, 1]$. Also normalize the weights to unit norm: $\sum_j w_{ij}^2 = 1$.

6. Feed the feed-forward input h_i to the adaptation dynamics (Equation 1) and compute the output rate r_i^{out} as a non-linear function of the activation variable:

$$r_i^{\text{out}}(t) = \frac{2}{\pi} \arctan\left[g_i(r_i^+(t) - \mu_i)\right] \Theta\left[r_i^+(t) - \mu_i\right], \tag{3}$$

   where g_i and μ_i are respectively the gain and threshold of neuron i, and Θ is the Heaviside step function. At each time step adapt the parameters g_i and μ_i such that the mean activity and the sparseness of the neurons in the output layer remain within a 10% relative error bound from $a_0 = 0.1$ and $s_0 = 0.3$, respectively. See [3] (page 486) for details.

7. Implement the learning dynamics of the feed-forward weights:

$$w_{ij}(t + \Delta t) = w_{ij}(t) + \epsilon\left(r_i^{\text{out}}(t) r_j^{\text{in}}(t) - \bar{r}_i^{\text{out}}(t) \bar{r}_j^{\text{in}}(t)\right) \tag{4}$$

   where $\epsilon = 0.005$ is the learning rate and $\bar{r}^{\text{out}}$ and $\bar{r}^{\text{in}}$ are running averages of input and output firing rates respectively (See [3] Eq. 8). Also keep the weights normalized to unit norm.

8. Simulate the activity of the network and the development of the synaptic weights as the rat explores the environment for 10 hours. Plot the weights at multiple time steps of the simulation. Also plot the average gain $\bar{g} = \sum_i g_i$ and threshold $\bar{\mu} = \sum_i \mu_i$ over time. What happens if one keeps these parameters constant?

Literatur

[1] Torkel Hafting, et al., "Microstructure of a spatial map in the entorhinal cortex", Nature 436, 801-806 (2005).

[2] Emilio Kropff and Alessandro Treves,"The Emergence of Grid Cells: Intelligent Design or Just Adaptation?", Hippocampus 18:1256-1269 (2008).

[3] Si, Bailu, Emilio Kropff, and Alessandro Treves. "Grid alignment in entorhinal cortex." Biological cybernetics 106.8-9 (2012).

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