# I. LNLN model of MT (an elaboration of Tony's description)

II. Bayes motion estimation

Simple Models of RGC Light Response



Simple Models of RGC Light Response

linear (L)

simple nonlinearity (LN)





Simple Models of RGC Light Response

linear (L)

simple nonlinearity (LN)

subunits (LNL)

... rectification ...





[from EJ's talk]

response

# LGN model



# V1 models



# V1 models



[from Nicole's talk]

The linear model of simple cells



The normalization model of simple cells



RC circuit implementation



Other cortical cells

• Basic cell properties (e.g., tuning/invariance) captured by linear model

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- This "toolbox" is surprisingly effective. How far can we go with it?

# Obviously missing: Recurrent processing

- Within single neurons: Spike generation (e.g., refractoriness, spike rate adaptation)
- Lateral connectivity
- Feedback connectivity

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Note: despite their existence and potential functional importance, these are much harder to understand and model, and are often underconstrained by existing experimental data (my opinion).

# A striking nonlinearity



Movshon etal, 1985

# A striking nonlinearity



Movshon etal, 1985



[from Tony's talk]

#### the "trick"

Find a way to describe pattern motion selectivity as a linear problem

# Motion is space-time orientation







Adelson & Bergen, 1985







White background, Gray bar, translating left





White background, I Gray bar, d translating left

Bar translating left, occluding a striped background moving right





White background,<br/>Gray bar,Bar tra<br/>occlud<br/>backgrtranslating leftbackgr

Bar translating left, occluding a striped background moving right



Striped background, looming



White background,Background,Background,Gray bar,octranslating leftbackground,

Bar translating left, occluding a striped background moving right



Striped background, looming

Transparently overlayed stripe patterns, moving in opposit directions



















 $x \rightarrow$ 





 $\omega_x \rightarrow$ 

 $x \rightarrow$ 



 $x \rightarrow$ 





 $\omega_x \rightarrow$ 



# XYT



























# Spectral power of translating power lies on a plane in the Fourier domain

Watson & Ahumada, 1985

# Direction-selective filter



Loosely speaking, V1 cells represent balls of spectral energy

# Filter is not velocity-selective



# Linear velocity selectivity





Add spectral energy on plane Subtract spectral energy off plane

# V1

Tuning

#### Linear weighting



ω<sub>t</sub>♠  $\omega_{\rm v}$ ¢ω<sub>x</sub>

# MT

#### Linear weighting

#### Tuning





**↓**Vy V<sub>X</sub>



Output: V1 neurons tuned for spatio-temporal orientation



Output: V1 neurons tuned for spatio-temporal orientation

Output: MT neurons tuned for local image velocity

#### Component cell











# Direction-tuning predictions

stimulus \ cell type	component	pattern
grating	unimodal	bimodal at low speeds
dots	bimodal at high speeds	unimodal

#### Component Cell / Drifting Dots



Simoncelli, Bair, Cavanaugh, Movshon, ARVO-96

Pattern Cell / Sine Grating



Simoncelli, Bair, Cavanaugh, Movshon, ARVO-96

Component

Plaid

Planar













Component



Planar









![](_page_53_Picture_8.jpeg)

![](_page_53_Picture_9.jpeg)

Component

Plaid

Planar

![](_page_54_Picture_4.jpeg)

![](_page_54_Picture_5.jpeg)

![](_page_54_Picture_6.jpeg)

![](_page_54_Picture_7.jpeg)

![](_page_54_Picture_8.jpeg)

![](_page_54_Picture_9.jpeg)

Component

![](_page_55_Figure_2.jpeg)

Planar

![](_page_55_Picture_4.jpeg)

![](_page_55_Picture_5.jpeg)

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![](_page_55_Picture_7.jpeg)

![](_page_55_Picture_8.jpeg)

Component

Plaid

Planar

![](_page_56_Picture_4.jpeg)

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![](_page_56_Picture_9.jpeg)

Component

![](_page_57_Figure_2.jpeg)

Planar

![](_page_57_Picture_4.jpeg)

![](_page_57_Picture_5.jpeg)

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Component

Plaid

Planar

![](_page_58_Picture_4.jpeg)

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![](_page_58_Picture_9.jpeg)

# Detection thresholds

![](_page_59_Figure_1.jpeg)