

ASSOCIATIVE MEMORY AND HIPPOCAMPAL PLACE CELLS

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Many hippocampal pyramidal neurons in rats are selectively activated at specific places in the environment. We present a network model for the CA3 area of the hippocampus. The network produced place selective activity even when the external sensory input was broadly tuned and noisy. The model predicts that the place fields should be nonuniformly distributed, clustering in the places where the synaptic interactions between neurons is strongest. This may occur at locations of special significance, such as locations where there has been food in the past.

1. Introduction

The place fields of rat hippocampal cells have been extensively studied^{1,9}. Recently, it has become possible to record from over one hundred hippocampal neurons simultaneously². There is sufficient information in these cells to encode the position of the animal in its environment, and thus place cells could be involved with some aspects of navigation². However, the evidence that these neurons are in fact used for navigation is not convincing and there are alternative explanations for the place fields³.

The activity of the place cells in the hippocampus is not simply a direct reflection of sensory inputs. A place cell can remain firing when the rat is in the appropriate location for some time after the removal of visual cues, or switching off the lights^{4,5}. Furthermore, the positions of the place fields in a given environment can be also modified by changing the behavior of the rat⁶. Therefore, the neurons represent a more abstract set of relationships between sensory cues and the past history of the rat in a particular environment.

In this paper, we describe a model for the CA3 region of the hippocampus and focus on the structure of the stable attractors of the network. The results of the model lead to a number of testable predictions.

2. The model

The CA3 region of rat hippocampus receives input from the perforant pathway from the entorhinal cortex directly and indirectly, from the dentate region of the hippocampus. The pyramidal neurons in the hippocampus form recurrent excitatory collaterals. This network were modeled by a set of neurons labeled by the position of their place fields, x_i , as would be determined by external sensory input; that is, the location in the environment where the cell is most strongly activated by sensory input. The model is based on the *mean-field* approximation in which only the average firing rates of the neurons enter into the model:

$$\begin{aligned} \frac{dr_i}{dt} &= -r_i + g(\sum_j J_{ij} r_j + I_i) \\ J_{ij} &= J_0 \exp(-|x_i - x_j|/\sigma) - J_1 \end{aligned} \quad (1)$$

where r_i is the average spiking rate of the neuron i , I_i is it's external sensory input, $g(x)$ is the gain function of neurons, J_{ij} is the strength of the synaptic coupling between the neurons i and j at locations x_i and x_j respectively. The excitatory connections in the model are mainly local and the coupling matrix J_{ij} is a gaussian function of the distance between their place fields centers. The uniform inhibitory inputs J_1 can be considered a global feedback inhibition. For simplicity, we used a semi-linear neuronal gain function of the form $g(h) = 0$ for $h < T$, $g(h) = \beta(h - T)$ for $T \leq h \leq T + \beta^{-1}$, and $g(h) = 1$ otherwise. The sensory input I_i reflects the position of the place field before learning, and is assumed to be a smooth function around the position:

$$I_i = I_0(1 + \lambda \exp(-|x_i - x_0|/l)) \quad (2)$$

where x_0 is the current position of the rat in the environment. Thus, the cell receives the maximal input when the rat is in the center of it's place field: $x_i = x_0$. The place specificity of the external input is described by two parameters: λ , the strength of modulation, and l , the width of tuning.

Similar models have been used to study for the population vector coding of the movement direction in motor cortex of monkey⁷ and the orientational selectivity in visual cortex in⁸.

Note that x_i are determined by the external input only, and thus *do not* represent the true position of the place fields after learning; that is, the matrix of synaptic coupling strengths J_{ij} is learned. The actual form of the place field is determined by the detailed structure of this matrix which may depend on the manner in which the rat explored the environment. It should also be noted that the position x_i is not simply related to the position of the cell in the hippocampus. There is no evidence for a topographic map in the hippocampus and cells with overlapping place fields may be far apart.

3. Distribution of the place fields

In this paper, we model a one-dimensional environment. Let x be the distance from one end of a linear maze. Consider first an ideal case where the initial place fields x_i are positioned equidistantly over the length of the environment. Then, from Eqs. 1, the synaptic coupling matrix is translational invariant and J_{ij} is only a function of $i - j$.

For a uniform input, $\lambda = 0$, the network had a set of stable *attractor* states, all with the same shape, as determined by the parameters of the interactions and gain function, centered

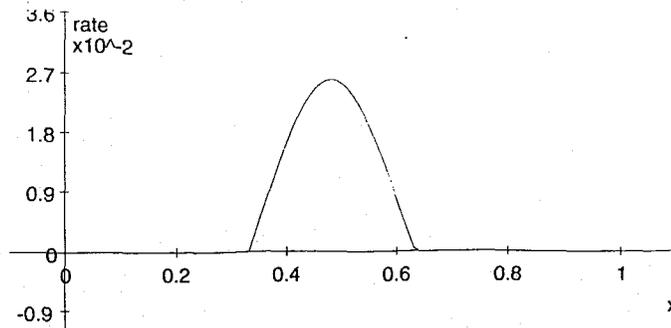


Figure 1: Firing rate of all of the neurons in the network in one of the stable states. Each neuron i is labeled by its corresponding x_i .

around each position x_i . An example of such attractor is shown in the Fig. 1. Since there were no barriers between nearby attractors, each of them was only marginally stable. The particular state of activation therefore depends entirely on the initial activation pattern. In practice, the external input has some variation and the actual position of peak activation would be determined by the peak of the input; that is, by the position of the rat x_0 . However, if λ is not too large, the shape of the place field was not strongly affected by the input, which served mainly to select the right attractor. While the animal moves through the environment, the peak of the input moves accordingly through the network, causing the activity to shift continuously from one attractor to another. As a consequence, there should be a uniform distribution of place fields throughout the environment.

This highly idealistic situation is unlikely to occur since the attractors are only marginally stable and any inhomogeneity in the distribution of the original place field centers, or in synaptic coupling parameters, should lead to their rearrangement. In fact, instead of having a large set of attractors, one for each neuron, there was a much smaller number of attractors, concentrated in the regions of the network with a higher density of place fields or higher synaptic strengths. For example, we considered a network of 100 neurons, as described by Eqs. 1, with uniform but random distribution of x_i . For a uniform external input, $\lambda = 0$, we solved the equations for 100 sets of initial conditions where the activation was concentrated around one of the neurons. All of the final solutions are shown in Fig. 2.

Instead of having one attractor centered on each neuron, the network had only 3 attractors at those locations where the density of place fields was highest. Each collective attractor resulted from the collapse of many others and thus had a large basin of attraction; that is, the attractor could be reached from many initial states of activation. The same collapse occurred when there was an inhomogeneity in the synaptic parameters (in fact, these two cases are equivalent, since the positions of the fields x_i are only relevant for determining the synaptic strengths (see 1)). This could occur if the synaptic strengths between the neurons with nearby place fields are reinforced while an animal explores its environment.

The situation is somewhat more complicated when the network received a nonuniform input with non-zero λ , (as when the rat moves through the environment). Some of the attractors differentiated by splitting from a collective attractor, as shown in Fig. 3. However, even in this case there was a considerable discontinuity in the activity as the input activity swept across

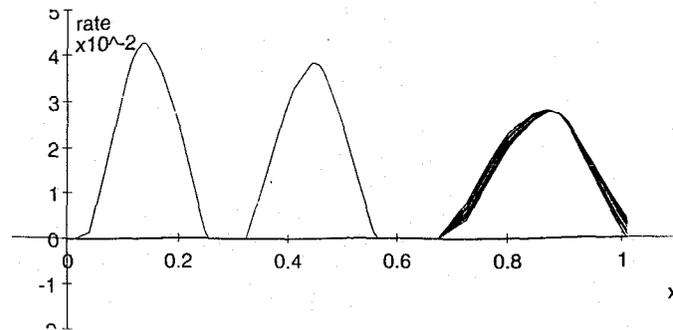


Figure 2: Superposition of the activity states of the network with uniform input and initial conditions around each of the neurons.

the network.

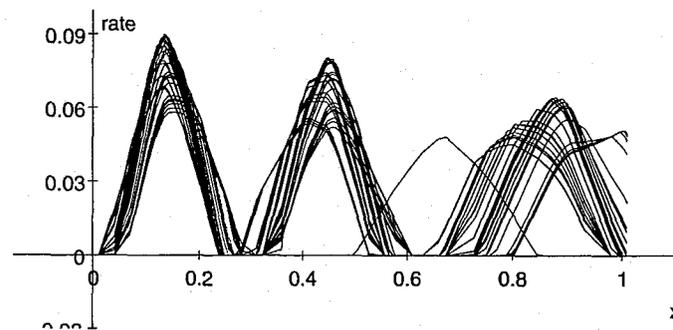


Figure 3: The same as in Fig. 2 with modulated input: $\lambda = 0.1$.

4. Predictions of the model

What would be the implication of this simple model for the properties of the place cells as revealed by multiunit recordings? First, the distribution of the place fields, instead of being uniform over the environment, should exhibit a considerable degree of clustering near the few places where many individual attractors collapse. This can be easily inferred from Fig. 2: as the input spans the part of the network corresponding to the basin of attraction of one of the collective attractors, the activity of the network almost remains fixed, implying that all of the neurons participating in this attractor have almost identical (and broad) place fields with different average firing rates. In multiunit recordings, one should see that, instead of smoothly varying, the activity in the populations of cells should jump from one group of neurons to another one as the rat crosses the boundary between the basins of attractions of different attractors. Experiments are underway to test this prediction ¹⁰.

In the model, the collapse of individual attractors into collective ones with large basins of attraction generally occurs in regions of increased strength of recurrent synapses. The inhomogeneity of recurrent synaptic couplings could result from the varying conditions in the environment, such as bends in the maze where the rat must turn, locations of food and other

unique conditions. Perhaps these places require a special attention from the animal and passes them with lower speed, which may lead to increased synaptic strength through Hebbian mechanisms. This possibility will be tested in a model that incorporates synaptic plasticity directly.

The central hypothesis in the model is that place cells in the CA3 area of hippocampus result from the interactive dynamics of an associative network of neurons. In this model, the sensory input played a major role only in the initial stage of learning, during the exploration of a new environment. During this exploration, the learning is guided by sensory and motivational inputs that lead to activity in a small group of neurons for each location of the environment. During exploration, synaptic couplings between the neurons corresponding to adjacent locations are reinforced. As a result, the network acquires a set of stable states with the activation localized to neurons with neighboring place fields. This hypothesis could be tested by examining the effects of different behaviors of the animal on the locations of the place fields during their formation.

5. Conclusions

What is the functional role of place cells in the hippocampus? The clustering of the place fields in the model in certain places of the environment could reduce the ability of these cells to code for the position of the animal. Because many of the place fields of cells in the model had the same shape, the precision with which the cells could be used to locate an animal in its environment would be limited to the sizes of the place fields, which were large.

Could the activation of place cells have some other function? The place fields could signal to the cortex of the animal the proximity of the animal to locations that had previously been important during exploration. Thus, instead of providing an unbiased map of space, the hippocampus may encode a *space memory* by associating the position of the animal with behaviorally important events. This is similar to the view proposed by O'Keefe and Nadel, who suggested that the hippocampus provides a "cognitive map" of the environment⁹.

Acknowledgments

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