Lab 9

March 3, 2010

Associative Recall

In the previous lab, we studied how STDP compensates for neuronal variations and input noise in a network of recurrently connected neurons. In this lab, we use the same network to store and retrieve a memory pattern, showing that the same mechanism we used to compensate for intrinsic and extrinsic variability can restore missing information.

9.1   Prelab

In this prelab, we consider how a recurrent network with potentiated synapses recalls a stored pattern.

For simplicity, we assume that all neurons receive the same number of potentiated synapses, n, from a randomly selected subset of neurons in the pattern. Further, we assume that a minimum number (k_{th}) of these potentiated synapses must be active for the neuron to spike. The number of active potentiated synapses (k) is drawn from a binomial distribution:

$$b(k, n, p) = \binom{n}{k} p^k (1-p)^{n-k} \tag{9.1}$$

where p is the probability that a neuron is stimulated, equal to m/N when m of N neurons are stimulated.

From this distribution, we can predict what fraction of the unstimulated neurons will be recruited by the stimulated ones. $b(k, n, p)$'s integral from 0 to k_{th} (with respect to k) yields $B(k_{\text{th}}, n, p)$, which is the probability that $b(k, n, p) < k_{\text{th}}$. Therefore, the probability that $b(k, n, p) \geq k_{\text{th}}$ is $1 - B(k_{\text{th}}, n, p)$.

Since k_{th} is a population average, it need not be an integer. Therefore, we use a continuous approximation for $B(k_{\text{th}}, n, p) \approx \Gamma(k_{\text{th}}, np)$.[1] Hence, the fraction of remaining neurons recruited is:

$$r = 1 - \Gamma(k_{\text{th}}, np) \tag{9.2}$$

We will measure the fraction of neurons active (f) versus the stimulated fraction (p). Knowing that the active fraction is made up of stimulated and recruited neurons, what is f as a function of p and r? Show that you can rearrange this relationship to solve for r:

$$r = \frac{f - p}{1 - p} \tag{9.3}$$

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[1] In Matlab $\Gamma(k_{\text{th}}, np)$ is computed as gammainc(k_{th}, np). In Mathematica, it is computed as Gamma[k_{th}, np]/Gamma[np].

9.2   Setup

As in previous labs, there will be a folder on the Desktop; this one is named **Memory Lab**. This folder contains the three instrument-control programs; they acquire and display the neuronal spikes and membrane potentials in real-time as well as record and clear the synaptic states. **experiment.exe** drives a patch of neurons and records their spikes; **read_syn.exe** records the states of synapses (potentiated or depressed), generating a plot of each neuron's synaptic weights; and **clear_syn.exe** initializes all synapses to the depressed state. The TA will instruct you on the use of the software.

Before each test, edit the contents of *parameters.txt*. In this lab, the parameters of interest are:

- Input current coefficient of variation (CV_I)
- STDP active (1) or inactive (0) (W_{stdp})
- Number of stimulated neurons (m)

Note that the mean input current (I_μ) is set such that neurons spike near the center of the decreasing phase of the theta inhibition. Also, the M-current strength and decay-constant are set to spike once per theta cycle.

9.3   Experiments

In the first experiment, we will drive a pattern (patch) of recurrently connected neurons with constant input current, enabling STDP to potentiate synapses among these neurons. In the second experiment, we will drive different-sized subsets of the original pattern, observing how well the potentiated synapses recruit additional neurons in the pattern.

Experiment 1: Storing the Pattern

In this experiment, we will

- Study pattern storage by potentiating recurrent synapses among coactive neurons

We will drive a 10 by 10 patch of neurons with (noisy) input current as well as an 8.75Hz inhibitory theta rhythm. Set the system to drive all 100 (N) neurons in the pattern by setting the number of stimulated neurons (m) to 100. Initialize the synapses to the depressed state by running **clear_syn.exe**. Then choose a low level of noise ($CV_I < 5.0$) for the input current. You may use the level of noise that resulted in the greatest average number of potentiated synapses per neuron from Lab 8 (CV_I near 2.0).

Then, run the data acquisition program **experiment.exe** with STDP active ($W_{stdp} = 1$). After the program runs for 20 seconds, record the states of the synapses with **read_syn.exe**. As in Lab 8, neurons do not receive the same number of potentiated synapses. Plot a histogram of the distribution of the number of potentiated synapses that each neuron receives. What is the mean number? We will use these synapse states in Experiment 2, so do not reset the board.

Experiment 2: Recalling the Pattern

In this experiment, we will

- Study how pattern recall performance depends on the number of neurons stimulated

We will drive a subset of the neurons in the 10 by 10 patch that was stored in experiment 1. To ensure we do not corrupt the stored pattern, set STDP inactive ($W_{\text{stdp}} = 0$). Vary m between 10 and 90 (about 10 points). For each m value, run **experiment.exe** a few (at least 3) times to obtain the firing rates of the neurons.

Calculate the number of neurons that are active in each experiment and plot the (average) fraction of the pattern activated versus the fraction of the pattern stimulated (with error bars of one standard deviation). Explain why the standard deviations are large when the activated fraction is near 0.5. On a separate graph, plot the average fraction (of unstimulated neurons) recruited, r (Equation 9.3), versus the fraction (of the total) stimulated, p, with error bars of one standard deviation. Fit the data with Equation 9.2 from the Prelab, using the average number of potentiated synapses per neuron measured in Experiment 1. Use a trial and error approach, increasing the threshold number of active synapses until the fit aligns with the data. Also, fit the data using twice the average number of potentiated synapses. Which fit is closer to the data? What does this imply about which neurons are being recruited, the lethargic ones with many potentiated synapses or the excitable ones with few?

9.4   Postlab

In Experiment 2, pattern recall performance was hindered by the most excitable neurons, which received few potentiated connections, lacking reciprocal connections from their targets. In cortex, symmetrical connections abound; if a layer V pyramidal neuron excites a target pyramidal neuron in the same layer, there is a 30% chance that the target reciprocally excites it [Markram 1997]. Symmetrical connections make recurrent networks robust, enabling reliable pattern storage and recall. However STDP at recurrent connections does not result in symmetric connections. In the presence of small amounts of noise, the proper STDP rule can give these connections. How would you design an STDP rule to take advantage of the noise to obtain more reciprocal connections?

Large amounts of noise can invalidate the previous method. Bursting could remedy this problem: CA3 pyramidal neurons are capable of firing bursts of spikes. Bursts can extend pyramidal neurons spike trains such that they overlap, resulting in many pre-before-post as well as post-before-pre pairings. Why is this more robust in the face of noise?