UNIVERSITY OF CAMBRIDGE
COMPUTER LABORATORY

RAINBOW GRAPHICS GROUP

Advanced Graphics and Image Processing

Models of early visual perception

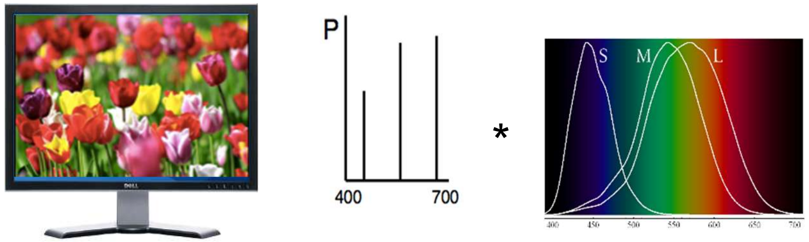
Part 1/6 – perceived brightness of light

Rafal Mantiuk
Computer Laboratory, University of Cambridge

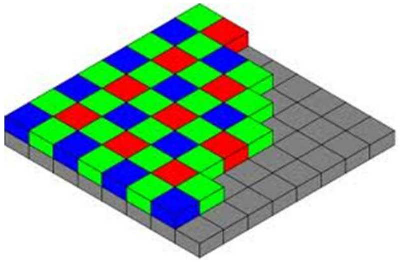
Many graphics/display solutions are motivated by visual perception

H.264
MPEG-4/AVC

Image & video compression

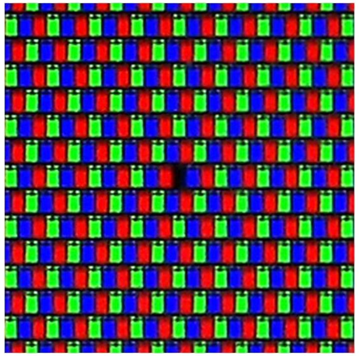


Display spectral emission - metamerism

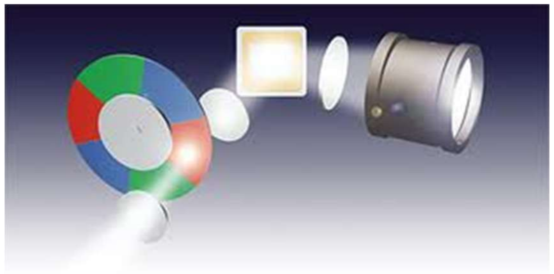


Camera's Bayer pattern

Halftonning



Display's subpixels



Color wheel in DLPs

■ ■ ■

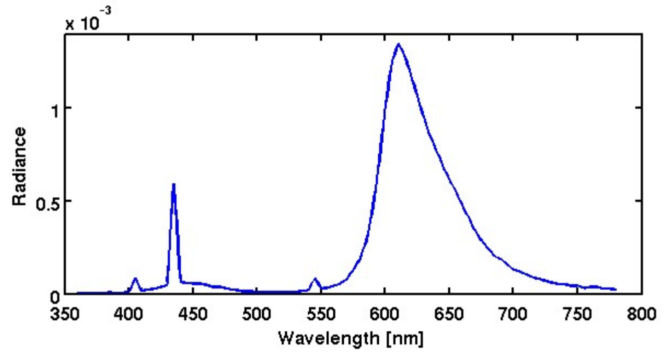
Luminance (again)

- Luminance – measure of light weighted by the response of the achromatic mechanism. Units: cd/m^2

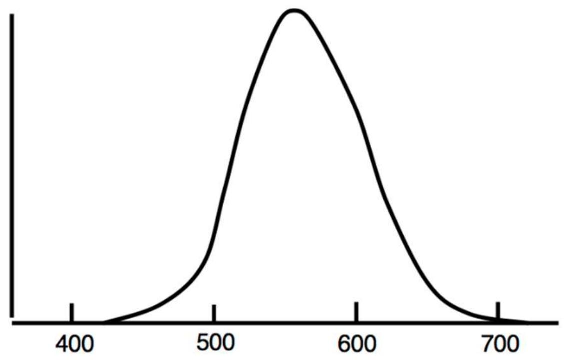
Luminance

$$L_V = \int_{350}^{700} kL(\lambda)V(\lambda)d\lambda \qquad k = 683.002$$

Light spectrum (radiance)



Luminous efficiency function (weighting)



Steven's power law for brightness

- Stevens (1906-1973) measured the perceived magnitude of physical stimuli
  - Loudness of sound, tastes, smell, warmth, electric shock and brightness
  - Using the magnitude estimation methods
    - Ask to rate loudness on a scale with a known reference
- All measured stimuli followed the power law:

$$\varphi(I) = kI^{a}$$

Perceived magnitude: $\varphi(I)$

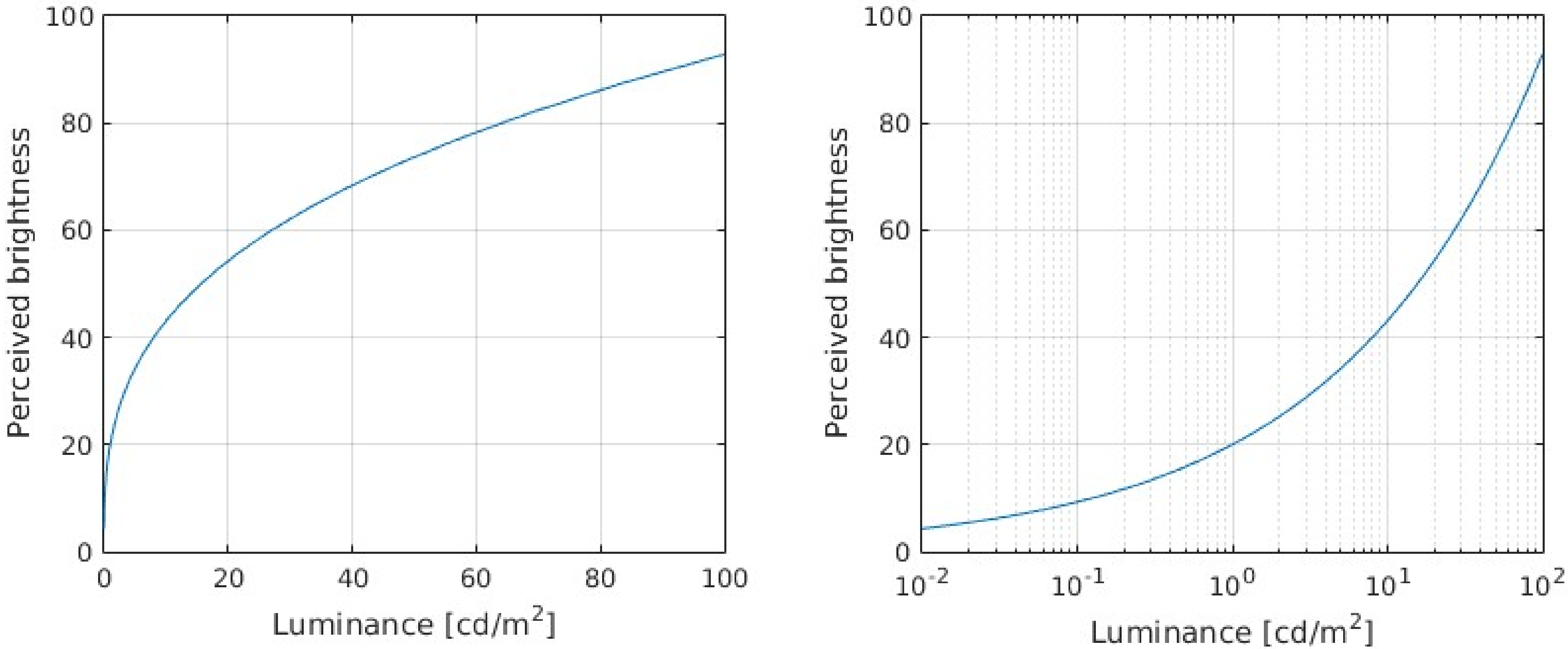
Constant: k

Physical stimulus: I

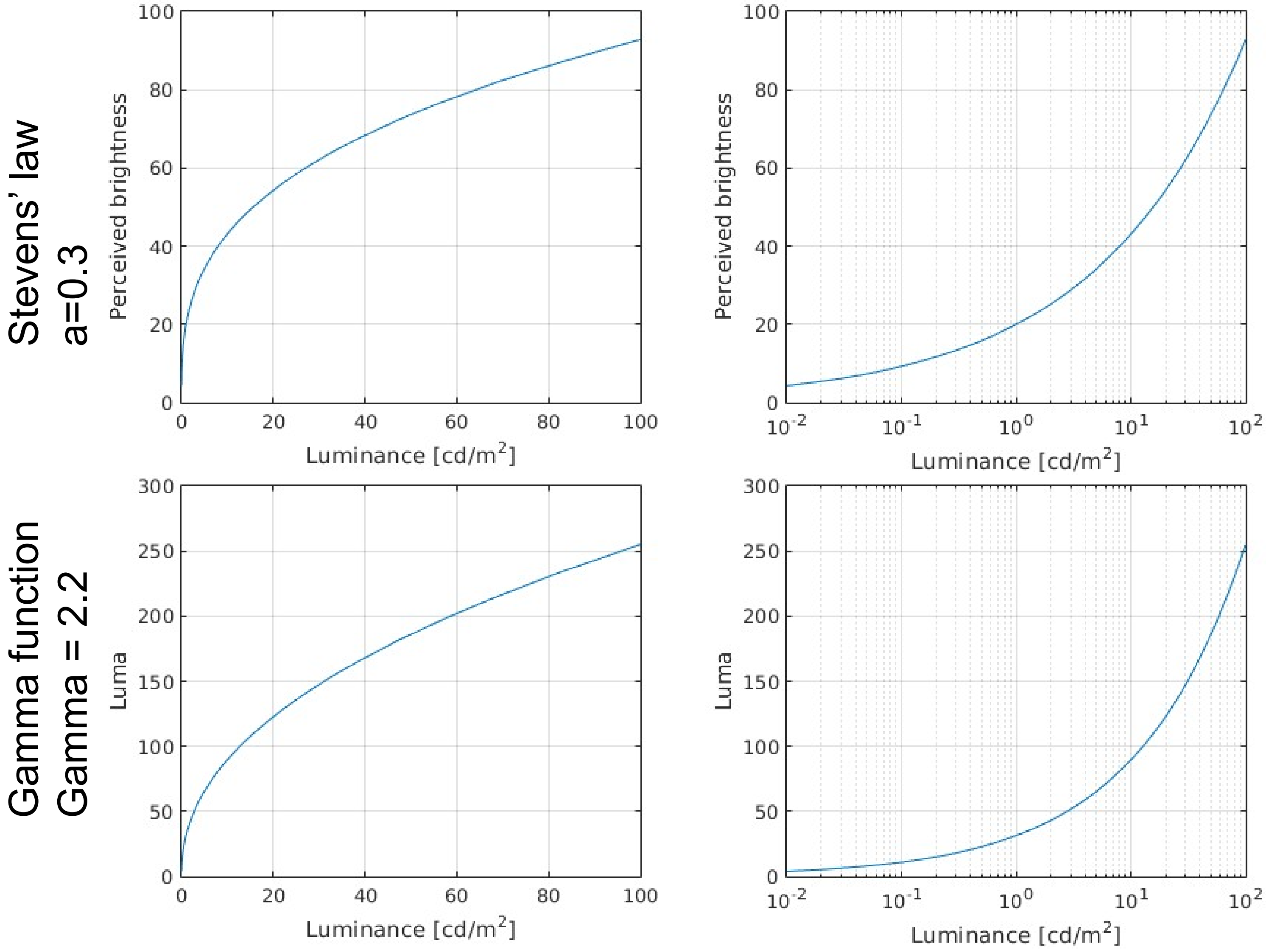
Exponent: a

- For brightness (5 deg target in dark), a = 0.3

Steven's law for brightness



Steven's law vs. Gamma correction



Advanced Graphics and Image Processing

Models of early visual perception

Part 2/6 – contrast detection

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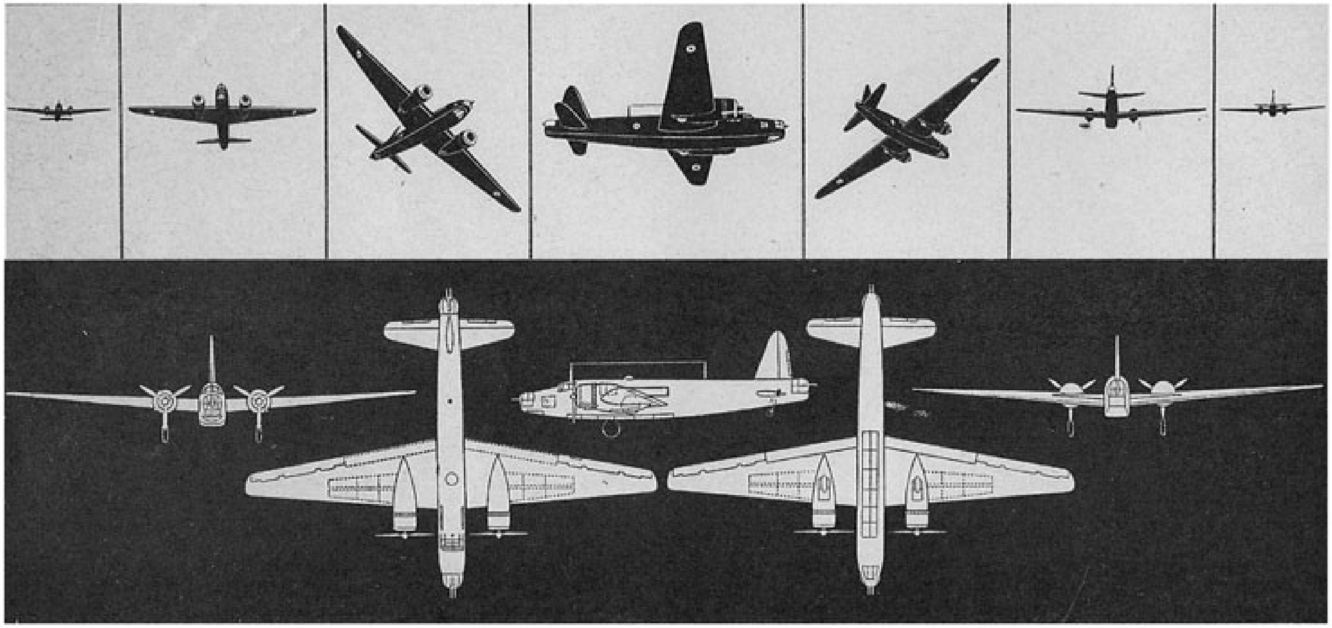
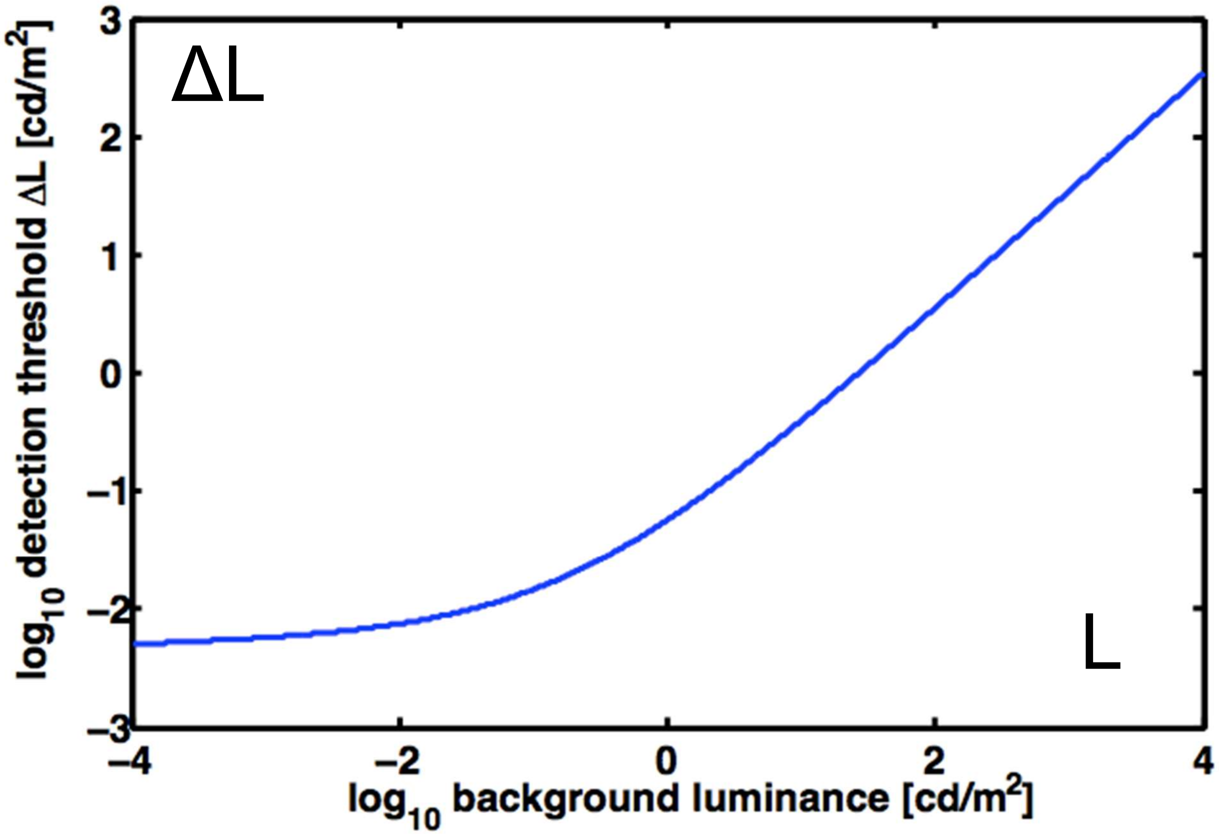
Detection thresholds

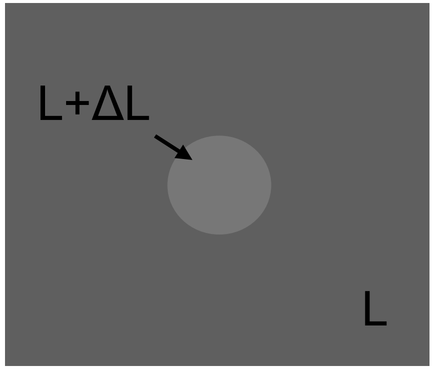


- The smallest detectable difference between
  - the luminance of the object and
  - the luminance of the background

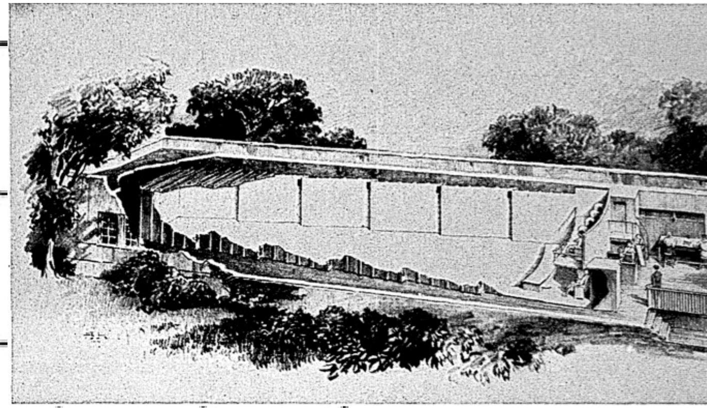
Threshold versus intensity (t.v.i.) function

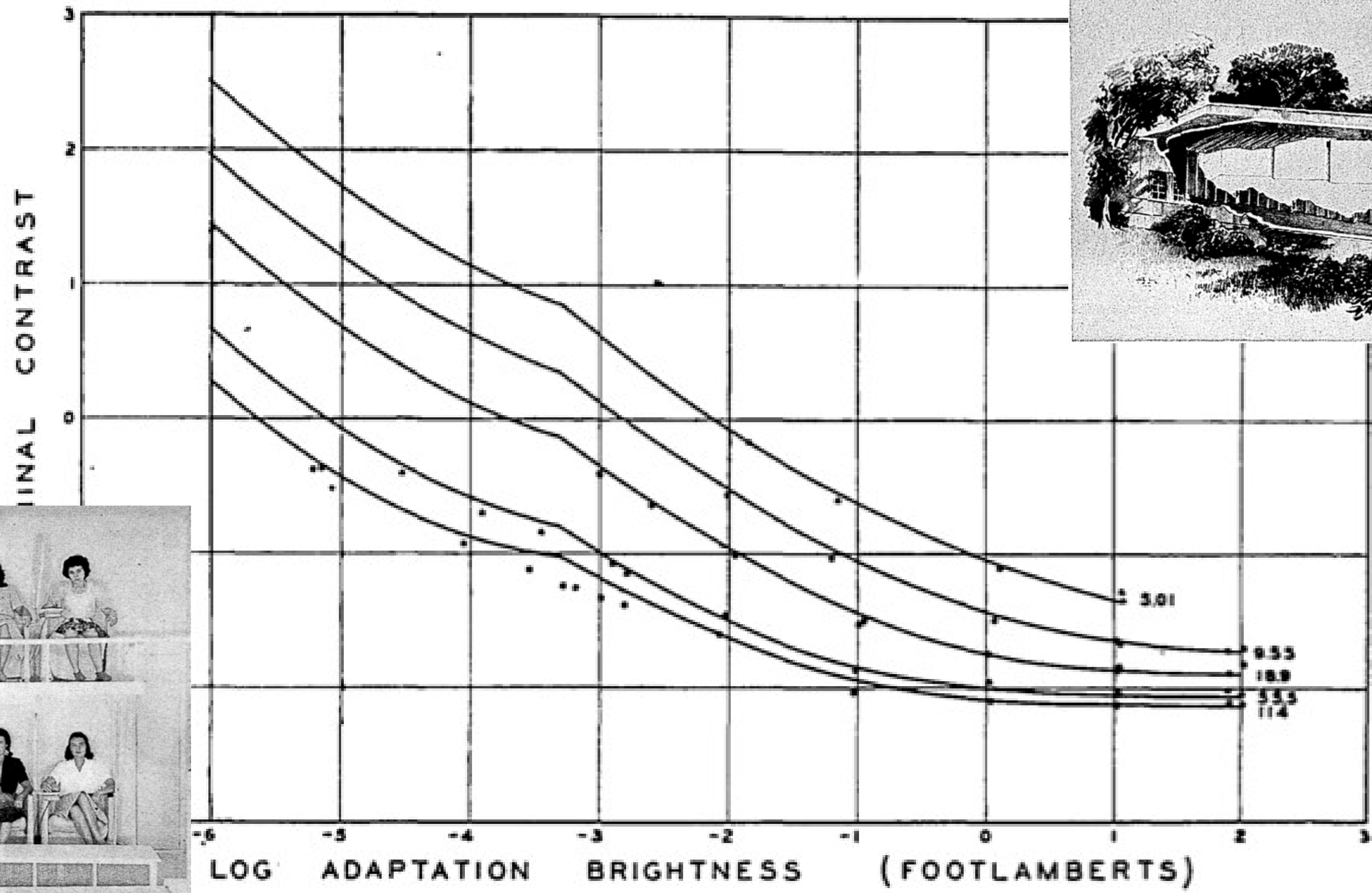
- The smallest detectable difference in luminance for a given background luminance



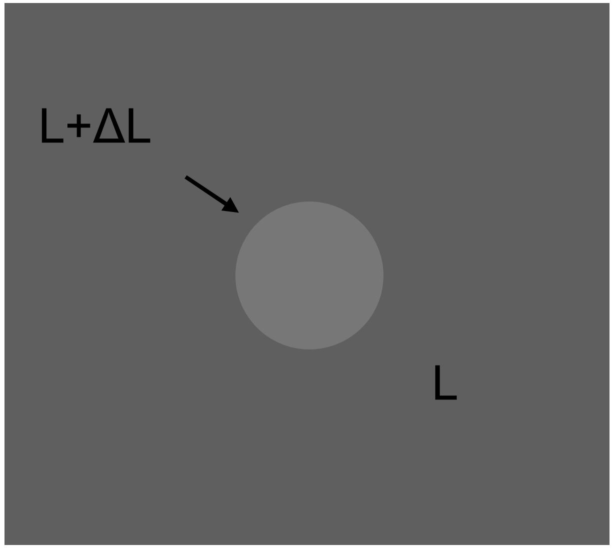


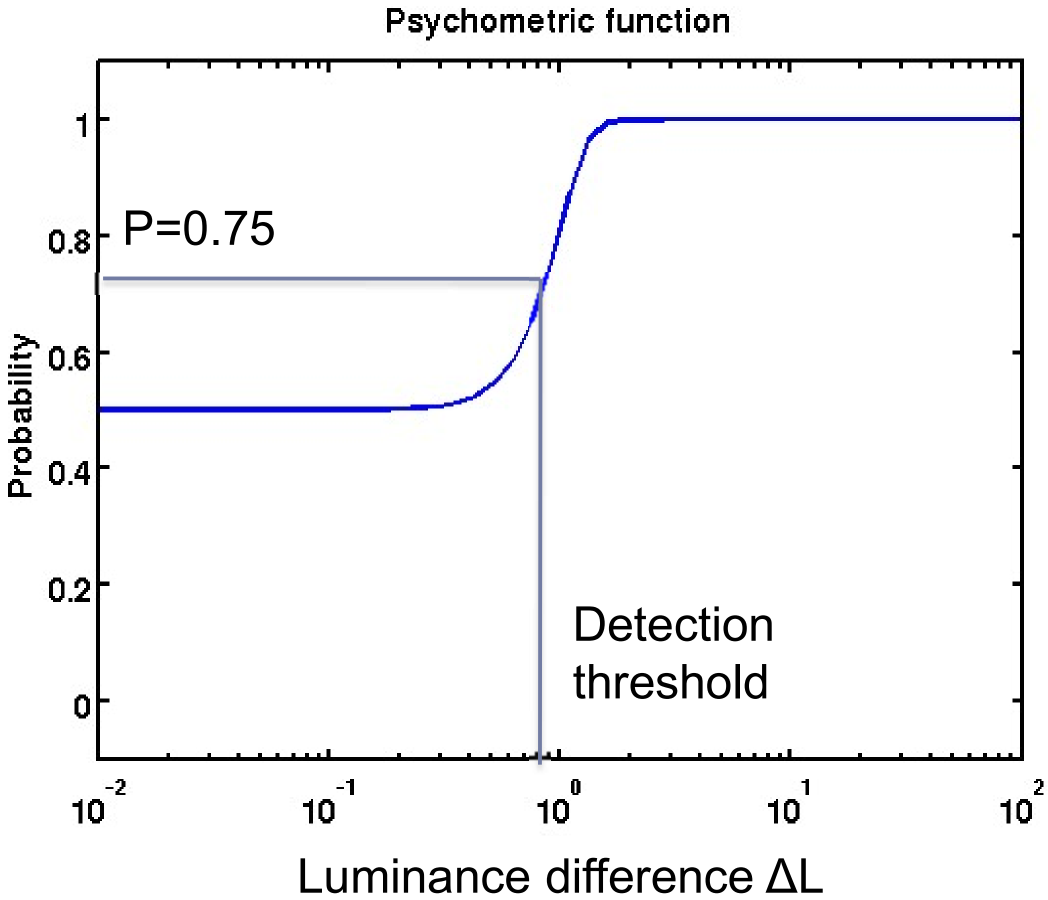
t.v.i. measurements – Blackwell 1946





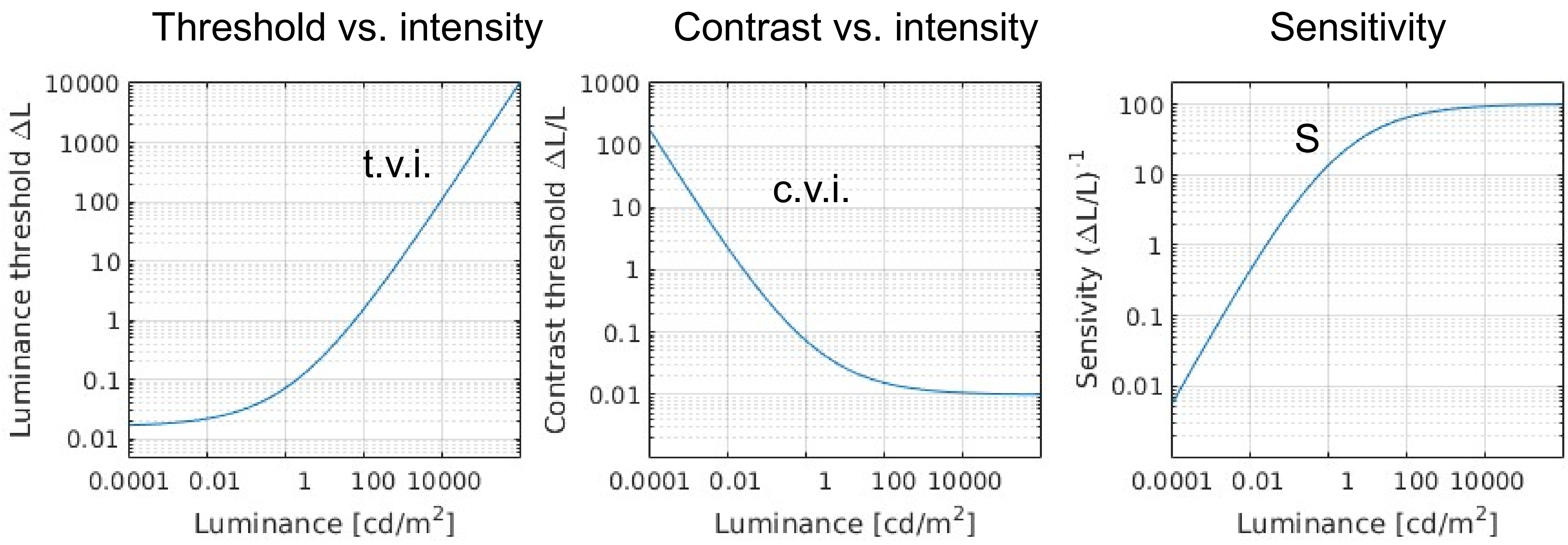
Psychophysics. Threshold experiments





t.v.i function / c.v.i. function / Sensitivity

- The same data, different representation



$$\Delta L = L_{disk} - L_{background}$$

$$C = \frac{\Delta L}{L_{background}}$$

$$S = \frac{1}{C} = \frac{L_{background}}{\Delta L}$$

Sensitivity to luminance

- Weber-law – the just-noticeable difference is proportional to the magnitude of a stimulus

The smallest detectable luminance difference

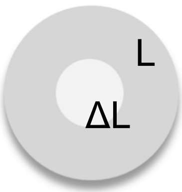
Background (adapting) luminance

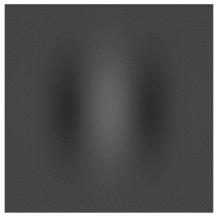
$$\frac{\Delta L}{L} = k$$

Constant

Ernst Heinrich Web
[From Wikipedia]

Typical stimuli:





Consequence of the Weber-law

- Smallest detectable difference in luminance

$$\frac{\Delta L}{L} = k$$

For k=1%

L	ΔL
100 cd/m^2	1 cd/m^2
1 cd/m^2	0.01 cd/m^2

- Adding or subtracting luminance will have a different visual impact depending on the background luminance

- Unlike LDR luma values, luminance values are **not** perceptually uniform!

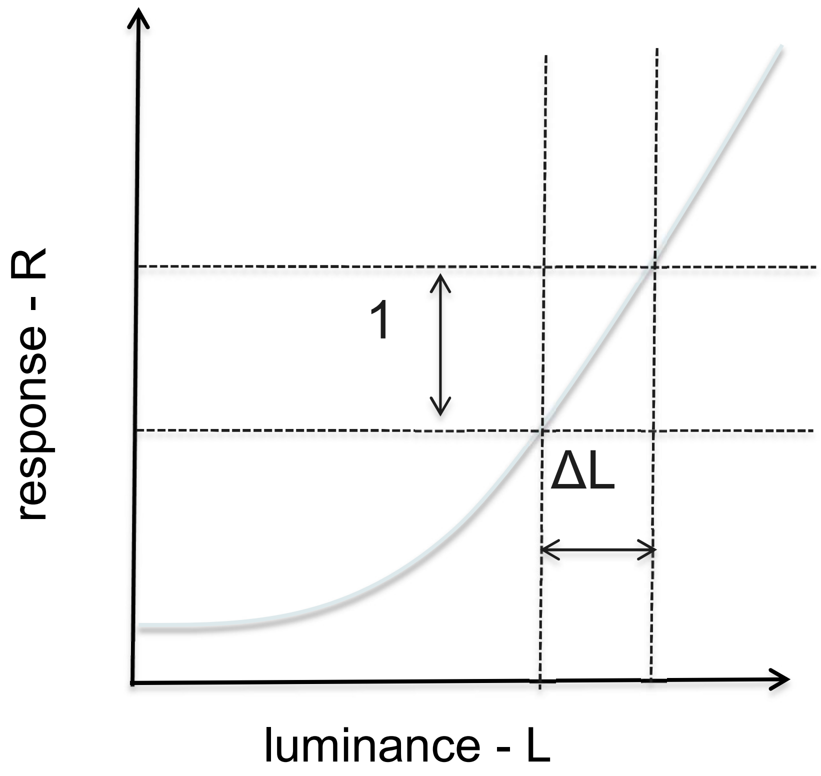
How to make luminance (more) perceptually uniform?

- Using "Fechnerian" integration

$$\frac{dR}{dl}(L) = \frac{1}{\Delta L(L)}$$

Derivative of response

Detection threshold



Luminance transducer: $$R(L) = \int_{L_{min}}^{L} \frac{1}{\Delta L(l)} dl$$

Assuming the Weber law

$$\frac{\Delta L}{L} = k$$

- and given the luminance transducer

$$R(L) = \int \frac{1}{\Delta L(l)} dl$$

- the response of the visual system to light is:

$$R(L) = \int \frac{1}{kL} dL = \frac{1}{k} \ln(L) + k_1$$

Fechner law

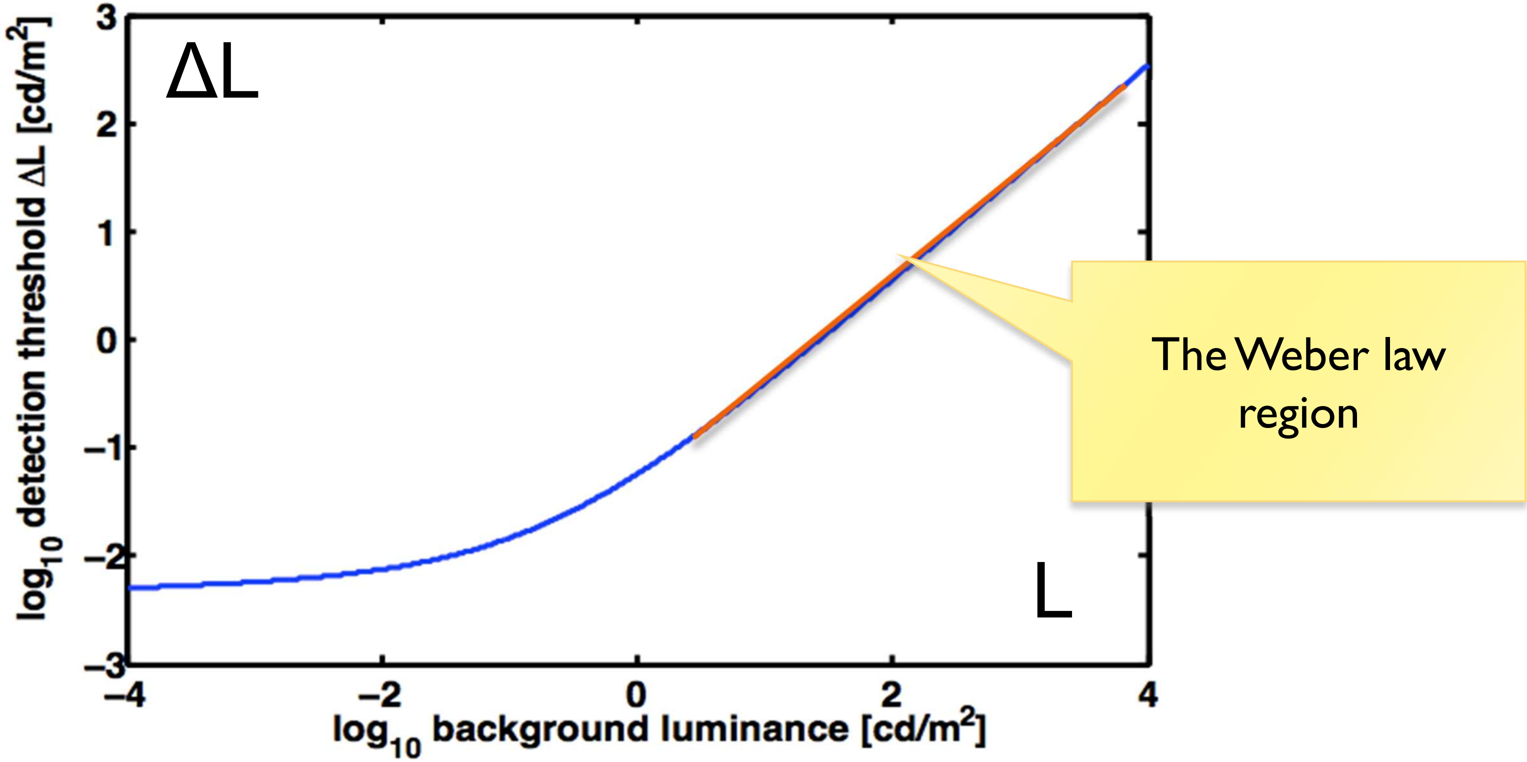
$$R(L) = a\ln(L)$$

- Response of the visual system to luminance is **approximately** logarithmic

Gustav Fechner
[From Wikipedia]

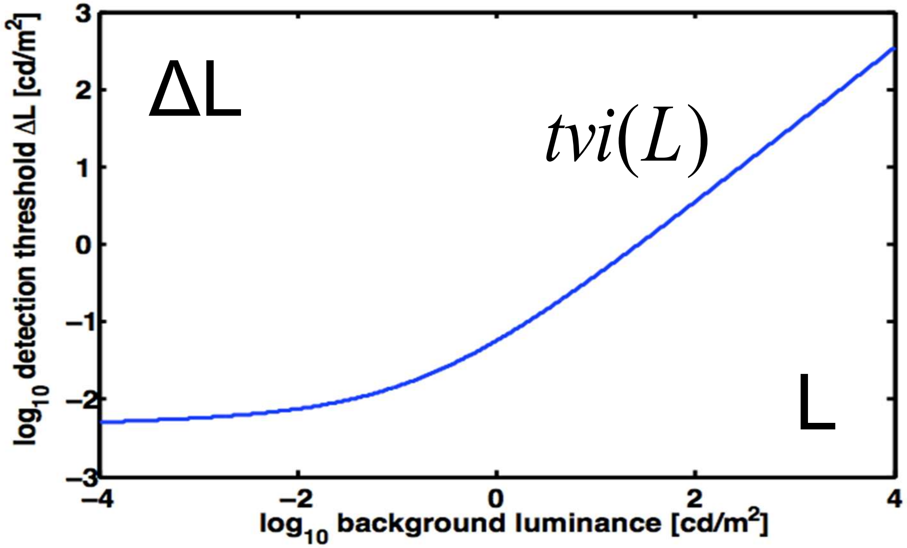
But…the Fechner law does not hold for the full luminance range

- Because the Weber law does not hold either
- Threshold vs. intensity function:



Weber-law revisited

- If we allow detection threshold to vary with luminance according to the t.v.i. function:



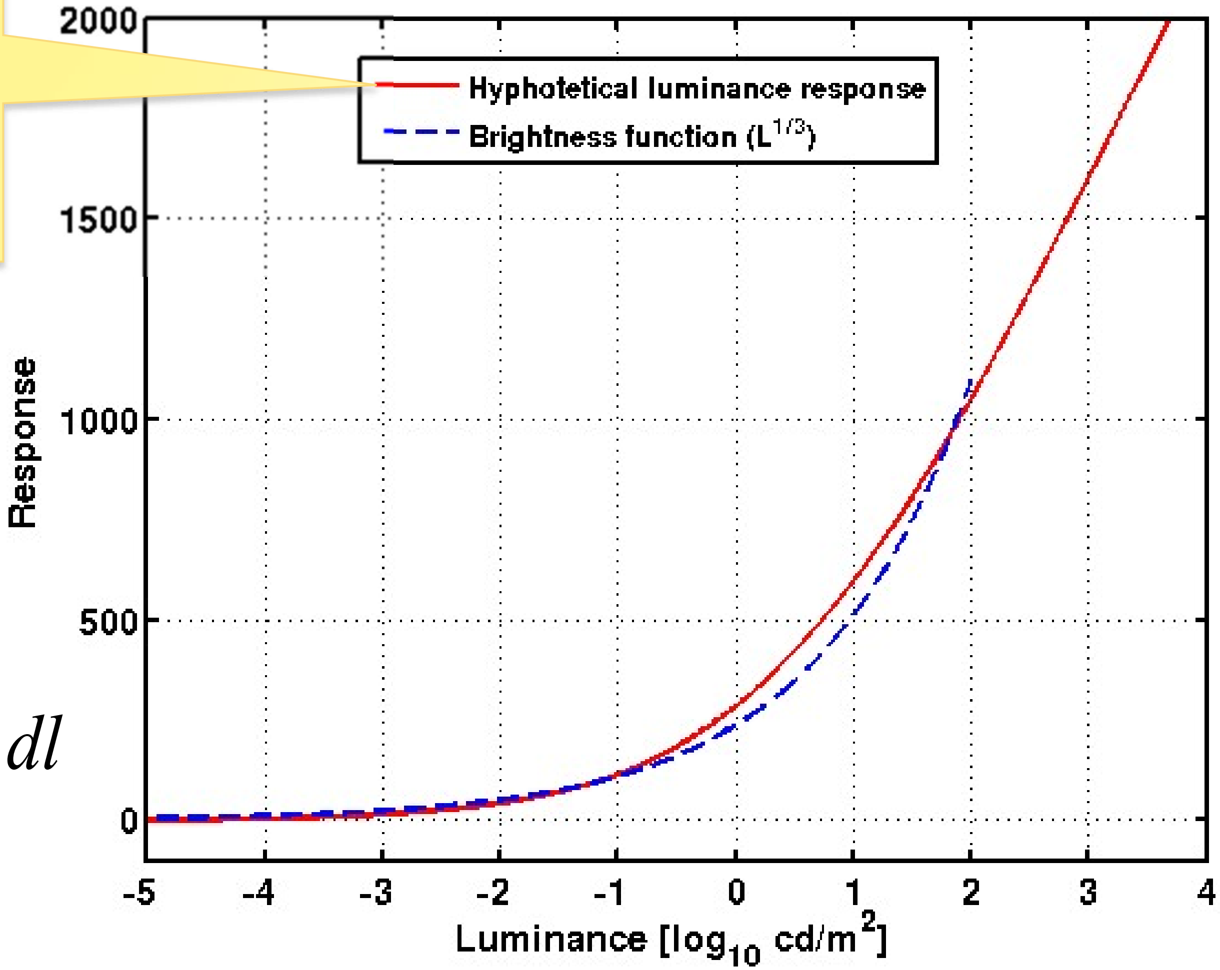
- we can get a more accurate estimate of the "response":

$$R(L) = \int_0^L \frac{1}{tvi(l)} dl$$

Fechnerian integration and Stevens' law

R(L) - function derived from the t.v.i. function

$$R(L) = \int_0^L \frac{1}{tvi(l)} dl$$



Applications of JND encoding – R(L)

- DICOM grayscale function
  - Function used to encode signal for medial monitors
  - 10-bit JND-scaled (just noticeable difference)
  - Equal visibility of gray levels

- HDMI 2.0a (HDR10)
  - PQ (Perceptual Quantizer) encoding
  - Dolby Vision
  - To encode pixels for high dynamic range images and video

DOLBY
VISION
The Future of Vision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Advanced Graphics and Image Processing

Models of early visual perception

Part 3/6 – spatial contrast sensitivity and contrast constancy

Rafal Mantiuk
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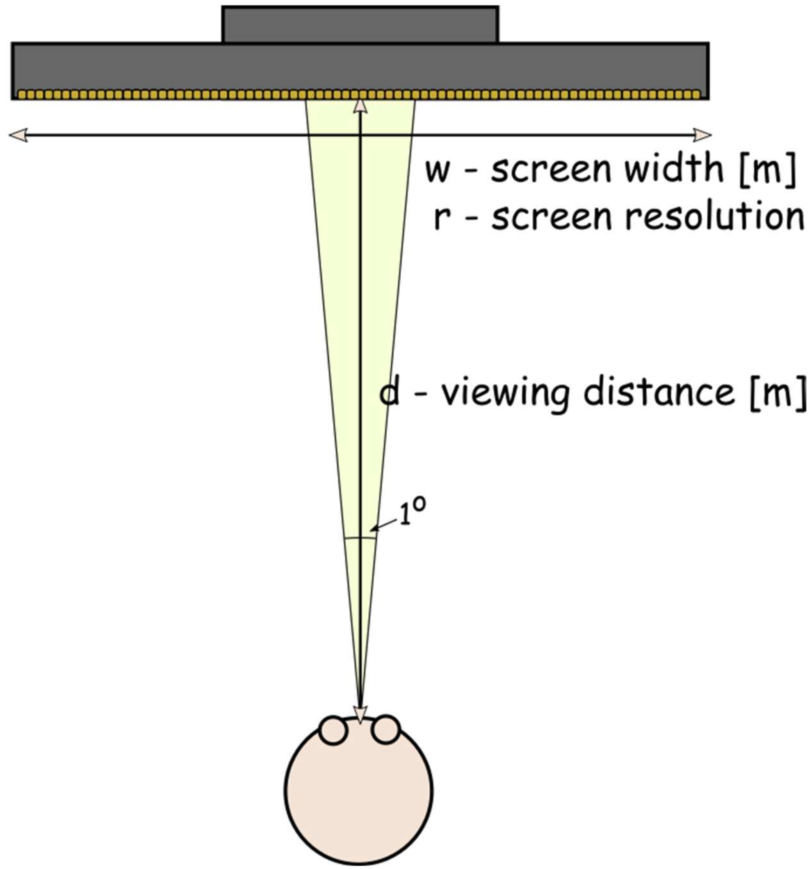
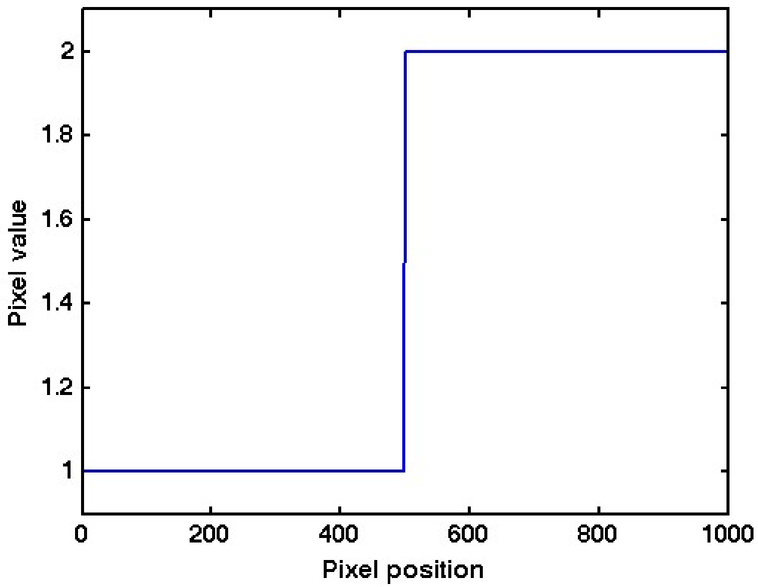
Resolution and sampling rate

- Pixels per inch [ppi]
  - Does not account for vision
- The visual resolution depends on
  - screen size
  - screen resolution
  - viewing distance
- The right measure
  - Pixels per visual degree [ppd]
  - In frequency space
    - Cycles per visual degree [cpd]

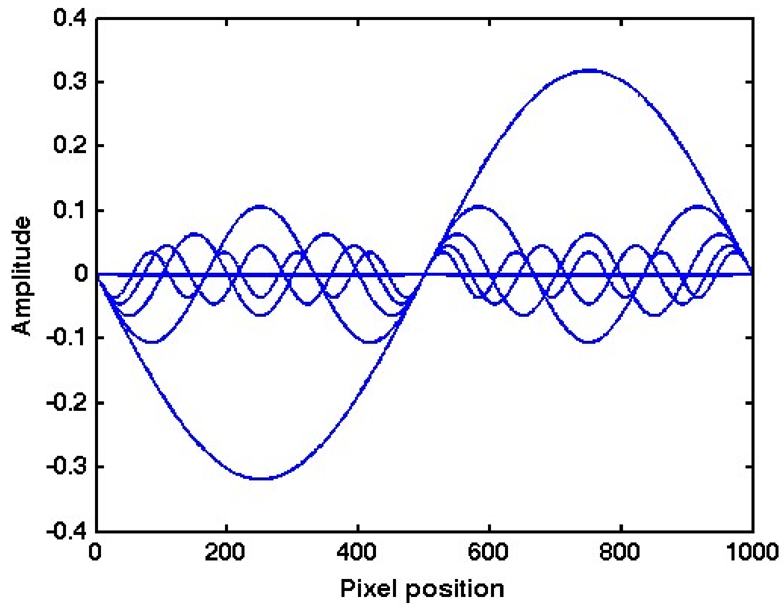


Fourier analysis

- Every N-dimensional function (including images) can be represented as a sum of sinusoidal waves of different frequency and phase



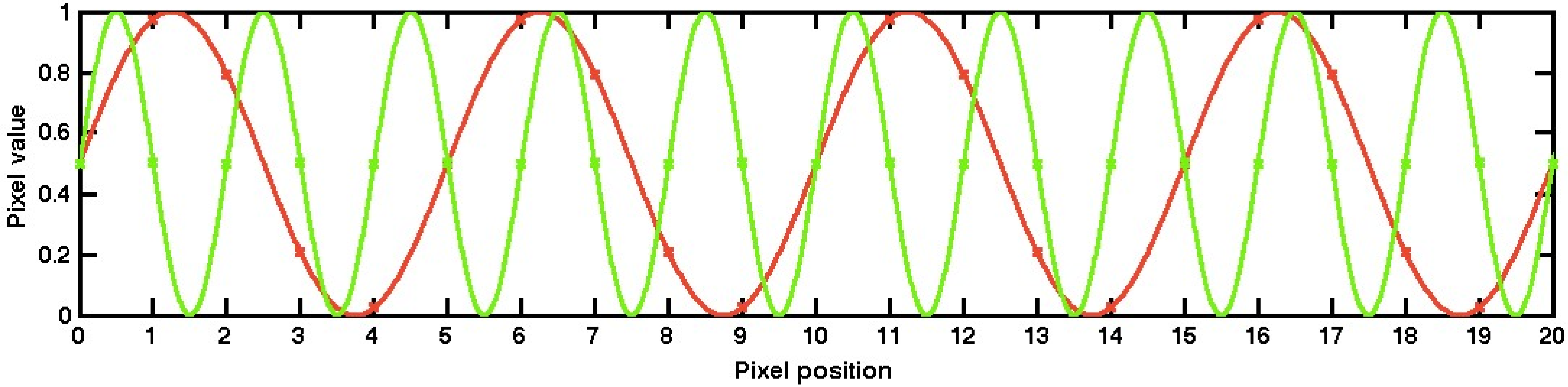
$$=\sum$$



- Think of "equalizer" in audio software, which manipulates each frequency

Spatial frequency in images

- Image space units: cycles per sample (or cycles per pixel)

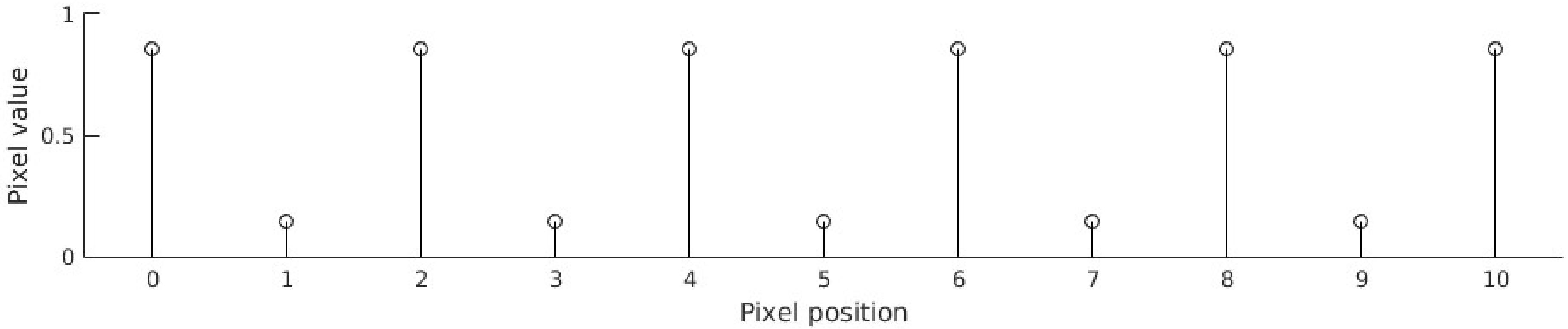


  - What are the screen-space frequencies of the red and green sinusoid?

- The visual system units: cycles per degree
  - If the angular resolution of the viewed image is 55 pixels per degree, what is the frequency of the sinusoids in cycles per degree?

Nyquist frequency

- Sampling density restricts the highest spatial frequency signal that can be (uniquely) reconstructed
  - Sampling density – how many pixels per image/visual angle/…



  - Any number of sinusoids can be fitted to this set of samples
  - It is possible to fit an infinite number of sinusoids if we allow infinitely high frequency

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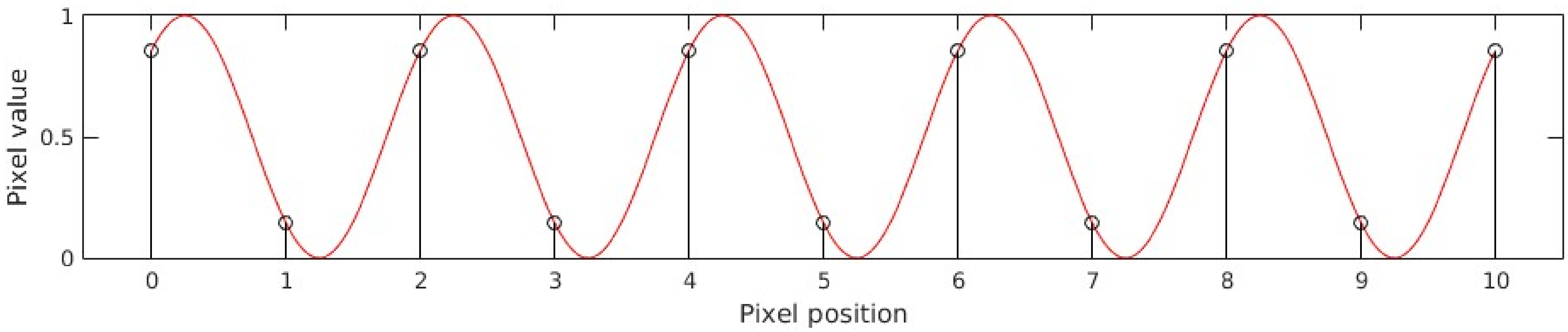

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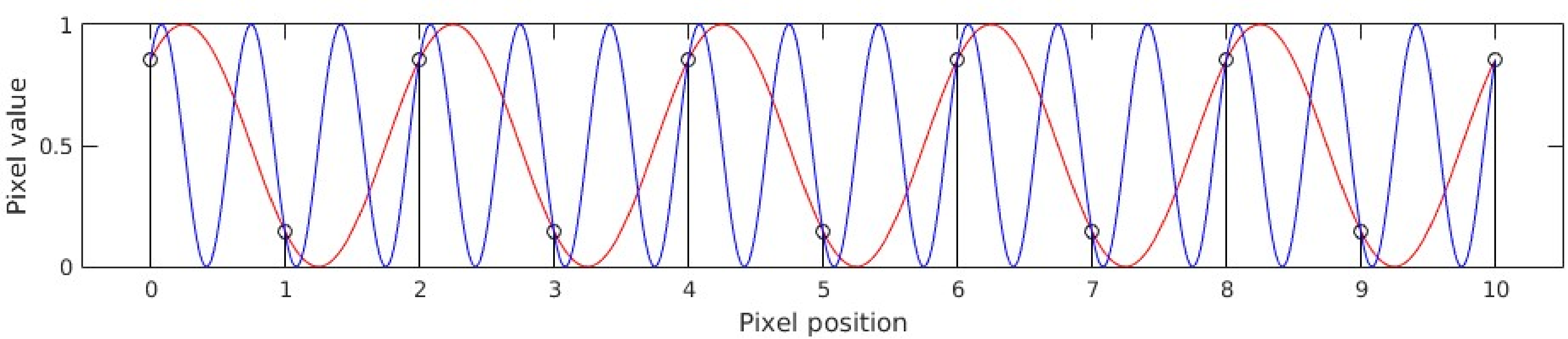

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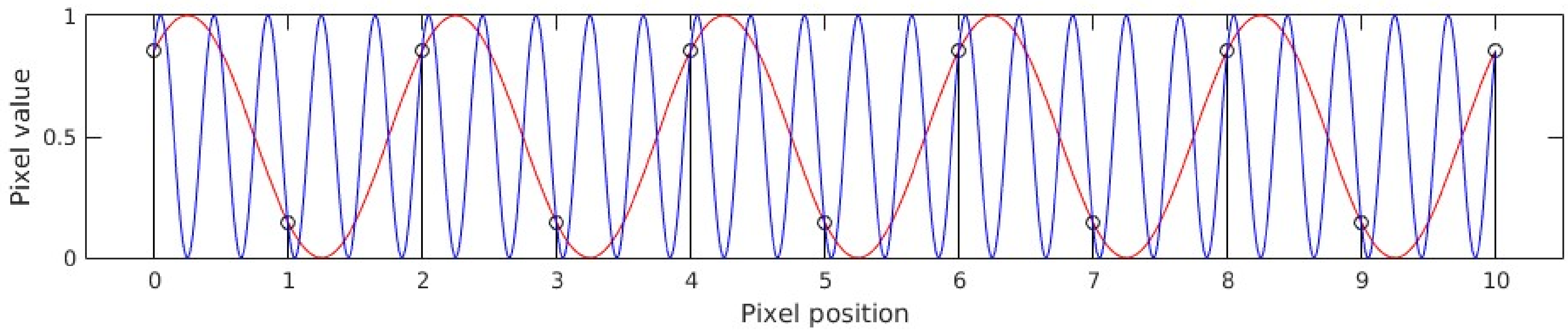
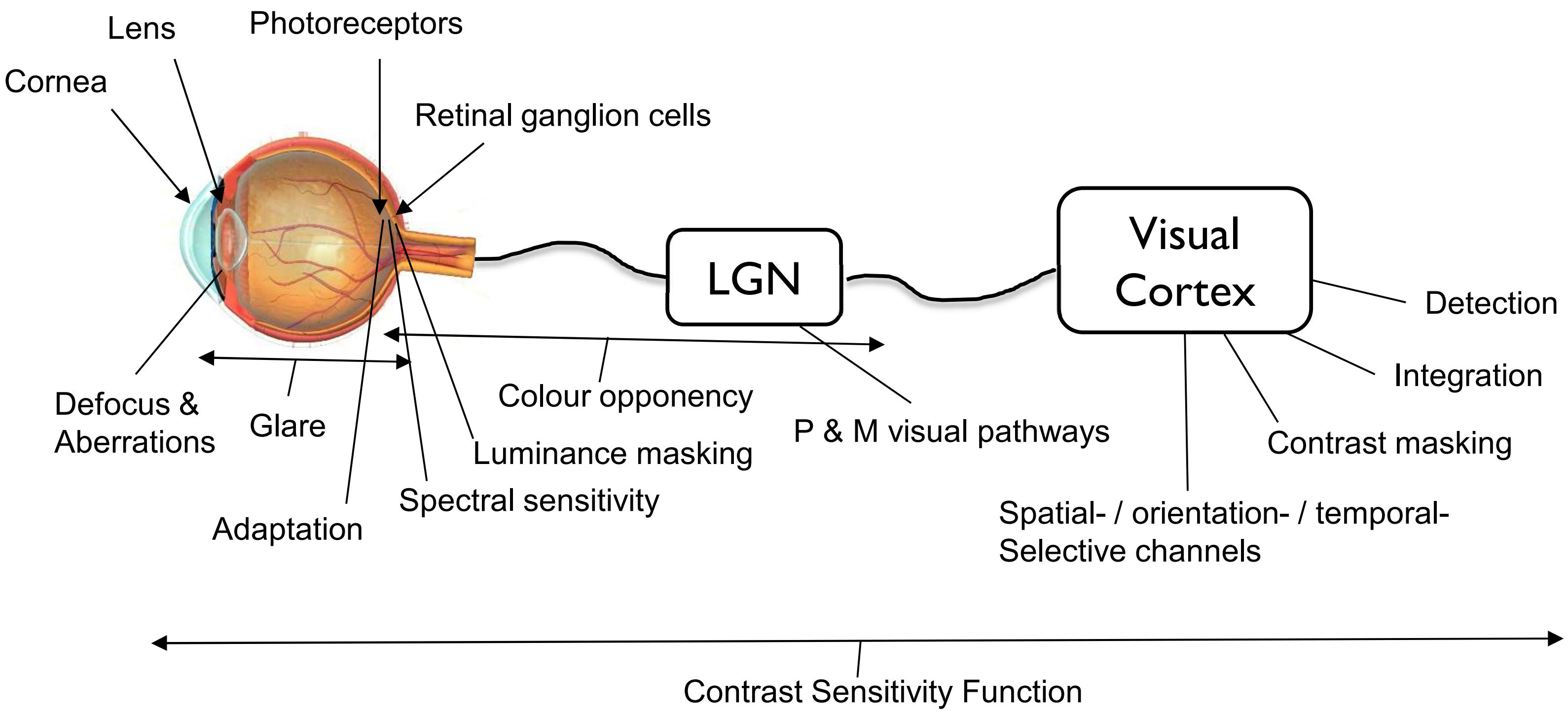


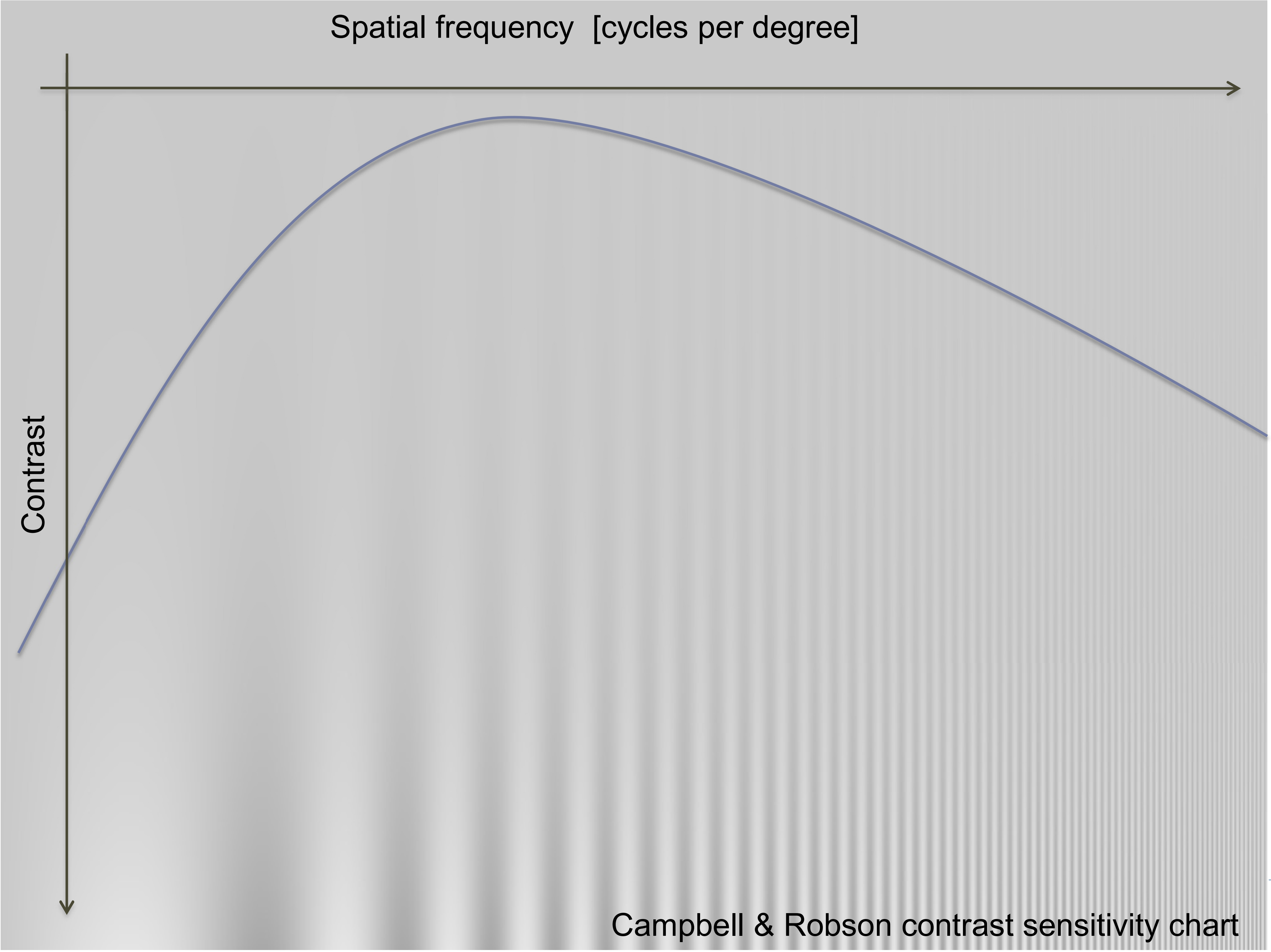
  - Any number of sinusoids can be fitted to this set of samples
  - It is possible to fit an infinite number of sinusoids if we allow infinitely high frequency

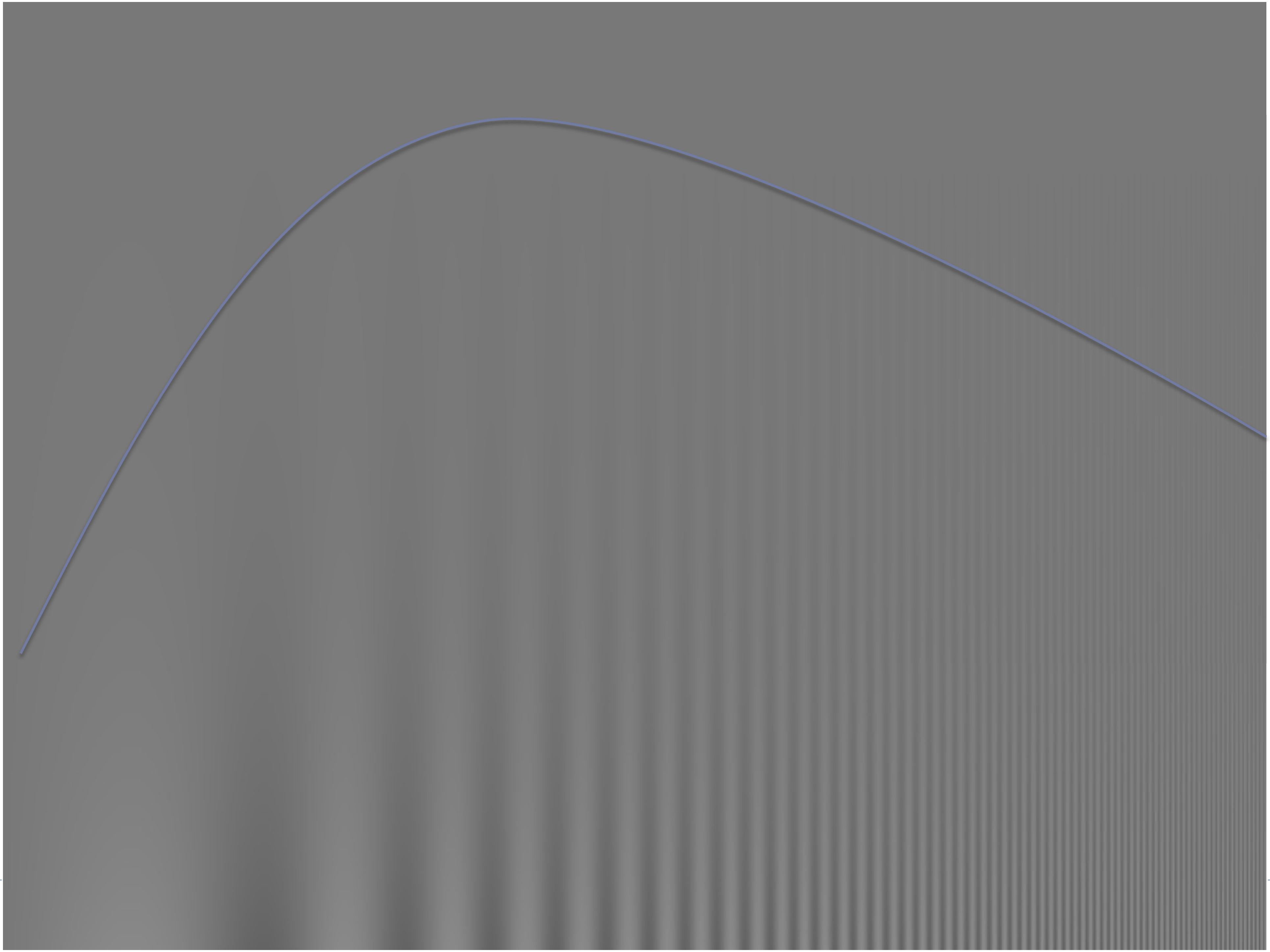
Nyquist frequency / aliasing

- Nuquist frequency is the highest frequency that can be represented by a discrete set of uniform samples (pixels)
- Nuquist frequency = 0.5 sampling rate
  - For audio
    - If the sampling rate is 44100 samples per second (audio CD), then the Nyquist frequency is 22050 Hz
  - For images (visual degrees)
    - If the sampling rate is 60 pixels per degree, then the Nyquist frequency is 30 cycles per degree
- When resampling an image to lower resolution, the frequency content above the Nyquist frequency needs to be removed (reduced in practice)
  - Otherwise **aliasing** is visible

Modeling contrast detection




Spatial frequency [cycles per degree]
Contrast
Campbell & Robson contrast sensitivity chart



Contrast sensitivity function

Temporal frequency

Stimulus size

Spatial frequency

Eccentricity

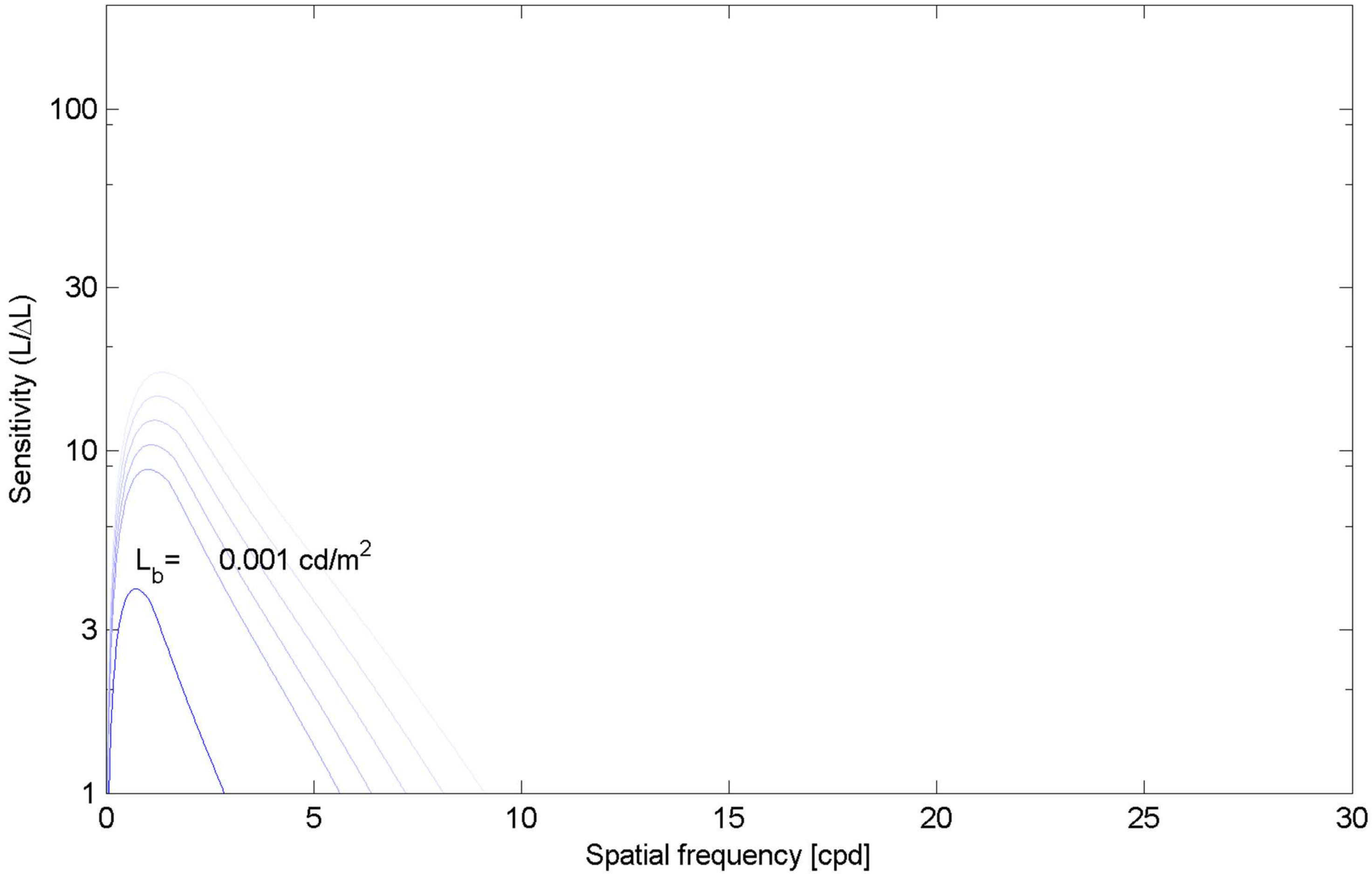
$$CSF = S(\rho, \theta, \omega, l, i^2, d, e)$$

Orientation

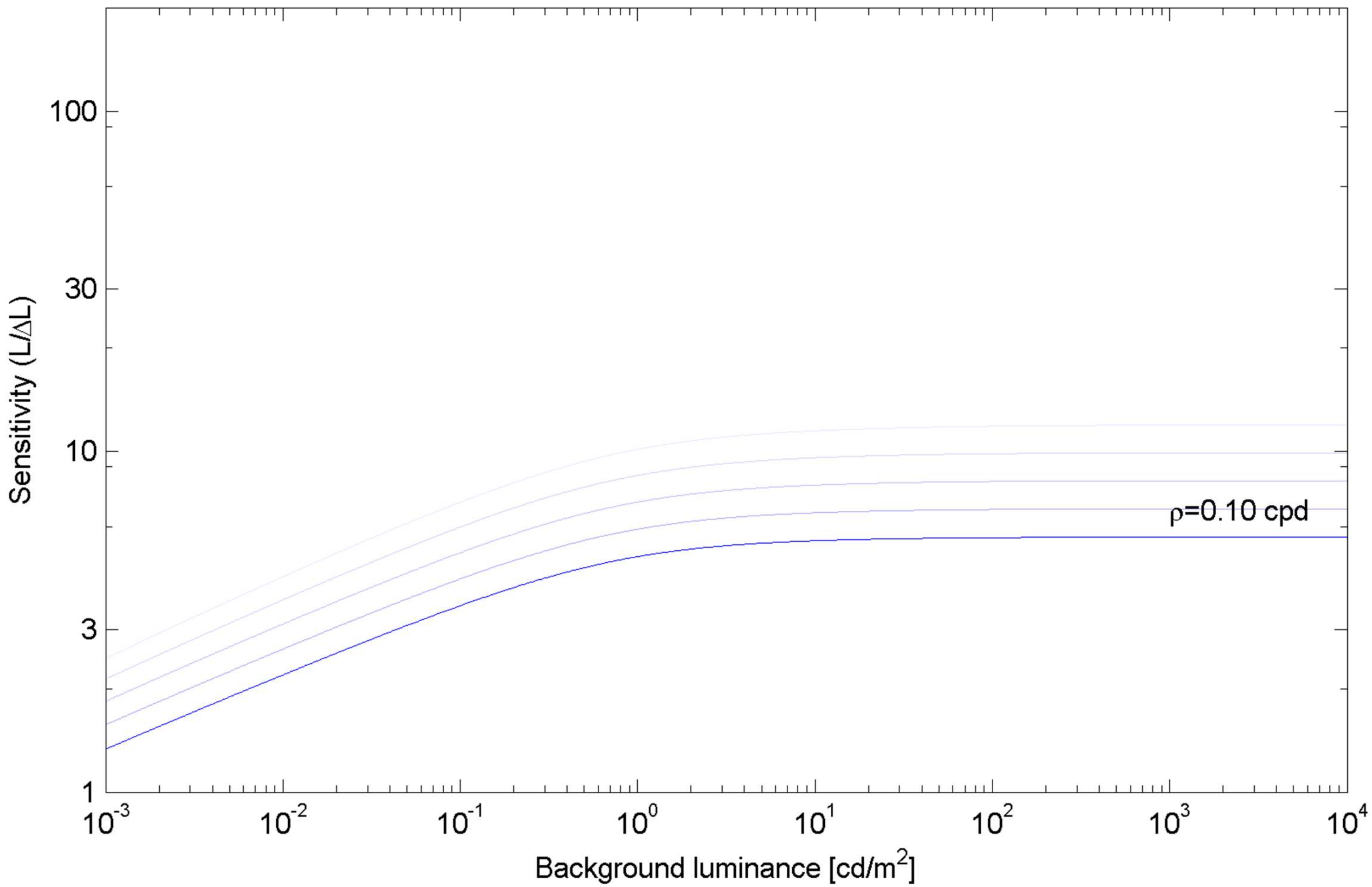
Viewing distance

Adapting luminance

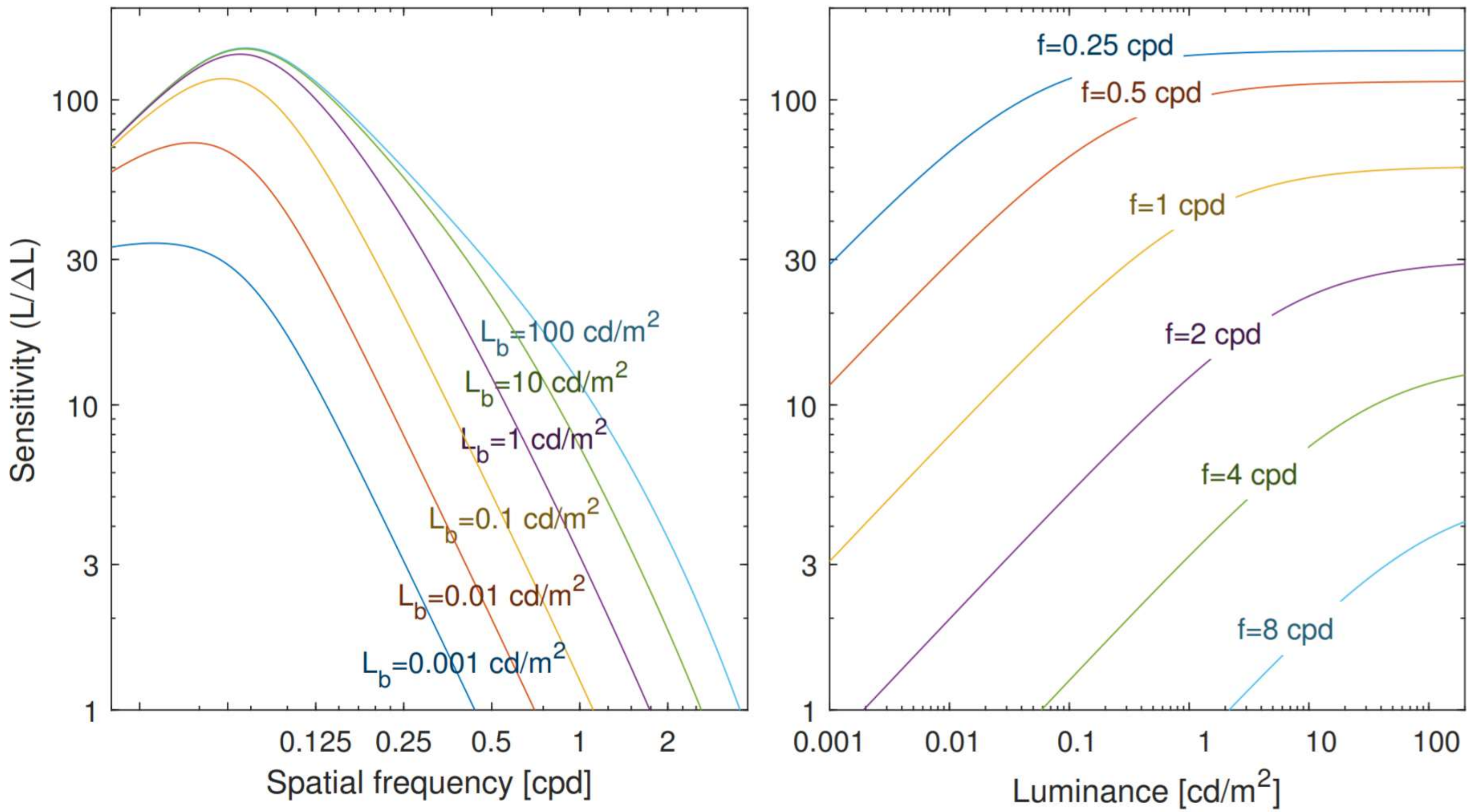
CSF as a function of spatial frequency



CSF as a function of background luminance

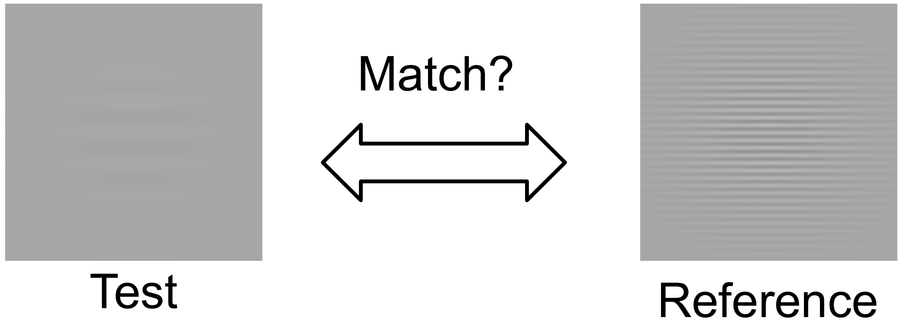


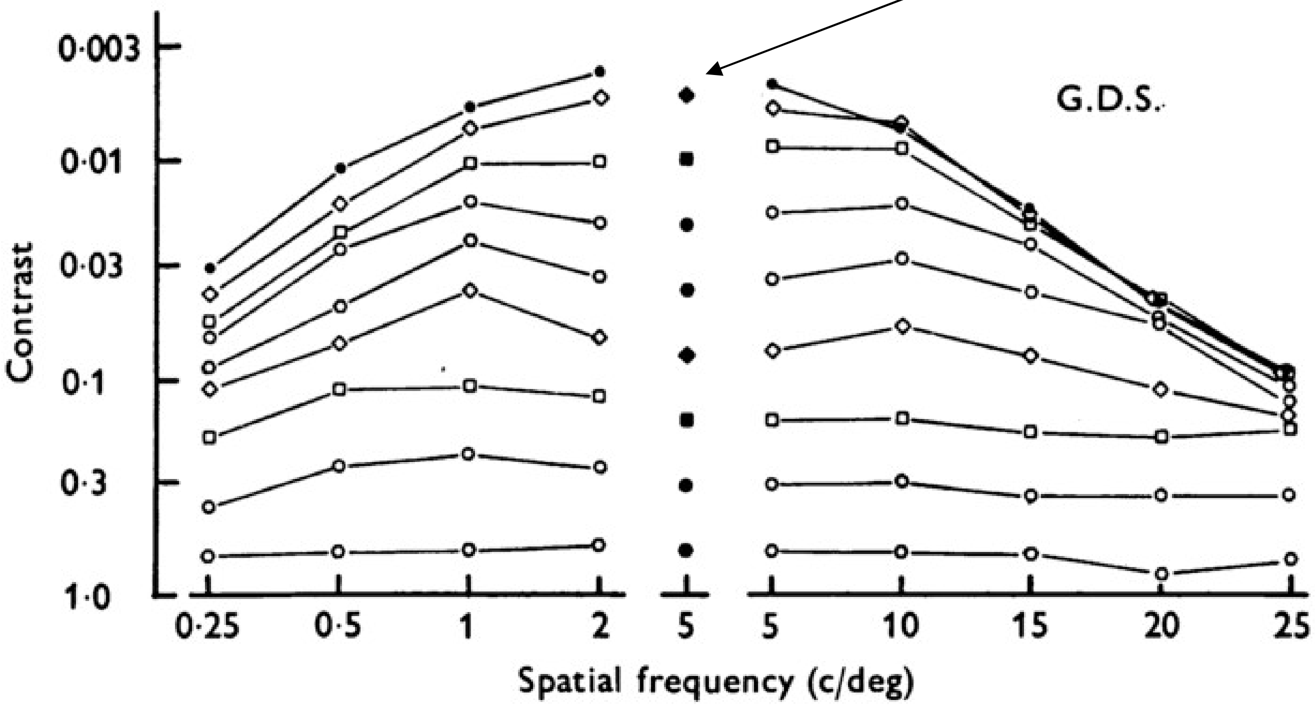
CSF as a function of spatial frequency and background luminance



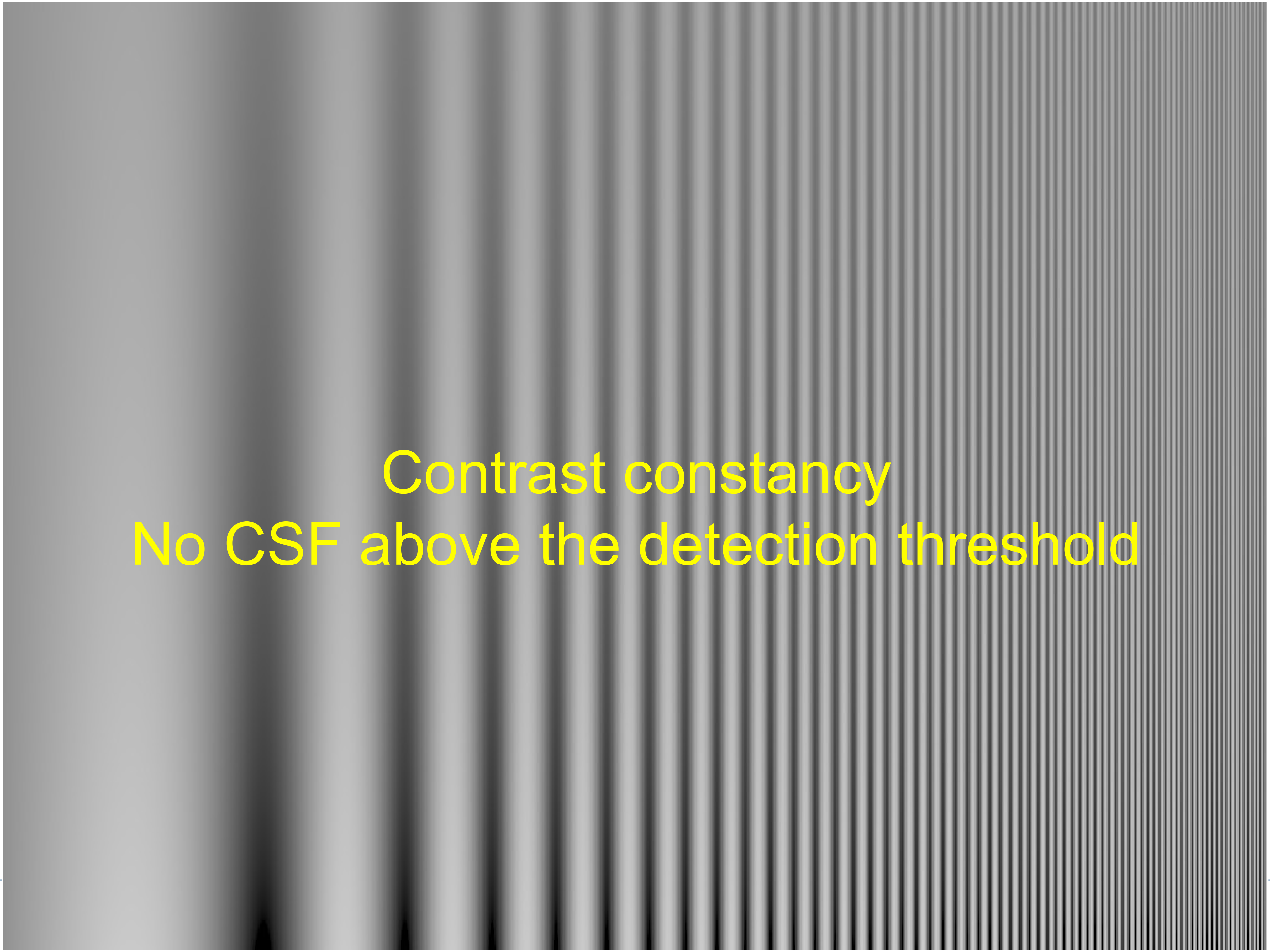
Contrast constancy

Experiment: Adjust the amplitude of one sinusoidal grating until it matches the perceived magnitude of another sinusoidal grating.





From: Georgeson and Sullivan. 1975. J. Phsysio.

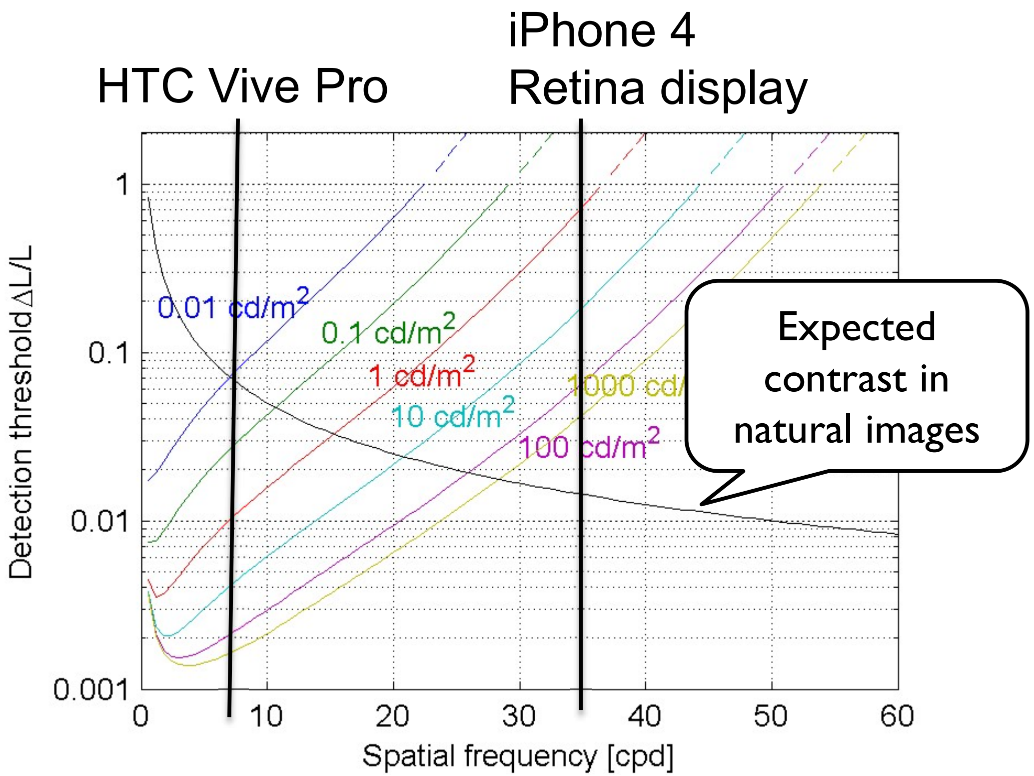

Contrast constancy
No CSF above the detection threshold

CSF and the resolution

- CSF plotted as the detection contrast

$$\frac{\Delta L}{L_b} = S^{-1}$$

- The contrast below each line is invisible
- Maximum perceivable resolution depends on luminance



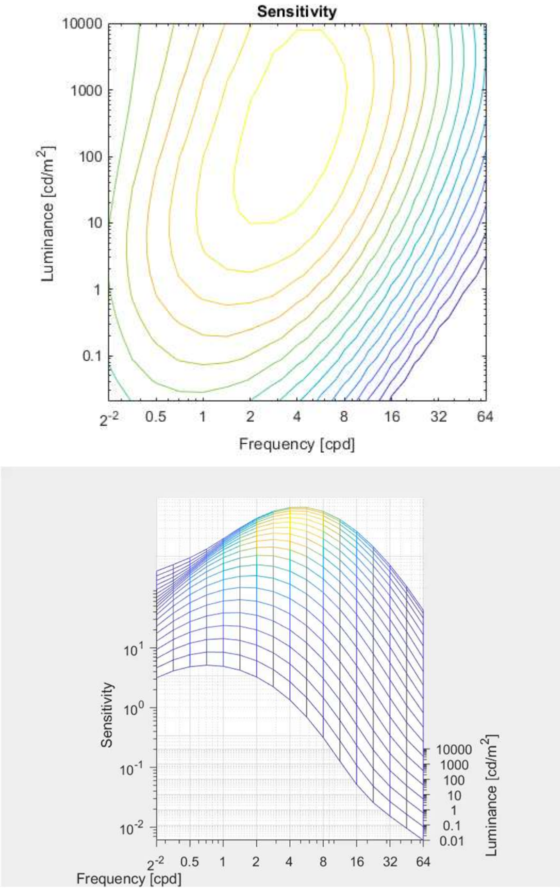
CSF models:
Barten, P. G. J. (2004).
https://doi.org/10.1117/12.537476

Spatio-chromatic CSF

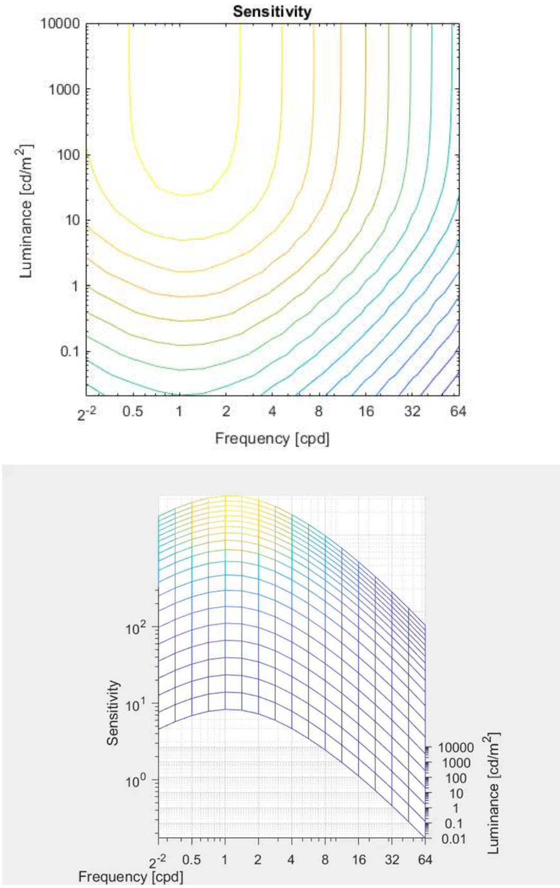
Spatio-chromatic contrast sensitivity

- CSF as a function of **luminance** and **frequency**

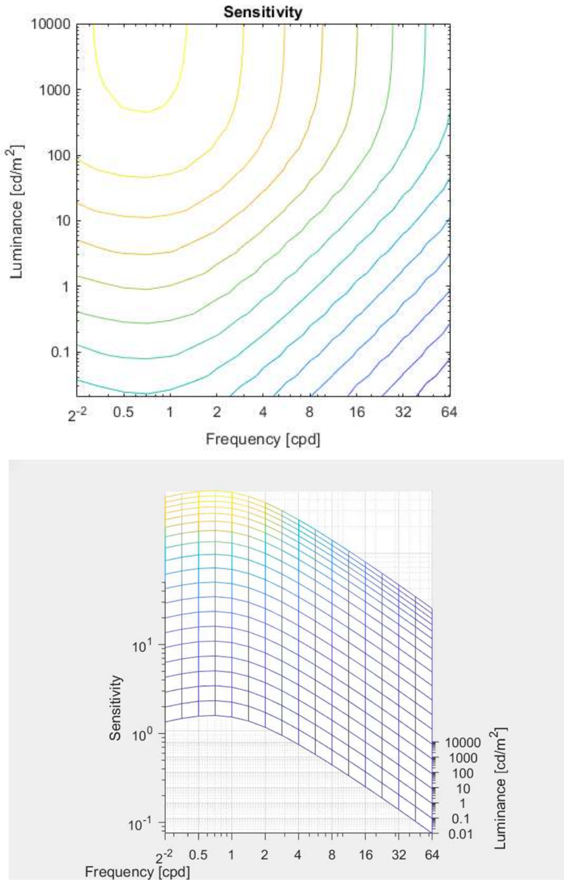
Black-White



Red-Green



Violet-Yellow



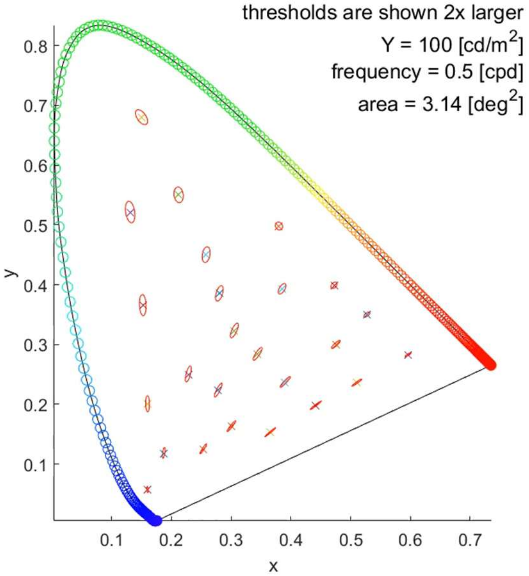
Rafał Mantiuk, University of Cambridge

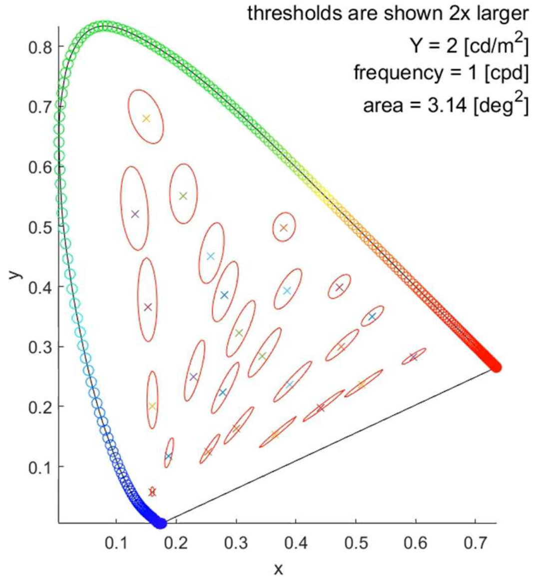
http://dx.doi.org/10.2352/issn.
2169-2629.2020.28.1

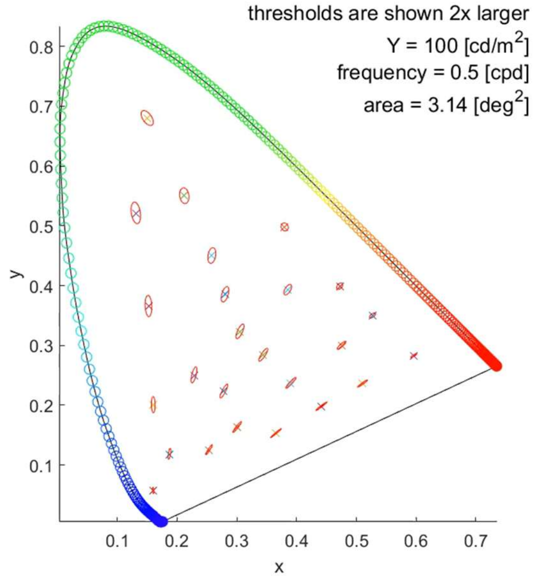
CSF and colour ellipses

Colour discrimination as a function of

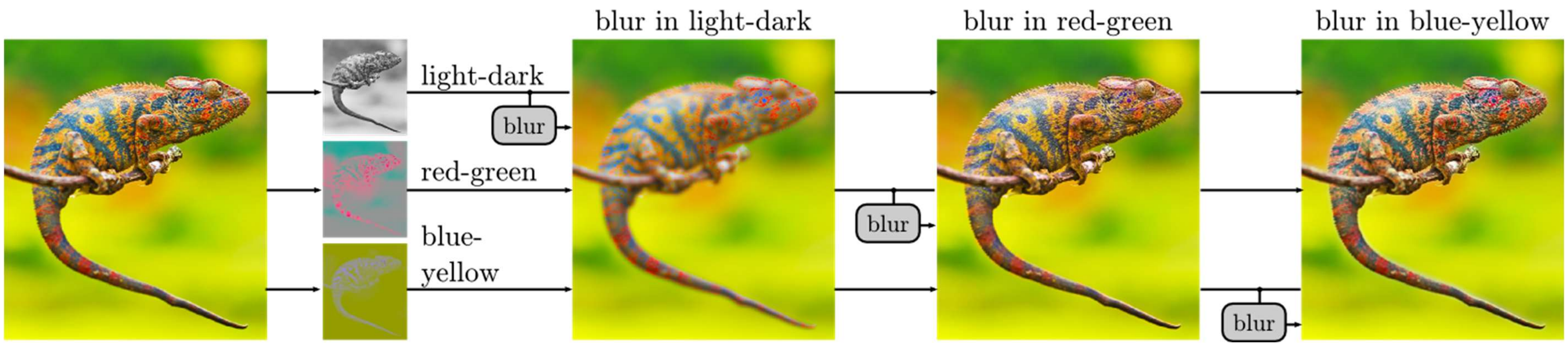
- Background colour and luminance [LMS]
- Spatial frequency [cpd]
- Size [deg]







Visibility of blur



- The same amount of blur was introduced into light-dark, red-green and blue-yellow colour opponent channels
- The blur is only visible in light-dark channel
- This property is used in image and video compression
  - Sub-sampling of colour channels (4:2:1)

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Models of early visual perception

Part 4/6 – lateral inhibition and multi-resolution models

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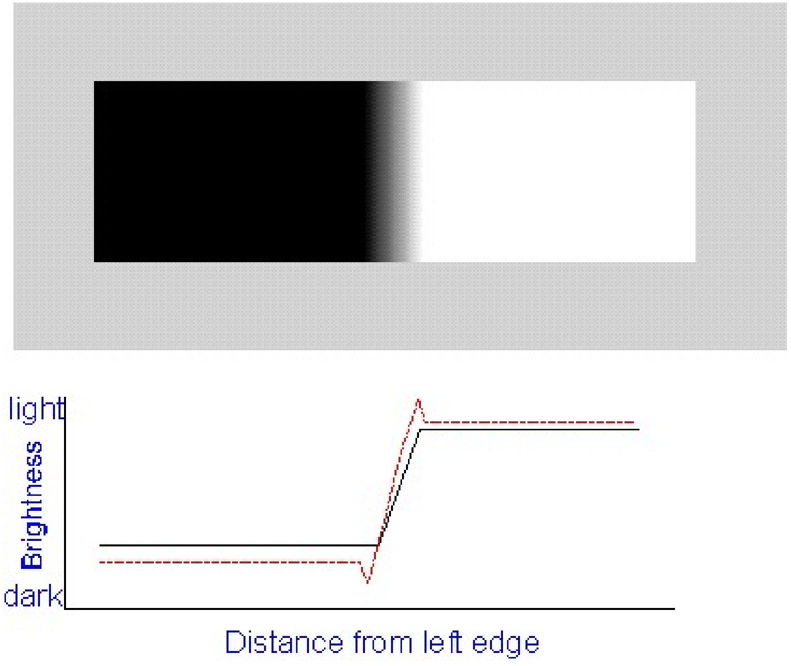
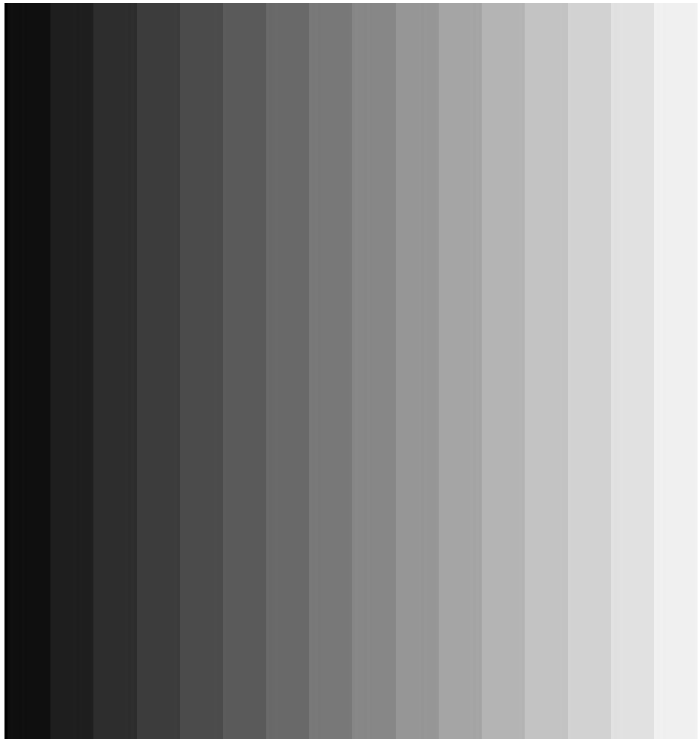
Computer Laboratory, University of Cambridge

Mach Bands – evidence for band-pass visual processing

- “Overshooting“ along edges
  - Extra-bright rims on bright sides
  - Extra-dark rims on dark sides
- Due to “Lateral Inhibition“

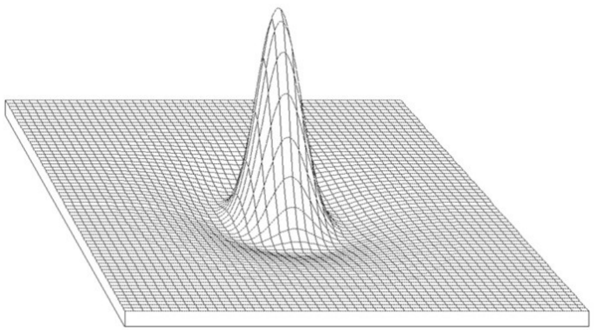


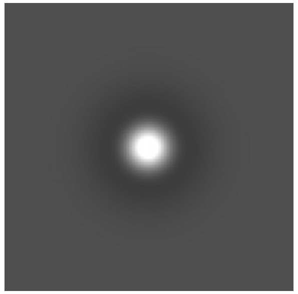


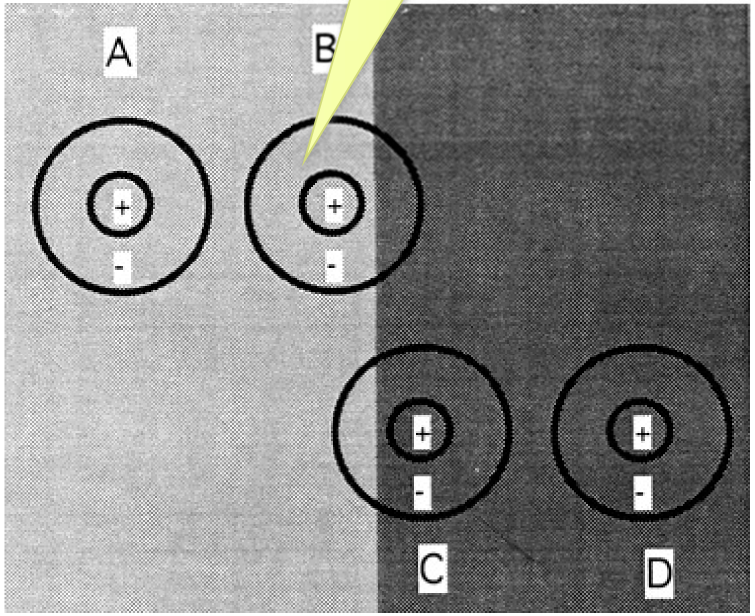
Centre-surround (Lateral Inhibition)

- "Pre-processing" step within the retina
  - Surrounding brightness level weighted negatively
    - A: high stimulus, maximal bright inhibition
    - B: high stimulus, reduced inhibition & stronger response
    - D: low stimulus, maximal inhibition
    - C: low stimulus, increased inhibition & weaker response

Center-surround receptive fields (groups of photoreceptors)







Centre-surround: Hermann Grid

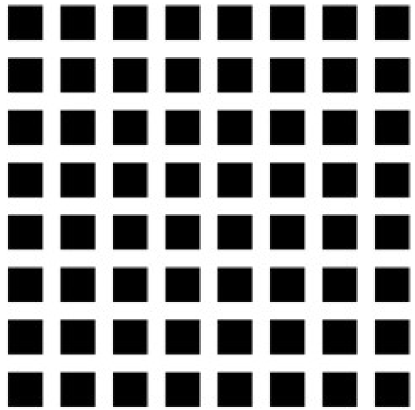
Dark dots at crossings

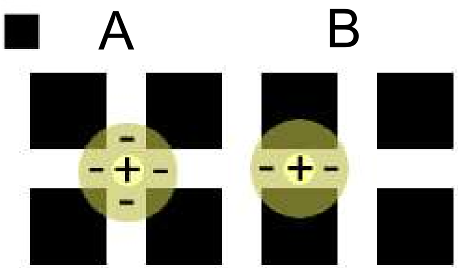
Explanation

- Crossings (A)
  - More surround stimulation (more bright area)
  - ⇒ Less inhibition
  - ⇒ Weaker response
- Streets (B)
  - Less surround stimulation
  - ⇒ More inhibition
  - ⇒ Greater response

Simulation

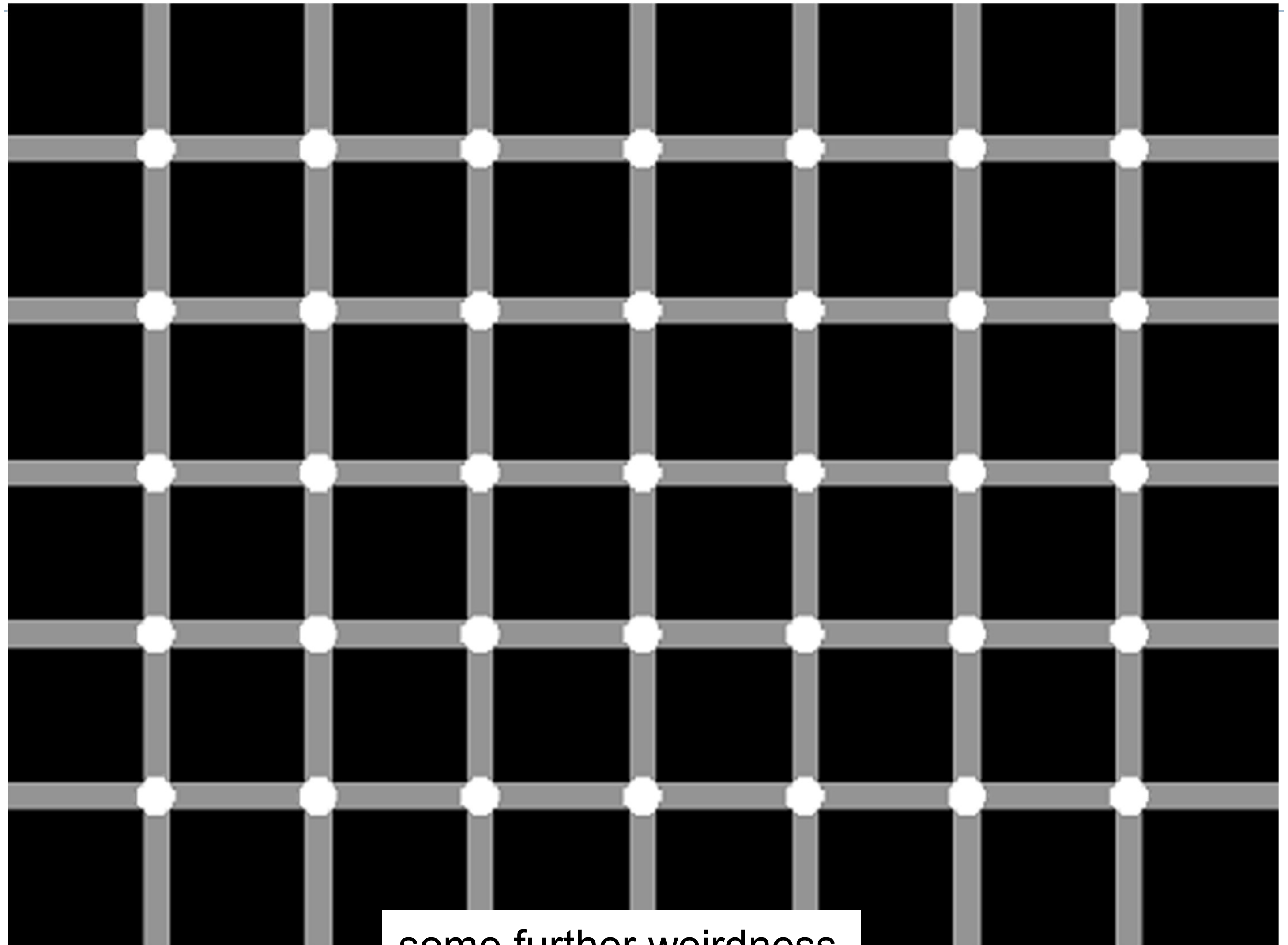
- Darker at crossings, brighter in streets
- Appears more steady
- What if reversed ?





Simulation

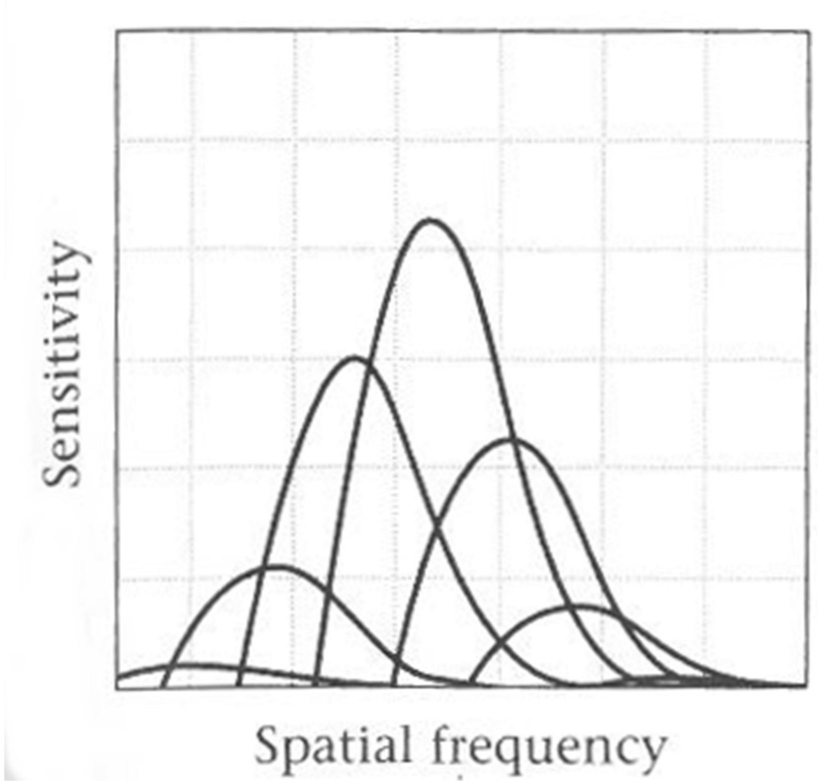
Psychedelic



some further weirdness

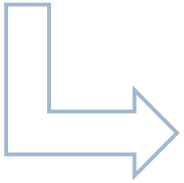
Spatial-frequency selective channels

- The visual information is decomposed in the visual cortex into multiple channels
  - The channels are selective to spatial frequency, temporal frequency and orientation
  - Each channel is affected by different „noise" level
  - The CSF is the net result of information being passed in noise-affected visual channels

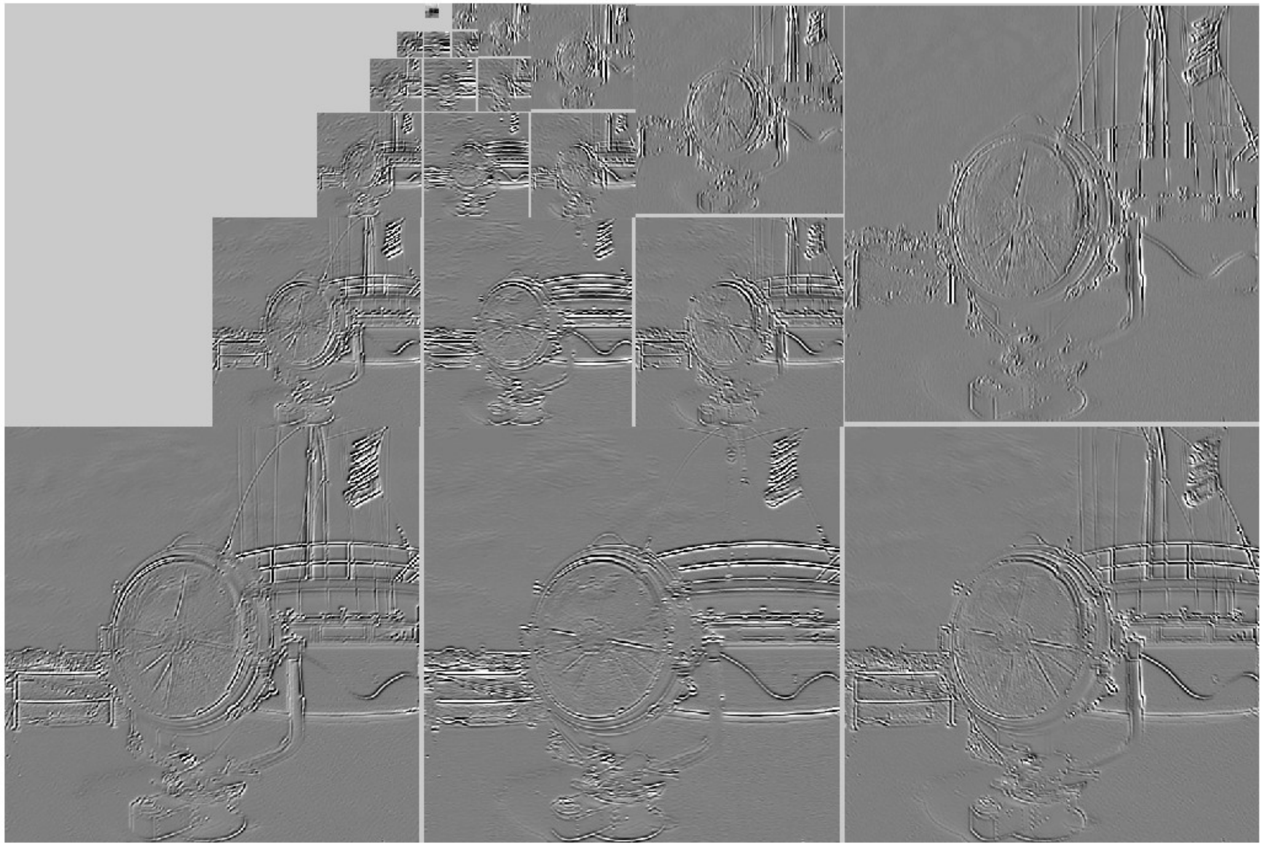


From: Wandell, 1995

Multi-scale decomposition

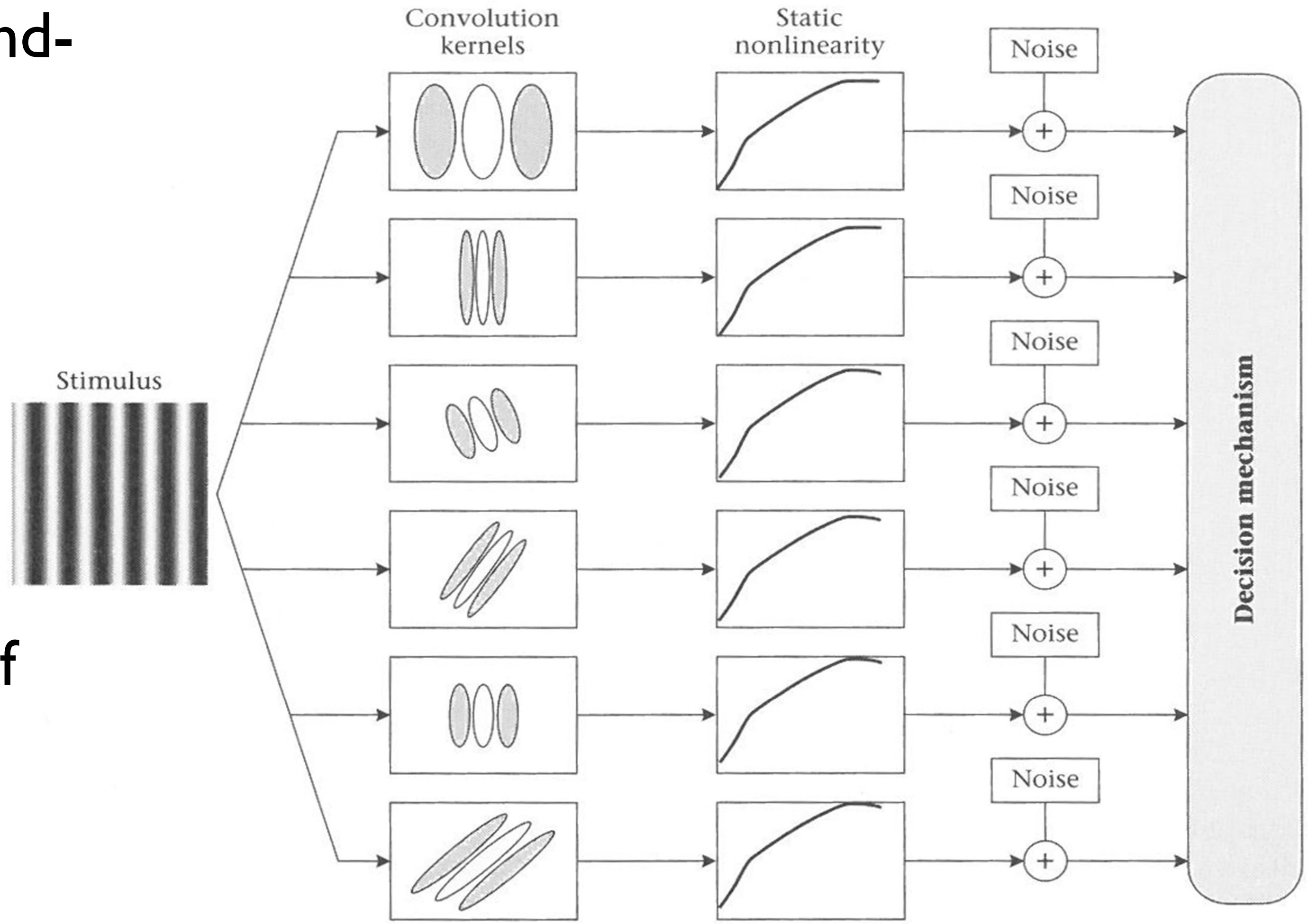


Steerable pyramid decomposition



Multi-resolution visual model

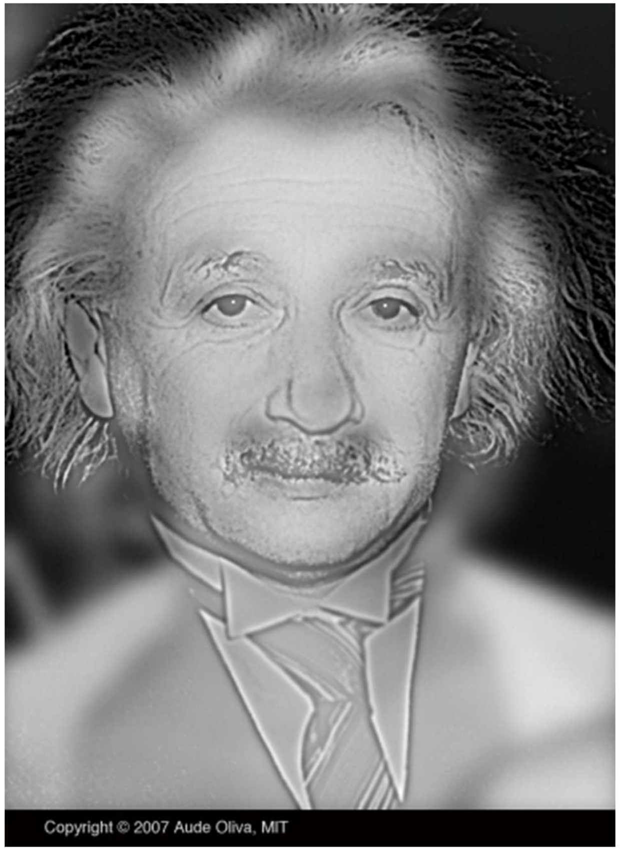
- Convolution kernels are band-pass, orientation selective filters
- The filters have the shape of an oriented Gabor function

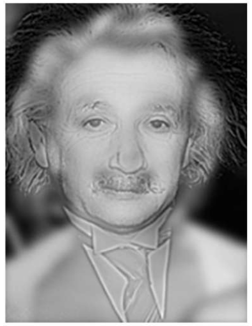


From: Wandell, 1995

Applications of multi-scale models

- JPEG2000
  - Wavelet decomposition
- JPEG / MPEG
  - Frequency transforms
- Image pyramids
  - Blending & stitching
  - Hybrid images





Hybrid Images by Aude Oliva
http://cvcl.mit.edu/hybrid_gallery

Advanced Graphics and Image Processing

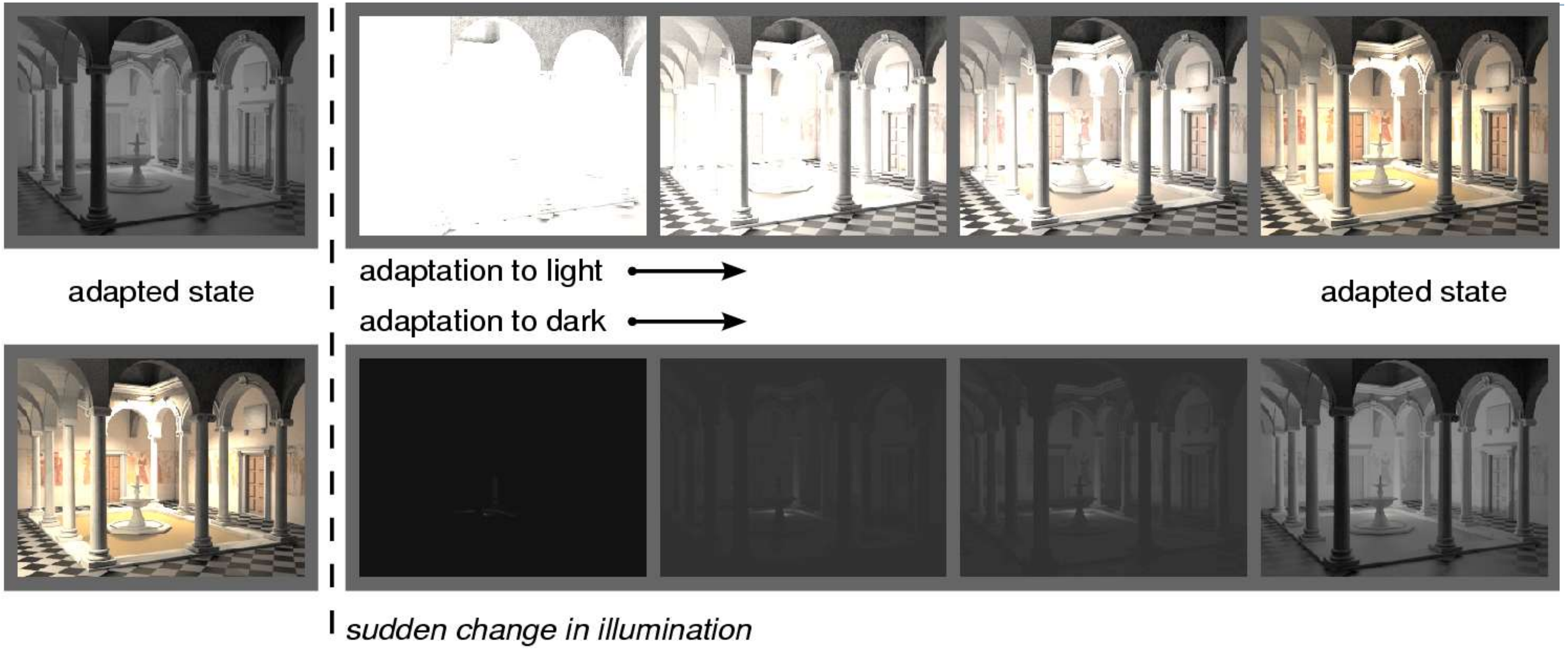
Models of early visual perception

Part 5/6 – light and dark adaptation

Rafal Mantiuk

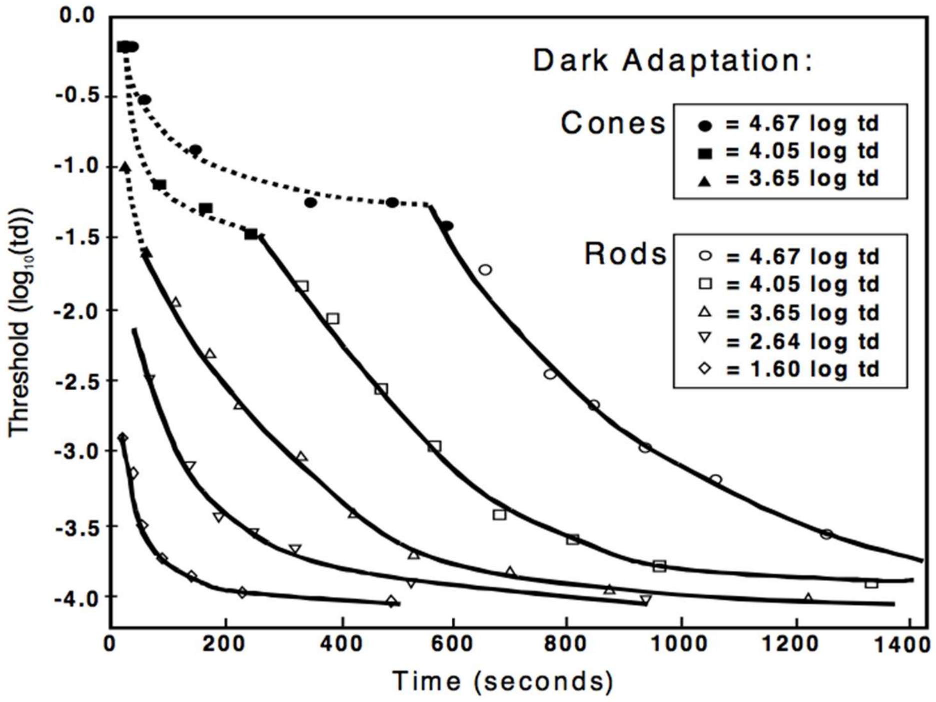
Computer Laboratory, University of Cambridge

Light and dark adaptation

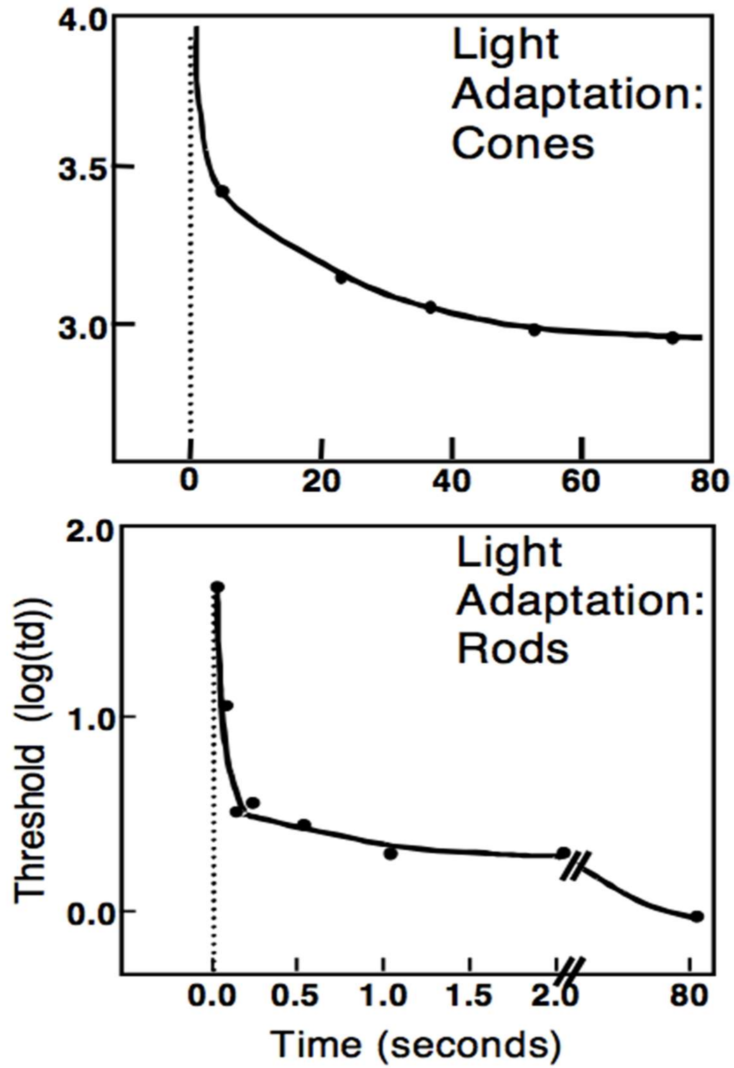


- Light adaptation: from dark to bright
- Dark adaptation: from bright to dark (much slower)

Time-course of adaptation



Bright -> Dark



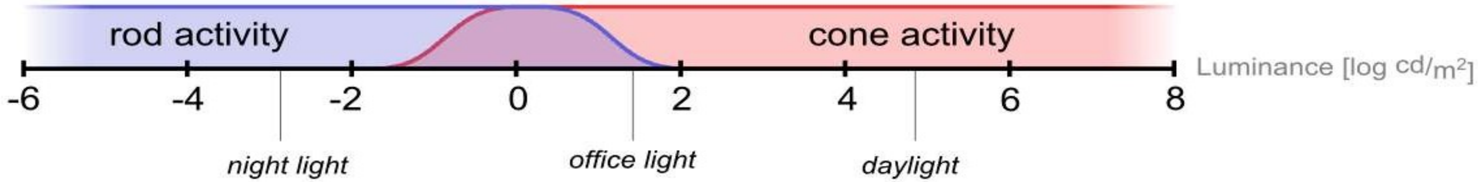
Dark -> Br

Temporal adaptation mechanisms

- Bleaching & recovery of photopigment
  - Slow assymetric (light -> dark, dark -> light)
  - Reaction times (1-1000 sec)
  - Separate time-course for rods and cones
- Neural adaptation
  - Fast
  - Approx. symmetric reaction times (10-3000 ms)
- Pupil
  - Diameter varies between 3 and 8 mm
  - About 1:7 variation in retinal illumunation

Night and daylight vision

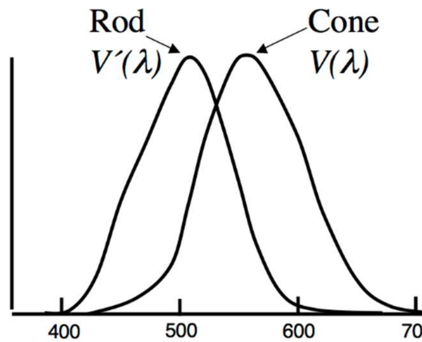
Vision mode: SCOTOPIC MESOPIC PHOTOPIC



Mode properties: monochromatic vision
limited visual acuity

good color perception
good visual acuity

Luminous efficiency



UNIVERSITY OF CAMBRIDGE
COMPUTER LABORATORY

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Advanced Graphics and Image Processing

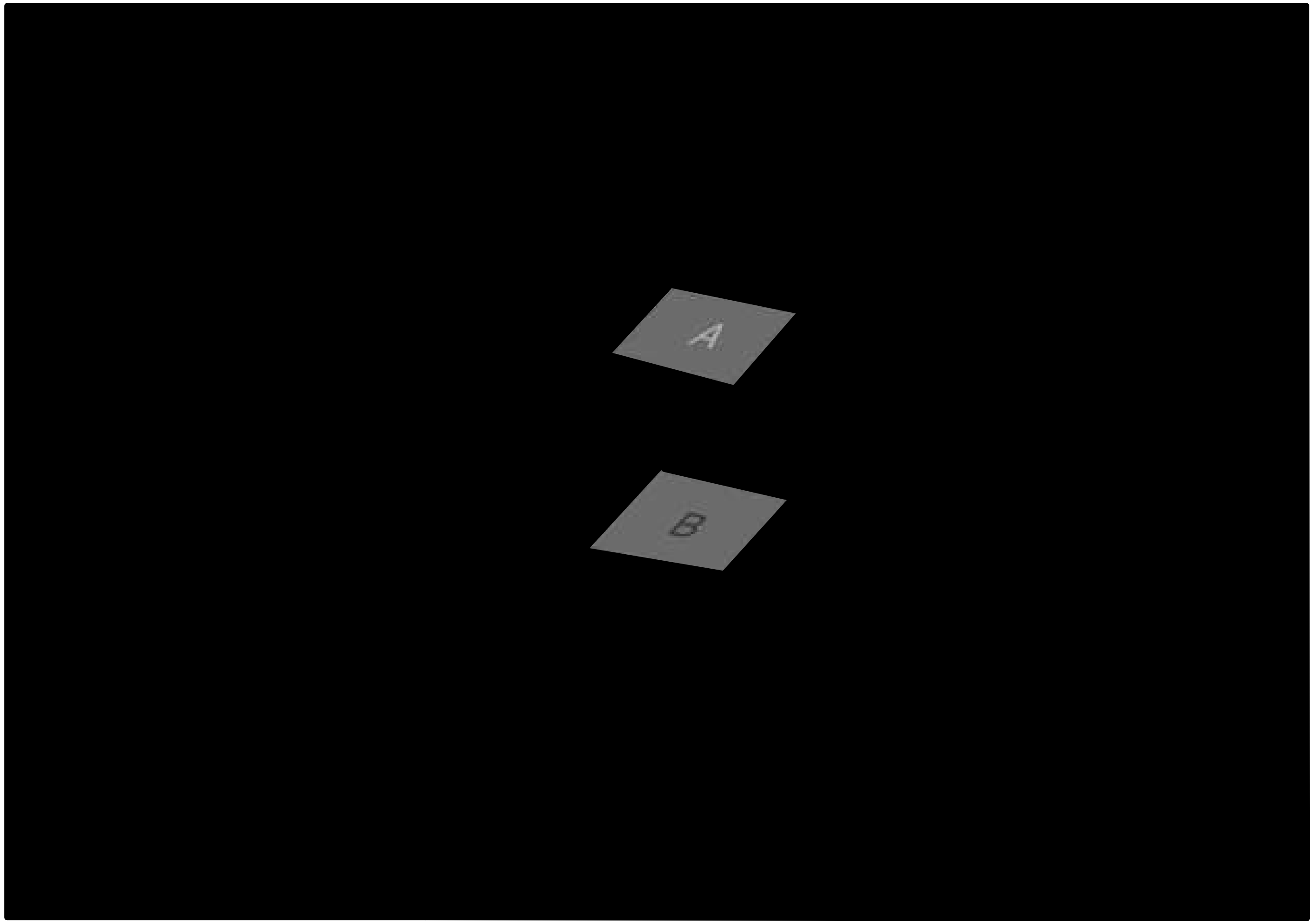
Models of early visual perception

Part 6/6 – high(er) level vision

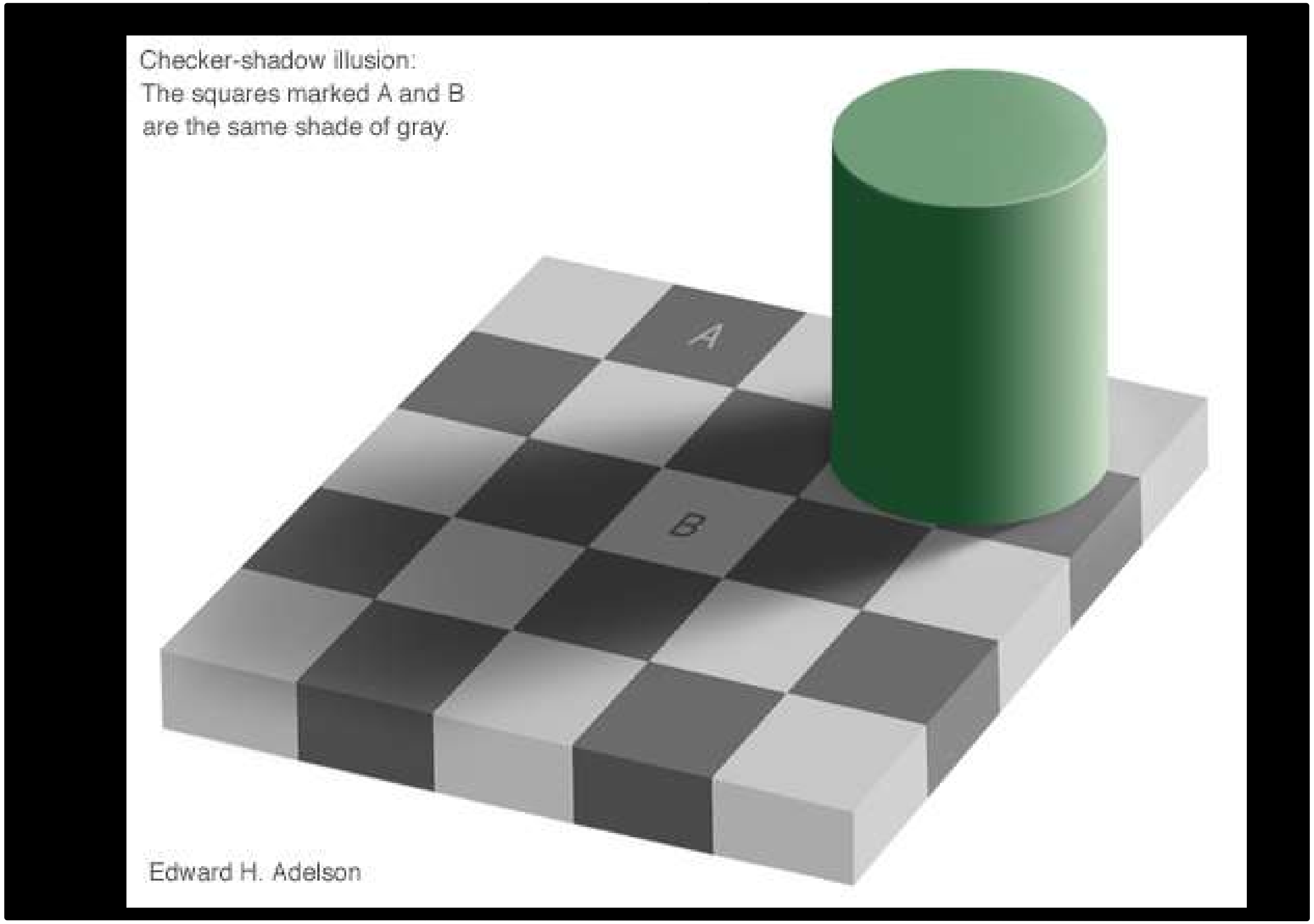
Rafal Mantiuk
Computer Laboratory, University of Cambridge

Simultaneous contrast

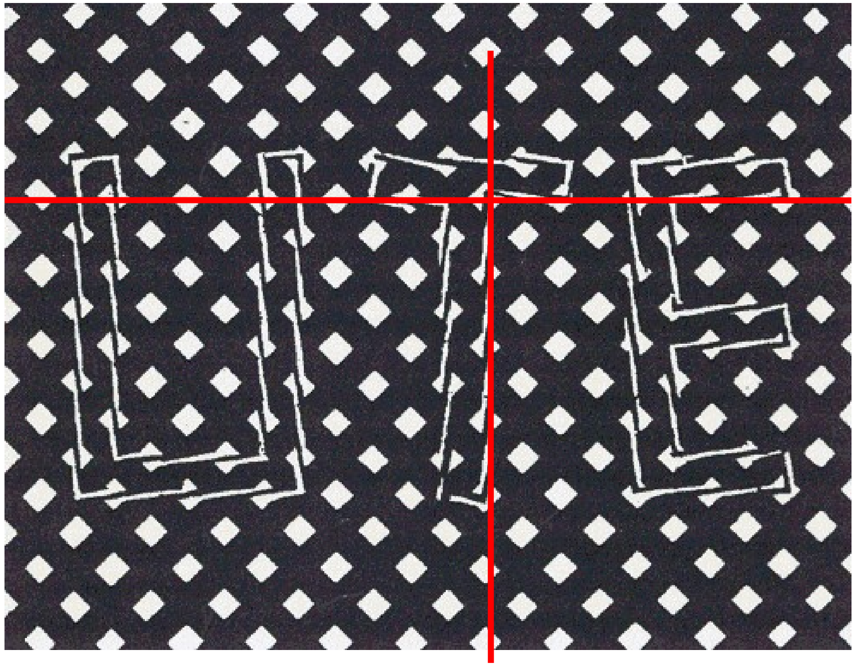
High-Level Contrast Processing

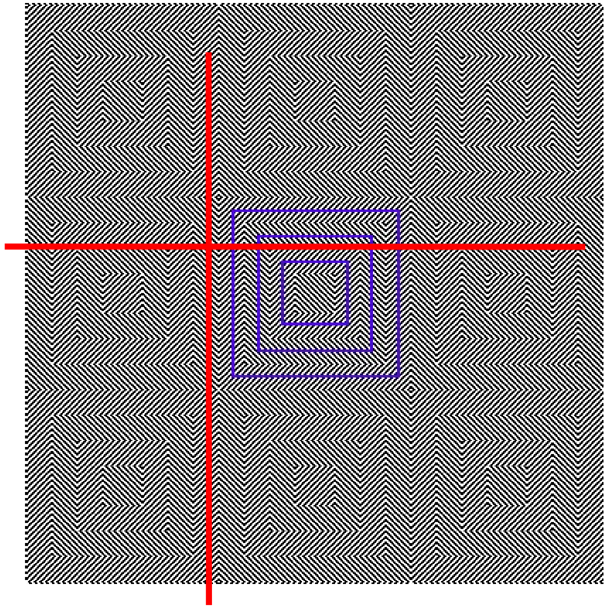


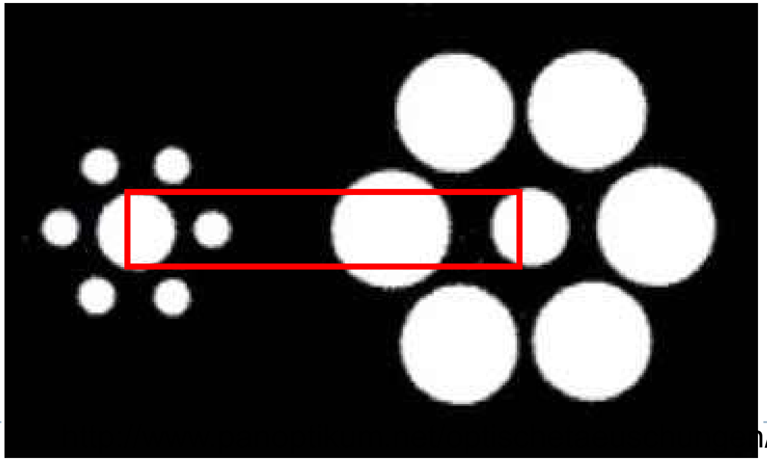
High-Level Contrast Processing



Shape Perception



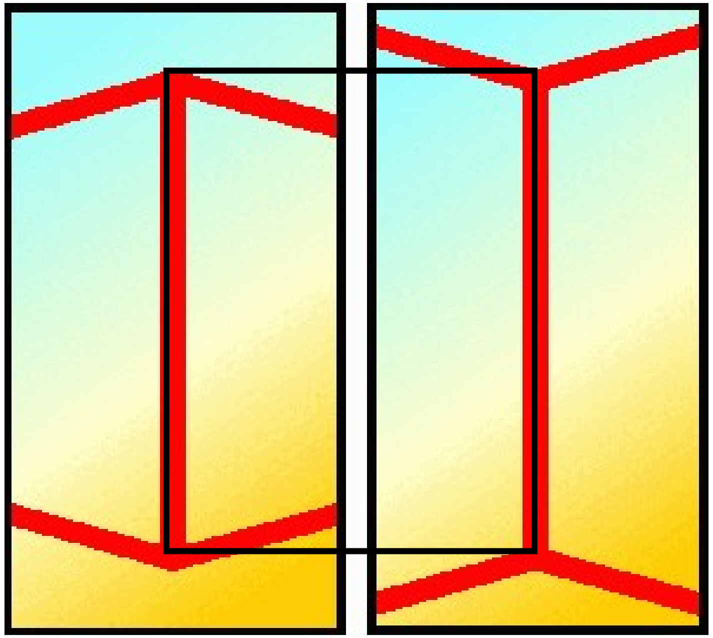


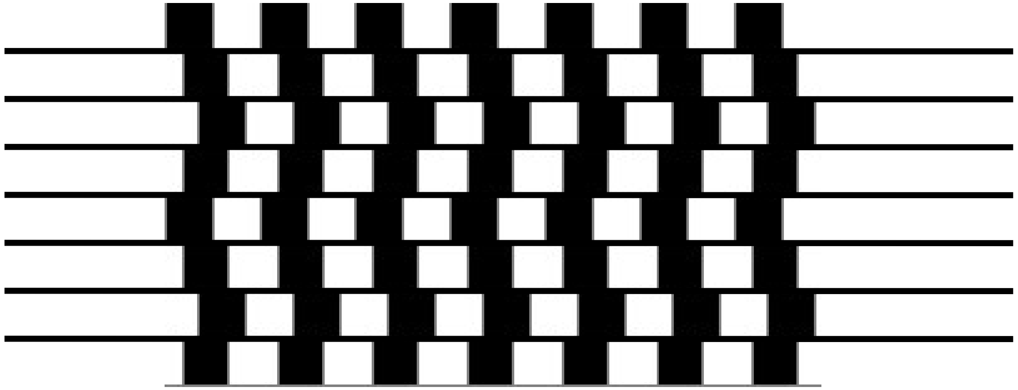


- Depends on surrounding primitives
  - Directional emphasis
  - Size emphasis

/index.html

Shape Processing: Geometrical Clues





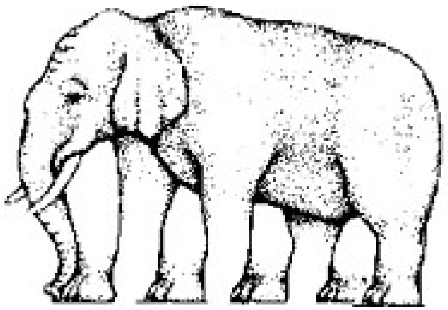
http://www.panoptikum.net/optischetaeuschungen/index.html

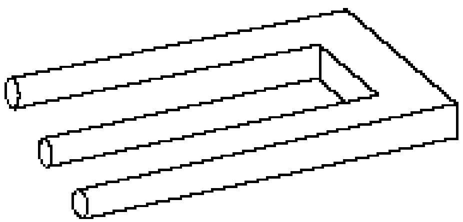
Automatic geometrical interpretation

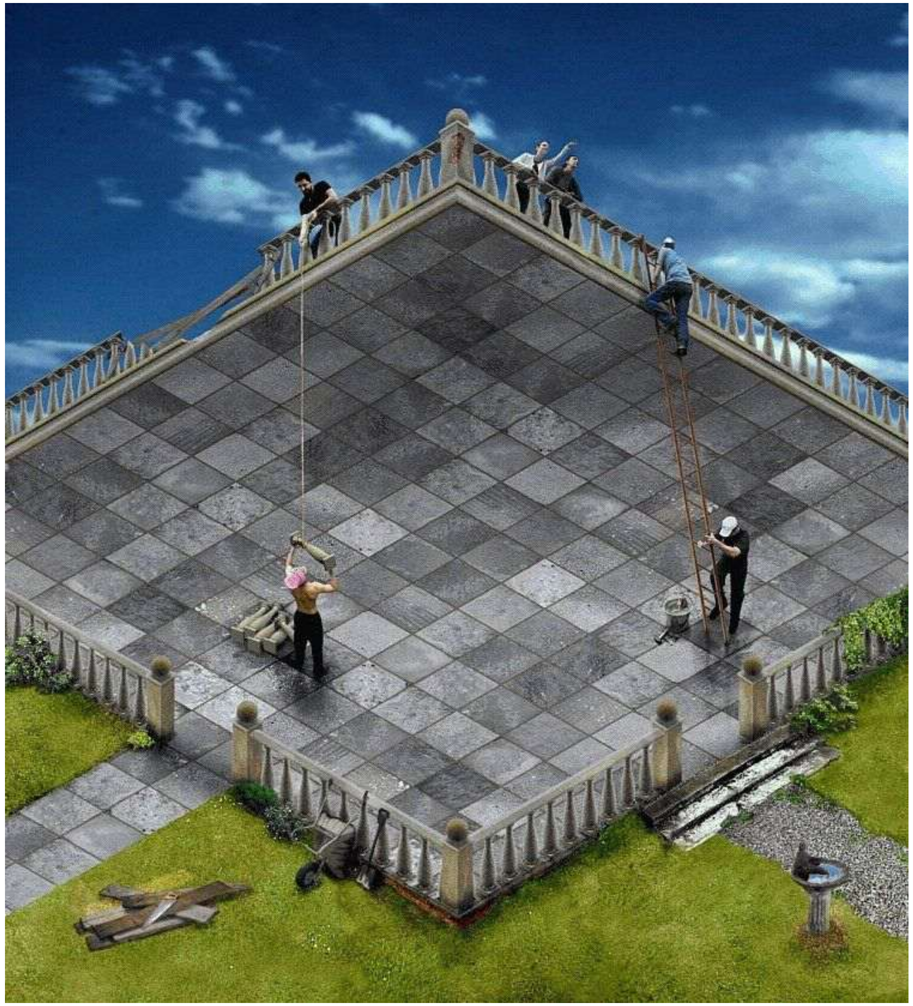
- 3D perspective
- Implicit scene depth

Impossible Scenes

- Escher et.al.
  - Confuse HVS by presenting contradicting visual clues
  - Local vs. global processing







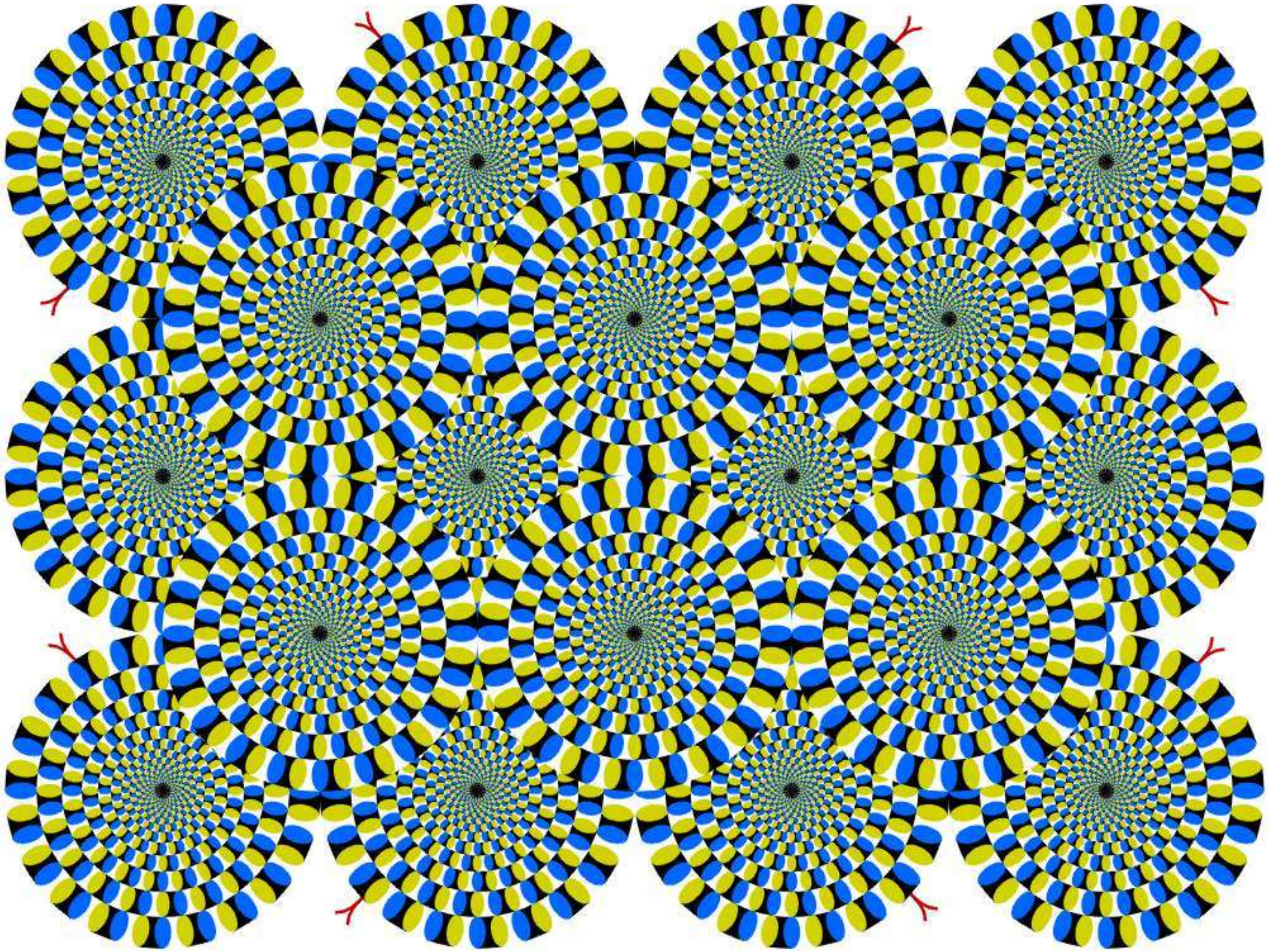
http://www.panoptikum.net/optischetaeuschungen/index.html

What is wrong with this graphics?

- AI-generated images may also lack global consistency

From: https://gizmodo.com/loki-s2-poster-ai-art-generated-disney-marvel-1850914705

Virtual Movement



caused by saccades, motion from dark to bright areas

Law of closure

References

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- Mantiuk, R. K., Myszkowski, K., & Seidel, H. (2015). High Dynamic Range Imaging. In *Wiley Encyclopedia of Electrical and Electronics Engineering*. Wiley.
  - Section 2.4
  - Available online: http://www.cl.cam.ac.uk/~rkm38/hdri_book.html