Computational Vision

Primary visual cortex

- Orientation selectivity
- Spatial frequency
- Normalization
- Color opponency



Frequency channels

Low spatial frequency







Hybrid Images



Aude Oliva (MIT)

Image pyramids vs. frequency channels



brains

computers



Fig. 2a. The Gaussian pyramid. The original image, G_0 is repeatedly filtered and subsampled to generate the sequence of reduced resolution image G_1 , G_2 , etc. These comprise a set of lowpass-filtered copies of the original image in which the bandwidth decreases in one-octave steps.

Image pyramids vs. frequency channels













Theories of object recognition



source: Peter Schiller



Coarse-to-fine processing

% correct 80 70 60 50 40 30 30ms 20 10 0 Match Match **High SF** Low SF 40ms The second image can be: New image Match to Low SF (city) Match to High SF (highway) **Same or different ?** time

Duration: 30 ms

Schyns & Oliva '94

Coarse-to-fine processing

% correct 80 70 60 50 40 30 120ms 20 10 0 Match Match Low SF **High SF** 40ms The second image can be: New image Match to Low SF (city) Match to High SF (highway) **Same or different ?** time

Duration: 120 ms

Schyns & Oliva '94

Application to machine vision

e.g, multi-scale object detection







Application to machine vision

e.g, coarse-to-fine object strategies



speed-up: over 300 times



Heisele Serre & Poggio '01

see also Fleuret & Geman '01

Application to machine vision

e.g, coarse-to-fine object strategies



Heisele Serre & Poggio '01

Frequency channels

Low spatial frequency







Freeman et al 2012

Spatial acuity and eccentricity

Low spatial acuity



Spatial acuity and eccentricity



Perceptual crowding



Pelli & Tillman 2008

Spatial resolution and acuity



Renoir's Madame Henriot (1876)

Degas' Woman ironing (1869)





Ingres' Mrs Charles Badham (1816)

Spatial resolution and acuity





Subtle expression Leonardo da Vinci's Mona Lisa



Low

Spatial frequency



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On the need for normalization circuits

$$y(x) = \sum w_i x_i$$

= $\mathbf{w} \cdot \mathbf{x}$
= $||\mathbf{w}|| ||\mathbf{x}|| \cos(\theta)$

$$y(x) = \sum w_i x_i$$
$$= \frac{\mathbf{w} \cdot \mathbf{x}}{||\mathbf{w}||||\mathbf{x}||}$$
$$= \cos(\theta)$$



Gain-control circuits in the (turtle) retina



$$y(\mathbf{x}) = \frac{\mathbf{w}^* \cdot \mathbf{x}}{||\mathbf{x}|| + c}$$

B Normalization model

$$y(\alpha \mathbf{x}) = \frac{\mathbf{w}^* \cdot \alpha \mathbf{x}}{||\alpha \mathbf{x}|| + c}$$
$$= \frac{\alpha \mathbf{w}^* \cdot \mathbf{x}}{\alpha(||\mathbf{x}|| + c/\alpha)}$$



Carandini Heeger & Movshon '96





Figure 1. Tuning Curves and Population Responses to Single Orientation Stimuli

(A) Orientation tuning curves of all responsive sites (66 of 96), sorted according to preferred orientation. Each tuning curve is normalized by its mean across orientations.

(B) Population response to a 45° stimulus: responses of all sites (dots) as a function of preferred orientation of each site.

(C) The population response in (B) after binning sites with similar orientation preference (bin width: 15°). The curve is the best fitting circular Gaussian. Error bars indicate ± 1 SE of responses across sites in each bin.

(D) Population response to a 0° stimulus for three contrasts: 12%, 50%, and 100%. The abscissa indicates preferred orientation relative to stimulus orientation. Data for stimuli of multiple orientations (0°, 30°, and 60°) are combined to obtain each population response. Error bars indicate ± 1 SE of responses across sites in each bin. The curves fitting the data are circular Gaussians differing only in amplitude.

(E) Amplitude of the population responses as a function of stimulus contrast. The curve is the best-fitting hyperbolic ratio function ($c_{50} = 42.1\%$, n = 1.0). All fits are given by Equation (1). Experiment 84-12-16.





Busse et al 2008

Gain control circuits in computer vision!

What is the Best Multi-Stage Architecture for Object Recognition?

Kevin Jarrett, Koray Kavukcuoglu, Marc'Aurelio Ranzato and Yann LeCun The Courant Institute of Mathematical Sciences New York University, 715 Broadway, New York, NY 10003, USA koray@cs.nyu.edu

• Normalization appears to be the most important component of a good computer vision system (over learning algorithms, architecture, etc)