Information Processing in Neural Populations

selective tutorial introduction

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Disclaimers

• The visual system is taken as a model (but it's a good one!)
• I will skip many details to try to paint a big picture
• I will emphasize other details because I don't often get a chance to do so
### The Big Picture

<table>
<thead>
<tr>
<th>retina</th>
<th>signals</th>
<th>responses</th>
<th>variability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>graded</td>
<td>linear</td>
<td>mildly interesting, mostly understood</td>
</tr>
<tr>
<td></td>
<td></td>
<td>non-linear; simple models work</td>
<td>more interesting, somewhat understood</td>
</tr>
<tr>
<td></td>
<td>spikes</td>
<td>non-linear; simple models fail</td>
<td>very interesting, poorly understood</td>
</tr>
</tbody>
</table>

- photoreceptors
- ganglion cells
- thalamus (lateral geniculate nucleus, LGN)
- cortex
Overview: retina, thalamus, cortex

Schmolesky: http://webvision.med.utah.edu/imageswv/
Retinal Anatomy 101

Kolb, Fernandez, Nelson:
http://webvision.med.utah.edu/imageswv/
V1
= primary visual cortex
= striate cortex
= area 17

Van Essen (1992); Schmolesky: http://webvision.med.utah.edu/imageswv/
Visual Processing is NOT Serial

Anatomic evidence

• Retinal synapses are (nearly) always reciprocal
• Thalamic “relay” neurons receive the retinal output BUT 90% of their synapses are not from the retina
  – feedback from cortex
  – non-visual inputs from brainstem
• Cortical areas have a definable hierarchy based on laminar pattern of inputs and outputs BUT
  – ascending and descending projections are equally prominent
  – ascending and descending projections are always reciprocal
Visual Processing is NOT Serial

Physiologic evidence

• Lateral interactions within V1 rely on thin unmyelinated fibers (slow)
  – \((3 \text{ mm})/ (0.1 \text{ m/sec}) = 30 \text{ ms}\)
• Lateral interactions between V1 and V2 rely on myelinated fibers (fast)
  – \((20 \text{ mm})/(6 \text{ m/sec}) = 3 \text{ ms}\)
• Signal spread between cortical areas is faster than within areas
• Perhaps, the processing "unit" spans multiple cortical areas

After Bullier
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Support

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Framing the Problem

\[ R(t) = F[S(x,t)] \]

- **Stimulus**
  - light intensity or contrast \((L = L_0 + L_1 S(x,t))\)
  - current injection
- **Response**
  - intracellular voltage
  - transmembrane current
  - firing rate

Really want to study

\[ R(x,t) = F[S(x,t, \lambda, behavior)] \]
Framing the Problem, II

• Full probabilistic formulation: study $p(R|S(x,t))$

• Typical simplification
  – For non-spiking neurons: $R(t) = F[S(x,t)] + \text{noise}$
  – For spiking neurons: assume an underlying "rate", and then a model for generating spikes
    • Inhomogeneous Poisson (possibly with refractory period)
    • Inhomogeneous renewal

• Ideally, study $p(R|S(x,t,\lambda,\text{behavior}))$, and do this for many neurons at the same time
Simplifying the deterministic part: some generic models

\[ R(t) = F[S(x,t)] \]

- Linear
  \[ R(t) = \int K(x, \tau) S(x, t - \tau) dx d\tau \]
- Nonlinear but analytic (Volterra)
  \[ R(t) = K_0 + \int K_1(x_1, \tau_1) S(x_1, t - \tau_1) dx_1 d\tau_1 + \]
  \[ \int\int K_2(x_1, \tau_1, x_2, \tau_2) S(x_1, t - \tau_1) S(x_2, t - \tau_2) dx_1 dx_2 d\tau_1 d\tau_2 + \cdots \]
- Orthogonal expansion (Wiener)
- Other forms?
Kernel Measurement: Linear System

Assume: single input $S(t)$, and

$$R(t) = \int K(\tau)S(t - \tau)d\tau$$

$R(t)$: intracellular voltage

$S(t)$: injected current (e.g., pseudorandom binary “m-sequence”)

Since the spectrum of $S(t)$ is white, cross-correlation of $S$ and $R$ yields an estimate of impulse response of best-fitting linear system

$$K(\tau) \approx \frac{1}{N} \langle R(t)S(t - \tau) \rangle$$
Photoreceptors

- Graded responses to light
  - depolarized in dark
  - hyperpolarize to light (vertebrates)
- Approximately linear for moderate depths of modulation (<30%)
- Linear kernel is separable
  \[ K(x, \tau) = X(x)T(\tau) \]
- Spatial profile \( X(x) \) determined by optics, waveguide properties, electrical coupling (gap junctions)
Photoreceptor Dynamics I

Assume linearity: \[ R(t) = \int K(\tau)S(t - \tau)\,d\tau \]

The impulse response \( K(t) \) is the response \( R(t) \) to \( S(t) = \delta(t) \).

Response scales with impulse size (8-fold range).

Directly measured impulse response predicts step response.

macaque cones Schnapf et al., 1990

Linear behavior for moderate input range
Photoreceptor Dynamics II

Nonlinear behavior (change in dynamics) over wide input range

With increasing light level, sensitivity decreases and response speed increases.

70000-fold change in background intensity, 1000-fold change in flash intensity

turtle cones
Daly and Normann, 1985
Horizontal Cells

- Basic dynamical features similar to photoreceptors
  - Non-spiking
  - Approximately linear
- A functional syncytium
- Spatiotemporal kernel only approximately separable, due to “cable” (i.e., disk) properties
Bipolar Cells

- Non-spiking
- On-off dichotomy
  - Sublaminar organization
  - Consequences of Dale’s Law
- Center-surround organization
  - Non-separable for light input:
    \[ K(x, \tau) = X_C(x)T_C(\tau) + X_S(x)T_S(\tau) \]
  - Consequence: spatiotemporal coupling
- Approximately linear but only for very small inputs
Bipolar Cell Dynamics

Impulse response varies with mean input current

Mao et al., 2002
Amacrine Cells

- Many (~40) morphological types
- Recurrent connectivity
- Complex dynamics
  - Some are highly nonlinear
    - On/Off behavior
    - Directional selectivity
  - Some are spiking
Amacrine Cells: On-Off Responses

Intracellular voltage records of responses to abrupt increases and decreases of illumination

Note depolarizing responses at both ON and OFF transients

Toyoda et al., 1973
Kernel Measurement: Nonlinear System

\[ R(t) = K_0 + \int K_1(\tau_1)S(t - \tau_1)d\tau_1 + \int\int K_2(\tau_1, \tau_2)S(t - \tau_1)S(t - \tau_2)d\tau_1d\tau_2 + \cdots \]

Estimation of \( K_0, K_1, K_2, \ldots \) is also a linear regression.

White noise (Wiener-Lee-Schetzen): If \( S(t) \) is drawn from Gaussian white noise, design matrix is (eventually) simple, and:

\[ K_0 \approx \langle R(t) \rangle \]
\[ K_1(\tau_1) \approx \frac{1}{N_1} \langle R(t)S(t - \tau_1) \rangle \]
\[ K_2(\tau_1, \tau_2) \approx \frac{1}{N_2} \langle R(t)S(t - \tau_1)S(t - \tau_2) \rangle \quad (\tau_1 \neq \tau_2) \]

\( K \)'s are not universal; they depend on power.

Lots of parameters.

Not clear what kind of input signal will yield the best design matrix. e.g., m-sequences have \( S(t-\tau_1)S(t-\tau_2) = S(t-\lambda(\tau_1, \tau_2)) \).
Amacrine Cells: Second-order Kernel

\[ K_2(\tau_1, \tau_2) \]

second-order kernel of catfish amacrine cell intracellular voltage response to light

first- and second-order kernels provide a good approximation to response

Sakuranaga and Naka, 1985
Retinal Ganglion Cells

- This is the output of the retina to the (rest of the) brain
- Linear center-surround is a caricature
  - All ganglion cells show changes in gain and dynamics as contrast varies ("contrast gain control")
  - Some ganglion cells are highly nonlinear even for small inputs
Analysis in the Frequency Domain: Linear System

Assume: single input $S(t)$, and

$$ R(t) = \int K(\tau)S(t - \tau)d\tau $$

Consider the Fourier transforms

$$ \tilde{K}(\omega) = \int e^{-i\omega \tau} K(\tau)d\tau , \text{ etc.} $$

The convolution theorem yields:

$$ \tilde{R}(\omega) = \tilde{S}(\omega)\tilde{K}(\omega) $$

So, $\tilde{K}(\omega)$ may be measured by sinusoids, white noise, sums of discrete sinusoids, …

Why work in the frequency domain?
Boxes turn into algebra

parallel

\[ \tilde{K}(\omega) = \tilde{G}(\omega) + \tilde{H}(\omega) \]

serial

\[ \tilde{K}(\omega) = \tilde{G}(\omega)\tilde{H}(\omega) \]

feedback

\[ \tilde{K}(\omega) = \frac{\tilde{G}(\omega)}{1 - \tilde{G}(\omega)\tilde{H}(\omega)} \]
Comparison: time vs. frequency domain

X-type retinal ganglion cell
high spatial frequency grating, \( S(t) \) modulates its contrast

Note smoothness of kernel in frequency domain.

\( K_1(\tau_1) \)

\( \tilde{K}_1(\omega_1) \)

Victor 1979
Comparison: Time vs. Frequency Domain

Y-type retinal ganglion cell, 
$S(t)$ modulates contrast of 
high spatial frequency grating

Victor 1979
Frequency domain kernels can have revealing functional forms

\[ \tilde{K}_2(\omega_1, \omega_2) \propto \tilde{F}(\omega_1)\tilde{F}(\omega_2)\tilde{G}(\omega_1 + \omega_2) \]

but

\[ K_2(\tau_1, \tau_2) \propto \int F(\tau_1 - \tau)F(\tau_2 - \tau)G(\tau)d\tau \]

are special cases
Retinal ganglion cells: Dynamic adaptation to contrast

X cell responses to contrast modulation of a grating

Sum-of-sinusoids responses

Contrast also modulates second-order response, primarily via the first filter of $F \rightarrow N \rightarrow G$.

Spikes
Retinal ganglion cells: detailed firing pattern

"linear" ganglion cell responses to sinusoidal modulation

contrast=0.32

contrast=1.0

At high contrasts, spikes lock to stimulus phase. This behavior is consistent with a "noisy leaky integrate-and-fire model"

Reich et al. 1997
Each thalamic neuron has a retinal output neuron as its primary input.

The retinal neuron's spike is necessary but not sufficient for an output event.
Spike Editing by Thalamic Relay Neurons

retinal S-potential, no LGN spike

retinal S-potential followed by LGN spike

Kaplan and Shapley 1984
Thalamic editing is not just deleting

- Most "relay" neuron inputs are not retinal
  - From visual cortex
  - From brainstem (? arousal)
- Depending on the recent past history, a relay neuron's output event can be
  - a spike
  - no spike
  - a burst
- This is typical of thalamic relay neurons, not only visual
Bursts rely on a voltage-dependent Ca\(^{++}\) channel. Brainstem inputs modulate membrane potential on 100-ms timescale, appropriate to the activation/inactivation dynamics of the channel.

McCormick 1989
Stretch!
A reasonably satisfying picture

Kolb, Fernandez, Nelson:
http://webvision.med.utah.edu/imageswv/

- Processing steps correspond to anatomy
- Goal of processing is clear: redundancy reduction for efficient coding to get through the bottleneck of the optic nerve

Boxes are gently parametric in input mean and variance
Onward to primary visual cortex

• Major differences between retinal and cortical anatomy and physiology
  – Multilaminated structure, even more cell types
  – All neurons spike
  – Even "input" layer synapses are mostly intrinsic
  – Anatomical and physiological substrate for top-down influences

• Unlikely that cortical processing has the same goals
  – No "bottleneck"
  – Much redundancy has already been removed

• But current computational models have the same computational structure -- LN cascades, with tweaks

Adapted from Llinas et al. 1994, by Purpura and Schiff 1997
The “New Standard Model” for V1 neurons

An LN model with "tweaks" (just as in retina); selectivity is governed by the initial linear stage

adapted from Rust and Movshon, 2005
Is something qualitative missing?

• Models are built from neural responses to simple stimuli but have only fair predictive accuracy for natural scenes
  – Because of “top-down” factors: attention?
  – Because of low-level factors: high-order correlations
    • They distinguish local features (lines, edges) from noise
    • They distinguish natural scenes from traditional analytical stimuli
  – Unclear whether explaining V1’s computations requires a departure from the “new standard” architecture
    • We don't have a concise predictive model for the gain controls
    • We can't collect enough data to characterize them

• Strategy: Use designed stimuli that neutralize the gain controls
Two-Dimensional Hermite Functions

Successive ranks are orthogonal.

Decreasing confinement
Neutralizing the gain controls

Two-dimensional Hermite functions

- All elements have the same mean-squared contrast.
- Within each rank, the two sets have the same spatial extent, frequency spectrum, and linear span.

Strategy: build LN-type models from neural responses to each set. The inferred filters should match. If not, then we cannot blame some special property of natural scenes, or the effect of gain controls.
Responses of a typical V1 neuron

layer 3, non-directional, broad orientation tuning
Testing the model

Fitting an LN-type model to the responses

\[ L \]

\[ \sum \]

\[ Y \]

\[ R \]

sensitivity of \( L \) to \( Y \) = \frac{\text{resp}[\text{image}]}{2} - \frac{\text{resp}[\text{image}]}{2}

sensitivity of \( E \) to \( Y \) = \frac{\text{resp}[\text{image}]}{2} + \frac{\text{resp}[\text{image}]}{2}

"New Standard Model prediction: Cartesian and polar stimuli yield the same filters"
Prediction holds: filters determined from C and P are similar
Responses of another typical cortical neuron

Cartesian

polar

layer 3, non-directional, narrow orientation tuning

100 imp/s

250 ms

c3003u
Prediction fails: filters determined from C and P differ in shape
A third neuron

upper layer 6,
directionally-selective
complex cell

50 imp/s
250 ms

c3301t
Third cell

Prediction fails: filters determined from C and P differ in size.
Population summary, and relationship to laminar organization

- 41/70 neurons: prediction fails, filters differ in shape
- 32/70 neurons: prediction fails, filters differ in size
- 17/70 neurons: prediction holds (neither difference)

Prediction failure is typical in all layers, even in layer 4 (input)
Contour orientation is key

The apparent change in the filters is a signature of departure from LN behavior. What stimulus characteristics are driving it?

Cartesian, **aligned** to preferred orientation

Cartesian, **oblique** to preferred orientation

Cartesian, **aligned** to preferred orientation

Cartesian, **oblique** to preferred orientation

Changing contour orientation has a larger effect than removing them.
Summary so far

• Most V1 neurons show qualitative departures from the predictions of cascade models
  – for simple non-natural stimuli
  – that neutralize the gain controls
  – even in the input layers

• The presence of oriented contours drives this departure

• Since orientation selectivity first appears in V1, this suggests recurrent nonlinear processing

• But is this finding specific to these peculiar matched basis sets? Can we more directly test the idea that high-order correlations matter?
Cross-correlate the spike trains with the stimulus, pixel by pixel, to generate a receptive field sensitivity profile.

This works if the stimulus pixels are uncorrelated in pairs.

We can create stimuli in which pixels are uncorrelated in pairs, but correlated at higher orders -- and use them to study whether V1 neurons care about these correlations.
Implementing the idea

- No pairwise correlations
- Strong fourth-order correlation: every "glider" has an even number of white checks

Each texture is a probe for neural sensitivity to a specific kind of high-order correlation.
Mapping V1 neurons with correlated stimuli

Large changes in sensitivity profiles; some neurons only "mappable" with correlated stimuli

But maybe we could build dedicated, parallel combinations of LN models to recover this behavior.
"Invisible" correlations can affect the map

<table>
<thead>
<tr>
<th>random</th>
<th>even</th>
<th>odd</th>
<th>bright triangle</th>
<th>dark triangle</th>
<th>wye</th>
<th>repeat random</th>
</tr>
</thead>
</table>

![LN models](image1)

![real V1 neurons](image2)
Principal components analysis of RF maps

RF changes are highly significant, including changes induced by "invisible" correlations (the wye stimulus).
Recurrence makes it sensible

- With feedforward architecture
  - We would have to build a parallel set of LN modules, with dedicated circuitry for each kind of correlation
  - We would have to include circuitry for correlations that aren't perceptible (and don't seem to correspond to edges and regions)
- But what if the recurrence dominates?

  - Each path through the network traverses a different combination of nonlinearities
  - This generates lots of useful combinations (e.g., local edge detection followed by interactions along extended contours)
  - But it also generates some crosstalk -- accounting for sensitivity to "invisible" correlations
  - And it meshes well with anatomy
What is a “natural scene”?

“I know it when I see it”.

Potter Stewart, Jacobellis v. Ohio (1964)
What is the goal of the computations in primary visual cortex?

Lab meeting, April 2011