CISC 3250
Systems Neuroscience

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Objectives
To understand information processing in biological neural systems from computational and anatomical perspectives
• Understand the function of key components of the nervous system
• Understand how neurons interact with one another
• Understand how to use computational tools to examine neural data

Systems Neuroscience
• How the nervous system performs computations
• How groups of neurons work together to achieve intelligence
• Requirement for the Integrative Neuroscience major
• Elective in Computer and Information Science

Recommended student background
Prerequisite:
• Officially: CISC 2500 Information and Data Management
  or CISC 1800/1810 Intro to Programming
  Math
  Computer Science
  Some calculus    Some programming
Textbook(s)

• **Suggested**
• We will focus on the ideas and study a relatively *small set* of equations

Computational Cognitive Neuroscience, by O’Reilly et al.
• **Optional**, alternate perspective

Website

http://storm.cis.fordham.edu/leeds/cisc3250/

Go online for
– Announcements
– Lecture slides
– Course materials/handouts
– Assignments

Requirements

• Attendance and participation
  – 1 unexcused absence allowed
  – Ask and answer questions in class
• Homework: Roughly 5 across the semester
• Exams
  – 2 midterms, in February and April
  – 1 final, in May
• Don’t cheat
  – You may discuss course topics with other students, but you must answer homeworks yourself (and exams!) yourself

Matlab

Popular tool in scientific computing for:
• Finding patterns in data
• Plotting results
• Running simulations

Student license for $50 on Mathworks site
Available in computers at JMH 330 and LL 612
Your instructor
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Introducing systems and computational neuroscience
- How groups of neurons work together to achieve intelligence
- How the nervous system performs computations

Levels of organization

From a psychological perspective...

What are elements of cognition?
Systems neuroscience

Regions of the central nervous system associated with particular elements of cognition

• Visual object recognition

Computational neuroscience

Strategy used by the nervous system to solve problems

• Visual object perception through biological hierarchical model “HMAX”

Systems neuroscience

Regions of the central nervous system associated with particular elements of cognition

• Visual object recognition
• Motion planning and execution
• Learning and remembering

Computational neuroscience as “theory of the brain”

David Marr’s three levels of analysis (1982):
• **Computational theory**: What is the computational goal and the strategy to achieve it?
• **Representation and algorithm**: What are the input and output for the computation, and how do you mathematically convert input to output?
• **Hardware implementation**: How do the physical components perform the computation?
Marr’s three levels for “HMAX” vision

- **Computational theory:** Goal is to recognize objects
- **Representation and algorithm:**
  - **Input:** Pixels of light and color
  - **Output:** Label of object identity
  - **Conversion:** Through combining local visual properties
- **Hardware implementation:**
  - Visual properties “computed” by networks of firing neurons in object recognition pathway

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Course outline

- Philosophy of neural modeling
- The neuron – biology and input/output behavior
- Learning in the neuron
- Neural systems and neuroanatomy
- Representations in the brain
- Perception
- Memory/learning
- Motor control

**Plus:** Matlab programming

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The neuron

- Building block of all the systems we will study
- Cell with special properties
  - **Soma** (cell body) can have 5-100 μm diameter, but **axon** can stretch over 10-1000 cm in length
  - Receives input from neurons through **dendrites**
  - Sends output to neurons through **axon**
Neuron membrane voltage

- Voltage difference across cell membrane
  - Resting potential: ~-65 mV
  - Action potential: quick upward spike in voltage

Example neural signals

The action potential

- Action potential begins at axon hillock and travels down axon
- At each axon terminal, spike results in release of neurotransmitters
- Neurotransmitters (NTs) attach to dendrite of another neuron, causing voltage change in this second neuron

Inter-neuron communication

Neuron receives input from 1000s of other neurons

- **Excitatory** input can increase spiking
- **Inhibitory** input can decrease spiking

A **synapse** links neuron A with neuron B

- Neuron A is **pre-synaptic**: axon terminal outputs NTs
- Neuron B is **post-synaptic**: dendrite takes NTs as input

More on neuron membrane voltage

- Given no input, membrane stays at resting potential (~ -65 mV)

Inputs:

- Excitation temporarily increases potential
- Inhibition temporarily decreases potential

*Continual drive to remain at rest*
**Patch clamp experiment**

- Attach electrode to neuron
- Raise/drop voltage on electrode
- Measure nearby voltage (with another electrode)

**Simplification of neurophysiology experiment**

**More on the action potential**

1. Accumulated excitation passes certain level
2. Non-linear increase in membrane voltage
3. Rapid reset

** Modeling voltage over time**

Equations focusing on *change* in voltage \( v \)

Components:
- Resting state potential (voltage) \( E_L \)
- Input voltages \( RI \)
- Time \( t \)

\[
\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)
\]

- change towards resting state
- incorporate new input information

**Simulation**

- Initial voltage
- Time interval for update
- Input at each time
- Apply rule to compute new voltage at each time
Applying $dv/dt$ step-by-step

$E_L = -65mV \quad v(0ms) = -65mV \quad \tau = 1$

$R(t) = 20mV \quad $ from $t=0ms$ to $1000ms$

time step: 10ms

$v(t) = \frac{dv(t)}{dt} \times 10 \frac{1000}{10} = -(v(t) - E_L) + R(t)$

- $v(10ms) = v(0ms) + \frac{dv(10ms)}{dt} \times 10 \frac{1000}{10}$
  
  $= -65 + [-65 - -65] + 20 \times \frac{10}{1000}$
  
  $= -65 + 20 \times \frac{10}{1000}$
  
  $= -64.8$

- $v(20ms) = v(10ms) + \frac{dv(10ms)}{dt} \times 10 \frac{1000}{10}$
  
  $= -64.8 + [-64.8 - -65] + 20 \times \frac{10}{1000}$
  
  $= -64.8 + 19.8 \times \frac{10}{1000}$
  
  $= -64.602$

Changing model terms

$\tau$ has inverse effect

- increase $\tau$ decreases update speed
- decrease $\tau$ increases update speed

$R(t)$ has linear effect

- increase $R(t)$ increases update speed
- decrease $R(t)$ decreases update speed

Voltage over time: reset

$\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + R(t)$

When voltage passes threshold $v_{\text{thresh}}$, voltage reset to $v_{\text{res}}$

$v(t') = v_{\text{thresh}}$

$v(t' + \delta) = v_{\text{res}}$

$\delta$ is a small positive number close to 0
Voltage over time

\[ \tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t) \]

Simulated

Biological

Below and above threshold

Newly added:

If input constant for long time \( RI(t) = k \) mV

Output \( v(t) \) will plateau to \( E_L + k \) if \( E_L + k < v_{\text{thresh}} \)

Accumulating information over inputs

Positive and negative weighted inputs from dendrites \( w_\alpha \) added together:

\[ RI(t) = \sum_j w_j \alpha_j(t) \]

\( j \) is index over dendrites; first-pass model
Accumulating inputs

Chemical level: NT receptors

Pre-synaptic: $\alpha$
- Amount of NT released

Post-synaptic: $w$
- Number of receptors in dendrite membrane
- Efficiency of receptors
  - $+w$ or $-w$
  - Reflect excitation or inhibition
- One NT type per synapse
- Fixed sign per NT

Form of dendrite input

\[
\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)
\]
Activation function

Often non-linear relation between dendrite input and axon output

\[ \tau \frac{dv(t)}{dt} = -(v(t) - E_L) + g(RI(t)) \]

\[ RI(t) = \sum_j w_j a_j(t) \]

Sum inputs

Apply (non-linear?) transformation to input

“Leaky integrate-and-fire” neuron

- Sum inputs from dendrites (“integral”)
  \[ RI(t) = \sum_j w_j a_j(t) \]
- Decrease voltage towards resting state (“leak”)
  \[ \tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t) \]
- Reset after passing threshold (“fire”)
  \[ v(t_f + \delta) = v_{res} \]
An example sigmoid

\[ g(2) = 0.9 \]
\[ g(1) = 0.5 \]
\[ g(0) = 0.1 \]
\[ g(-4) = 0 \]

Tuning curves

Some single neurons fire in response to “perceiving” a quality in the world

Adrian, \textit{J Physiol} 1926.

Henry et al., \textit{J Neurophys} 1974.

Variations in activation functions

- Activation function has fixed shape
  - Sigmoid is S shape, Radial is Bell shape
- By default, transition between 0 and 1
- Some details of shape may vary
  - Smallest and lowest value
  - Location of transition between values

Neural coding

Perception, action, and other cognitive states represented by firing of neurons

- Coding by rate: high rate of pre-synaptic spiking causes post-synaptic spiking
- Coding by spike timing: multiple pre-synaptic neurons spiking together causes post-synaptic spiking
Time coding at t=290ms

Rate coding: 3.5 – 5.5s

Spike time coding, 3-6s

Inhibition can be informative

Inputs of interest can produce
• Below-normal spike rate
• Decreased synchrony among neurons

Coding through rate inhibition, roughly in 2-3s interval

Take note of baseline. Rate and time coding are deviations from baseline
Computing spike rate

• Add spikes over a period of time

\[ v(t) = \frac{\text{num spikes in } \Delta T}{\Delta T} \]

• Average spikes over a set of neurons

\[ A(t) = \lim_{\Delta T \to 0} \frac{1}{\Delta T} \frac{\text{num spikes in } N \text{ neurons}}{N} \]