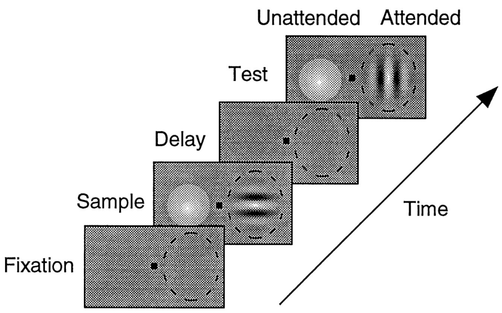
Attention

Gain Control and Biased Competition

Suggested reading:

- Hamker, F. H. (2004) Predictions of a model of spatial attention using sum- and max-pooling functions. Neurocomputing. 56C:329-343.
- Hamker, F. H. (2005) Modeling Attention: From computational neuroscience to computer vision. In: L. Paletta et al. (eds.), Attention and Performance in Computational Vision. LNCS 3368. Berlin, Heidelberg: Springer-Verlag, 118-132.

Attention: Gain Control and Biased Competition



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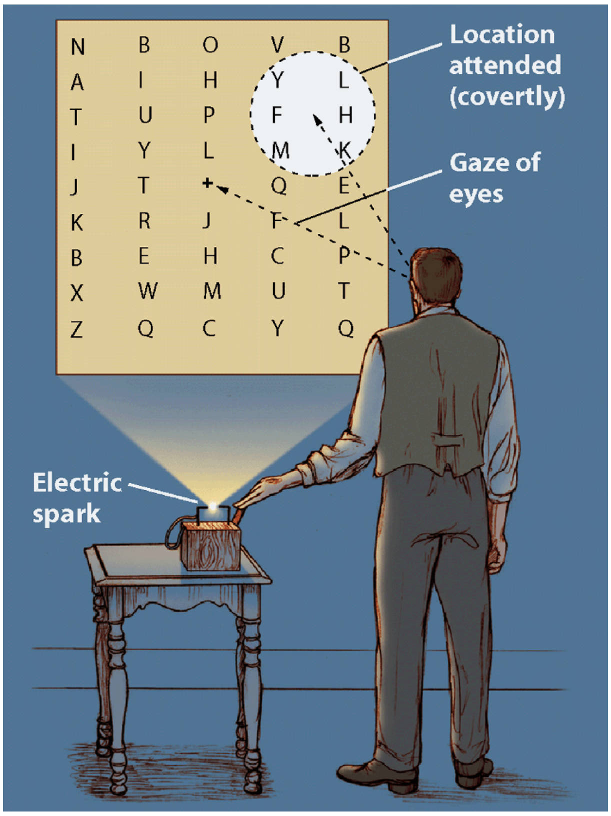
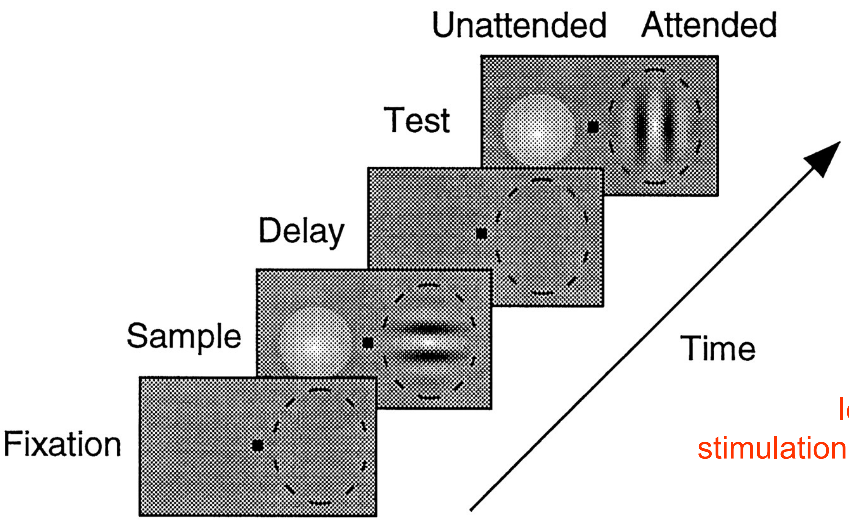
- Gain Control – results
- Biased Competition – results
- Contrast dependence of attention

Covert attention



HERMANN VON HELMHOLTZ

Gain control – experimental observations

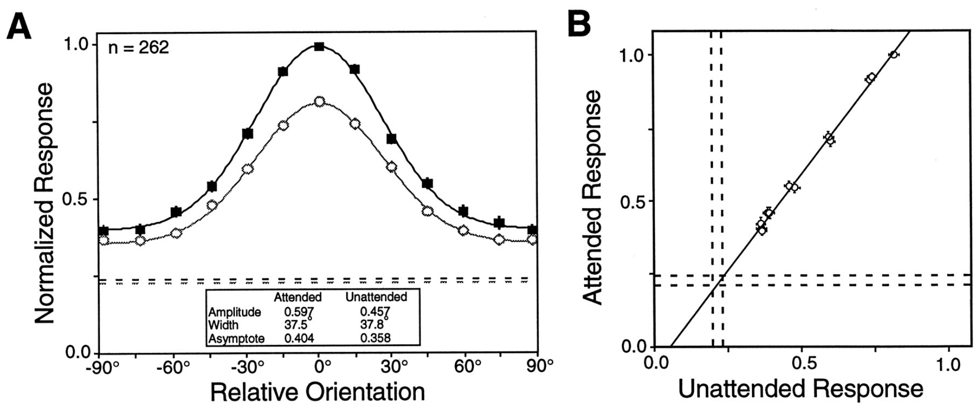


Identical visual stimulation in either case

The monkey was required to bring his gaze to the fixation spot and depress a lever to begin the trial. A Gabor and a colored Gaussian were presented in the sample period. In the attended mode, the monkey was required to pay attention to the orientation of the stimulus in the receptive field. In the other mode, the monkey was required to pay attention to the color of the stimulus outside the receptive field. In the test period, the animal had to report whether the test stimulus at the attended location matched the sample stimulus previously presented there.

Gain control – experimental observations

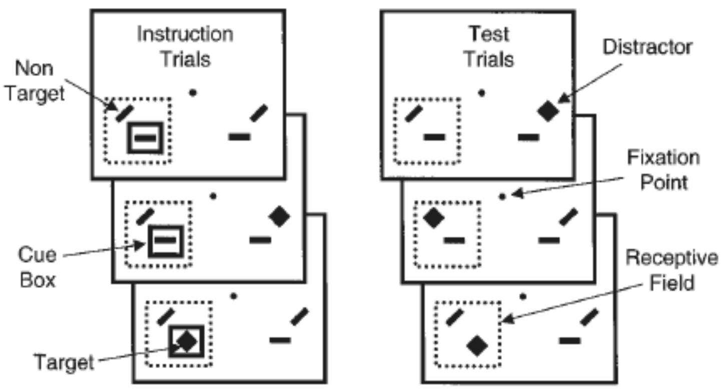
Gain modulation is a prominent feature of neuronal activity recorded in behaving animals, but the mechanism by which it occurs is unknown.



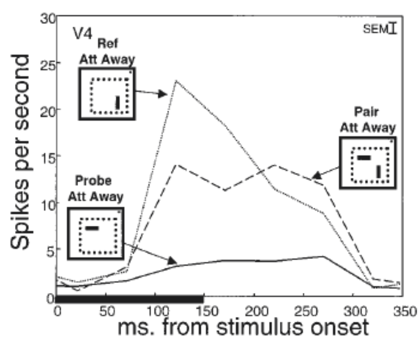
McAdams CJ, Maunsell JH., (1999) A multiplicative scaling of orientation-tuning curves by attention. J Neurosci. 19:431-441.

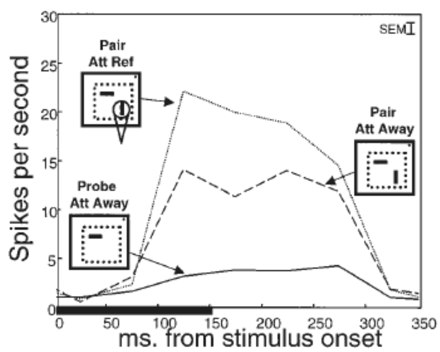
Normalized population-tuning curves constructed from 262 neurons recorded from area V4.

Biased competition - experimental observations



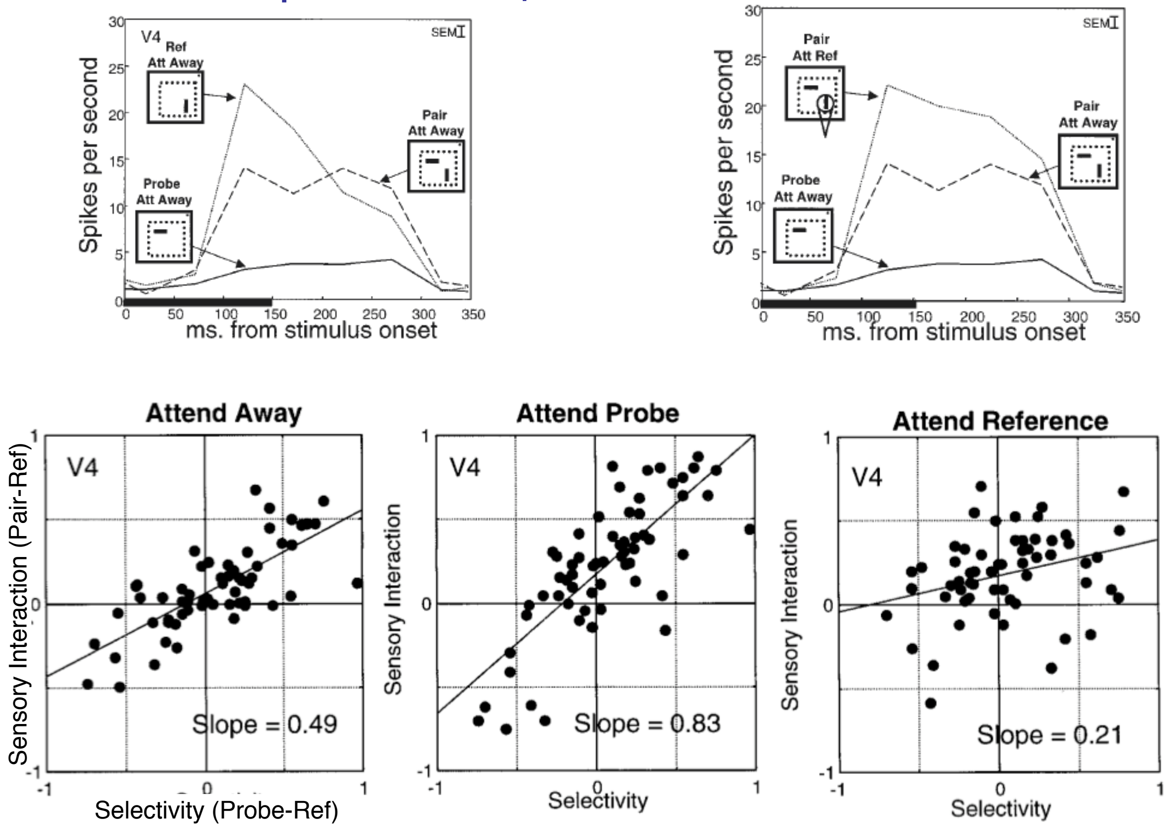
The monkey's task was to respond when a diamond-shaped target appeared at the attended location, while ignoring distractor targets, which occasionally appeared at the other locations.





Reynolds JH, Chelazzi L, Desimone R (1999) Competetive mechanism subserve attention in macaque areas V2 and V4. J Neurosci 19:1736-1753.

Biased competition - experimental observations



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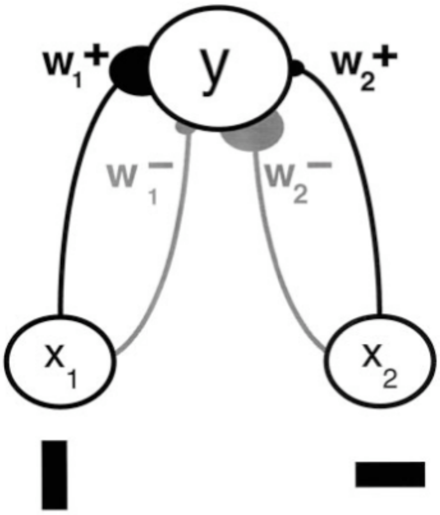
Principles of biased competition



$$E = x_1 w_1^+ + x_2 w_2^+ \quad (1)$$

$$I = x_1 w_1^- + x_2 w_2^- \quad (2)$$

$$\frac{dy}{dt} = (B-y)\,E - y\,I - A\,y \quad (3)$$

$$\lim_{t \to \infty} y = \frac{B\,E}{E+I+A} \quad (4)$$

See Grossberg (1988) for the equations

Model circuit diagram. The circle on top represents the neuron being recorded. The variable *y* is the firing rate of this neuron. The two circles at the bottom represent populations of input neurons that respond to the reference (left) and probe (right) stimuli and that project to the measured cell. The average response of the i^{th} input population is designated x_i.

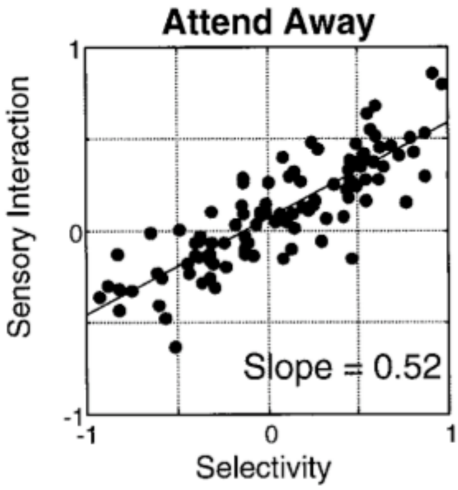
Principles of biased competition - model results

$$E = x_1 w_1^+ + x_2 w_2^+$$

$$I = x_1 w_1^- + x_2 w_2^-$$

$$\frac{dy}{dt} = (B-y)\,E - y\,I - A\,y$$

$$\lim_{t \to \infty} y = \frac{B\,E}{E+I+A}$$



B=1, A=0.2

For each model neuron, the excitatory and inhibitory weights projecting from the populations of neurons activated by the reference and probe stimuli were selected at random from a uniform distribution ranging from 0 to 1. To simulate the stochastic nature of neural responses, 10% random noise, selected from a uniform distribution, was added to the response of the cell in each condition. Attention was implemented by increasing by a factor of 5 the excitatory and inhibitory synaptic weights projecting from the input neuron population responding to the attended stimulus.

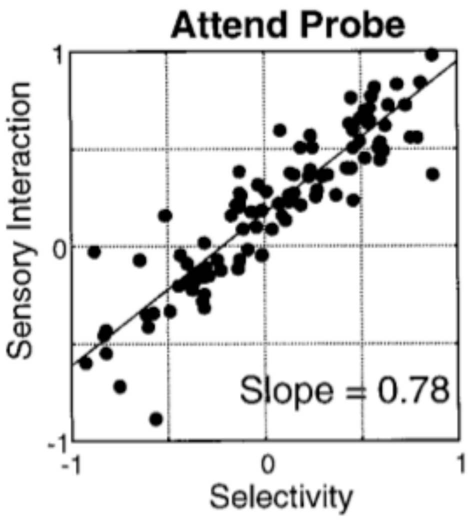
Principles of biased competition - model results

$$E = x_1 w_1^+ + x_2 w_2^+$$

$$I = x_1 w_1^- + x_2 w_2^-$$

$$\frac{dy}{dt} = (B-y)\,E - y\,I - A\,y$$

$$\lim_{t \to \infty} y = \frac{B\,E}{E+I+A}$$



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Principles of biased competition - model results

$$E = x_1 w_1^+ + x_2 w_2^+$$

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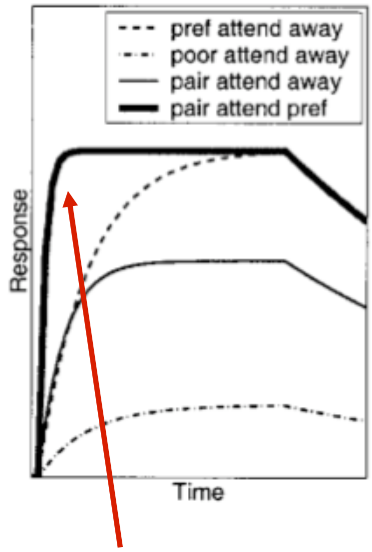
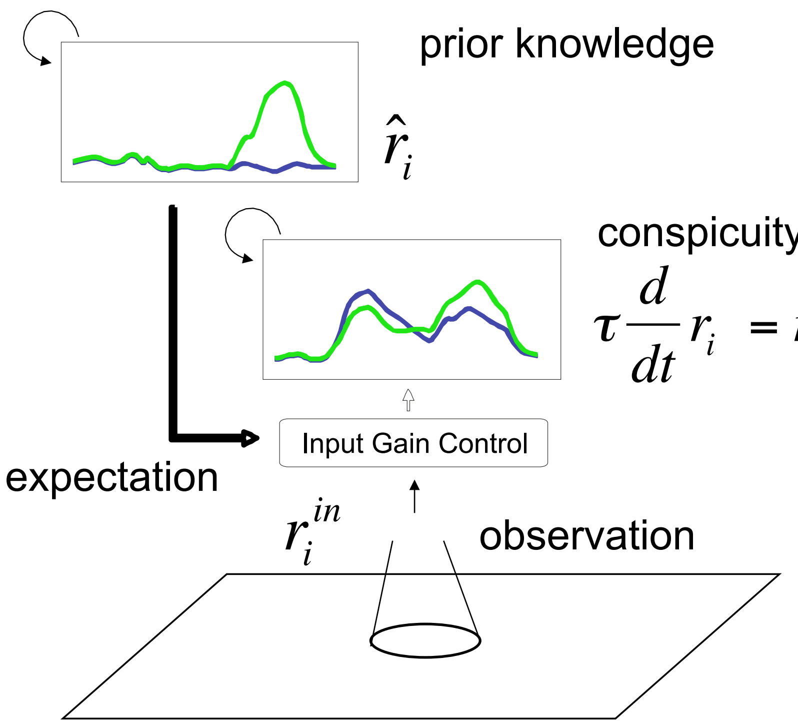


From: Spratling MW, Johnson MH. (2004)
A feedback model of visual attention.
J Cogn Neurosci. 16:219-37.

Early attentive effects not observed in the neural responses.

Population-based Inference



$$\hat{r}_i$$

$$\tau \frac{d}{dt} r_i = r_i^{in} \left(1 + w \cdot \hat{r}_i\right) - I^{inh}$$

$$r_i^{in}$$

Population-based Inference

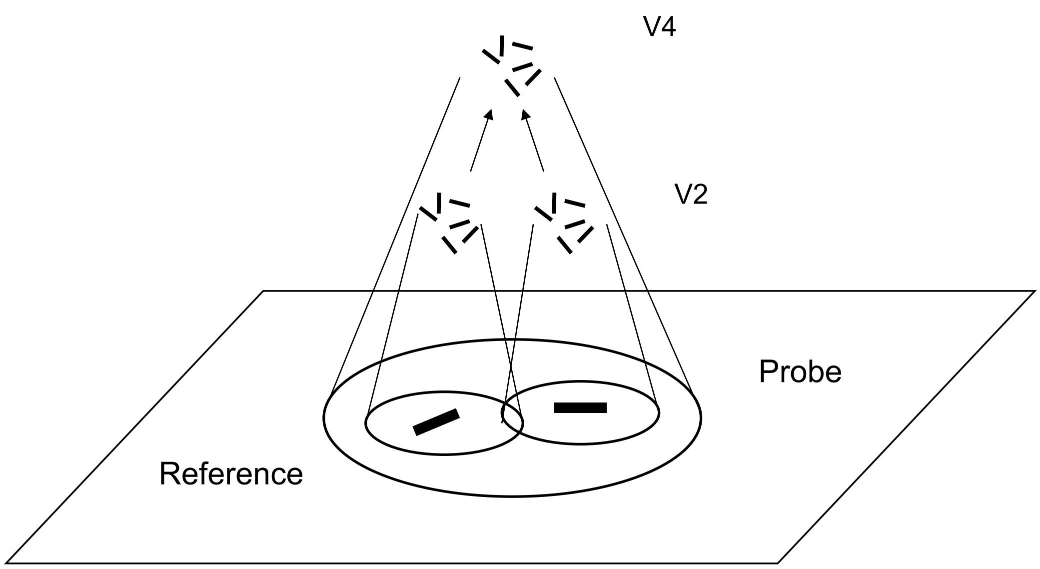
Neuronal dynamic of the inference mechanism:

$$\tau \frac{d}{dt} r_i = r_i^{\text{in}} \left(1 + w \cdot \hat{r}_i \right) - \left(a + r_i\right) w_{inh} \sum_j r_j$$

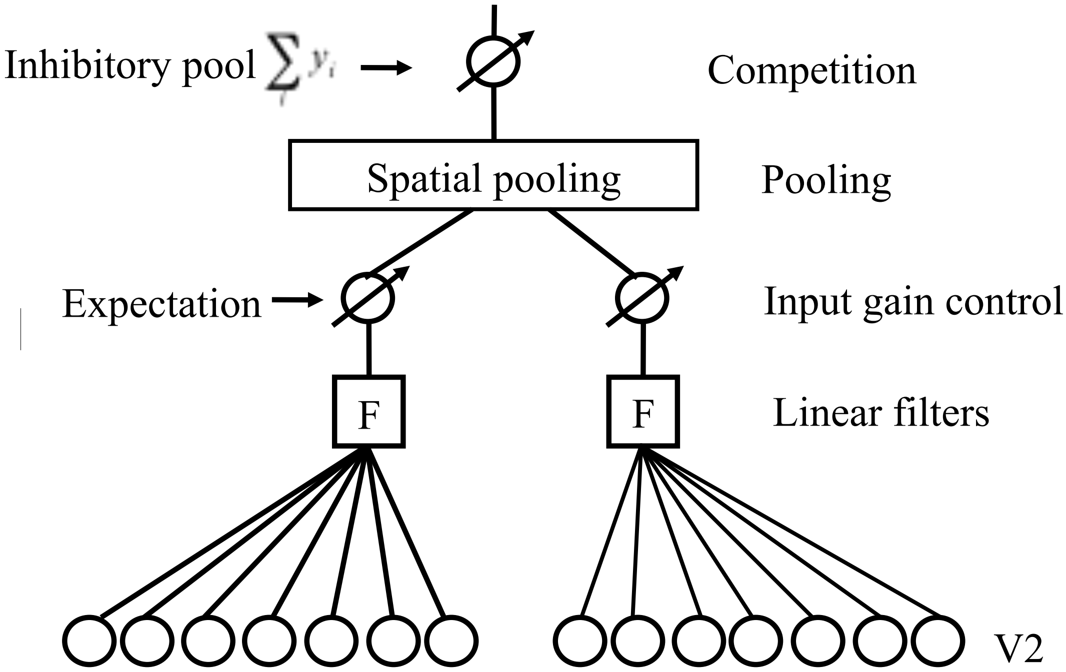
Feedback enhances the gain of feedforward signals.

Inhibition normalizes the activity and ensures that alternative interpretations are encoded sufficiently long such that they can be tested in parallel.

Interactions among populations within a RF



Elementary neural circuit



Elementary neural circuit

$$\tau \frac{\mathrm{d}}{\mathrm{d}t} y_k^{V4} = I_k^{\mathrm{F}} + I_k^{\mathrm{L}} + I_k^{\mathrm{A}} - I_k^{\mathrm{inh}}$$

$$I_k^{\mathrm{F}} = f(a_{i,x}^{\mathrm{F}}), \quad I_k^{\mathrm{L}} = f(a_{i,x}^{\mathrm{L}}), \quad I_k^{\mathrm{A}} = f(a_{i,x}^{\mathrm{A}}); \quad f = \max_{i,x} \vee f = \sum_{i,x}$$

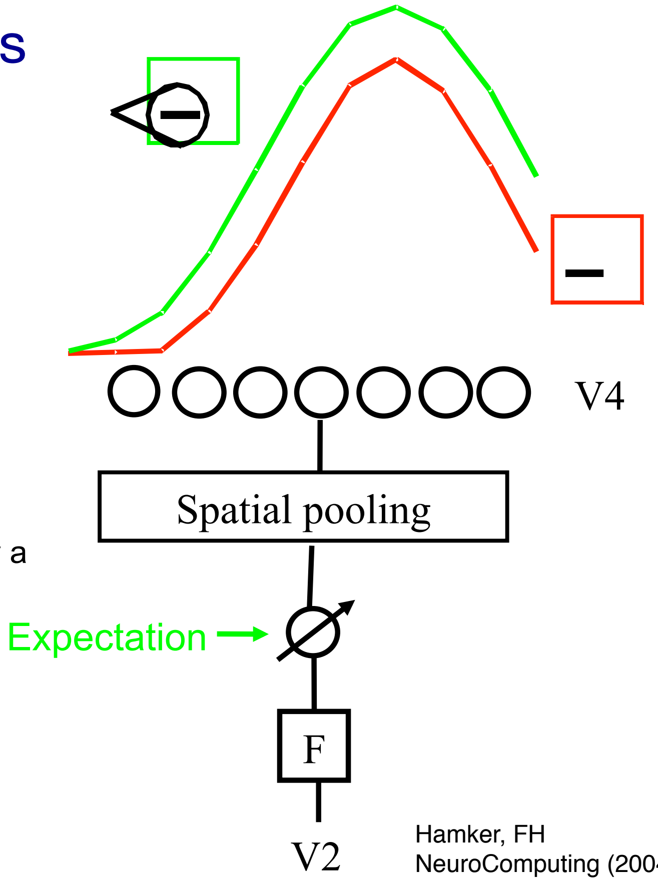
$$I_k^{\mathrm{inh}} = (w_{\mathrm{inh}} y_k^{V4} + w_{\mathrm{inh}}^{\mathrm{f}}) \sum y_j^{V4} + B y_k^{V4}$$

$$a_{i,x}^{\mathrm{F}} = w_{ik} y_{i,x}^{V2} + N,$$

$$a_{i,x}^{\mathrm{L}} = w_{ik} y_{i,x}^{V2} \cdot \sum_j w_{kj}^{\mathrm{L}} y_j^{V4} + N,$$

$$a_{i,x}^{\mathrm{A}} = w_{ik} y_{i,x}^{V2} \cdot A_x + N.$$

Gain Control - results

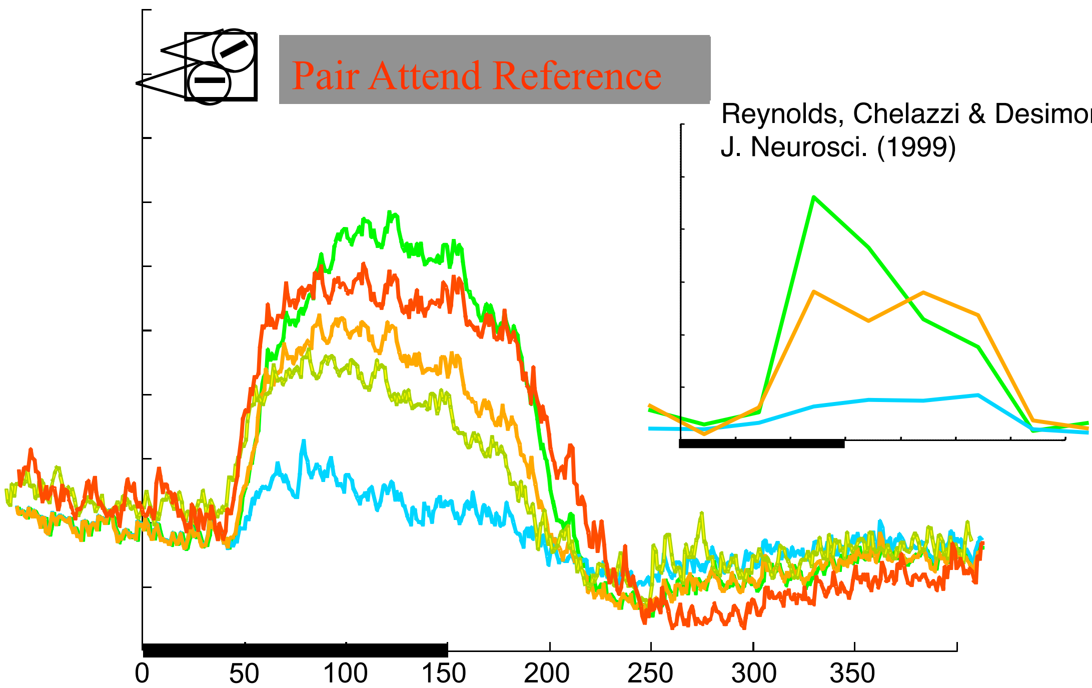


Hamker, FH
NeuroComputing (2004)

Model V4 shows a multiplicative enhancement, if the RF contains only a single stimulus.

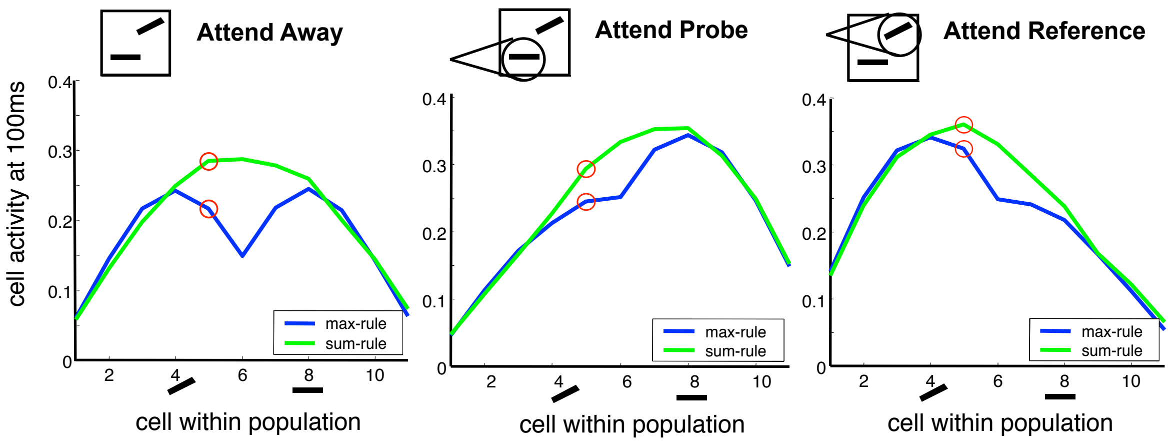
Consistent with:
McAdams & Maunsell (1999) in V4
Treue & Maunsell (1999) in MT/MST

Biased Competition - results



Reynolds, Chelazzi & Desimone
J. Neurosci. (1999)

Biased Competition - results



Hamker, F.H. (2004) Predictions of a model of spatial attention using sum- and max-pooling functions. Neurocomputing, 56:329-343.

Biased Competition - results

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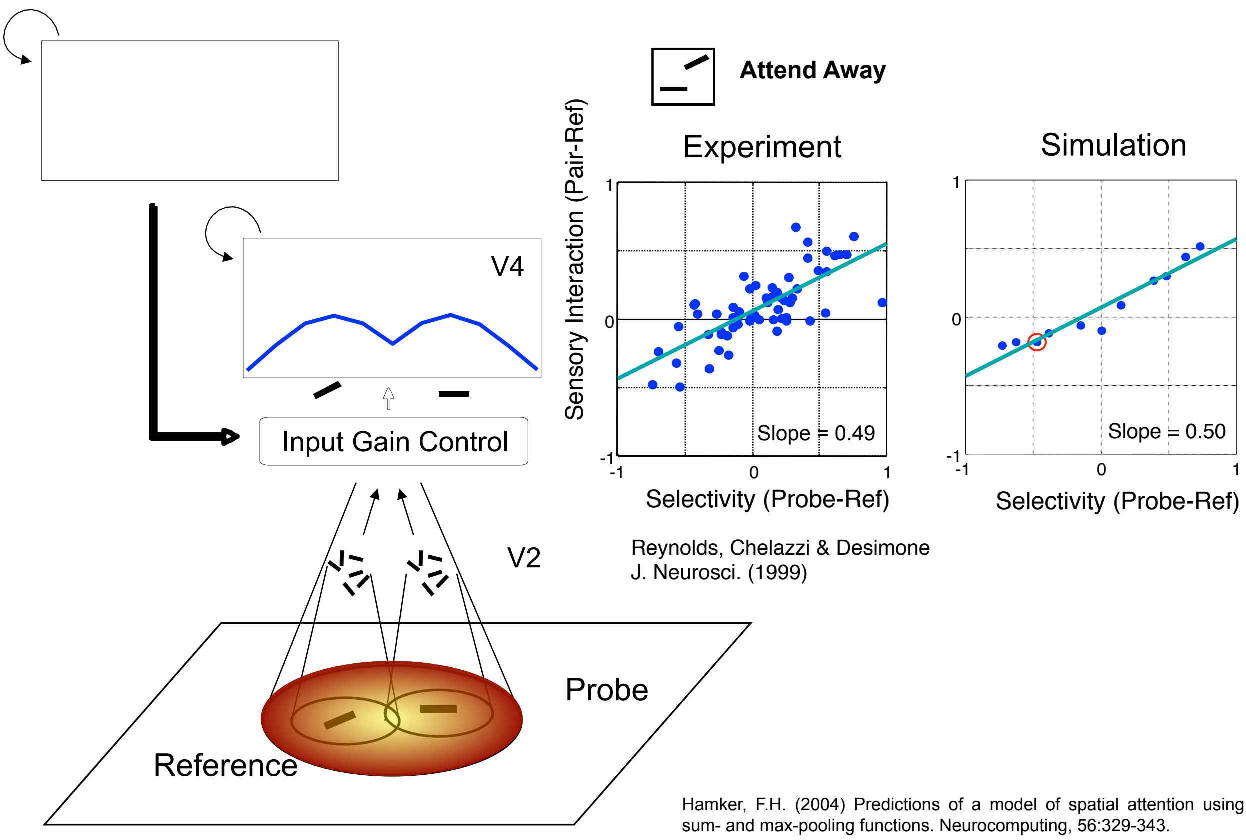

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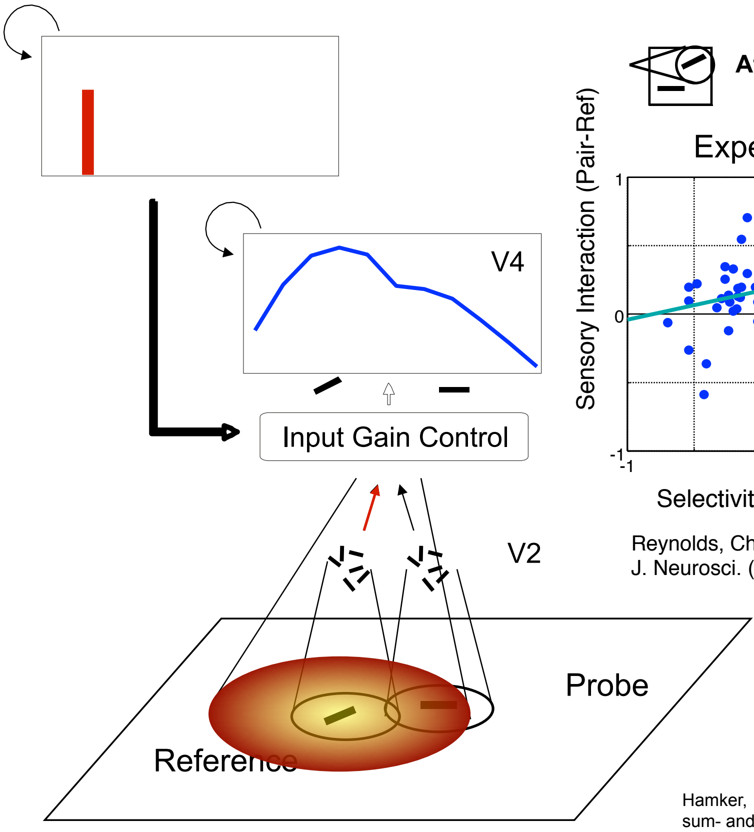

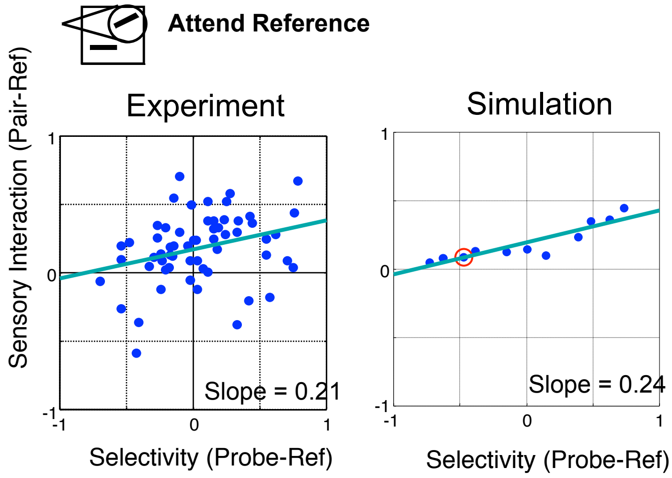

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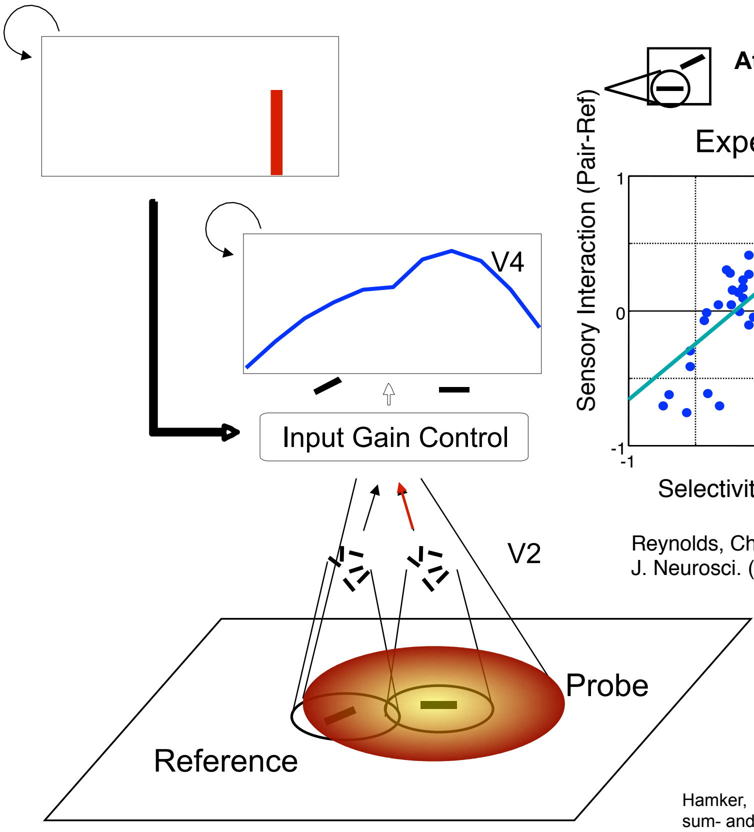

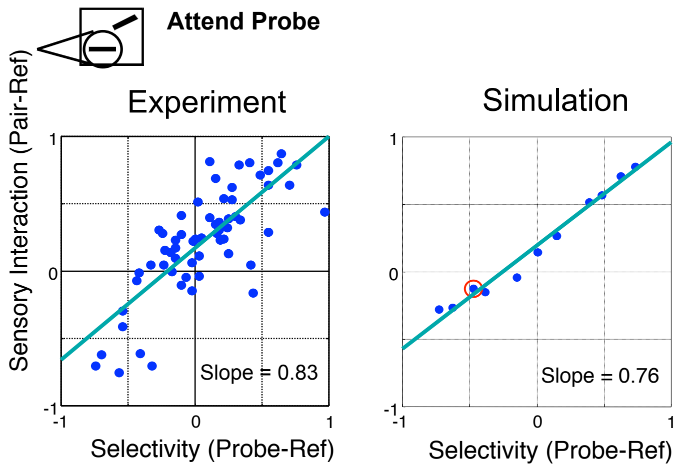

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J. Neurosci. (1999)

Hamker, F.H. (2004) Predictions of a model of spatial attention using sum- and max-pooling functions. Neurocomputing, 56:329-343.

Model revision

$$\tau \frac{\mathrm{d}}{\mathrm{d}t} y_k^{V4} = I_k^{\mathrm{F}} + I_k^{\mathrm{L}} + I_k^{\mathrm{A}} - I_k^{\mathrm{inh}}$$

Previous model of spatial attention:

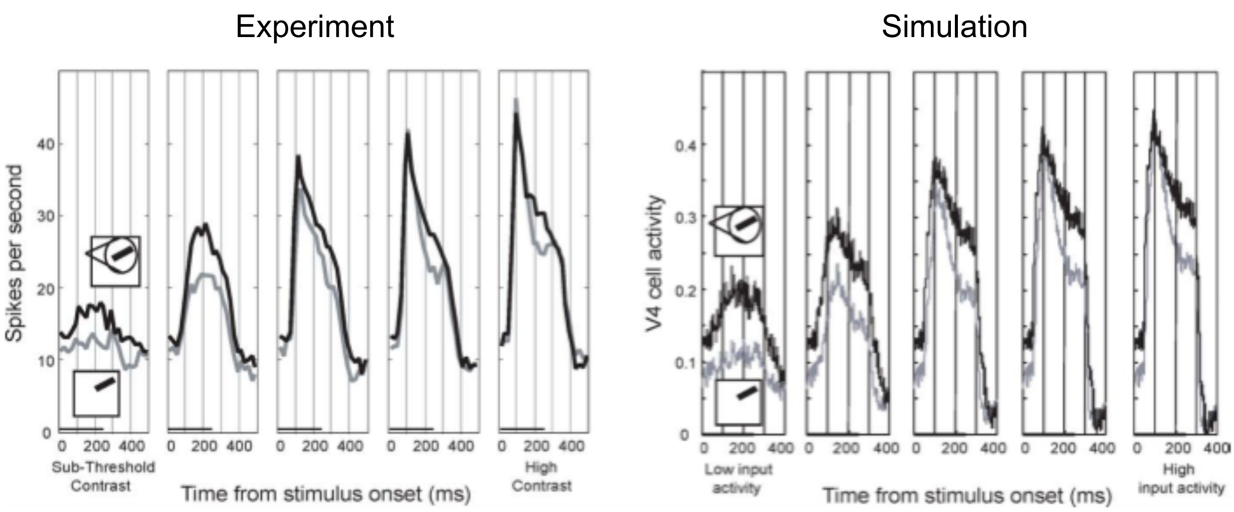
$$I_k^{\mathrm{A}} = f(a_{i,x}^{\mathrm{A}});$$

$$a_{i,x}^{\mathrm{A}} = w_{ik}\, y_{i,x}^{V2} \cdot A_x + N.$$

Revised model
of spatial attention:

$$A_{k,x} = \sigma(\alpha - r_k) \cdot A_x$$
$$\sigma(a) = max(a, 0)$$

Modeling contrast dependence of attention



References:

- Grossberg, S (1988) Nonlinear Neural Networks: Principles, Mechanisms, and Architectures. Neural Networks, 1:17-61.

Additional reading:

- Reynolds JH, Heeger DJ (2009) The normalization model of attention. Neuron 61: 168-185.