Introduction to Computational Neuroscience

Lecture 7: Network models
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Appropriate level of models

Biological processes (molecular)

Biological detail

Electrical properties (morphology)

Electrical properties (average)

Computational properties (processing)
McCulloch-Pitts (idea)

McCulloch and Pitts (1943): pioneers to formally define neurons as computational elements

The idea: explore simplified neural models to get the essence of neural processing by ignoring irrelevant detail and focusing in what is needed to do a computational task
McCulloch-Pitts (states)

In mathematical terms:

$$y = \phi \left( \sum_{i=1}^{n} \omega_i \cdot x_i \right)$$

where $\phi$ represents a threshold or a sigmoid function

```matlab
total_input = sum(w.*x);
if total_input >= 0
    y = 1;
else
    y = 0;
end
```
Neuron as an electric circuit

Ohm law:
\[ I = \frac{V}{R} = gV \]

Kirchoff’s law: the total current flowing across the cell membrane is the sum of the capacitive current and the ionic currents

\[ I_{\text{app}} = C \frac{dV}{dt} + I_{\text{ion}} \]
Hodgkin-Huxley (full model)

\[
C \frac{dV}{dt} = - \sum_i g_i (V - V_i) + I_{\text{app}}
\]

Action potentials come naturally
What about the synapses?

Now, we can couple a synaptic model with I&F or HH

\[ \tau_m \frac{dV_m(t)}{dt} = -V_m(t) + RI(t) \]

+ synaptic currents

\[ g_{exc}(t)(E_{exc} - V_m(t)) + g_{inh}(t)(E_{inh} - V_m(t)) \]

= Full model

\[ \tau_m \frac{dV_m(t)}{dt} = (V_{rest} - V_m(t)) + g_{exc}(t)(E_{exc} - V_m(t)) + g_{inh}(t)(E_{inh} - V_m(t)) \]

Ready to simulate any neuronal circuit!
Neurons need colleagues

Single neurons integrate presynaptic spike trains and respond with firing patterns but...

...mental functions are an emergent property of specialized networks with many neurons

Rather than rebuild the brain, we aim to understand the organization of neurons in specific structures and how they support particular functions.
Learning objectives

- Understand the advantages of having excitatory and inhibitory classes of neurons
- Understand the computational function of small neuronal circuits
Neural circuits

Synaptic microcircuits

Oscillations and CPGs

Feed-forward and recurrent networks
What is the appropriate scale?

Looking at properties of all the classes of neurons in the brain is important but that alone will not lead us to understand how the brain works.

Copying a full brain in the computer will not automatically lead us to major understanding neither.

Idea: to find patterns of connected neurons (canonical circuits) that are used as modules for implementing higher and more complex operations (hierarchy of levels).
Example (similar circuits)
Neural networks

Nodes

Classes of neurons

Edges

Synaptic connectivity

Detailed models need to adjust their parameters from anatomy and physiology of a particular brain region and animal
Classes of neurons (synapse)

Excitatory

- glutamate
- local & long projections
- 80% in cortex
- weak synapses
  (eg., pyramidal)

Inhibitory

- GABA
- local projections
- 20% in cortex
- strong synapses
  (eg., basket cells)
Inhibitory functions

Excitation just generates further excitation independent of any factor

**Inhibition** makes the spread of activity depend on fine details of connection and synaptic strength and generates non-linear behavior
Inhibitory neurons are considered the traffic lights that control the spread of neuronal activity (route information).

When inhibitory synapses are pharmacologically blocked, many neurons lose their selectivity (e.g., orientation).
Neural circuits

Synaptic microcircuits

Oscillations and CPGs

Feed-forward and recurrent networks
Synaptic microcircuits

A neuron receive contacts from up to 10000 presynaptic neurons, and, in turn, any one neuron contact up to 10000 postsynaptic neurons, giving rise to enormous complexity of networks

**Idea:** to examine properties of a subset of small circuit configurations that appear very frequently (canonical)

Microcircuits or network motifs
Synaptic microcircuits

Synaptic divergence

Multiple outputs from single axon (Fan-out)

Allows one neuron to communicate with many

Operational functions:
  Amplification
  Synchronization
  Safety factor
Synaptic microcircuits

Synaptic convergence
Convergence of many axons onto single neuron (Fan-in)

Allows one neuron to receive input from many

Operational functions:

Temporal summation
Spatial summation
Non-linear interactions
Synaptic divergence and convergence (stretch reflex)
Synaptic microcircuits

Presynaptic inhibition

Special type of convergence where a presynaptic terminal (a) is inhibited (b) before it affects its postsynaptic target (c)

Allows a very specific control of input
Synaptic microcircuits

Feedforward inhibition

Excitatory input arrives to a principal and an inhibitory neuron, so the later inhibits the first.

The extra synapse in the inhibitory pathway helps to delay the inhibitory input, so that the combined effect is an excitatory-inhibitory sequence.

Produces a sharpening of excitatory events.
Synaptic microcircuits

Lateral inhibition

A neuron excites an inhibitory neurons, and they inhibit neighboring cells in the network

Very important for processing sensory information

It is implemented in virtually every region of the brain
Synaptic microcircuits

Lateral inhibition (edge enhancement)
Synaptic microcircuits

Lateral inhibition (edge enhancement)

without lateral inhibition
Synaptic microcircuits

Lateral inhibition (edge enhancement)
Synaptic microcircuits

**Lateral inhibition** (Mach bands)

As a result of lateral inhibition, the information transmitted and our perception is of enhanced edges or borders.
Synaptic microcircuits

**Lateral inhibition** (direction selectivity)

Retina of most vertebrate species have neurons that selectively respond to objects moving in one direction

Implemented by inhibitory neurons with asymmetric connections
Synaptic microcircuits

Feedback/Recurrent inhibition

Feedback inhibition has a general role of damping excitation through a neural circuit (thermostat like)

Feedback inhibition also is responsible for generating rhythmic activity in the NS
Neural circuits

Synaptic microcircuits

Oscillations and CPGs

Feed-forward and recurrent networks
Oscillations (different rhythms)
Oscillations (why?)

Quantifying brain waves is a great tool for the clinics:

* epilepsy
* coma/anesthesia
* sleep
* encephalopathies
* brain death
* BCI
Oscillations (why?)

* More prominent and regular oscillations during sleep
* 3 orders of magnitude
* Phylogenetically conserved
* Change with stimulus, behavior, or disease
Oscillations (inhibition)

How are oscillations produced? What is difficult is to not oscillate!

Neural rhythmicity arises through interactions among neurons (network) or among currents in a single neuron (endogenously)

**Excitation** (+) followed by delayed **inhibition** (-) generates oscillations

Gamma oscillations in cortex (30-90 Hz)
Central pattern generator (CPG)

CPG are neuronal circuits that when activated can produce rhythmic motor patterns (walking, breathing, flying, swimming) in the absence of input that carries timing information.

Small cluster of neurons oscillating at certain phase differences.

Located in spinal cord and brain stem.
Central pattern generator (CPG)

How does the NS generates these gaits?
Are separate neural circuits necessary for each one?
Central pattern generator (CPG)

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Are separate neural circuits necessary for each one?

Walk  Trot  Bound  Gallop
Central pattern generator (CPG)

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Central pattern generator (CPG)

Each cluster of neurons oscillates and controls a specific limb

Slight drifts in the periods of the four independent clusters would cause the pattern to become uncoordinated

How to keep the appropriate phase relationships to generate each gate?

The clusters need to be coupled!
Central pattern generator (CPG)

Inhibitory coupling between the clusters solves everything

The same circuit, with small changes in the properties of the individual clusters, can generate each of the four gates

Dynamic reconfiguration, no need of four different circuits!

Walk  Trot  Bound  Gallop
Central pattern generator (CPG)

CPGs can work largely autonomously and independently from cortical input

Experiments from largely decorticated cats
Neural circuits

Synaptic microcircuits

Oscillations and CPGs

Feed-forward and recurrent networks
Feed-forward networks

\[
0 \times (-3) + 1 \times 1 + 1 \times 2.1 + 0 \times 1.7 + 1 \times (-0.5) = \text{summed input} = 1.6
\]
Feed-forward networks: the connections between neurons do not form a directed cycle
Feed-forward networks

The convergence of input generates more and more abstract representations in each layer (level of the hierarchy).

If continued it could lead to **Grandmother cells**
Recurrent networks

Recurrent networks: connections between neurons form many directed cycles

Most of real networks show lateral and feedback connections leading to directed cycles (recurrent networks)

The cycles create an internal state which allows the network to exhibit dynamic temporal behavior
Recurrent networks

An important property of recurrent networks is that they exhibit internal memory
Neural networks

Artificial neural networks: interconnected units (neurons) that can compute values from inputs by feeding information through the network.

In AI: the goal is to train these networks (find the appropriate weights) to implement a certain input-output relationship.
Neural networks

**In computational neuroscience:** the goal is to simulate the behavior of realistic networks of a brain area to understand its function.
Neural networks (neuroinspired)

Auto-associator network (hippocampus)

Before learning

After learning
Neural networks (neuroinspired)

Liquid state machines (cortex)
Summary

- **Inhibitory neurons** provide a great variety of non-linear behavior and **computational functions** (e.g., spatial and temporal contrast)

- **CPGs maintaining basic rhythmic processes** (walking, breathing, ...) are implemented by circuits of oscillatory neurons

- **Feed-forward and recurrent circuits** exhibit powerful processing abilities

- **Hierarchical and modular designs** are solutions widely used by the circuitry of the NS

- **Neuroinspired systems** have provided some of the best ML and AI algorithms
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