Introduction

• Reponses of V1 neurons to drifting compound gratings of equal energy reveal tuning to edge-like, line-like, and intermediate profiles (Mechler et al. 2002).

• Neither linear neurons nor energy-operator neurons can account for the observed tuning.

• Recurrent connections have been used to explain simple and complex cell responses to single drifting gratings. (Chance et al. 1999) Here we ask if this model can explain the feature tuning of V1 neurons to lines, edges and intermediate waveforms.

Conclusions

• Rough feature preference is endowed by the Gabor carrier phase, but is eliminated if the nonlinearity is a perfect half-wave rectifier.

• Feature selectivity is sharpened by the firing rate generator via the iceberg effect of a threshold nonlinearity but weakened by increased recurrent gain.

 High gain also decreases the diversity of preferred features because of indiscriminate phase pooling.

• A family of models can account for much of the diversity of feature preference and selectivity seen in V1.

Feature tuning in V1

1D feature space



Stimuli form a single parameter feature space of equalenergy waveforms, defined by the relative phase of the component gratings. Tuning in a single neuron

Feature tuning is quantified by 3 response energy measures: Total, Odd and Even.



Tuning in the V1 population



Wedge diagrams show the distribution of optimal congruence phase in cell populations.

Recurrent Network Model with Variable Gain (Chance et al.)

- Recurrent connections pool responses across all spatial phases and scales, diluting the phase sensitivity of the Gabor-filter, linear afferents. The network results in ideal simple and complex cells at opposite ends of the gain range.
- We explore the dependence of feature tuning on two aspects of the network: the strength of the recurrent gain and the type of the rectifying nonlinearity.

References:

Mechler F, Reich DS, Victor JD. Detection and Discrimination of Relative Spatial Phase by V1 neurons. J.Neurosci. 22,6129–615 (2002).

Chance FS, Nelson SB, Abbott LF. Complex cells as Cortically Amplified Simple Cells. Nat. Neurosci. 2,277-282 (1999).



low gain "feed-forward"



high gain "recurrent"

On the right are the tuning curves of model neurons for different network parameters. For each spatial scale, circular vector plots summarize neurons' optimal congruence phase (direction) and selectivity or the circular variance of tuning (radius). Wedge diagrams show the model distribution of optimal congruence phase across all scales.

A Recurrent Network Model for Detection and Discrimination of Relative Spatial Phase by V1 Neurons

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