A Model for the Attentional Modulation of Spatial Vision, Continued

#2934

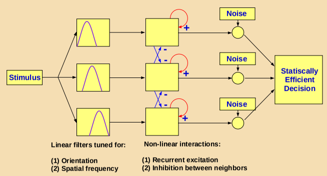
Laurent Itti, Christof Koch and Jochen Braun
California Institute of Technology, Computation and Neural Systems, Pasadena, California 91125

1. Introduction

We propose a unified model which quantitatively accounts for a variety of human psychophysical thresholds and their modulation by attention (see poster #2938 for experimental details).

Section 2: General architecture of the model;
Section 3: Unified account of spatial vision;
Section 4: Unified account of attentional modulation of spatial vision thresholds;
Section 5: Role of attentional modulation?

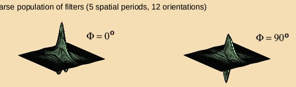
2. Model Architecture



2.1. Visual Filters

Separable Gaussian tuning in orientation θ (width σ_θ) and spatial period λ (width σ_λ)

Sparse population of filters (5 spatial periods, 12 orientations)

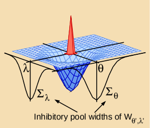


Quadrature pairs → phase-independent energy response $E_{\theta,\lambda}$

2.2. Excitatory and Inhibitory Pooling

Self excitation and divisive inhibition:

$$R_{\theta,\lambda} = \frac{E^G_{\theta,\lambda}}{S_\lambda + \sum_{\theta',\lambda'} W_{\theta',\lambda'} E^H_{\theta',\lambda'}}$$



Excitatory pool is the single unit (θ, λ)

Inhibitory pool is locally weighted around (θ, λ) by Gaussians in orientation (θ') and spatial period (λ')

2.3. Statistically Efficient Decision

Stimulus → Filters, interactions and noise → Statistically efficient estimator T

parameter γ (contrast, orientation, or spatial period)

only partial information about γ preserved in responses $R_{\theta,\lambda}$ (variance $V_{\theta,\lambda}$)

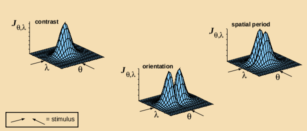
T is an unbiased efficient statistic for γ based on population response $R_{\theta,\lambda}$

mean(T) = γ **var(T) = $1/J_{\theta,\lambda}$**

$$J_{\theta,\lambda} = \frac{1}{V^2_{\theta,\lambda}}\left[\left(\frac{\delta R_{\theta,\lambda}}{\delta\gamma}\right)^2 + 2\left(\frac{\delta V_{\theta,\lambda}}{\delta\gamma}\right)^2\right]$$ Fisher Information

$$J_{total} = \sum_{\theta,\lambda} J_{\theta,\lambda}$$

For single unit responses $R_{\theta,\lambda}$, $J_{\theta,\lambda}$ tells us how much information about γ each unit (θ, λ) carries:

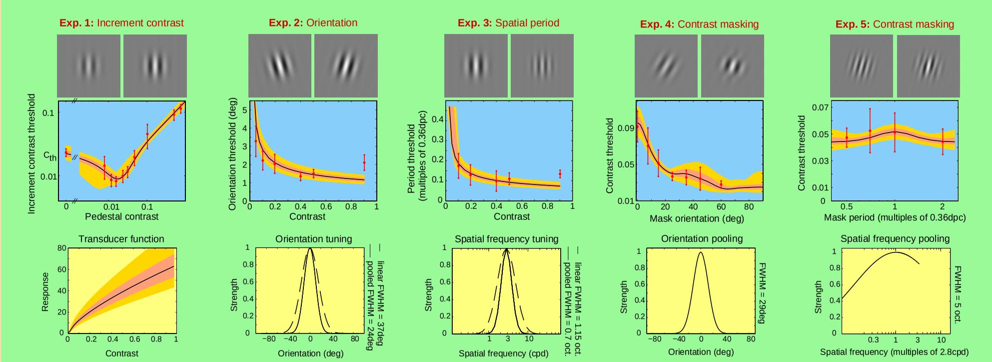


3. Unified Account of Spatial Vision Thresholds — 2AFC Thresholds on Consistent Gabor Stimuli

A consistent dataset (using the same Gabor patches for all experiments) was acquired with three naive subjects. A variety of classical spatial vision thresholds was investigated with attention fully available (also see poster #2938).

The model was fit to the data using an automated procedure (multidimensional downhill simplex with simulated annealing overhead). The resulting model parameters are in good agreement with known physiology.

Thus, the simple computational model proposed is capable of simultaneously and quantitatively reproducing a variety of human psychophysical thresholds.

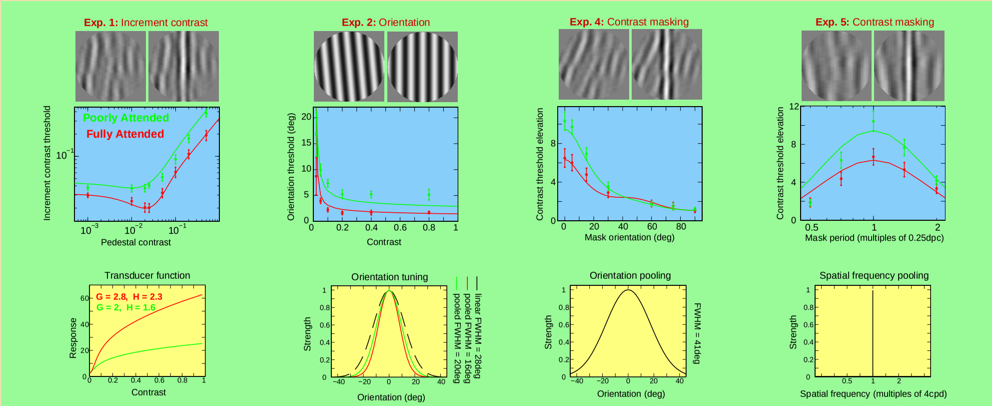


4. Unified Account of Attentional Modulation — Yes/No Thresholds on Fully or Poorly Attended Stimuli

The model was then fit to similar data (although the addition of a second simultaneous task required slight modification of the stimuli; see poster #2938), with attention fully available.

It was found that an increase of the strength of interactions among visual filters (i.e., exponents G and H in Section 2.2) accounts best for the transition from poorly to fully attended thresholds.

Thus, the proposed model suggests a unique, task-independent and prototypical modulatory effect of attention on simple spatial vision thresholds.



5. Discussion

The proposed model is able to simultaneously reproduce a variety of human thresholds.

Detailed study of the model internal parameters suggests that attention principally modulates the strength of interactions among visual filters.

Below we investigate putative computational roles for attention, based on this finding.

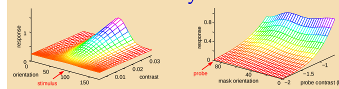
The following plots illustrate the behavior of single cells in the model, in two behaviorally meaningful situations:

- Presence of a single stimulus in the display;
- Presence of both a strong (masking) and a weak (probe) stimuli, with variable orientation difference between the two.

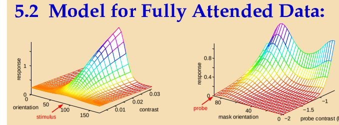
Response to a unique stimulus:

Differential response to a weak stimulus in the presence of a strong stimulus:

5.1 Model for Poorly Attended Data:



5.2 Model for Fully Attended Data:



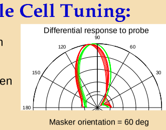
Attention enhances the non-linear behavior of the system with respect to stimulus contrast (left);

Attention enhances the responses to the weak (probe) stimulus only when its orientation is close to that of the strong (masker) stimulus, and suppresses them otherwise (right).

5.3 Effect on Single Cell Tuning:

Sharper orientation tuning when fully attended

Stronger repulsion effect between strong masker and weak probe when fully attended.

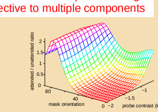


6. Conclusion

We have proposed a quantitative computational model which quantitatively accounts for a range of human psychophysical thresholds.
The same model was used to investigate the modulatory effect of attention on these thresholds. Our findings suggest that attention principally enhances the strength of non-linear interactions among early visual filters:

Increased Competition ⇒ Increased contrast gain; Sharper orientation and period tuning; More selective to multiple components

These findings are consistent with the idea that attention increases the amount of competition between multiple stimuli.



7. Acknowledgements

Supported by NSF, ONR and NIMH. Thanks to Pietro Perona.