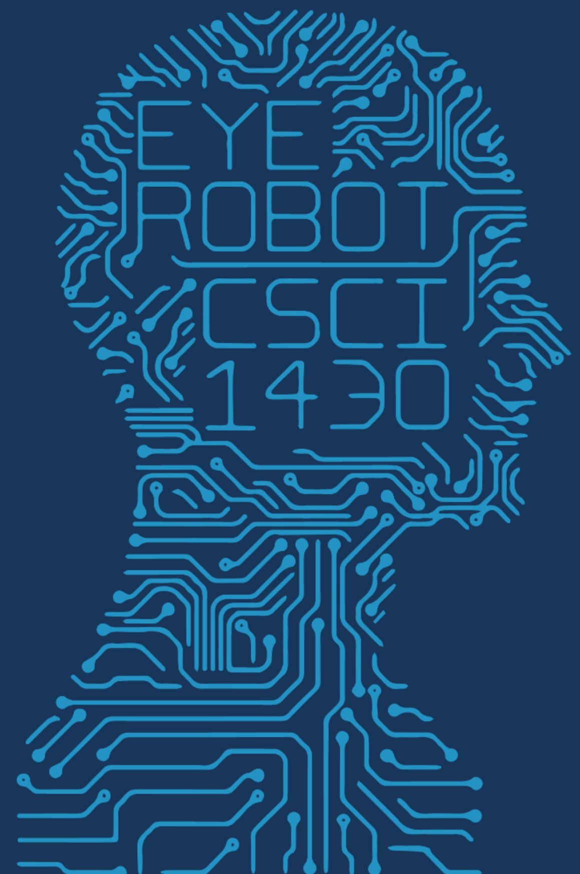
1950

Future Vision



2017 MWF 1pm

Computer Vision

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

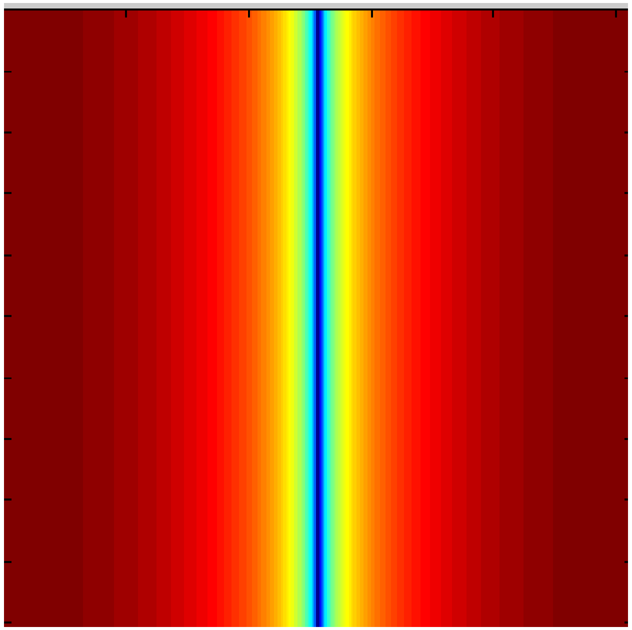
Did anyone play with the code?

Hays

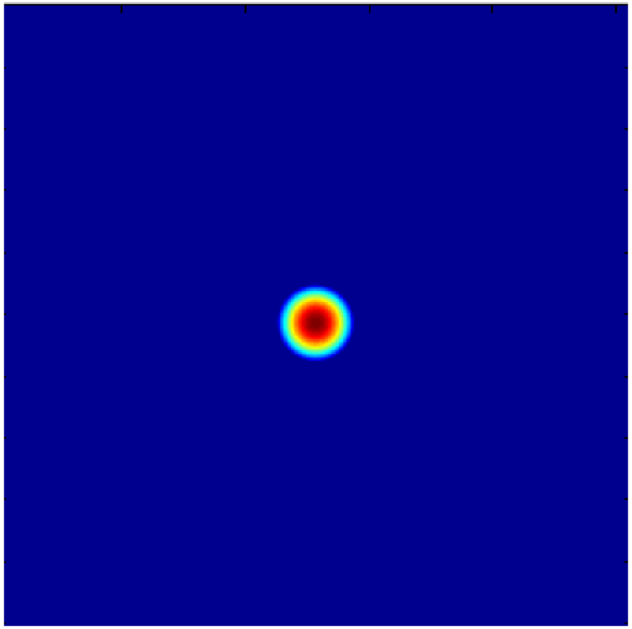
Review of Filtering

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

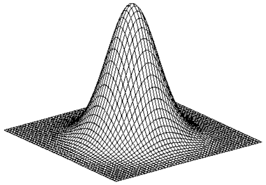
[-1 1]



FFT of Gradient Filter



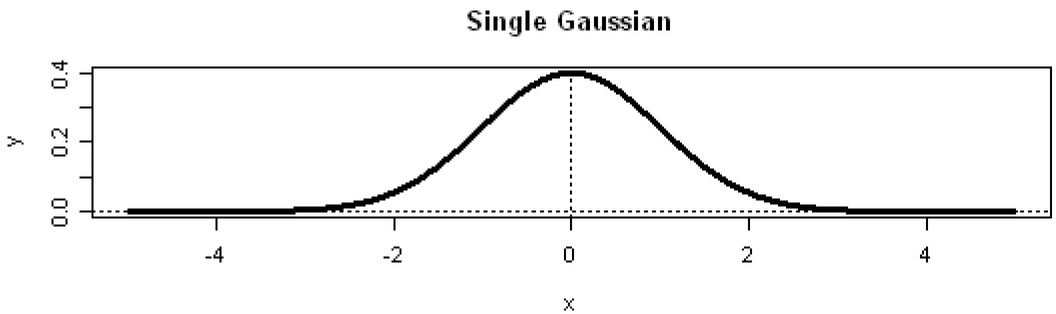
FFT of Gaussian

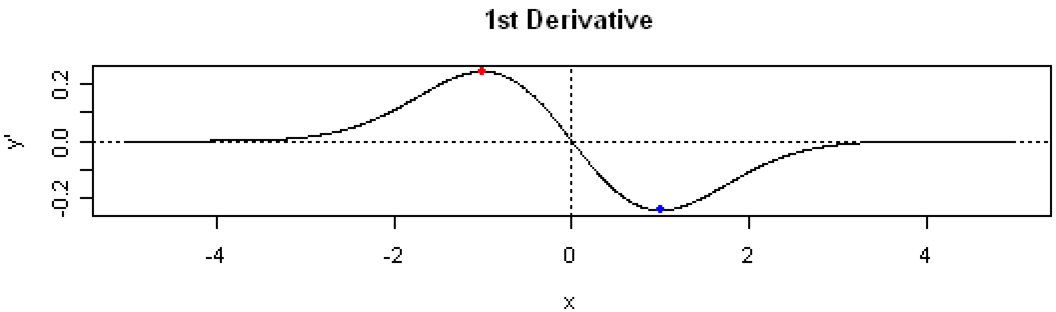


Gaussian

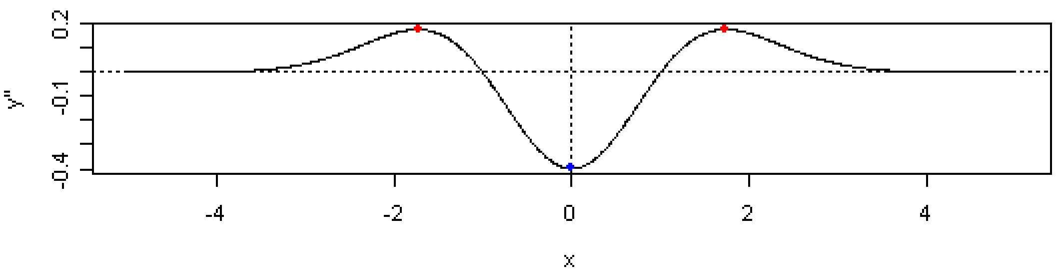
Hays

More Useful Filters

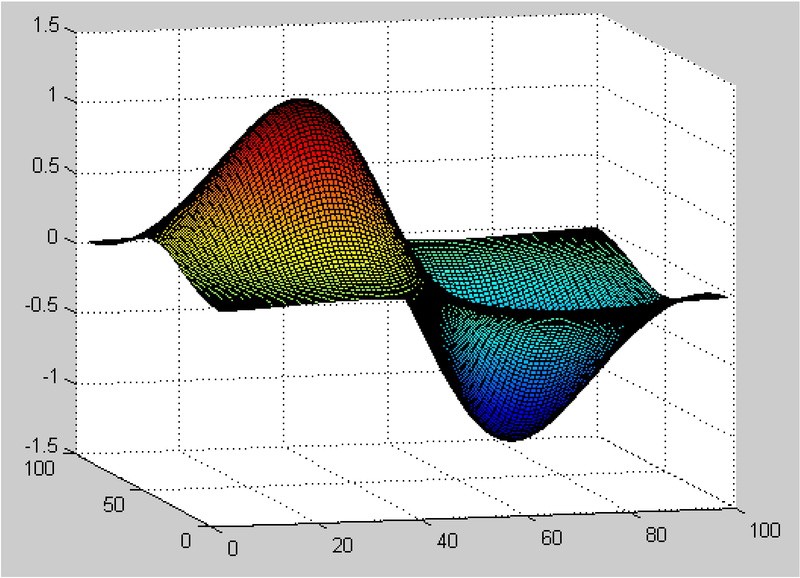




2nd Derivative (Laplacian of Gaussian)

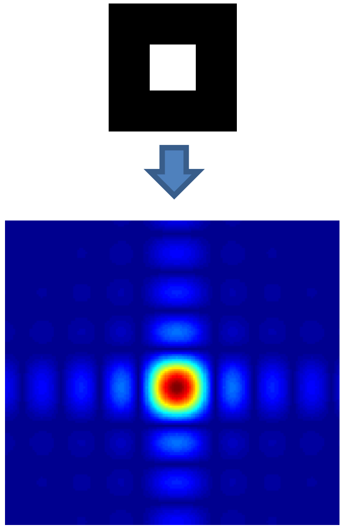


1st Derivative of Gaussian

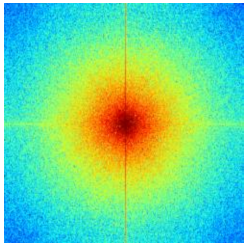


Earl F. Glynn

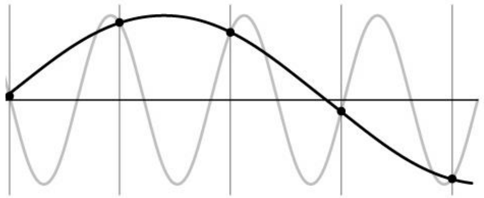
Things to Remember



- 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

EDGE / BOUNDARY DETECTION

Szeliski 4.2

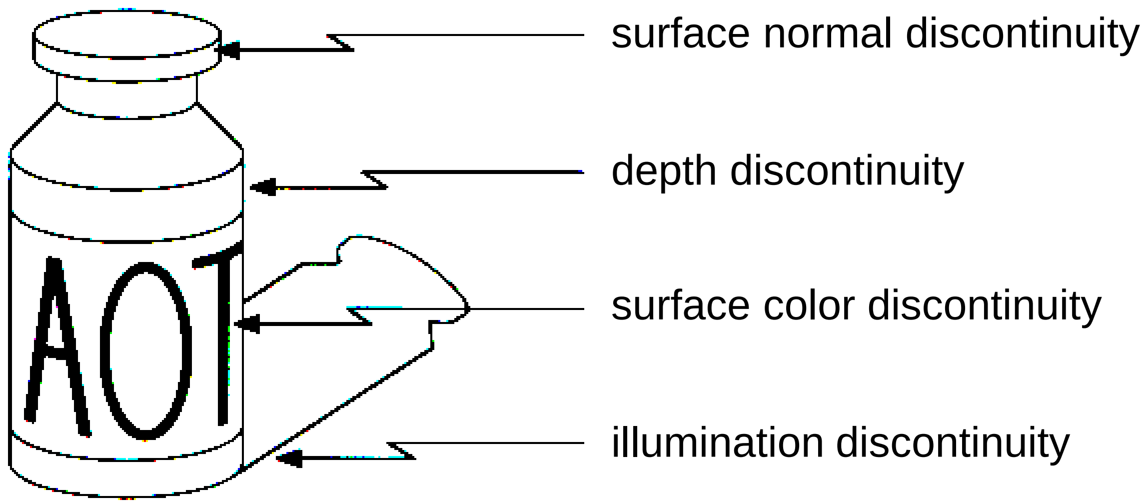
Many slides from James Hays, Lana Lazebnik, Steve Seitz, David Forsyth, David Lowe, Fei-Fei Li, and Derek Hoiem

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



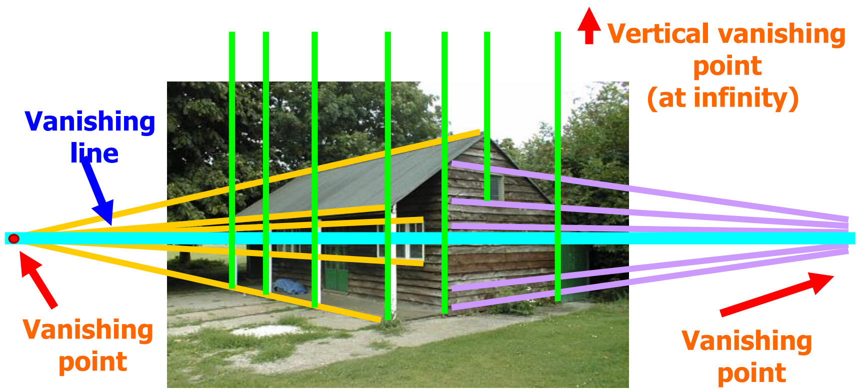
- Edges are caused by a variety of factors

Source: Steve Seitz

Why do we care about edges?

- Extract information
  - Recognize objects

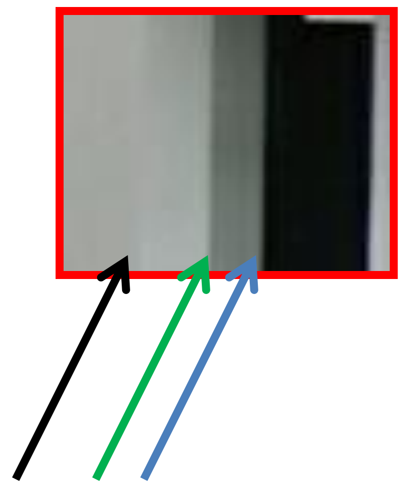
- Help recover geometry and viewpoint



Closeup of edges

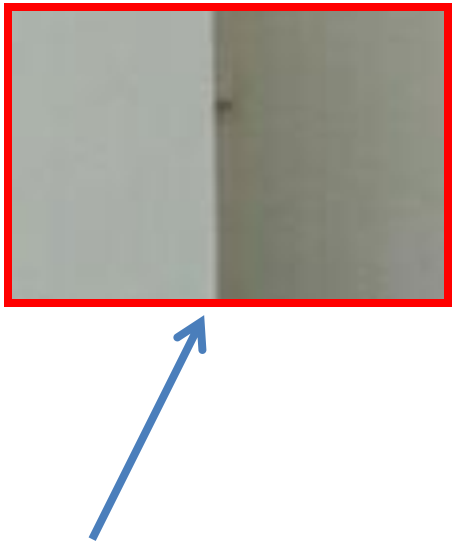
Source: D. Hoiem

Closeup of edges



Source: D. Hoiem

Closeup of edges



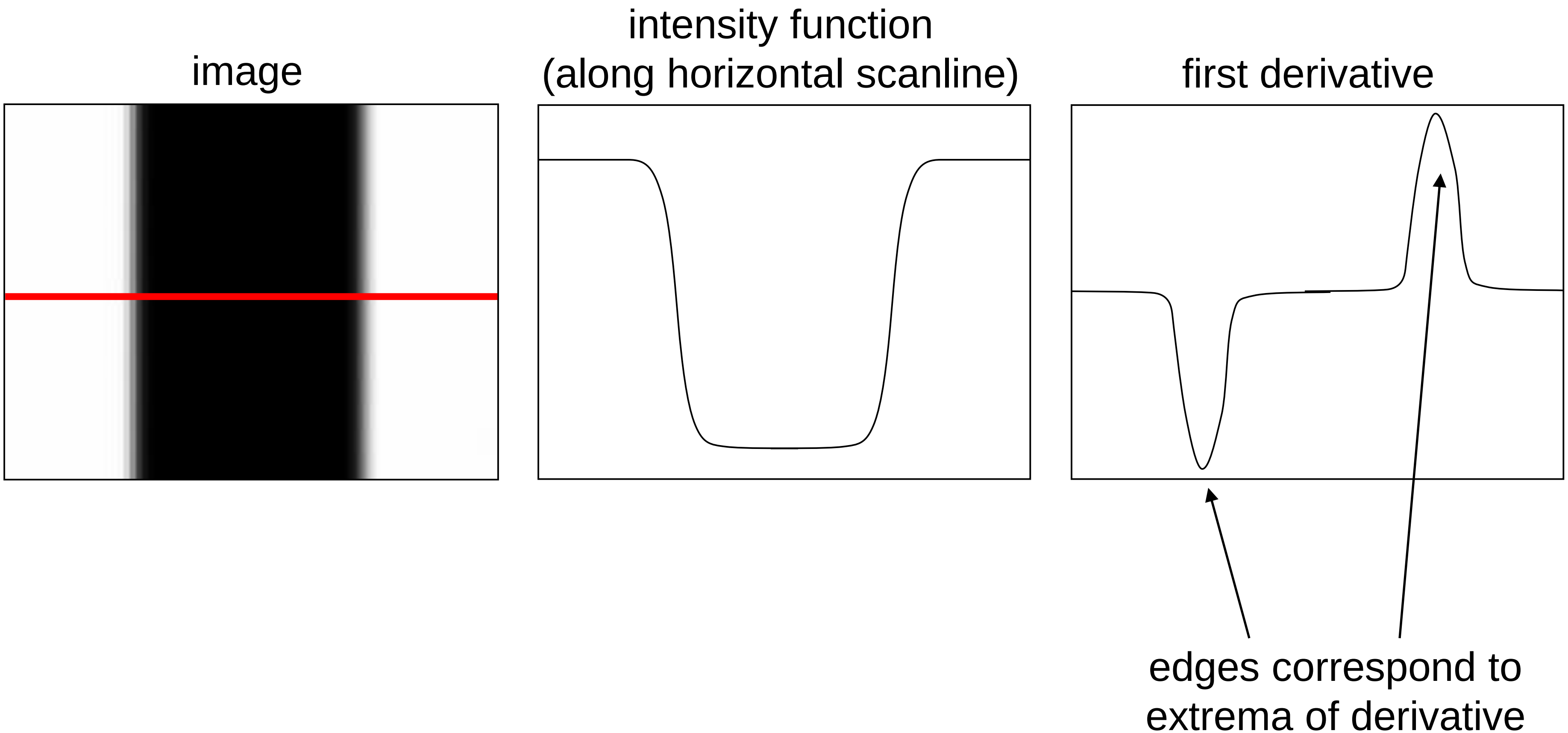
Source: D. Hoiem

Closeup of edges

Source: D. Hoiem

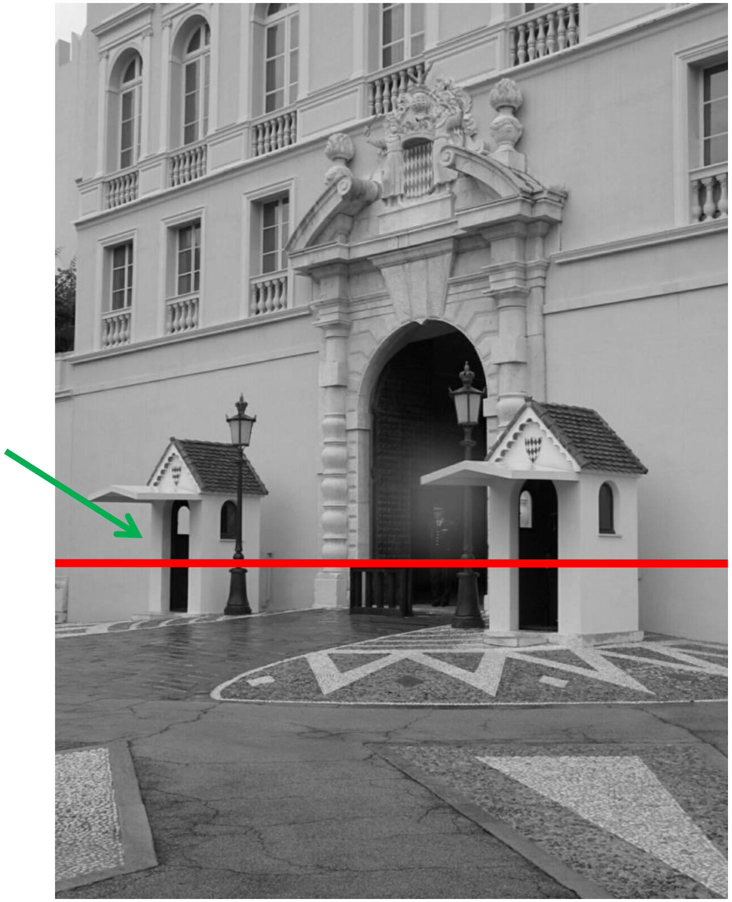
Characterizing edges

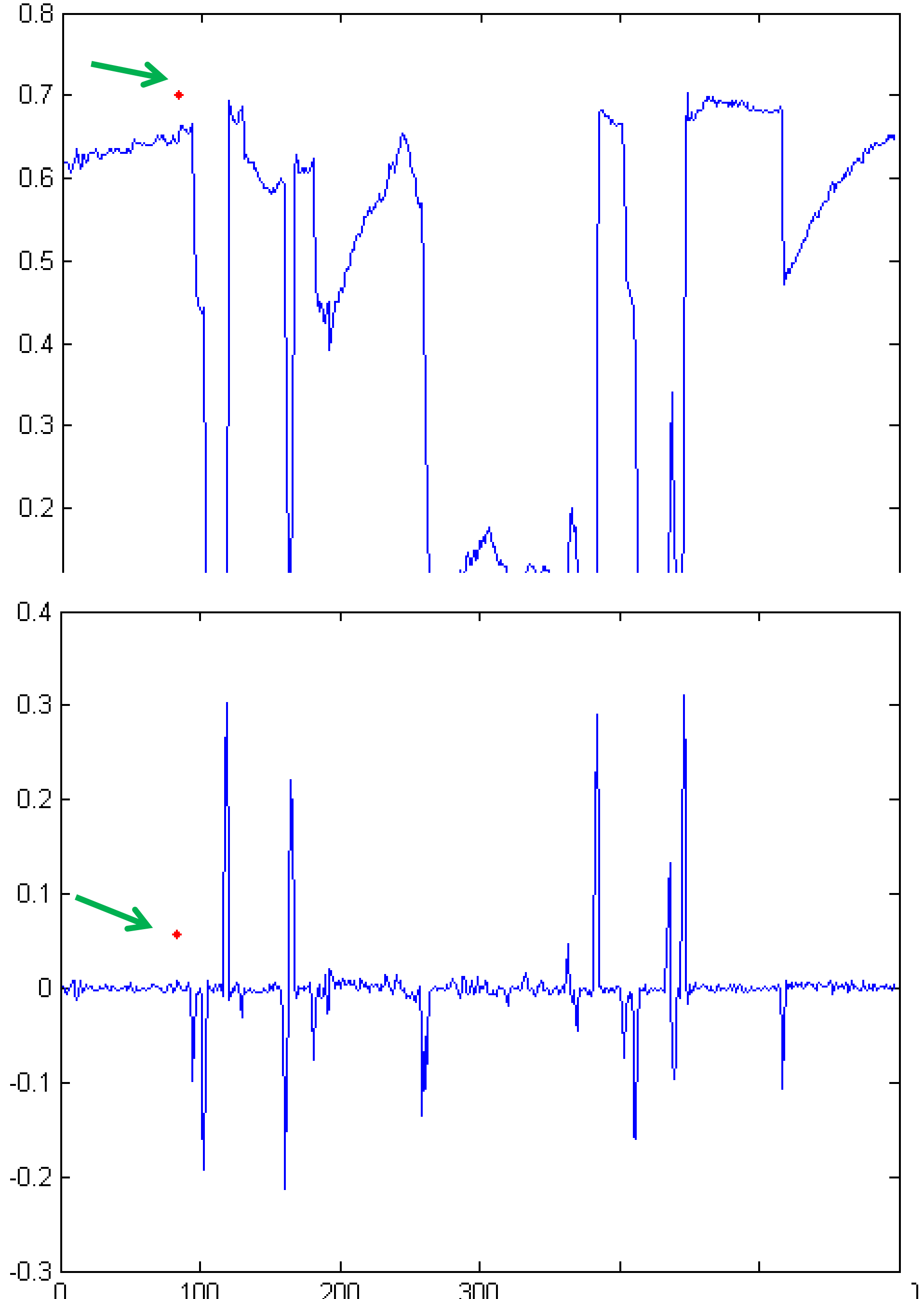
- An edge is a place of rapid change in the image intensity function



Hays

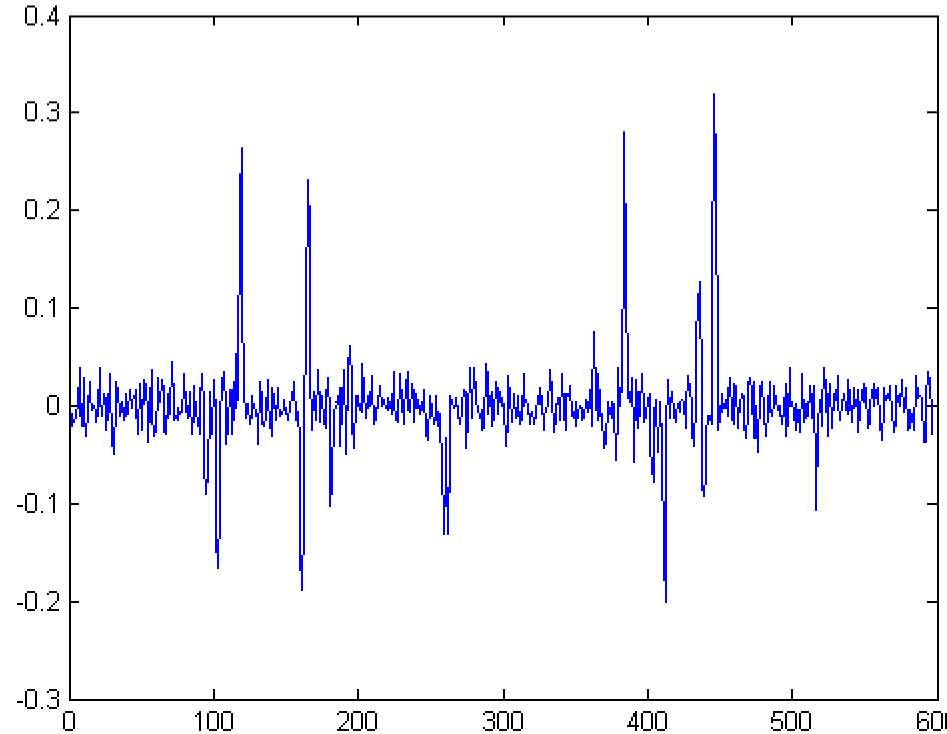
Intensity profile





Source: D. Hoiem

With a little Gaussian noise

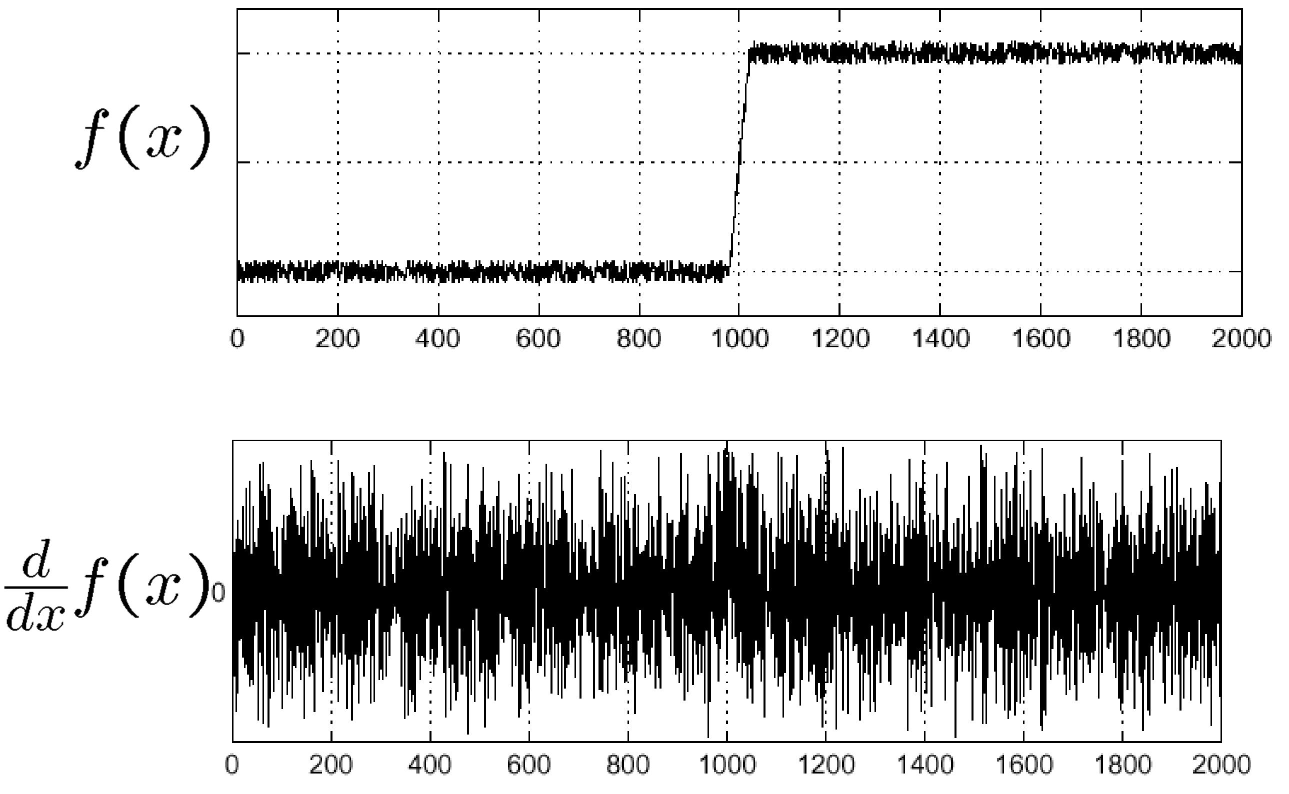


Gradient

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?

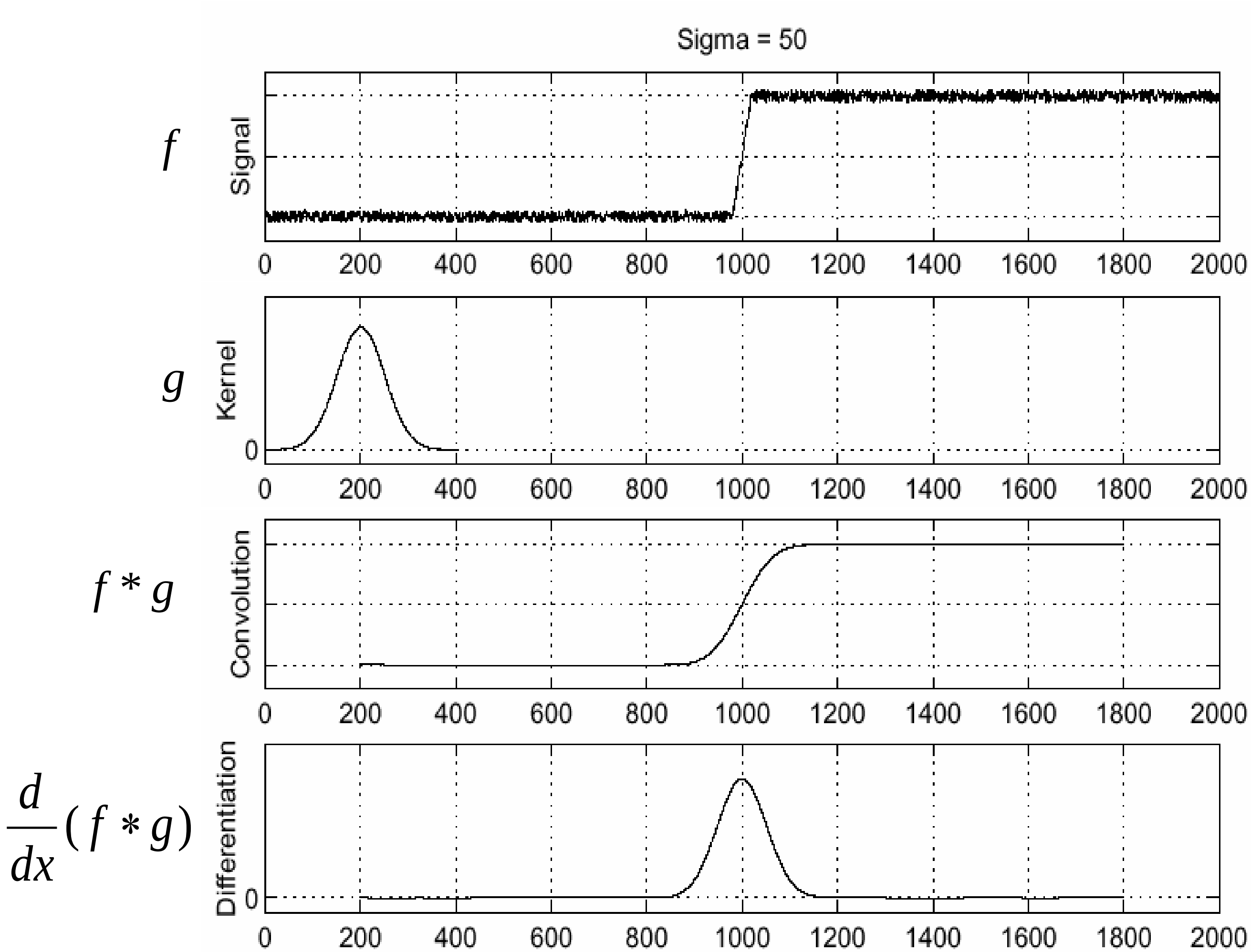
Source: S. Seitz

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

- Convolution is differentiable:

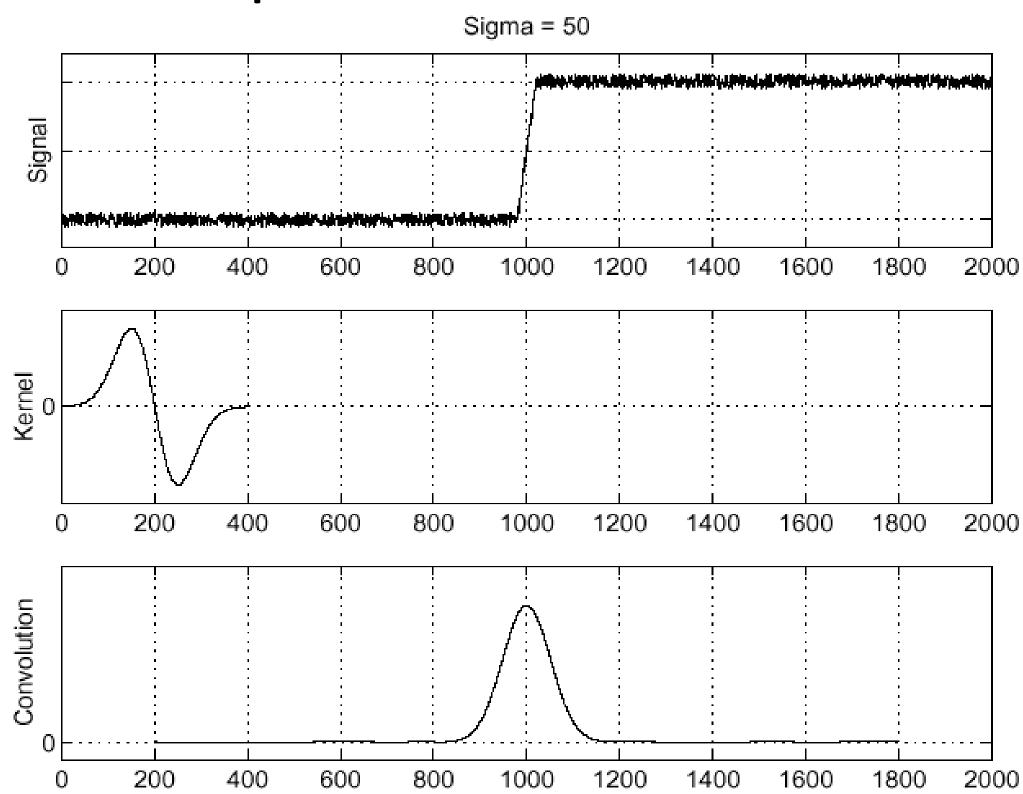
$$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$

- This saves us one operation:

f

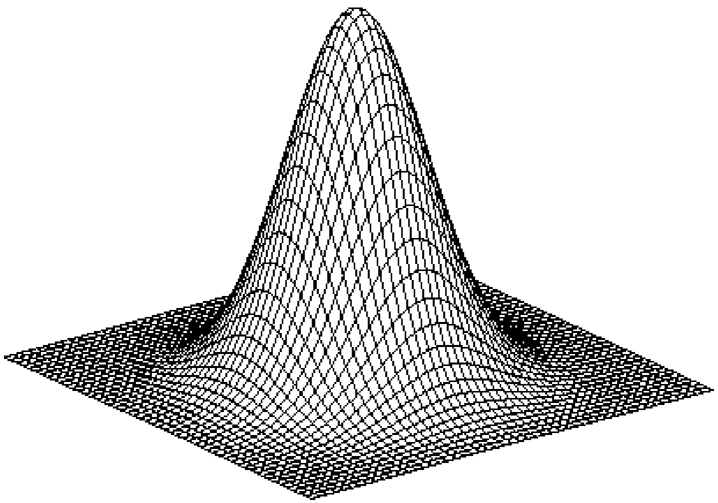
$\frac{d}{dx} g$

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

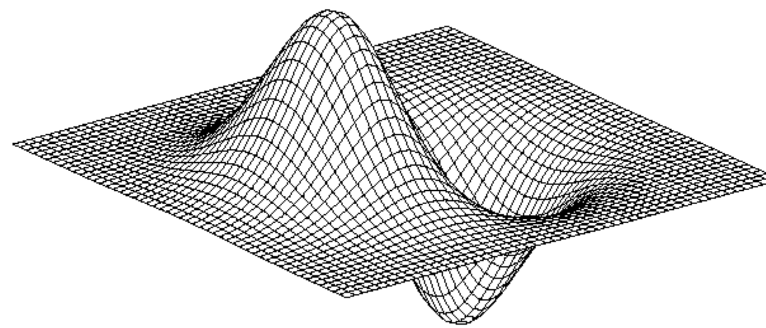


Source: S. Seitz

Derivative of 2D Gaussian filter

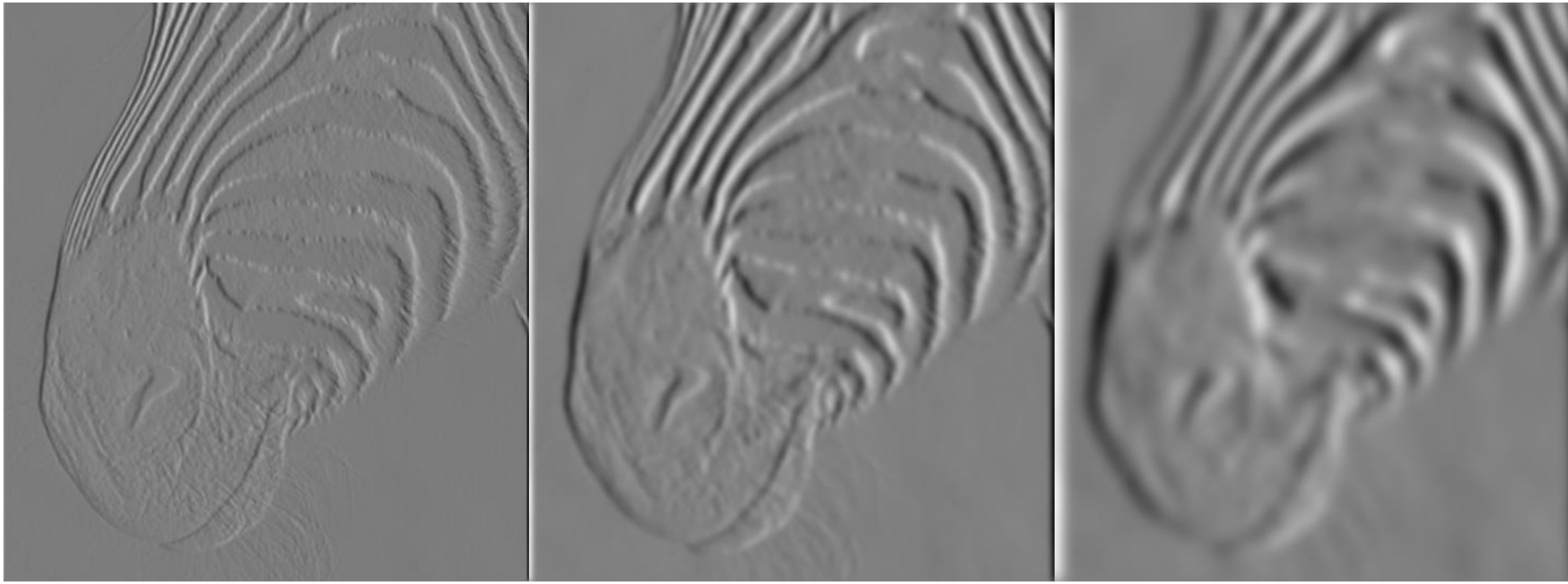


* [1 -1] =



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 ‘complete’ 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

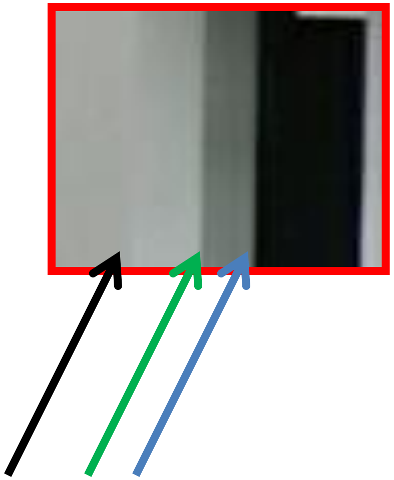
Source: L. Fei-Fei

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

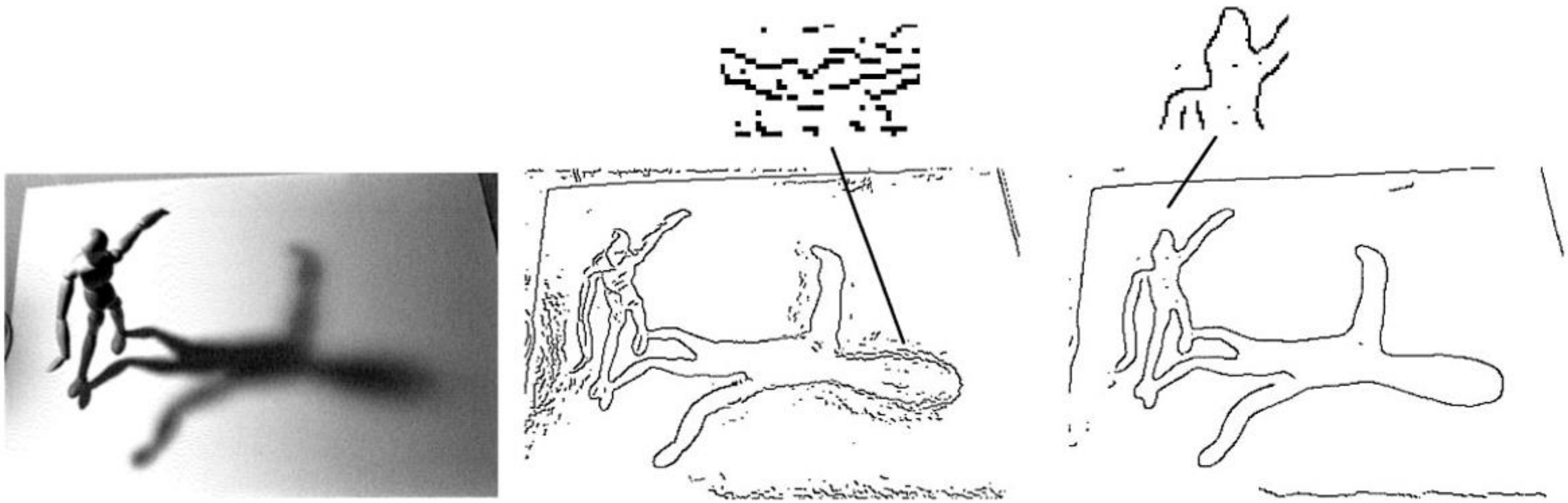


Figure 2. The problem of local estimation scale. Different structures in a natural image require different spatial scales for local estimation. The original image contains edges over a broad range of contrasts and blur scales. In the middle are shown the edges detected with a Canny/Deriche operator tuned 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.

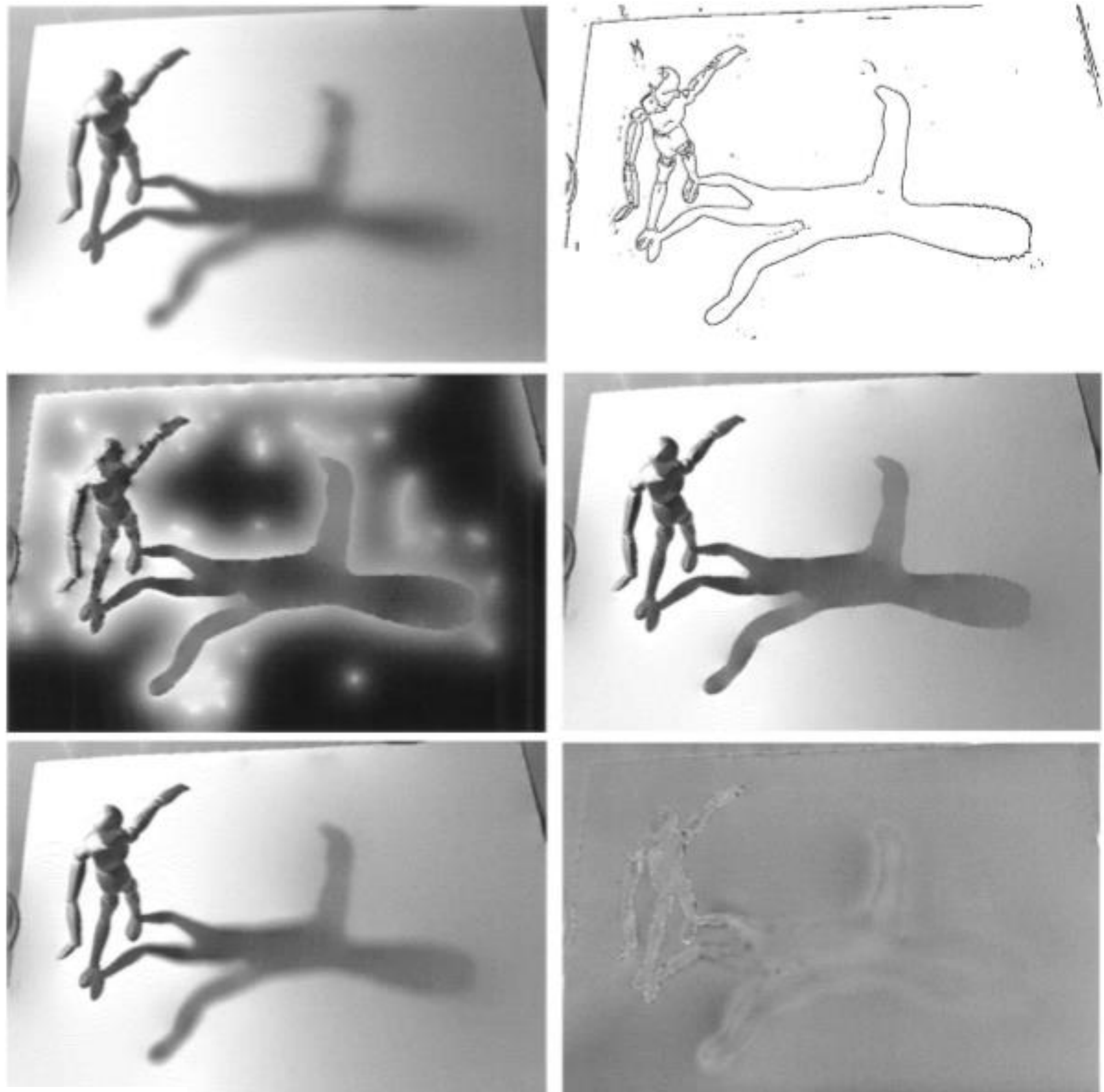


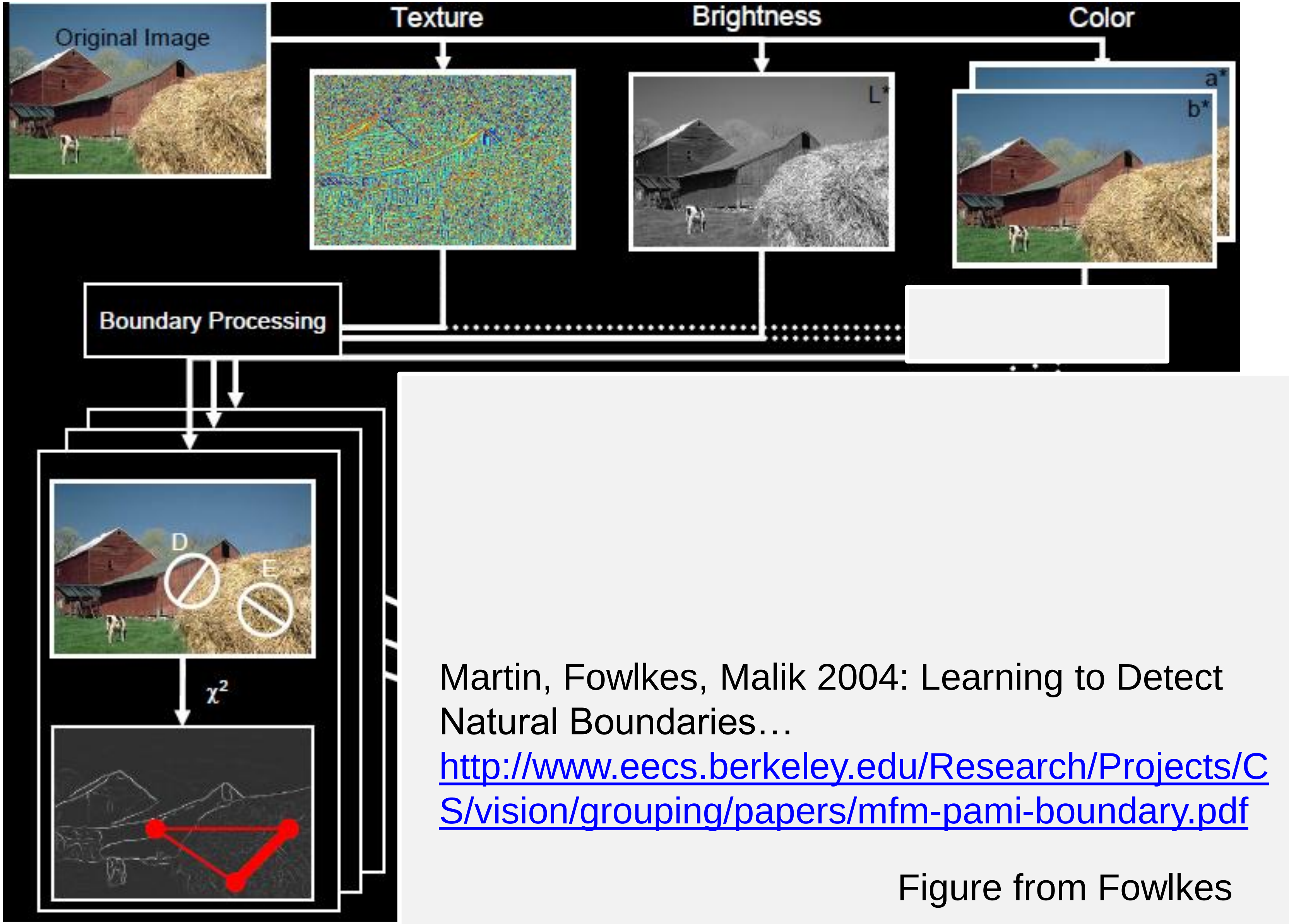
Figure 8. *Top left*: Original image. *Top right*: Detected edge locations. *Middle left*: Intermediate solution to the heat equation. *Middle right*: Reconstructed luminance function. *Bottom left*: Reblurred result. *Bottom right*: Error map (reblurred result—original). Bright indicates overestimation 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

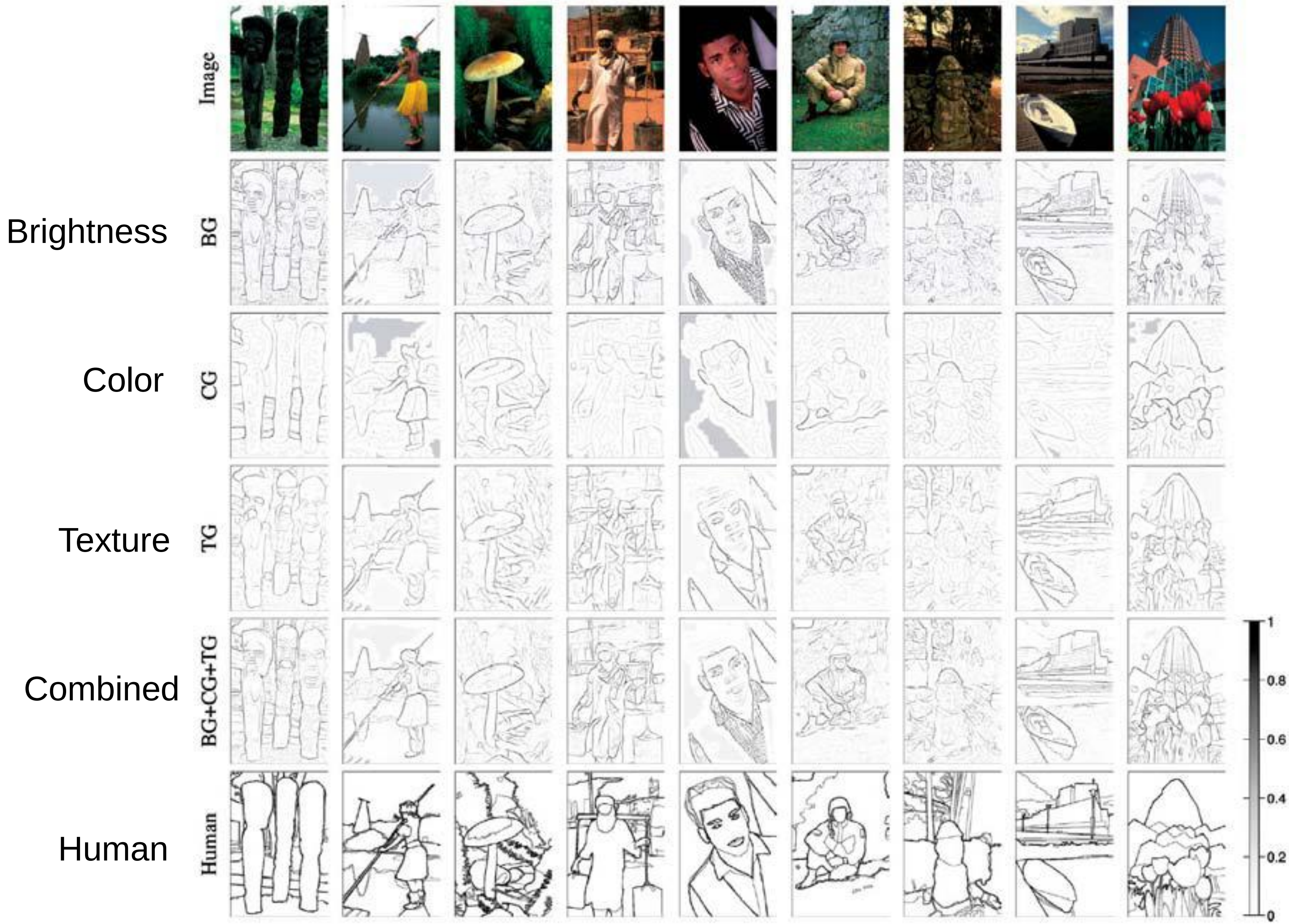
- Berkeley segmentation database:
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

pB 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


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

pB Boundary Detector

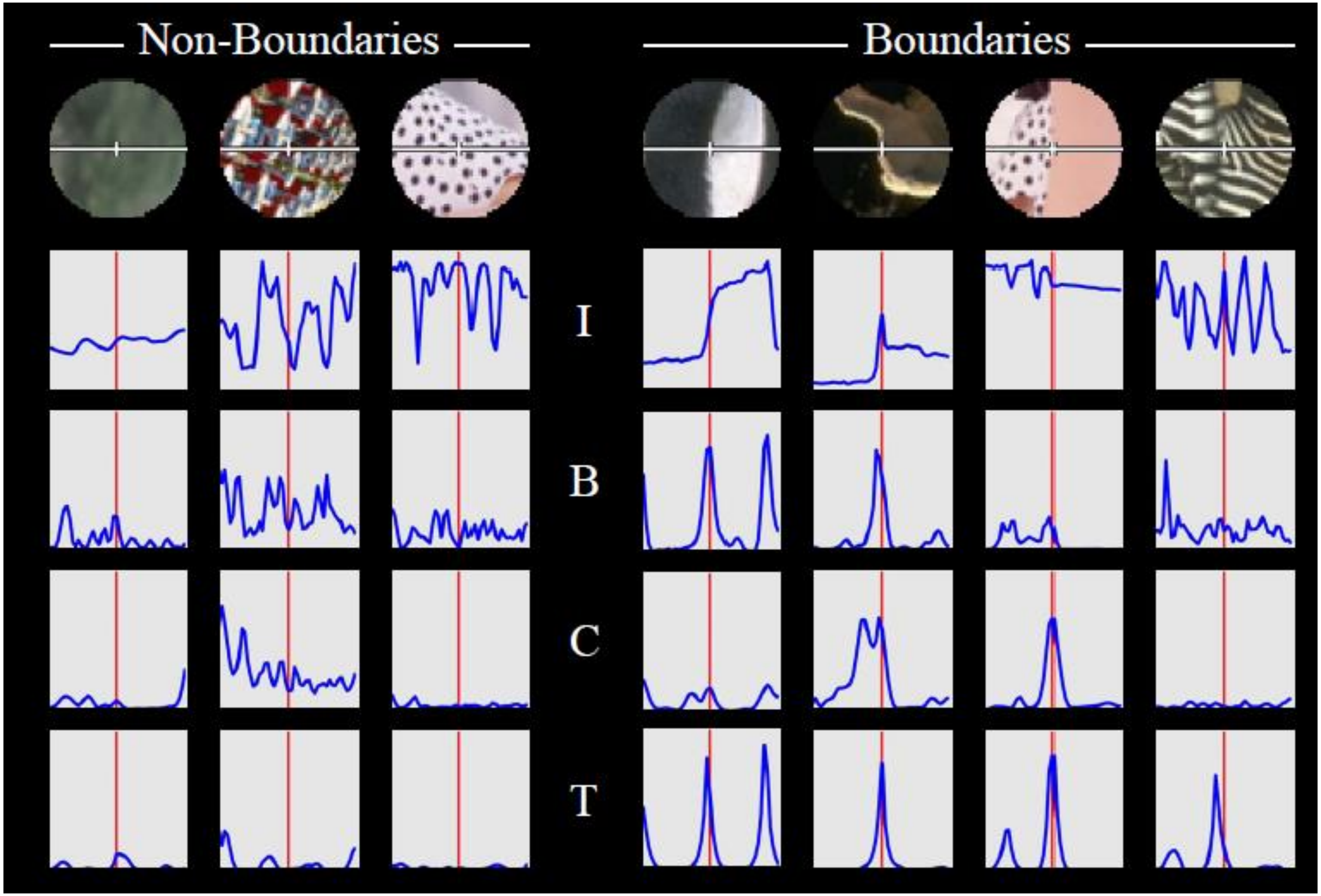
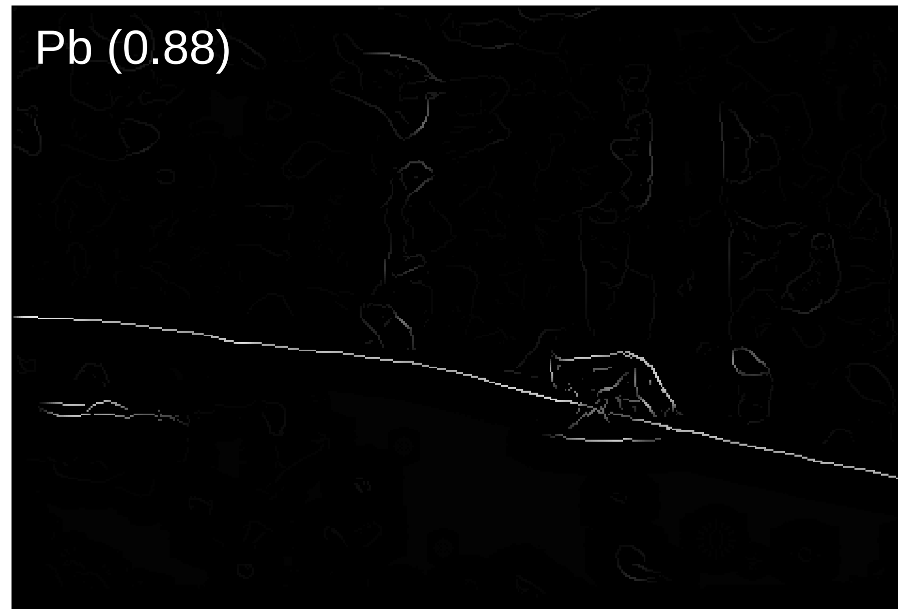
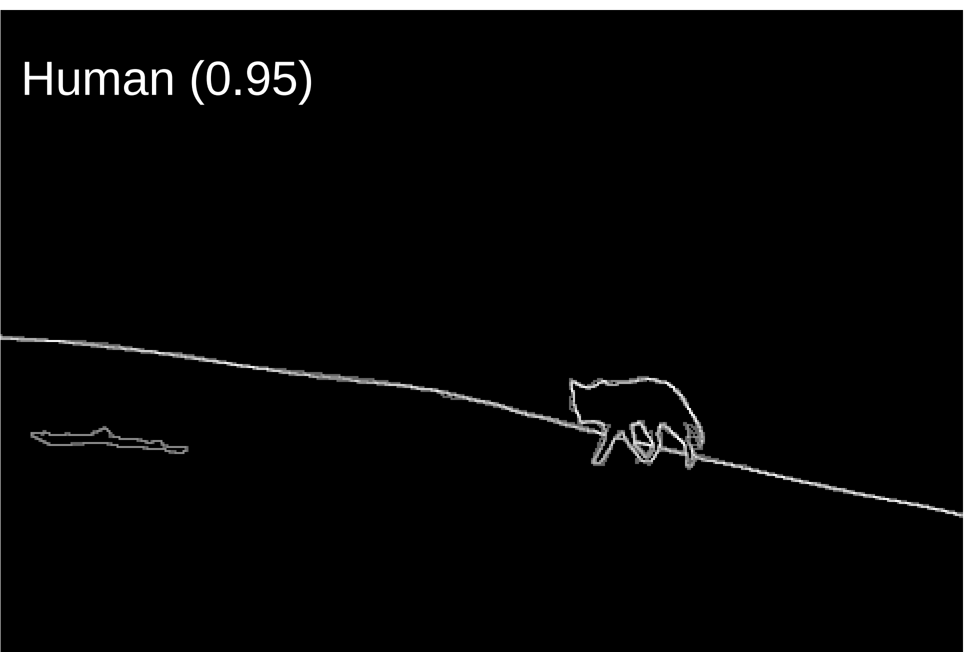


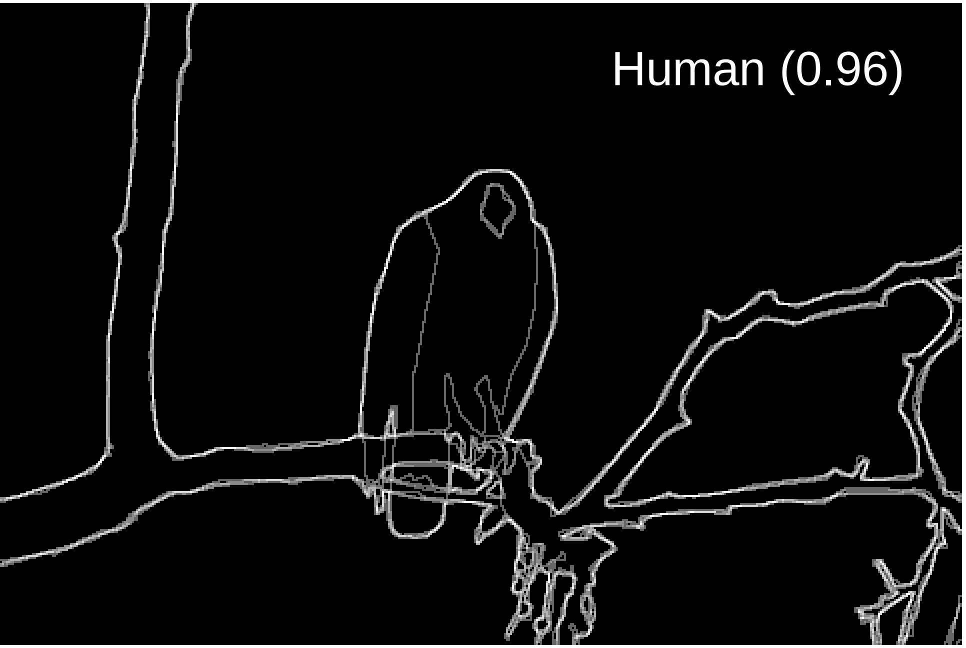
Figure from Fowlkes

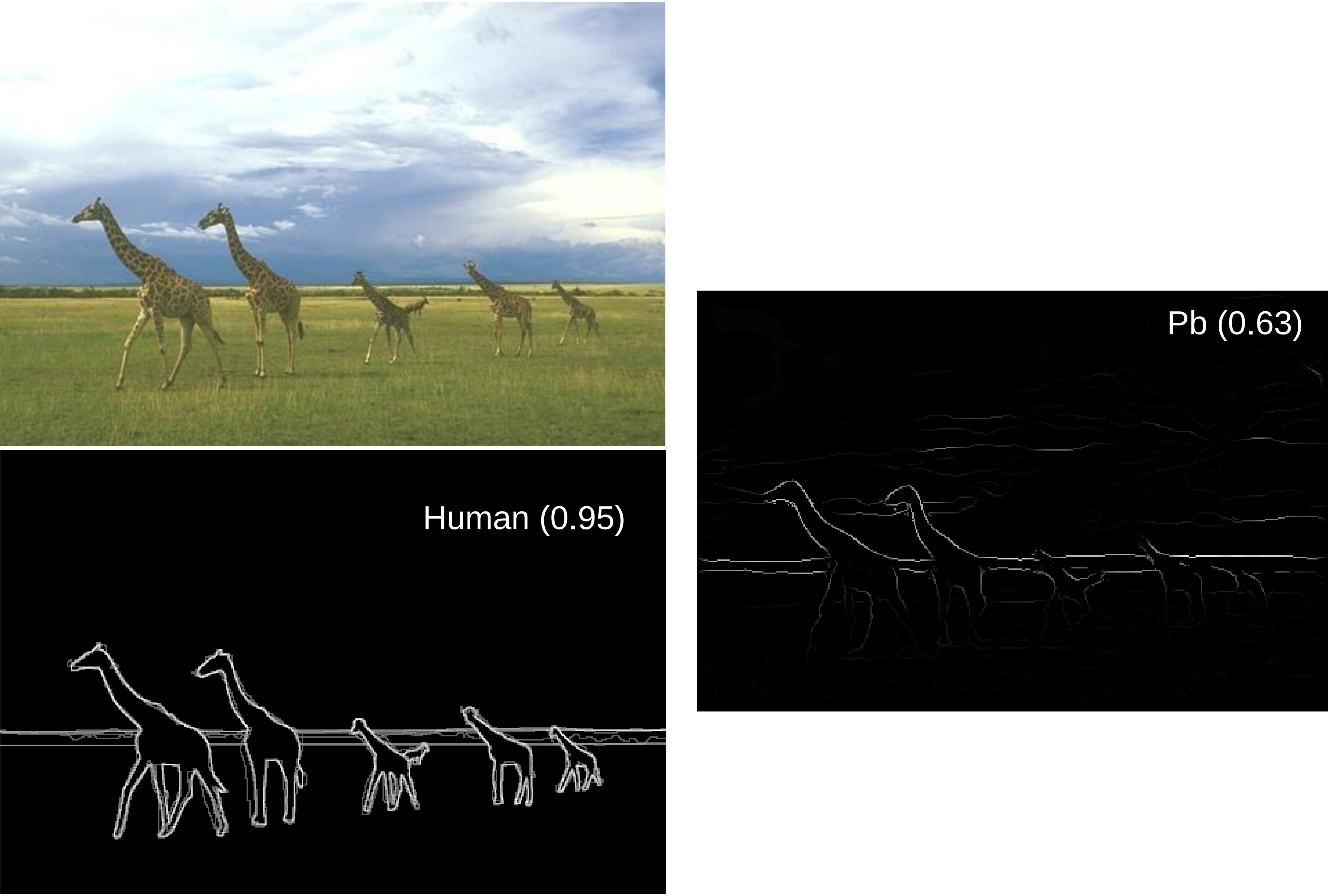
Results

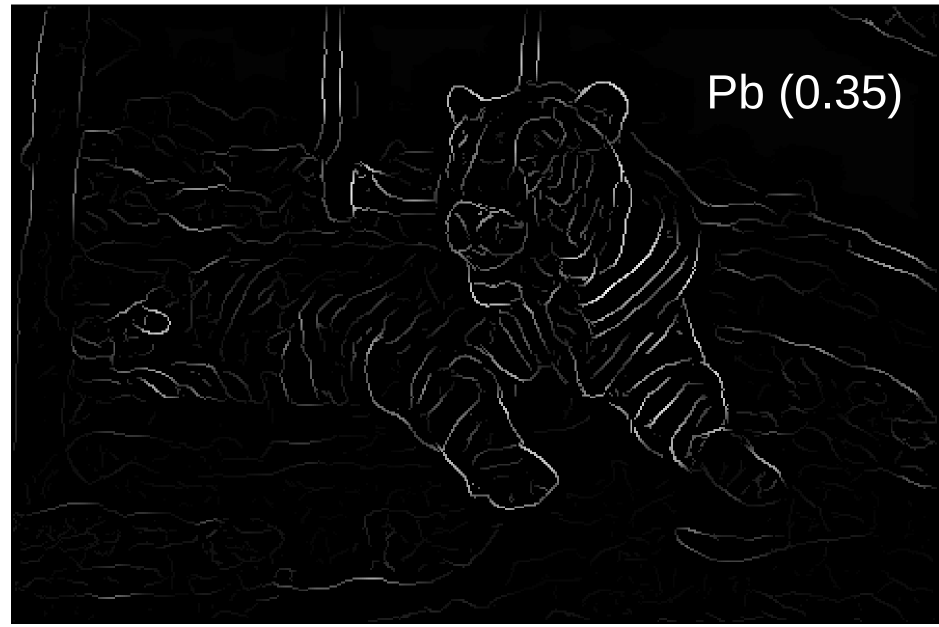


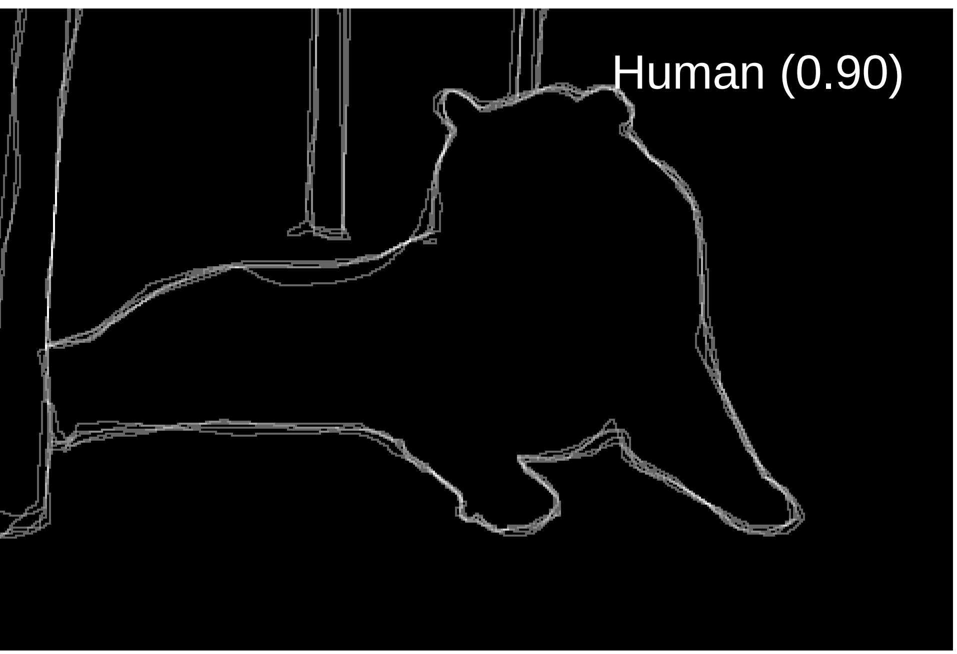


Results



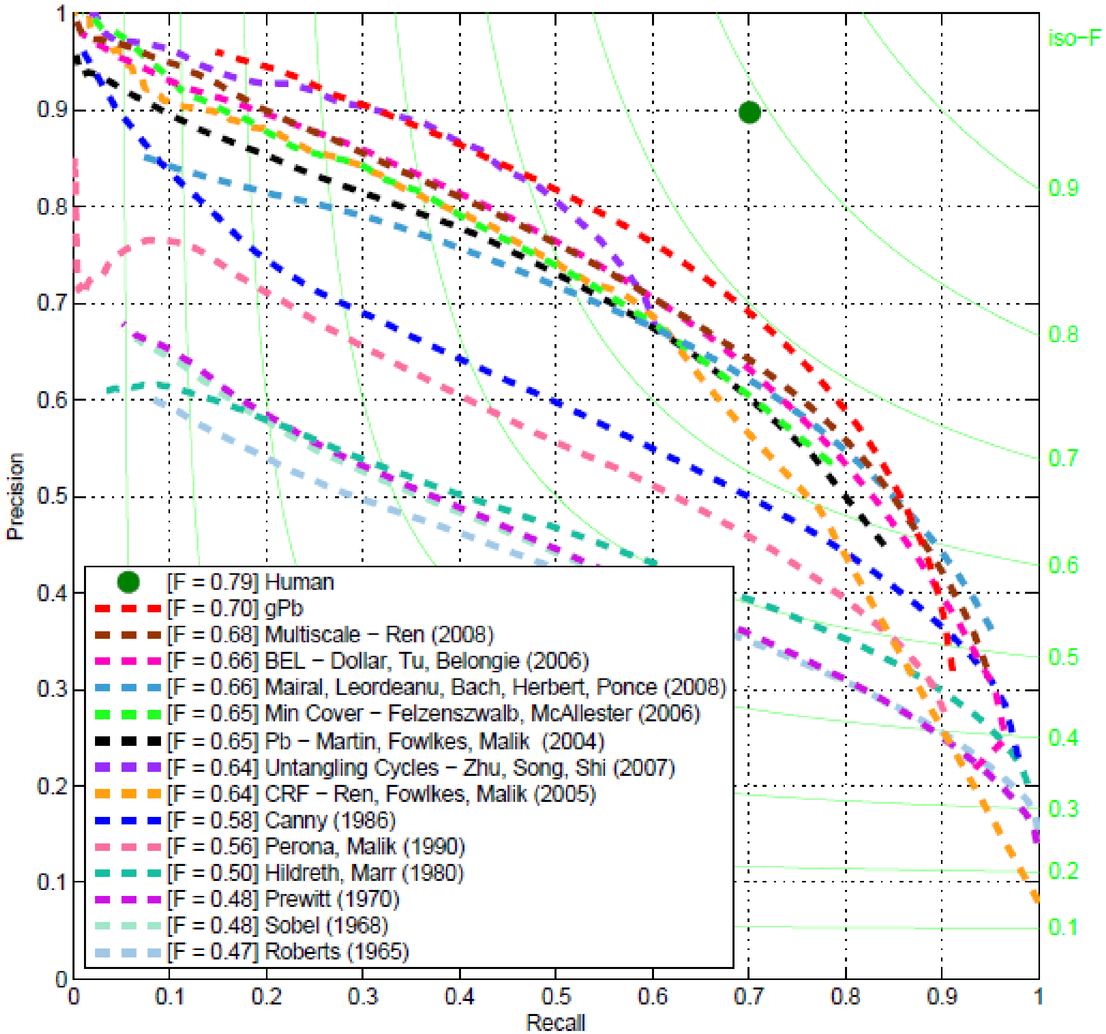

Human (0.95)
Pb (0.63)





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

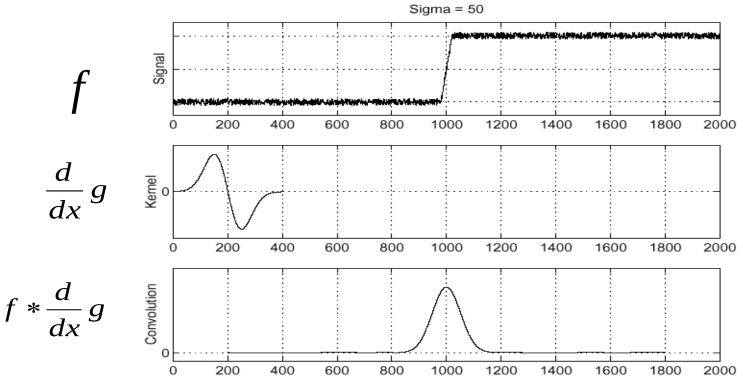
- Local edge detection works well
  - ‘False positives’ from illumination and texture edges (depends on our application).
- Some methods to take into account longer contours
- Modern methods that actually “learn” from data.
- Poor use of object and high-level information.

Hays

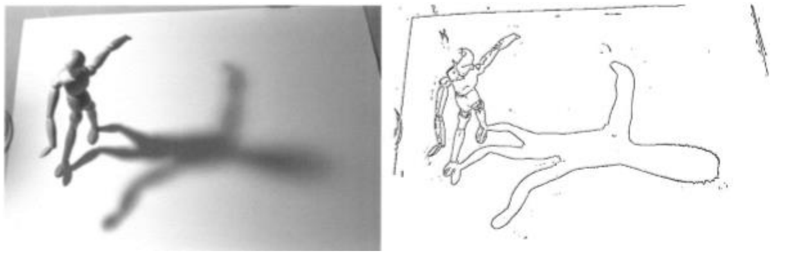
Summary: Edges primer

- Edge detection to identify visual change in image

- Derivative of Gaussian and linear combination of convolutions



- What is an edge?
  What is a good edge?



Canny edge detector

- Probably the most widely used edge detector in computer vision.

- Theoretical model: step-edges corrupted by additive Gaussian noise.
- Canny showed that first derivative of 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.

22,000 citations!

L. Fei-Fei

Demonstrator Image

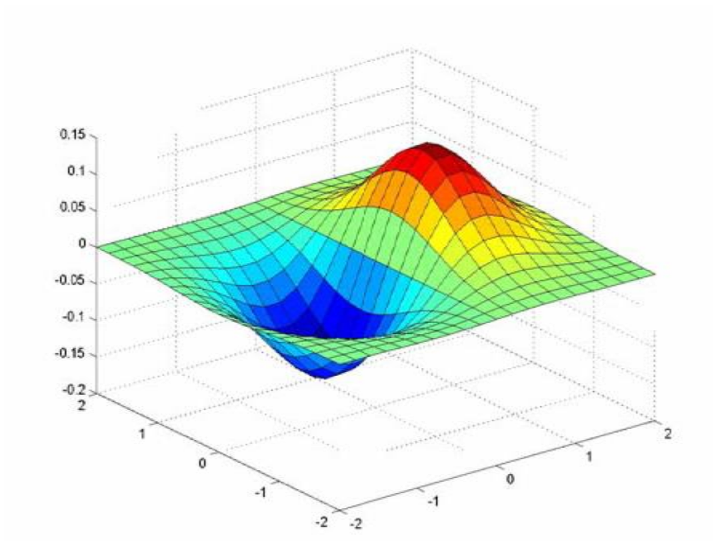
`rgb2gray('img.png')`

Canny edge detector

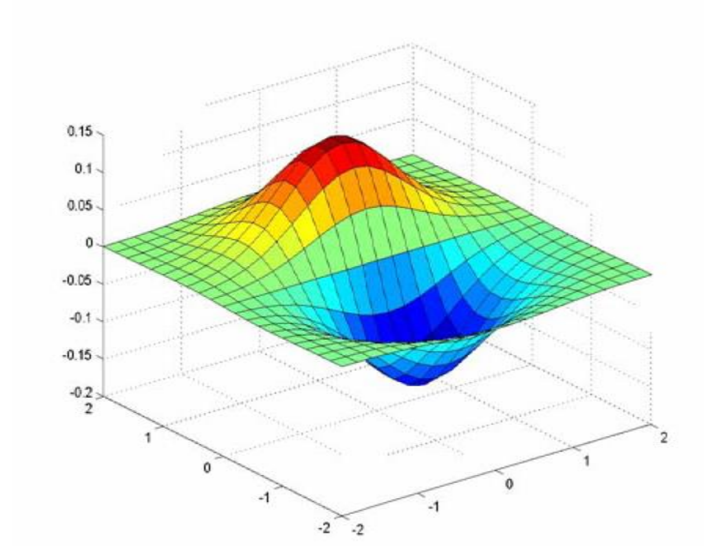
1. Filter image with x, y derivatives of Gaussian

Source: D. Lowe, L. Fei-Fei

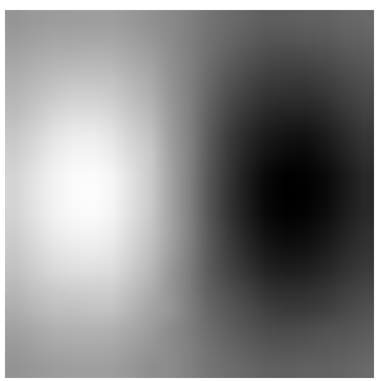
Derivative of Gaussian filter

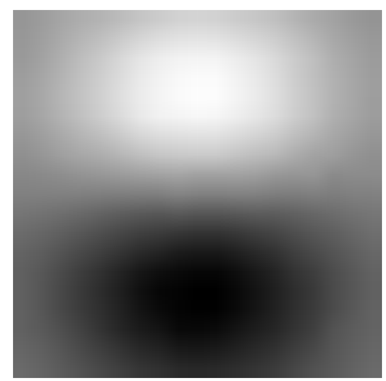


x-direction

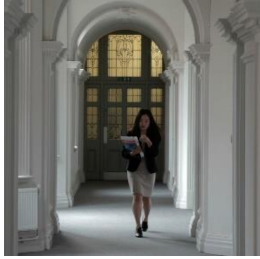


y-direction



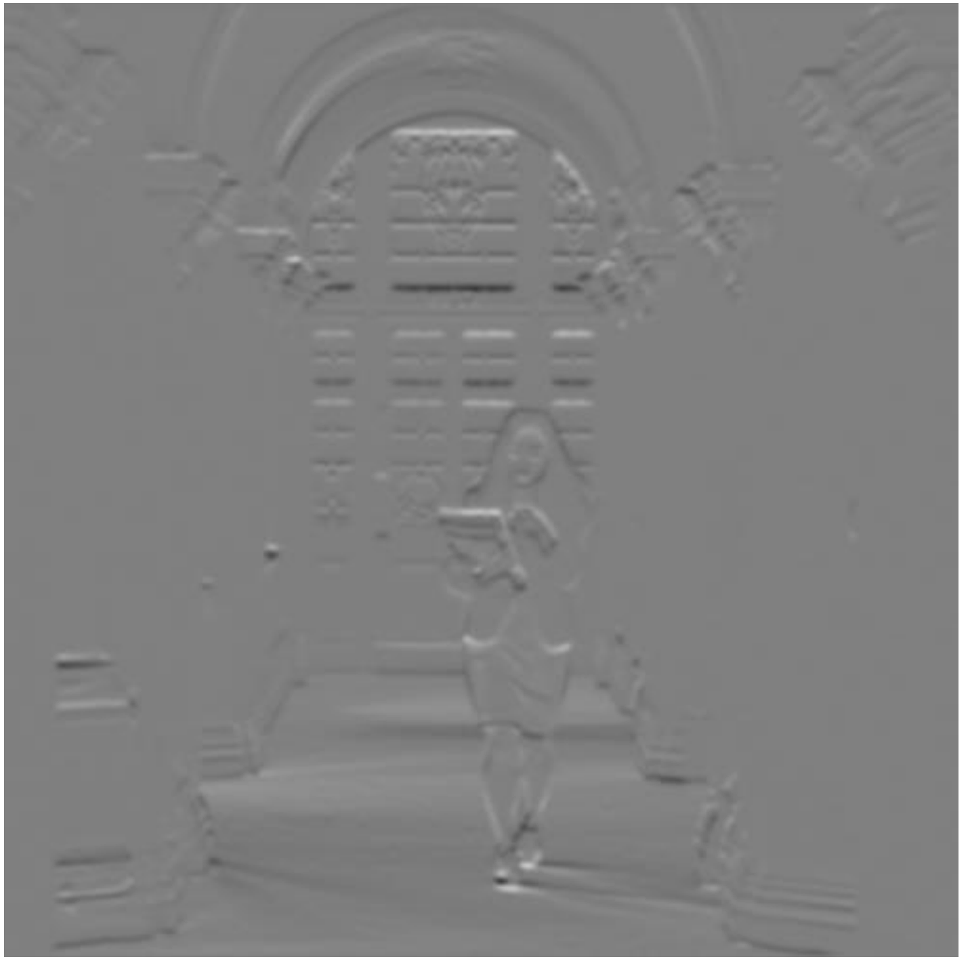


Compute Gradients



X Derivative of Gaussian

Y Derivative of Gaussian



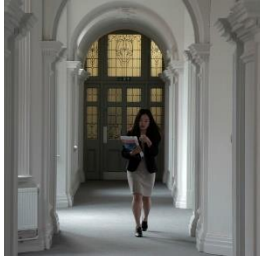
(x2 + 0.5 for visualization)

Canny edge detector

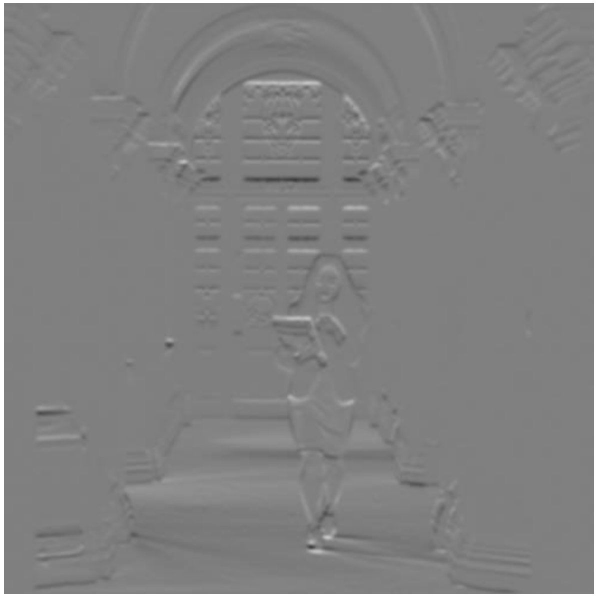
1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient

Source: D. Lowe, L. Fei-Fei

Compute Gradient Magnitude



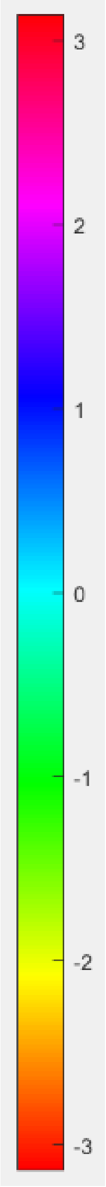
sqrt(XDerivOfGaussian .^2 + YDerivOfGaussian .^2) = gradient magnitude

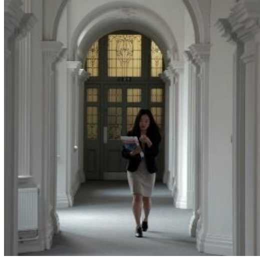


(x4 for visualization)

Compute Gradient Orientation

- Threshold magnitude at minimum level
- Get orientation via $\theta = \mathrm{atan2}(gy, gx)$



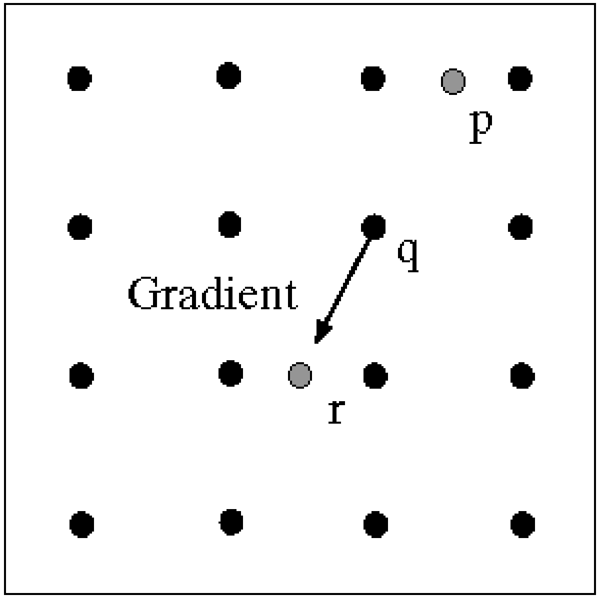


Canny edge detector

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” to single pixel width

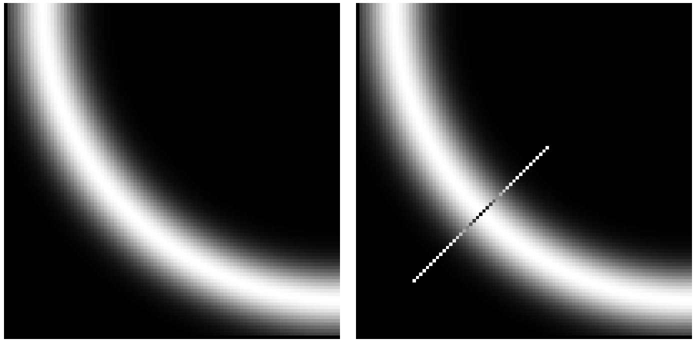
Source: D. Lowe, L. Fei-Fei

Non-maximum suppression for each orientation



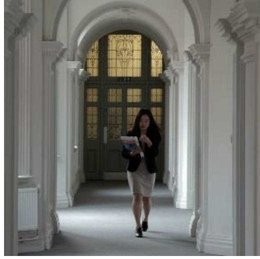
At pixel q:
We have a maximum if the value is larger than those at both p and at r.

Interpolate along gradient direction to get these values.



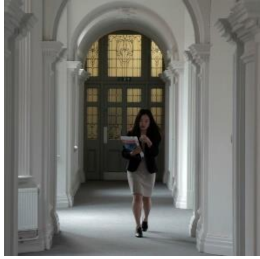
Source: D. Forsyth

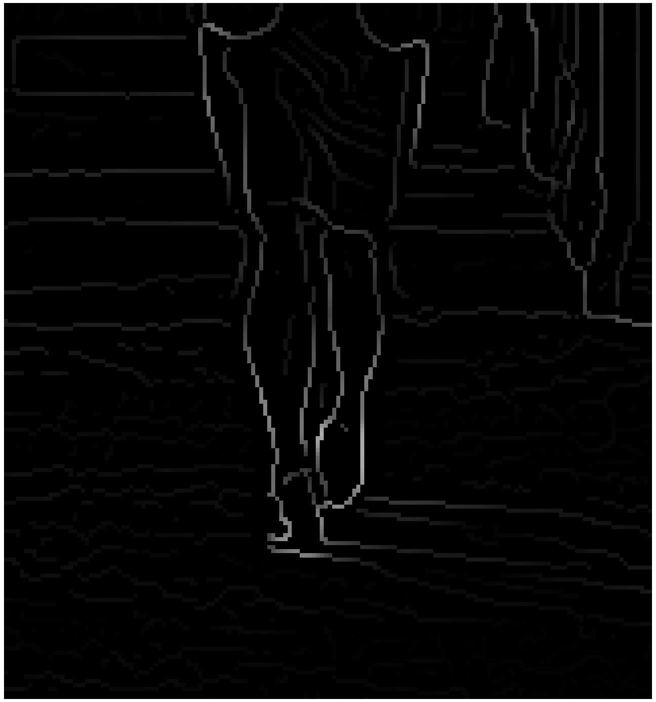
Before Non-max Suppression



Gradient magnitude (x4 for visualization)

After non-max suppression





Gradient magnitude (x4 for visualization)

Canny edge detector

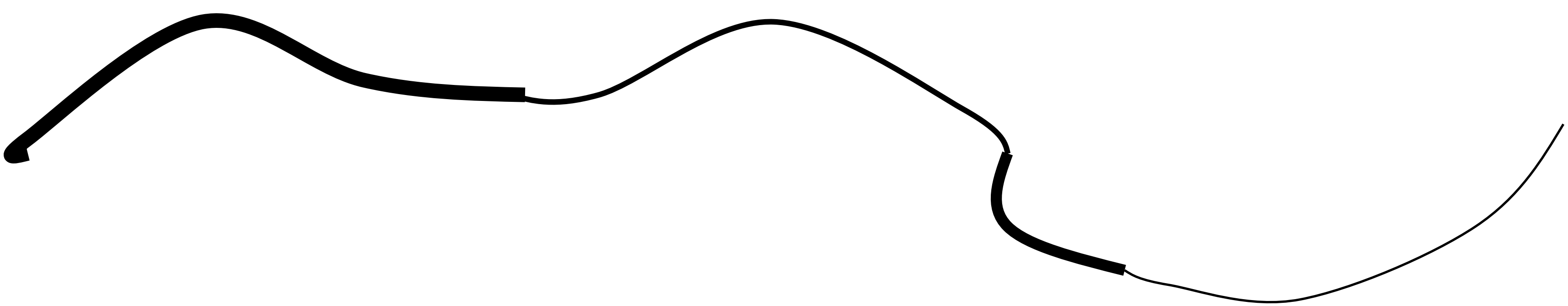
1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   – Thin multi-pixel wide “ridges” to single pixel width
4. ‘Hysteresis’ Thresholding

Source: D. Lowe, L. Fei-Fei

‘Hysteresis’ thresholding

- Two thresholds – high and low
- Grad. mag. > high threshold? = strong edge
- Grad. mag. < low threshold? noise
- In between = weak edge

- ‘Follow’ edges starting from strong edge pixels
- Continue them into weak edges
    - Connected components (Szeliski 3.3.4)



Source: S. Seitz

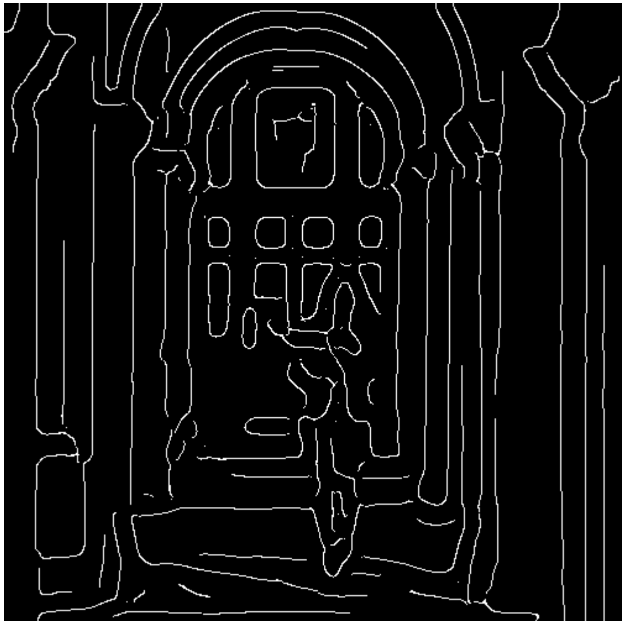
Final Canny Edges

$$\sigma = \sqrt{2}, t_{low} = 0.05, t_{high} = 0.1$$

Effect of σ (Gaussian kernel spread/size)

Original

$\sigma = \sqrt{2}$



$\sigma = 4\sqrt{2}$

The choice of σ depends on desired behavior

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

Source: S. Seitz

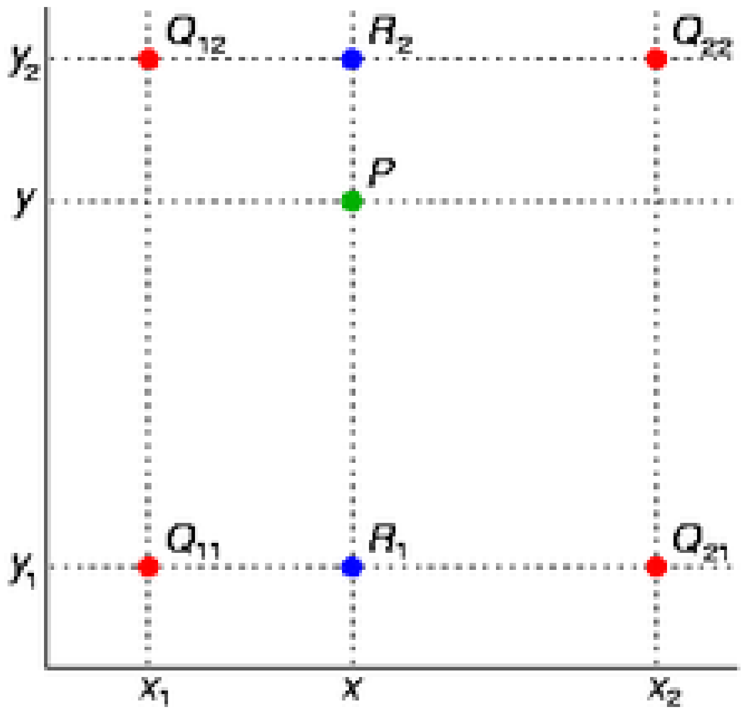
Canny edge detector

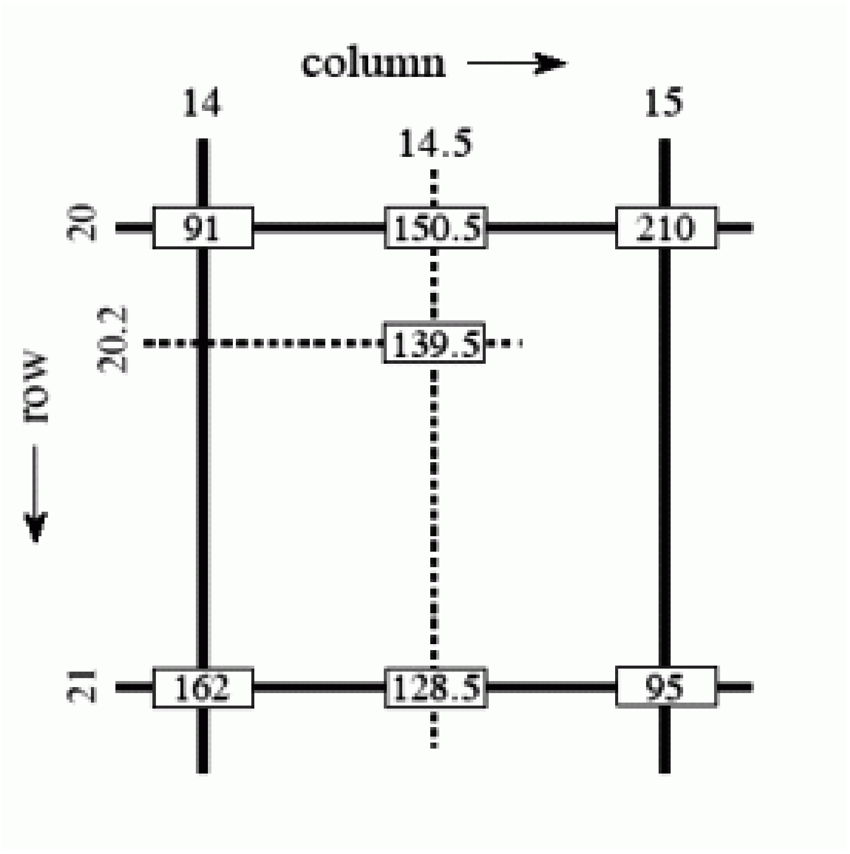
1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel wide “ridges” to single pixel width
4. ‘Hysteresis’ Thresholding:
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them
   - ‘Follow’ edges starting from strong edge pixels
     - Connected components (Szeliski 3.3.4)

- MATLAB: edge(image, ‘canny’)

Source: D. Lowe, L. Fei-Fei

Sidebar: Bilinear Interpolation





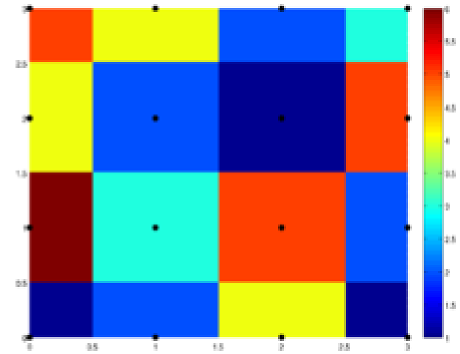
$$f(x,y) \approx \begin{bmatrix} 1-x & x \end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}.$$

http://en.wikipedia.org/wiki/Bilinear_interpolation

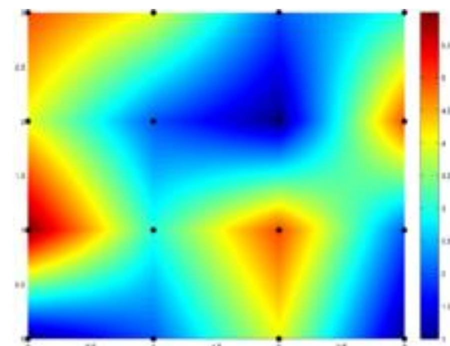
Sidebar: Interpolation options

- imx2 = imresize(im, 2, interpolation_type)

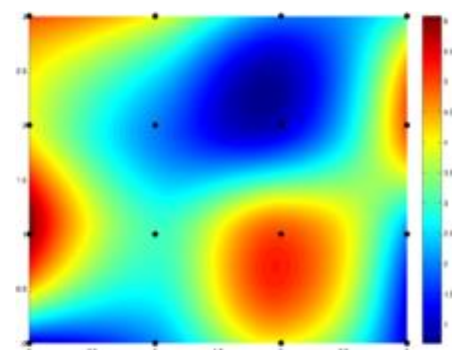
- 'nearest'
  - Copy value from nearest known
  - Very fast but creates blocky edges



- '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