Decision-theoretic saliency: computational principles, biological plausibility and implications for neurophysiology and psychophysics

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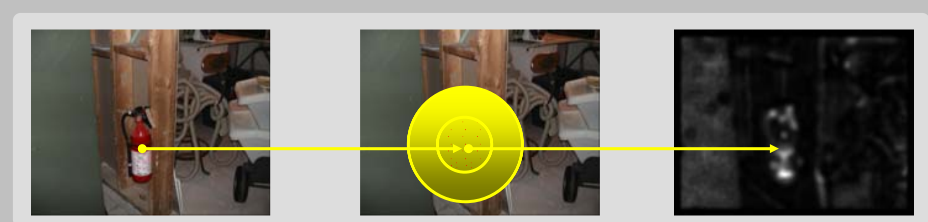
Discriminant Saliency

- Rooted on a *decision-theoretic interpretation of perception*
- *Saliency as a discriminant process*
  - it requires a null hypothesis of stimuli that are not salient
  - salient locations: can be classified from the null hypothesis with low probability of error
  - this has been applied for top-down saliency detection *(Gao & Vasconcelos, NIPS 2004)*

Bottom-up Discriminant Saliency

- *Center-surround saliency*
  how distinct an image location is from its surround



- *Infomax saliency measure*

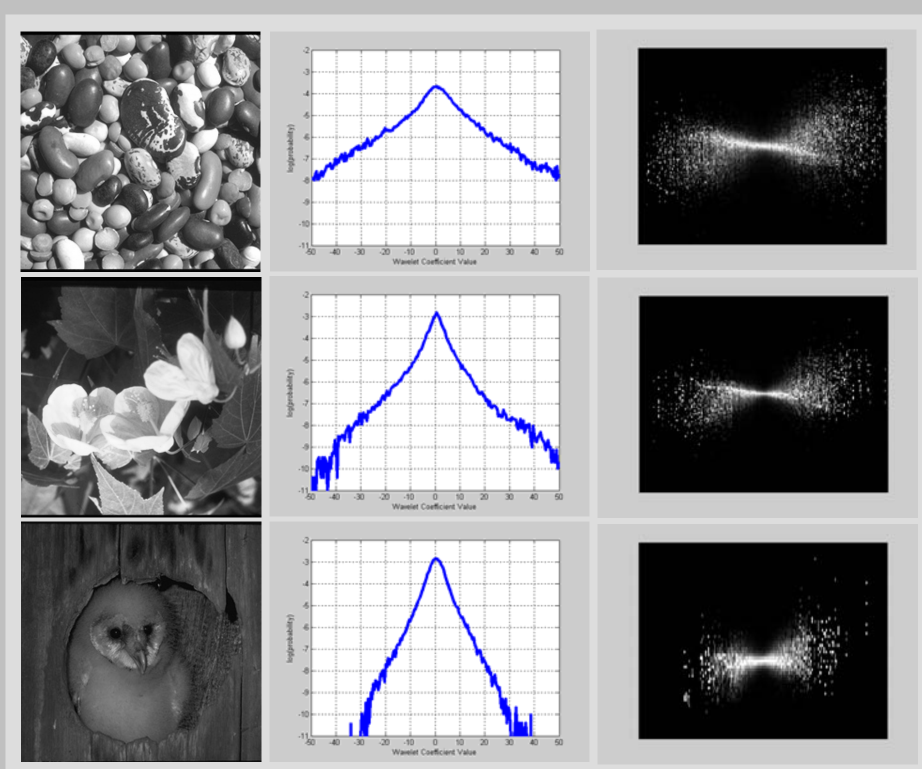
$$S_{(i,j)}(\mathbf{X};Y) = I_{(i,j)}(\mathbf{X};Y) = \sum_i \int_{\mathbf{x}} P_{\mathbf{X},Y}(\mathbf{x},y) \log \frac{P_{\mathbf{X},Y}(\mathbf{x},y)}{P_{\mathbf{X}}(\mathbf{x})P_Y(y)} dx$$

X: features, Y: {center, surround}

Computational Parsimony and Image Statistics

- Biological visual systems exploit the regularities of the natural stimuli to achieve computational parsimony (Attneave, 1954; Barlow, 1961, 2001; etc.)
  - ➢ Constancy of feature dependence (Buccigrossi & Simoncelli,1999; Huang & Mumford, 1999)

- bow-tie joint distribution
- although fine details may vary from scene to scene, coarse structure follows a universal law for all natural scenes



Left: three images. Center: each plot presents the histogram of the same coefficient from a wavelet decomposition of the image on the left. Right: conditional histogram of the same coefficient, conditioned on the value of its parent. Note the constancy of the shape of both the marginal and conditional distributions across image classes.

Approximation of mutual information by the sum of marginal mutual information

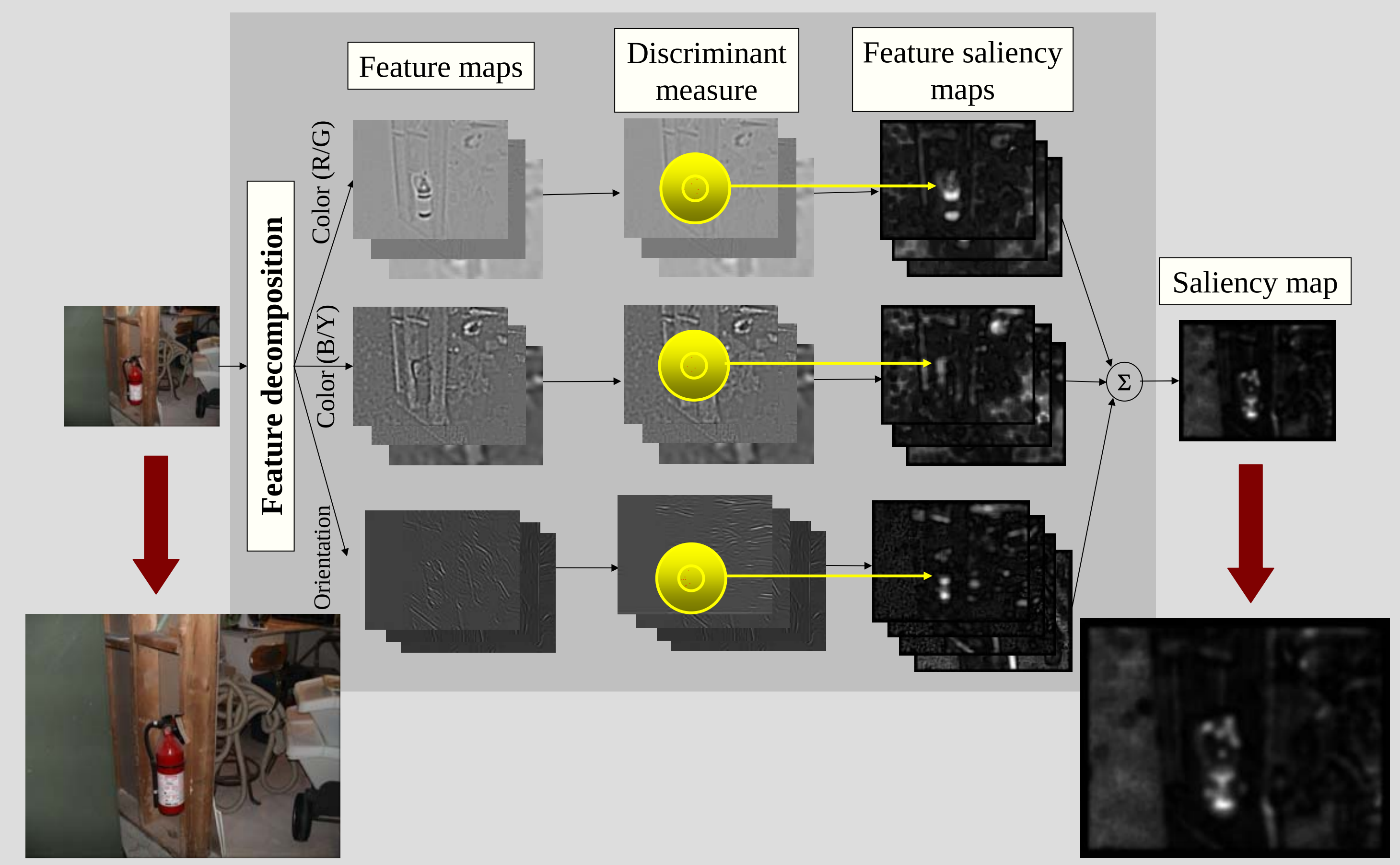
$$I_{(i,j)}(\mathbf{X},Y) = \sum_{k=1}^{n} I_{(i,j)}(X_k;Y)$$

$$I(\mathbf{X}_{1,n};Y) = \sum_{i=1}^{n} I(X_i;Y) - \sum_{i=2}^{n}[I(X_i;\mathbf{X}_{1,i-1}) - I(X_i;\mathbf{X}_{1,i-1}|Y)]$$ (Vasconcelos, 2004)

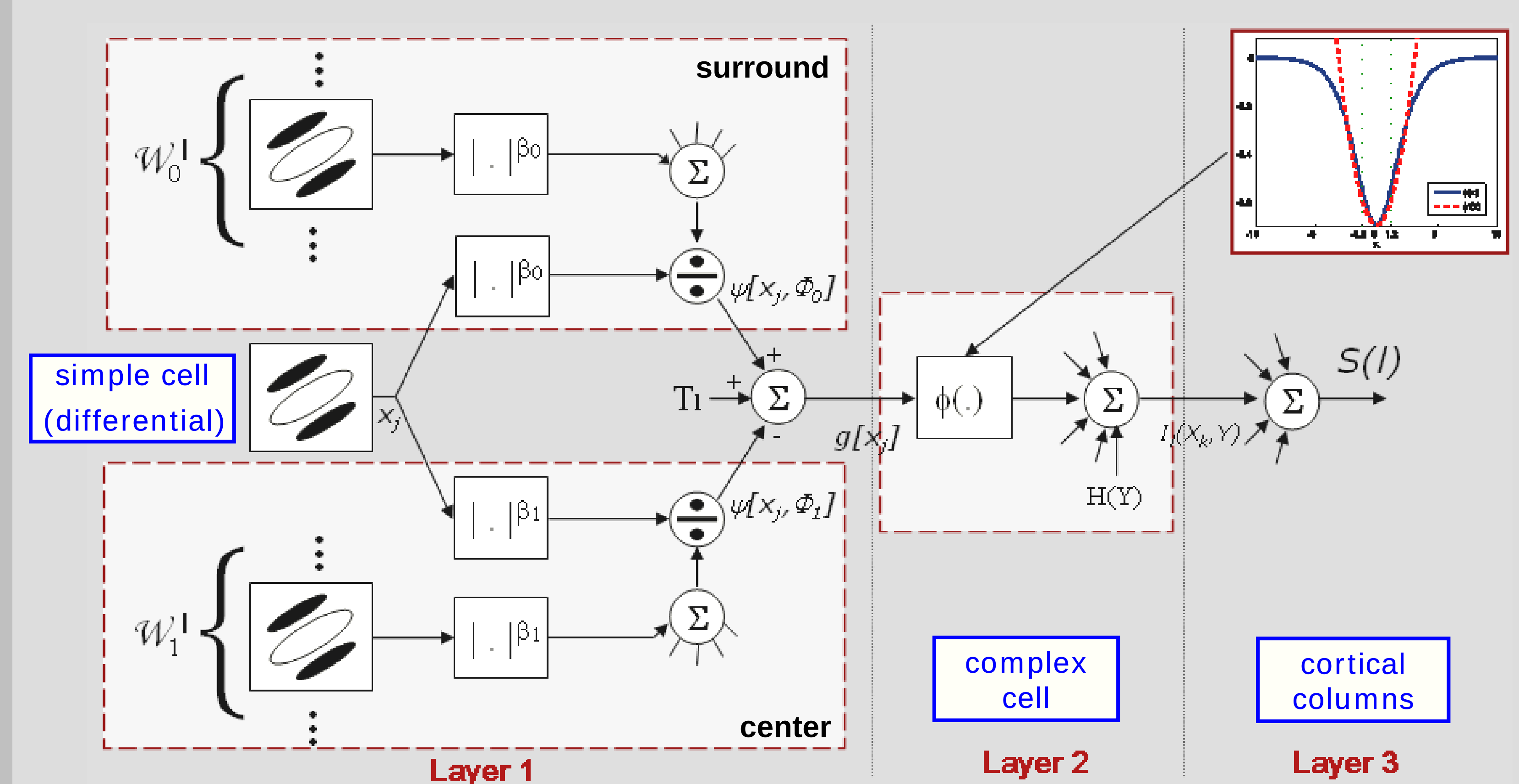
$$\mathbf{X}_{1,i} = \{X_1,\ldots,X_i\}$$

$$\frac{\sum_{i=2}^{d}\left[I_l(X_i;\mathbf{X}_{1,i-1}) - I_l(X_i;\mathbf{X}_{1,i-1}|Y)\right]}{\sum_{i=1}^{d} I_l(X_i;Y)} \approx 0$$

Bottom-up Discriminant Saliency Model



Biologically Plausible Implementation



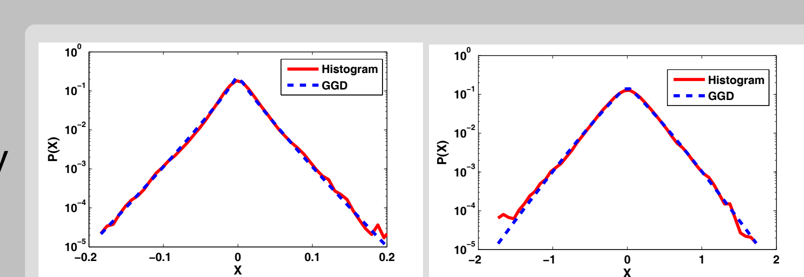
➢ Generalized Gaussian Density (GGD)

- the marginal distributions of natural image features follow a generalized Gaussian density

$$p(x;\alpha,\beta) = \frac{\beta}{2\alpha\Gamma(1/\beta)} \exp\left(-(|x|/\alpha)^{\beta}\right)$$

α a *scale* parameter, β a *shape* parameter

For β =1, a Laplace distribution, and a Gaussian when β =2

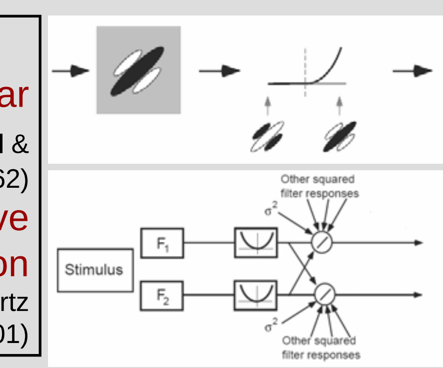


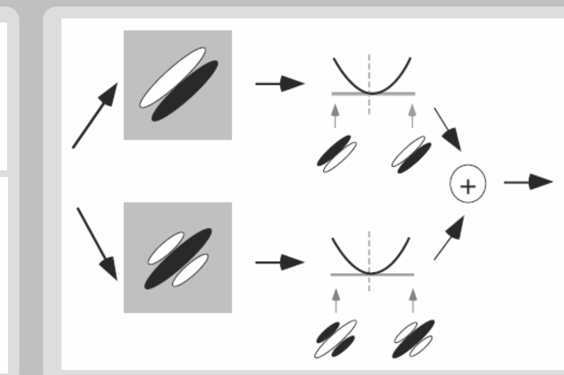
Examples of GGD fit for responses of two Gabor filters

Plausibility in Neurophysiology

- Compatible with standard models of V1 cells
  Standard V1 model: a cascades of linear filter, divisive normalization, a quadratic nonlinearity, and spatial pooling (Carandini et al., 2005)

Simple cell classical linear model (Hubel & Wiesel, 1962) divisive normalization (Heeger, 1992; schwartz et al., 2001)

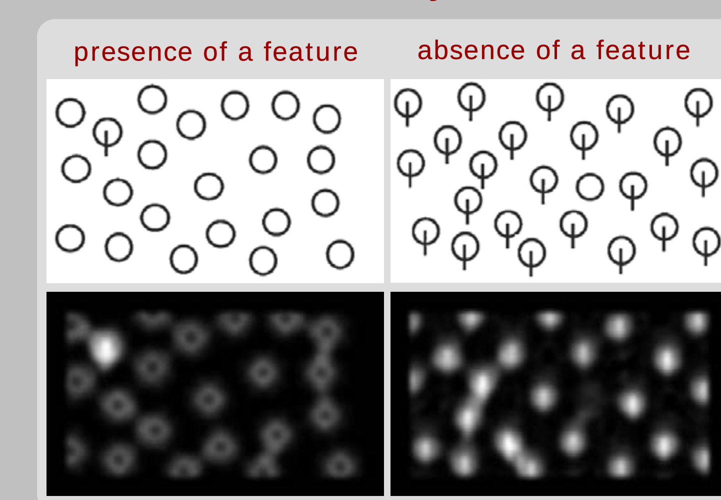


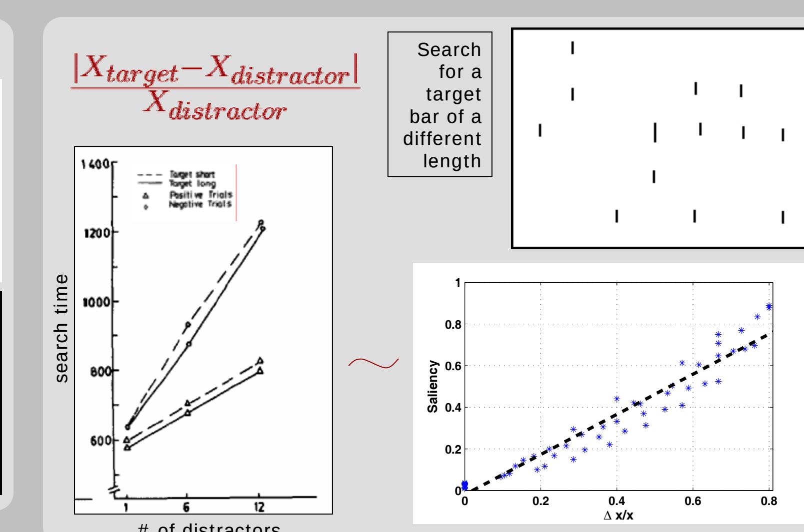


Complex cell energy model (Adelson & Berson, 1985)

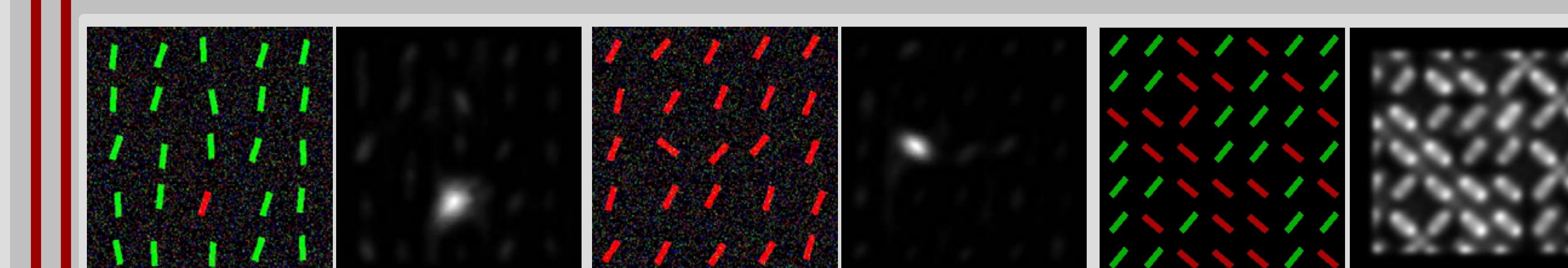
Consistency with Psychophysics

- Visual search asymmetries and the Weber's law (Treisman & Gormican, 1988)





- Conjunction search and Feature Integration Theory (Treisman & Gelade, 1980)
  What the image statistics suggests (approximation of MI) is consistent with FIT



Implications

- Connects a number of "disjoint" observations from neurophysiology and psychophysics
  - divisive normalization and saliency asymmetries
- A (unified) holistic functional justification for V1
  - V1 has the capability to optimally detects salient locations in the visual field in a decision-theoretic sense under certain approximations for the sake of computational parsimony
- Statistical inference in V1
  - probability inference, decision rule, and feature selection

cell type	function	description
simple	$-\log P_{X\|Y}[x\|c]$	negative log-likelihood
simple, differential	$\log \frac{P_{X\|Y}[x\|1]}{P_{X\|Y}[x\|0]}$	log likelihood ratio
complex	$I(X;Y)$	mutual information

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