SYDE 556/750

Simulating Neurobiological Systems Lecture 3: Representations

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Visua'**,** ∩ortex

Mapping receptive fields

cell activity





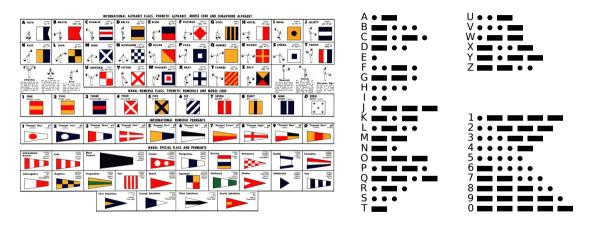


NEF Principle 1: Representation

NEF Principle 1 – Representation

Groups ("populations", or "ensembles") of neurons *represent* represent values via nonlinear encoding and linear decoding.

Lossless Codes



Encoding: $\mathbf{a} = f(\mathbf{x})$

Decoding: $\mathbf{x} = f^{-1}(\mathbf{a})$

Binary numbers: Nonlinear encoding, linear decoding

- ▶ Represent a natural number between 0 and $2^n 1$ as n binary digits.
- ► Nonlinear encoding

$$\mathbf{a}_i = \left(f(\mathbf{x}) \right)_i = \begin{cases} 1 & \text{if } \mathbf{x} - 2^i \left\lfloor \frac{\mathbf{x}}{2^i} \right\rfloor > 2^{i-1}, \\ 0 & \text{otherwise}. \end{cases}$$

► Linear decoding

ecoding
$$x=f^{-1}(\mathbf{a})=\sum_{i=0}^{n-1}2^ia_i=\mathbf{Fa}=\begin{pmatrix}1&2&\dots&2^{n-1}\end{pmatrix}\begin{pmatrix}a_0\\a_1\\\vdots\\a_{n-1}\end{pmatrix}$$
 .

This is a distributed code. But, not robust against additive noise!

Lossy codes

► Lossy code

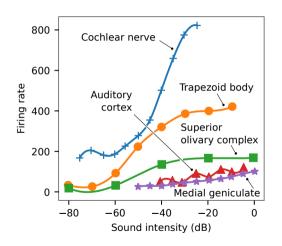
Inverse f^{-1} does not exist, instead approximate the represented value

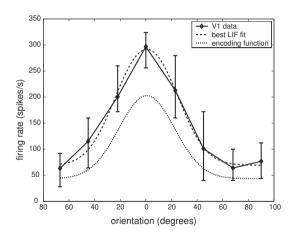
Encoding:
$$\mathbf{a} = f(\mathbf{x})$$

Decoding: $\mathbf{x} \approx g(\mathbf{a})$

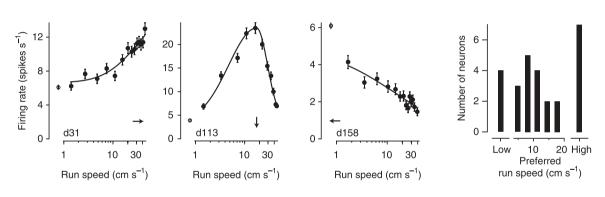
- Examples
 - Audio, image, and video coding schemes (MP3, JPEG, H.264)
 - ightharpoonup Basis transformation onto first n principal components (PCA)
 - ► Neural Representations

Tuning curves (I)

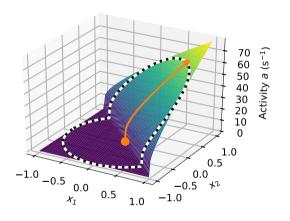


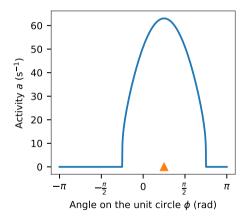


Tuning curves (II)

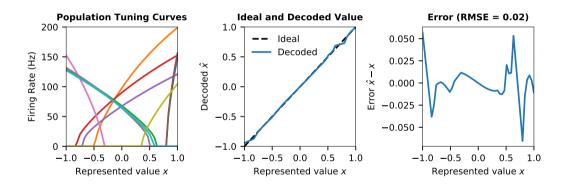


Preferred Directions in Higher Dimensions: Representing 2D Values



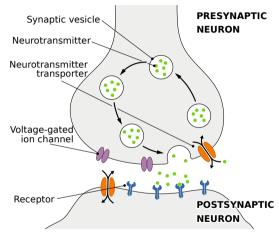


Decoding Without Taking Noise Into Account



Sources of Noise in Biological Neural Networks

- Axonal jitterActive axonal spike propagation
- ► Vesicle release failure 10-30% of pre-synaptic events cause post-synaptic current
- Neurotransmitter per vesicle
 Varying amounts of neurotransmitter
- Ion channel noise lon-channels are "binary", stochastic
- Thermal noise
- Network effects
 Simple, noise-free inhibitory/excitatory
 networks produce irregular spike trains



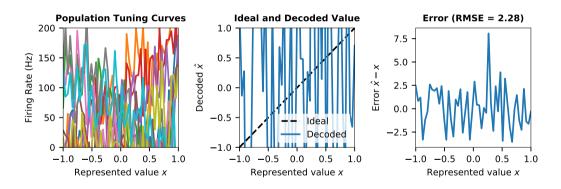
► How to model? Gaussian noise

NEF Principle 0: Noise

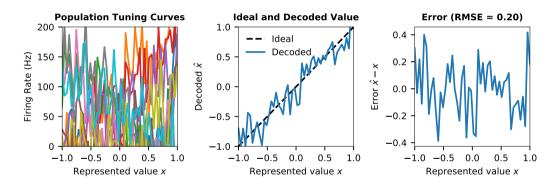
NEF Principle 0 – Noise

Biological neural systems are subject to significant amounts of noise from various sources. Any analysis of such systems must take the effects of noise into account.

Decoding Noisy A Without Taking Noise Into Account



Decoding Noisy A Accounting for Noise

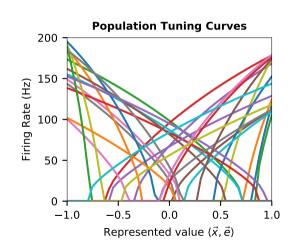


Summary: Building a model of neural representation (Encoding)

Encoding

- Select d, possible range $\mathbf{x} \in \mathbb{X}$, usually $\mathbb{X} = \left\{ \mathbf{x} \mid ||\mathbf{x}|| \leq r, \mathbf{x} \in \mathbb{R}^d \right\} (r = 1)$
- ► Select number of neurons n
- ► Select tuning curves, maximum rates \Rightarrow \mathbf{e}_i , α_i , J_i^{bias}
 - ightharpoonup Sample e_i from unit-sphere
 - ▶ Uniformly distribute α_i , J_i^{bias}
- ► Encoding equation:

$$a_i(\mathbf{x}) = G[\alpha_i \langle \mathbf{e}_i, \mathbf{x} \rangle + J_i^{\text{bias}}]$$



Summary: Building a model of neural representation (Decoding)

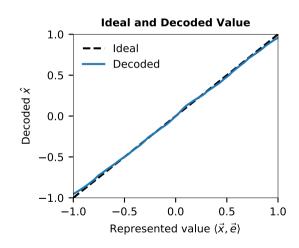
Decoding

- ► Uniformly sample N samples from X, $X = (x_1, ..., x_N)$
- ► Compute **A**, where $(\mathbf{A}) = a_i()$
- ▶ Decoder computation:

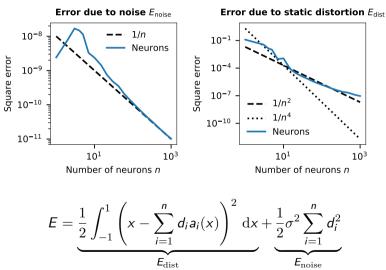
$$\mathbf{D} = (\mathbf{A}\mathbf{A}^{\mathrm{T}} + N\sigma^{2}\mathbf{I})\mathbf{A}\mathbf{X}^{T}$$

► Decoding equation:

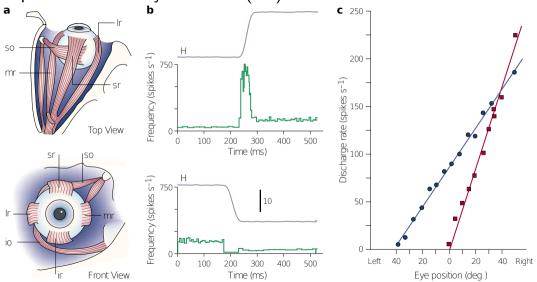
$$\hat{\mathbf{X}} = \mathbf{D}\mathbf{A}$$



Analysing Sources of Errors



Example: Horizontal Eye Position (1D)



Example: Horizontal Eye Position (1D) (cont.)

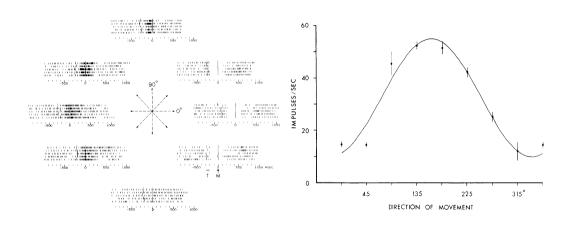
- ► Step 1: System Description
 - ► What is being represented?
 - x is the horizontal eye position
 - What is the tuning curve shape?
 - ightharpoonup Linear, low $au_{
 m ref}$, high $au_{
 m RC}$
 - ▶ $e_i \in \{1, -1\}$
 - Firing rates up to $300 \,\mathrm{s}^{-1}$

- ► Step 2: Design Specification
 - Range of values

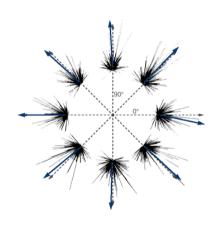
$$ightharpoonup X = [-60, 60]$$

- Amount of noise
 - ▶ About 20% of $max(\mathbf{A})$
- ► Step 3: Implementation
 - Choose tuning curve parameters
 - Compute decoders

Example: Arm Movements (2D)



Example: Arm Movements (2D) (cont.)



- Experiment by Georgopoulos et al., 1982
- ightharpoonup Preferred arm movement directions e_i
- ▶ Idea: Population Vectors, decode using

$$\hat{\mathbf{x}} = \sum_{i=1}^{n} a_i(\mathbf{x}) \mathbf{e}_i = \mathbf{E} \mathbf{A}$$

- Good direction estimate
- Cannot reconstruct magnitude

The NEF does not use population vectors!

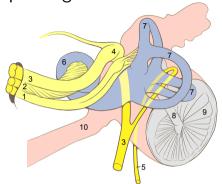
Example: Arm Movements (2D) (cont.)

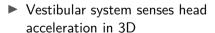
- ► Step 1: System Description
 - ► What is being represented?
 - x the movement direction (or hand position)
 - ► What is the tuning curve shape?
 - Bell-shaped
 - Encoders are randomly distributed along the unit circle
 - ► Firing rates up to 60 s⁻¹

- ► Step 2: Design Specification
 - Range of values

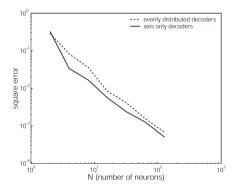
- Amount of noise
 - ▶ About 20% of $\max(\mathbf{A})$
- ► Step 3: Implementation
 - Choose tuning curve parameters
 - Compute decoders

Example: Higher Dimensional Representation





▶ Axis aligned, must choose $e_i \in \{[1,0,0],[-1,0,0],\dots,[0,0,-1]\}$



- ► Same as three 1D populations
- Slightly lower precision
- **Encoders affect accuracy**

Administration

► Assignment 1 has been released.

The due date has been adjusted to January, 30.

► Some new potential times for office hours

Mon 15:30-16:30, Mon 16:30-17:30, Tue 15:00-16:00,

Thu 11:30-12:30 (current slot), Thu 12:30-13:30

Image sources

Title slide

"The Ultimate painting." Author: Clark Richert. From Wikimedia.