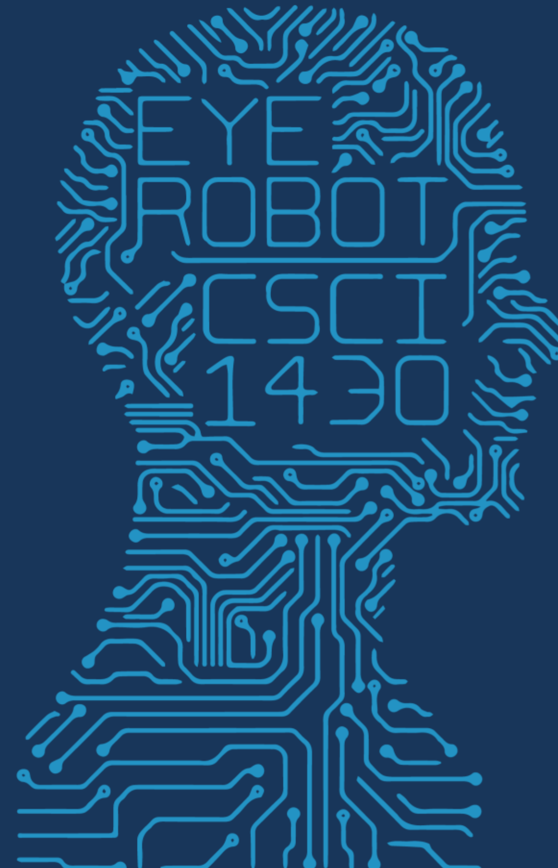
1950

Future Vision



3 February 2020

Computer Vision

Piazza etiquette with 300 students

- Read the project description
- Check top-level notes post on Piazza
- Search for similar questions on Piazza

- Question number in title
- Description of problem
- Description of how you have tried to debug it
- Code: divide and conquer; minimal non-working example really helps

Gradescope – Late submissions

- Yes, there is a grace period

Gradescope – question PDFs

- Change of plan to help with grading 300 scripts
- No longer asking you to assign pages
- Now: please stick to pages
  – we give you plenty of space.

Grok

To understand intuitively; completely; [to the point of sharing an existence.]

1961	Robert A. Heinlein book; coined term
1980s	Took on meaning in computing circles

"There isn't any software! Only different internal states of hardware. It's all hardware! It's a shame programmers don't grok that better."

https://en.wikipedia.org/wiki/Grok

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 Fourier domain (e.g., numpy.fft.fft2())
    2. Element-wise multiply their decompositions
    3. Convert result to spatial domain with inverse Fourier transform (e.g., numpy.fft.ifft2())

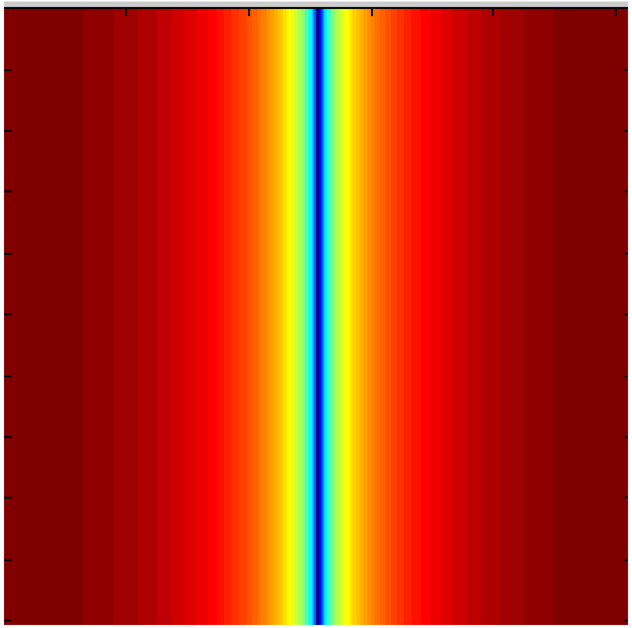
You will play with code in Proj2 questions

Hays

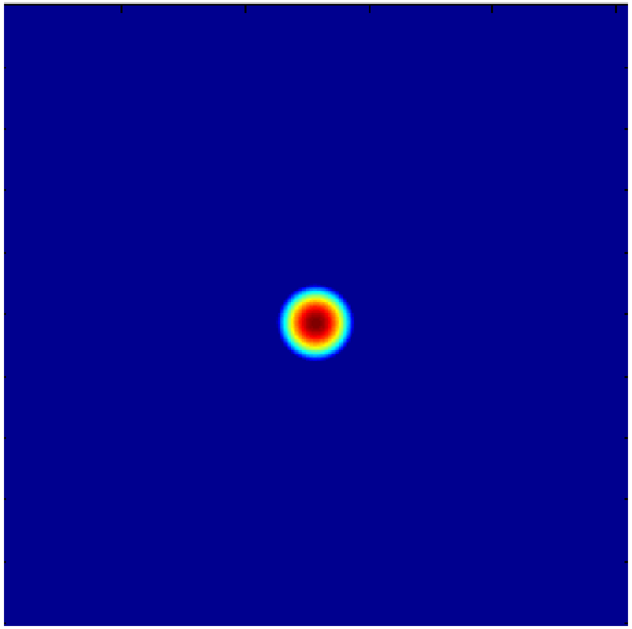
Review of Filtering

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

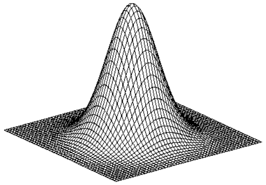
[-1 1]



FFT of Gradient Filter



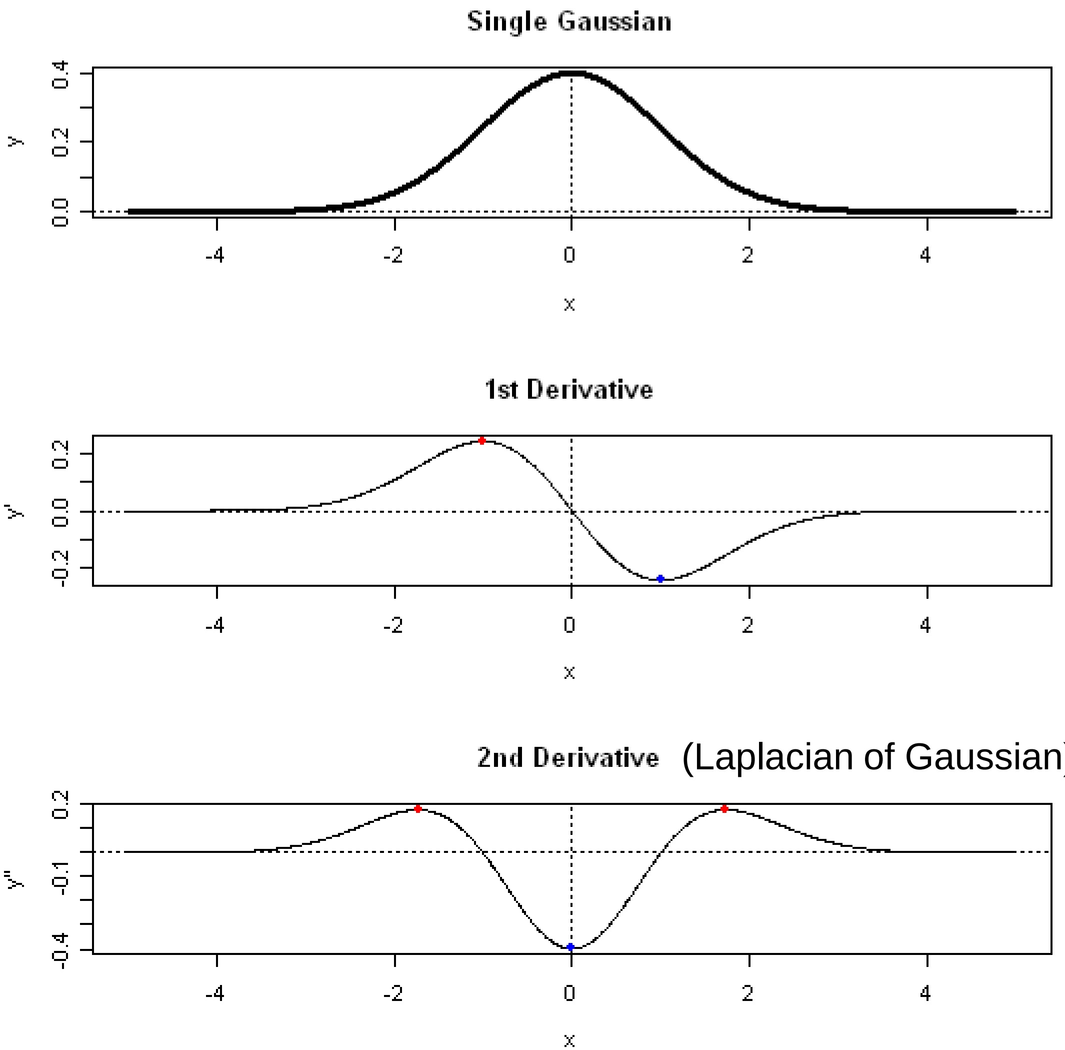
FFT of Gaussian



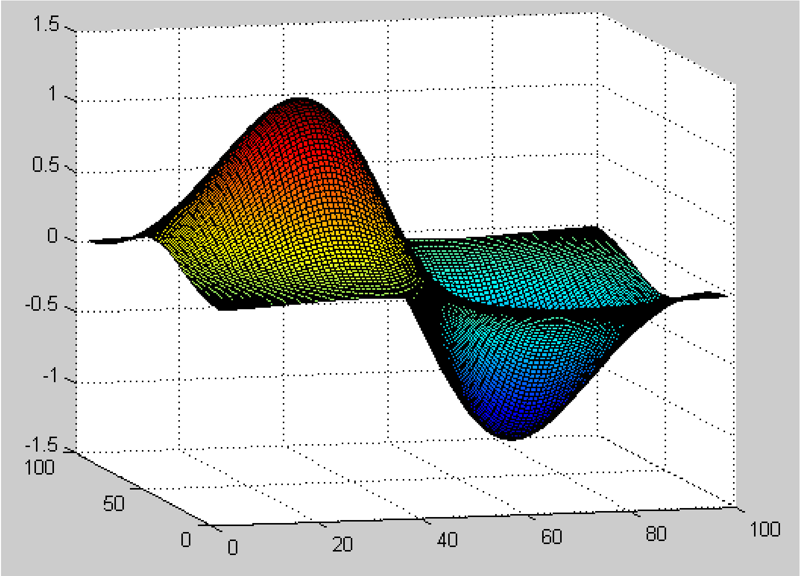
Gaussian

Hays

More Useful Filters

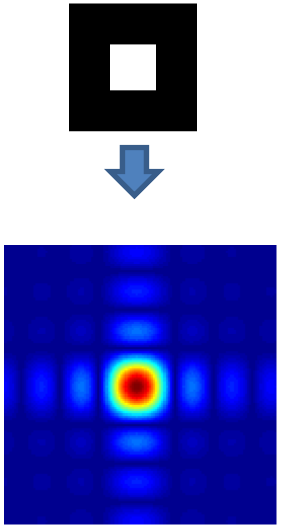


1st Derivative of Gaussian



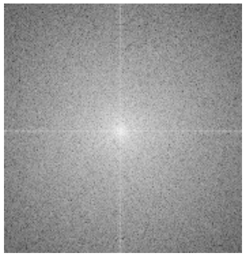
Earl F. Glynn

Things to Remember

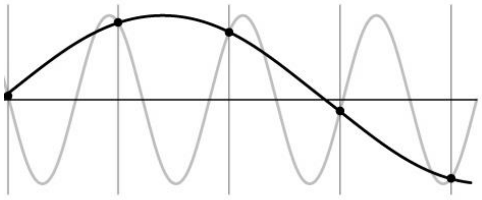


Sometimes it helps to think of images and filtering in the frequency domain
- Fourier analysis

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

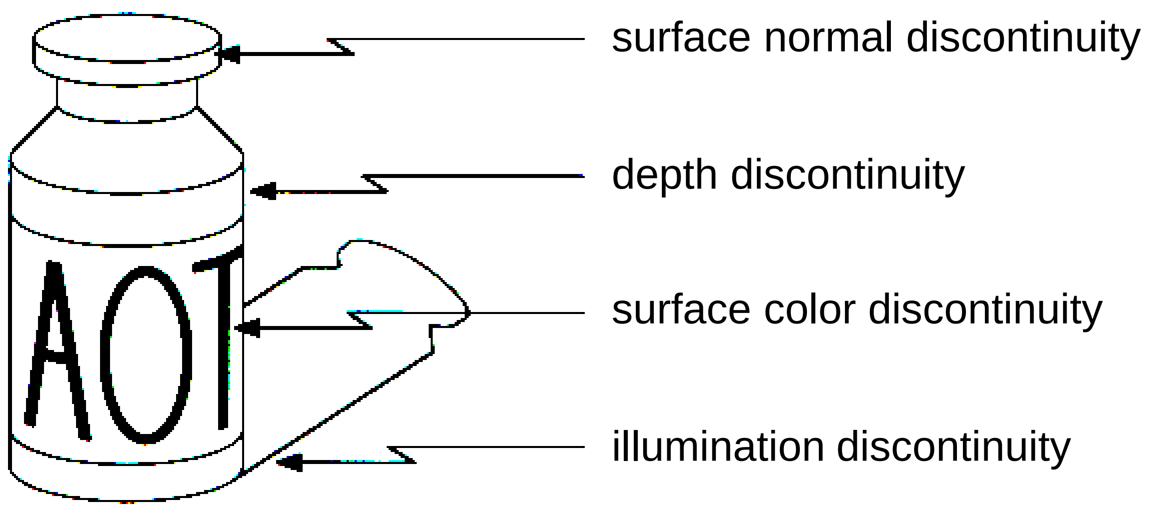
Goal: Identify visual changes (discontinuities) in an image.

Intuitively, semantic information is encoded in edges.

Think-pair-share:
What are some ‘causes’ of visual edges?

Source: D. Lowe

Origin of Edges



- Edges are caused by a variety of factors

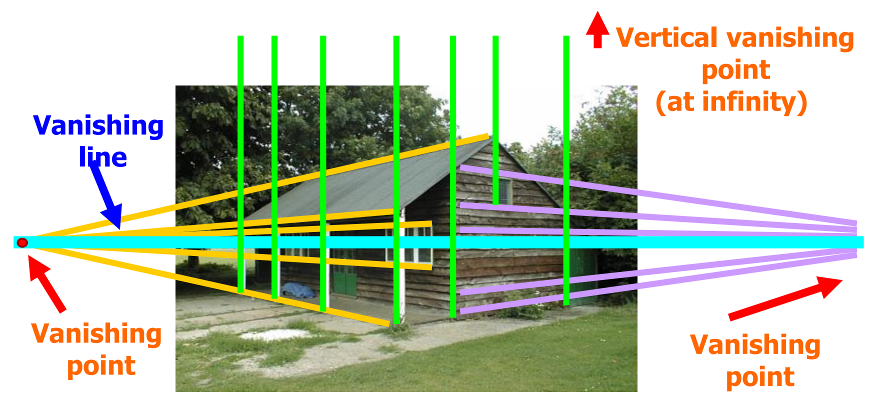
Source: Steve Seitz

Why do we care about edges?

Extract information

– Recognize objects

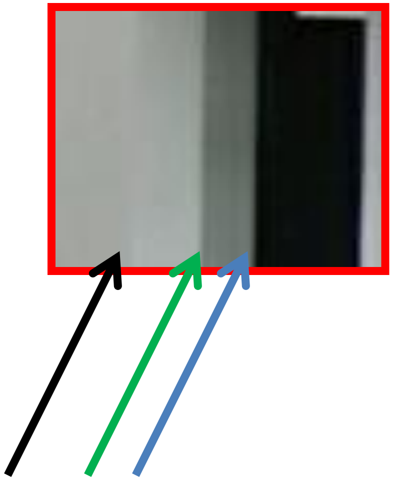
Help recover geometry and viewpoint



Closeup of edges

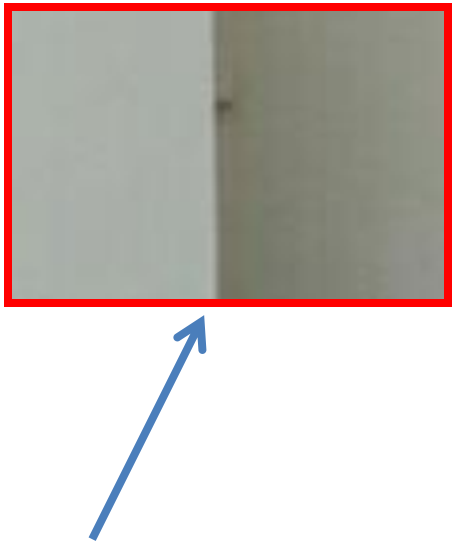
Source: D. Hoiem

Closeup of edges



Source: D. Hoiem

Closeup of edges



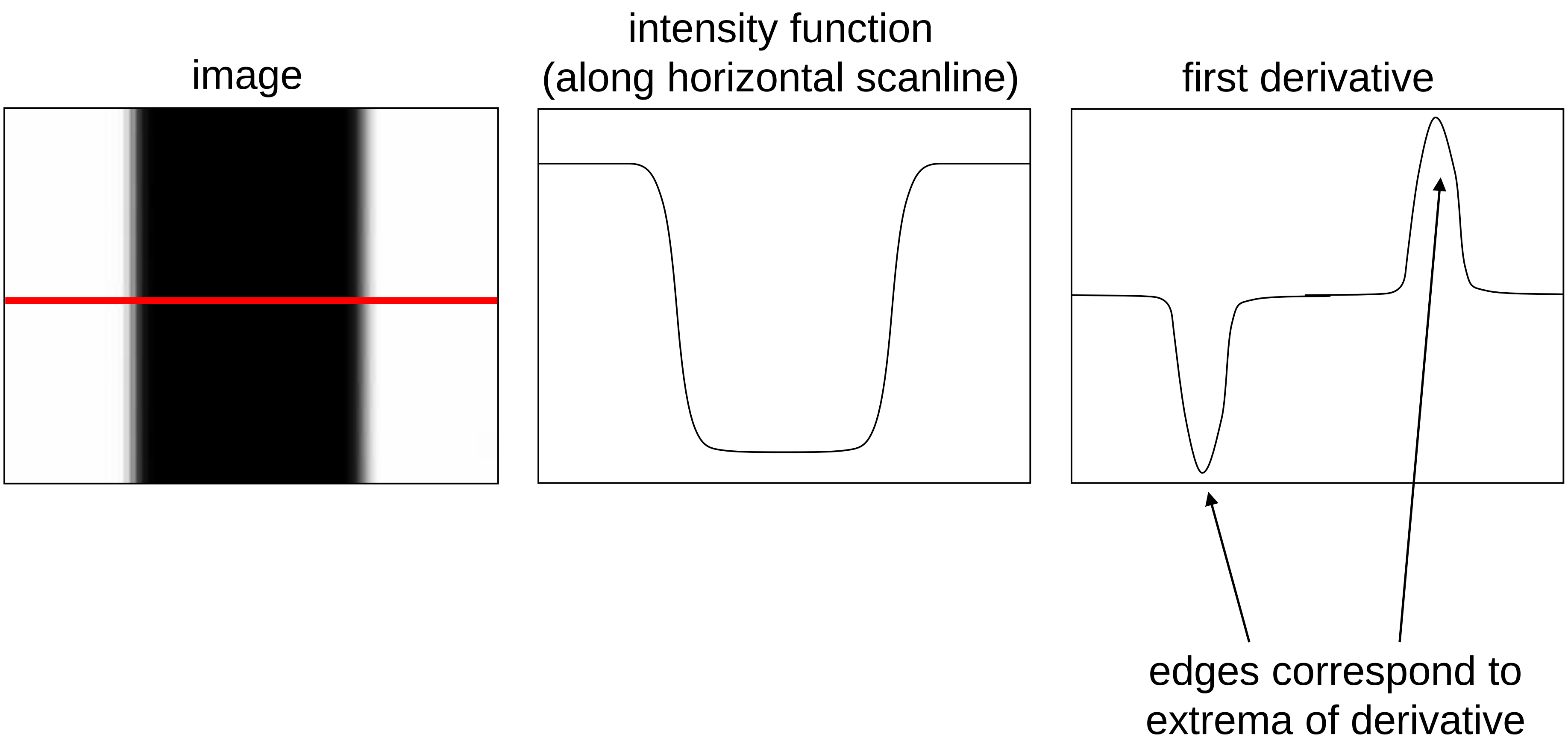
Source: D. Hoiem

Closeup of edges

Source: D. Hoiem

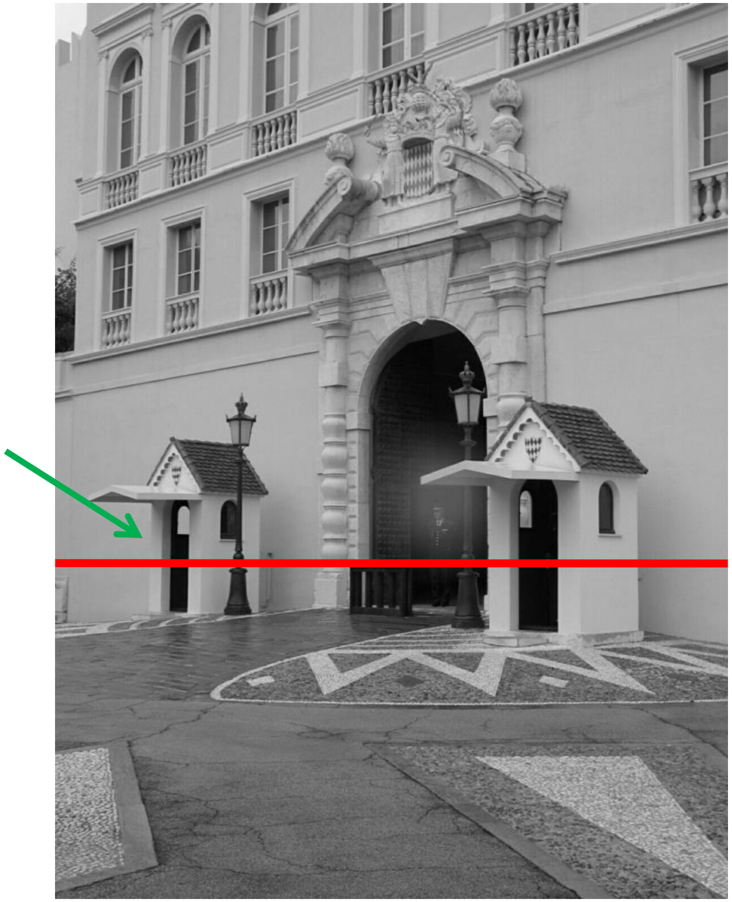
Characterizing edges

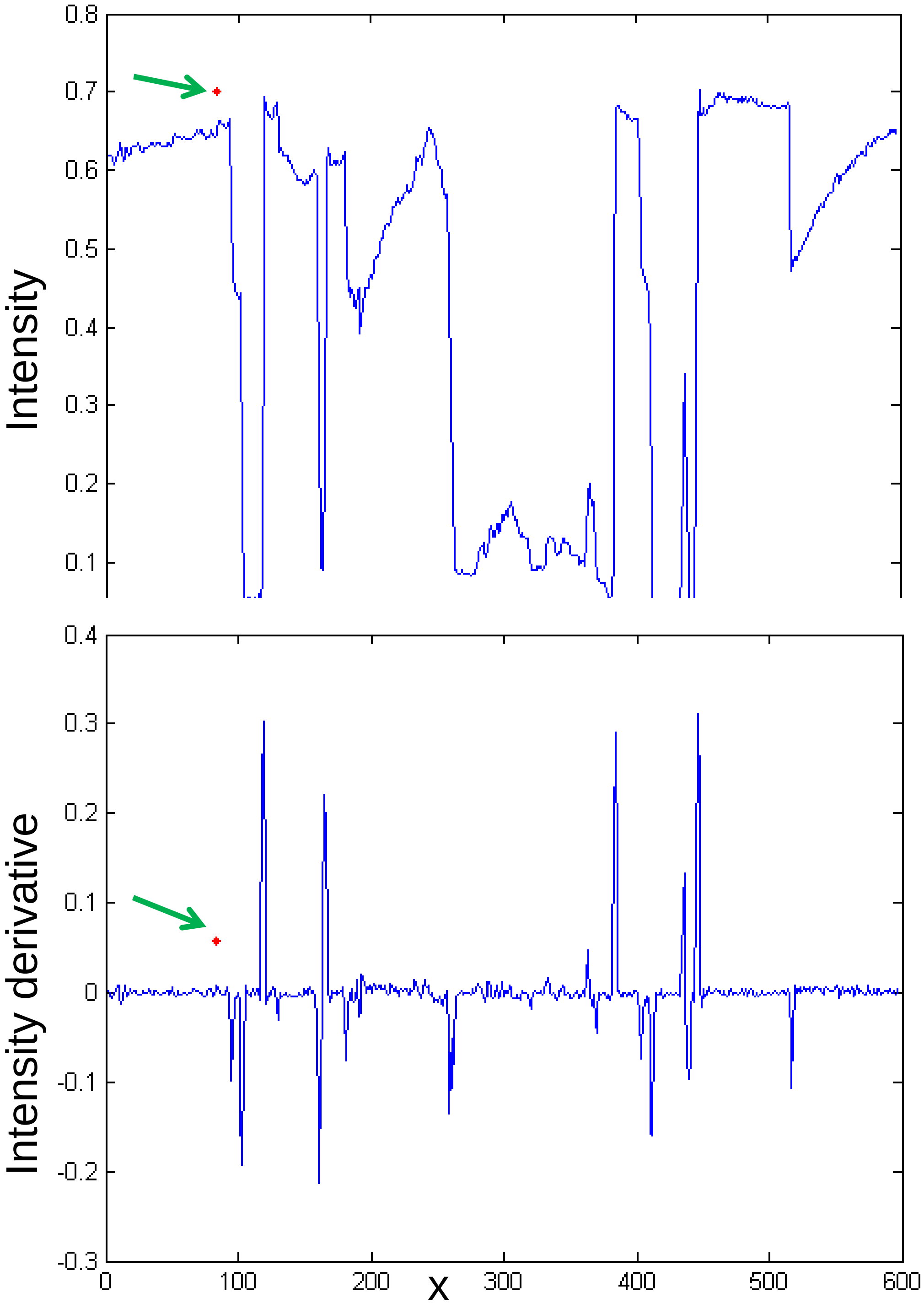
- An edge is a place of rapid change in the image intensity function



Hays

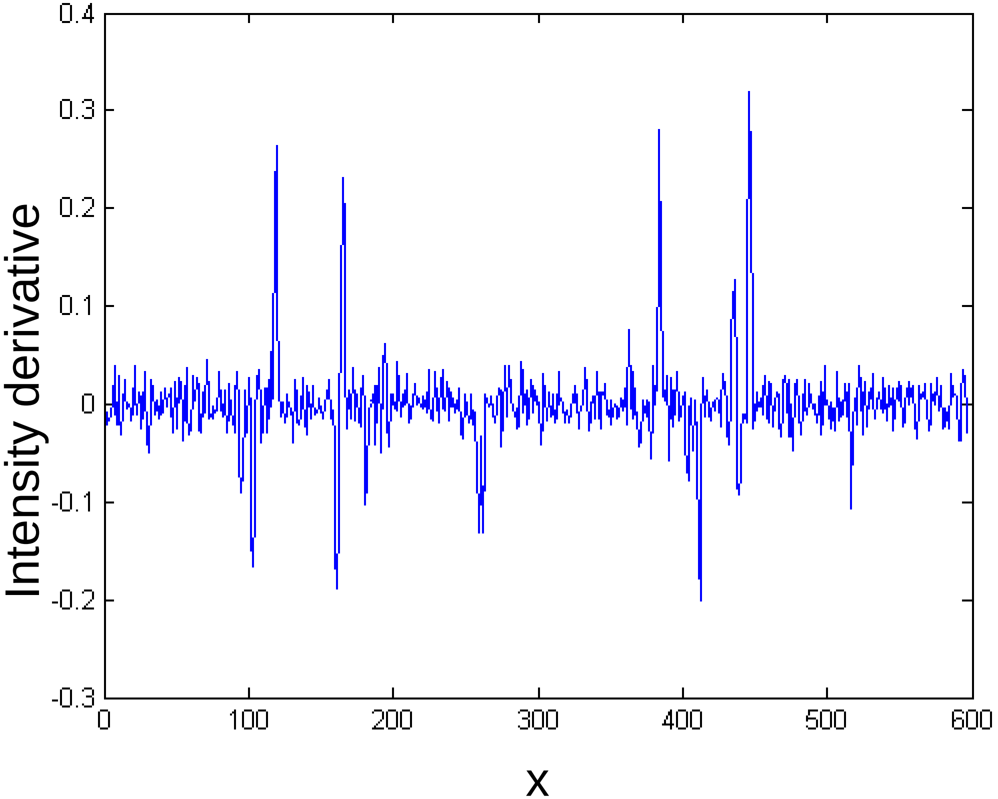
Intensity profile





Source: D. Hoiem

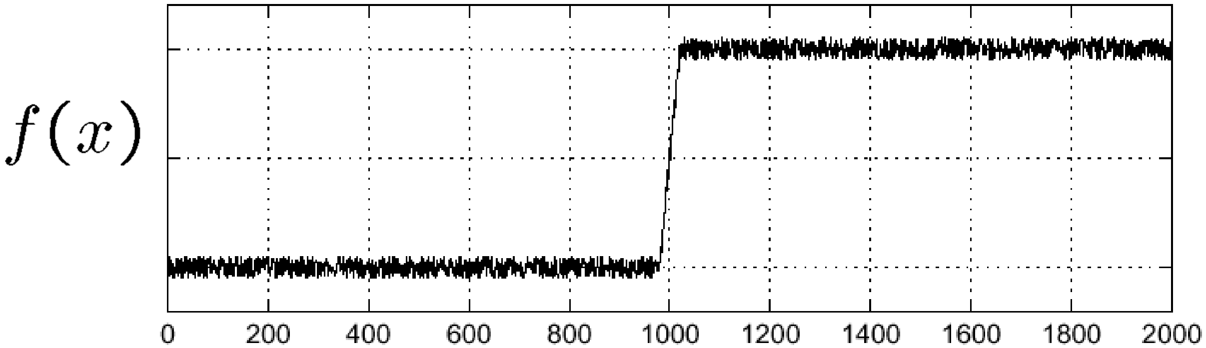
With a little Gaussian noise

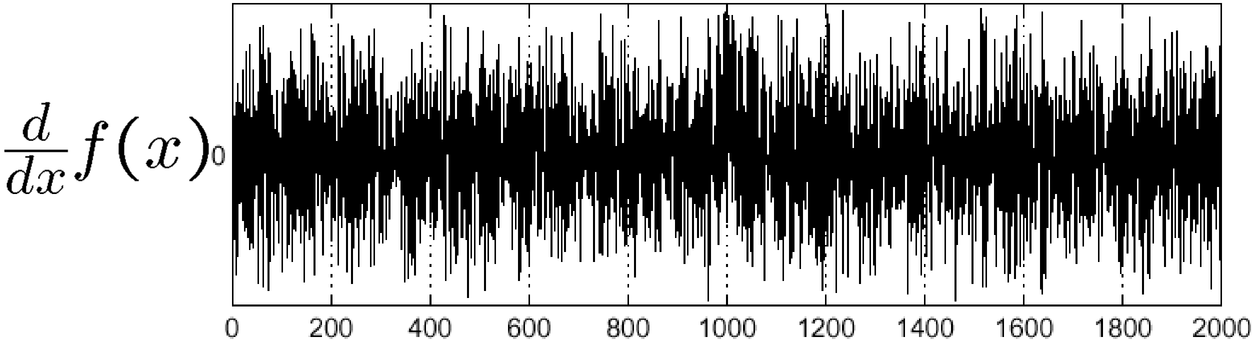


Source: D. Hoiem

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?

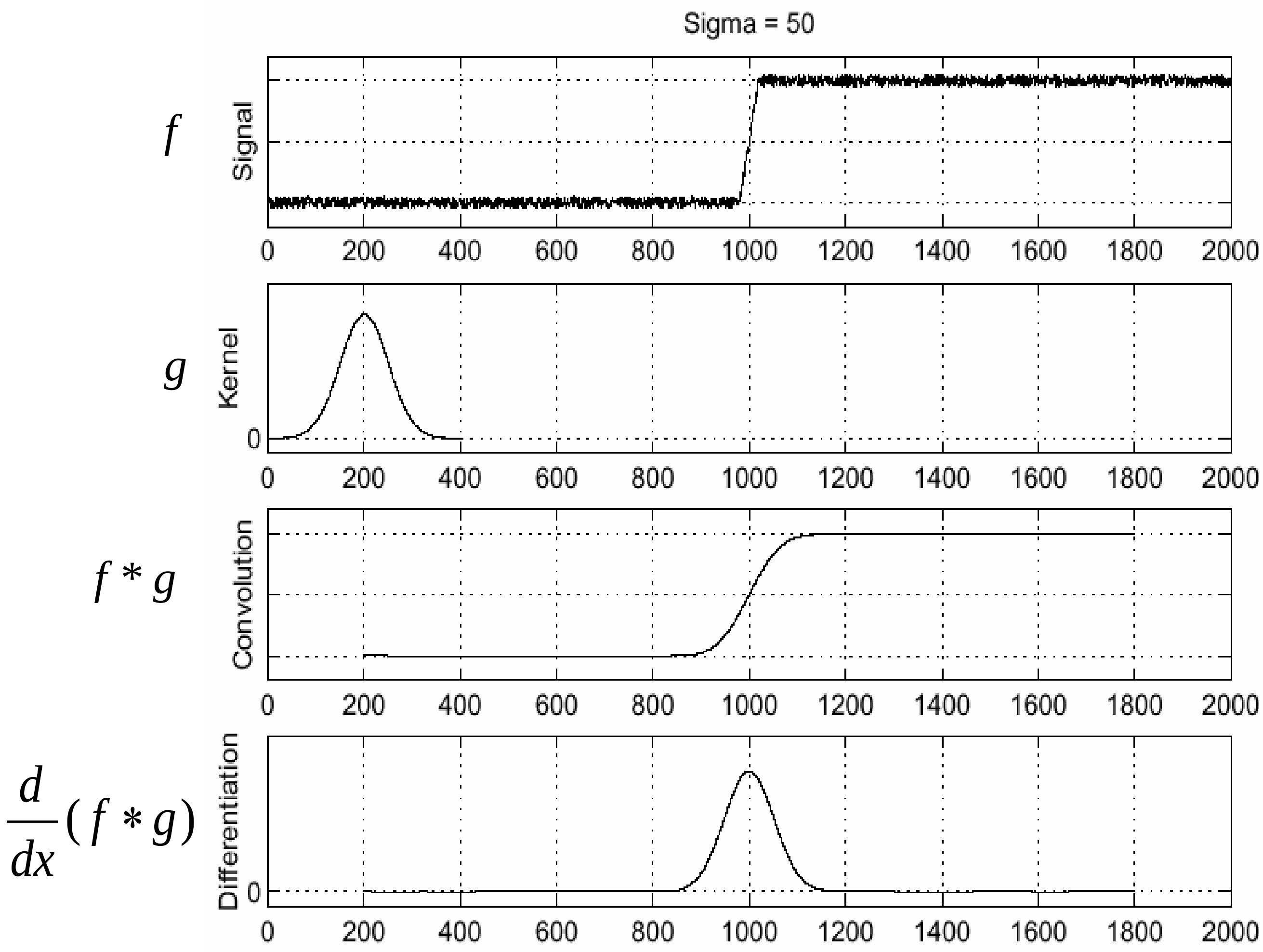
Source: S. Seitz

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:

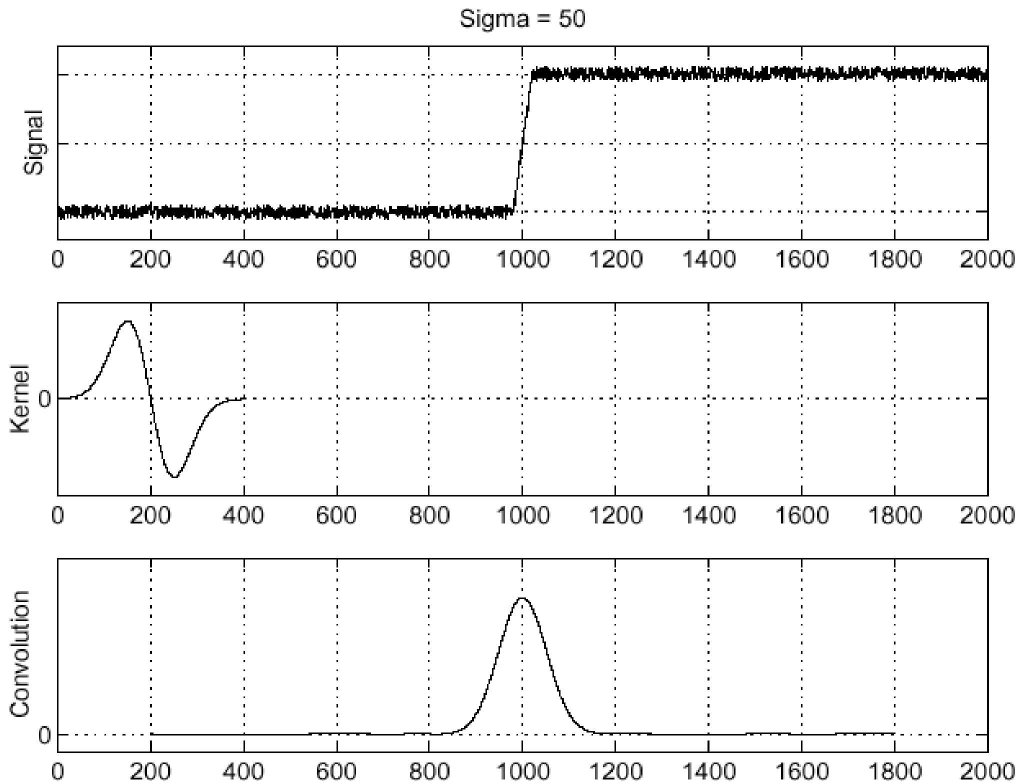
$$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$

- This saves us one operation:

$$f$$

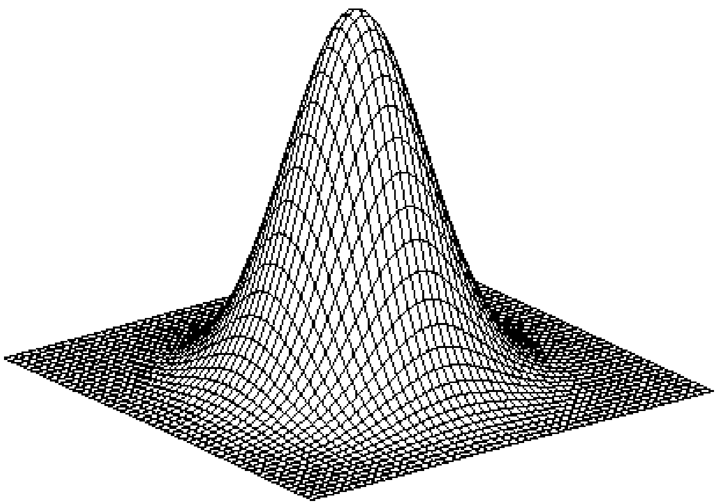
$$\frac{d}{dx} g$$

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

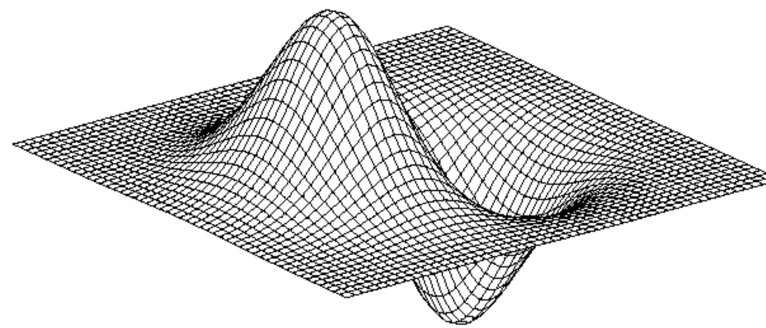


Source: S. Seitz

Derivative of 2D Gaussian filter

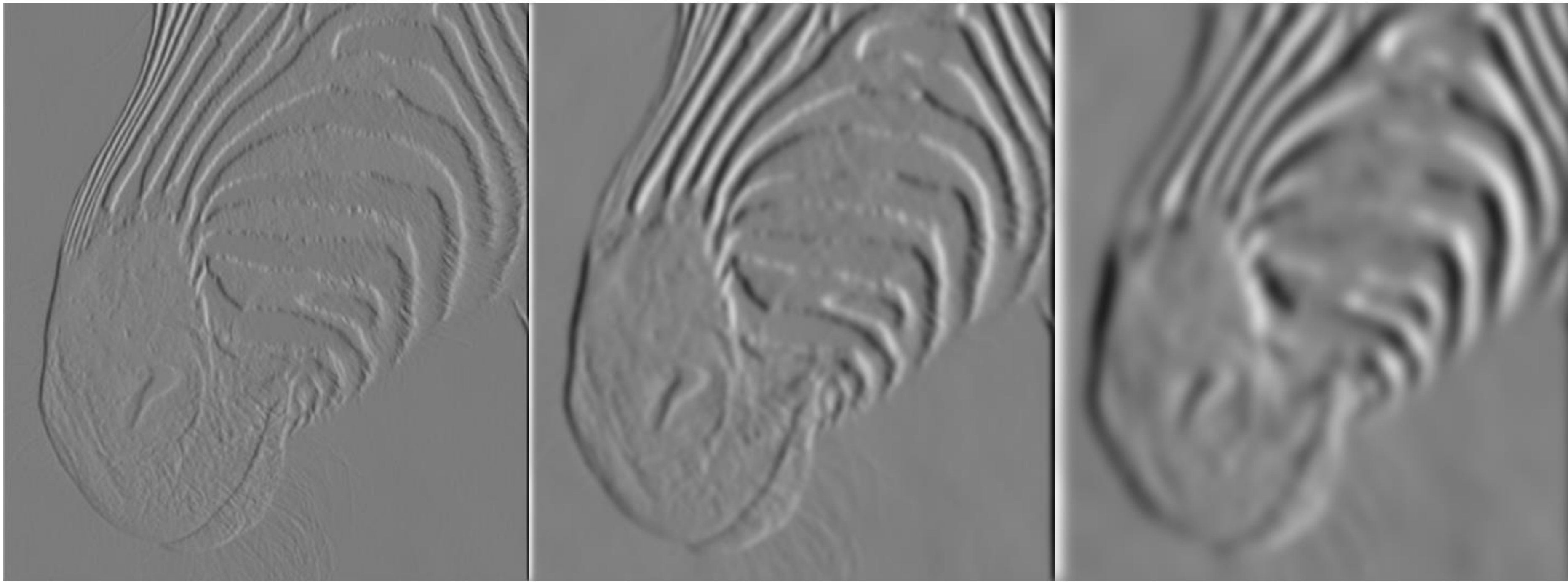


* [1 -1] =



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

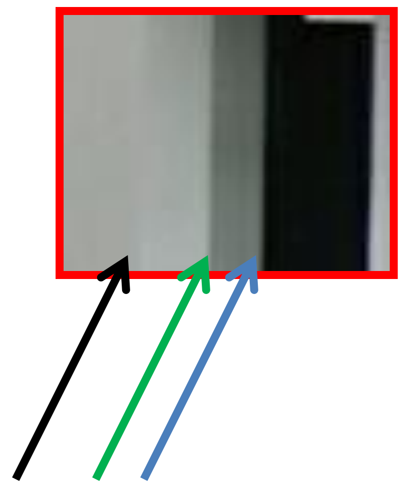
Source: L. Fei-Fei

Designing an edge detector

- “All real edges”
  - We can aim to differentiate later 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

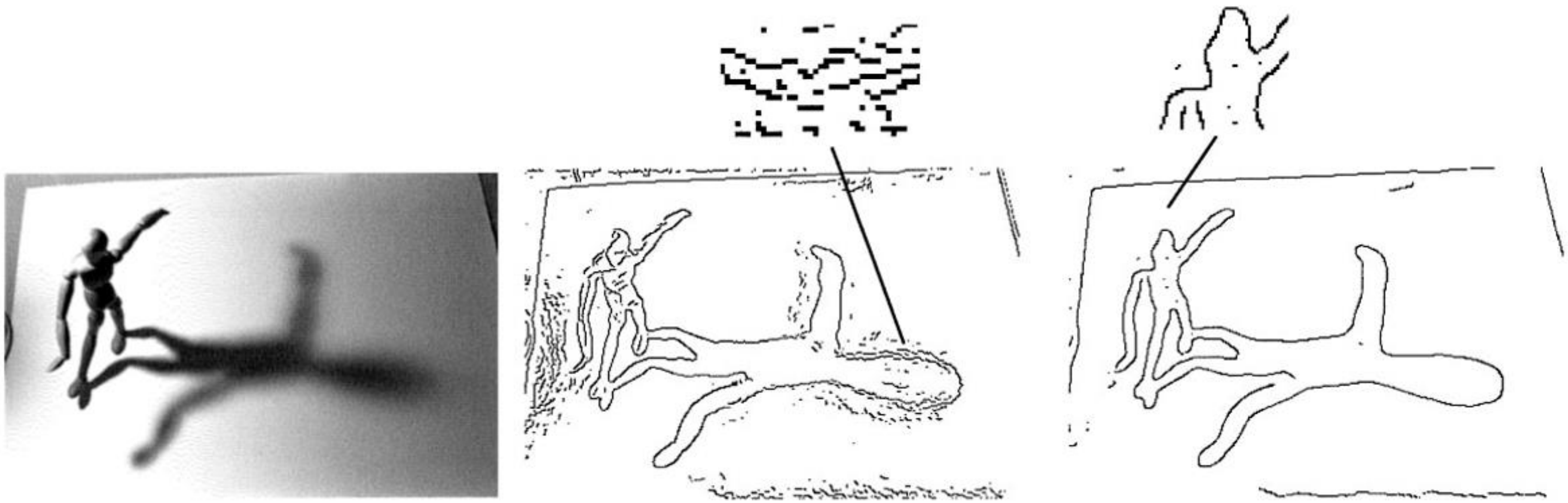


Figure 2. The problem of local estimation scale. Different structures in a natural image require different spatial scales for local estimation. The original image contains edges over a broad range of contrasts and blur scales. In the middle are shown the edges detected with a Canny/Deriche operator tuned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

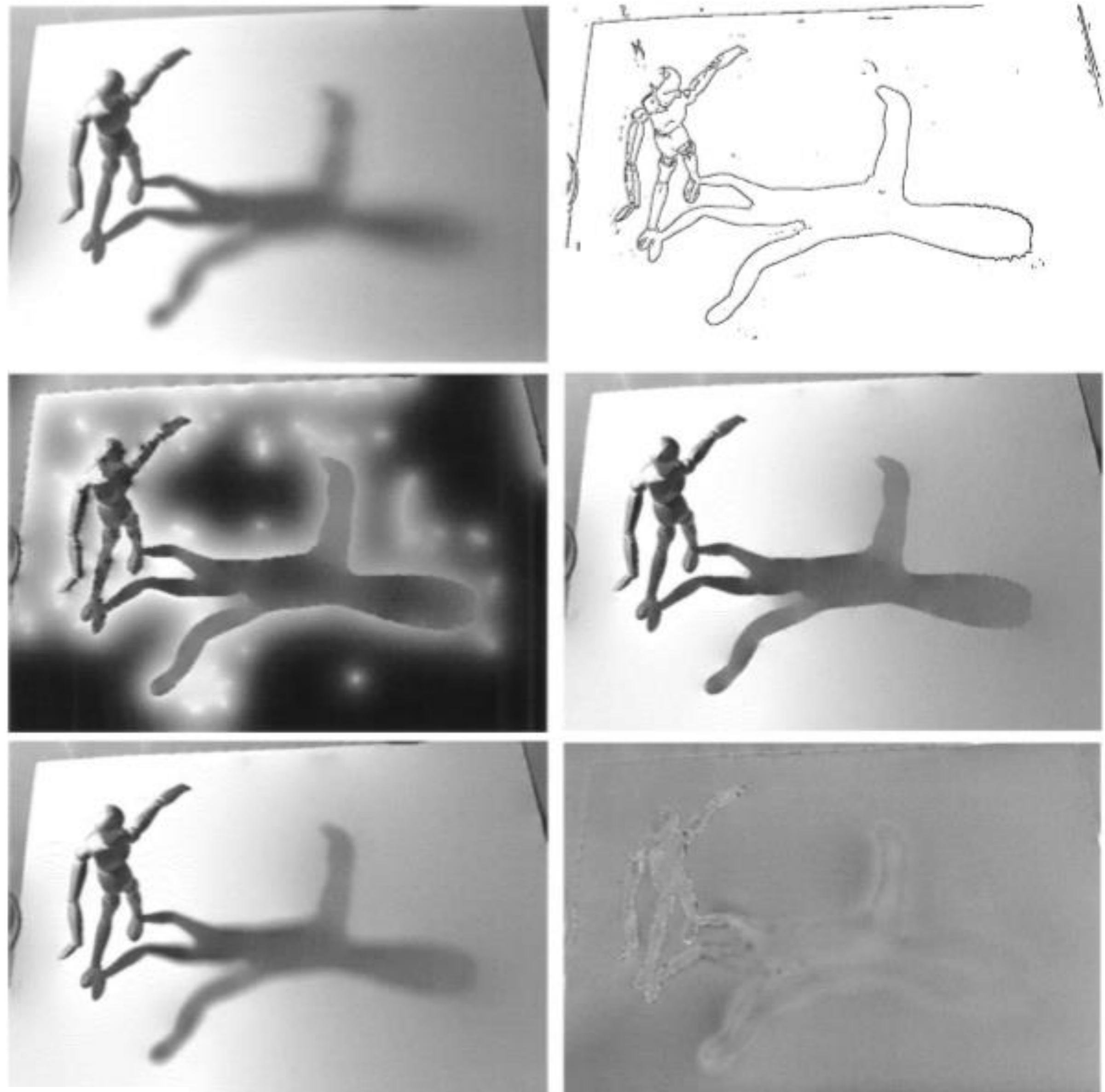


Figure 8. *Top left*: Original image. *Top right*: Detected edge locations. *Middle left*: Intermediate solution to the heat equation. *Middle right*: Reconstructed luminance function. *Bottom left*: Reblurred result. *Bottom right*: Error map (reblurred result—original). Bright indicates overestimation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

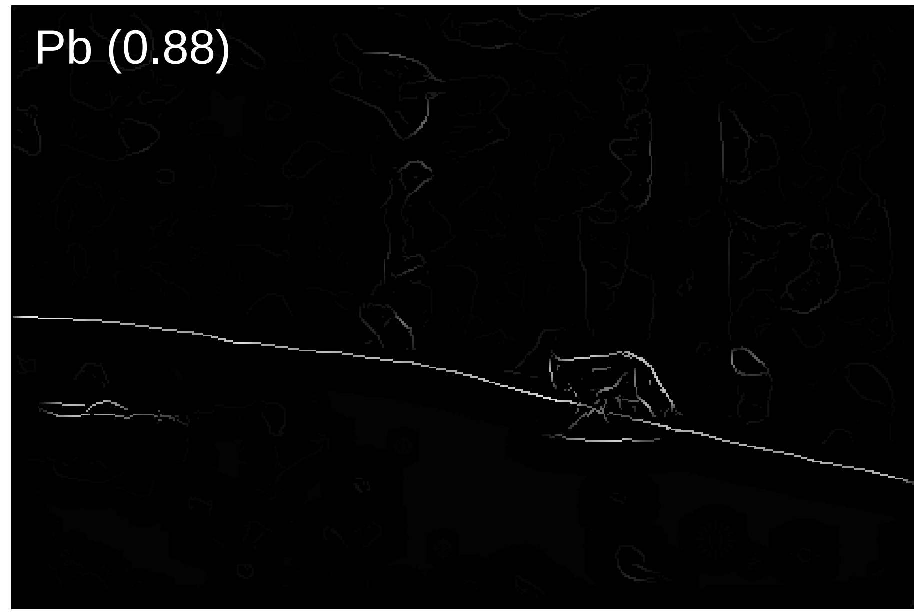
image | human segmentation | gradient magnitude

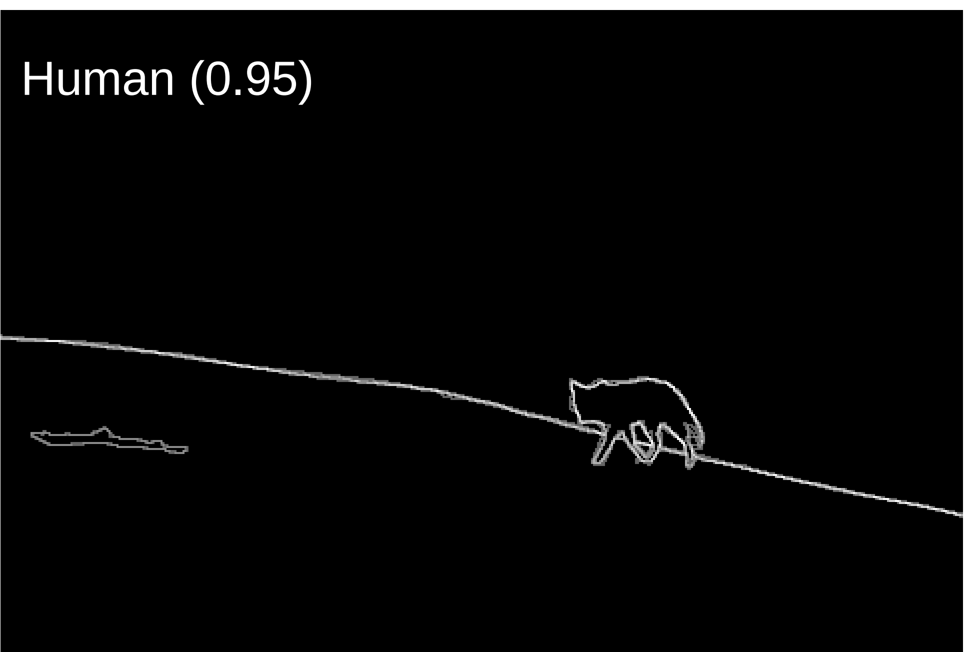
- Berkeley segmentation database:
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

pB slides: Hays

Results

Score = confidence of edge.
For humans, this is averaged across multiple participants.





Results

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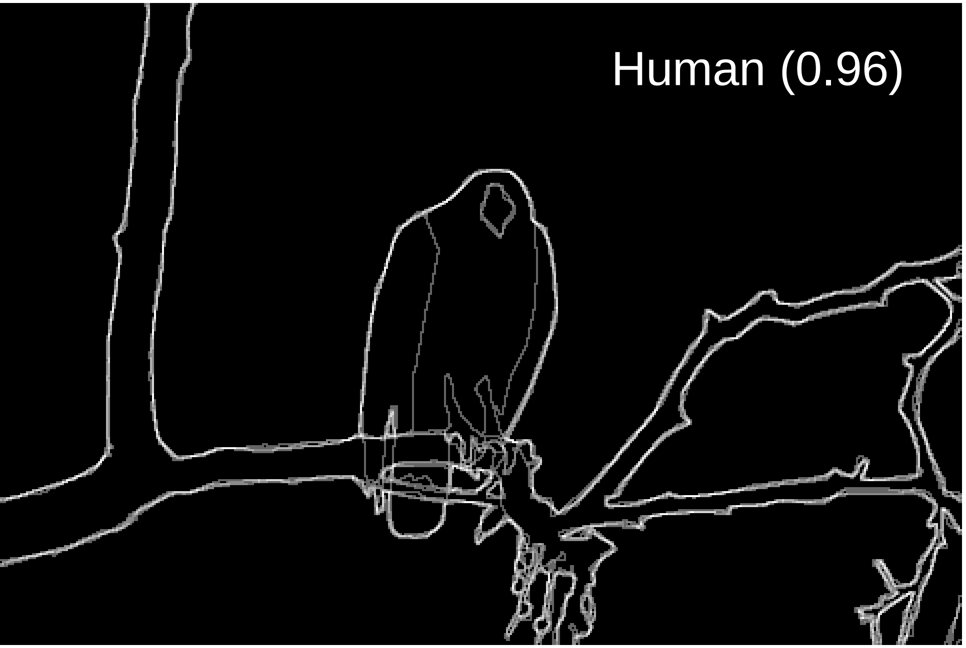

Score = confidence of edge.
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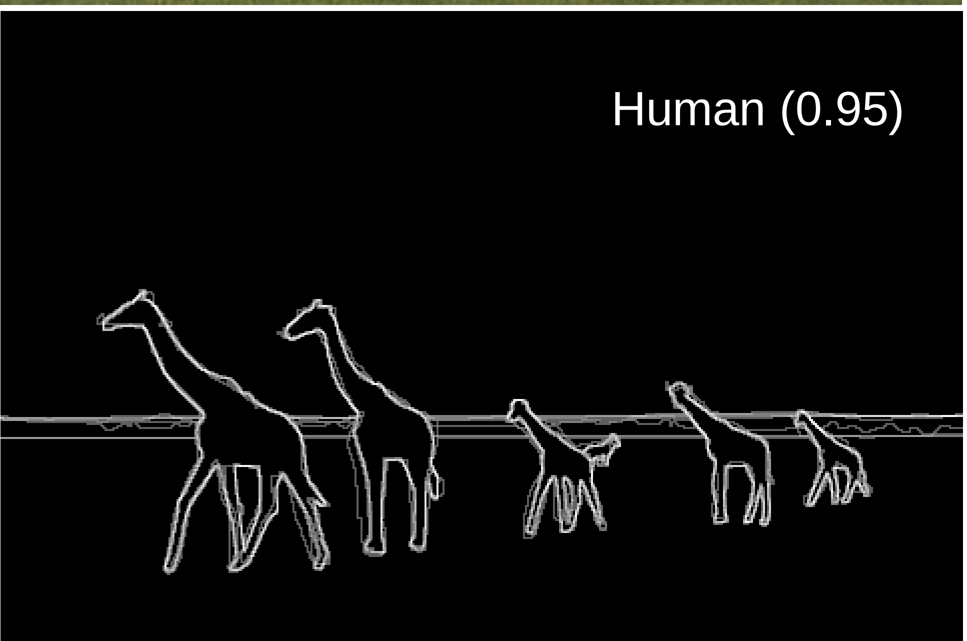

Score = confidence of edge.
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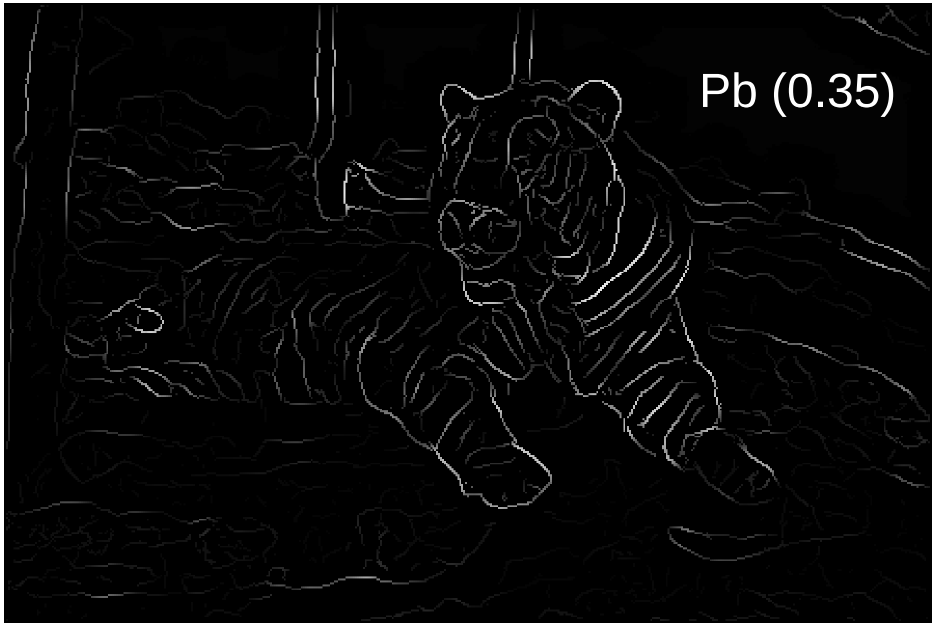
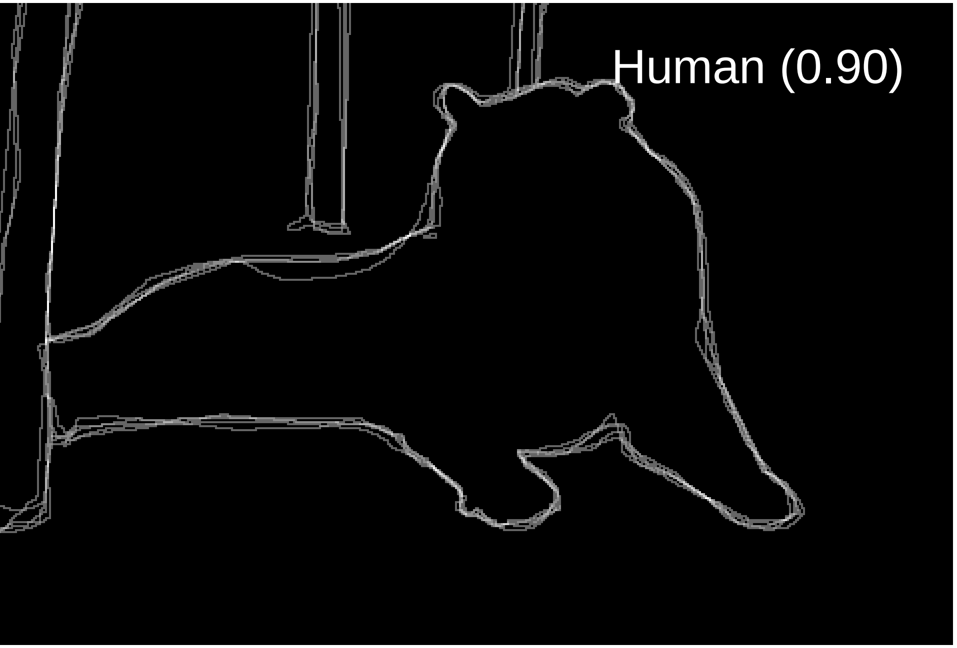
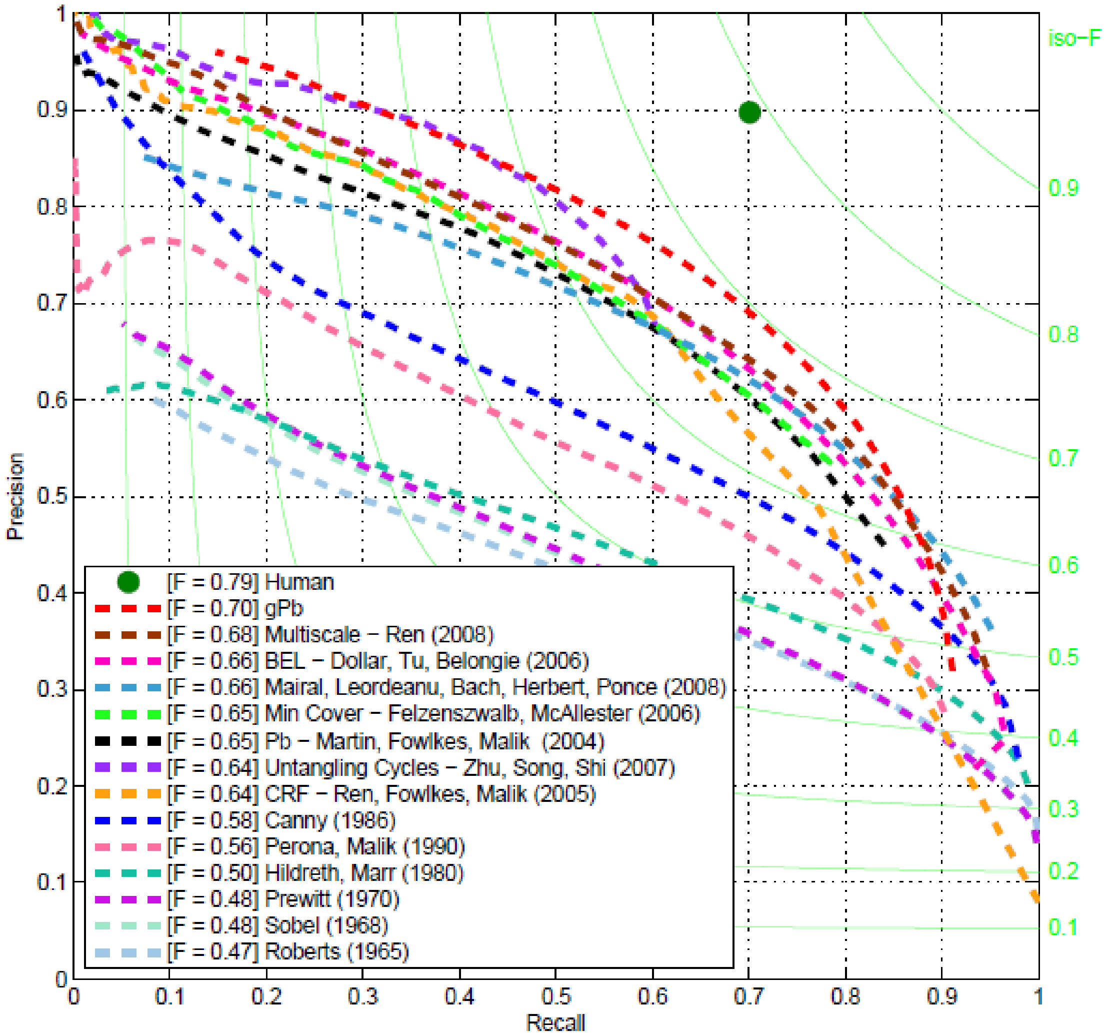




For more:
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/bench/html/108082-color.html

45 years of boundary detection

[Pre deep learning]



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 consider longer contours

Modern methods that actually "learn" from data.

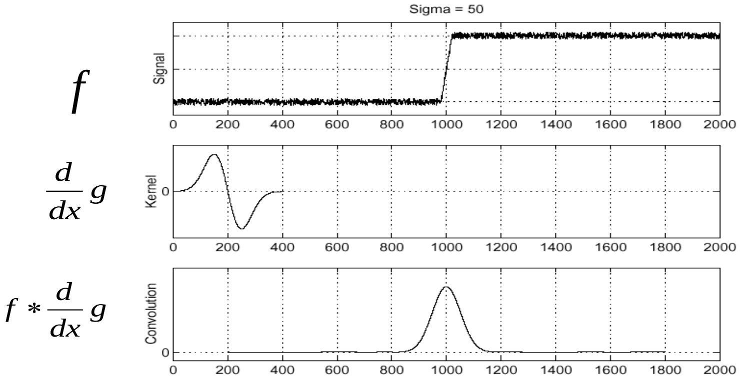
Poor use of object and high-level information.

Hays

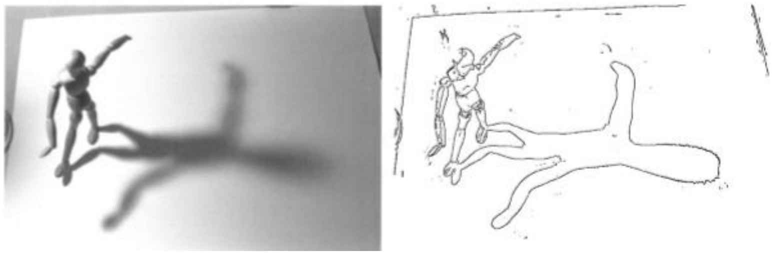
Summary: Edges primer

- 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

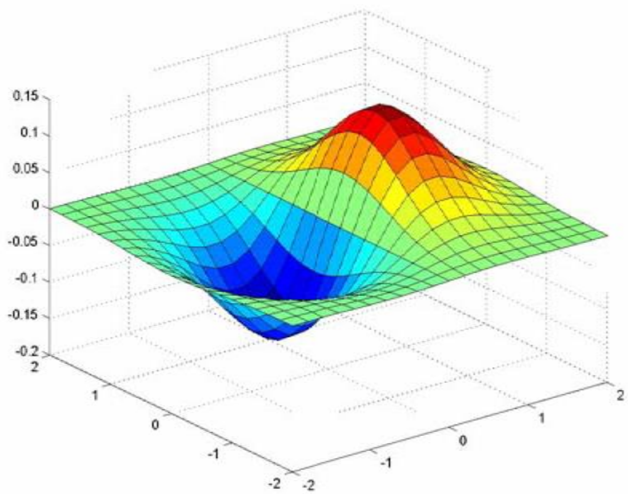
rgb2gray('img.png')

Canny edge detector

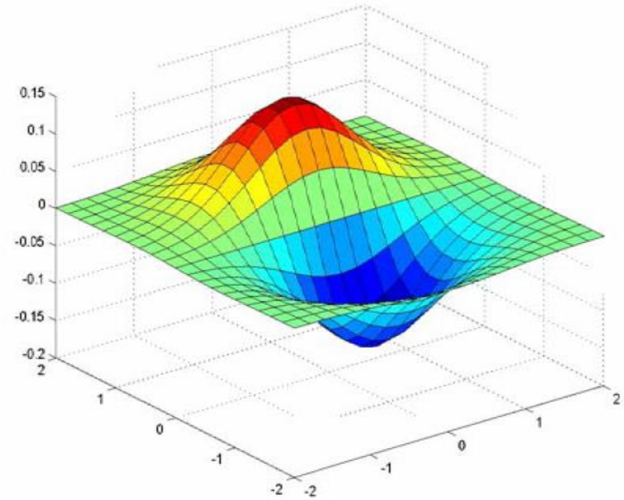
1. Filter image with x, y derivatives of Gaussian

Source: D. Lowe, L. Fei-Fei

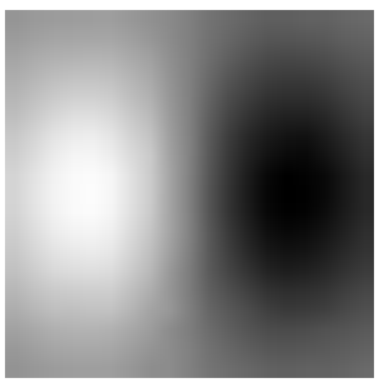
Derivative of Gaussian filter

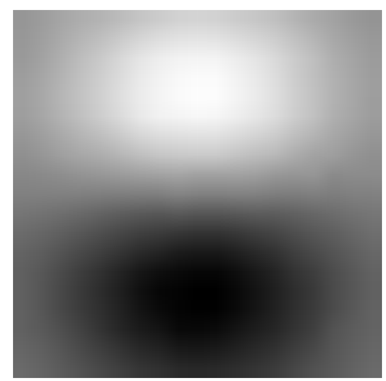


x-direction

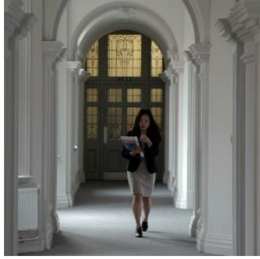


y-direction



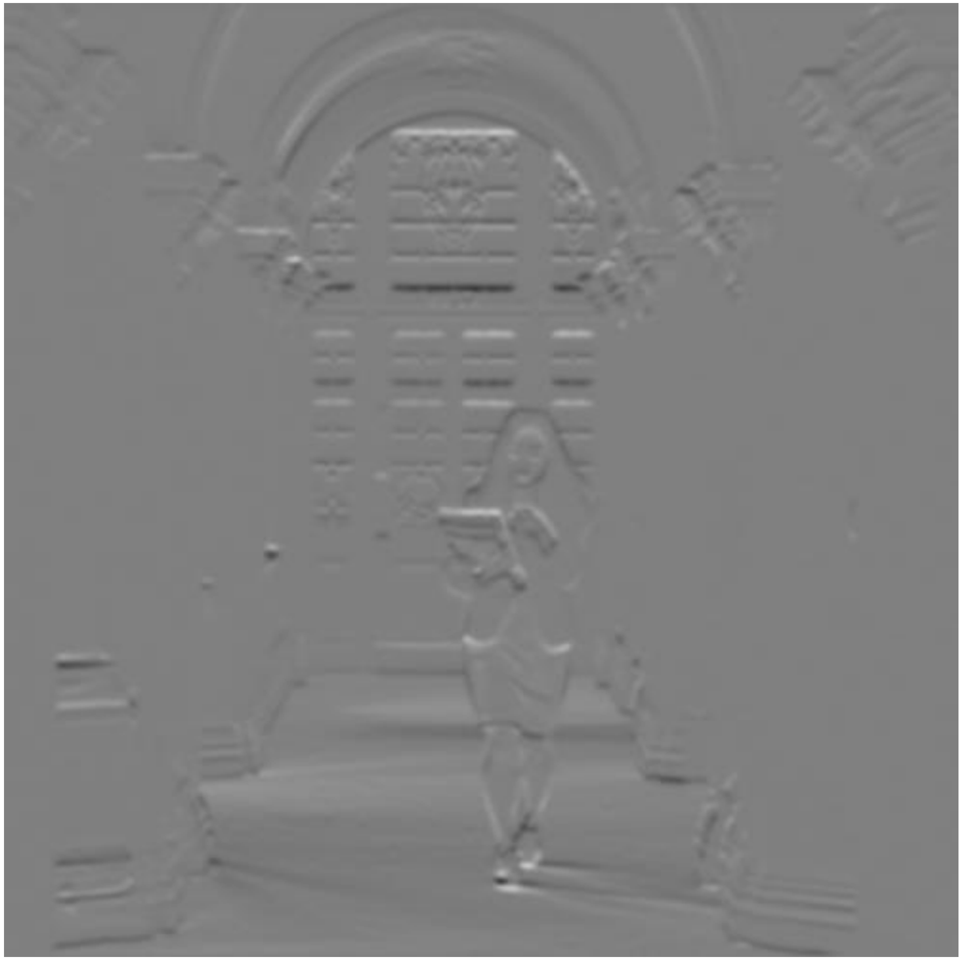


Compute Gradients



X Derivative of Gaussian

Y Derivative of Gaussian



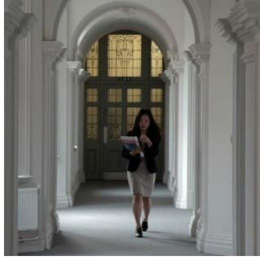
(x2 + 0.5 for visualization)

Canny edge detector

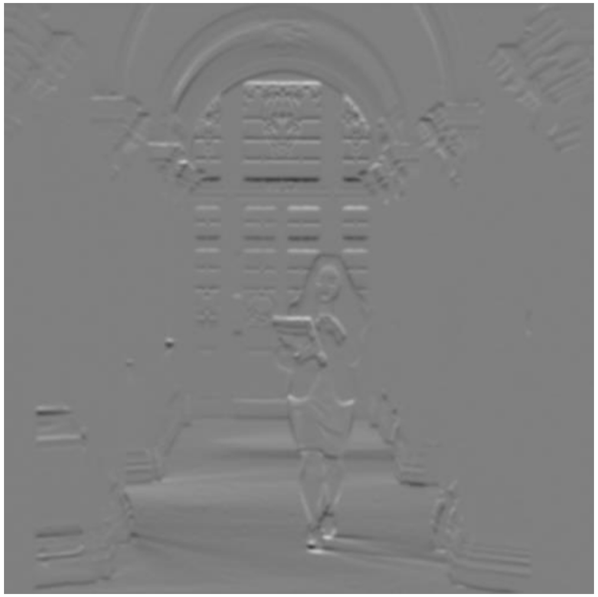
1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient

Source: D. Lowe, L. Fei-Fei

Compute Gradient Magnitude



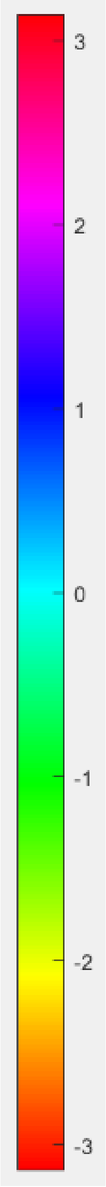
sqrt(XDerivOfGaussian .^2 + YDerivOfGaussian .^2) = gradient magnitude

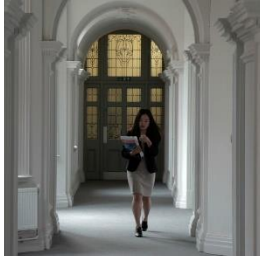


(x4 for visualization)

Compute Gradient Orientation

- Threshold magnitude at minimum level
- Get orientation via theta = atan2(yDeriv, xDeriv)



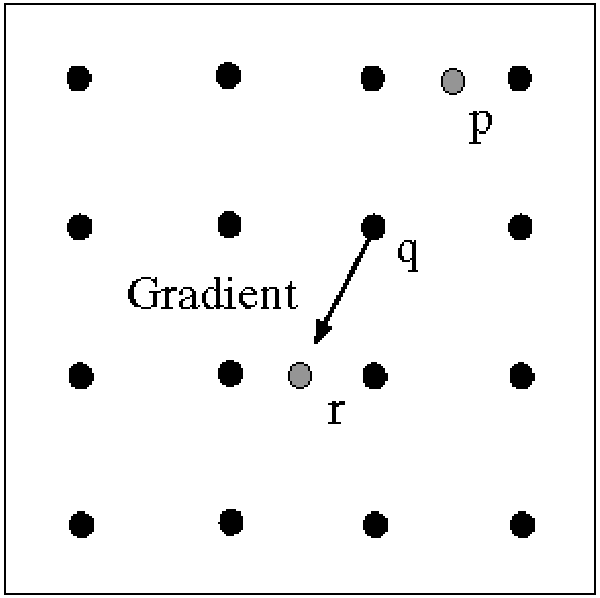


Canny edge detector

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

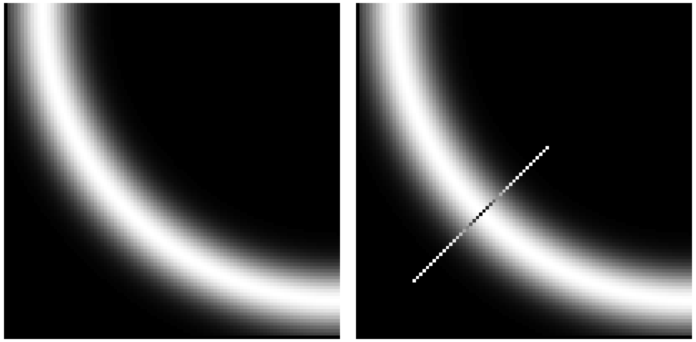
Source: D. Lowe, L. Fei-Fei

Non-maximum suppression for each orientation



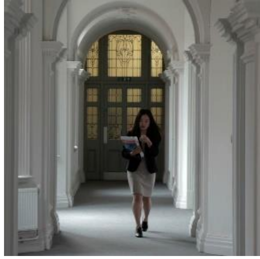
At pixel q:
We have a maximum if the value is larger than those at both p and at r.

Interpolate along gradient direction to get these values.



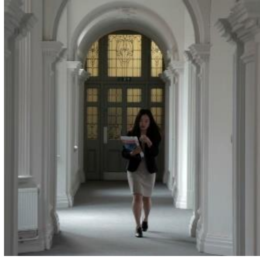
Source: D. Forsyth

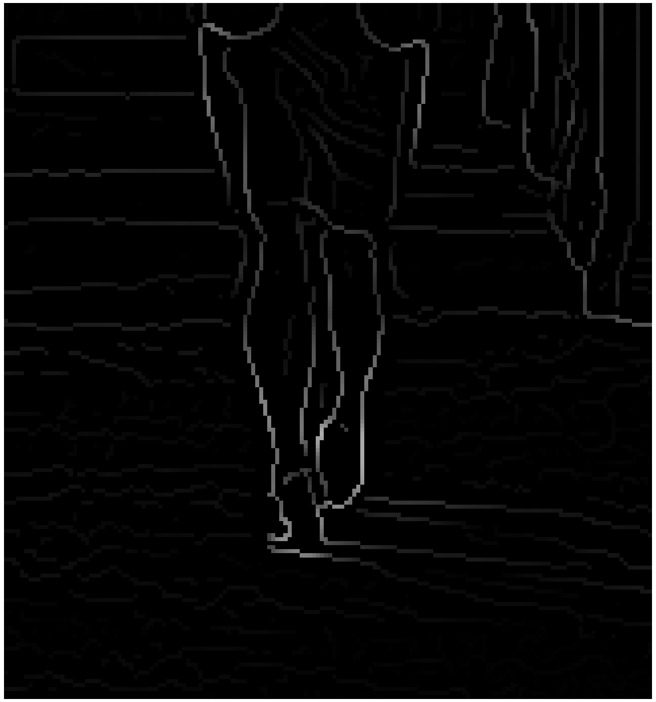
Before Non-max Suppression



Gradient magnitude (x4 for visualization)

After non-max suppression





Gradient magnitude (x4 for visualization)

Canny edge detector

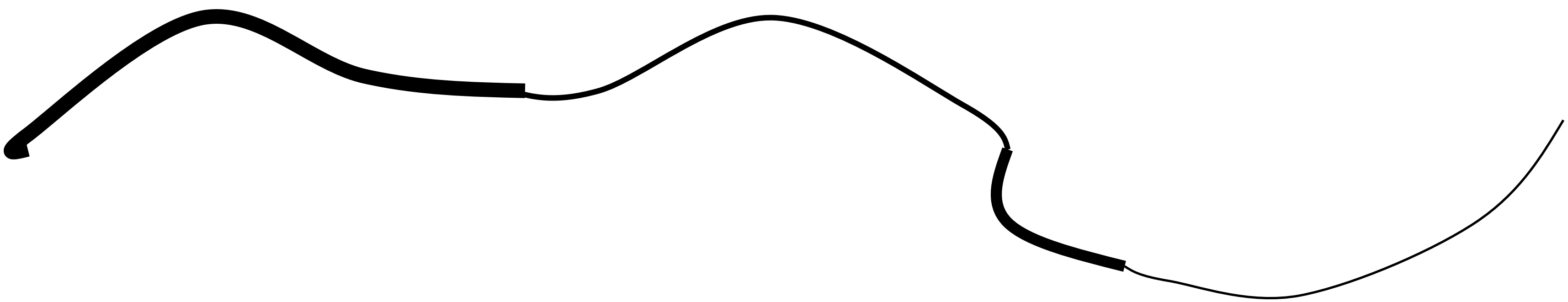
1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel wide "ridges" to single pixel width
4. 'Hysteresis' Thresholding

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

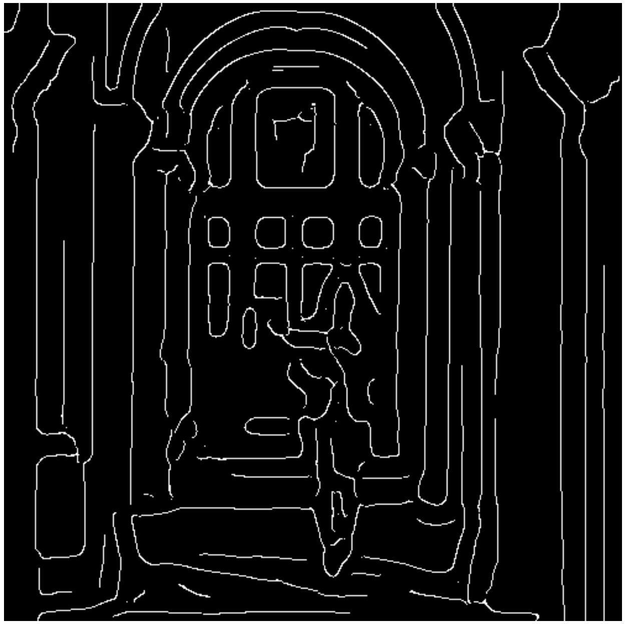
Final Canny Edges

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

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

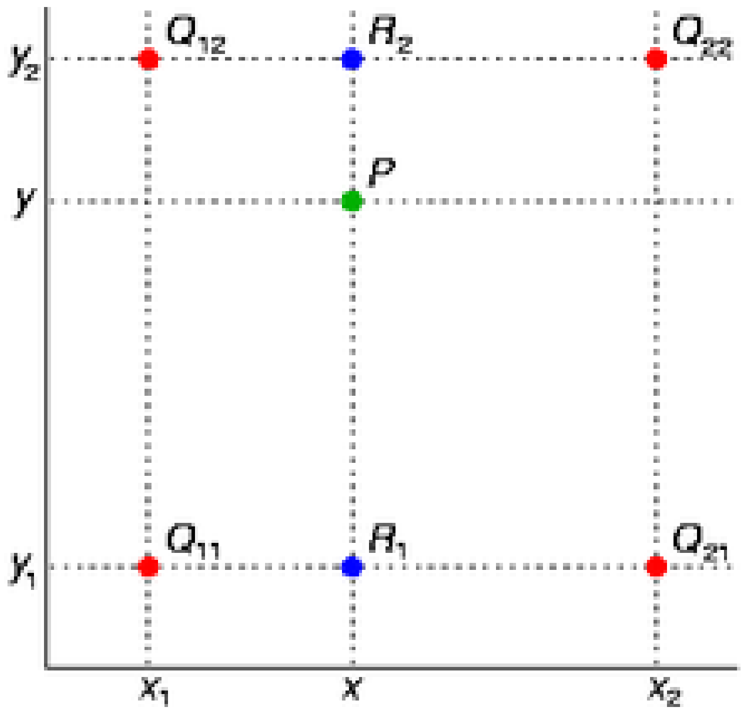
Canny edge detector

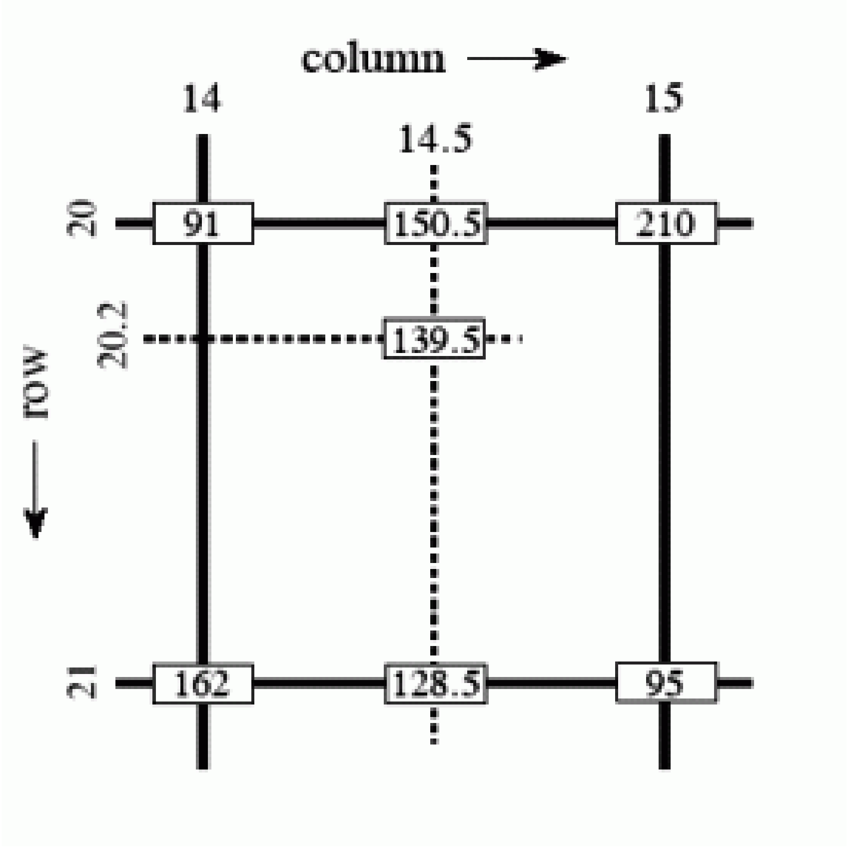
1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel wide “ridges” to single pixel width
4. ‘Hysteresis’ Thresholding:
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves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

- Python: e.g., skimage.feature.canny()

Source: D. Lowe, L. Fei-Fei

Sidebar: Bilinear Interpolation





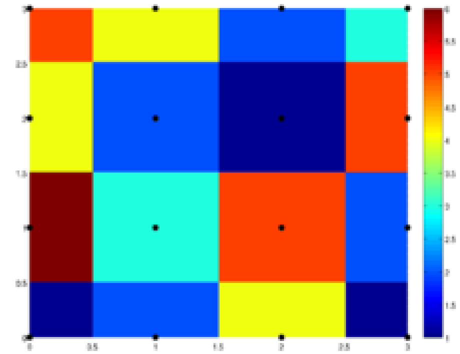
$$f(x,y) \approx \begin{bmatrix}1-x & x\end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}.$$

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

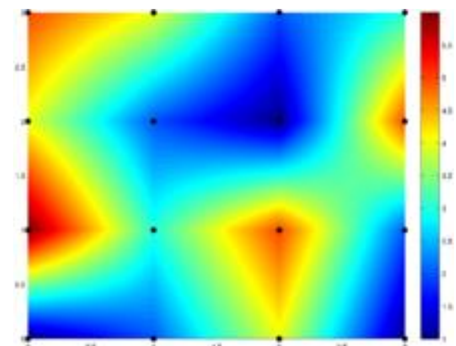
Sidebar: Interpolation options

e.g., skimage.transform.rescale(I, 2, order=x)

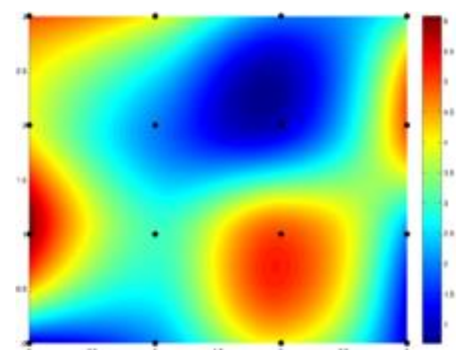
x == 0 -> ‘nearest neighbor’
- Copy value from nearest known
- Very fast but creates blocky edges



x == 1 -> ‘bilinear’ (default)
- Weighted average from four nearest known pixels
- Fast and reasonable results



x == 3 => ‘bicubic’
- Fit cubic spline to pixel intensities
- Non-linear interpolation over larger area (4x4)
- Slower, visually appealing, may create negative pixel values in cubic function fitting



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

Canny edge demo!!!

From Luke Murray (Fall 2017 TA)

- https://cse442-17f.github.io/Sobel-Laplacian-and-Canny-Edge-Detection-Algorithms/
- Written in https://idyll-lang.org/

[Additional information]