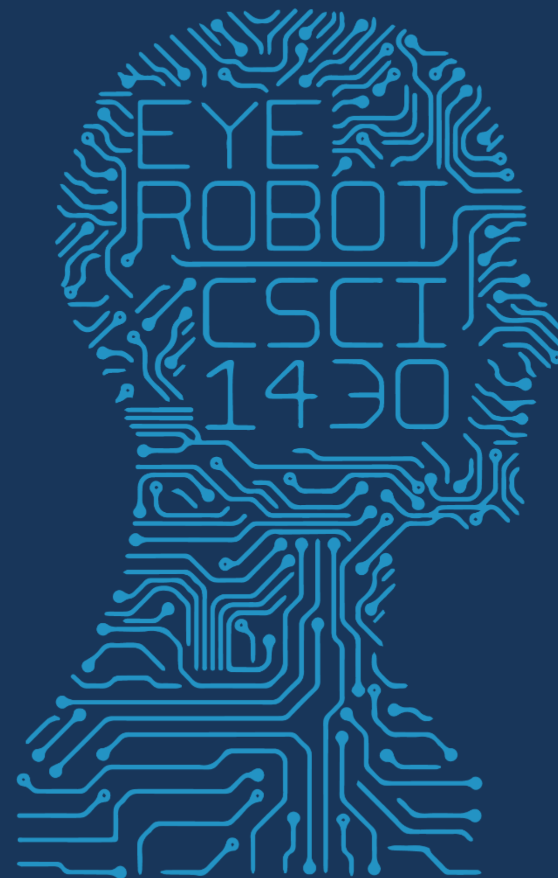
1950

Future Vision



2017 MWF 1pm 368

Computer Vision

Does everyone have an override code?

Project 1 due Friday 9pm

Review of Filtering

- Filtering in frequency domain
  - Can be faster than filtering in spatial domain (for large filters)
  - Can help understand effect of filter
  - Algorithm:
    1. Convert image and filter to fft (fft2 in matlab)
    2. Pointwise-multiply ffts
    3. Convert result to spatial domain with ifft2

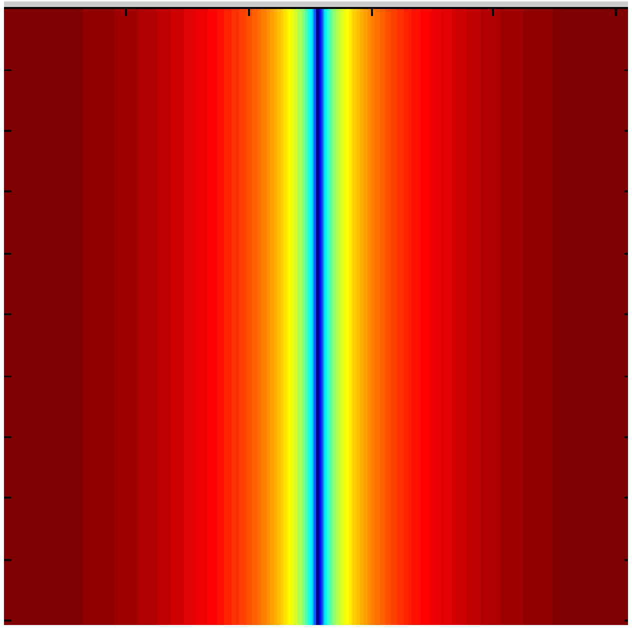
Did anyone play with the code?

Hays

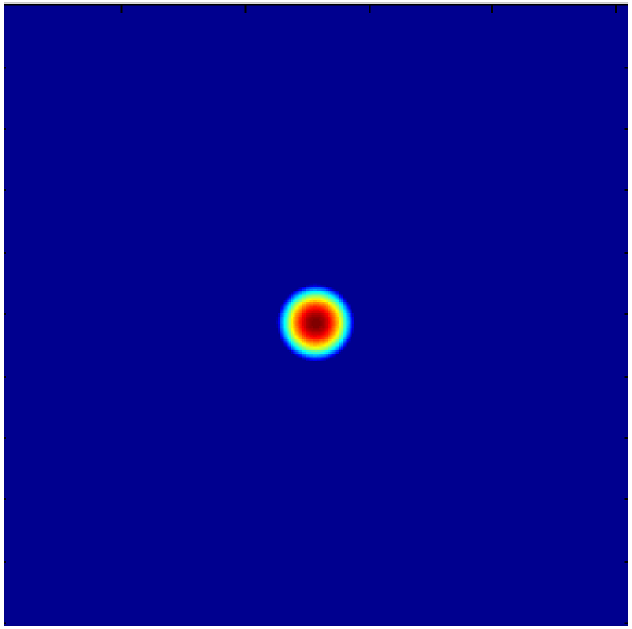
Review of Filtering

- Linear filters for basic processing
  - Edge filter (high-pass)
  - Gaussian filter (low-pass)

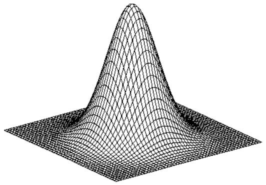
[-1 1]



FFT of Gradient Filter



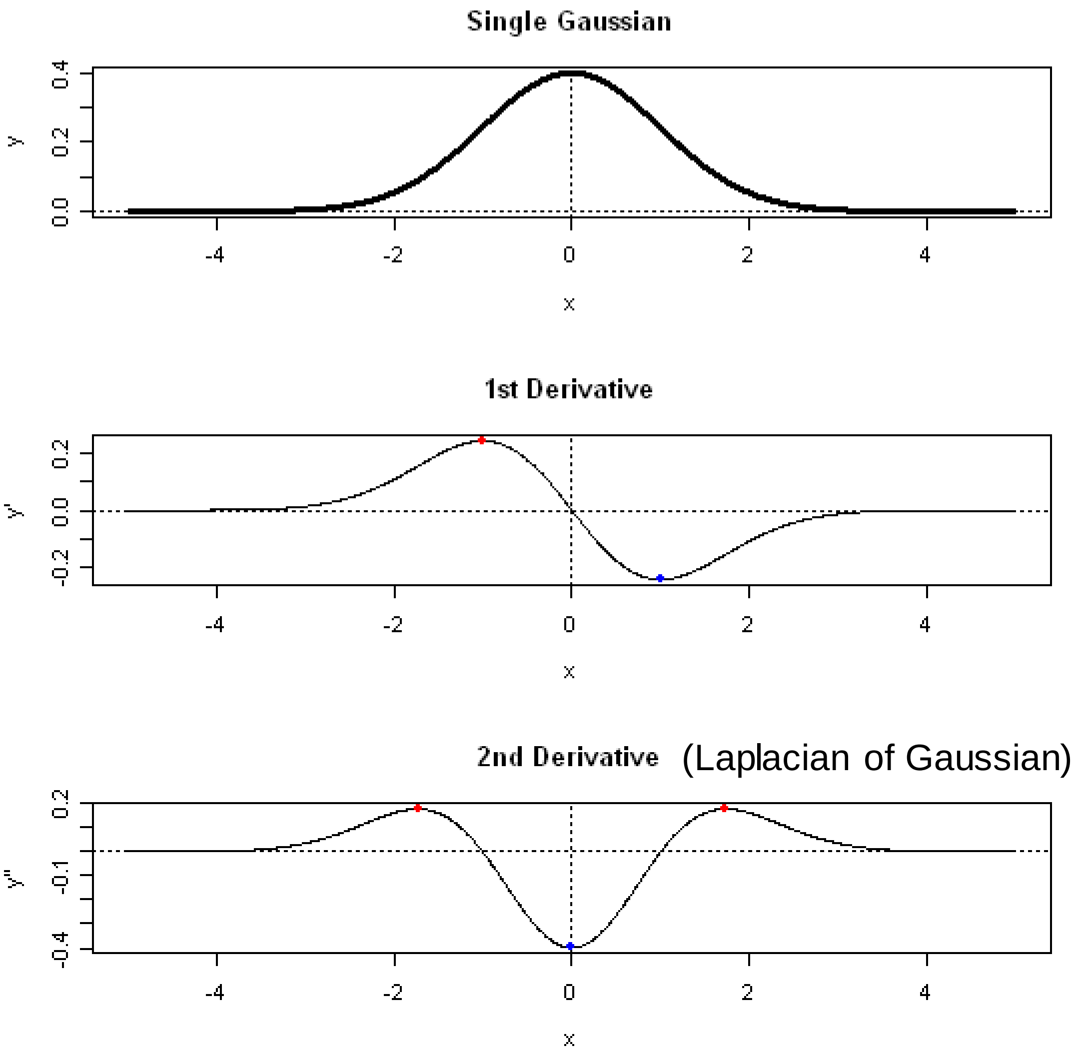
FFT of Gaussian



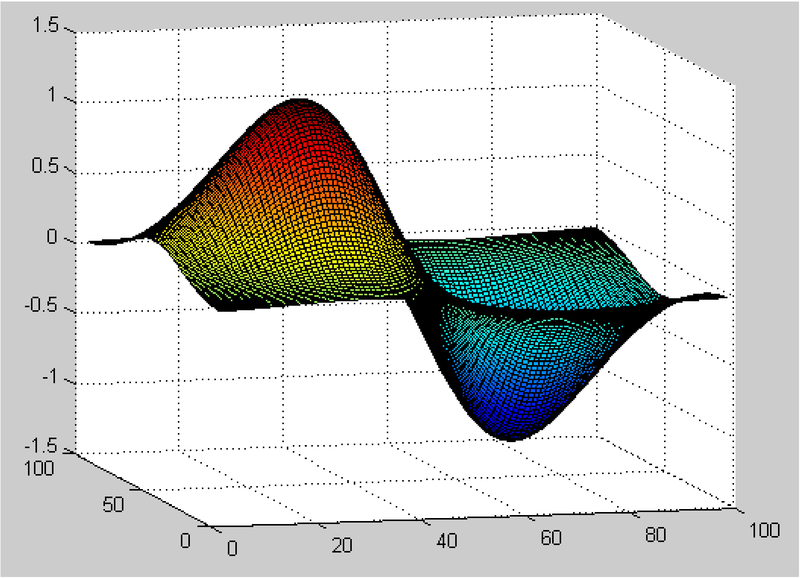
Gaussian

Hays

More Useful Filters

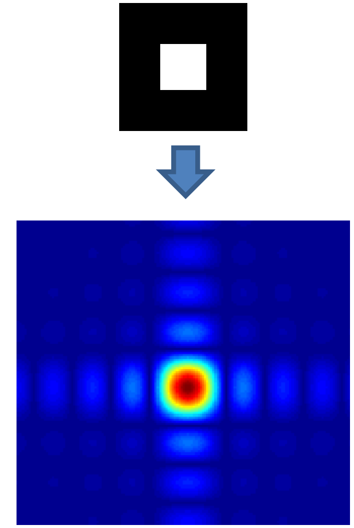


1st Derivative of Gaussian



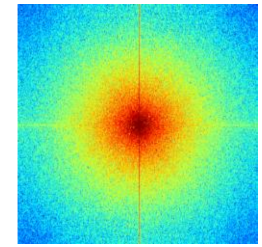
Earl F. Glynn

Things to Remember

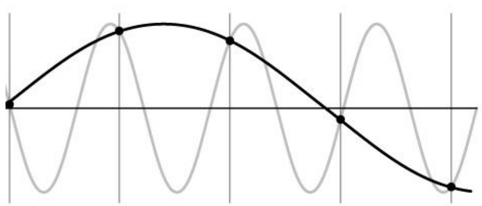


- Sometimes it makes sense to think of images and filtering in the frequency domain
  – Fourier analysis

- Can be faster to filter using FFT for large images
  - N logN vs. N^2 for auto-correlation



- Images are mostly smooth
  – Basis for compression

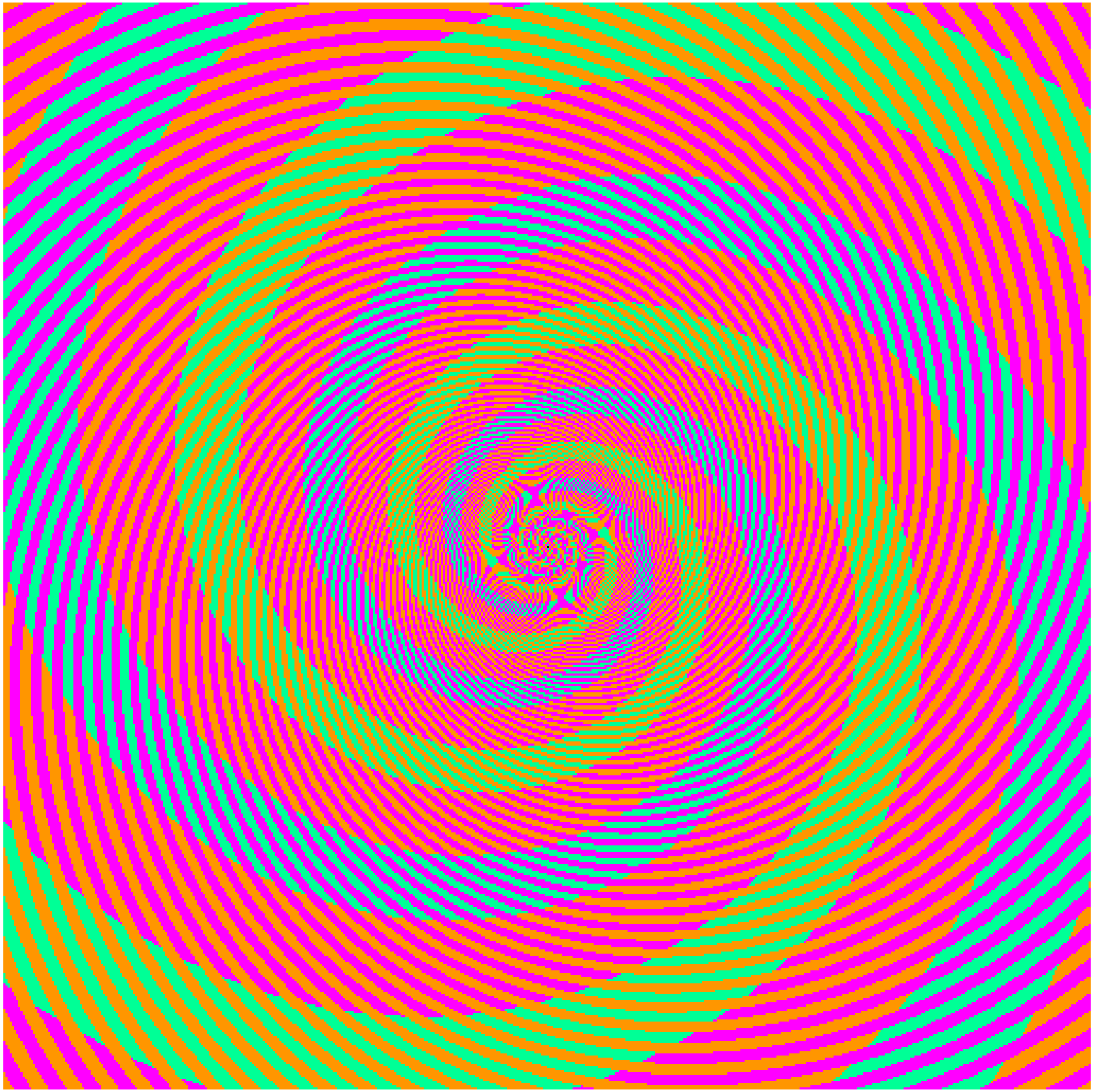


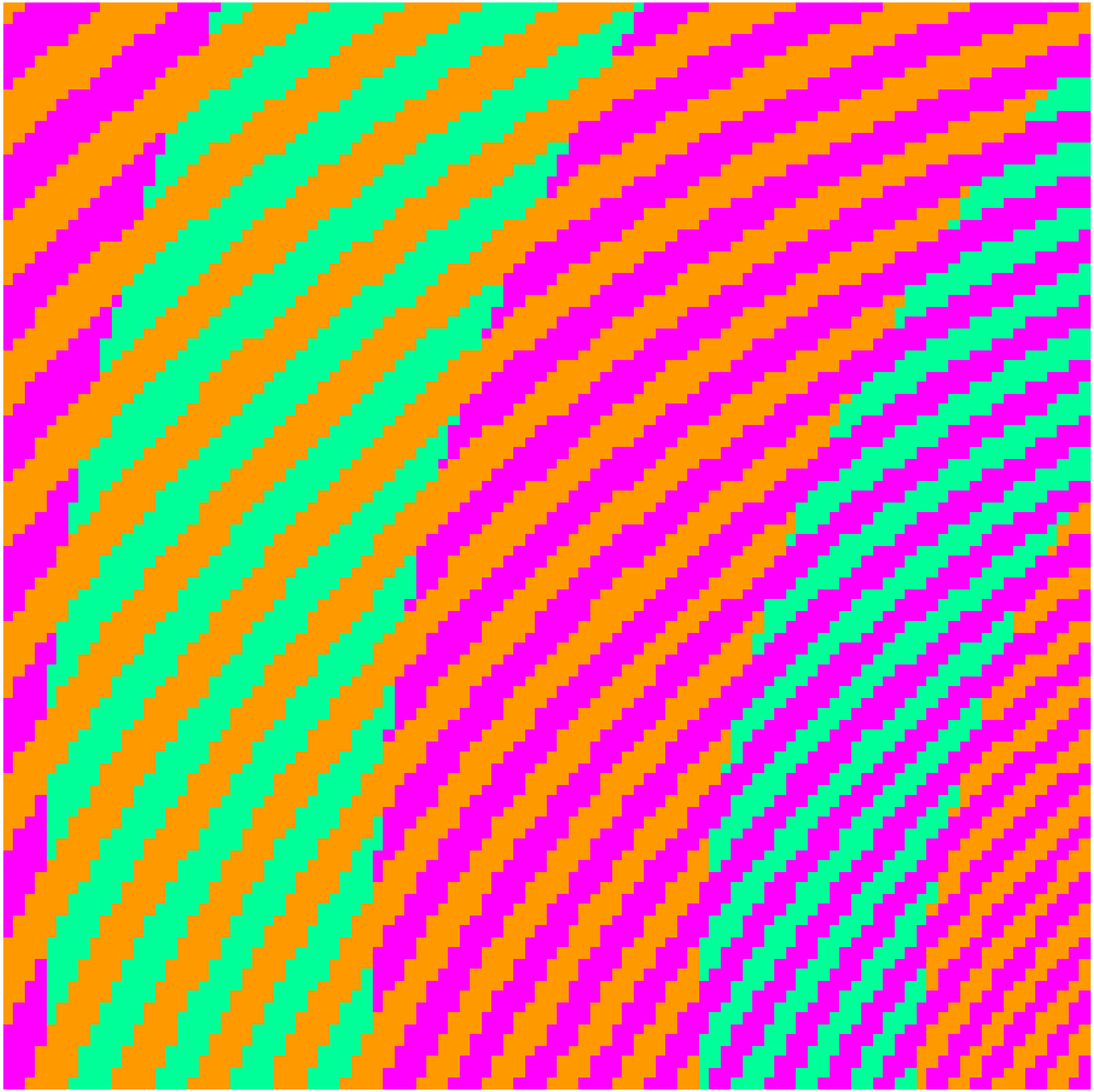
- Remember to low-pass before sampling
  - Otherwise you create aliasing

Hays

Aliasing and Moiré patterns

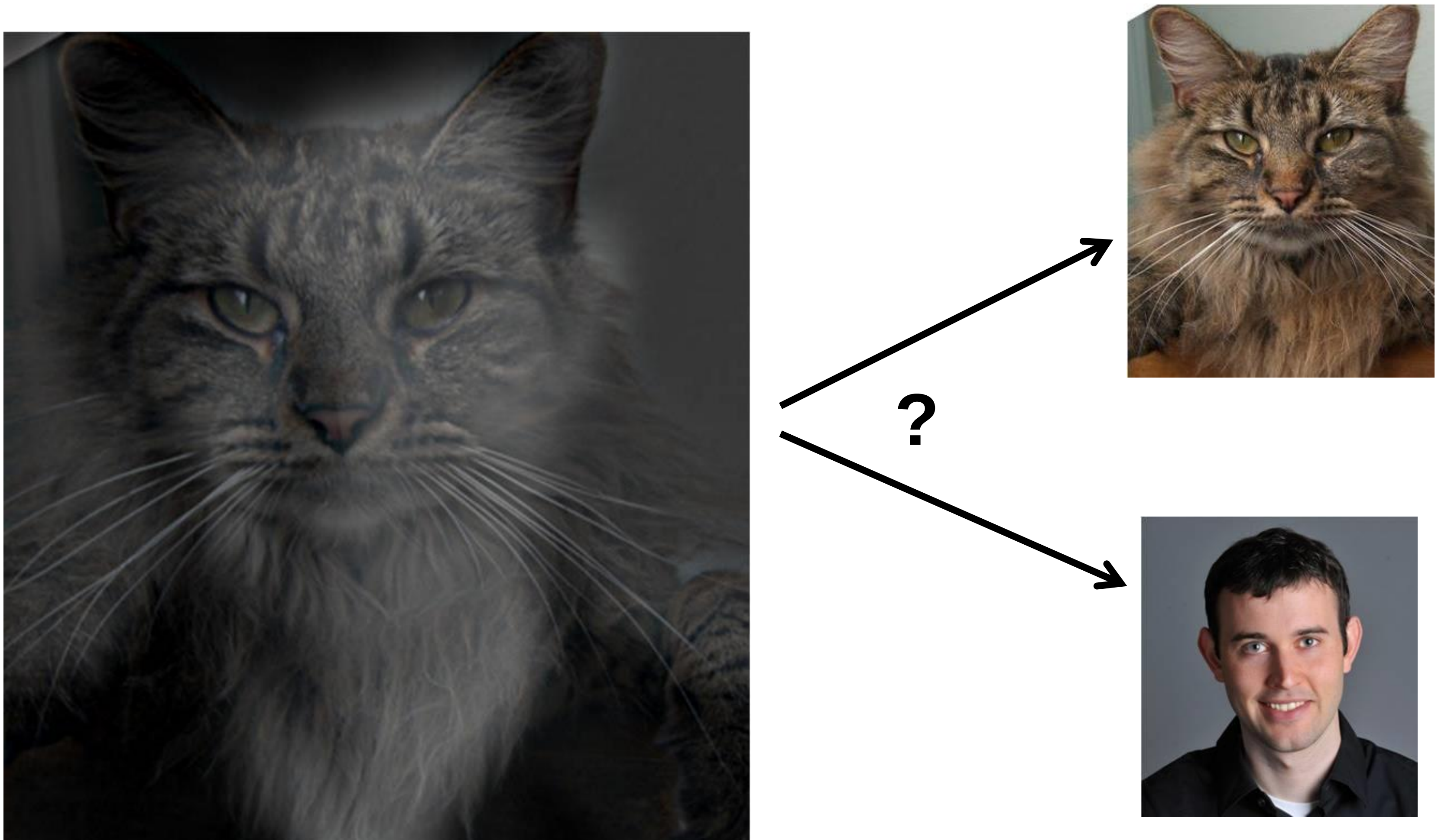
Gong 96, 1932, Claude Tousignant, Musée des Beaux-Arts de Montréal





The blue and green colors are actually the same
http://blogs.discovermagazine.com/badastronomy/2009/06/24/the-blue-and-the-green/

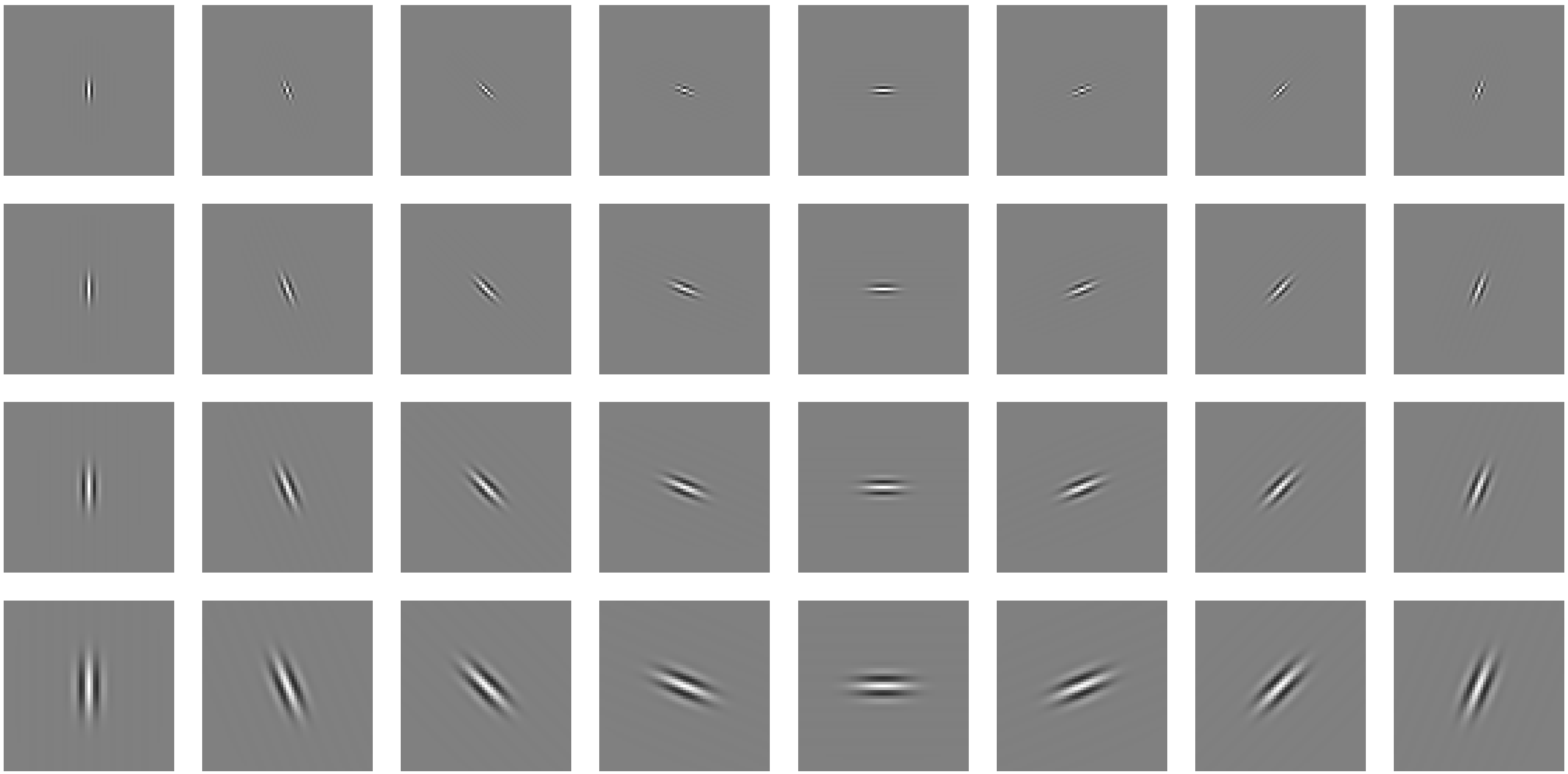
Why do we get different, distance-dependent interpretations of hybrid images?



Hays

Clues from Human Perception

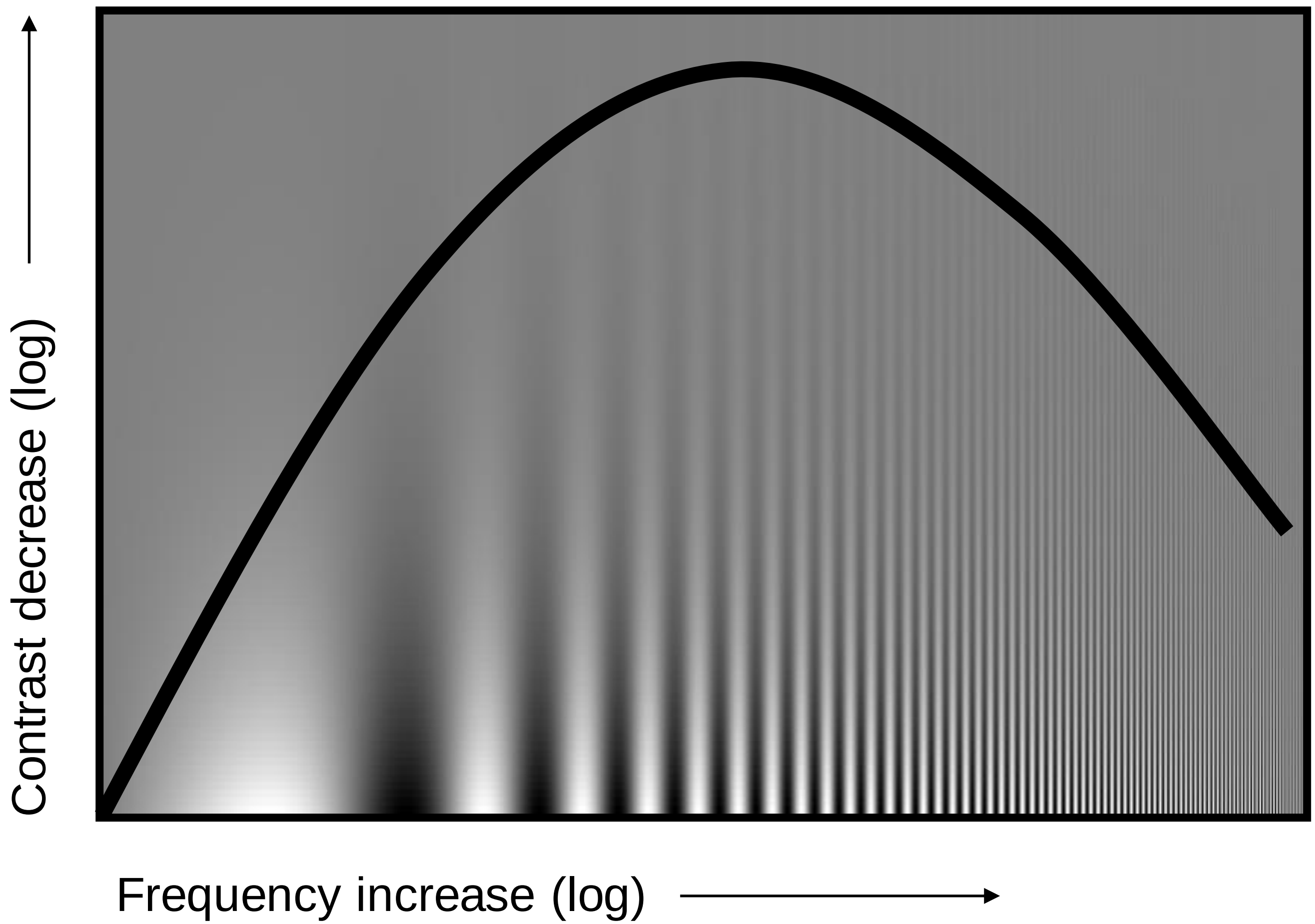
- Early processing in humans filters for orientations and scales of frequency.



Early Visual Processing: Multi-scale edge and blob filters

Campbell-Robson contrast sensitivity curve

Perceptual cues in the mid-high frequencies dominate perception.



Application: Hybrid Images

When we see an image from far away, we are effectively subsampling it!

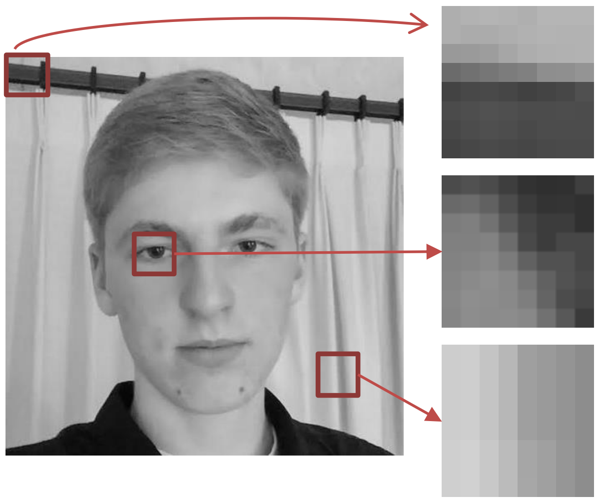
- A. Oliva, A. Torralba, P.G. Schyns, "Hybrid Images," SIGGRAPH 2006

Thinking in Frequency - Compression

How is it that a 4MP image can be compressed to a few hundred KB without a noticeable change?

Lossy Image Compression (JPEG)

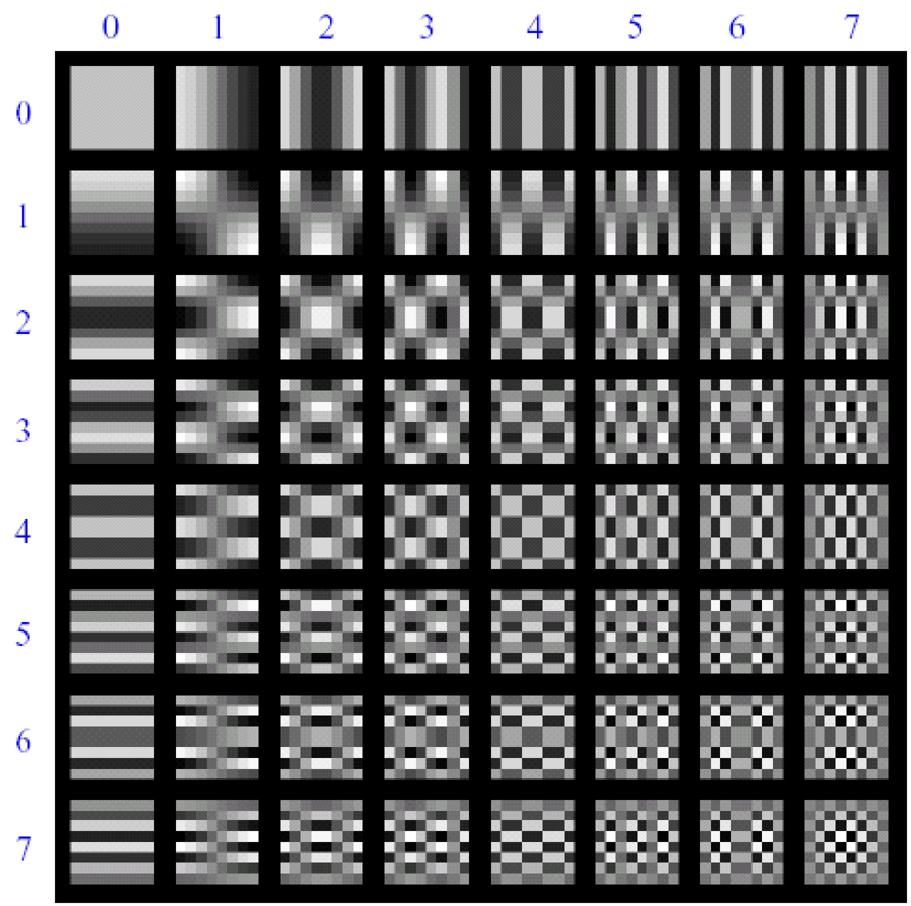
8x8 blocks



The first coefficient B(0,0) is the DC component, the average intensity

The top-left coeffs represent low frequencies, the bottom right represent high frequencies

8x8 blocks



Block-based Discrete Cosine Transform (DCT)

Slides: Efros

Image compression using DCT

- Compute DCT filter responses in each 8x8 block

Filter responses

$$
\begin{array}{cc}
 & \overset{u}{\longrightarrow} \\
G = \begin{bmatrix}
-415.38 & -30.19 & -61.20 & 27.24 & 56.13 & -20.10 & -2.39 & 0.46 \\
4.47 & -21.86 & -60.76 & 10.25 & 13.15 & -7.09 & -8.54 & 4.88 \\
-46.83 & 7.37 & 77.13 & -24.56 & -28.91 & 9.93 & 5.42 & -5.65 \\
-48.53 & 12.07 & 34.10 & -14.76 & -10.24 & 6.30 & 1.83 & 1.95 \\
12.12 & -6.55 & -13.20 & -3.95 & -1.88 & 1.75 & -2.79 & 3.14 \\
-7.73 & 2.91 & 2.38 & -5.94 & -2.38 & 0.94 & 4.30 & 1.85 \\
-1.03 & 0.18 & 0.42 & -2.42 & -0.88 & -3.02 & 4.12 & -0.66 \\
-0.17 & 0.14 & -1.07 & -4.19 & -1.17 & -0.10 & 0.50 & 1.68
\end{bmatrix} & \Big\downarrow v
\end{array}
$$

- Quantize to integer (div. by magic number; round)
  - More coarsely for high frequencies (which also tend to have smaller values)
  - Many quantized high frequency values will be zero

Quantization divisers (element-wise)

$$
Q = \begin{bmatrix}
16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\
12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\
14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\
14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\
18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\
24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\
49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\
72 & 92 & 95 & 98 & 112 & 100 & 103 & 99
\end{bmatrix}
$$

Quantized values

$$
B = \begin{bmatrix}
-26 & -3 & -6 & 2 & 2 & -1 & 0 & 0 \\
0 & -2 & -4 & 1 & 1 & 0 & 0 & 0 \\
-3 & 1 & 5 & -1 & -1 & 0 & 0 & 0 \\
-3 & 1 & 2 & -1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

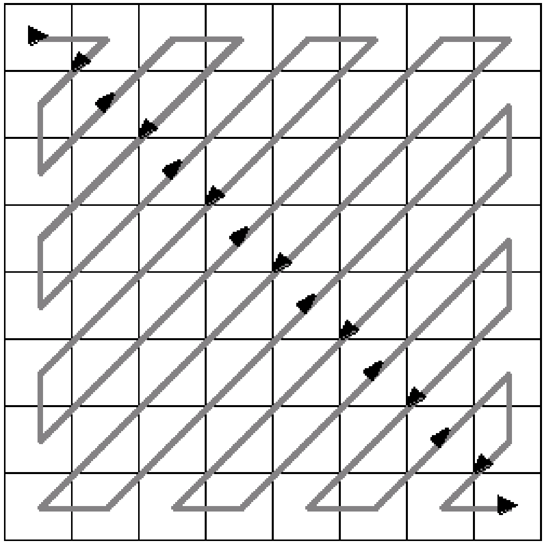
JPEG Encoding

- Entropy coding (Huffman-variant)

Quantized values

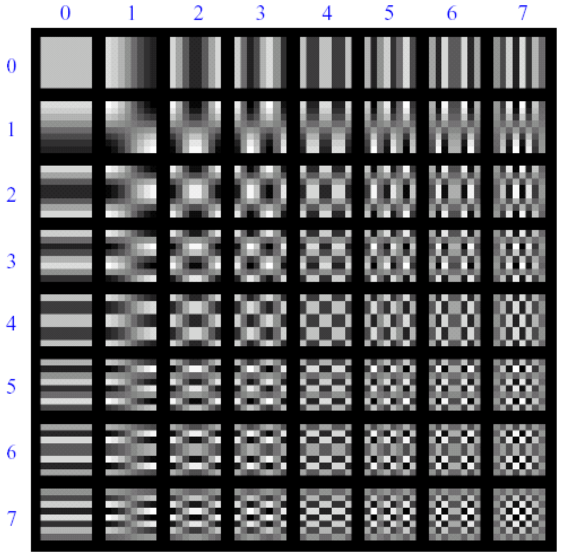
$$B = \begin{bmatrix} -26 & -3 & -6 & 2 & 2 & -1 & 0 & 0 \\ 0 & -2 & -4 & 1 & 1 & 0 & 0 & 0 \\ -3 & 1 & 5 & -1 & -1 & 0 & 0 & 0 \\ -3 & 1 & 2 & -1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Linearize *B* like this.



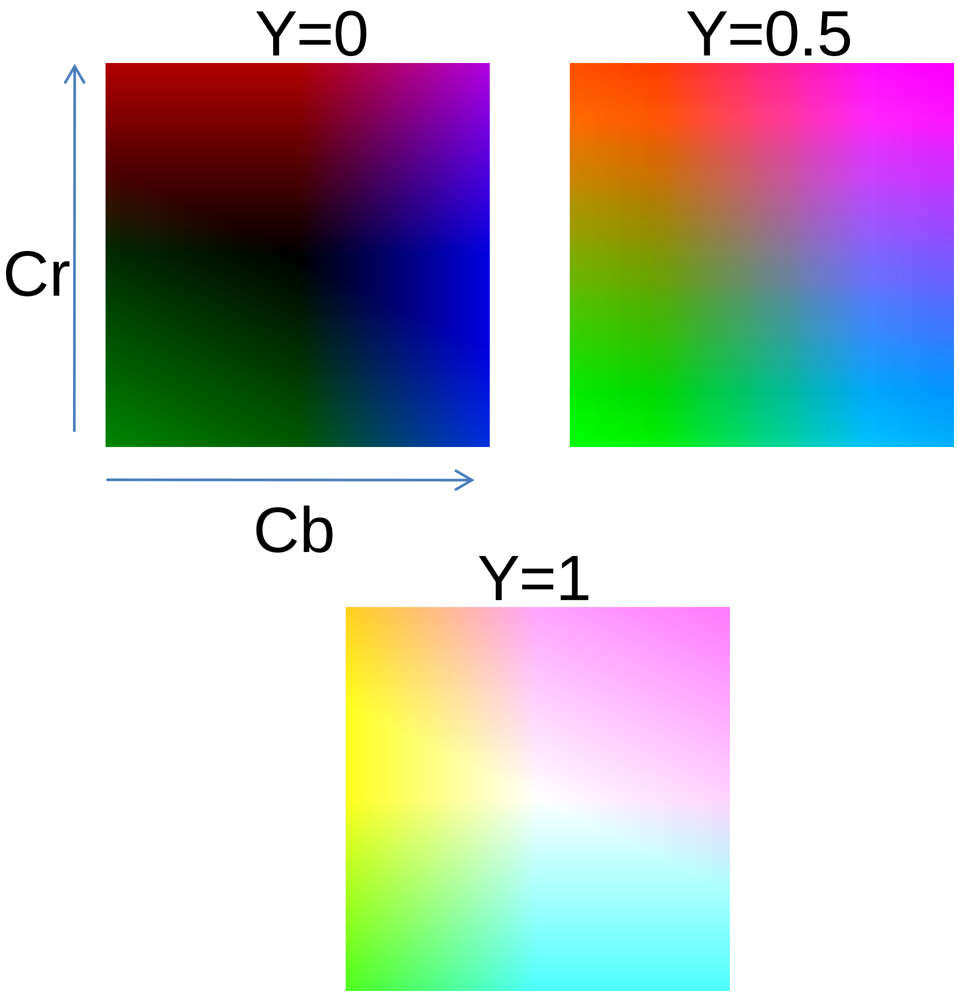
Helps compression:

- We throw away the high frequencies ('0').
- The zig zag pattern increases in frequency space, so long runs of zeros.



Color spaces: YCbCr

Fast to compute, good for compression, used by TV



Y
(Cb=0.5,Cr=0.5)

Cb
(Y=0.5,Cr=0.5)

Cr
(Y=0.5,Cb=05)

James Hays

Most JPEG images & videos subsample chroma

PSP Comp 3
2x2 Chroma subsampling
285K

Original
1,261K lossless
968K PNG

JPEG Compression Summary

1. Convert image to YCrCb
2. Subsample color by factor of 2
   - People have bad resolution for color
3. Split into blocks (8x8, typically), subtract 128
4. For each block
   a. Compute DCT coefficients
   b. Coarsely quantize
      - Many high frequency components will become zero
   c. Encode (with run length encoding and then Huffman coding for leftovers)

http://en.wikipedia.org/wiki/YCbCr
http://en.wikipedia.org/wiki/JPEG

EDGE / BOUNDARY DETECTION

Szeliski 4.2

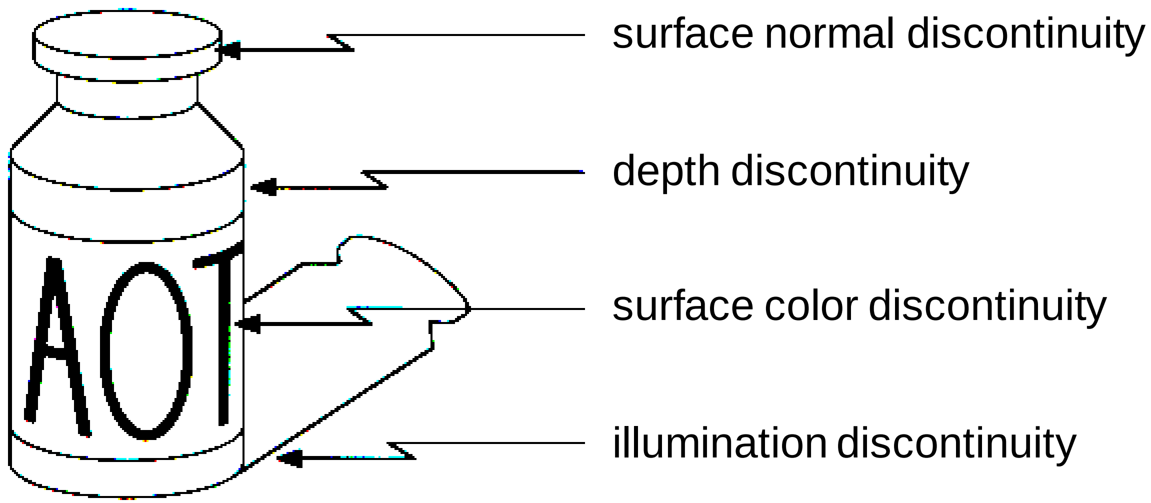
Many slides from James Hays, Lana Lazebnik, Steve Seitz, David Forsyth, David Lowe, Fei-Fei Li, and Derek Hoiem

Edge detection

- **Goal:** Identify visual changes (discontinuities) in an image.
- Intuitively, semantic information is encoded in edges.
- What are some ‘causes’ of visual edges?

Source: D. Lowe

Origin of Edges



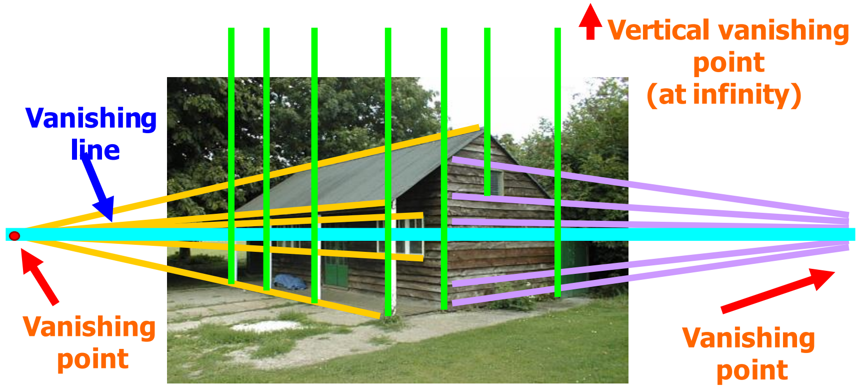
- Edges are caused by a variety of factors

Source: Steve Seitz

Why do we care about edges?

- Extract information
  - Recognize objects

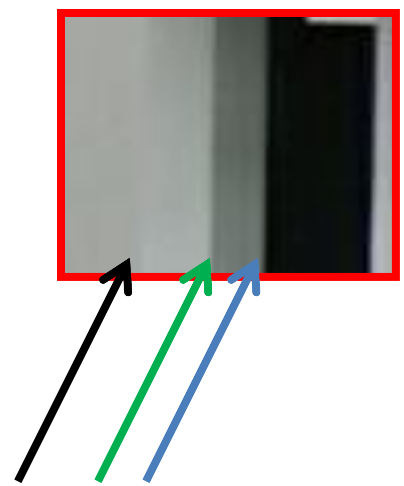
- Help recover geometry and viewpoint



Closeup of edges

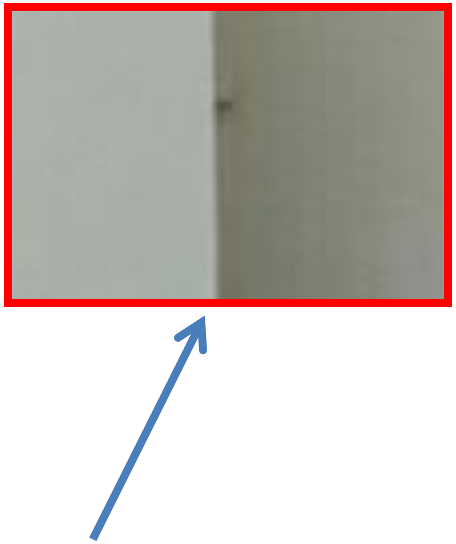
Source: D. Hoiem

Closeup of edges



Source: D. Hoiem

Closeup of edges



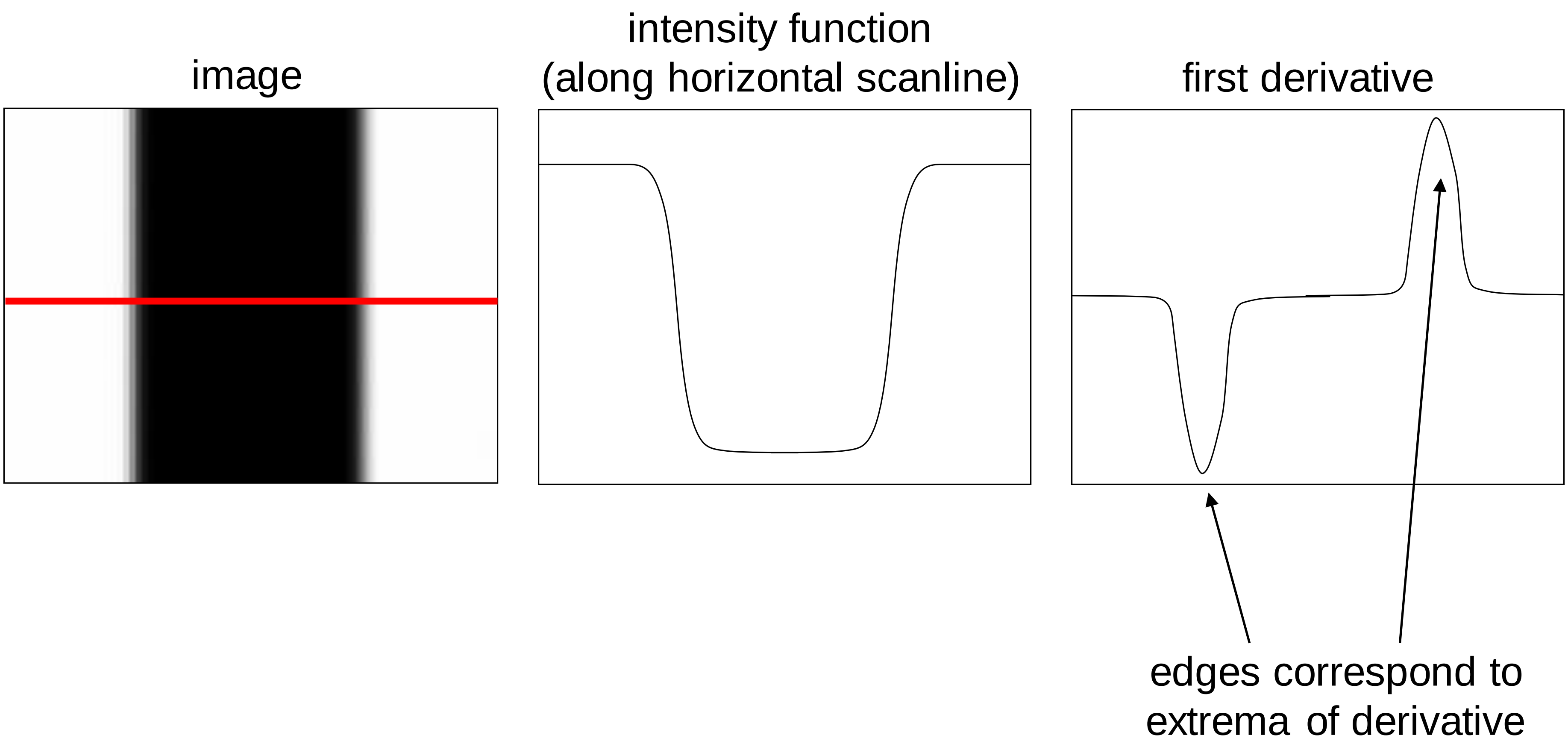
Source: D. Hoiem

Closeup of edges

Source: D. Hoiem

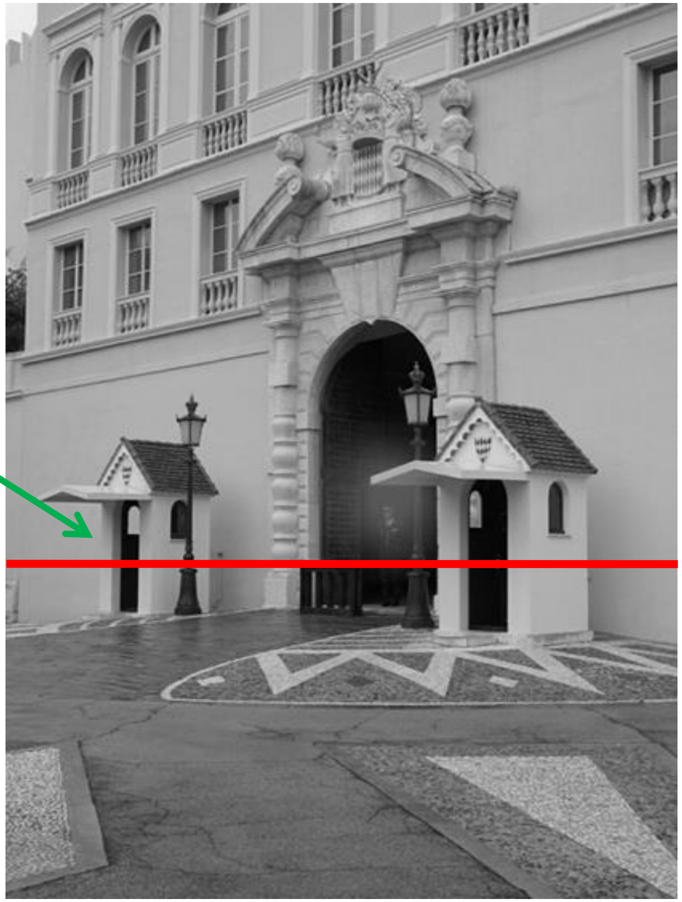
Characterizing edges

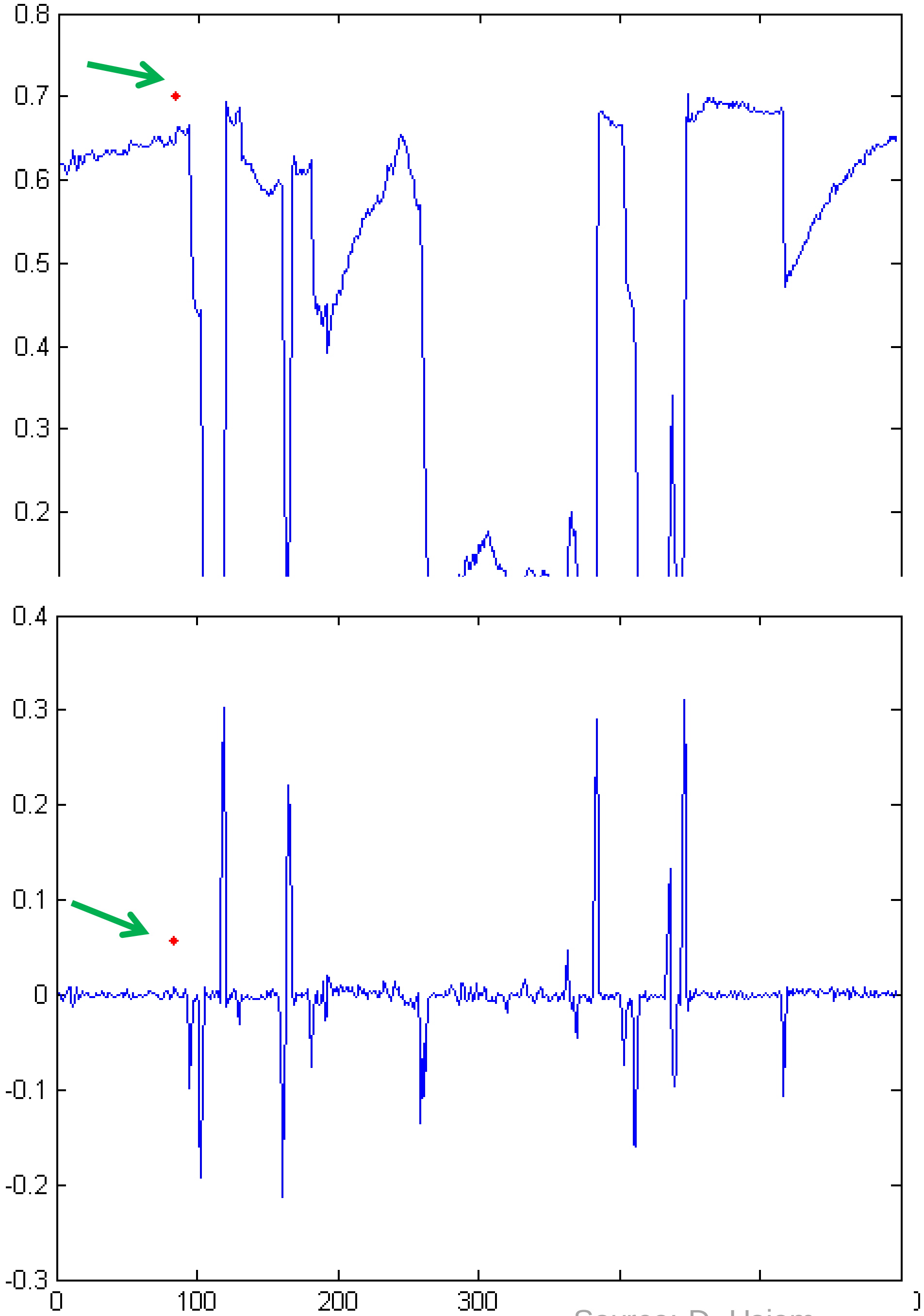
- An edge is a place of rapid change in the image intensity function



Hays

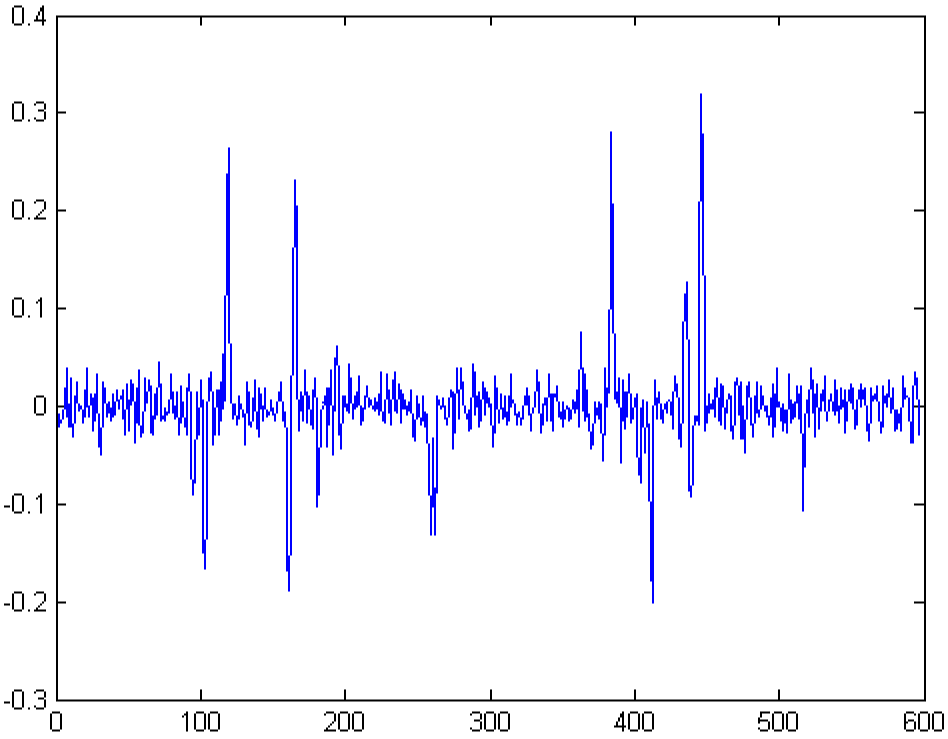
Intensity profile





Source: D. Hoiem

With a little Gaussian noise

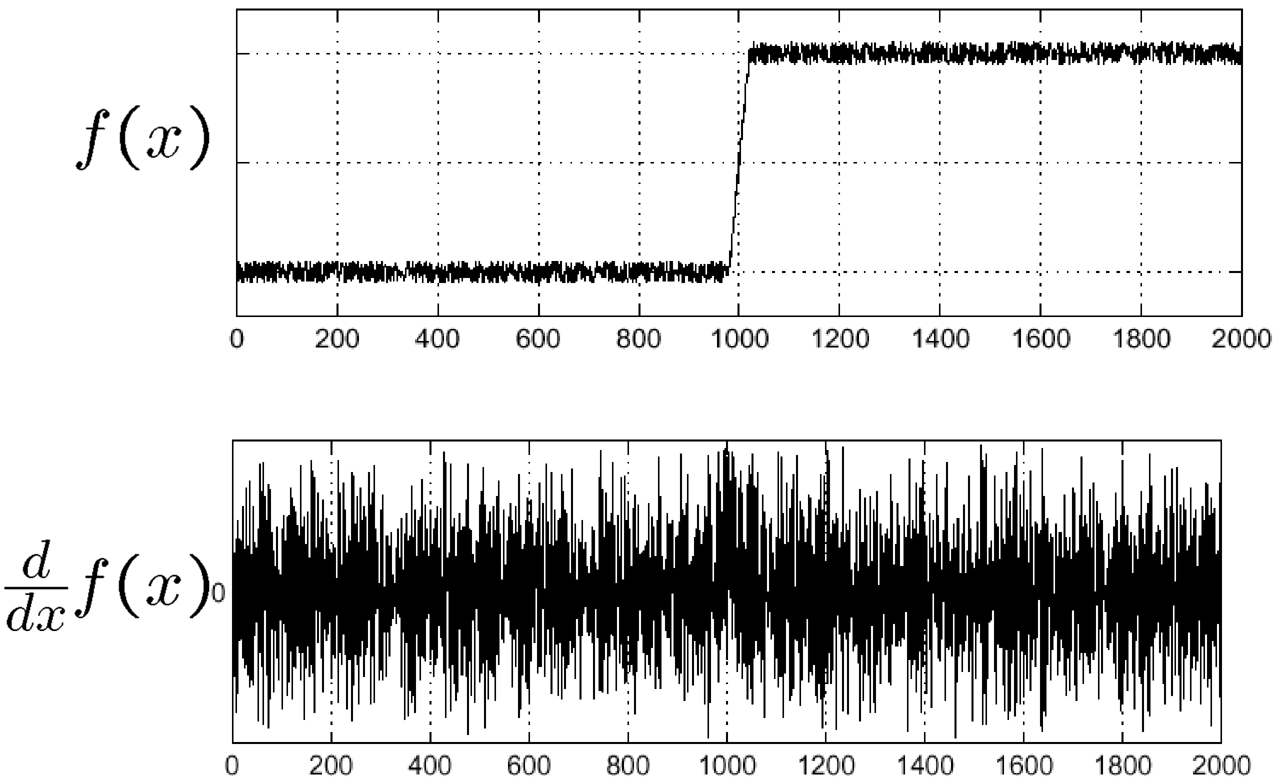


Gradient

Source: D. Hoiem

Effects of noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal



Where is the edge?

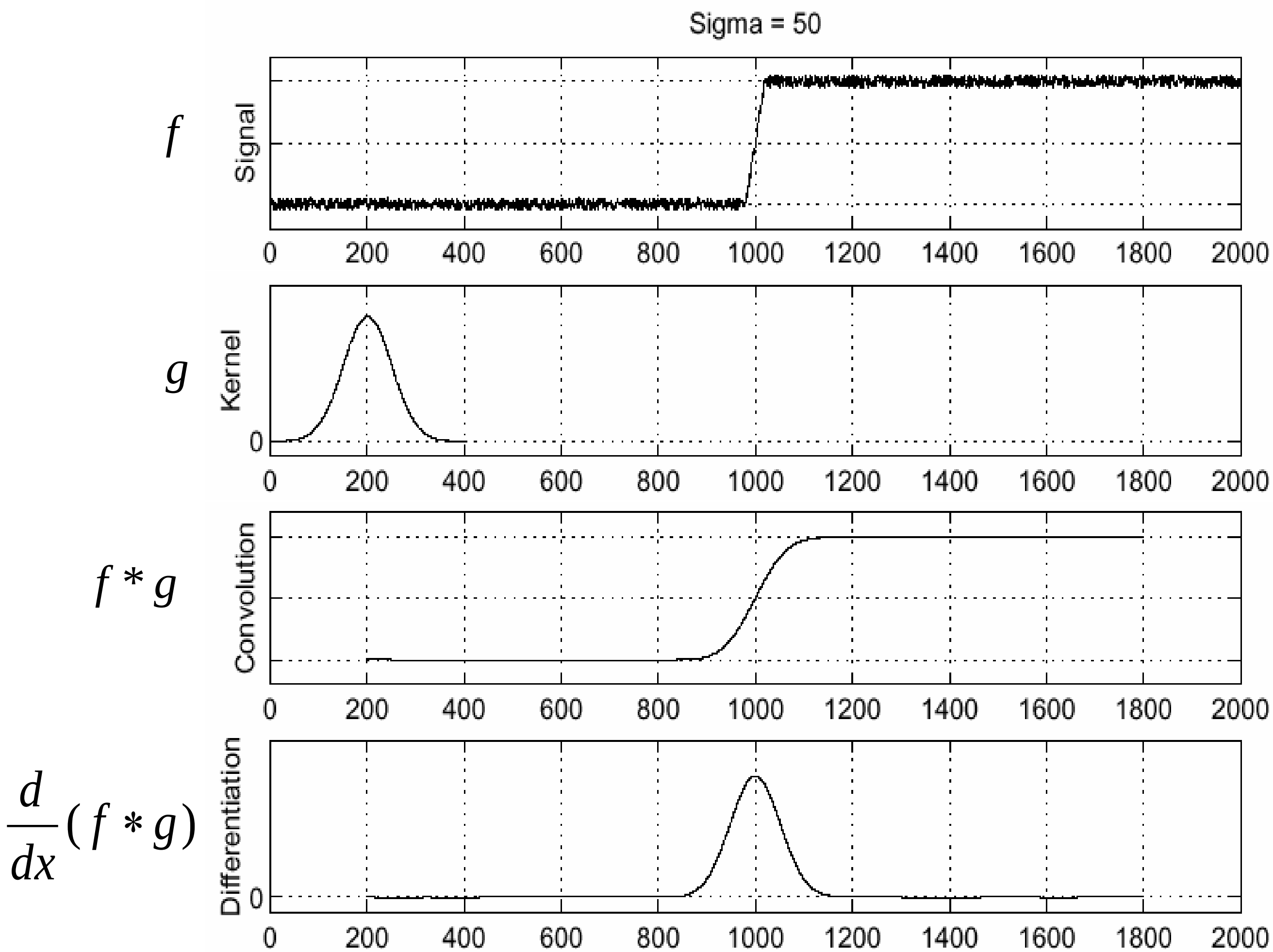
Source: S. Seitz

Effects of noise

- Difference filters respond strongly to noise
  - Image noise results in pixels that look very different from their neighbors
  - Generally, the larger the noise the stronger the response
- What can we do about it?

Source: D. Forsyth

Solution: smooth first



- To find edges, look for peaks in $\frac{d}{dx}(f * g)$

Source: S. Seitz

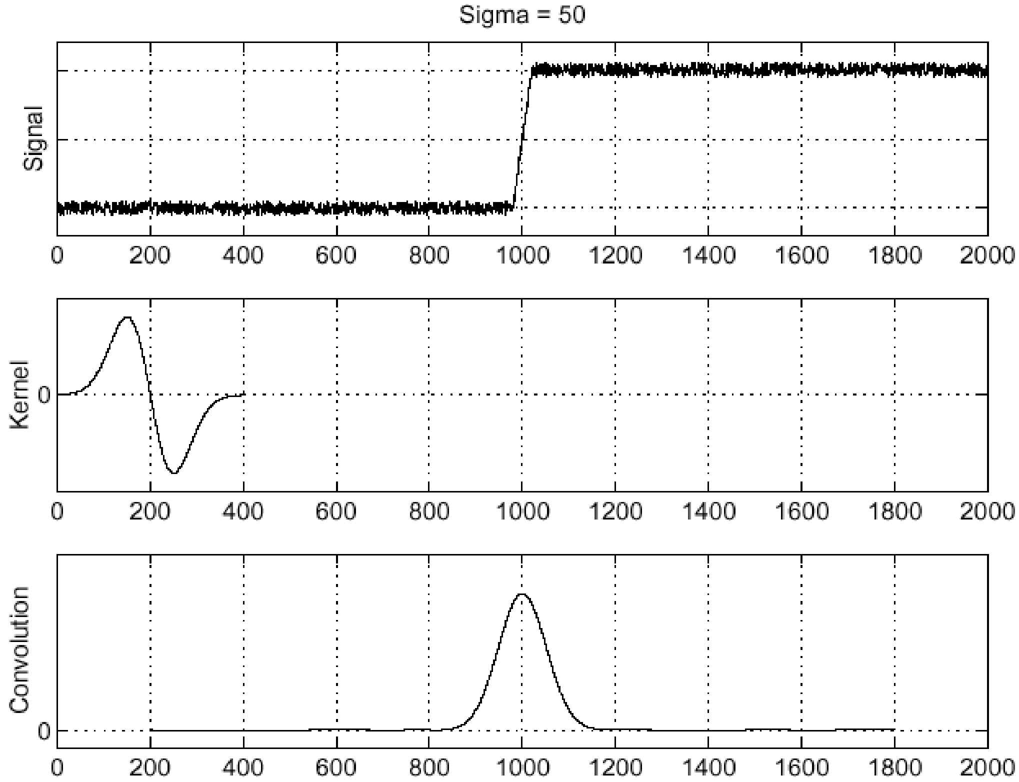
Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative: $$\frac{d}{dx}(f*g) = f*\frac{d}{dx}g$$
- This saves us one operation:

f

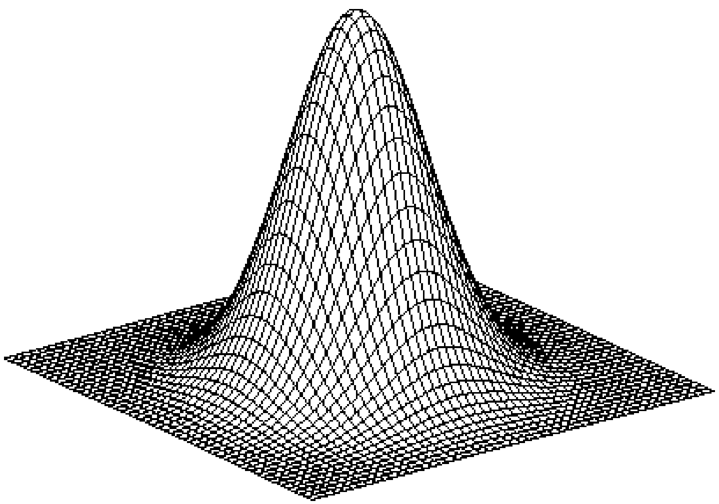
$\frac{d}{dx}g$

$f*\frac{d}{dx}g$

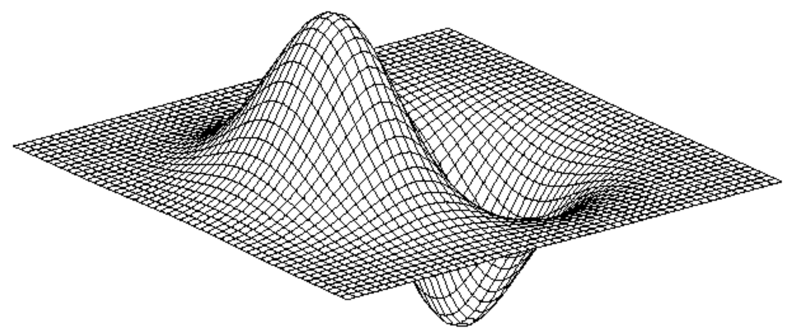


Source: S. Seitz

Derivative of 2D Gaussian filter

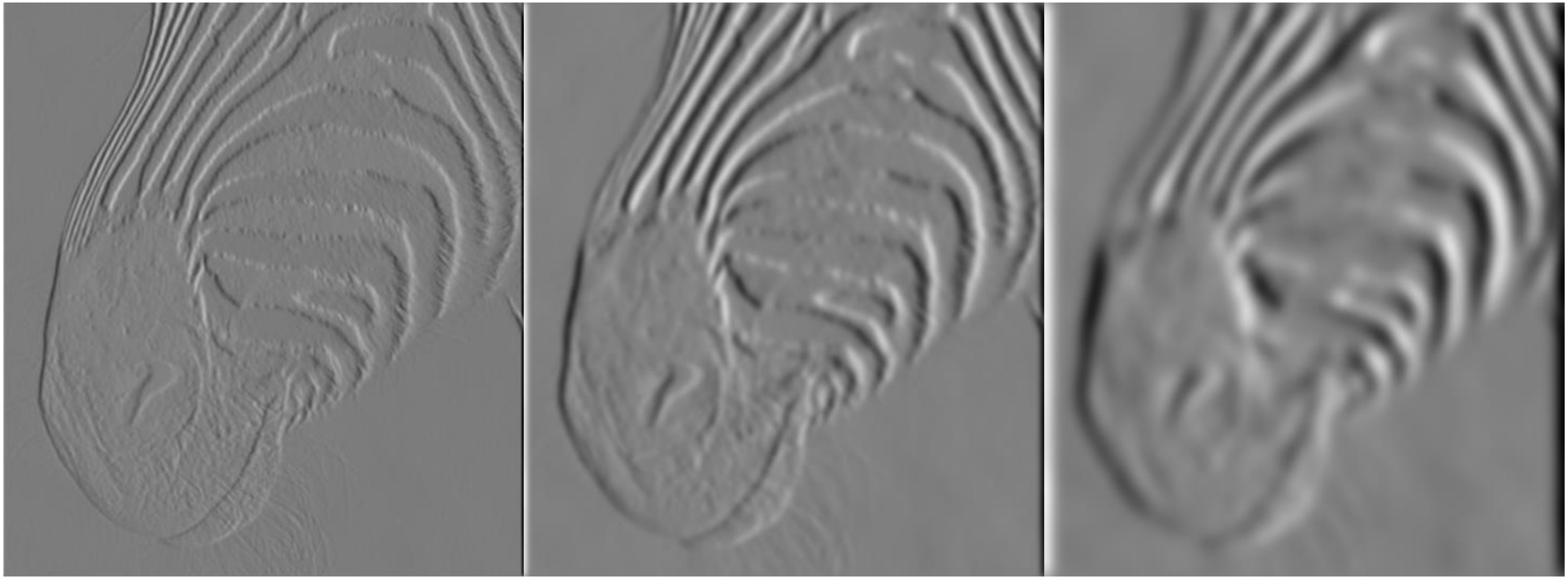


* [1 -1] =



Hays

Tradeoff between smoothing and localization



1 pixel 3 pixels 7 pixels

- Smoothed derivative removes noise, but blurs edge. Also finds edges at different "scales".

Source: D. Forsyth

Think-Pair-Share

- What is a good edge detector?

- Do we lose information when we look at edges? Are edges ‘incomplete’ as a representation of images?

Designing an edge detector

- Criteria for a good edge detector:
  - **Good detection:** the optimal detector should find all real edges, ignoring noise or other artifacts
  - **Good localization**
    - the edges detected must be as close as possible to the true edges
    - the detector must return one point only for each true edge point
- Cues of edge detection
  - Differences in color, intensity, or texture across the boundary
  - Continuity and closure
  - High-level knowledge

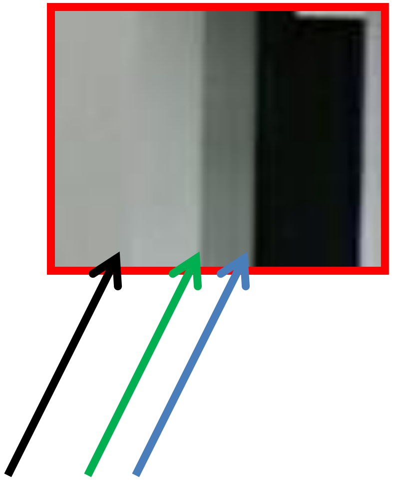
Source: L. Fei-Fei

Designing an edge detector

- "All real edges"
  - We can aim to differentiate later on which edges are 'useful' for our applications.
  - If we can't find all things which *could* be called an edge, we don't have that choice.

- Is this possible?

Closeup of edges



Source: D. Hoiem

Elder – Are Edges Incomplete? 1999

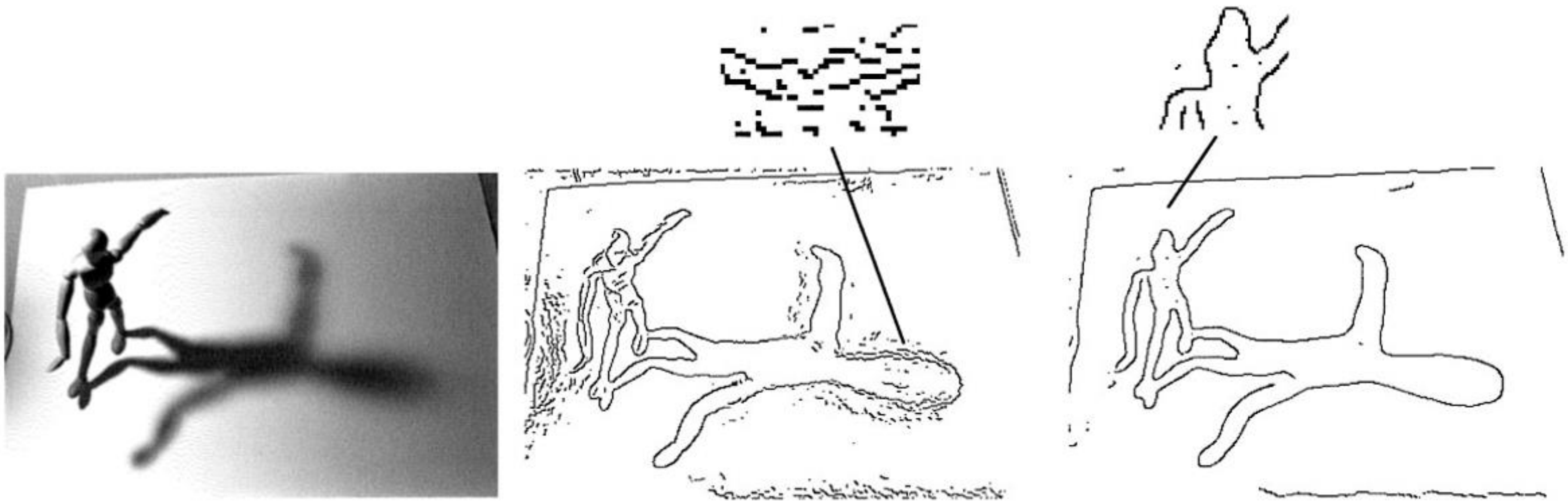


Figure 2. The problem of local estimation scale. Different structures in a natural image require different spatial scales for local estimation. The original image contains edges over a broad range of contrasts and blur scales. In the middle are shown the edges detected with a Canny/Deriche operator tuned to detect structure in the mannequin. On the right is shown the edges detected with a Canny/Deriche operator tuned to detect the smooth contour of the shadow. Parameters are ($\alpha = 1.25, \omega = 0.02$) and ($\alpha = 0.5, \omega = 0.02$), respectively. See (Deriche, 1987) for details of the Deriche detector.

What information would we need to
'invert' the edge detection process?

Elder – Are Edges Incomplete? 1999

Edge 'code':

- position,
- gradient magnitude,
- gradient direction,
- blur.

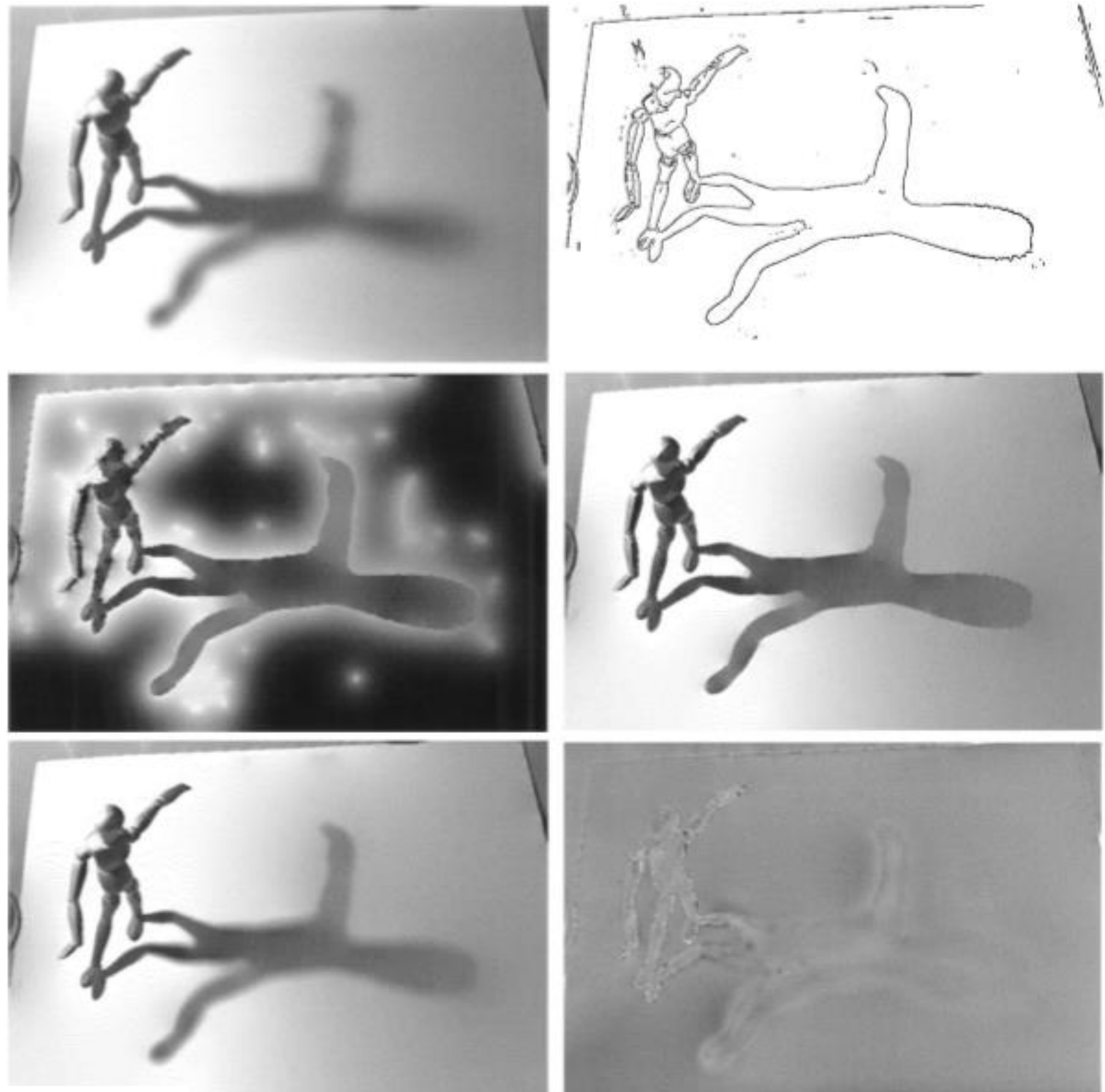


Figure 8. *Top left*: Original image. *Top right*: Detected edge locations. *Middle left*: Intermediate solution to the heat equation. *Middle right*: Reconstructed luminance function. *Bottom left*: Reblurred result. *Bottom right*: Error map (reblurred result—original). Bright indicates overestimation of intensity, dark indicates underestimation. Edge density is 1.7%. RMS error is 10.1 grey levels, with a 3.9 grey level DC component, and an estimated 1.6 grey levels due to noise removal.

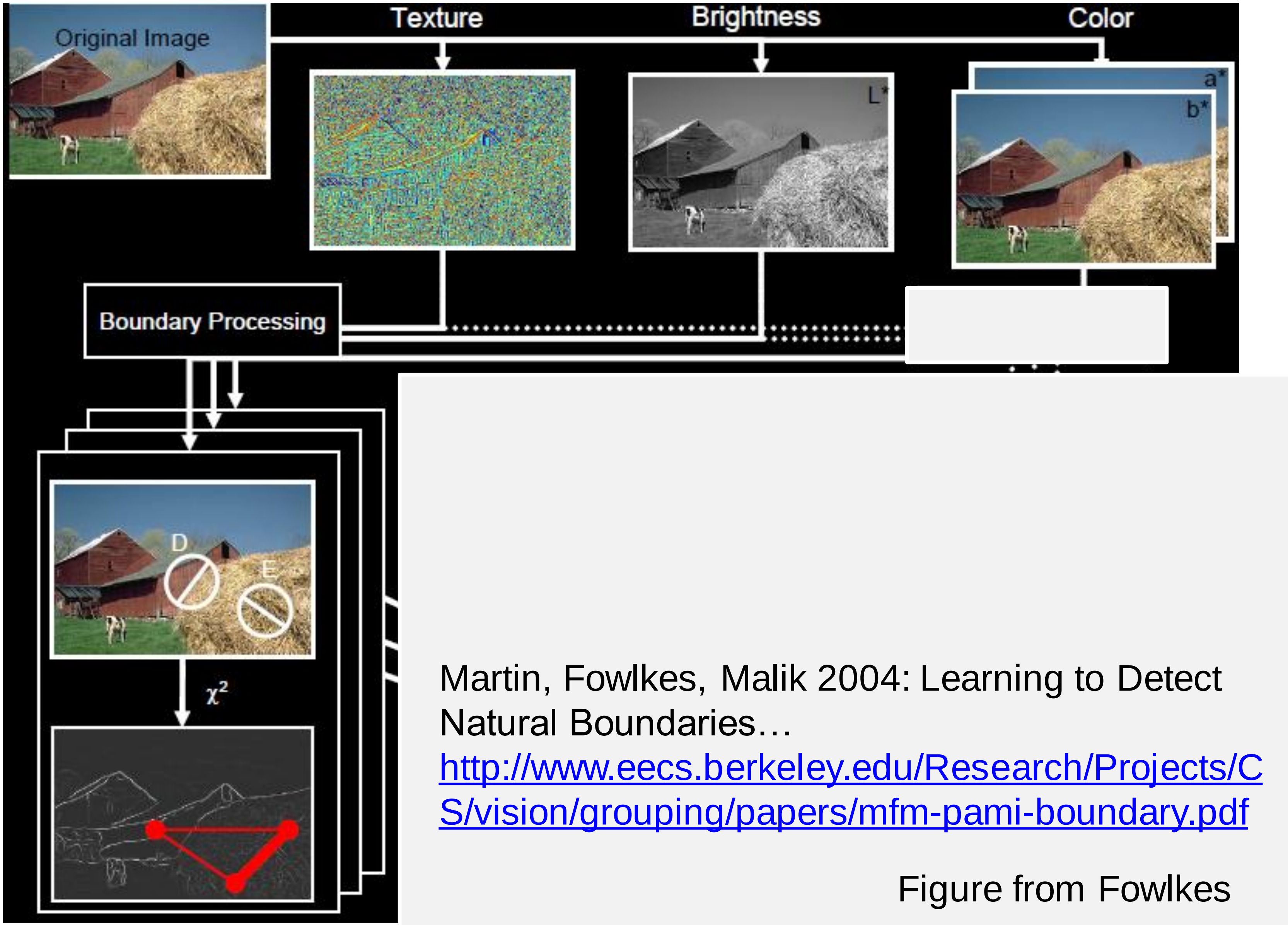
Where do humans see boundaries?

image | human segmentation | gradient magnitude

- Berkeley segmentation database:
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

pB slides: Hays

pB boundary detector



Martin, Fowlkes, Malik 2004: Learning to Detect Natural Boundaries…
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/papers/mfm-pami-boundary.pdf

Figure from Fowlkes

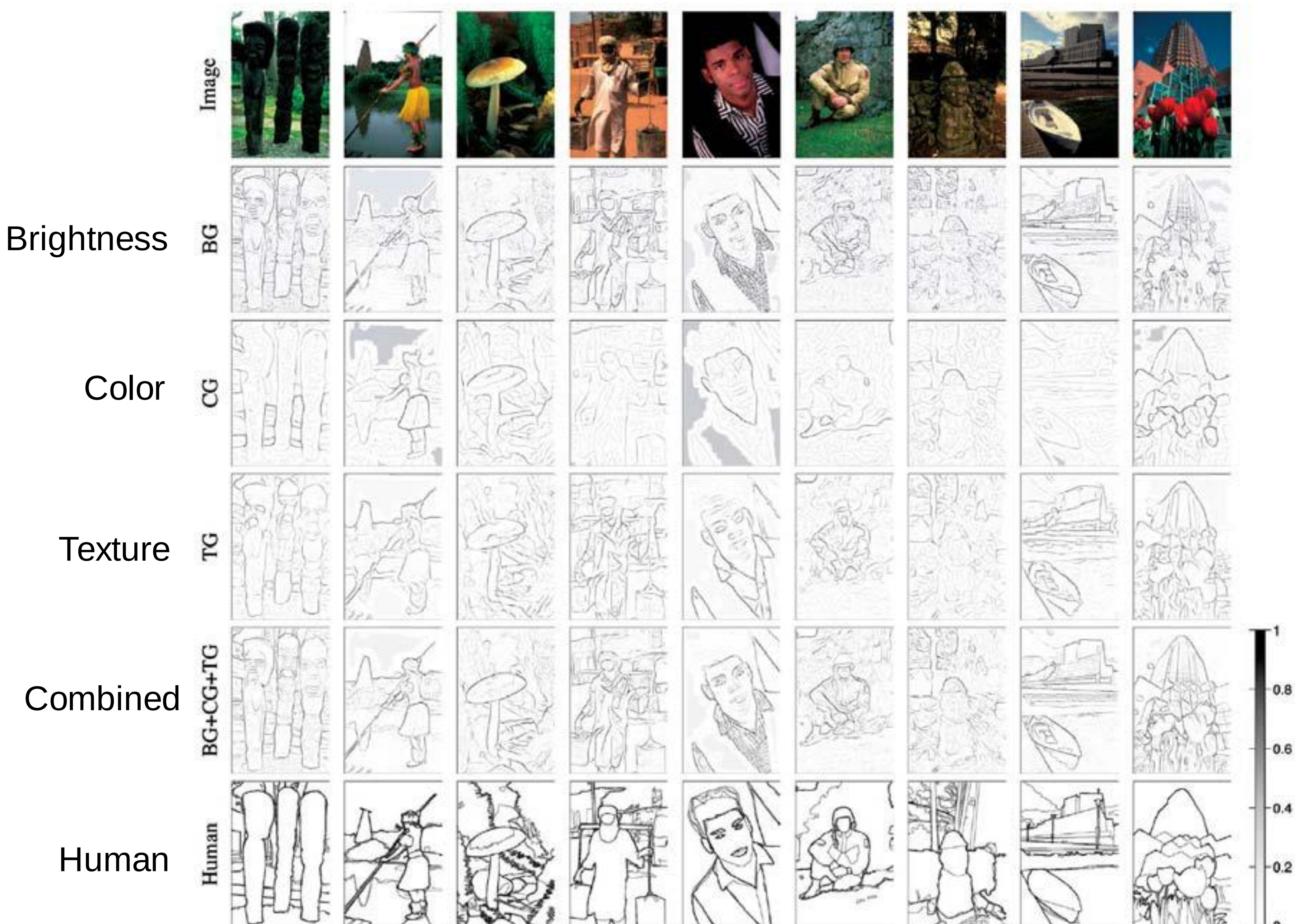


Image
Brightness
BG
Color
CG
Texture
TG
Combined
BG+CG+TG
Human
1
0.8
0.6
0.4
0.2
0

pB Boundary Detector

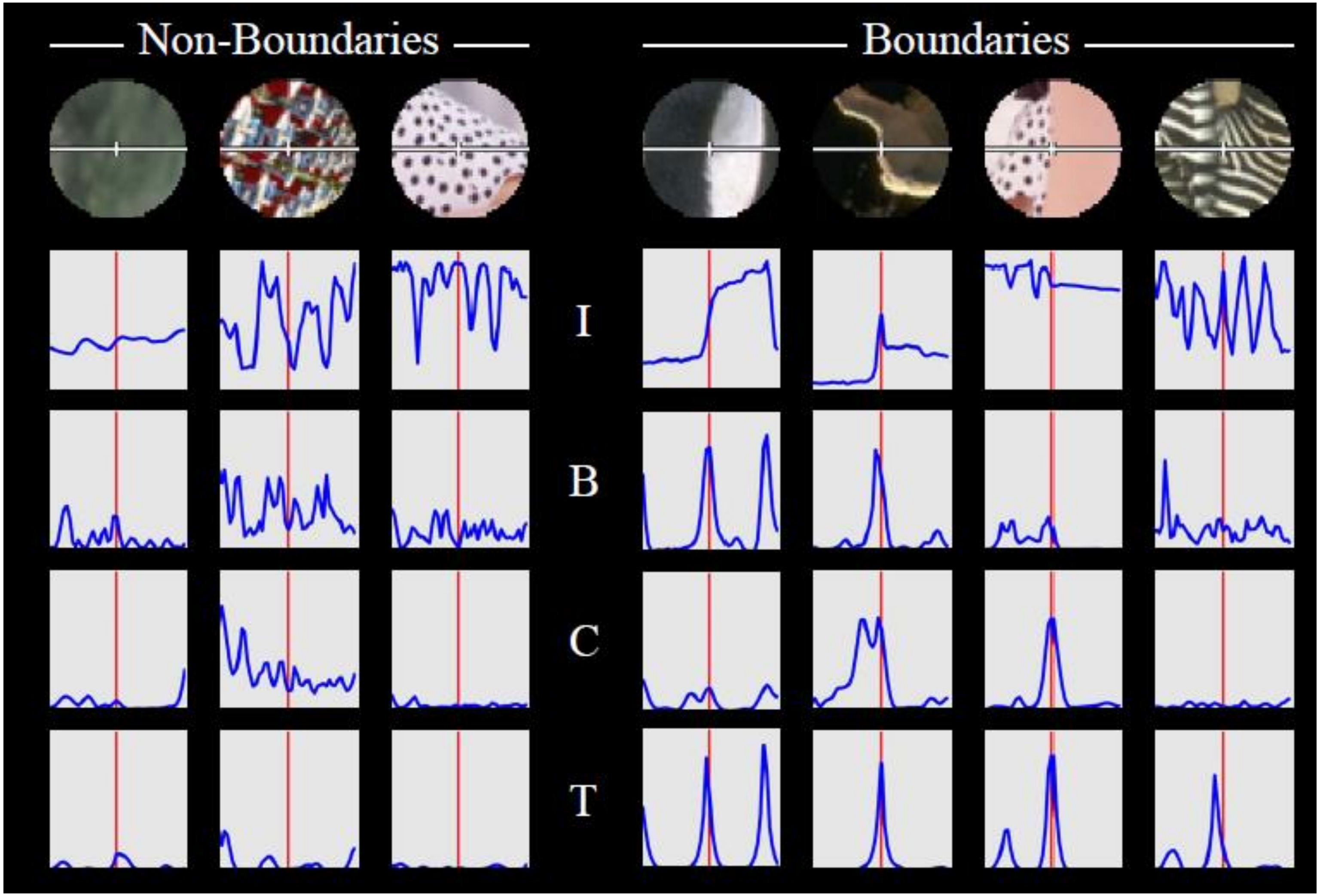
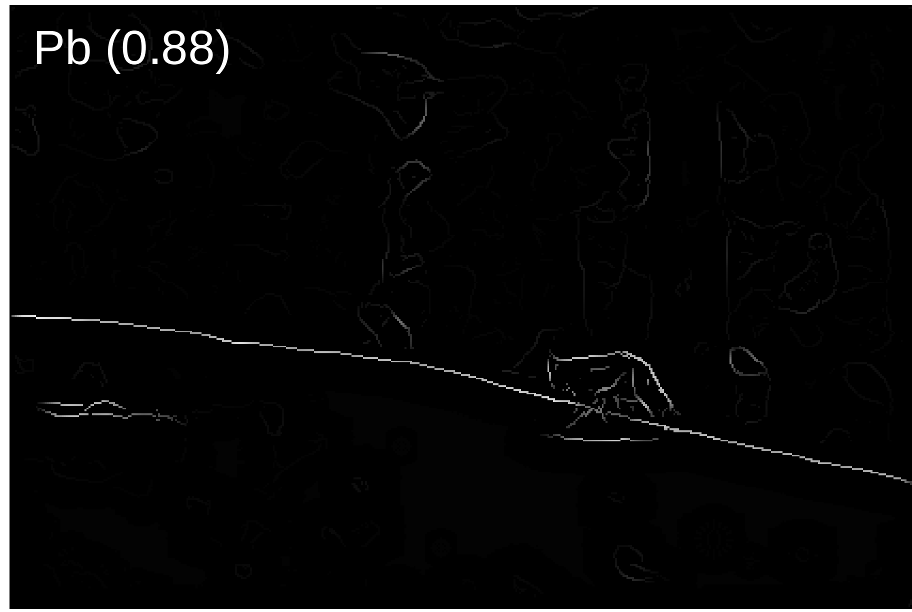
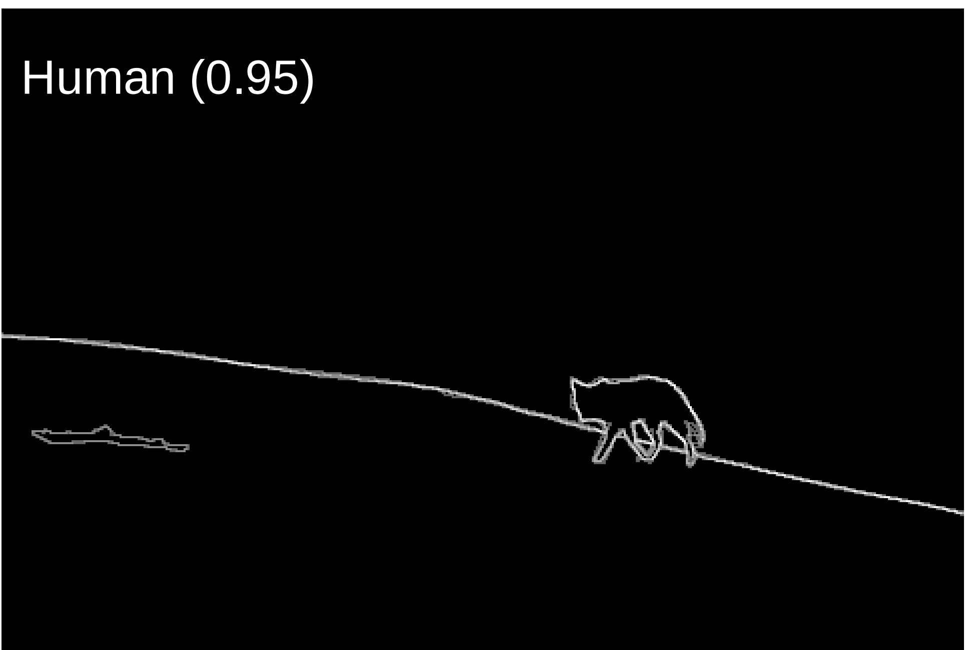


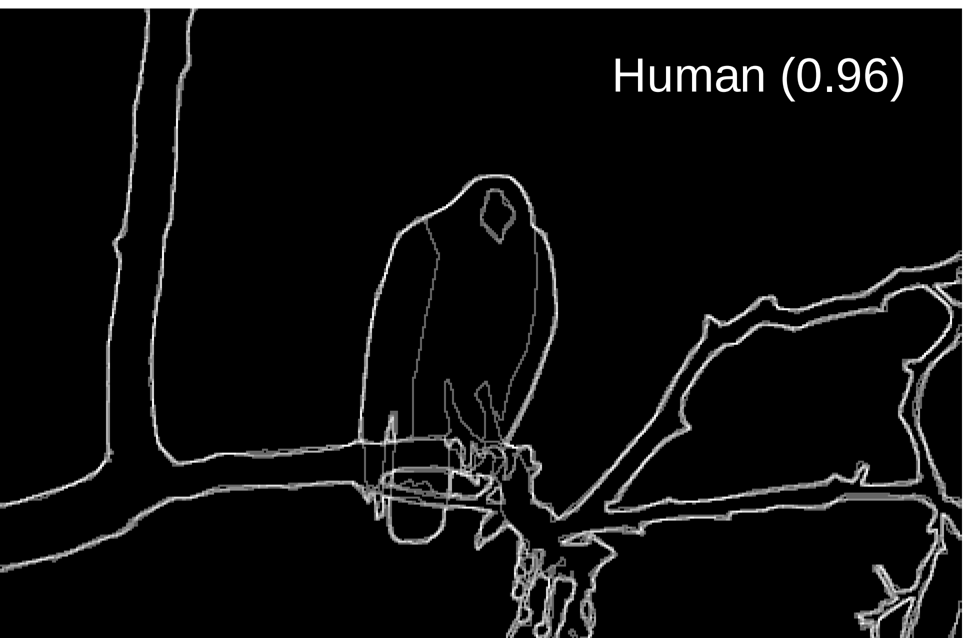
Figure from Fowlkes

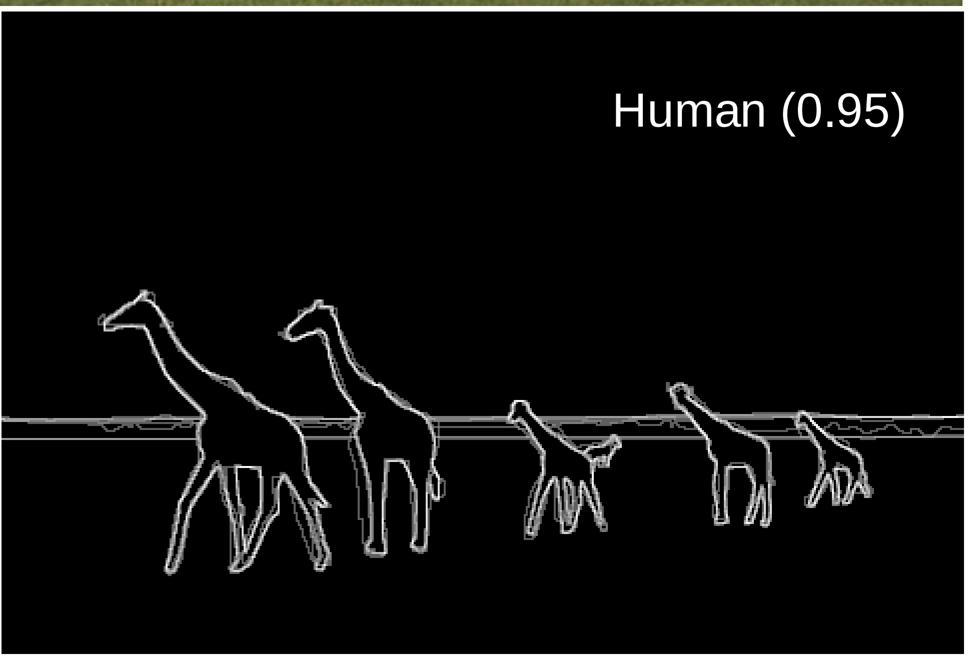
Results



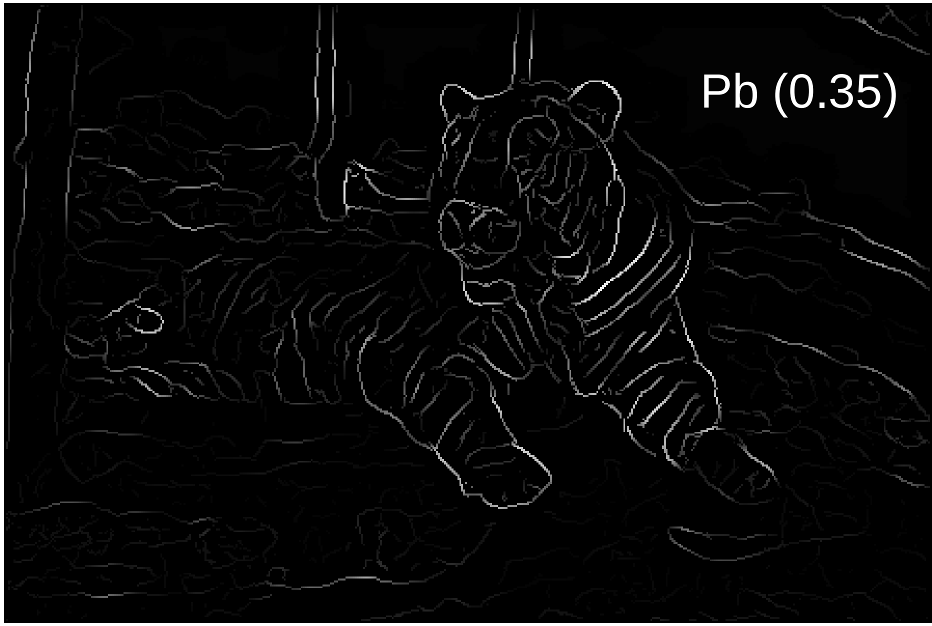


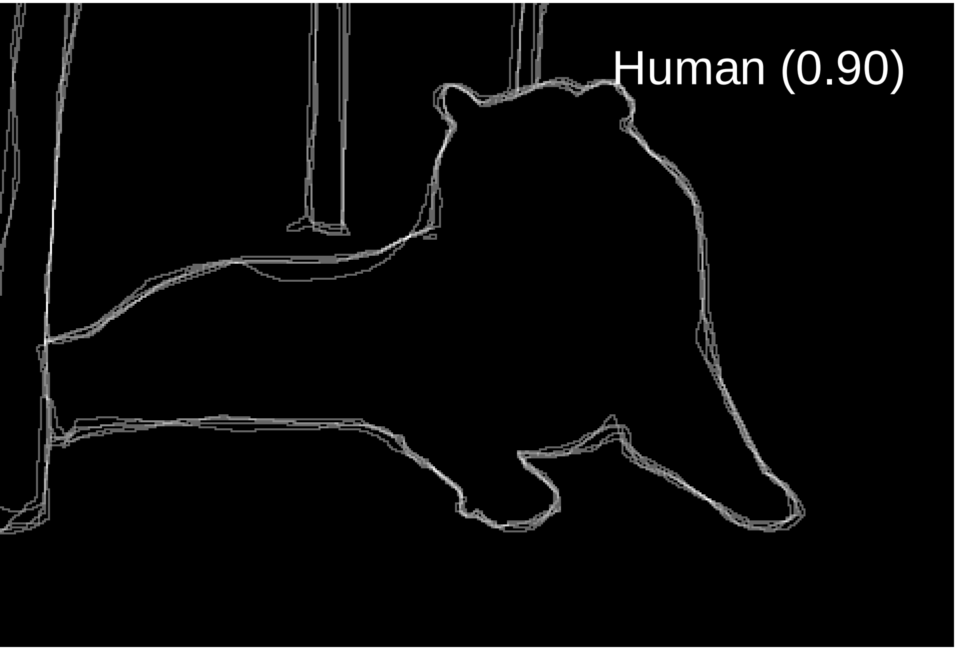
Results




Human (0.95)

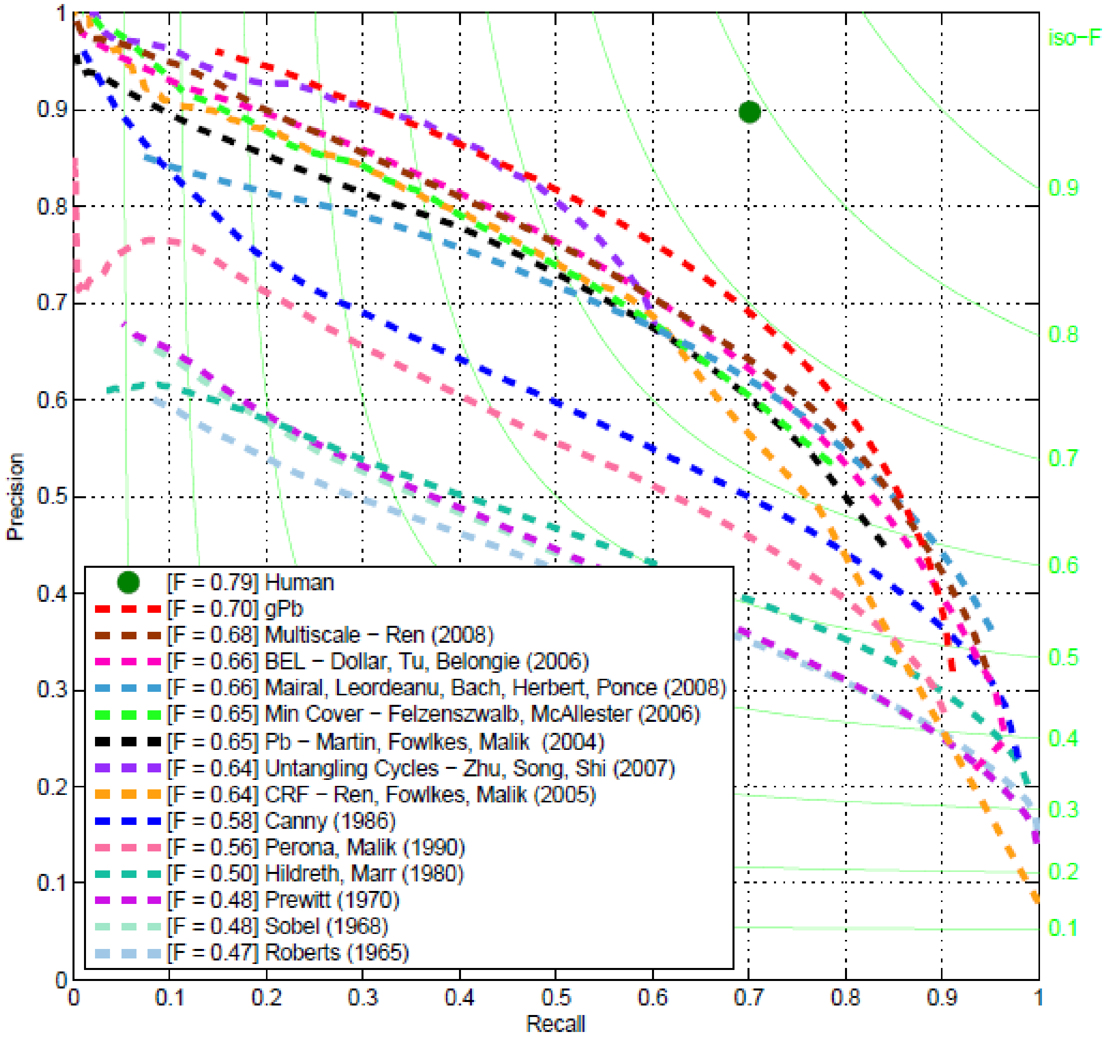

Pb (0.63)





For more:
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/bench/html/108082-color.html

45 years of boundary detection



Source: Arbelaez, Maire, Fowlkes, and Malik. TPAMI 2011 (pdf)

State of edge detection

- Local edge detection works well
  - 'False positives' from illumination and texture edges (depends on our application).
- Some methods to take into account longer contours
- Modern methods that actually "learn" from data.
- Poor use of object and high-level information.

Hays

Wednesday

- Classic Canny edge detector – 22,000 citations
- Interest Points and Corners