## Models of visual neuron function

### Quantitative Biology Course Lecture Dan Butts

### What is the "neural code"?



Electrical activity: nerve impulses

## How does neural activity relate to brain function?

Use visual system:

Well characterized

Intuitive function

Lateral Geniculate Nucleus (LGN)

Population input to the cortex

 $\gamma >$ 

## Starting point: recordings in the LGN



### Visual stimulus



"Cat-cam" movies from Peter Koenig's Lab

### (Kayser et al, 2004)

### LGN neuron responses





### **Understanding and Decoding Neural Signals**





## Outline

1. Introduction to "receptive fields"

2. Building a visual neuron model
The LN (Linear-Non-linear) model

**3.** The problem of temporal precision and the need for new statistical methods

Maximum-likelihood modeling

**4. Research:** Application of maximum-likelihood modeling to explain precise timing of neuronal responses

## Coding like the muscle

Little contraction

Muscle picture with motoneuron

Lots of contraction

## The receptive field



 $R = \sum_{\vec{x}} K_{sp}(\vec{x}) S(\vec{x})$ 

## The receptive field



Spatial stimulus

## The receptive field



Spatial stimulus

Neuron is tuned for a given stimulus over a certain range.

## Circuitry of the retina



## ...but vision involves motion



Motion in the visual scene/ self motion



Eye movements

saccades, microsac.ocular drift

### LGN response during movie Raster plot





### What does neural activity look like during a time-varying stimulus?



Time (sec)

## Visual neuron function: the spatiotemporal receptive field

What stimuli are represented by a neuron's response?





Spike-Triggered Average (STA) stimulus:"receptive field"



## Visual neuron function: the spatiotemporal receptive field







### Implicit Problems with Modeling



### The "temporal receptive field"

### **Spatiotemporal Stimuli**



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### The "temporal receptive field"



### How measure the receptive field? The spike-triggered average



## Linear model predictions



$$r_{est}(t) = r_0 + \int d\tau \ k(\tau) \, s(t-\tau)$$

## Mathematical result

(take functional derivative of MSE)

### Layman's summary:

In the presence of Gaussian noise (uncorrelated) stimuli, the best linear model for the neuron is proportional to the spike triggered average.

$$r_{est}(t) = r_0 + \int d\tau \ k(\tau) \ s(t - \tau)$$

Mean Squared Error (MSE)

$$MSE = \sum_{t} [r(t) - r_{est}(t)]^2$$

**Stimulus-response cross-correlation** 

$$k(\tau) \propto \int dt \ r(t) \, s(t-\tau)$$

### Linear model predictions



### now map linear tunction to tring rate?

"LN" (Linear-Non-Linear) model of encoding



### Measuring reliability of RF "model": the non-linearity



### Measuring reliability of RF "model": the non-linearity



## Bussgang's Theorem

### Layman's summary:

In the context of simple non-linearities, the "optimal" receptive field is STIL given by the spike-triggered average in the context of Gaussian white noise \*\*\*

### Receptive field predictions



## How quantify quality of model fit?

Matlab Interlude

## Problems with visual neuron modeling

I. Looking at higher time resolution reveals that the LN model is insufficient

2. Non-linearities "force" the use of Bussgang's theorem -> only use STA, and need noise stimuli

3. r2 is not the best measure for evaluating a nonlinear system

(also, it requires multiple repeats to estimate a good firing rate)

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### Maximum Likelihood Approach

#### Stimulus



Likelihood: probability that model explains data

### Find the "maximum likelihood":

The probability that the spikes were generated by a model with a certain choice of parameters

$$LL = \sum_{t_{spk}} \log Pr\{spk|t_{spk}\} - \sum_{t} Pr\{spk|t\}$$

Firing rate when there is an observed spike Firing rate when there is no observed spike



### Problem: complicated function to Maximize!



### The maximum likelihood:

$$LL = \sum_{t_{spk}} \log Pr\{spk|t_{spk}\} - \sum_{t} Pr\{spk|t\}$$

### PANINSKI (2004):

No local minima in likelihood surface given certain forms of non-linearity (f)

Matlab can solve for optimal parameters in very little time!

[e.g., 2 minutes of data, 0.5 ms resolution ~ 20 seconds]

### LN model is fit "optimally" using maximum likelihood

Quick Matlab Interlude

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### Receptive field predictions



### Receptive field predictions

#### **Neuron's Response**











### How to generate precision?



Need to "suppress" neuron's response during periods of stimulus that matches RF

### Refractoriness and Neural Precision

e.g., Berry and Meister, 1998 Brillinger, 1992 Keat et al., 2001 Paninski, 2004 Pillow et al., 2005

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### Generalized Linear Model (GLM)





### PANINSKI (2004):

Optimal solution for model parameters (no matter how many parameters!)

But, spike history term does not explain the temporal resolution of the data.

### GLM model does not explain LGN temporal precision





Response (Spike Train) **Suppression** 

after spikes

# What about "network" suppression?

Refractoriness and precision model

Network suppression model





### Directly fit \*multiple\* receptive fields



-- Alternative to spiketriggered covariance

-- Simplest way to incorporate two RFs

-- Application to neurons that process stimuli non-linearly (e.g., on-off cells in mouse retina)

## "Precision" explained by suppression



### Cross-validation



### Significant improvement across all recorded neurons







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### General role of local inhibition?

### Retina

Exc: bipolar cell Inh: spiking amacrine

local inhibitory interneuron

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long-range excitatory proj<sub>ection</sub>

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LGN

Exc: RGC input Inh: interneurons Exc: LGN input Inh: interneurons

**V1** 

## Circuitry of the retina



#### OUTER PLEXIFORM LAYER

Role in spatial processing?

#### INNER PLEXIFORM LAYER

Role in temporal processing?

## Conclusions/Parting Thoughts

### 1. Visual neuron modeling

- Don't forget the LN model -- it is everywhere
- Basis for sensory models in neuroscience ("minimal model")

## 2. Neuroscience has been (but no longer is?) stuck with standard statistics

- Brought field to where it is (VERY USEFUL) but ... could not go much further
- Neuroscience-statisticians are having large impact on basic science (Emory Brown, Liam Paninski, Rob Kass, Valerie Ventura, Han Amarsingham,...)

### 3. Maximum likelihood modeling

- System of models that have smooth likelihood surface
- Ability to solve higher-order models with limited data