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BME PARIS
BioMedical Engineering
MASTER'S PROGRAM

Modeling neuronal representation of spatial orientation: a head direction cells analysis

Brain Plasticity Lab, C4 team (Cerebral Codes and Circuits Connectivity), ESPCI

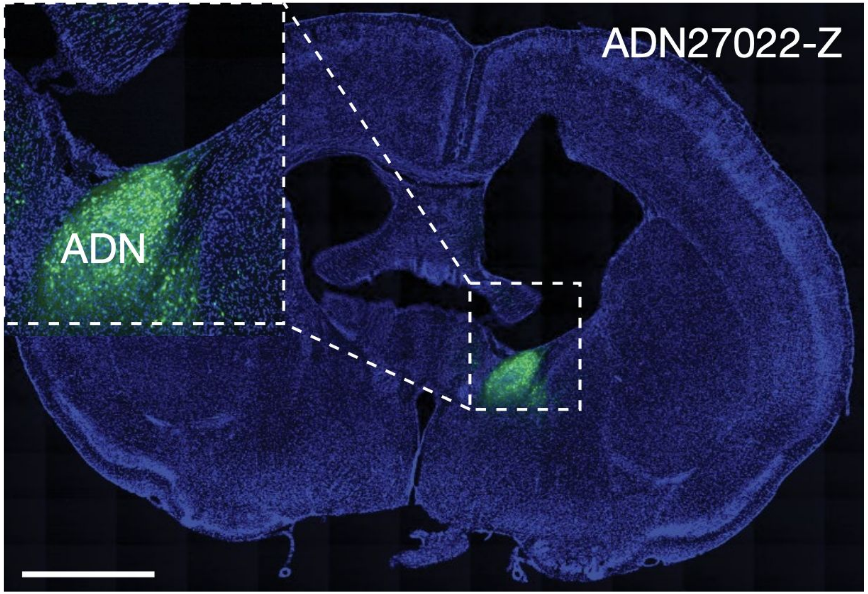
Supervisor: Prof. Gisella VETERE

June 25th, 2025

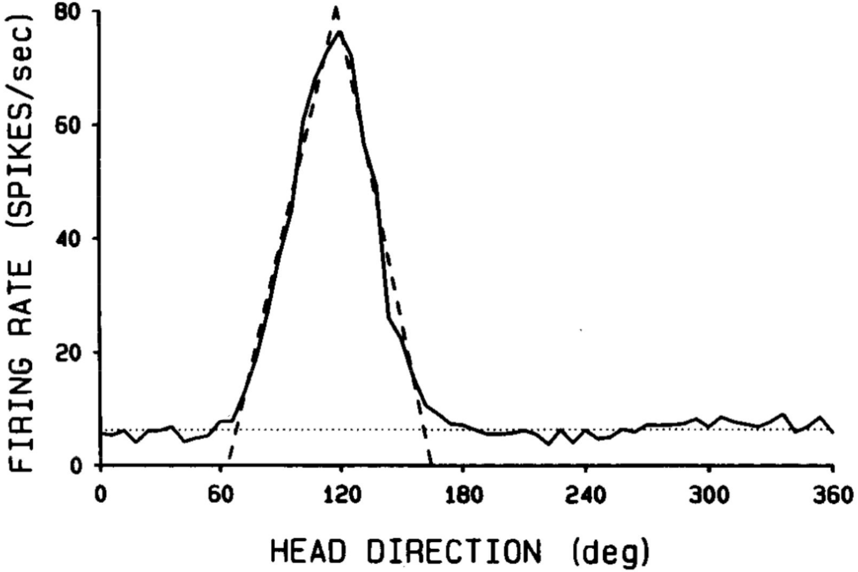
Introduction: the brain's internal compass

Head Direction (HD) cells fire when head points in specific direction

ADN = Anterodorsal Thalamus
Over 60% of cells are HD cells



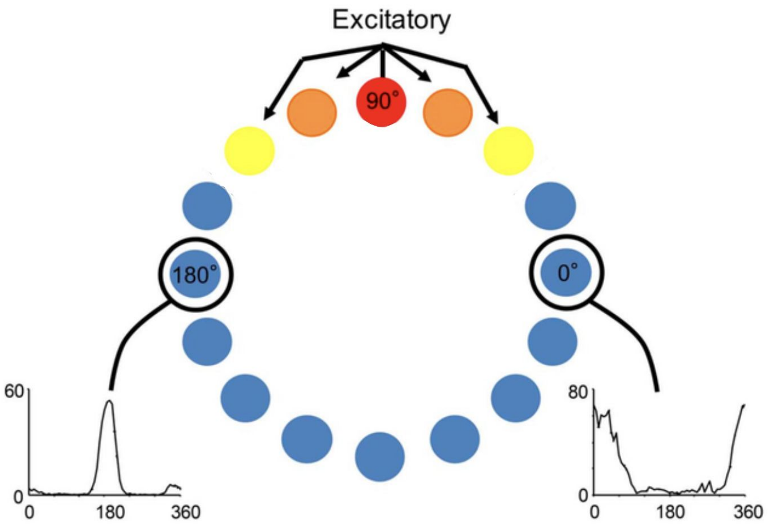
Ajabi et al (2023).

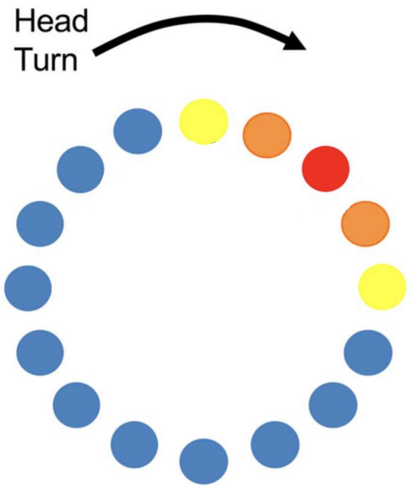


Taube et al. (1990).

HD cells arranged conceptually in a ring by preferred direction

Local excitation between similar cells creates "activity bump"
Bump moves around ring as animal turns



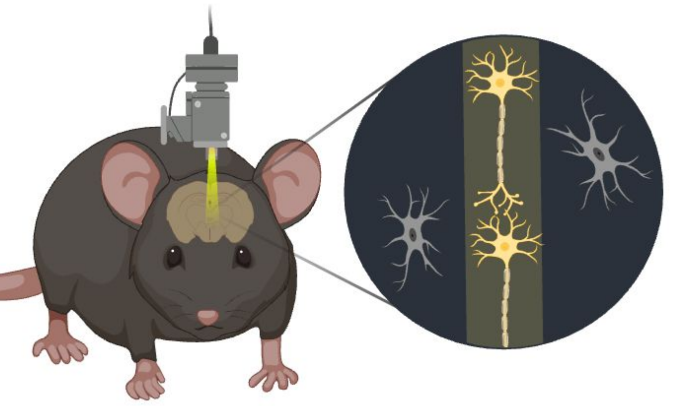


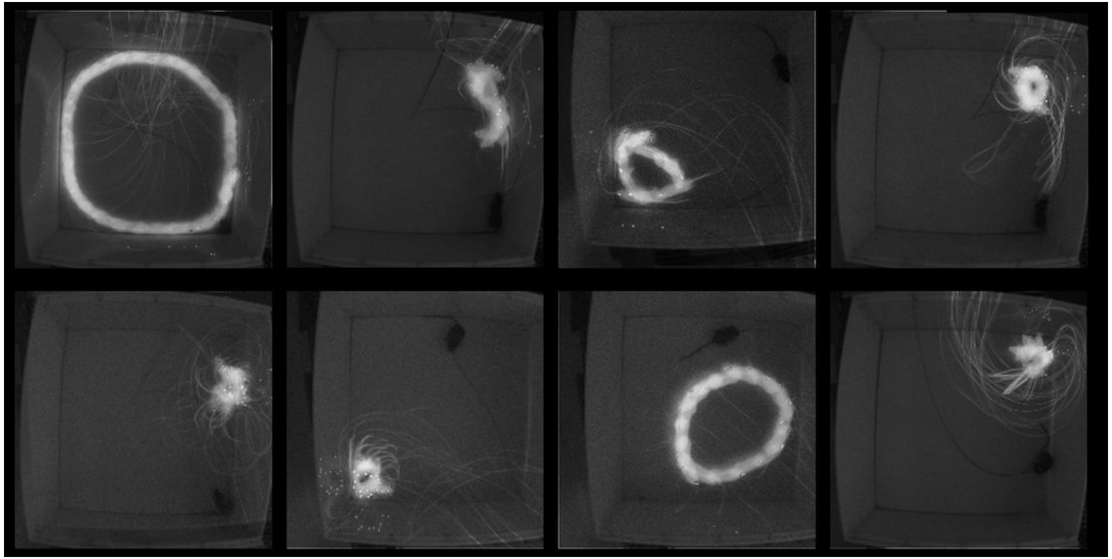
Adapted from Clark and Taube(2012).

Using optogenetics, stimulation of ADN causes mice to spin continuously

Internship Research Question:
Can the ring attractor network model explain this effect?

First part:
Can we implement an ADN-inspired model in Python?





Data by Gisella Vetere and Charlotte Andrews, C4 team

Objective and Hypothesis

Main Objective:
Build and validate a ring attractor model that:

1. Forms stable activity bumps
2. Accurately tracks head direction during movement
3. Maintains directional memory without input

4. Explains optogenetic spinning behavior (for 2nd part of internship)

Hypotheses:

1) Ring attractor connectivity: activity bump driven continuously around ring (only one direction activated at a given time)
   or
2) Independent cell activation: simultaneous activation causes confusion in mice

Materials and Methods - overview

CPU was used initially, but NVIDIA GPU was necessary for training

jupyter

NVIDIA

ANACONDA

Visual Studio Code

Python 3.12

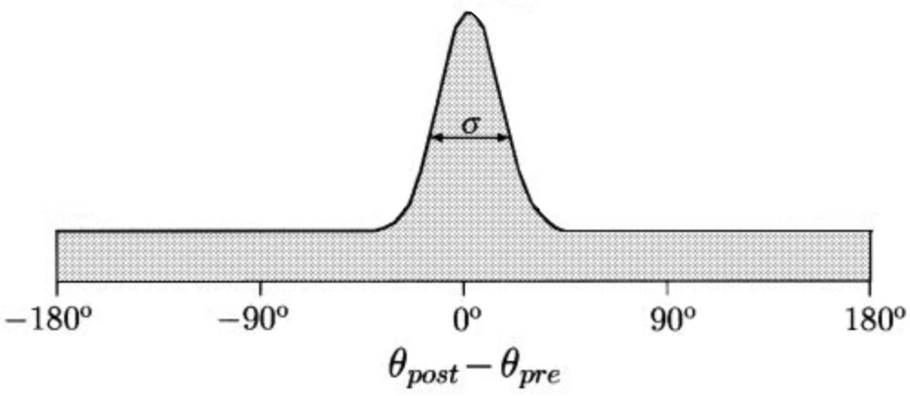
Introduction - previous literature

Plasticity and sensory integration in the HD System

- *Ajabi, Z., Keinath, A. T., Wei, X.-X., & Brandon, M. P. (2023). Population dynamics of head-direction neurons during drift and reorientation. Nature, 615(7951), 892-898.*
- *Valerio, S., & Taube, J. S. (2012). Path integration: How head direction cell signals maintain and correct spatial orientation. Nature Neuroscience, 15(10), 1445-1453.*
- *Goodridge, J. P., Dudchenko, P. A., Worboys, K. A., & Taube, J. S. (1998). Cue control and head direction cells. Behavioral Neuroscience, 112(4), 749-761.*
- *Zugaro, M. B., Berthoz, A., & Wiener, S. I. (2003). Rapid spatial reorientation and head direction cells. Journal of Neuroscience, 23(8), 3478-3492.*
- *Vantomme, G., Rovo, Z., Cardis, R., et al. (2020). A thalamic reticular circuit for head direction cell tuning and spatial navigation. Cell Reports, 31(10), 107747.*

Materials and Methods: Ring attractor Network parameters

$N_E = 800$	HD cells (excitatory)
$N_I = 200$	Inhibitory neurons
$\sigma_{EE} = 0.5$ rad	Connection width
$g_{EE} = 1.0$	E$\rightarrow$E synaptic gain
$g_{EI} = 1.5$	E$\rightarrow$I synaptic gain
$g_{IE} = 2.0$	I$\rightarrow$E synaptic gain
$\tau_E = 10$ ms	Excitatory time constant
$\tau_I = 5$ ms	Inhibitory time constant
$\lambda_E = 0.1$	Excitatory Poisson rate
$\lambda_I = 0.05$	Inhibitory Poisson rate



Adapted from Compte et al. (2000).

$$W_{EE}^{ik} = \frac{1}{Z} \exp\left(-\frac{(\theta_i - \theta_k)^2}{2\sigma_{EE}^2}\right)$$

Neuron equations follow leaky integrator dynamics

Excitatory neurons:

$$\tau_E \frac{dr_E^i}{dt} = -r_E^i + f(I_E^i)$$

Inhibitory neurons:

$$\tau_I \frac{dr_I^j}{dt} = -r_I^j + f(I_I^j)$$

- Song & Wang, 2005, J. Neurosci.
- Vafidis et al., 2022, eLife

Neuron Equations

Excitatory neuron input:

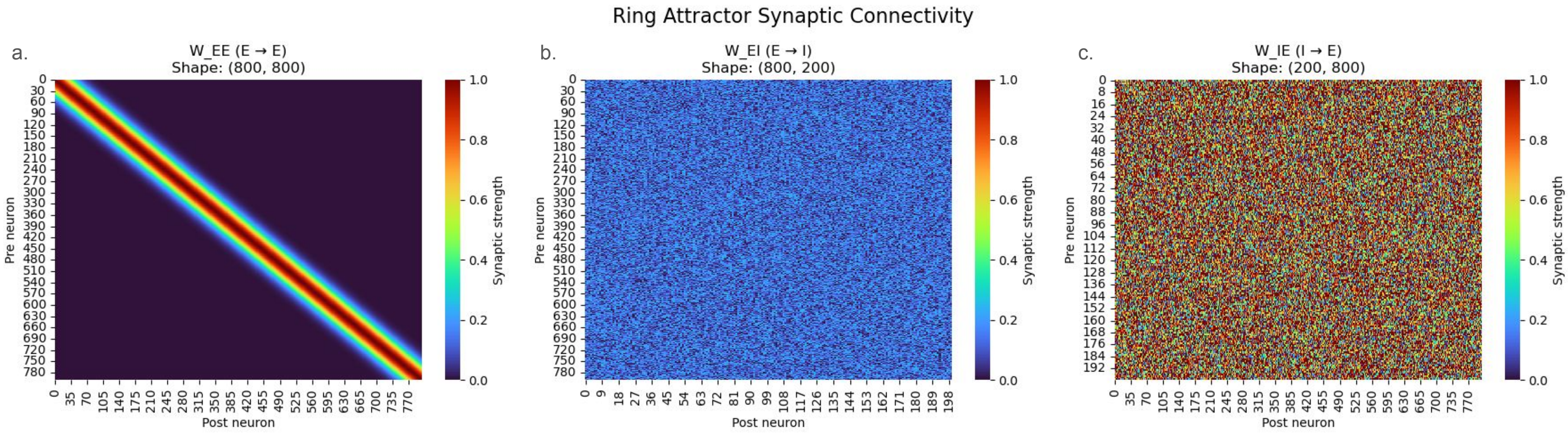
$$I_E^i = g_{EE} \sum_k W_{EE}^{ik} r_E^k - g_{IE} \sum_l W_{IE}^{il} r_I^l + g_{input} I_{ext}^i + \xi_E^i$$

Inhibitory neuron input:

$$I_I^j = g_{EI} \sum_k W_{EI}^{jk} r_E^k + \xi_I^j$$

- Song & Wang, 2005, J. Neurosci.
- Vafidis et al., 2022, eLife

Materials and Methods - Ring attractor Network



a. Excitatory to excitatory neurons
b. Excitatory to inhibitory neurons
c. Inhibitory to excitatory neurons

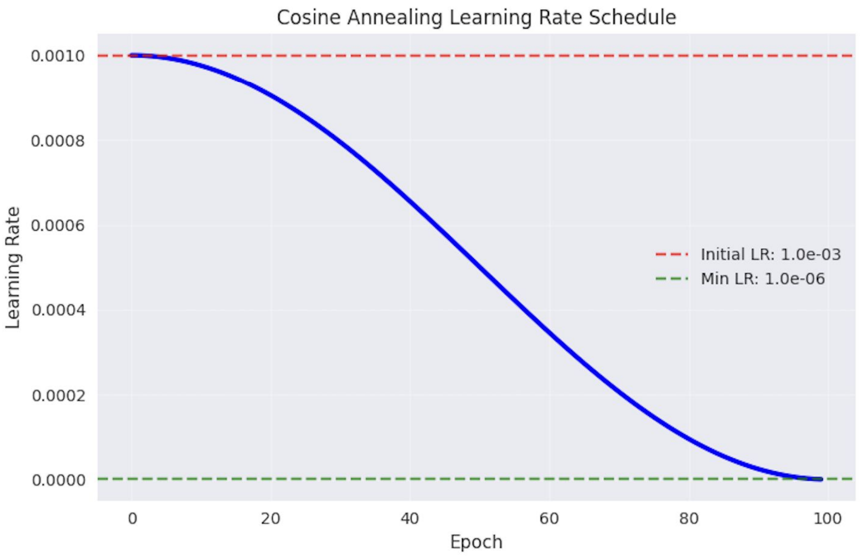
Materials and Methods - Optimization Approach

Training Data:

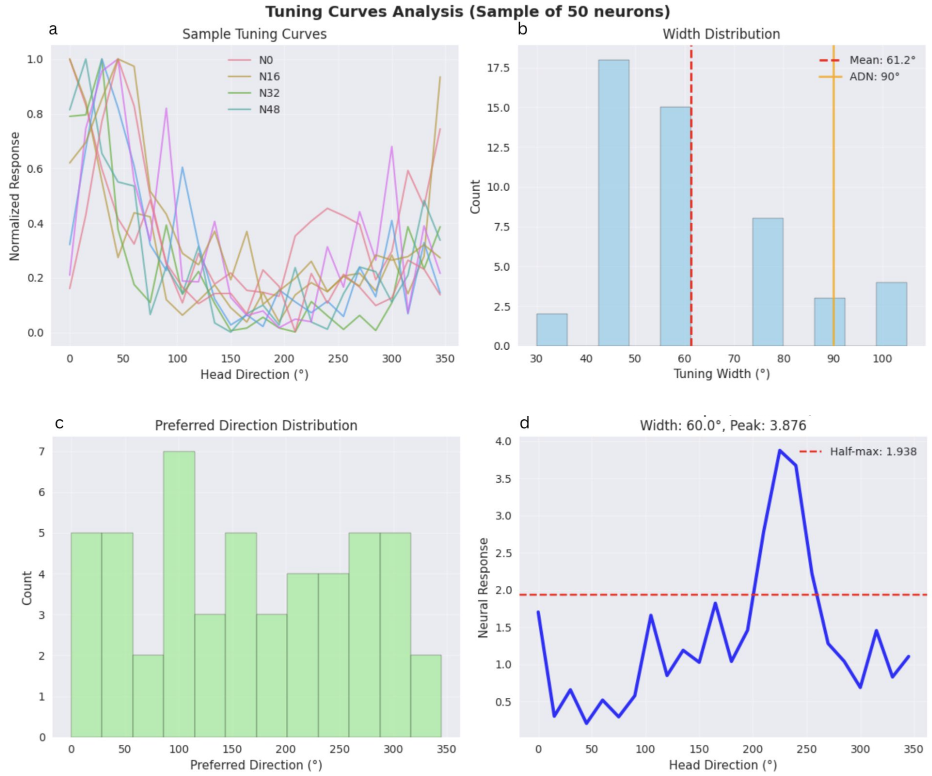
- 1000 simulated movement trajectories
- Slow turns, fast turns, oscillations, random walks
- Angular velocity: 0.1-18°/timestep

Optimization:

- Adam optimizer with cosine annealing
- 100 epochs training

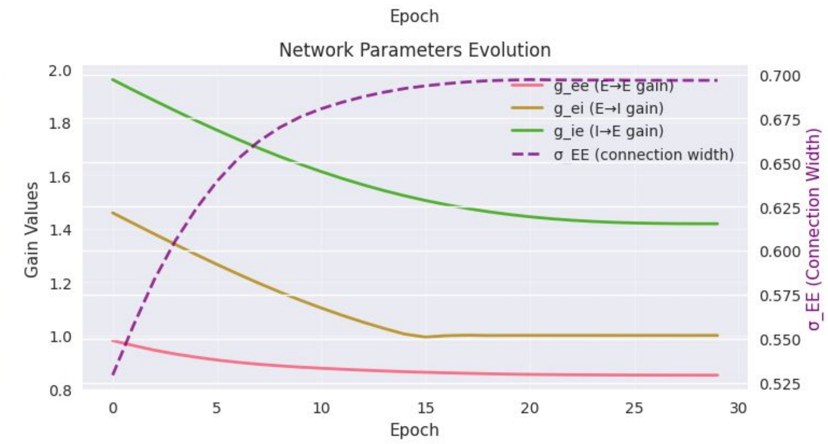


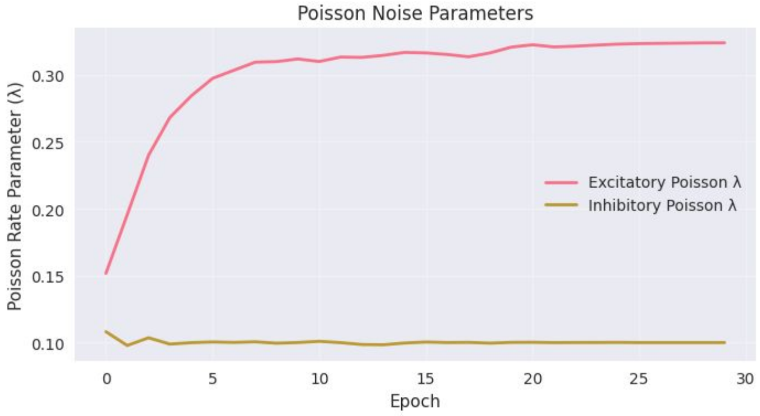
Results - Tuning curves



- Tuning width of model vs biology: 61° vs 90°
- Preferred directions span 360°
- Stable bump formation
- Clear directional selectivity

Results - Training dynamics

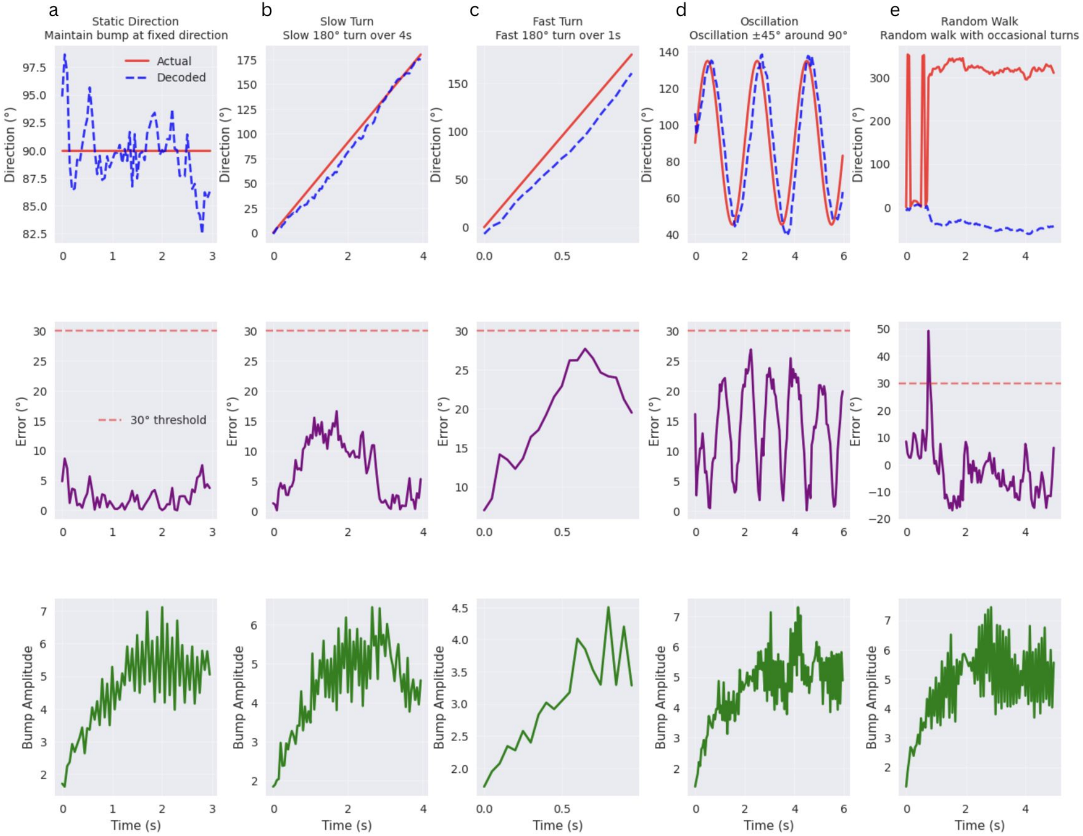




Connectivity width increased 38% (0.53 →0.69)
All synaptic gains decreased 25-40%
Excitatory noise tripled, inhibitory stayed constant

"Spread out but tone down" strategy emerges

Results - Head Direction Tracking

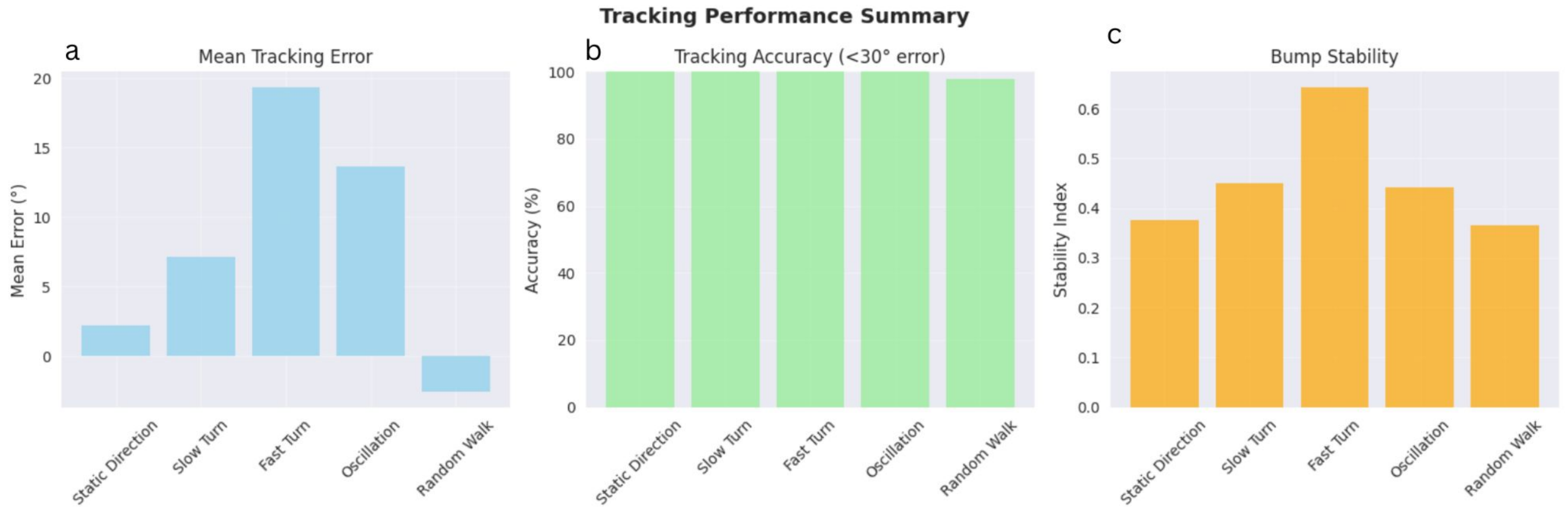


Performance Across Conditions:

- Static: 2.2° error
- Slow turn: 7.1° error
- Fast turn: 19.3° error
- Overall accuracy: 98-100%

Error increases with speed - matches biology

Results - HD Tracking



$$\text{error}(t) = \theta_{\text{decoded}}(t) - \theta_{\text{actual}}(t)$$

$$\text{error}(t) = ((\text{error}(t) + \pi) \bmod 2\pi) - \pi \quad (\text{wrap to } [-\pi, \pi])$$

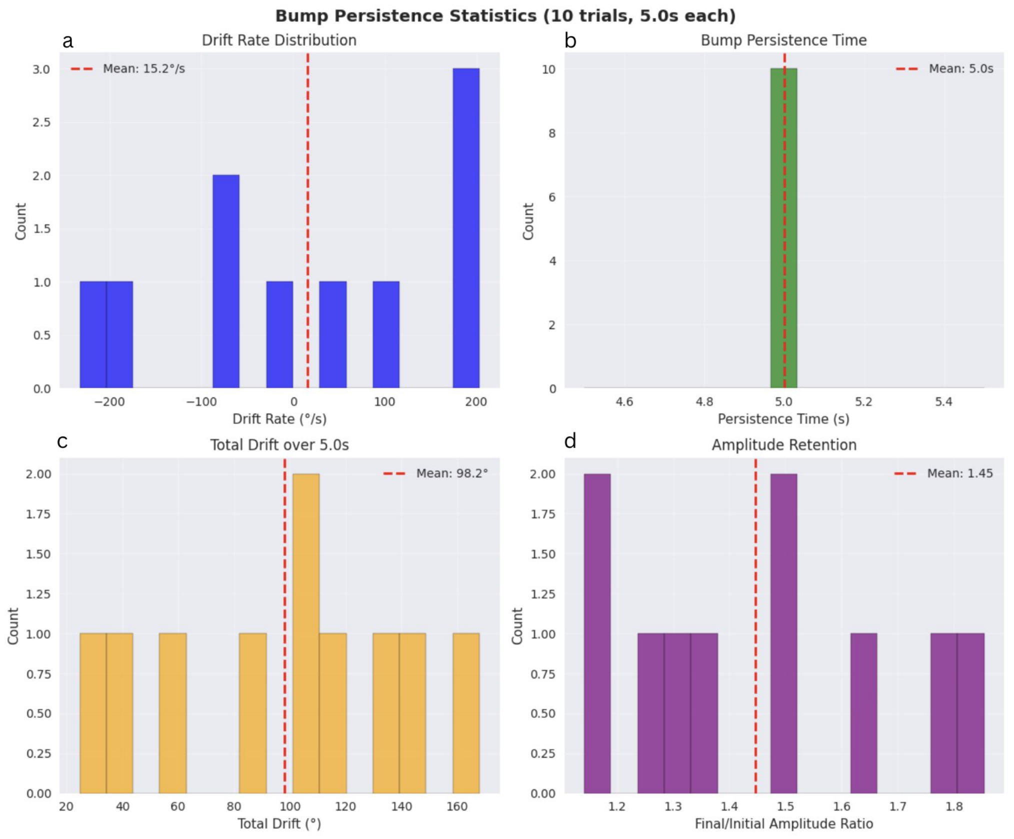
$$\text{error}(t) = \text{error}(t) \times \frac{180}{\pi} \quad (\text{convert to degrees})$$

$$\text{Mean Error} = \frac{1}{T}\sum_{t=1}^{T} \text{error}(t)$$

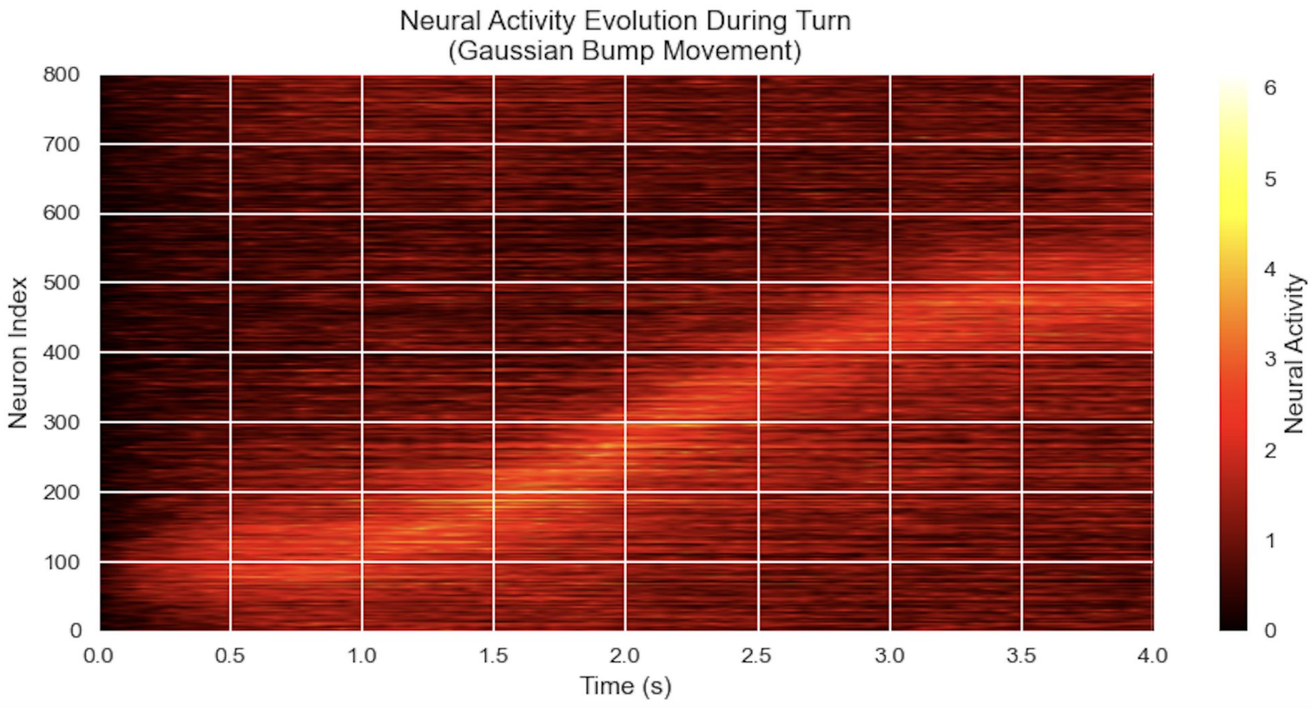
Positive mean = systematic lag
Negative mean = anticipatory behavior
Zero mean = unbiased tracking

Results - Bump Persistence

Maintains activity for 5+ seconds
Drift rate: 15.6°/s (matches biology: 5-15°/s)
All trials preserved bump structure



Bump travels smoothly maintaining shape



Discussion: challenges & limitations

Conclusion & further directions

✓ 98-100% tracking accuracy across naturalistic movements
✓ Biologically plausible properties emerged through learning
✓ Testable predictions for future experiments

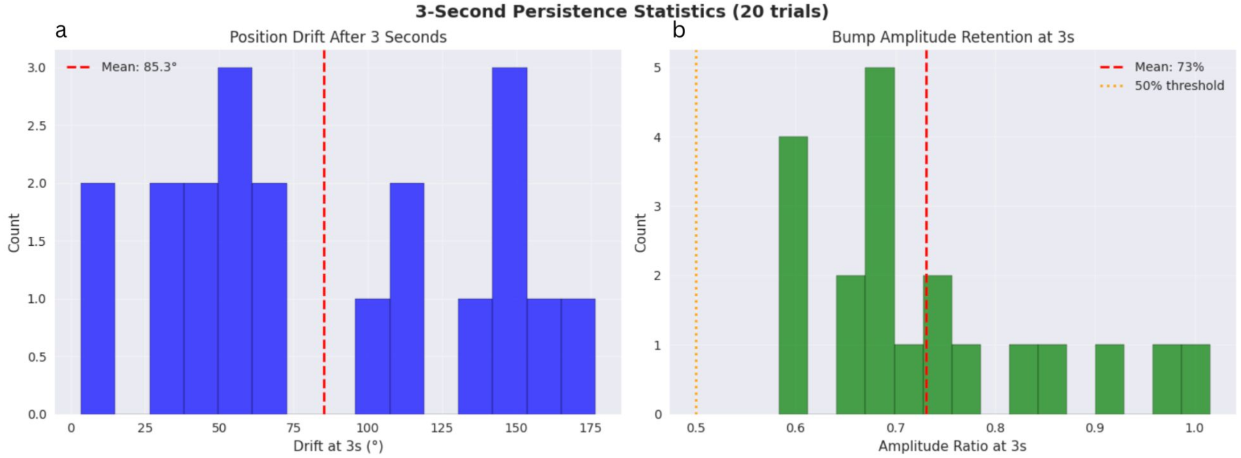
1. Model channelrhodopsin dynamics
2. Simulate heterogeneous expression (60-80% transfection)
3. Test stimulation protocols (continuous vs pulsed)
4. Compare with experimental spinning data

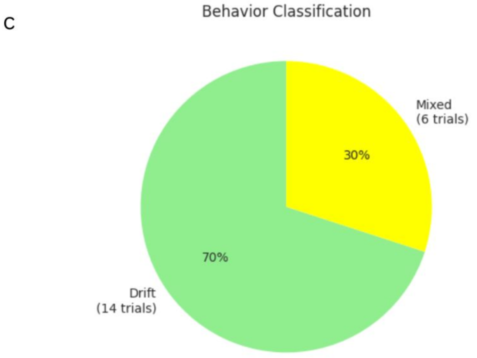
5. Incorporate angular velocity cells for complete circuit

Thank you for your attention

Q&A

Results: input cue tracking





Statistical Summary

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Metric	Mean ± Std	Range
Drift at 3s	85.3 ± 52.3°	3.4 - 176.7°
Amplitude at 3s	73% ± 12%	58% - 102%
Drift rate	15.6 ± 129.1°/s	
Persistence	6.0 ± 0.0s	

Materials and Methods - Optimization Approach

Data Generation Process:

Generate 1000 trajectories using random walk approach
Angular velocity sampled from Gaussian distribution
Three movement types:

Slow exploration: $\sigma = 0.1$ rad/s (≈5.7°/s)
Normal navigation: $\sigma = 0.3$ rad/s (≈17.2°/s)
Rapid turns: $\sigma = 0.5$ rad/s (≈28.6°/s)

Update equation: $\theta(t+1) = \theta(t) + \omega(t) \times dt$
Wrap angles to maintain continuity $[0, 2\pi]$

Materials and Methods - Optimization Approach

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad \text{// first-moment (momentum)}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad \text{// second-moment (RMSProp)}$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad \text{// bias correction}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad \text{// bias correction}$$

$$\theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}.$$

$$\eta_t = \eta_{\min} + (\eta_{\max} - \eta_{\min}) \frac{1 + \cos(\pi t / T)}{2}$$