CISC 3250
Systems Neuroscience

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JMH 332

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
Some calculus

Computer science
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
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
- Motion planning and execution
- Learning and remembering

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**Computational neuroscience**

Strategy used by the nervous system to solve problems

- Visual object perception through biological hierarchical model “HMAX”

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**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

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

Levels of organization

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)

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 $t$

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

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

\[ E_L = -65 \text{mV} \quad v(0\text{ms}) = -65 \text{mV} \quad \tau = 1 \]

RI(t)=20mV (from t=0ms to 1000ms)

time step: 10ms

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

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

- \( v(20\text{ms}) = v(10\text{ms}) + \frac{dv(10\text{ms})}{dt} \times \frac{10}{1000} \)
  \[ = -64.8 + [\{-64.8\,-65\} + 20] \times \frac{10}{1000} \]
  \[ = -65 + -0.2 + 20 \times \frac{10}{1000} \]
  \[ = -65 + -19.8 \times \frac{10}{1000} \]
  \[ = -64.602 \]

Changing model terms

\( \tau \) has inverse effect
- increase \( \tau \) decreases update speed
- decrease \( \tau \) increases update speed

RI(t) has linear effect
- increase RI(t) increases update speed
- decrease RI(t) decreases update speed

Voltage over time: reset

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

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 small positive number close to 0

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 \( E_L + k < v_{\text{thresh}} \)
Voltage over time

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

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

\( w_1 = 1 \)

\( w_2 = 1 \)

\( w_2 = -3 \)
Chemical level: NT receptors

Form of dendrite input

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

“Leaky integrate-and-fire” neuron

- Sum inputs from dendrites (“integral”) \[ RI(t) = \sum_j w_j \alpha_j(t) \]
- Decrease voltage towards resting state (“leak”) \[ \tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t) \]
- Reset after passing threshold (“fire”) \[ v(t^f + \delta) = v_{res} \]
**Activation function**

Often non-linear relation between dendrite input and axon output:

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

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

Sum inputs

\[ g(RI(t)) \]

Apply (non-linear?) transformation to input

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**An example sigmoid**

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

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**Tuning curves**

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

Adrian, *J Physiol* 1926.

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

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

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