Lecture 4
Edges

Lecture Outline

- What makes an edge?
- Gradient-based Edge Detectors
- Canny Edge Detector
- Knowing True Edges

What makes an edge?

Edge Detection

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

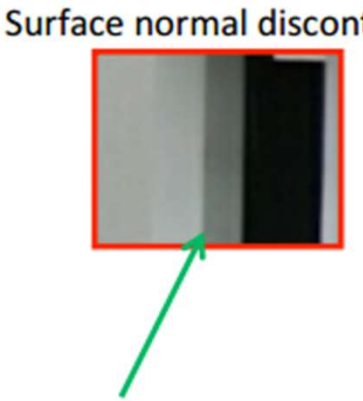
Source: D. Lowe

Edge Detection

- **Goal**: Identify sudden changes (discontinuities) in an image
  - Map image from 2D array of pixels to a set of curves or line segments/contours
- **Main Idea**: Look for strong gradients, post-process

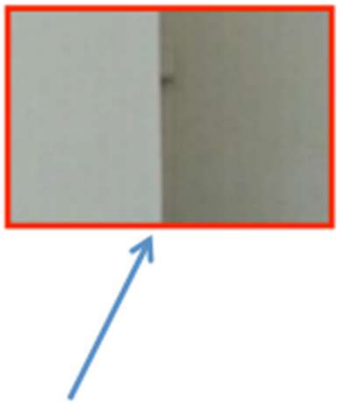
A close lookout for “edges”

A close lookout for “edges”



Source: D. Hoiem

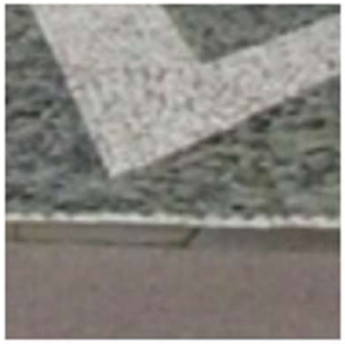
A close lookout for “edges”



Source: D. Hoiem

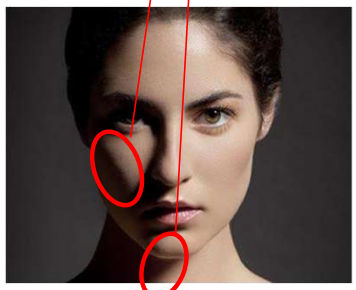
A close lookout for “edges”

Surface color discontinuity



Source: D. Hoiem

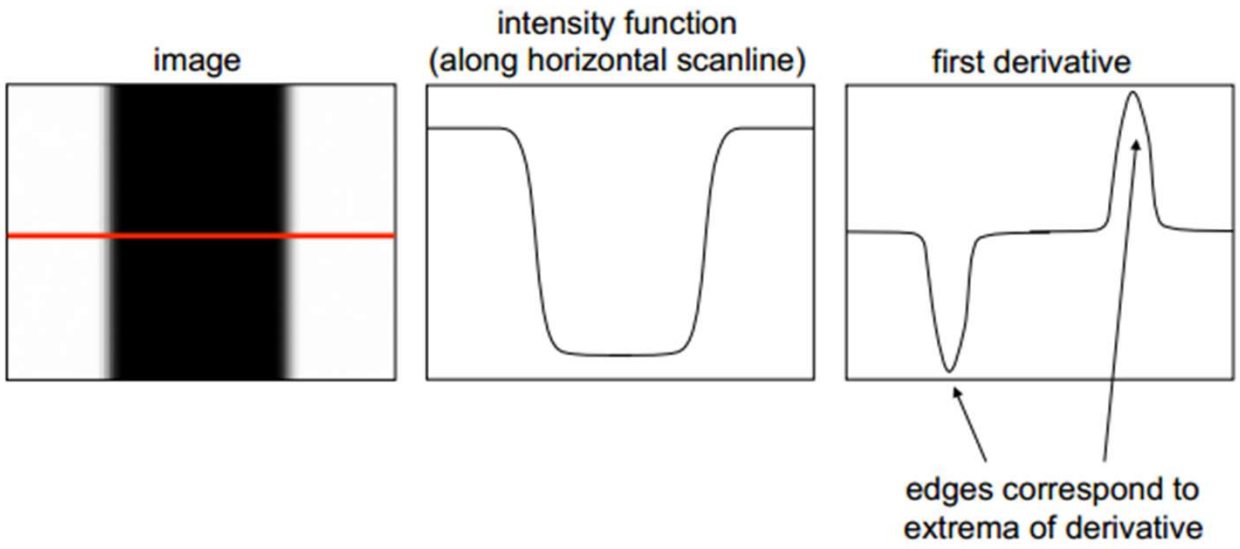
A close lookout for “edges”



Gradient/Derivative-based Edge Detectors

Derivatives and Edges

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



Derivatives with convolution

› For 2D function $f(x,y)$, the partial derivative:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon, y) - f(x,y)}{\varepsilon}$$

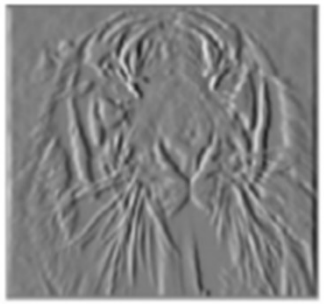
› For discrete data, we can approximate using finite differences:

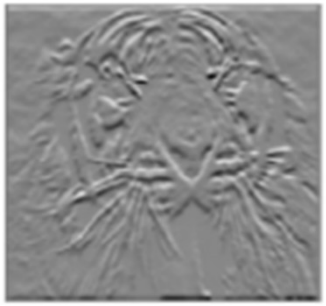
$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1,y) - f(x,y)}{1}$$

› To implement it by convolution, what would be the associated filter?

Partial derivatives of an image

$$\frac{\partial f(x,y)}{\partial x}$$





$$\frac{\partial f(x,y)}{\partial y}$$

-1	1

-1
1

or

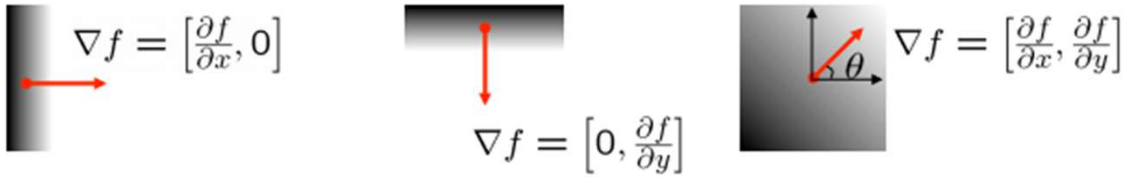
1
-1

Image Gradient

› The gradient of an image:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

› Gradient – Points in the direction of most rapid increase in intensity



› **Direction**: $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

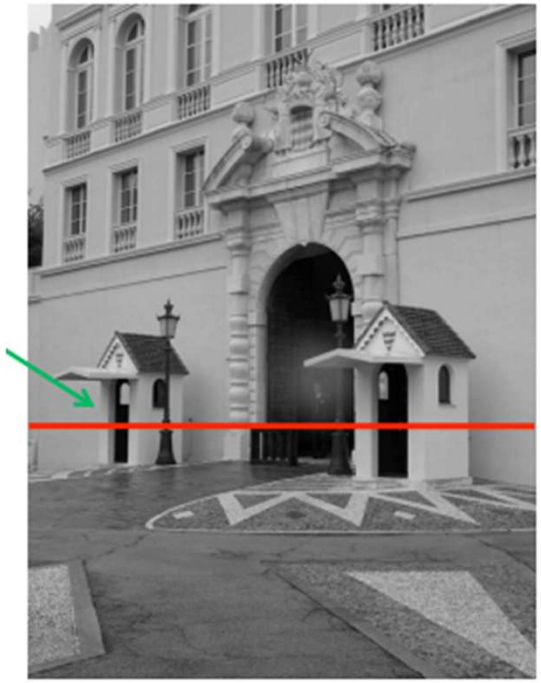
› **Magnitude** ("edge strength"): $\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$

Partial derivatives of an image

› Taking both partial derivatives in the x direction and y direction, we get the full set of derivatives or "**gradients**" corresponding to both directions

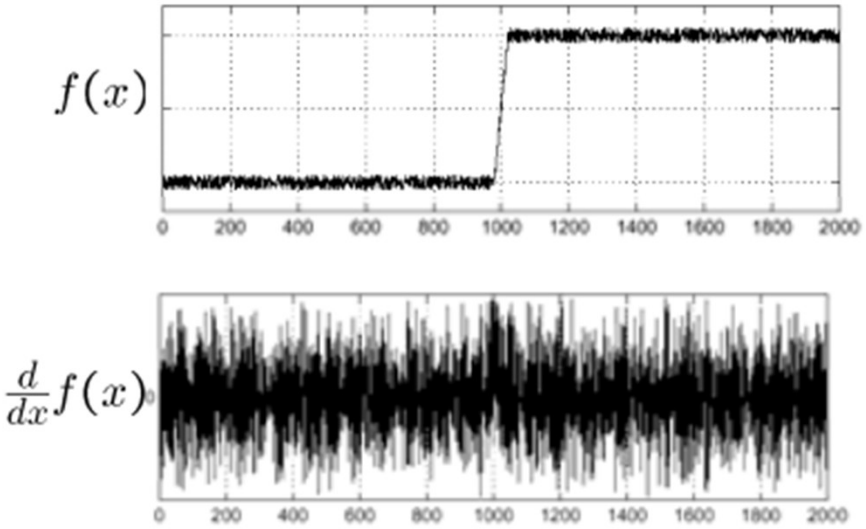
Looking at a row profile

Intensity profile



Effects of Noise

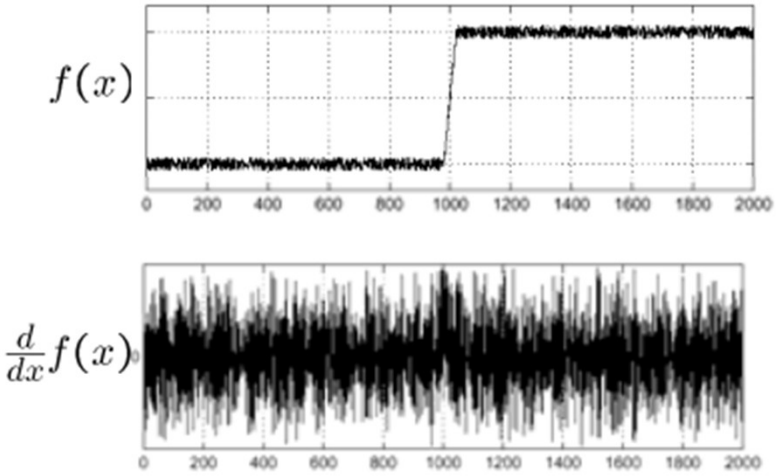
› Consider a single row or column of the image
  – Plotting intensity as a function of position gives a signal



Where's the edge?

Effects of noise

- Gradient filters respond strongly to noise
  - Image noise results in pixels that look very different from their neighbours
  - What can be done?



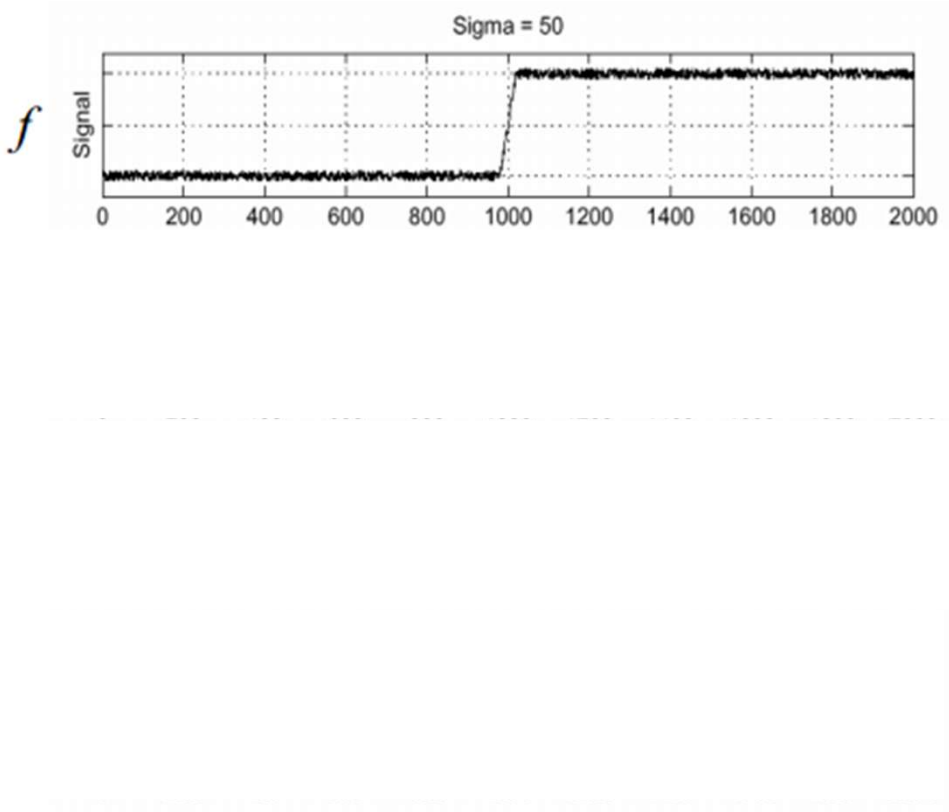
A. Smoothing to make pixels look more like their neighbours

B. Thresholding to remove all the noise pixels

C. Filtering to transform the pixels into a clearer format

D. Nothing can be done

Solution



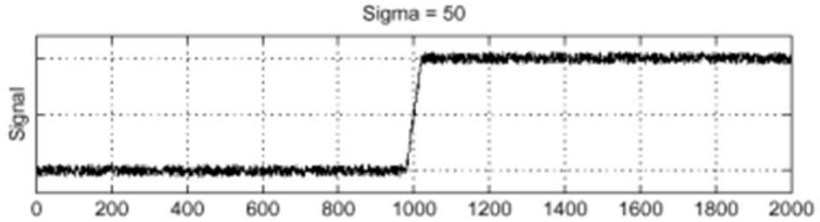
To find edges, look for **peaks** in the gradient of the smoothened image

Derivative theorem of convolution

› Differentiation is convolution, convolution is associative

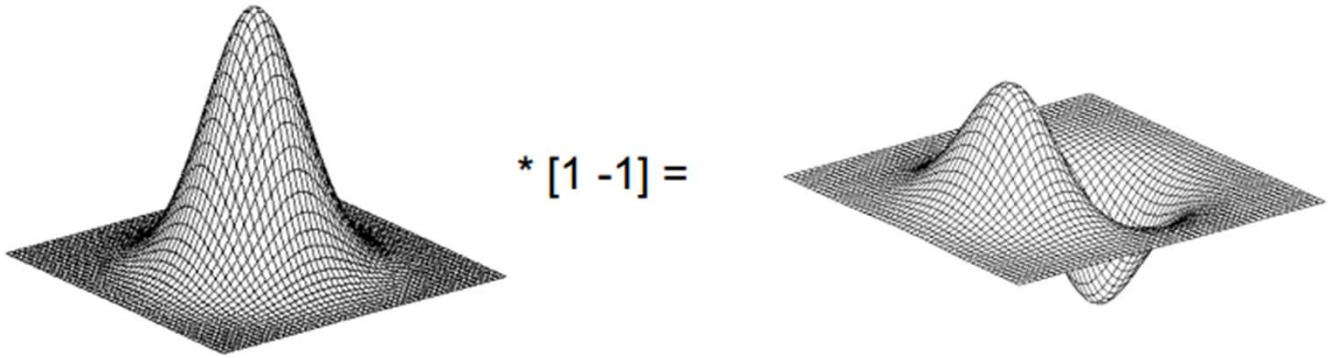
$$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$

f



Saves one operation

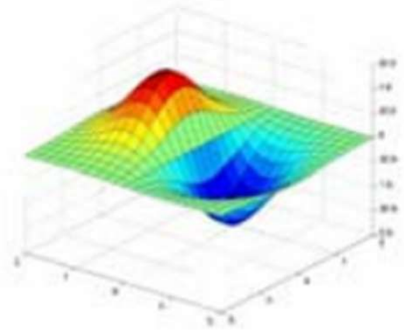
Derivative of Gaussian filter



Derivative of Gaussian filter

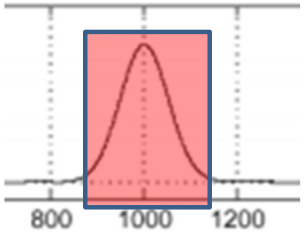
$$(I \otimes g) \otimes h = I \otimes (g \otimes h)$$

$$\begin{bmatrix} 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0219 & 0.0983 & 0.1621 & 0.0983 & 0.0219 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \end{bmatrix} \otimes \begin{bmatrix} 1 & -1 \end{bmatrix}$$



Using 1st order gradient filter

Recall, 1st derivative of Gaussian

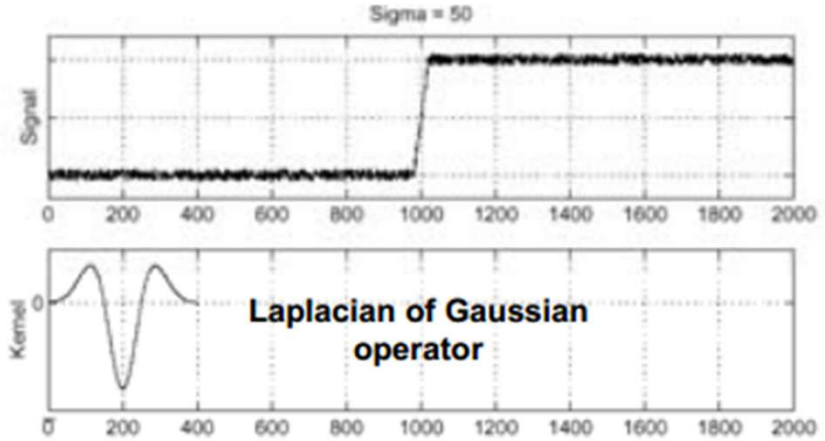


› Gradient magnitude is larger along a thick ridge
  – So, how to identify the actual edge points?
  – If we can, then how do we link the actual edge points to form curves?

Laplacian of Gaussian

f

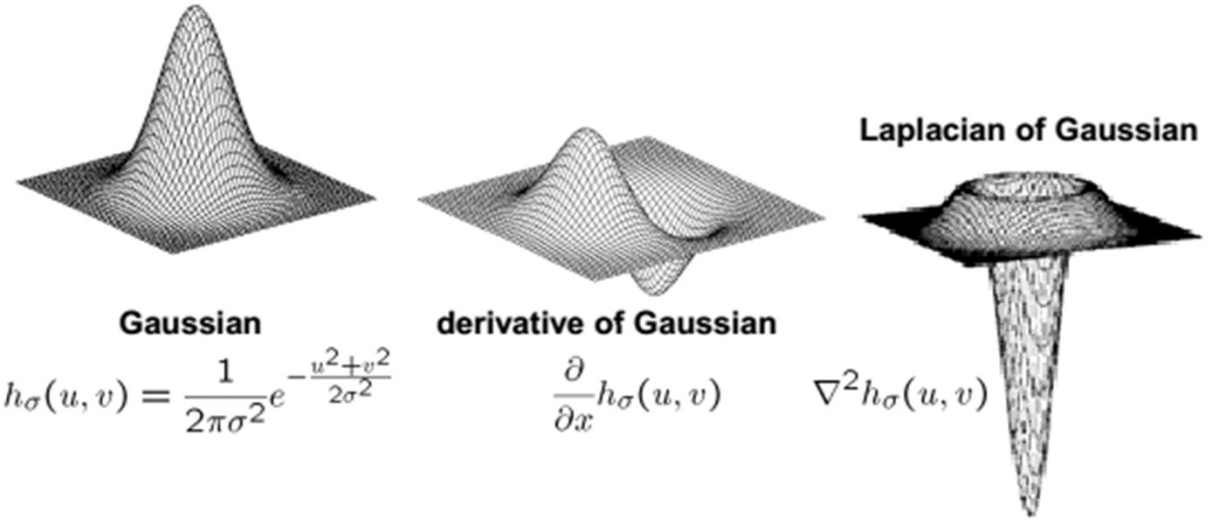
$\frac{\partial^2}{\partial x^2} h$



› 2nd derivative of the Gaussian

› Where is the edge? **Zero-crossings of last graph**

2D Gradient-based Edge Filters



Gaussian

$$h_\sigma(u,v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$

derivative of Gaussian

$$\frac{\partial}{\partial x} h_\sigma(u,v)$$

Laplacian of Gaussian

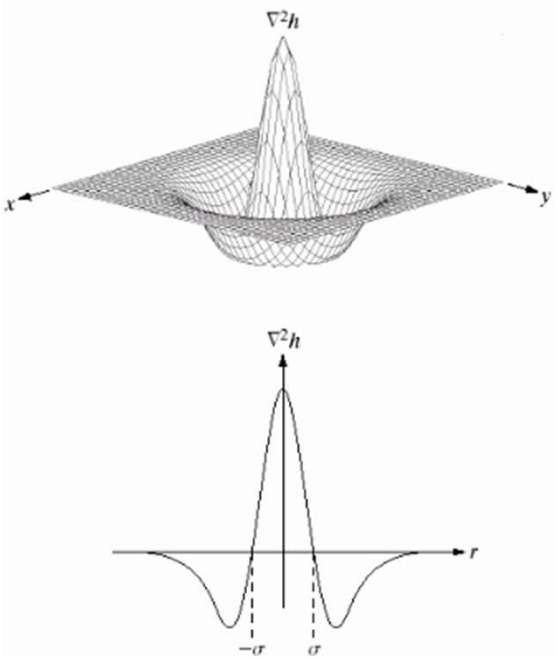
$$\nabla^2 h_\sigma(u,v)$$

∇^2 **Laplacian operator**

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

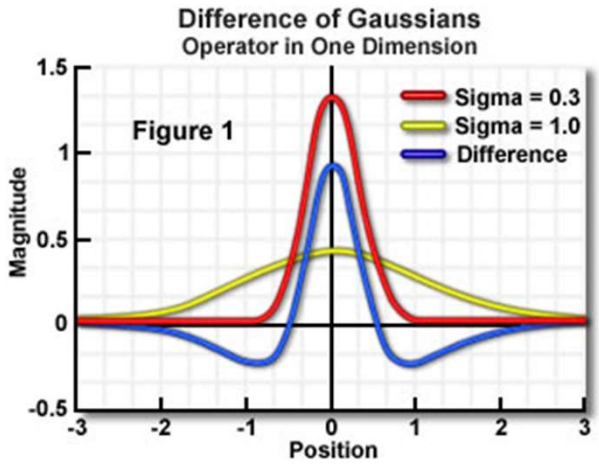
Laplacian of Gaussian (LoG) filter

- LoG filter – also known as Marr-Hildreth algorithm
  - Convolution of the image with the Laplacian of the Gaussian function
  - Zero crossings are detected to obtain edges
  - Its operator sometimes known as **Mexican hat operator**



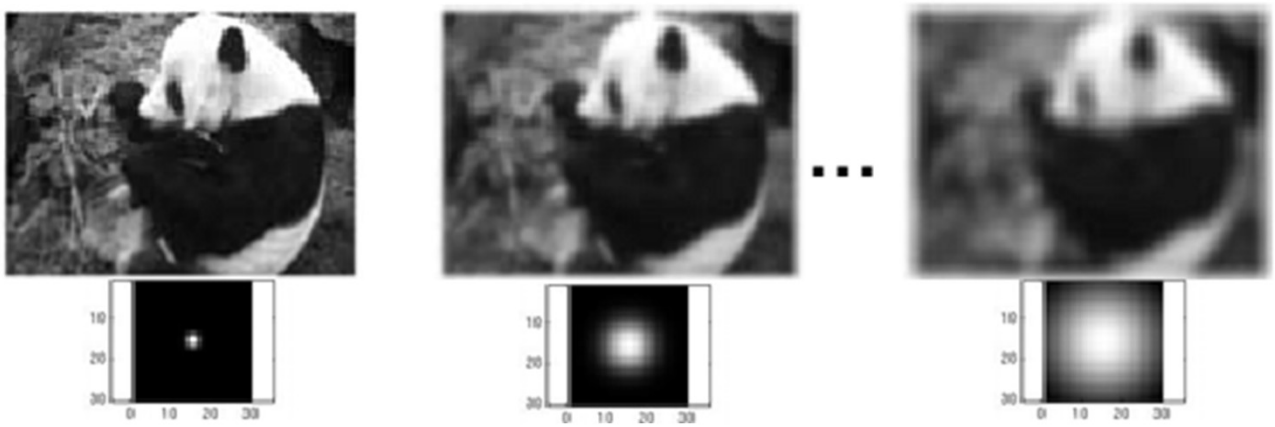
DoG ⟹ LoG

- **Difference of Gaussians (DoG) filter** – a fast approximation of the LoG filter
  - Subtract one blurred version of original image (by Gaussian filter) from another, less blurred version of original
    - Just use different σ values to create the two different blurred versions



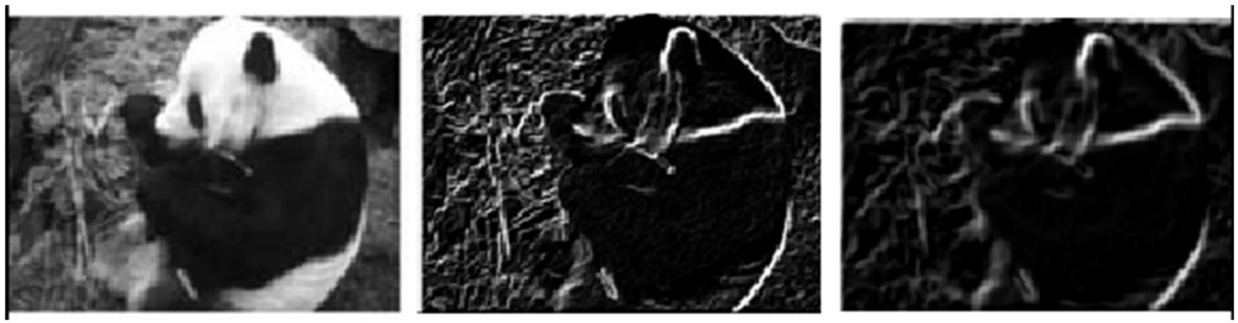
Smoothing with a Gaussian

› **Recall**: Parameter σ is the "scale" or "width" of the Gaussian kernel, controls amount of smoothing



Effect of σ on derivatives

› Edge structure differs depending on Gaussian kernel's scale parameter



› **Larger** values: thick, only important edges detected

› **Smaller** values: finer edges detected, but too much details

› So, what scale to choose?

Other finite difference filters

› "Finite difference filters" – approximates the gradient of image intensity function

Roberts

$$\begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \qquad \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

Prewitt

$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

Sobel

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Other finite difference filters

› "Finite difference filters" – approximates the gradient of image intensity function

0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

*

1	0	-1
1	0	-1
1	0	-1

=

Other finite difference filters

› "Finite difference filters" – approximates the gradient of image intensity function

0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

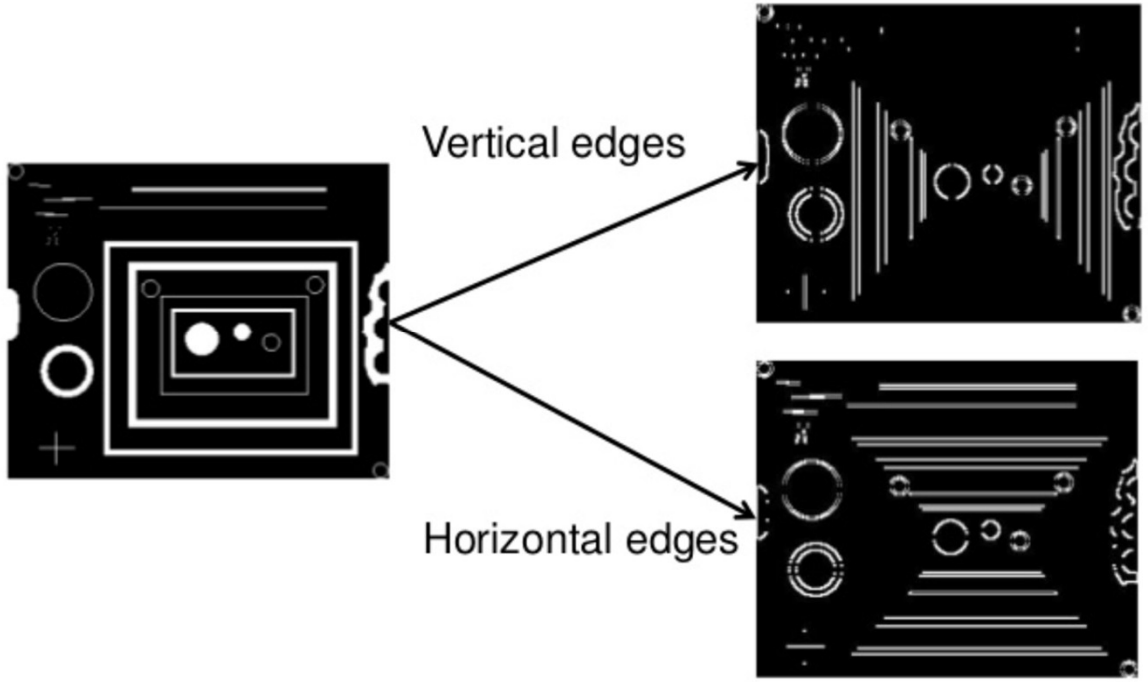
*

1	0	-1
1	0	-1
1	0	-1

=

0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
0	-30	-30	0

Other finite difference filters



Mask properties

› Smoothing
  – Values positive
  – Sum to 1 ⟹ constant regions same as input
  – Amount of smoothing proportional to mask size

› **Edge Derivatives**
  – Different signs (positive, negative) are used to get high response in regions of high contrast
  – Sum to ? ⇒ no response in constant regions
  – High absolute value at points of high contrast

A. 3
B. 2
C. 1
D. 0

Designing an edge detector

› Criteria of an “optimal” edge detector

- Good detection: Must minimize probability of false positives (spurious edges due to noise), and false negatives (missing real edges)
- Good localization: Edges detected are as close as possible to true edges
- Single response: Detector must return one point only for each true edges

Designing an edge detector

- Primary edge detection steps:
  - **Smoothing**: Suppress noise
  - **Edge enhancement**: Filter for contrast
  - **Edge localization**: Determine which local maxima from filter output are actually edges
    - **Thresholding**

Thresholding

› Choose a threshold value t

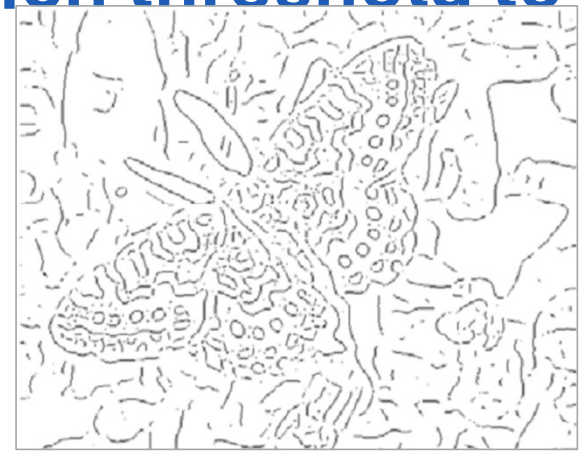
› Set any pixels less than t to zero (off)

› Set any pixels greater or equal to t to one (on)

Original image

Thresholding: Gradient magnitude image

Which threshold to use?



Lower threshold value

Higher threshold value

› What can we conclude from using different threshold values?

A. A universal value can be used for the best thresholding.
B. Lower threshold will detect all edges we need.
C. Higher threshold may miss out on some edges.
D. A random value can be used to perform thresholding.

Canny Edge Detector

Canny edge detector

› Most widely used edge detector – Stable, consistent

› Steps:

1. **Filter image with Gaussian filter**, find magnitude and orientation of gradient
2. **Non-maximum suppression**
   - › Thin wide "ridges" down to single pixel width (get rid of spurious responses)
3. **Hysteresis thresholding and linking**
   - › Define 2 thresholds: low and high (to find strong and weak edges)
   - › Start edge curves from the true edges and continue tracking based on weak edges that are connected to the true edges

Normally we just threshold after filtering

Canny edge detector

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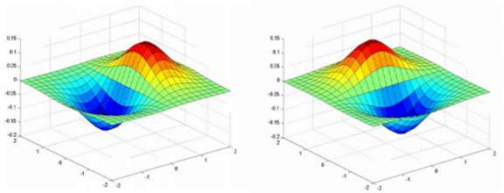
Step 1

› Lena Example:

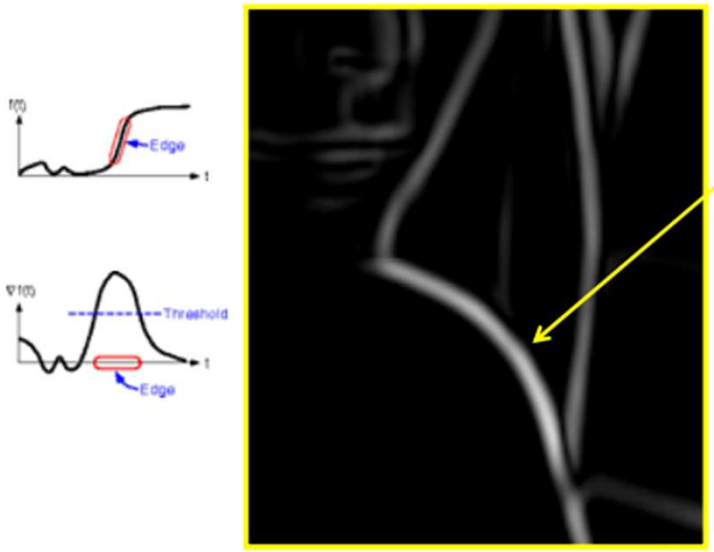
– Step 1 can be done in one pass, by filtering with the derivative of Gaussian filter (both x and y directions)



2 Problems when thresholding

› Problem #1:

– Edges from many gradient-based edge detectors are too thick



How to turn these thick regions into single pixel edges?

Canny edge detector

› Most widely used edge detector – Stable, consistent

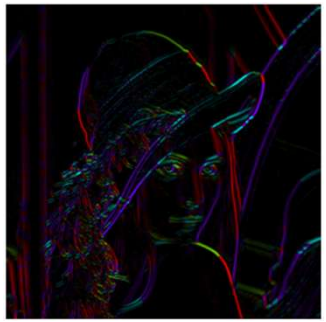
› Steps:

1. **Filter image with Gaussian filter**, find magnitude and orientation of gradient
2. **Non-maximum suppression**
   - › Thin wide “ridges” down to single pixel width (get rid of spurious responses)
3. **Hysteresis thresholding and linking**
   - › Define 2 thresholds: low and high (to mark strong and weak edges)
   - › Start edge curves from the true edges and continue tracking based on weak edges that are connected to the true edges

Step 2

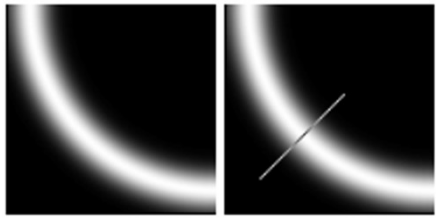
› Get orientation at each pixel

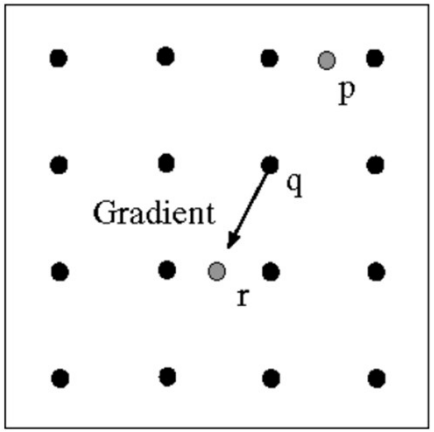
$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y}/\frac{\partial f}{\partial x}\right)$$



› **Non-maximum suppression**

– Check if pixel is local maximum along gradient direction e.g. maximum at q if value larger than p and r (interpolated pixels). So, suppress p and r.





2 Problems when thresholding

› Problem #2:

– Pixels along weak edges will not survive if standard thresholding is applied (using a threshold determined globally)

How can we keep the pixels along these weak edge?

A. They are weak, we should not keep them.
B. Multiply the weak to strengthen them.
C. The strong ones can guide the weak.
D. All the above does not make sense.

Canny edge detector

› Most widely used edge detector – Stable, consistent

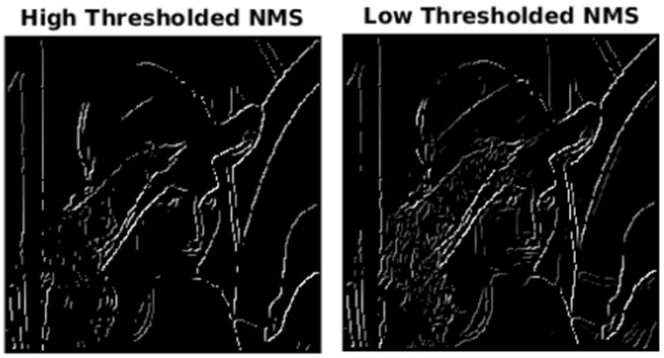
› Steps:

1. **Filter image with Gaussian filter**, find magnitude and orientation of gradient
2. **Non-maximum suppression**
   › Thin wide "ridges" down to single pixel width (get rid of spurious responses)
3. **Hysteresis thresholding and linking**
   › Define 2 thresholds: low and high (to mark strong and weak edges)
   › Start edge curves from the true edges and continue tracking based on weak edges that are connected to the true edges

Step 3

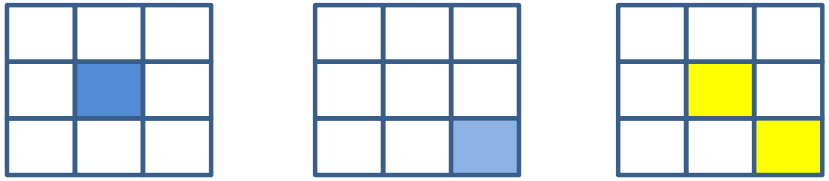
› Double threshold

- **High threshold** – (Gradient higher than this threshold) ⟹ **strong** edges
- **Low threshold** – (Gradient higher than low threshold but lower than high threshold) ⟹ **weak** edges
- The plan: Ensure continuity in edges of different strengths



Step 3

› To “link” edges, perform connected components, starting from strong edge pixels
  – Search 8-neighbourhood for weak edge pixels
  – Usually a weak edge pixel caused by true edges will be connected to a strong edge pixel while noise responses are unconnected.



Strong edge pixel Weak edge pixel Linked edges

Final Result

Effect of σ (Gaussian kernel width)

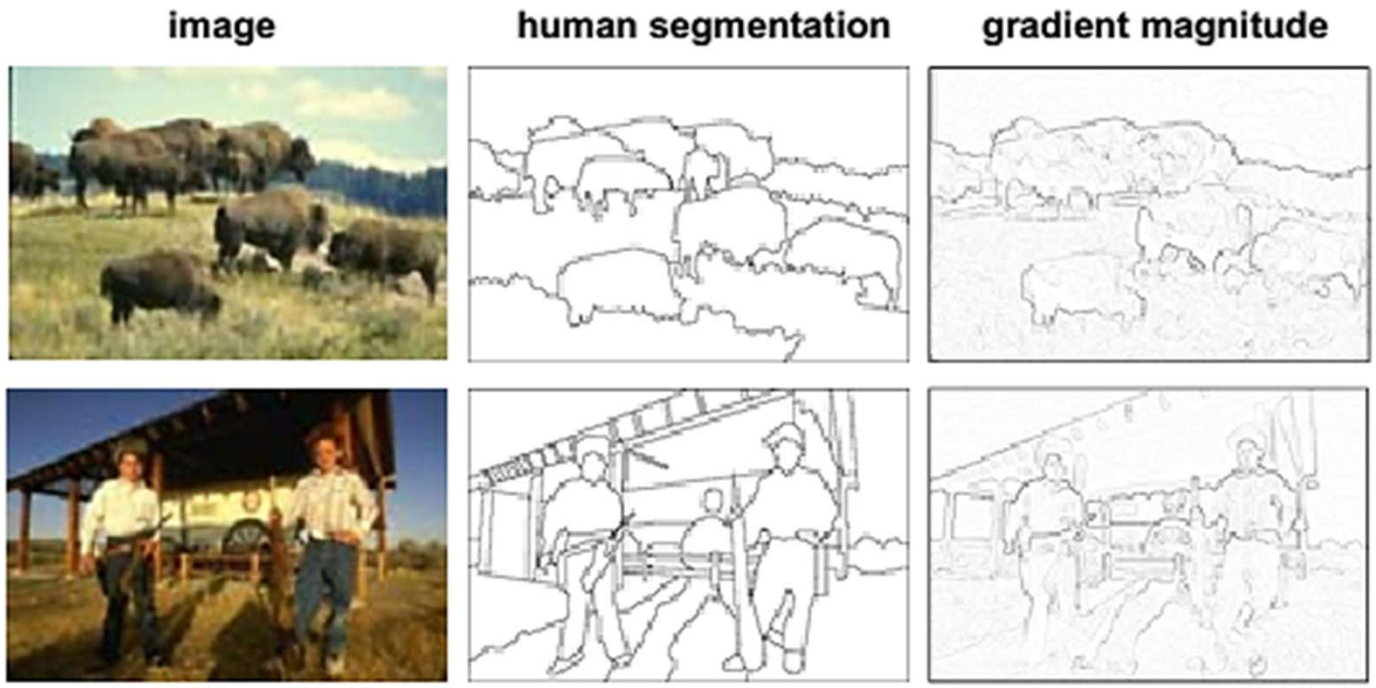
original | Canny with $\sigma = 1$ | Canny with $\sigma = 2$

› The choice of σ depends on desired behaviour
  - Large σ detect large scale edges (less edges typically)
  - Small σ detects fine features (more edges typically)

Knowing True Edges

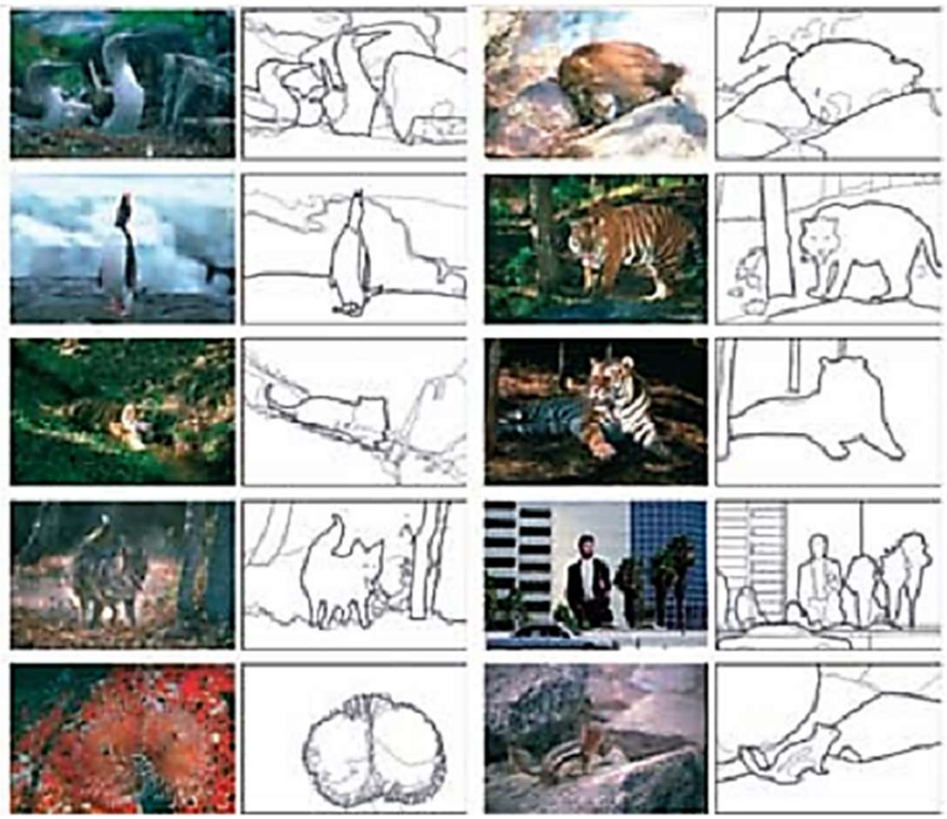
How do we know if the edges found are really the **TRUE** edges?

Gradient edges vs. Human segmentation

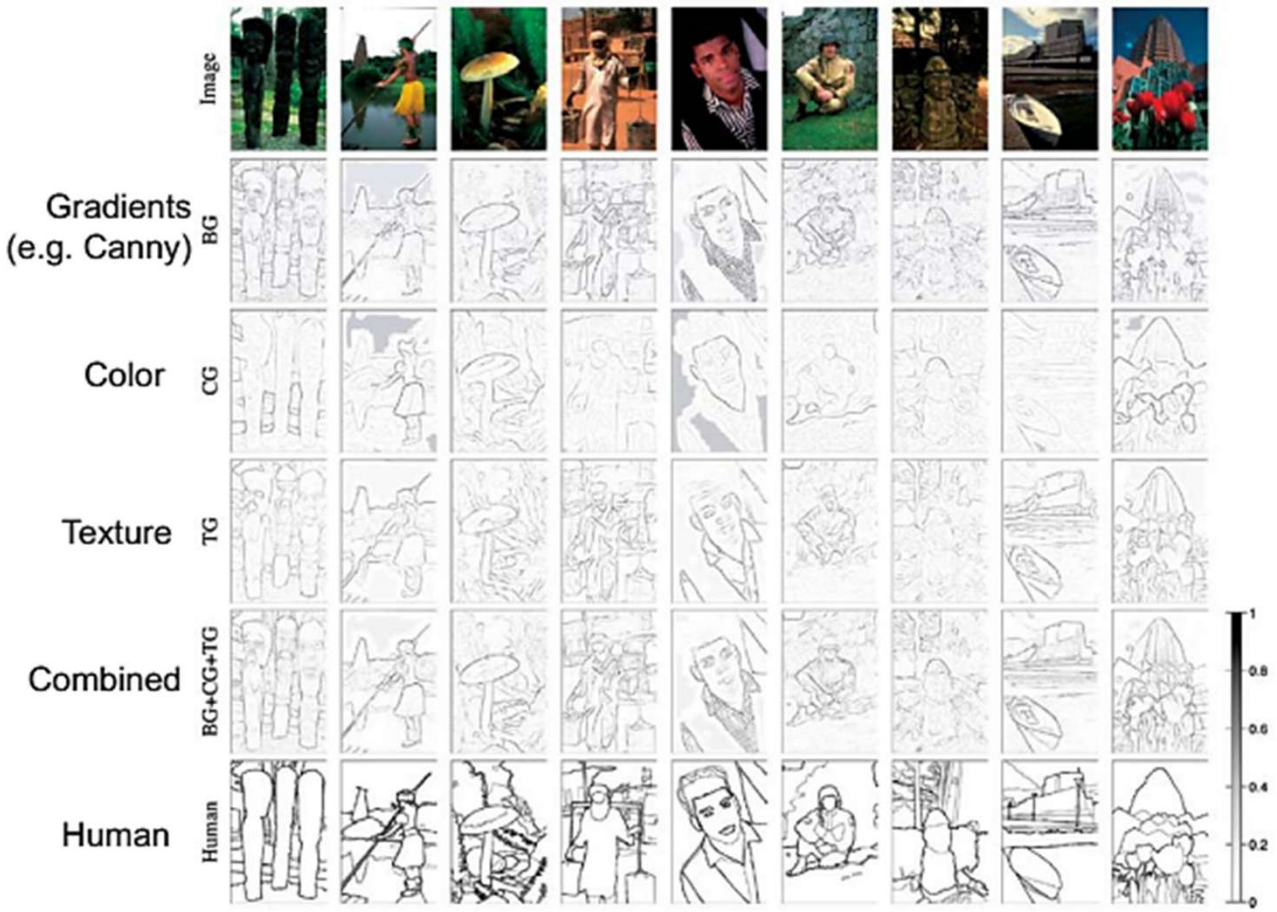


Berkeley segmentation database
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

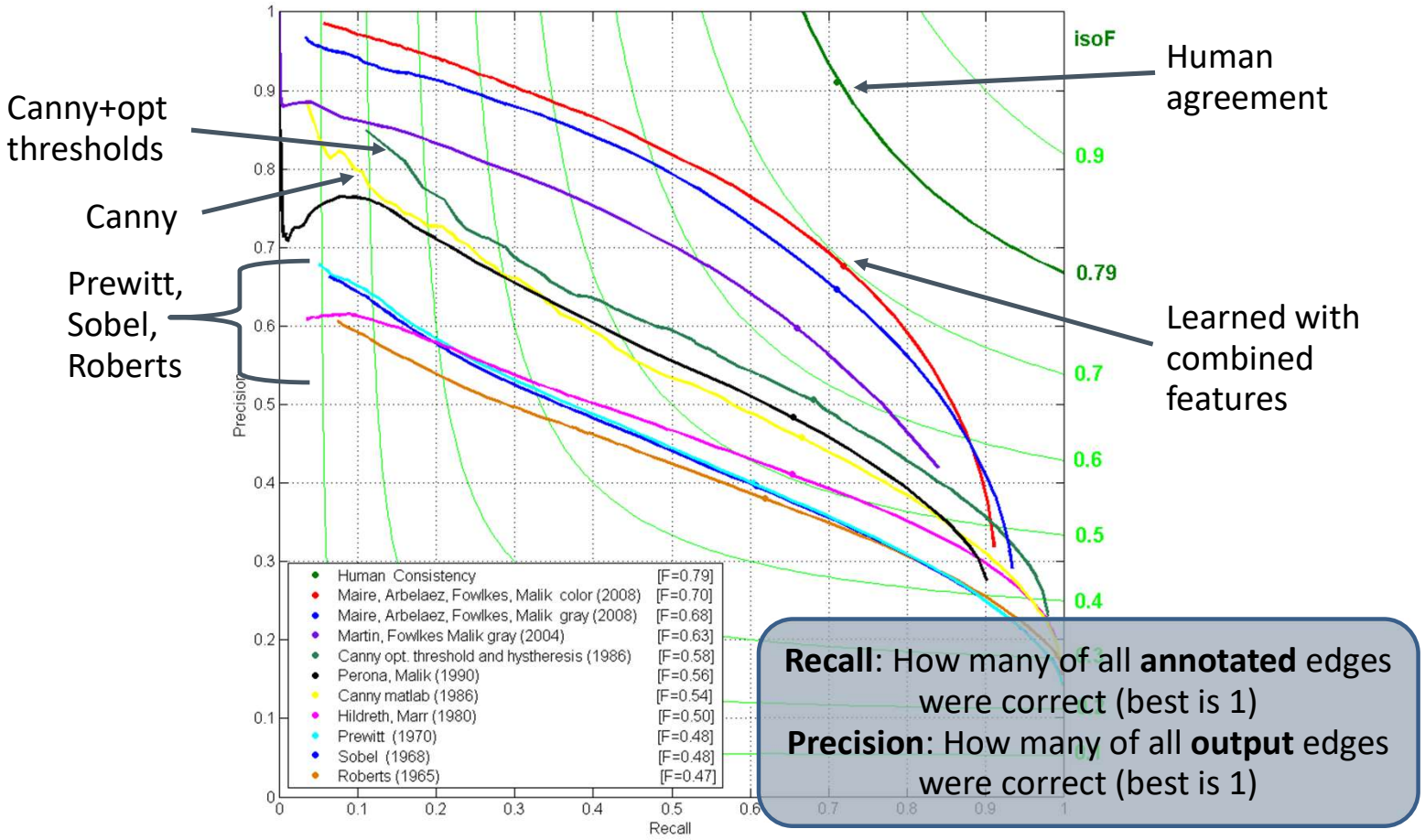
Human-perceived edges



Features used vs. Human-marked



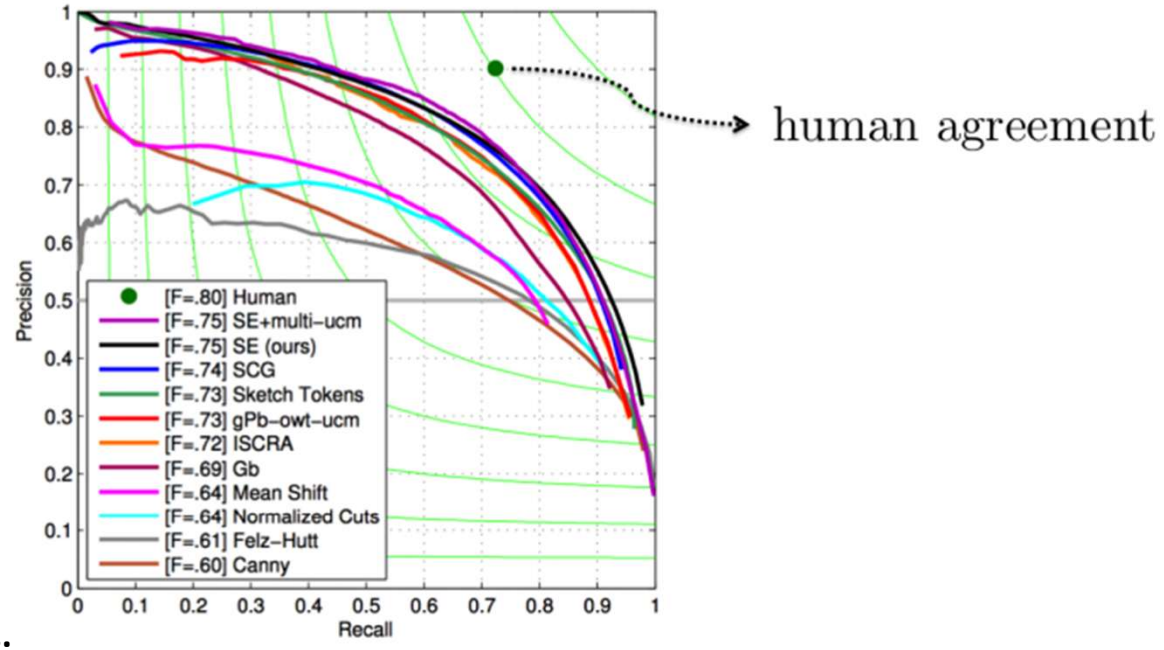
Contour Detection (CVPR 2008)



Recall: How many of all **annotated** edges were correct (best is 1)

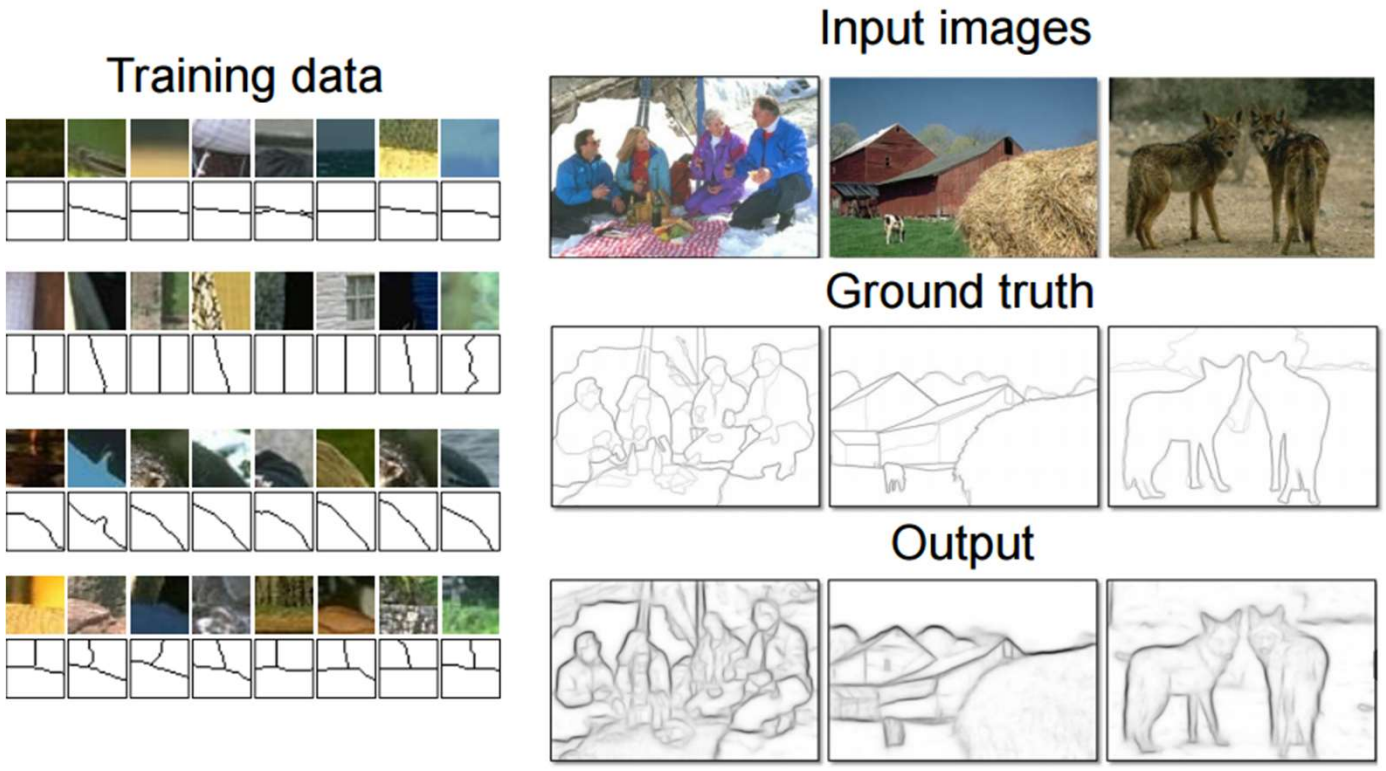
Precision: How many of all **output** edges were correct (best is 1)

Contour Detection (ICCV 2013)



Best performing:
P. Dollar and C. Zitnick, **"Structured Forests for Fast Edge Detection"** (ICCV 2013)
Code:
Original (Matlab/C++): https://www.microsoft.com/en-us/download/details.aspx?id=52370
Python: https://github.com/ArtanisCV/StructuredForests
OpenCV (C++): https://docs.opencv.org/3.3.1/d0/da5/tutorial_ximgproc_prediction.html

Data-driven edge detection



Machine learning: How can we “train” an edge detector to learn what is an edge?

Deep Learning-based Edge detection

› State-of-the-arts deep-learning based edge detection:

- **Holistically-Nested Edge Detection**
  https://ieeexplore.ieee.org/abstract/document/7410521/
- **Learning Relaxed Deep Supervision for Better Edge Detection**
  https://ieeexplore.ieee.org/document/7780401
- **DeepContour: A deep convolutional feature learned by positive-sharing loss for contour detection**
  https://ieeexplore.ieee.org/document/7299024/

SUMMARY

- What makes an edge?
- Gradient-based Edge Detectors
  - Using derivatives or gradients to find edges
  - LoG and DoG
- Canny Edge Detector
  - Gaussian Filtering, Non-maximal suppression, hysteresis
- Knowing True Edges
- Next:
  - Binary Image Processing
- Recommended Reading
  - [Gonzalez & Woods] Chapter 10
  - [Forsyth & Ponce] Chapter 8