Newark, New Jersey, USA

Rutgers University

Center for Molecular and Behavioral Neuroscience

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PhD Program in
Behavioral & Neural Sciences

Goal: Integrative multi-disciplinary training that spans molecular, systems, behavioral, clinical & cognitive neuroscience. Dissertations often span multiple labs and mentors to promote interdisciplinary research careers.

Training Philosophy: "Learning by doing" through multiple lab rotations, interactive seminars, and comprehensive introductory active-learning courses.

Support: Five years of state-supported tuition and stipend for all students, plus funding for conference travel and supplemental training opportunities.

Application deadline is December 15, 2015. Apply online:

www.bns.rutgers.edu
Lab Research Questions

• Perceptual Stability
  • Why does the world not move when we move our eyes?
  • How do we know where things are in the world?

• Recurrent Network Dynamics
  • What can recurrent networks compute?

• Transcranial Current Stimulation
  • What does it do at the neural level?
  • Can we use it to modulate the brain noninvasively?
Lab Research Methods

Behavioral Studies
(Humans, Monkeys)

Transcranial Stimulation
(Humans, Monkeys)

Functional Imaging
(Humans, Monkeys)

Intracortical Recordings
(Monkeys)

Modeling
(Math, Computers)
Outline

• Part 1:
  Quantitative Methods to Estimate Models of Sensory Processing
  • Visual System
  • Linear/Nonlinear models & Spike Triggered Analysis
  • Recurrent Networks

• Part 2:
  Linking motor and visual processing
  • Gain fields
Sensation/Perception

- Light
- Sound
- Smell
- Temperature
- Pain
- Taste

Receptors → Ganglion Cells → Thalamus → Primary Sensory Cortex → Sensory Association Cortex → Percept?
A more principled approach

- Present noise as stimuli (s)
- Use observed stimulus/response relationship to estimate parameters that approximate R(s)
- **Wiener/Volterra**: (Taylor expansion)
  \[ R(x) = \text{polynomial in } x \]

\[
y = k_0 + \vec{k}_1 \cdot \vec{x} + \vec{x}^t K_2 \vec{x} + K_3 \cdot \vec{x}^3 + \ldots
\]

- **# pars:**
  - 1 (const)
  - \(n\) (vector) 20
  - \(n^2\) (matrix) 400
  - \(n^3\) (3-tensor) 8000
The Linear-Nonlinear Model

- \( R(s) = N(L^s) \)
  - (almost) any \( N \)
  - Any \( L \) (but just one)

- With these assumptions, estimating both \( L \) and \( N \) is easy:
  - \( L \sim <R^s> \) (Bussgang: Chichilnisky 2001)
  - Once you have \( L \), you can fit \( N \).
Matlab Tutorial

• staContinuous.m - intro to STA
  • Matlab cell mode
  • Raise hand when ready
Spike triggered average
Matlab Tutorial

- staSpikes.m - spike triggered averaging
Spike Triggered Analyses - Geometry
Matlab Tutorials

• stcContinuous.m  - intro to STC

• stcTutorial.m  - *spike* triggered covariance of a motion model (Rust).
STA/STC of a V1 Motion Cell

Rust et al. Neuron, 2005
Spike Triggered Motion

A. Grid showing vertical and horizontal positions.
B. Circular patterns indicating vertical position.
C. Arrangement of circles showing time and spikes.
D. Scattered points indicating vertical and horizontal positions.
E. Matrix with color gradient indicating vertical position.
F. Color wheel with preferred direction and tuning strength.
STA of MT cells

Dogma:

Richert et al. 2013
STA of MT cells

Multiple Directions

Richert et al. 2013
Gaps

Richert et al. 2013
<table>
<thead>
<tr>
<th>Pros</th>
<th>Cons</th>
</tr>
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<tr>
<td>• Unbiased</td>
<td>• Restrictions on stimuli (e.g. Gaussian noise)</td>
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**Pros**

- Unbiased  
- Quantitative  
- Generative model  
- Arbitrary nonlinearity  
- Extensions (GLM, MID, LNLN)  
- Code available (iSTAC, NIM)  

**Cons**

- Restrictions on stimuli (e.g. Gaussian noise)  
- The model cannot fail  
- Must test model validity  
- No dynamics  
- What not How
Humans can distinguish among these classes. (Victor)

V2 cells respond differentially to these classes of patterns

V1 cells not so much (Yu et al. 2015)
Model

1. Goal: understand how neurons generate texture tuning. The model should reproduce neurons’ average response to the 7 classes.

2. Lit Review: V2 finding is 2015. No model yet.

3. Ingredients: we have access to spiking response of many V2 cells to 1024 examples per texture class.

4. Math: \( R = f(w_1*s, w_2*s, w_3*s, \ldots) \) : an LN model based on STA and STC.

5. Toolkit: we use iSTAC to estimate the LN model based on mean spiking responses and exact replicas of stimuli.

6. Draft. (Not much to do here)

7. Implement/Adjust

8. Evaluate/Test
LN-model example V2 cell

Texture tuning

Linear filters

Nonlinearities

Information
Model Performance

- White Triangle
- Random
- Black Triangle
- Even
- Odd
- Wye
- Foot

Texture tuning

Correlation V2-LN

Firing rate (sp/s)

# Filters LN model
Performance LN-model V2 population
New Model – with dynamics

1. Goal: understand how neurons generate texture tuning. The model should reproduce neurons’ average response to the 7 classes and their dynamics.

2. Lit Review: V2 finding is 2015. No model yet.

3. Ingredients: we have access to spiking response of many V2 cells to 1024 examples per texture class.

4. Math: \( R = N(s) \): a recurrent neural network maps exact replicas of the stimuli to the measured time course of neural responses.


6. Draft. (Not much to do here)

7. Implement/Adjust (#hidden units, #layers, training algorithm)

8. Evaluate/Test
Recurrent Form Analysis Model (RFAM)

Output
Mean response to 1024 textures per class (dynamic over time)

Input
256 input units

50 hidden units

50 hidden units

1024 textures per class (static over time)
Performance RFAM

RFAM population

RFAM single cells
Temporal dynamics are critical components
Motion tuning generates texture tuning

Texture tuning

- Hidden unit #58
- Activation
- Random
- White Triangle
- Black Triangle
- Even
- Odd
- Wye
- Foot

Motion tuning

- Speed index
- Activation
- Up
- Right
- Left
- Down
- Speed (check/40 ms)

- Hidden 1
  - R² = 0.53
- Hidden 2
  - R² = 0.69

Random-Even index (absolute)
Summary

• LN models are powerful ways to quantify sensory neurons’ potentially nonlinear input-output mappings. (WHAT)

• LN models reveal the messy details of sensory processing.

• Recurrent neural networks can capture the nonlinear mapping of sequences of inputs to sequences of outputs (dynamics)

• By probing hidden units of RNN’s one can gain insight into the computations that the network performs (HOW).
Part 2
Eye Movements & Visual Perception
How does he know where to reach?
Coordinate transformations

Object position relative to head $H_x$ = Object position relative to fovea $R_x$ + Eye position relative to head $E_x$

e.g.

$H_x = +30^\circ$

$R_x = +60^\circ$

$E_x = -30^\circ$
PERCEPTION:
Our sense of visual position remains stable across eye movements.

→ “visual stability”

MOTOR CONTROL:
Our ability to interact with (e.g. reach for) visual objects is not disrupted by eye movements.

→ “action stability”

How does the brain construct meaningful representations of visual space from the ever-changing retinal input?
Perceptual Stability

V1

Body-Centered

Head Position

Head-Centered

Eye Position

Eye-Centered
Head-centered receptive fields

Single cells in VIP represent the world relative to the head

*Duhamel, Bremmer et al. Nature 1997*
Stability Based on Head-Centered Cells?

- Head-centered cells are far and few between.
- Head-centered cells have
  - coarse spatial selectivity
  - no color selectivity
  - no orientation selectivity
Perceptual Stability

- Eye-Centered
- Head-Centered
- Body-Centered

V1
The alternative solution: gain fields

Position relative to the head

- Position on retina
- Eye position

- a “distributed” representation of visual space
A neural basis for visual and action stability

\[ f(\text{Hx}, \text{Rx}, \text{Ex}, \text{Ax}) \]  \[ g(\text{Hx}, \text{Rx}, \text{Ex}, \text{Ax}) \]

Orientation  \( Hx \)

Head position  \( Rx \)

Position on retina  \( Ex \)

Eye position  \( Ax \)

Motion direction
Stability based on EPS?

• Evidence Pro:
  • All visual areas have eye position signals.
  • Visual areas have the visual selectivity we need.

• Evidence Contra?
  • Eye position signals are inaccurate/imprecise
  • Eye position signals are slow
  • Eye position signals are not robust
PPC Recordings

Azimuth (°)

Elevation (°)

LIP (N=75) \( \text{VIP (N=115)} \)

MT/MST (N=100)
EPS in PPC are Damped

Morris et al., Current Biology (2012)
Decoding Eye Position

Firing rates of neurons

$[r_1, r_2, r_3, \ldots, r_N]$ MEASURE

Estimate position of eye

$[\hat{e}_x, \hat{e}_y]$
Decoding Eye Position

Neuron 1

Firing rate vs. Eye position
Decoding Eye Position

Neuron 1

Firing rate

Eye position

High

Low

Prob.
Decoding Eye Position

Neuron 1

Firing rate

Prob.

High

Prob.

Low

Eye position

PDF$_1$
Decoding Eye Position

Neuron 1

Neuron 2

Firing rate

Prob.

Eye position

Eye position

High

Low

$PDF_1$

$PDF_2$

$PDF_{POP}$
EPS in PPC are Accurate

Bias less than 3° for 300 neurons

Approx 1000 neurons needed for SD < 3°

V1 Recordings

- 32-channel per array
- Implanted in parafoveal V1
- 2-3° eccentricity

Fixation/saccade

15°

75Hz
EPS in V1 are Accurate

50ms samples
$N = 233$
Decoding during Eye Movements

Neuron #

EYE MOvements

50ms window

Time

Eye position

1
2
N
EPS in V1 are Fast

Updating latency = 67ms

$N = 233$
Robustness

Fixation/saccade

Smooth pursuit

15°

75Hz
EPS in V1 are Robust

Actual eye (hor.)

Decoded eye (hor.)

Actual eye (vert.)

Decoded eye (vert.)

Eye position (°)

Time (ms)

N = 128
Summary

• Gain fields are found throughout visual cortex.
• In V1 they are accurate during fixation, robust against eye movements, and very fast.
• In PPC they are accurate during fixation, but damped at the time of saccades.

Gain modulation provides a flexible substrate for sensorimotor integration. An explicit representation in a specific reference frame is unnecessary.
Matlab Tutorials

Gain field neural network model

See instructions.docx