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
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
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

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](image)

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

![Neuron membrane voltage](image)

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

![Inter-neuron communication](image)

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 \( \nu \)

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

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

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

- $E_L = -65 \text{mV}$
- $v(0\text{ms}) = -65 \text{mV}$
- $\tau = 1$
- $R(t) = 20 \text{mV}$ (from $t=0\text{ms}$ to $1000\text{ms}$)
- Time step: 10ms

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

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

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

### 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

When voltage passes threshold $v_{\text{thresh}}$, voltage resets 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 $R(t) = k \text{ mV}$

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

\[ w_1 = 1 \]
\[ w_2 = 1 \]

\[ w_1 = 1 \]
\[ w_2 = -3 \]
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

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

**Pre-synaptic neuron spikes**

**Neurotransmitter (NT) released**

**NT received by post-synaptic dendrite at time $t'$**

**Post-synaptic voltage rises and then fades, $\alpha(t)$**

$$ RI(t) = \sum_j w_j \alpha_j(t) $$

“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

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, *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

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