A computational feature binding model

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Binding Problem

Overview

Information processing in the human brain is highly parallel. This means that different features of an object are processed in different parts of the brain.

Figure: Brain

Binding Problem

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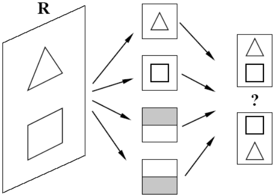


Figure: Binding Problem Illustration [Rosenblatt, 62]

Binding Problem

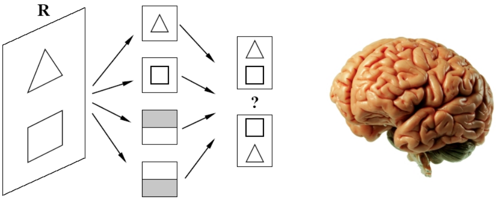


Figure: Binding Problem Illustration [Rosenblatt, 62]

Question?

How features that are processed in parallel are bound to the one unique percept?

The competitive layer model

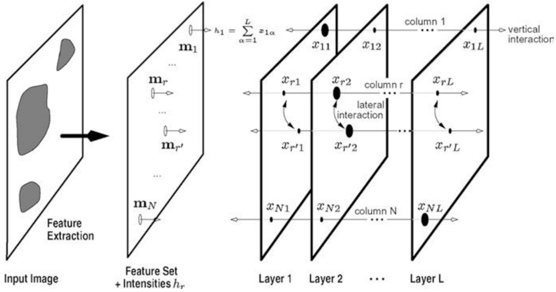
Principles

1. Finite set of features: Representation of the structure of the sensory input.
2. Measure of the mutual compatibility: Gestalt Laws.

Objective

To use these compatibilities to partition the input features into salient groups by the recurrent dynamics in a layered neural network with topographically structured competitive and cooperative interactions.

The competitive layer model



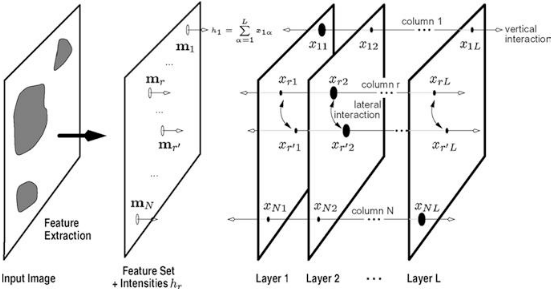
Architecture

Image positions: $r = (x, y) \in I$

Stimulus: m_r - spatial, texture or edge information.

Significance of the detection feature: h_r

The competitive layer model



Architecture

Number of Layers: L

Number of formal neurons with nonnegative activity $x_{r\alpha} \geq 0$: N

Superposition condition: $\Sigma_{\alpha=1}^{L} x_{r\alpha} \approx h_r$

The competitive layer model

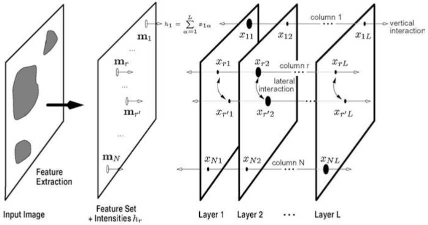
Energy function

$$E = \frac{J}{2}\Sigma_r(\Sigma_\beta x_{r\beta} - h_r)^2 + \frac{1}{2}\Sigma_\alpha \Sigma_{rr'} f_{rr'} x_{r\alpha} x_{r'\alpha}$$

Interaction function

$$\dot{x_{r\alpha}} = -x_{r\alpha} + \sigma(J(h_r - \Sigma_\beta x_{r\beta}) + \Sigma_{r'} f_{rr'} x_{r'\alpha})$$

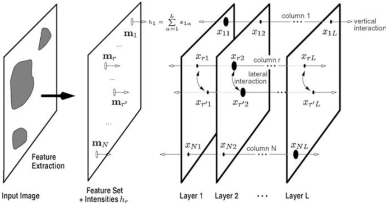
where $\sigma(x) = max(x, 0)$ and $f(m_r, m_{r'} = f_{rr'})$



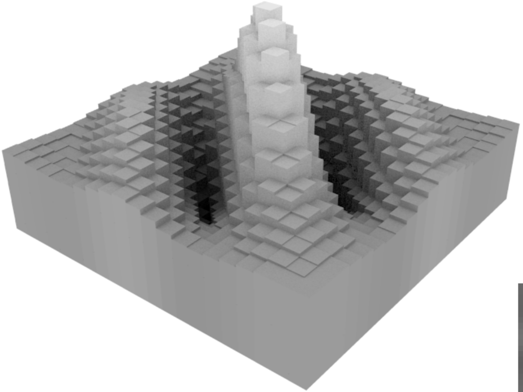
The competitive layer model

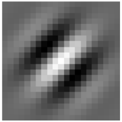
Image Segmentation

1. Initialize all $x_{r\alpha}$ with small random values $x_{r\alpha}(t=0) \in [h_r/L - \epsilon, h_r/L + \epsilon]$
2. Do NL times: choose (r, α) randomly and update $x_{r\alpha} = max(0, \xi)$, where $\xi = \frac{J(h_r - \Sigma_{\beta \neq \alpha} x_{r\beta}(t)) + \Sigma_{r' \neq r} f_{rr'} x_{r'\alpha}(t))}{J - f_{rr'}}$
3. Go to step 2 until convergence



Multiscale Filtering





Multiscale Filtering

2D Gabor Filters

$$g(x,y) = e^{\left(\frac{(x-x_0)^2}{2\sigma_x^2}+\frac{(y-y_0)^2}{2\sigma_y^2}\right)} e^{-ik(x-x_0)}$$

2D Gabor Filters

Center of the receptive field: (x_0, y_0)
Widths of the Gaussian envelope along the x- and y-axes: σ_x and σ_y
Spatial frequency of a complex plane wave with wave normal along the x-axis and wavelength λ: $k = 2\pi/\lambda$

Multiscale Filtering

2D Gabor Filters

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Gabor Wavelets

$g_{mn} = g(x', y')$
$x' = a^{-m}(x \cos \Theta_n + y \sin \Theta_n)$ and
$y' = a^{-m}(-x \sin \Theta_n + y \cos \Theta_n)$

Gabor Wavelets

A sparse sampling of the phase space (which is spanned by m, n, x_0 and y_0) is sufficient for a complete representation of arbitrary image data.

Multiscale Filtering

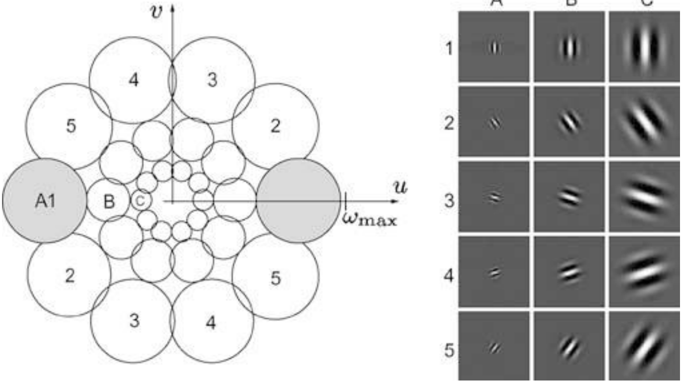


Figure: Set of 2D Gabor Filters for Feature Extraction

Multiscale Filtering

Algorithm

1. Compute a set of 2D Gabor filters tuned to five different orientations and three scales.
2. For each element of the filter bank, compute its response image, or channel, c_{mn} to the given input.
3. Apply the nonlinear contrast transfer function to each channel c_{mn}, yielding c_{mn}^{CTF}.
4. Compute the texture features μ_{mn} and σ_{mn} for each of the 15 channels according to steps (3) and (4).

$$\mu_{mn} = c_{mn}^{CTF} * gs_{mn}(x, y)$$

$$\sigma_{mn} = \sqrt{(c_{mn}^{CTF} - \mu_{mn})^2 * gs_{mn}(x, y)}$$

1. Introduction
2. The competitive layer model
3. Feature Extraction
4. **The CLM texture segmentation model**
5. Results
6. Conclusions

The CLM texture segmentation model

Multi-dimensional scaling

Feature space: 30-dimensional hyperellipsoid t_r
Principal component analysis: 4-dimensional p_r

Feature subsampling

Image 256 x 256 pixels: 65536 features
1024 8 x 8 regions: 1024 4D feature vectors p_r
Nearest neighbour: $|p_r - p_{near}| + |r - r_{near}| = min.$

The CLM texture segmentation model

Interaction matrix

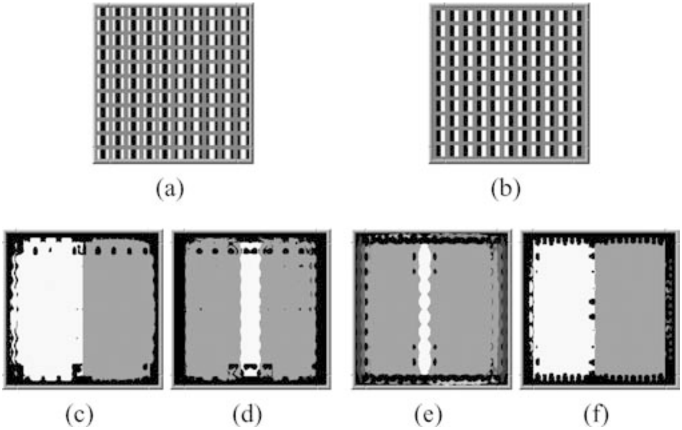
$$f_{rr'} = e^{-\frac{d_{text}(r,r')^2}{R_{sim}^2}} + ce^{-\frac{|x_r - x_{r'}|^2}{R_{prox}^2}} - k$$

$$d_{text}(r,r') = \sqrt[n]{\Sigma_{i=1}^{4}\left(\frac{|p_r^i - p_{r'}^i|}{\sqrt{\sigma(p^i)}}\right)^n}$$

CLM's output

$x_{r\alpha} = h_r + \frac{1}{J_1}\Sigma_{r'} f_{rr'} x_{r'\alpha}$ or $x_{r\alpha} = 0$
Threshold: $1/2h_r$

Artificial Textures



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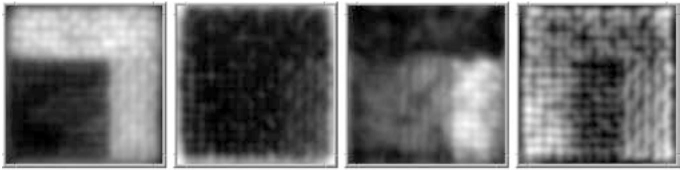
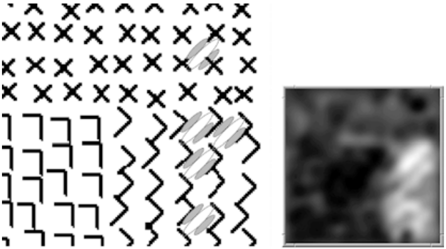


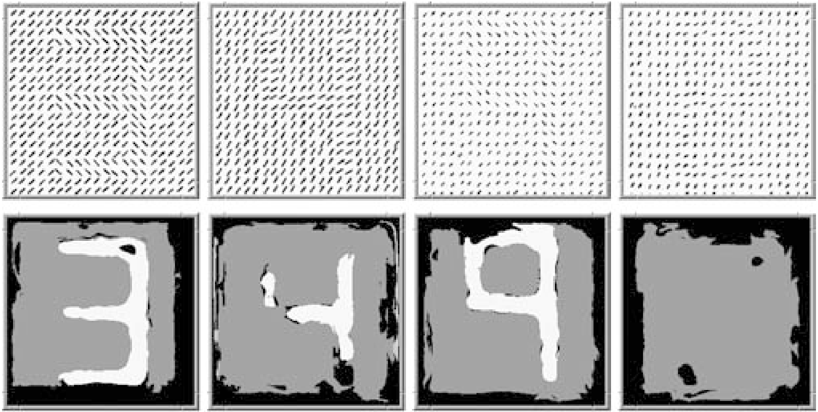
(a) 1st (b) 2nd (c) 3rd (d) 4th

Artificial Textures



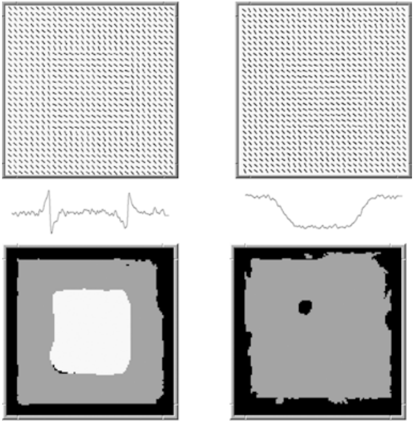
(a) (b)

Edge- and region-based phenomena



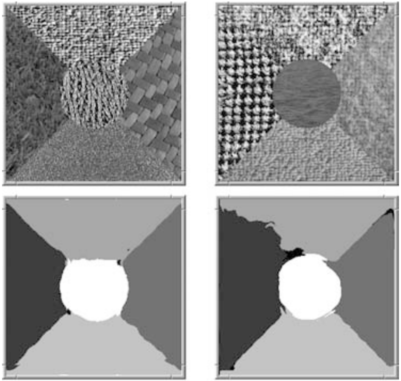
(a) (b) (c) (d)

Edge- and region-based phenomena



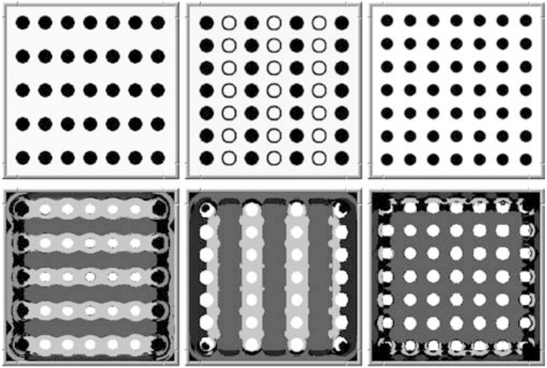
(a) (b)

Natural textures



(a) (b)

Gestalt laws



(a) (b) (c)

Conclusions

1. A feature extraction algorithm was developed to produce meaningful texture descriptor.
2. CLM Model reproduces edge-based as well as region-based phenomena.
3. The incorporation of Gestalt laws offers an interesting perspective to describe saliency groups.
4. Parameters tuning process was not necessary.
5. Model can mimic a large variety of human perception phenomena.

References

1. Jorg Ontrup and Heiko Wersing and Helge J. Ritter. A computational feature binding model of human texture perception. Cognitive Processing. pp. 31-44. 2004.