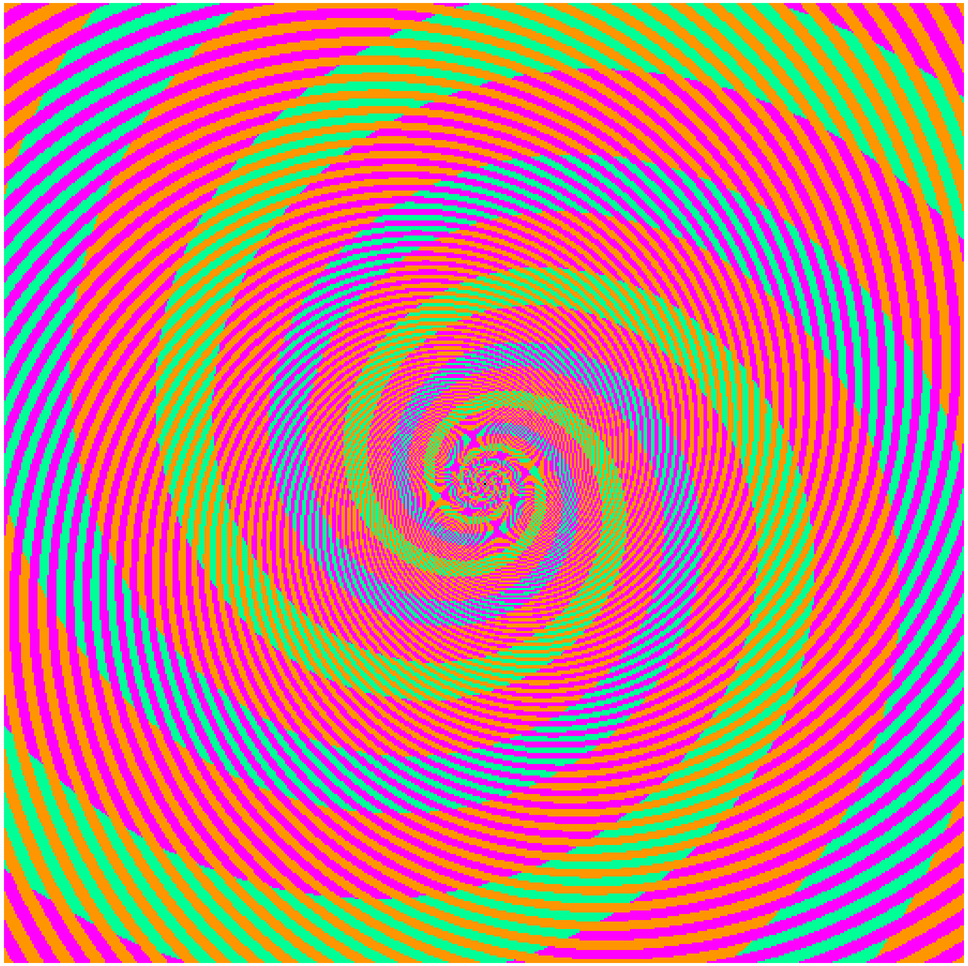
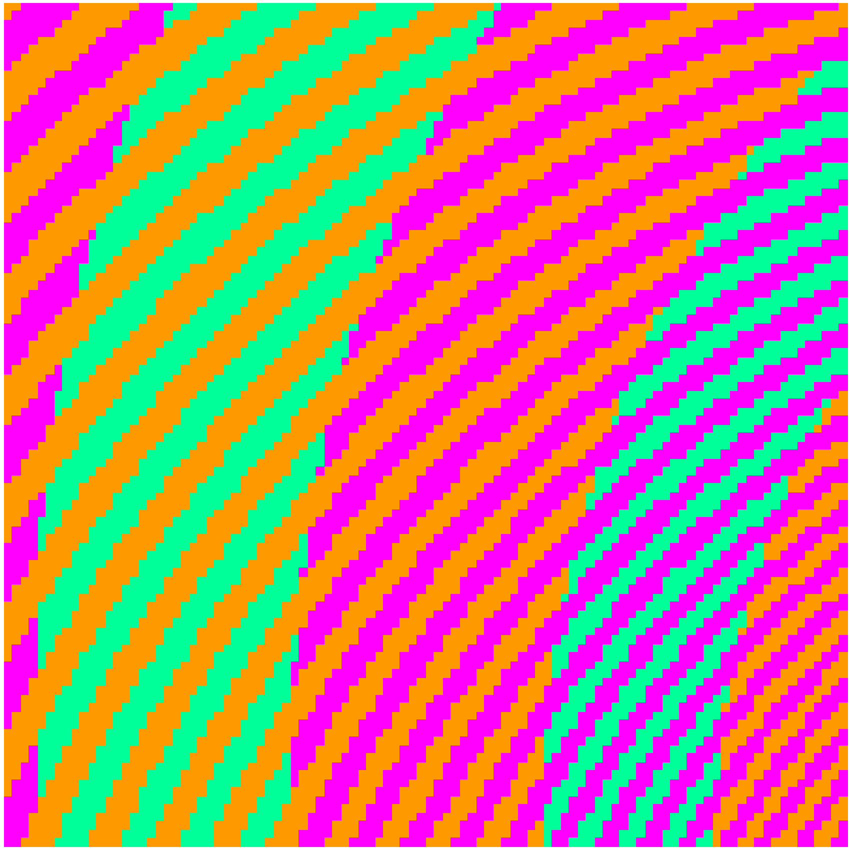


The blue and green colors are actually the same



http://blogs.discovermagazine.com/badastronomy/2009/06/24/the-blue-and-the-green/

Previous Lectures

- We’ve now touched on the first three chapters of Szeliski.
  - 1. Introduction
  - 2. Image Formation
  - 3. Image Processing
- Now we’re moving on to
  - 4. Feature Detection and Matching
  - Multiple views and motion (7, 8, 11)

Edge / Boundary Detection

Szeliski 4.2

Computer Vision

CS 143, Brown

James Hays

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

Edge detection

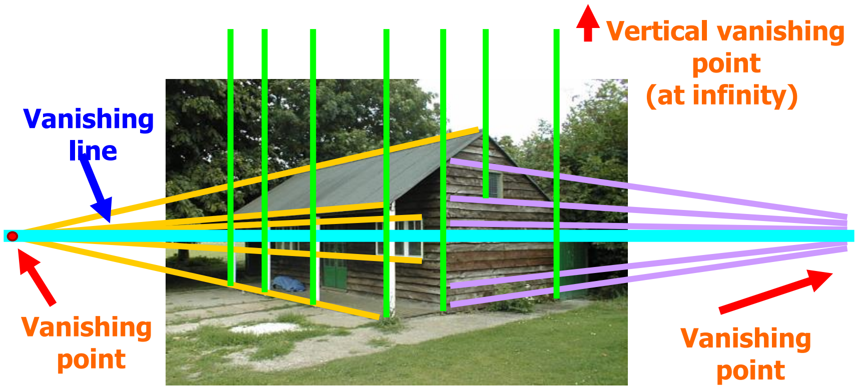
- **Goal:** Identify sudden changes (discontinuities) in an image
  - Intuitively, most semantic and shape information from the image can be encoded in the edges
  - More compact than pixels
- **Ideal:** artist's line drawing (but artist is also using object-level knowledge)

Source: D. Lowe

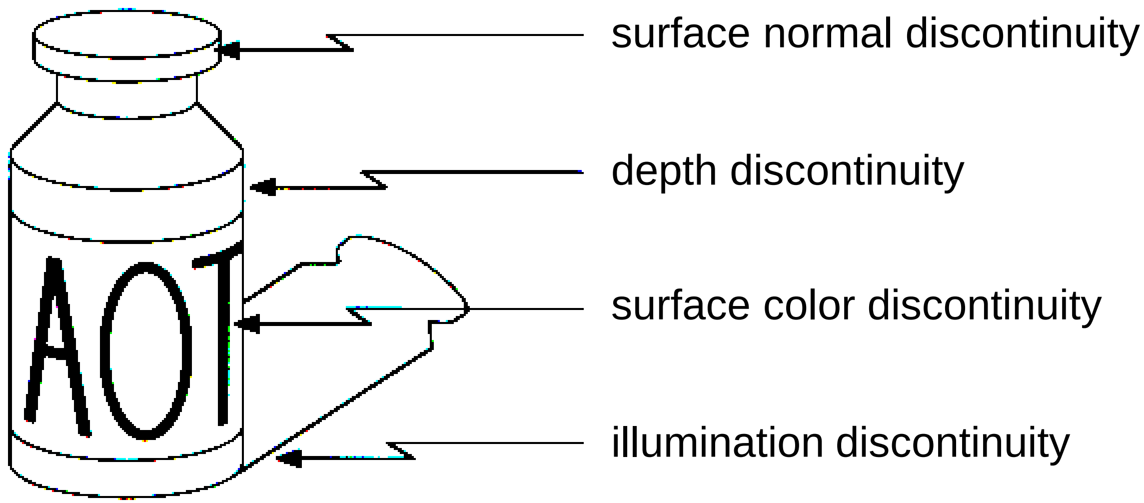
Why do we care about edges?

- Extract information, recognize objects

- Recover geometry and viewpoint



Origin of Edges



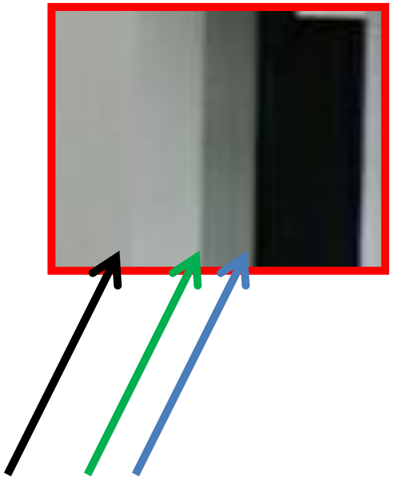
- Edges are caused by a variety of factors

Source: Steve Seitz

Closeup of edges

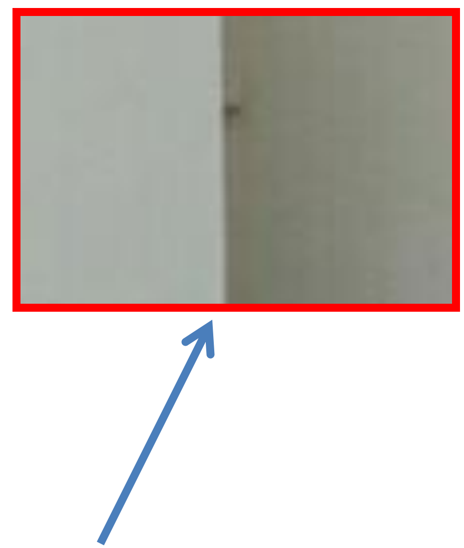
Source: D. Hoiem

Closeup of edges



Source: D. Hoiem

Closeup of edges



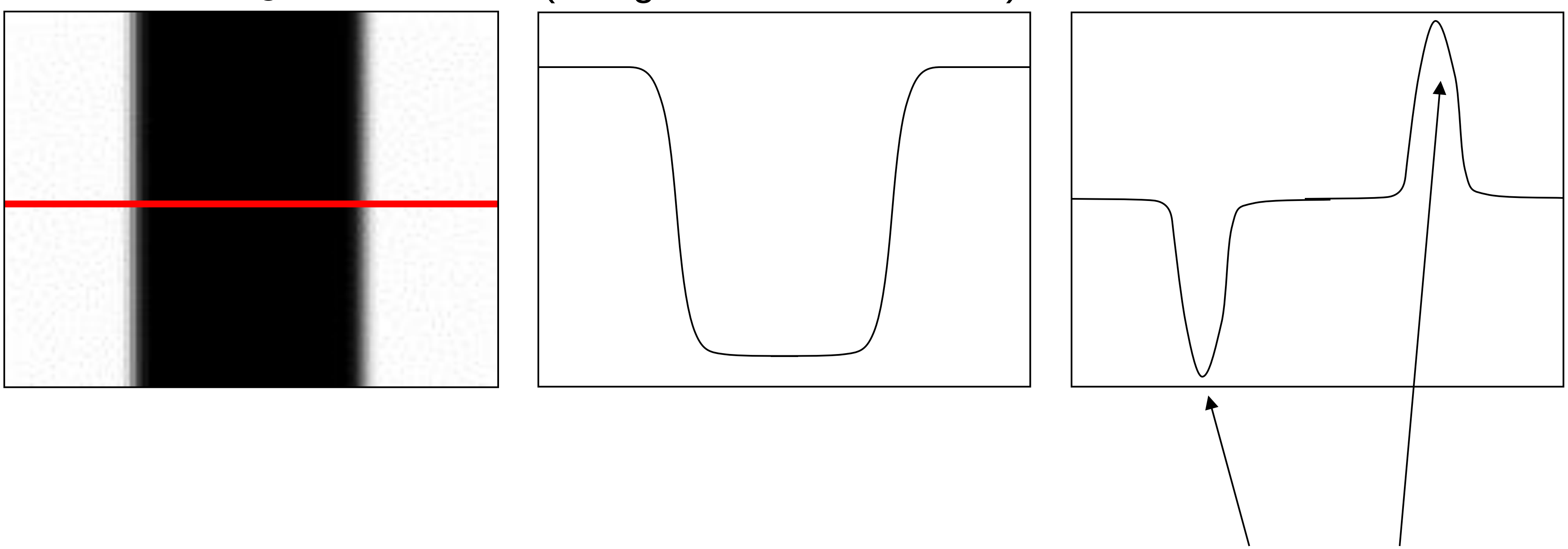
Source: D. Hoiem

Closeup of edges

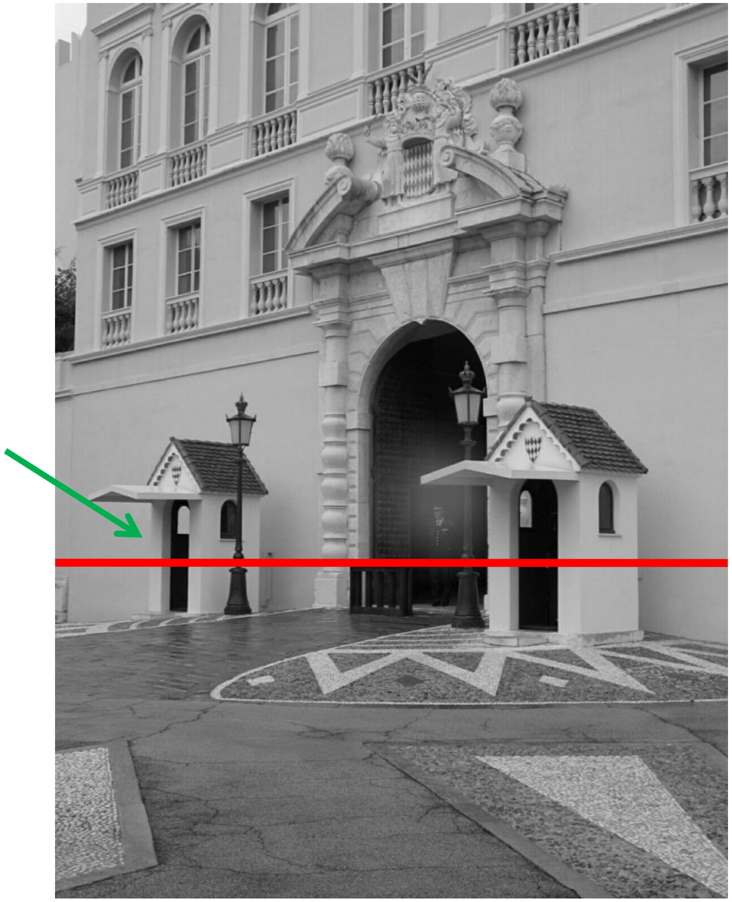
Source: D. Hoiem

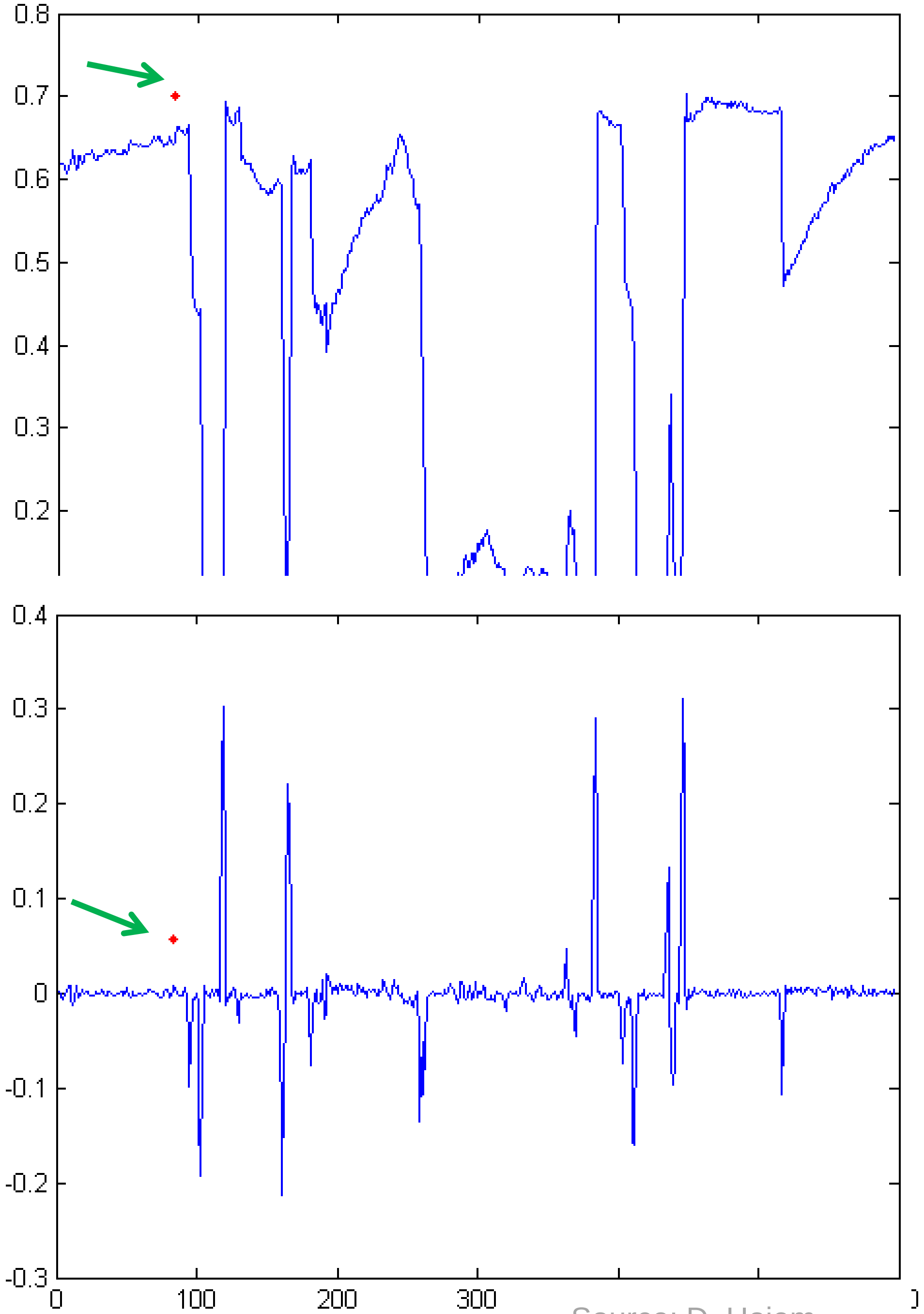
Characterizing edges

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



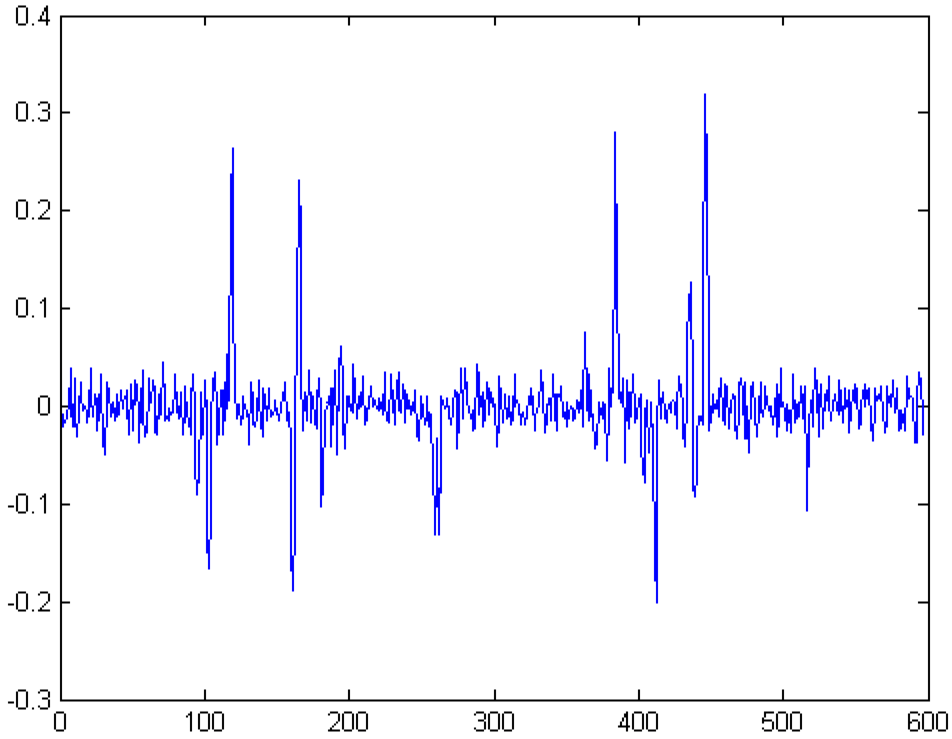
Intensity profile





Source: D. Hoiem

With a little Gaussian noise



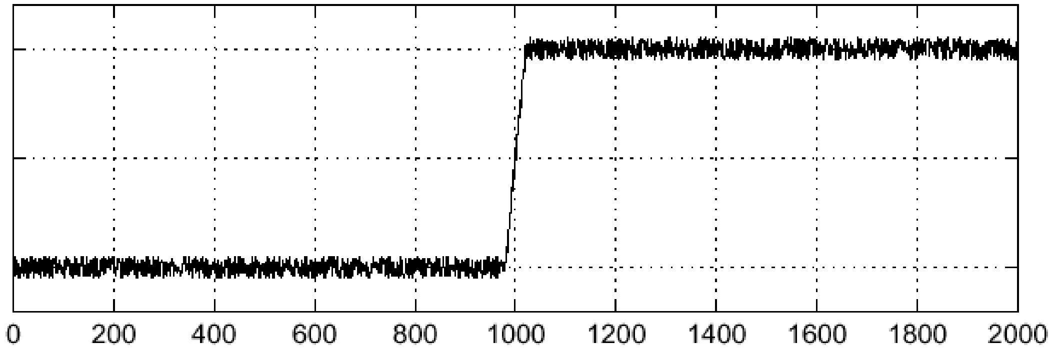
Gradient

Source: D. Hoiem

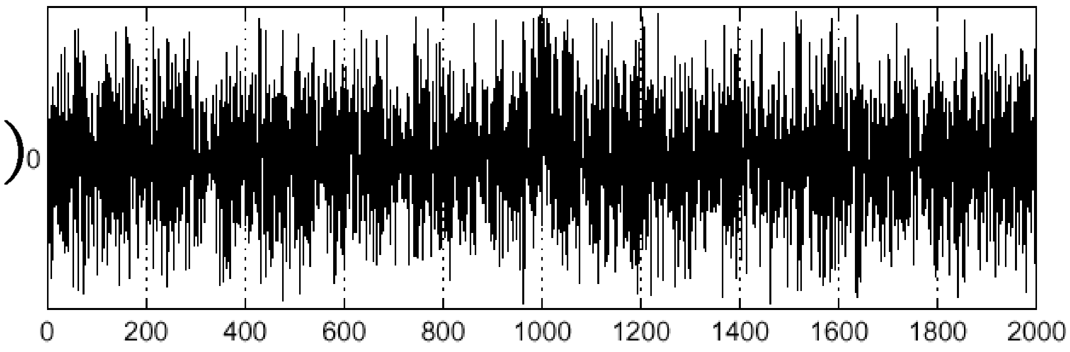
Effects of noise

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

$f(x)$



$\frac{d}{dx}f(x)$



Where is the edge?

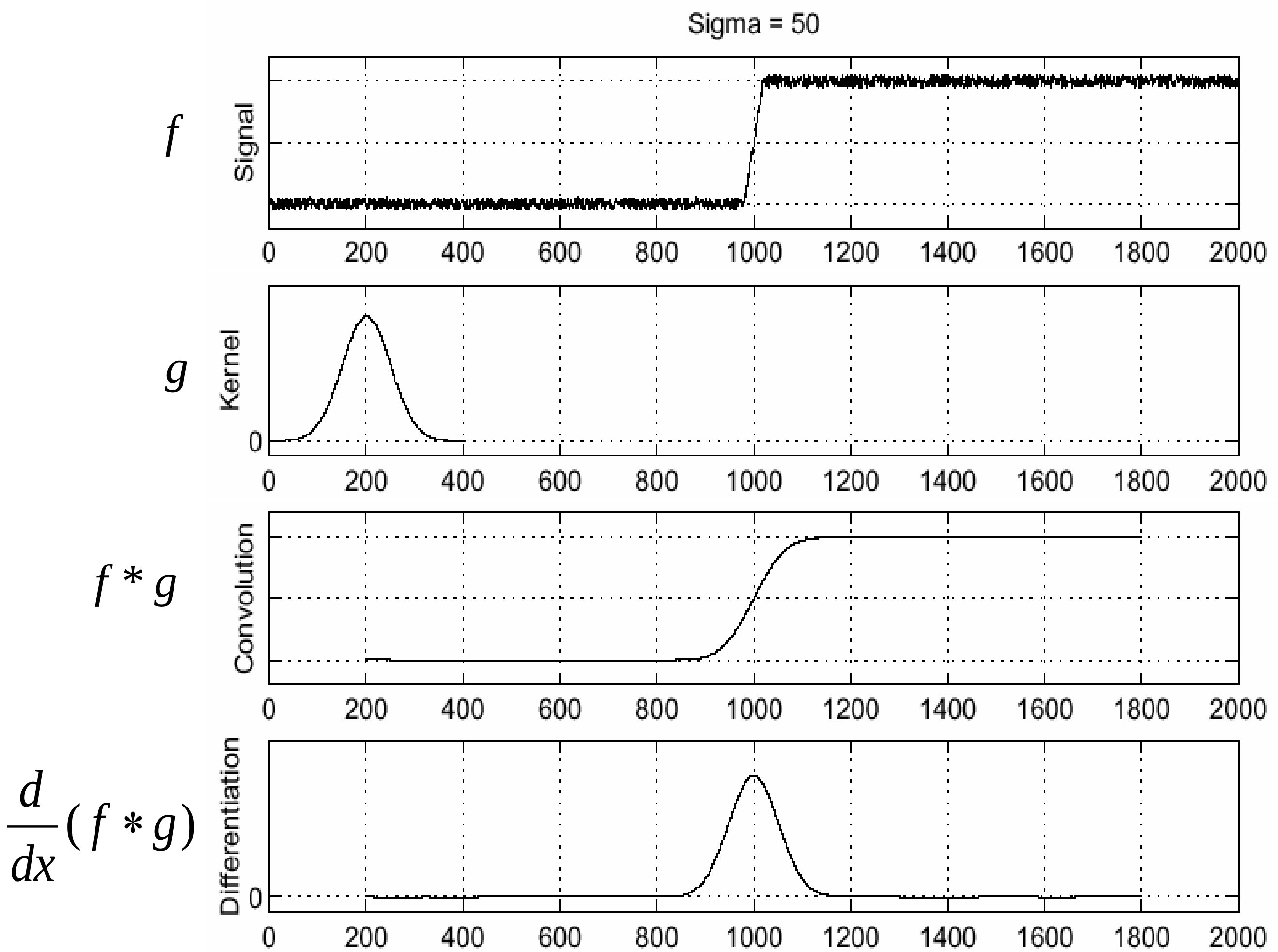
Source: S. Seitz

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:

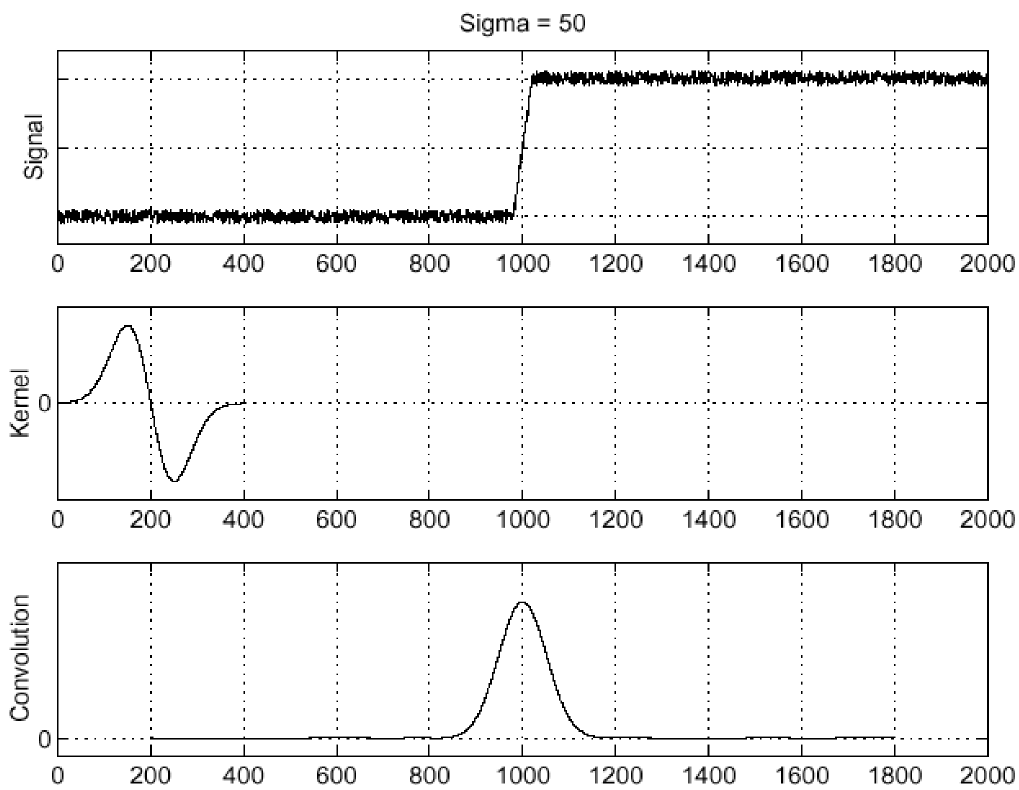
$$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$

- This saves us one operation:

f

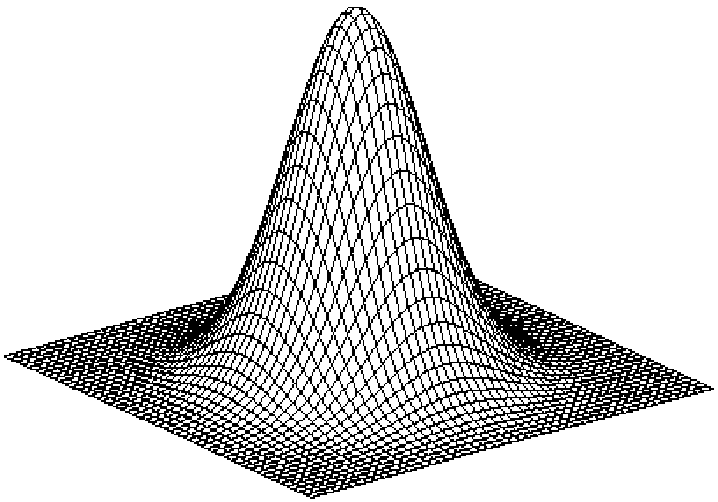
$\frac{d}{dx} g$

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

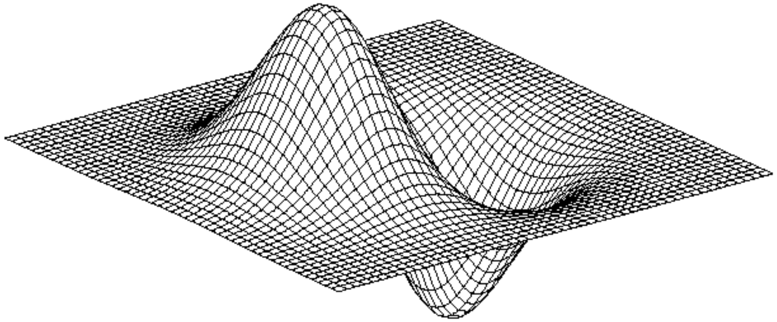


Source: S. Seitz

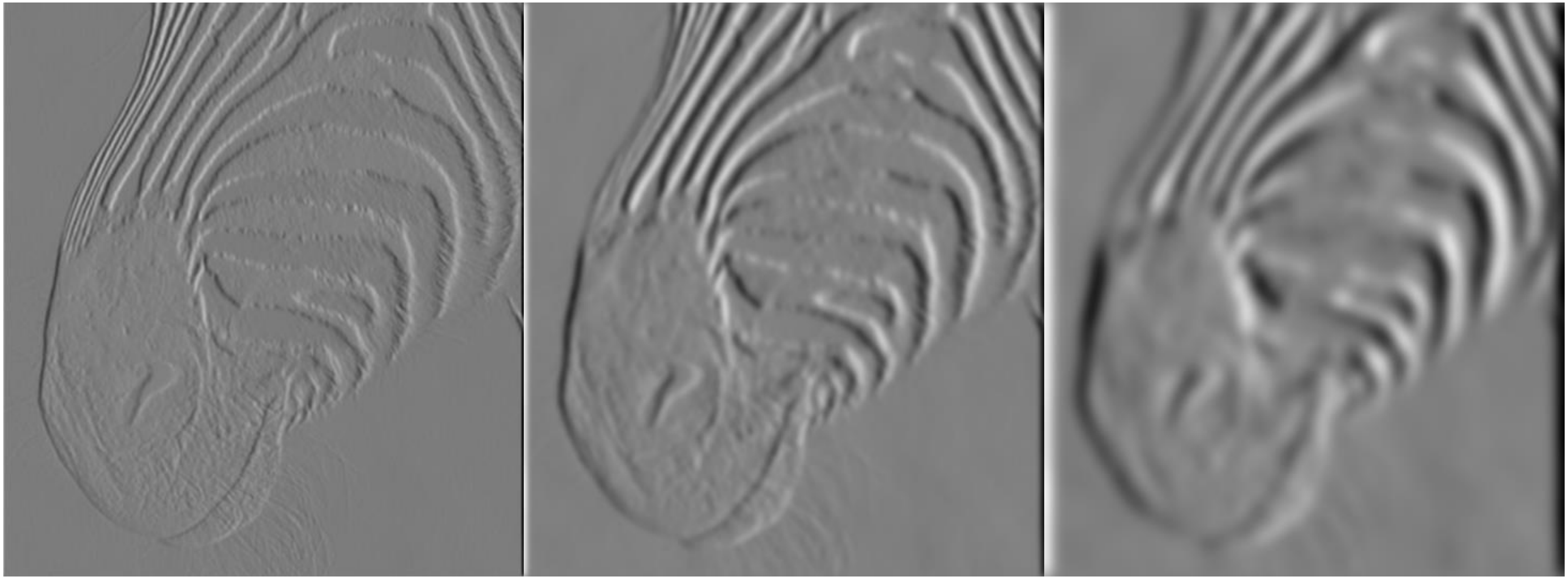
Derivative of Gaussian filter



* [1 -1] =



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

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

Canny edge detector

- This is probably the most widely used edge detector in computer vision
- Theoretical model: step-edges corrupted by additive Gaussian noise
- Canny has shown that the first derivative of the Gaussian closely approximates the operator that optimizes the product of *signal-to-noise ratio* and localization

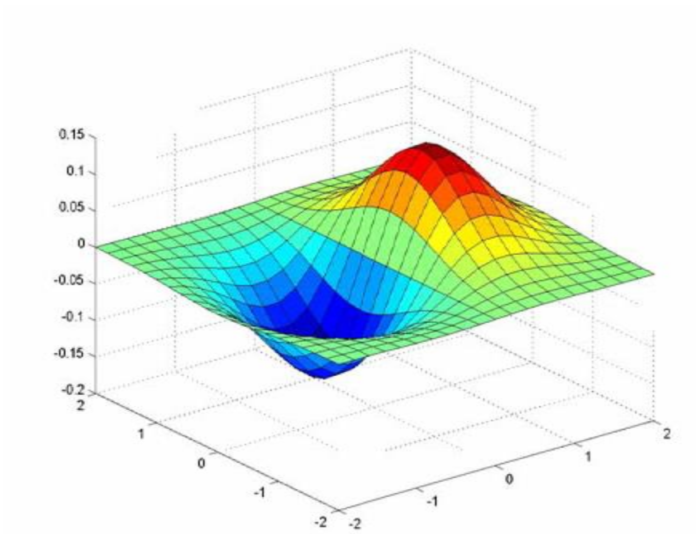
J. Canny, ***A Computational Approach To Edge Detection***, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

Source: L. Fei-Fei

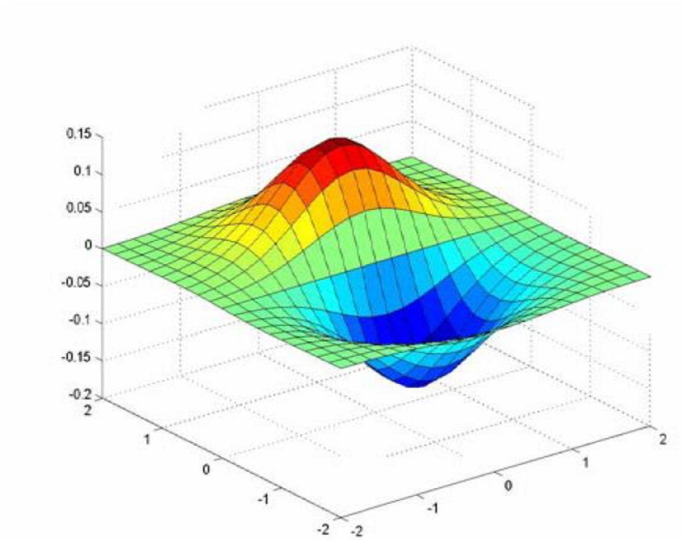
Example

original image (Lena)

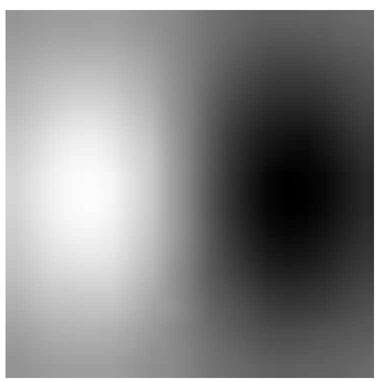
Derivative of Gaussian filter

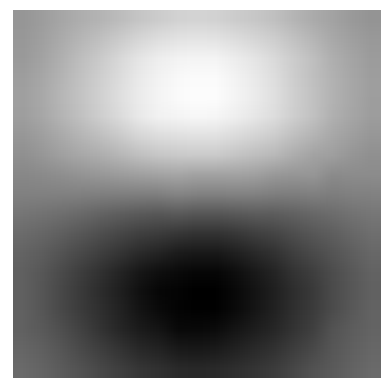


x-direction

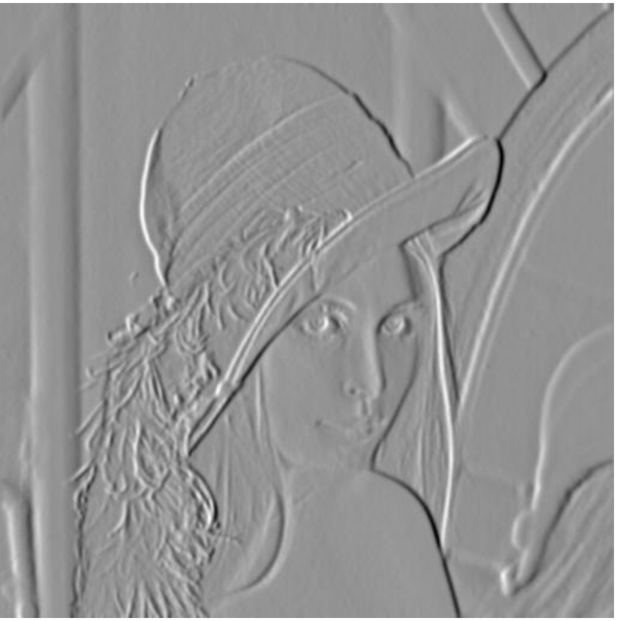


y-direction





Compute Gradients (DoG)



X-Derivative of Gaussian

Y-Derivative of Gaussian

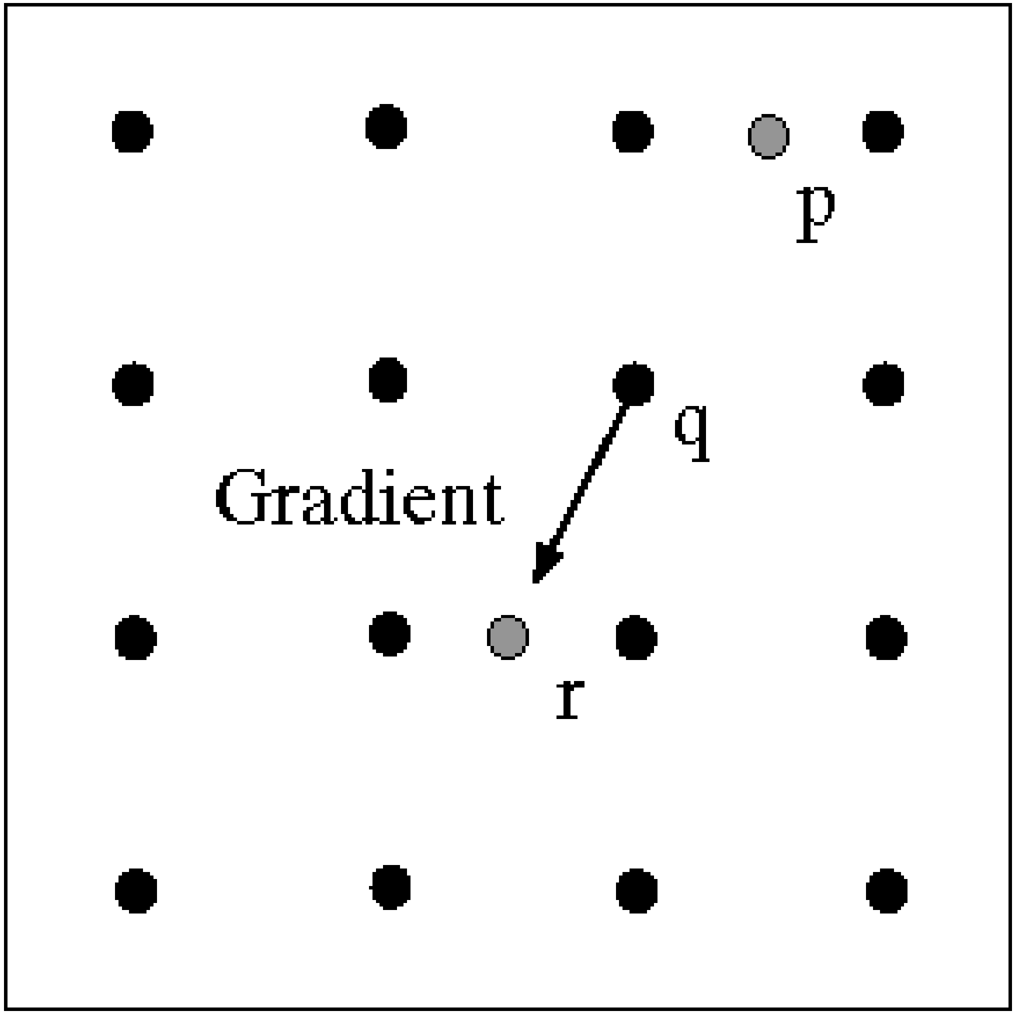
Gradient Magnitude

Get Orientation at Each Pixel

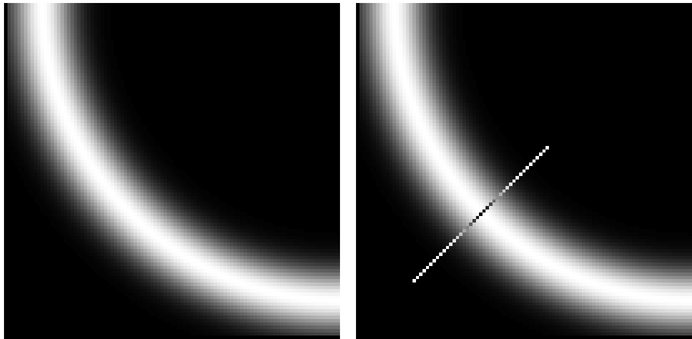
- Threshold at minimum level
- Get orientation

theta = atan2(gy, gx)

Non-maximum suppression for each orientation



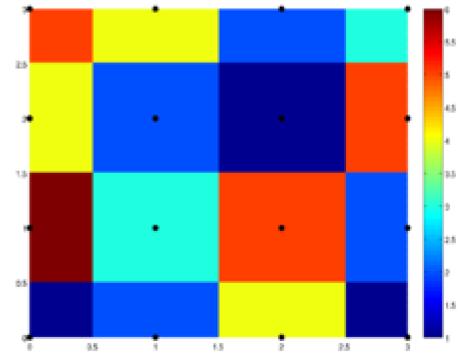
At q, we have a maximum if the value is larger than those at both p and at r. Interpolate to get these values.



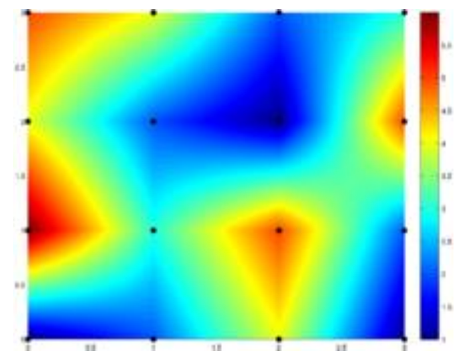
Source: D. Forsyth

Sidebar: Interpolation options

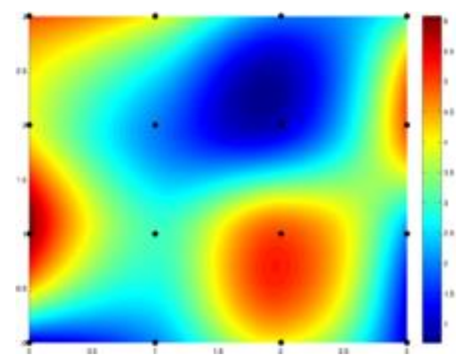
- imx2 = imresize(im, 2, interpolation_type)



- ‘nearest’
  - Copy value from nearest known
  - Very fast but creates blocky edges



- ‘bilinear’
  - Weighted average from four nearest known pixels
  - Fast and reasonable results



- ‘bicubic’ (default)
  - Non-linear smoothing over larger area (4x4)
  - Slower, visually appealing, may create negative pixel values

Examples from http://en.wikipedia.org/wiki/Bicubic_interpolation

Before Non-max Suppression

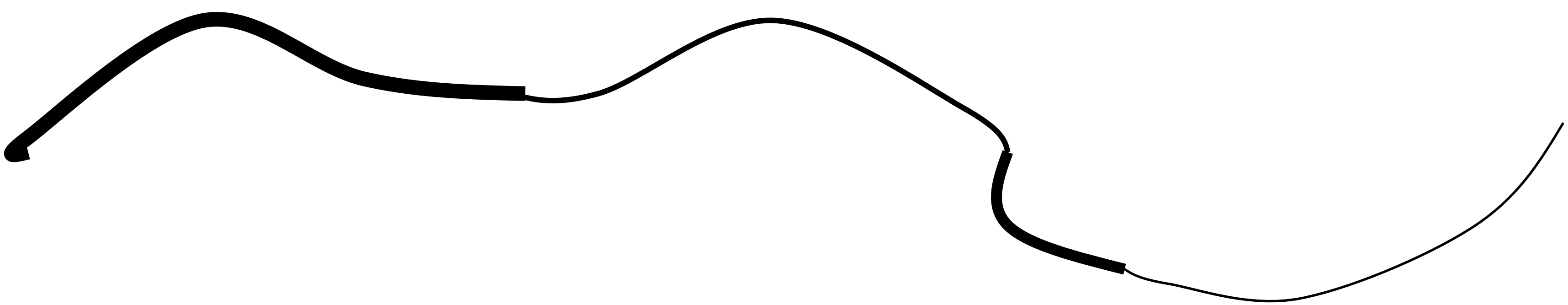
After non-max suppression

Hysteresis thresholding

- Threshold at low/high levels to get weak/strong edge pixels
- Do connected components, starting from strong edge pixels

Hysteresis thresholding

- Check that maximum value of gradient value is sufficiently large
  - drop-outs? use **hysteresis**
    - use a high threshold to start edge curves and a low threshold to continue them.



Source: S. Seitz

Final Canny Edges

Canny edge detector

1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel wide “ridges” down to single pixel width
4. Thresholding and linking (hysteresis):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

- MATLAB: edge(image, ‘canny’)

Source: D. Lowe, L. Fei-Fei

Effect of σ (Gaussian kernel spread/size)

original

Canny with $\sigma = 1$

Canny with $\sigma = 2$

The choice of σ depends on desired behavior

- large σ detects large scale edges
- small σ detects fine features

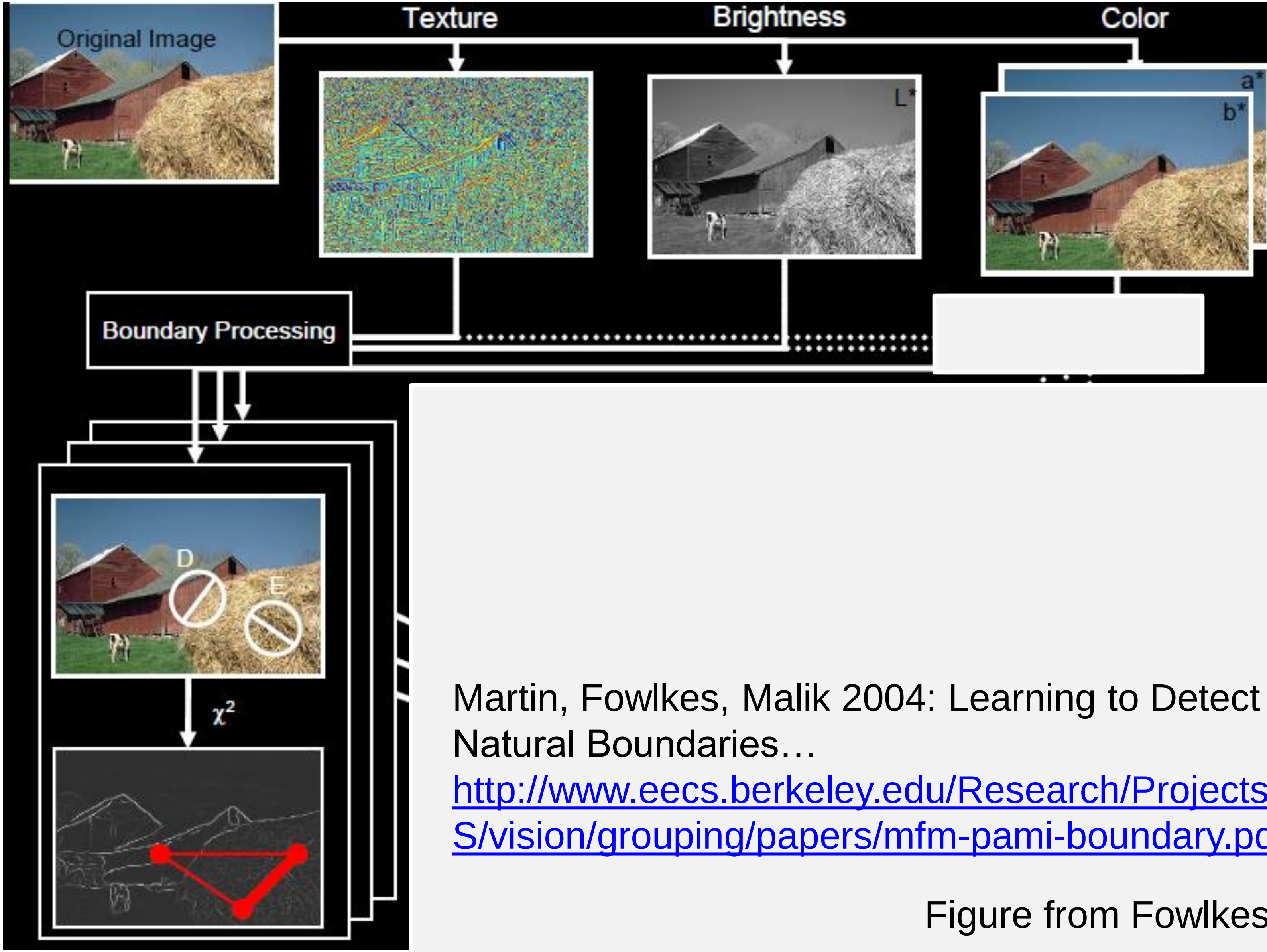
Source: S. Seitz

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 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

pB Boundary Detector

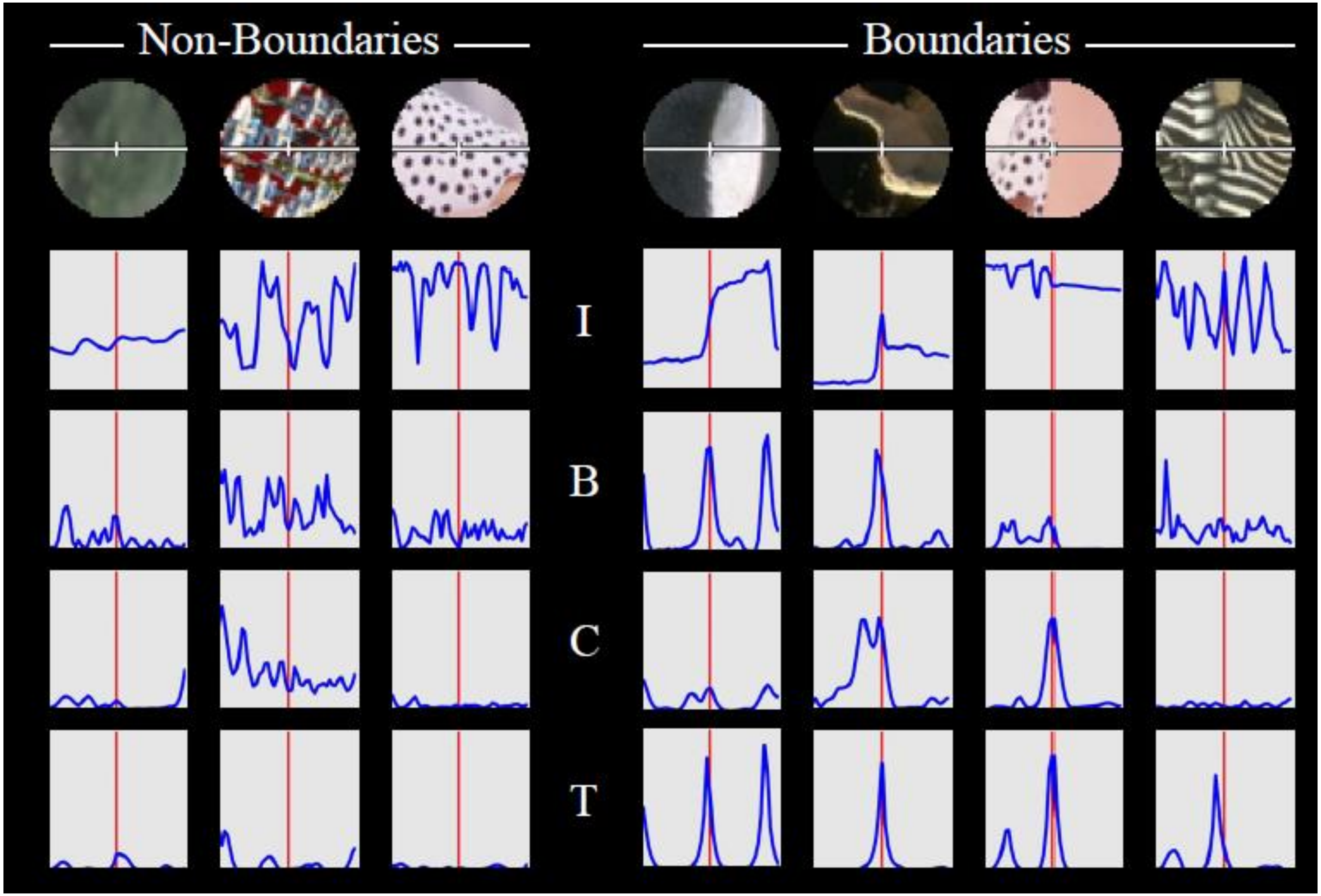


Figure from Fowlkes

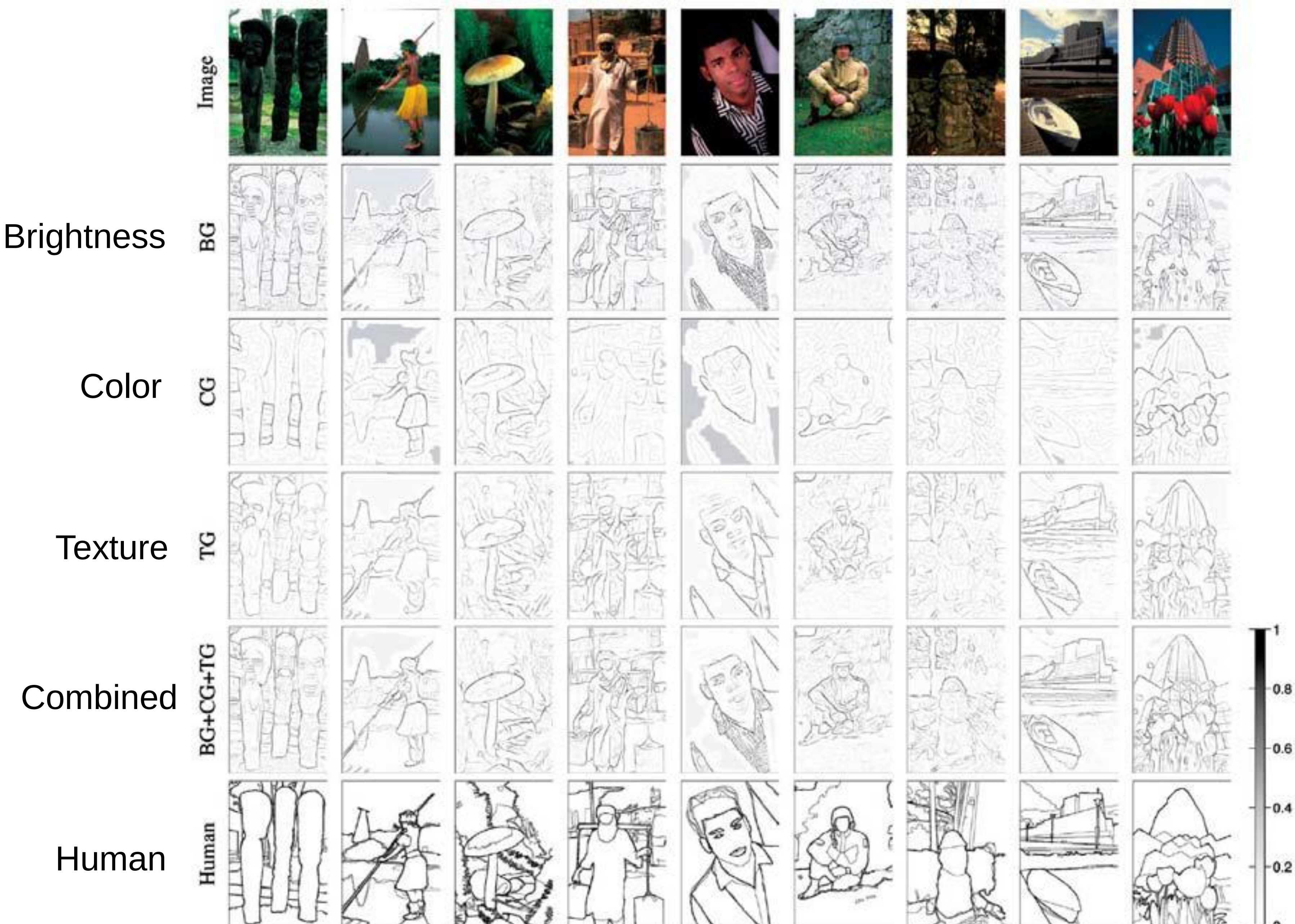
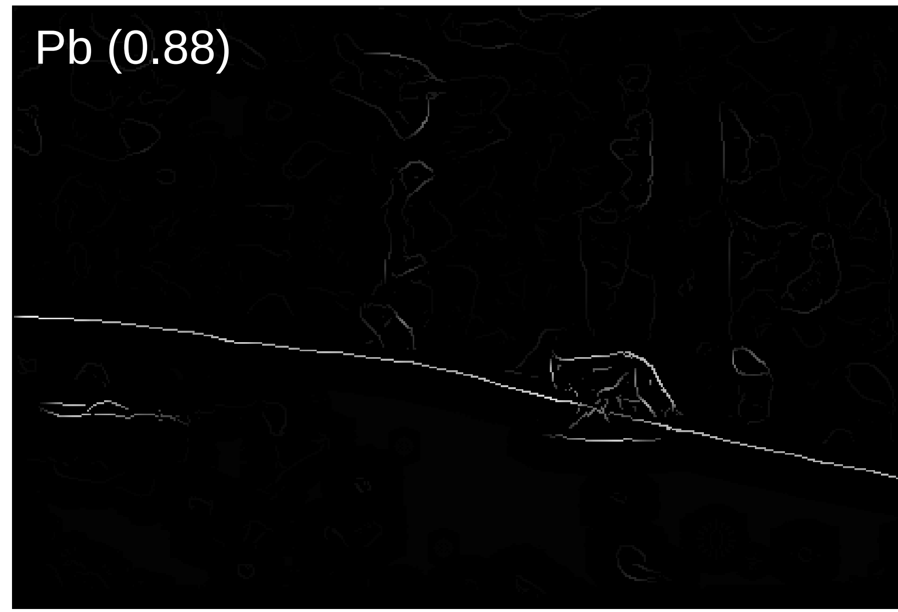
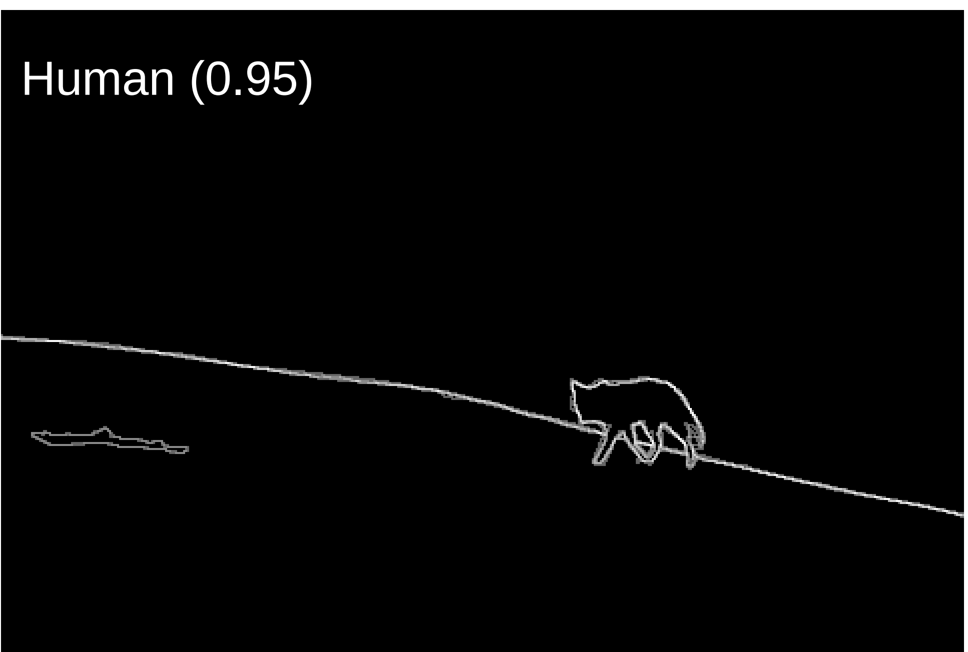


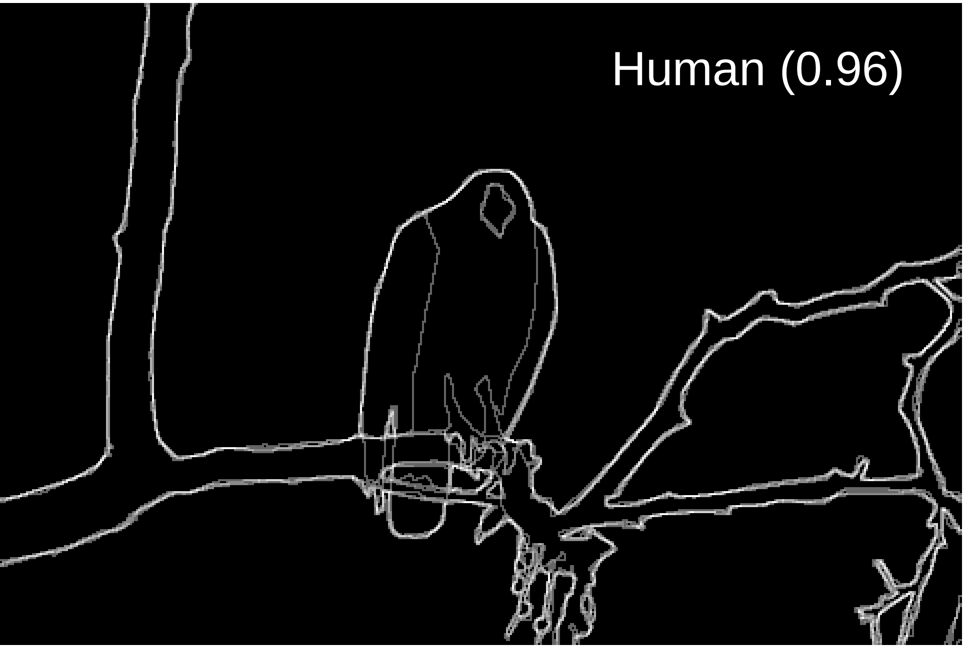
Image
Brightness
BG
Color
CG
Texture
TG
Combined
BG+CG+TG
Human
Human
1
0.8
0.6
0.4
0.2
0

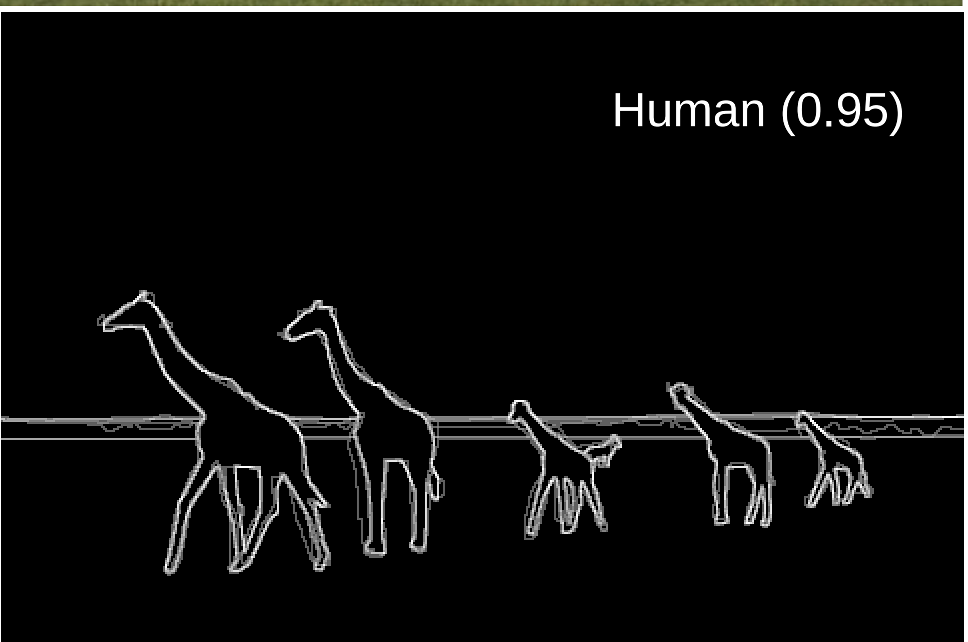
Results



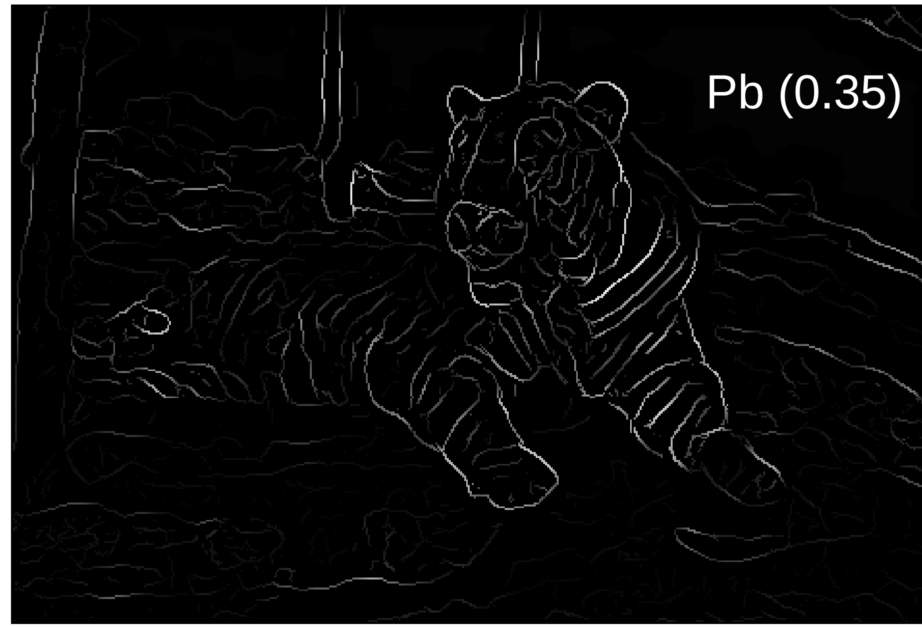


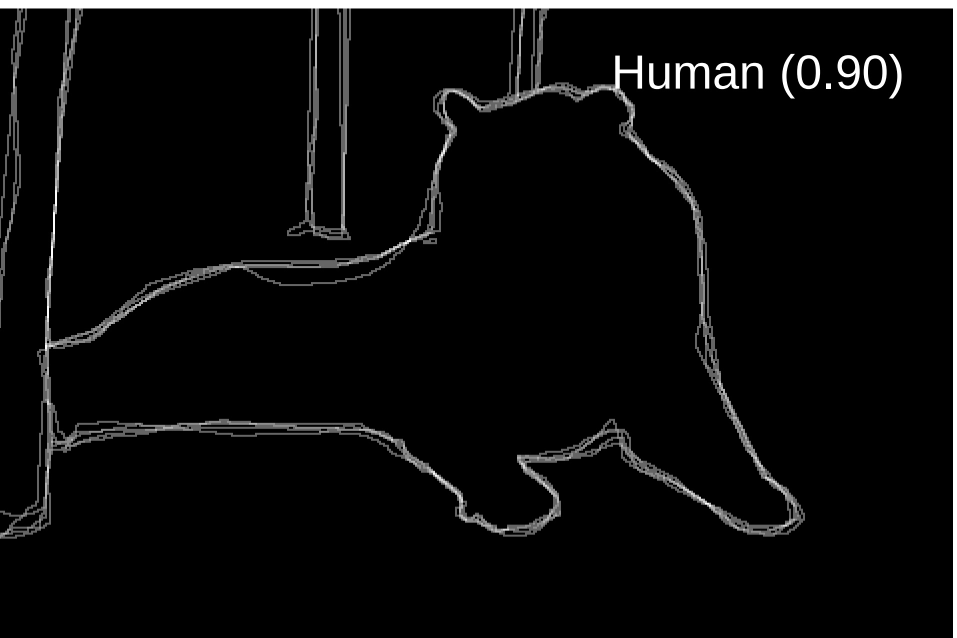
Results




Human (0.95)

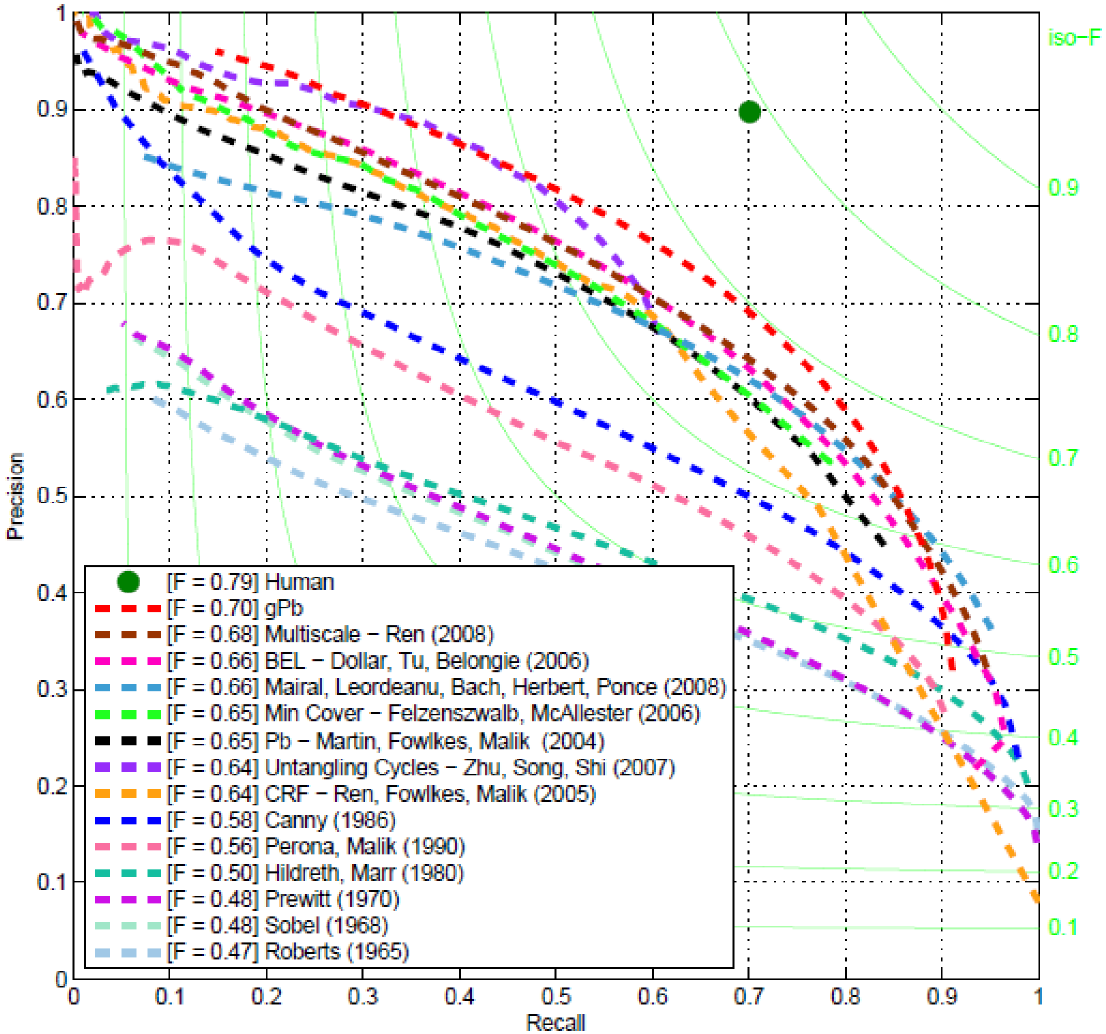

Pb (0.63)





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

45 years of boundary detection

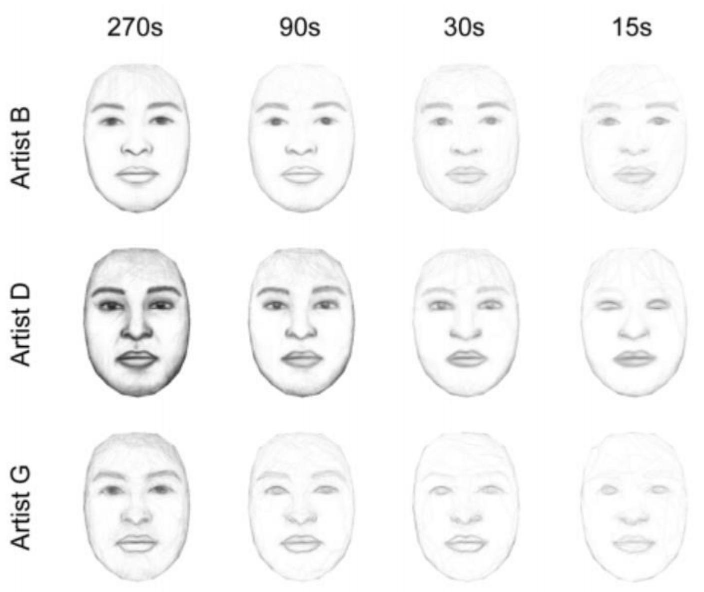


Source: Arbelaez, Maire, Fowlkes, and Malik. TPAMI 2011 (pdf)

State of edge detection

- Local edge detection works well
  - But many false positives from illumination and texture edges
- Some methods to take into account longer contours, but could probably do better
- Few methods that actually “learn” from data. Your project 5, Sketch Tokens, will do so.
- Poor use of object and high-level information

Style and abstraction in portrait sketching, Berger et al. SIGGRAPH 2013



- Learn from artist's strokes so that edges are more likely in certain parts of the face.

Questions