Winter 2017 PHYS 178/278 Project Topics

1. Recurrent Neural Integrator Network Model for Horizontal Eye Position

Stability of the Memory of Eye Position in a Recurrent Network of Conductance-Based Model Neurons, Seung, H. Sebastian, et al., *Neuron* 26.1 (2000): 259-271.

Develop an oculomotor integrator model as a network of conductance-based neurons which interact with each other by recurring excitatory synapses. The integrator neurons receive feedforward inputs from three neurons. The vestibular neuron which is tonically active at a constant rate, simulating the background activity present in vestibular afferents when the head is stationary. The excitatory and Inhibitory burst neurons that are normally silent, except for occasional brief burst of action potentials that cause saccadic eye movements. These bursts change the firing rates of neurons in the network which is maintained by recurrent excitation after the feedforward input is over. Signals from the integrator neurons lead to the oculomotor plant so that persistent changes in these signals cause persistent changes in the angular position of the eyes.

This model should reproduce the following properties of biological integrator:

- Each integrator neuron in the model should exhibit a linear relationship between firing rate and eye position when it is active. However, there is also a threshold eye position below which it is silent. The linear slope and the threshold vary from neuron to neuron.
- Because of some imperfection in persistence, there is some drift of neural activity with time, which leads to drift in the eye position during fixation. The drift velocity depends systematically on eye position, generally in a nonlinear manner.
- The persistence of neural activity degrades when synaptic strengths are mistuned, neurons are destroyed or the strength of feedback is otherwise perturbed.

2. Direction Selectivity

A Dendrite-Autonomous Mechanism for Direction Selectivity in Retinal Starburst Amacrine Cells, Hausselt, Susanne E., et al., *PLoS Biol* 5.7 (2007): e185.

Directional selectivity in Starbust Amacrine Cells can be computed by the dendrites themselves, relying on voltage-gated channels and a dendritic voltage gradient, which provides the spatial asymmetry necessary for direction discrimination. Starbust cells generate larger dendritic Ca2+ signals when motion is from their somata towards their dendritic tips than for motion in the opposite direction. Develop a two-compartment model representing distal and proximal dendrites in which each compartment contains, in addition to a linear leak conductance and a capacitance, a single type of voltage gated channel having the properties of high voltage activated Ca2+ channels. The compartments are connected by a resistor, representing the longitudinal intra dendritic current pathway. Show that even if both compartments are otherwise identical, a small difference in the resting potentials between the compartments allows a strongly directional selective response and thus, explain why the somatic voltage and the dendritic [Ca2+] both prefer centrifugal motion. Also, show that the model is consistent with the experimental data (given in the reference paper) in that directional selectivity is

- stronger for the second harmonic current injection
- somatic voltage dependent,
- largely independent of stimulus contrast and in the absence of distal stimulation
- response voltage at fundamental frequency for centripetal stimulation increases.

3. Coupled Pacemaker Neurons

Computational Model of Electrically Coupled, Intrinsically Distinct Pacemaker Neurons, Cristina Soto-Trevin, Pascale Rabbah, Eve Marder and Farzan Nadim., *J Neurophysiol*, 94 (2005): 590–604.

The rhythmically active pyloric network of the crustacean stomatogastric ganglion (STG) is driven by a pacemaker kernel consisting of one anterior burster (AB) neuron and 2 pyloric dilator (PD) neurons that are electrically coupled. The AB neuron is a small neuron that, when isolated from all local network interactions, produces rhythmic bursts of action potentials. The PD neurons are larger than the AB neuron and in isolation they fire tonically. Develop a 2-compartment model of electrically coupled AB and PD neurons, in which the 2 neurons are modeled as separate cells, considering their distinct intrinsic dynamics. In each model neuron, the action potentials were generated in the axon (A) compartment by fast sodium I_{Na} and delayed rectifier potassium I_{Kd} currents with Hodgkin–Huxley type dynamics. In the soma and primary neurite (S/N) compartment, the intrinsic outward currents were a delayed-rectifier I_{Kd}, a calcium-dependent I_{KCa}, and a transient I_A potassium current. The inward currents consisted of a transient I_{CaT} and a persistent I_{CaS} calcium current, a persistent sodium current I_{NaP}, and a hyperpolarization-activated inward current I_h. The model should capture the following properties of the qualitative dynamic behavior of actual network:

- Has a wide frequency range
- The burst amplitude decreases with increasing frequency
- As the frequency increases, the number of spikes per burst decrease
- There is a transition to tonic spiking in which irregular small bursting and irregular spiking occurs
- With sufficiently high depolarizing current the network produces tonic spiking.

Using this model at network level, illustrate that the intrinsic bursting neuron, when very strongly electrically coupled to a tonic spiking neuron, can drive the spiking neuron to burst synchronously with it.

4. Motion Detection in visual system of fly

Adaptation without parameter change: Dynamic gain control in motion detection, Alexander Borst, 6172–6176, doi: 10.1073/pnas.0500491102

Motion detection sensitive neuron of the fly visual system (H1) adapts its input-output relationship to changes in the statistics of the ambient stimulus. The rapid adaptation of the velocity response gain has been interpreted as evidence of optimal matching of the H1 response to the dynamic range of the stimulus, thereby maximizing its information transmission. Develop a motion detection model using Reichardt detectors, which extract the direction of motion by multiplying the brightness signals from neighboring image locations after asymmetric temporal filtering.

The model should illustrate the following properties:

- Increasing the amplitude of the velocity fluctuations (variance) suppresses the contribution of the stimulus past, which leads to a marked reduction in the response gain.
- Increasing the stimulus variance shortens the time scale of the motion detection response thereby reducing it to the correlation time of the stimulus fluctuations.

As we know that nervous system is inherently nonlinear and multidimensional, develop a simple neuron model which shows that changing the form of nonlinearity may have significant effects on the magnitude of the resultant adaptive response.

5. Swim Central Pattern Generator of sea slug *Melibe leonina*

Making a Swim Central Pattern Generator Out of Latent Parabolic Bursters

D. Alaçam, and A. Shilnikov, International Journal of Bifurcation and Chaos 25.07 (2015): 1540003.

Develop a Central Pattern Generator model (CPG) constituting 4 cells which characterizes the swimming locomotion of sea slug *Melibe Leonina.* The CPG should be made of Half Centre Oscillator (HCO) which is a pair of interneurons interacting with each other through reciprocally inhibitory synapses and exhibiting anti-phase bursting. Assume that the interneurons are intrinsic tonic spikers that become network bursters only when externally driven or coupled by inhibitory synapses. Network bursting in the swim CPG should be parabolic, i.e. the spike frequency within a burst increase at the middle, and decreases at the ends. The parabolic bursting can be incorporated with the framework of Hodgkin-Huxley formalism.

Observe the response of bursting neuron on synaptic drive and identify the transition boundary beyond which the parabolic bursting becomes a tonic-spiking and hyperpolarized quiescent. Show that the intrinsically tonic spiking activity becomes a network burster when it receives an inhibitory drive from a pre-synaptic neuron. Finally, employ all necessary components to assemble a truncated model of the Melibe swim CPG with the characteristic 3/4-body length phase lags between the bursting onsets in the four constituent interneurons

6. Coincidence Detection - (a building block model for sound localization)

Simple Models Show the General Advantages of Dendrites in Coincidence Detection, Dasika, Vasant K., John A. White, and H. Steven Colburn., *Journal of neurophysiology* 97.5 (2007): 3449-3459.

Simple models are used to elucidate mechanisms underlying the dendritic enhancement of coincidence detection. This paper focus on coincidence-detecting cells in the auditory system, which have bipolar dendrites and show acute sensitivity to ***interaural time difference (ITD)***, a critical cue for spatial hearing.

Build a model cell that consists of a single-compartment soma with two identical passive dendritic sections attached to the soma, where each dendritic section is composed of a single dendritic-compartment or either a finite number or an infinite number (i.e., a cable) of compartments.

Objective goals:

Based on the model neuron, identify the fundamental mechanisms that underlie the dendritic improvement of **coincidence detection**.

Constant-conductance inputs: How does the soma response change with different dendritic conductances for the two dendritic sections, each of which has either single-, multiple-, or infinite- dendritic compartments?

Dynamic inputs (Paired-pulse inputs): The precision/accuracy to detect coincidence depends on **a) the timing** and **b) the width of action potential** that triggers the presynaptic neuron to release neurotransmitters (let the waveform of potential is a pulse with a finite width), **c) the difference between two dendritic lengths** of postsynaptic neuron. Investigate how the three factors affect the coincidence sensitivity.

*The synaptic transmission can be model with the opening-closing dynamics of Ca^{2+} channels.

Other refs: http://gureckislab.org/courses/spring13/robots/SoundLocalization-5.html

7. Hebbian learning rule

Spike-Timing-Dependent Hebbian Plasticity as Temporal Difference Learning

Competitive Hebbian learning through spike-timing-dependent synaptic plasticity (STDP), S Song, K. D. Miller, and L. F. Abbott, *Nature Neurosci.* 3.9 (2000): 919-926.

A spike-timing-dependent Hebbian mechanism governs the plasticity of recurrent excitatory synapses in the neocortex: synapses that are activated a few milliseconds before a postsynaptic spike are potentiated, while those that are activated a few milliseconds after are depressed. We show that such a mechanism can implement a form of **temporal difference learning for prediction of input sequences**. Using a biophysical model of a cortical neuron, this paper show that a temporal difference rule used in conjunction with dendritic backpropagating action potentials reproduces the temporally asymmetric window of Hebbian plasticity observed physiologically. Furthermore, the size and shape of the window vary with the distance of the synapse from the soma. This work show how a spike-timing-based temporal difference learning rule can allow a network of neocortical neurons to predict an input a few milliseconds before the input's expected arrival.

Objective goals:

Reproduce the paper's simulation: model the balanced excitation network with LIF neurons (n = 1000). The (excitation) synapses are updated by STDP modification rule.

1) Given different mean presynaptic input rates (stochastic presynaptic spike trains), what is the a) equilibrium distribution of synaptic strengths arising from STDP; b) the spiking variability, i.e., coefficient of variation (CV) of the postsynaptic spike train.

2) Latency reduction: given the presynaptic inputs are correlated in various ways, how does the latency between post- and presynaptic spikes change, before and after the synaptic strengths are learned (and stable) through the STDP rule.

8. Excitability of Type III Neuron

Phasic Firing and Coincidence Detection by Subthreshold Negative Feedback: Divisive or Subtractive or, Better, Both, G. Huguet, X. Meng, and J. Rinzel, *Frontiers in Comp Neuroscience* 11 (2017): 3.

Phasic neurons may fire at the onset of a step input, typically once, but not during the steady portion and not for slowly varying inputs. This property of phasic firing is often called **type III excitability**, in contrast to repetitive firing for slow inputs for type I and II excitable neurons. By reducing a Hodgkin-Huxley-like neuron model developed by Rothman and Manis (2003), we can investigate **two** possible mechanisms for type III excitability:

1) *Subtractive mechanism*: due to an outward current (say, potassium K+) that activates relatively fast for subthreshold voltages.

2) *Divisive mechanism*: a fast-activating, but transient, inward (sodium Na+ or calcium) current with suitably recruitable inactivation, can also generate type III excitability.

Objective goals:

1) What is the contribution of each mechanism in shaping the properties of the system and what is gained by having two feedback processes?

2) Does a divisive mechanism combined with a subtractive one, guarantee the robustness of the **phasic properties** of the system with respect to changes in channel density?

9. Resistance of memory in continuous attractor networks to the ongoing noise

Fundamental limits on persistent activity in networks of noisy neurons

Yoram Burak, 17645–17650, doi: 10.1073/pnas.1117386109

Objective goals:

To analytical derive how the stored memory in continuous attractor networks of probabilistically spiking neurons (noisy neural spiking) will degrade over time through diffusion, and compare the analytical result with the numerical simulation using the ring structure neural network mentioned in the paper.

10. Decision making

A Recurrent Network Mechanism of Time Integration in Perceptual Decisions

K.-F. Wong, and X.-J. Wang, *Journal of Neuroscience* 26.4 (2006): 1314-1328.

Recent physiological studies using behaving monkeys revealed that, in a two-alternative forced-choice visual motion discrimination task, reaction time was correlated with ramping of spike activity of lateral intraparietal cortical neurons. The ramping activity appears to *reflect temporal accumulation*, on a timescale of hundreds of milliseconds, of sensory evidence before a decision is reached. In this paper, they adopt this reduced a biophysically based cortical microcircuit network model for decision making (Wang, 2002), to a **eleven-variable or two-variable version model** through mean-field approach.

Objective goals:

Understand the cortical circuit for decision making (Fig 1), and the re-derive the reduced version decision making model. With stability analysis and numerical simulation, try to investigate the following questions (you may use either **eleven-variable or two-variable** model for simulation depending on the questions),

1) How does the recurrent dynamics give rise to a much longer integration time? Is this slow linear ramping a consequence of a network with slow recurrent excitation?

2) Can the model still work when recurrent excitation is solely mediated by the much faster AMPA receptors (AMPARs)?

3) Is it necessary that neurons subserving integration during stimulation also show persistent activity during working memory?

11. FORCE Learning

Generating Coherent Patterns of Activity from Chaotic Neural Networks

Sussillo, David, and Larry F. Abbott, *Neuron* 63.4 (2009): 544-557.

Neural circuits display complex activity patterns both spontaneously and when responding to a stimulus or generating a motor output. How can apparently chaotic spontaneous activity be reorganized into the coherent patterns required to generate desired activity patterns? D. Sussillo et. al (2009) developed a network training procedure, called FORCE learning, for modifying synaptic strengths either external to or within a model neural network to change chaotic spontaneous activity into a wide variety of desired activity patterns.

Objective goal:

With FORCE learning, you are going to train a network for producing the desired outputs/activity patterns.

12. Integrate and fire neurons in the Hopfield model

Simple Networks for Spike-Timing-Based Computation, with Application to Olfactory Processing, C. D. Brody, and J. J. Hopfield., *Neuron* 37.5 (2003): 843-852.

Spike synchronization across neurons can be selective for the situation where neurons are driven at similar firing rates, a "many-are-equal" (MAE) computation. This can be achieved in the absence of synaptic interactions between neurons, through phase locking to a common underlying oscillatory potential. The authors instantiate an algorithm for **robust odor recognition** into a **model network of spiking neurons** whose main features are taken from known properties of biological olfactory systems. Here, recognition of odors is signaled by **spike synchronization** of specific subsets of "mitral cells." This synchronization is highly odor selective and invariant to a wide range of odor concentrations. It is also robust to the presence of strong distractor odors, thus allowing odor segmentation within complex olfactory scenes. They show that noisy spiking neurons, using (MAE) operation, can be configured, in a manner reminiscent of the anatomical and functional organization of the olfactory bulb, to solve some of the major computational problems faced by olfactory systems in a natural environment: recognition of odors over a range of concentrations and in the presence of distracting background odors.

Objective goal:

1) Simulation the noisy spiking neurons and reproduce the results of the paper.

2) Investigate how **the cell time constant (τ)** would affect the **synchronization of spiking neurons** (the odor recognition).

Note that the Code for this project needs to be written from scratch (i.e., the online cache is lost).