Perceptual Decision Making

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Contents

Background

In this seminar project we would be studying the competition neural model for perceptual decision making. Perceptual decision making refers to the decision making of an individual with respect to perception. Studying the neuronal basis of perceptual decision making has found the middle temporal visual area (MT) to respond large motion stimuli. The output of MT region further down the neural pathway activates the Lateral Intra-parietal Area (LIP) before a saccadic eye movement takes place. The LIP neuron activates if a saccadic eye movement would take place in its receptive field. Fig 1 shows the neuronal findings for LIP neurons as reported by Roitman et al [6]. Fig A records the response of LIP neurons from the onset of stimuli (triangle) to initiation of saccadic motion. For saccadic motion to the receptive field of the LIP neuron population, we see an increase in firing and a decrease vice versa. The strength of firing depends upon the coherence level of the dots. In fig B. we observe that the saccadic eye motion is initiated only when the neuron reaches a threshold. The threshold is same for different level of coherence. Also, post

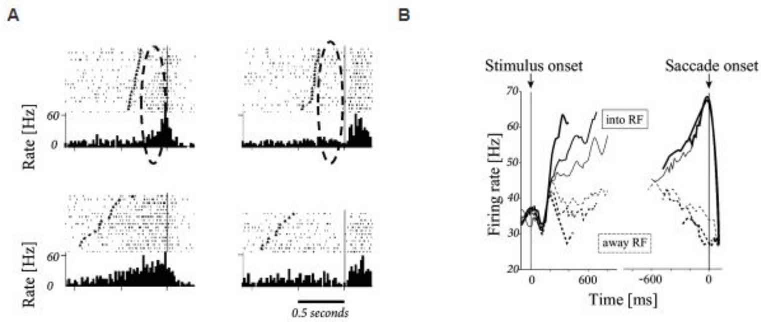


Figure 1: LIP neurons firing to motion discrimination stimuli

initiation of the stimuli, there is a dip in the firing rate. Post this dip, the discrimination against for or against the saccadic eye motion takes place.

The ramp-to-threshold dynamics of the LIP neurons have been modeled both mathematically and biophysiologically. Shadlen and Newsome [7] and other scientist have successfully been able to fit the neuronal behaviour to the Diffusion model. However, it leads to a long integration time in decision process making it biologically implausible.

Likewise, Wang [8] was able to replicate the results of Roitman et. al[6] and Shadlen et. al [7] in his biophysically based cortical microcircuit model. However, this model consists of thousands of spiking neurons that interact with each other non linearly. This makes it difficult to analyse the dynamics of the model

This seminar project deals with a reduced version of Wang's model as proposed by Wong et. al [9].

Model Description

Before discussing the reduced model. Let us discuss the cortical microcircuit model by Wang [8].

Cortical Micro Circuit Model

This model has been developed based on the following assumptions:-

1. Recurrent excitation of the neural network is largely mediated by NMDA receptors.
2. The network is dominated by recurrent inhibition.
3. The neurons receive large amount of stochastic background inputs.

The cortical micro circuit model consists of N neurons with N_E pyramidal neurons and N_I interneurons. The pyramidal neurons constitute of 80% of the total neuron population. The N_E neuron population is divided into stimuli sensitive population

(fN_E) and non sensitive population ($(1-2f)N_E$). The participating neurons are connected pyramid-pyramid neuron, pyramid-interneuron, interneuron-interneuron, interneuron-pyramid neurons. Both the neuron population are described by the leaky integrate and fire neuron with the membrane potential $V(t)$ characterised as :-

$$C_m \frac{dV(t)}{dt} = -g_L(V(t) - V_L) - I_{syn}(t)$$

C_m is the membrane capacitance, g_L is membrane leak conductance, V_L is resting potential, $I_{syn}(t)$ is the total synaptic current. The $I_{syn}(t)$ has both AMPA and NMDA receptors. These external synaptic inputs send outside world stimuli and background noise to the architecture.

Reduced Model

The initial model by Wang[8] used $N_E = 1600$ and $N_I = 400$ leaky-and-integrate spiking neurons to simulate the model. Inorder to analytically study this model, Wong et. al. [9] reduced it to a two variable model. Inorder to achieve this reduction, the following steps were undertaken-

1. The first step in this reduction is to reduce the entire population of 2000 neurons to a population consisting of 4 units namely 2 discriminatory excitatory units, 1 non selective unit and 1 inhibitory unit. Wong used mean field approach to achieve this. In order to apply the mean field approach, proper estimation of the firing activity of the population and the synaptic input currents were made. First, the driving force of the synaptic input currents has been considered to be constant (Brunel [2]). Second, the contribution to the variance of the membrane potential is driven by external input to the population (the all-in-all connectivity within the neurons averages out the inter neuron contribution) as suggested by Renart et. al [5]. The σ is fixed at constant. Finally, the firing rate was expressed by the simplified input-and-output function (Abott and Chance [1]):-

$$r = \phi(I_{syn}) = \frac{c_{E,I} I_{syn} - I_{E,I}}{1 - exp[i g_{E,I}(c_{E,I} I_{syn} - I_{E,I})]}$$

Here, ϕ is the function of the total synaptic input current

I_{syn} of a single cell. E,I represent either the excitatory or inhibitory neurons. $c_{E,I}$ is the gain factor and $g_{E,I}$ is the noise factor that determines the shape of the curvature of ϕ (which is linear threshold function for large g). This simplified model was derived from the first passage time formula of a single cell LIF model driven by a AMPA receptor mediated external gaussian noise.

Using this simplications and estimations, the entire neural population was able to be converted into 4 units (as mentioned initially). These units can be represented by 11 variables, mentioned below :-

$$\tau_r \frac{dr_i}{dt} = -r_i + \phi(I_{syn,i})$$

$$\tau_r \frac{dr_I}{dt} = -r_I + \phi(I_{syn,I})$$

$$\frac{S_{AMPA,i}}{dt} = -\frac{S_{AMPA,i}}{\tau_{AMPA}} + r_i$$

$$\frac{dS_{NMDA,i}}{dt} = -\frac{S_{NMDA,i}}{\tau_{NMDA}} + (1 - S_{NMDA,i})F(\psi(r_i))$$

$$\frac{dS_{GABA}}{dt} = -\frac{S_{GABA}}{\tau_{GABA}} + r_I$$

Here, $i = 1, 2, 3$ represent the 3 units namely 2 stimuli discriminatory excitatory neuron and 1 unit of non selective excitatory neuron. I is the inhibitory unit, $r_i(t)$ and r_I are the mean firing rate of the excitatory and inhibitory units. S is the synaptic gating variable and τ is the decay time constant.

2. Using the mean field approach, the model is represented by 11 variables. This model can be further reduced into 8 variables by observing the activity of the non selective excitatory unit. As the firing rate of the non selective unit is more or less constant, it can be replaced by a constant mean rate of 2 Hz. However, this simplification does introduce certain consequences. The first being the difference between the previous model and the current model's firing rate is about 1 Hz. The second consequence is that we would neglect the slightly increased inhibition on the selective excitatory unit by the slightly elevated activity of the non selective unit.

Additionally, the inhibitory interneurons can be linearised as the instantaneous firing rate 8 Hz and the mean firing rate 8 to 15 Hz meakes the single cell input-output relation linear which can be expressed as :-

$$\phi(I_{syn}) = \frac{1}{g_2}(c_I I_I) + r_0$$

The self inhibitory coupling term lowers the effective firing rate by a factor of $1 + (c_I/g_2)J_{II}$. This removes the self consistancy calculation of the inhibitory population.

3. The final reduction of the neural model was achieved by

analysing the time membrane constant of the neurons and the gating variables. The membrane time constant of an instantenous cell can be ignored as the firing rate of a cell is instantenous [Brunel et. al. [3] and [4]]. Among the gating variables, S_{NMDA} has the longest time decay and hence dominates the time evolution of the system. The gating NMDA variable is defined as:-

$$\frac{dS_{NMDA,i}}{dt} = -\frac{S_{NMDA,i}}{\tau_{NMDA}}(1 - S_{NMDA,i})F(\psi_i)$$

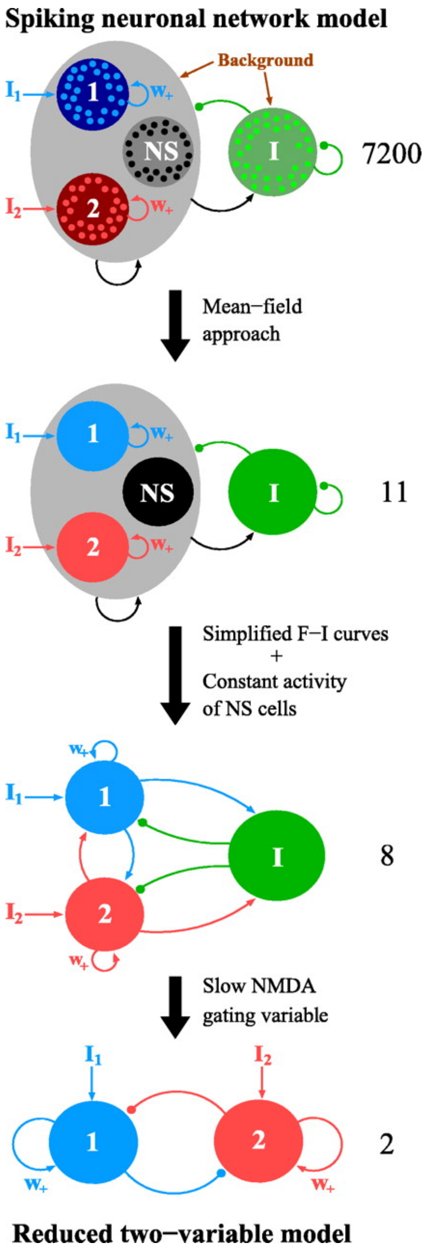
Where, i represents the two excitatory stimuli discriminatory units and S_{NMDA} is the gating variable of NMDA receptor and τ_{NMDA} is the time membrane constant of that receptor.

The above estimations finally reduced the 2000 spiking neurons into a two variable model, defined as :-

$$\boxed{\begin{aligned} \frac{dS_1}{dt} = G_1(S_1, S_2) = -\frac{S_1}{\tau_S} + (1 - S_1)\gamma H(x_1, x_2) \\ \frac{dS_2}{dt} = G_2(S_2, S_1) = -\frac{S_2}{\tau_S} + (1 - S_2)\gamma H(x_2, x_1) \end{aligned}}$$

Here, $H(x_1, x_2)$ and $H(x_2, x_1)$ are the firing rate of the two units. Again, x_1 and x_2 is defined as:-

$$\begin{aligned} x_1 = J_{N,11}S_1 - J_{N,12}S_2 + I_0 + I_1 + I_{noise,1} \\ x_2 = J_{N,22}S_2 - J_{N,21}S_2 + I_0 + I_1 + I_{noise,2} \end{aligned}$$



$I_{noise,i}$ is the noise term. I_0 is the common external input to both population. S is the gating variable. $J_{N,ij}$ are the effective coupling constants. $Fig2$ shows the entire reduction process.

Simulation and assignments

Package Requirement and Installation

We are using python 3.7 for simulating the network. The packages used are as follows:-

- Brian2
- neurodynex
- numpy
- matplotlib

As we are using Jupyter notebook, we installed the packages using conda.

To install a package, the command we use:-

```
pip install packageName
```

Installation of **Brian2** requires additional steps in anaconda. Listing them down here:-

- conda install -c conda-forge brian2
- conda config –add channels conda-forge

  Post this steps, normal installation and updation
- conda install brian2

For **pip** users, it is like normal package installation.

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