



Edges

09-Oct-2018

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Lecture: Edge Detection

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What we will learn today

- Edge detection
- Image Gradients
- A simple edge detector
- Sobel edge detector
- Canny edge detector
- Hough Transform
霍夫变换

Some background reading:

Forsyth and Ponce, Computer Vision, Chapter 8



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Edges

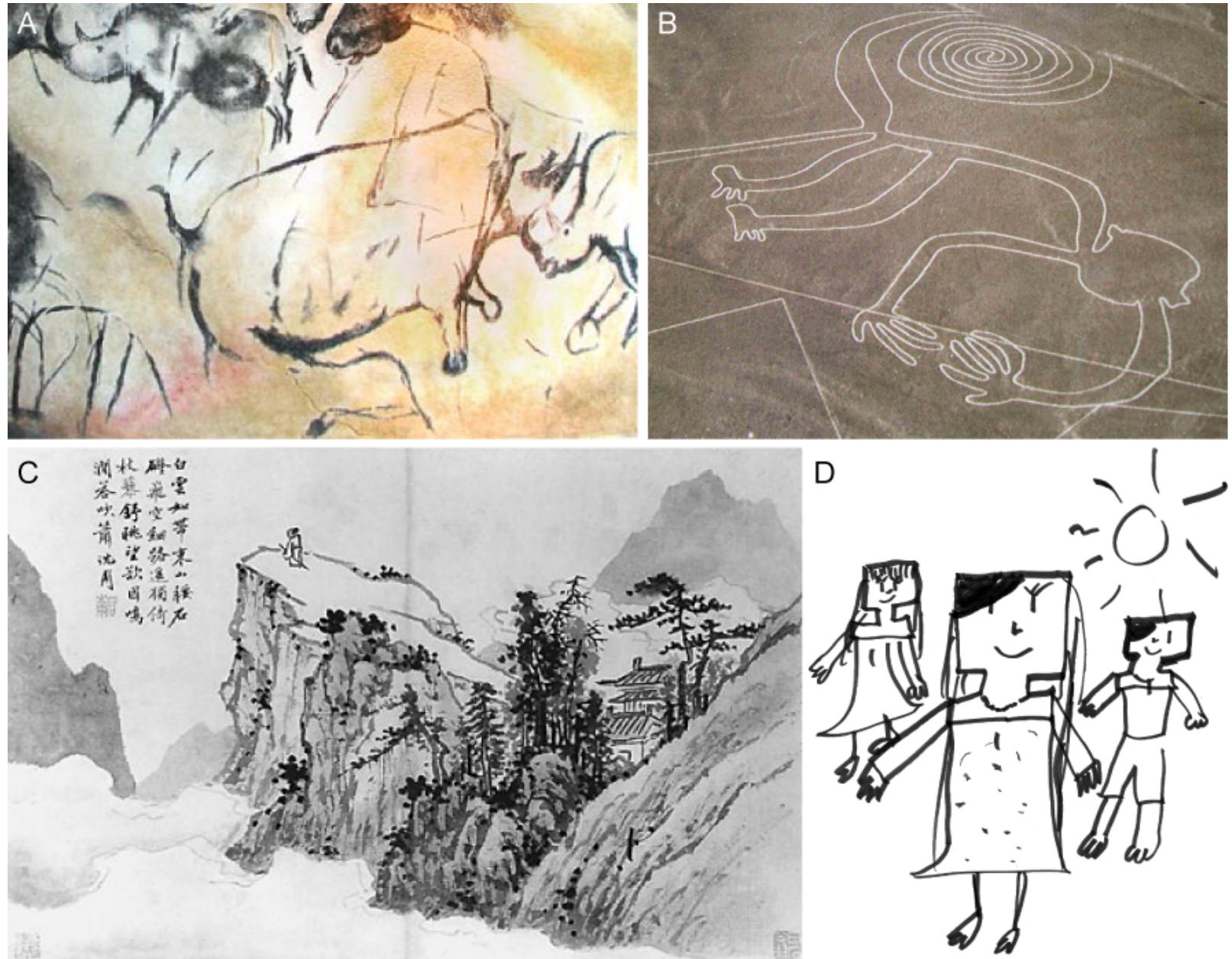
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- (A) Cave painting at Chauvet, France, about 30,000 B.C.;
(B) Aerial photograph of the picture of a monkey as part of the Nazca Lines geoglyphs, Peru, about 700 – 200 B.C.;
(C) Shen Zhou (1427-1509 A.D.): Poet on a mountain top, ink on paper, China;
(D) Line drawing by 7-year old I. Lleras (2010 A.D.).

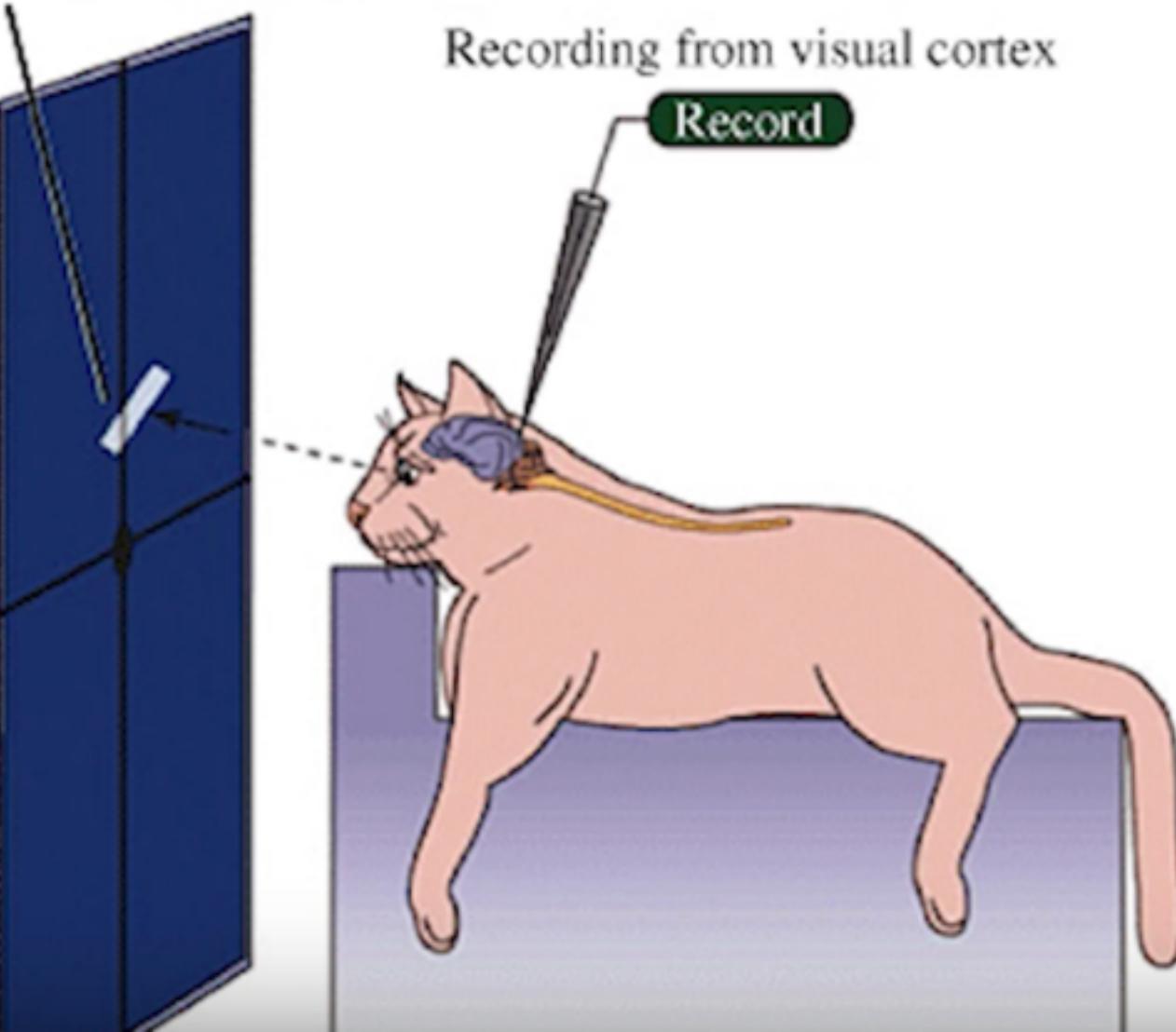


A Experimental setup

Light bar stimulus
projected on screen

Recording from visual cortex

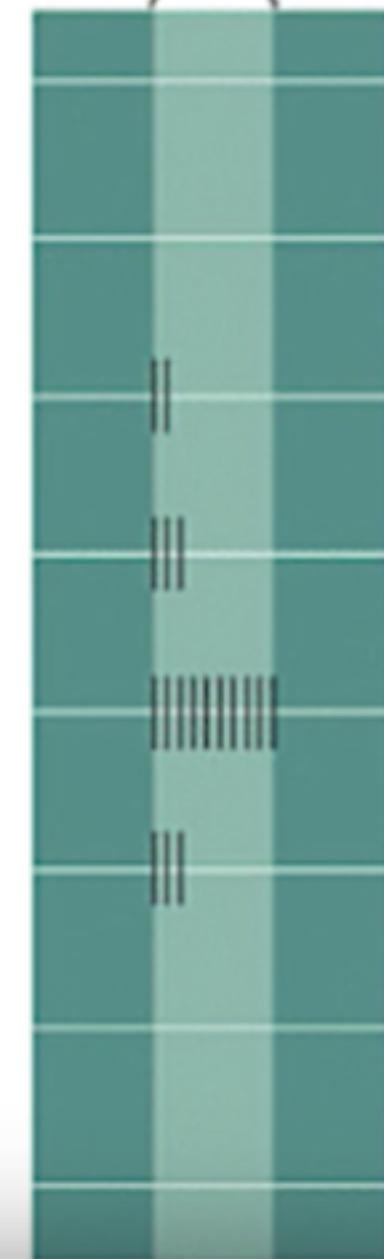
Record



B Stimulus orientation



Stimulus presented

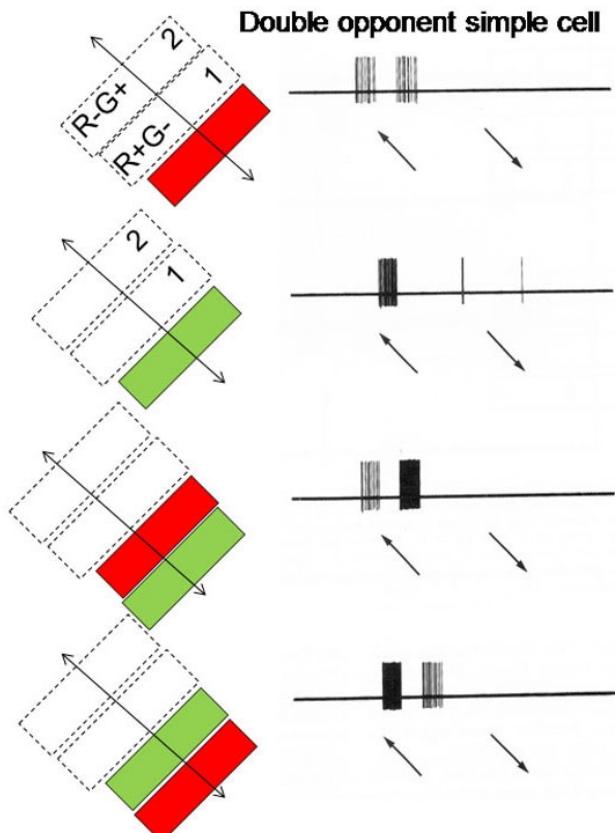


Hubel & Wiesel, 1960s





We know edges are special from human
(mammalian) vision studies



Hubel & Wiesel, 1960s

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We know edges are special from human (mammalian) vision studies

152 Biederman

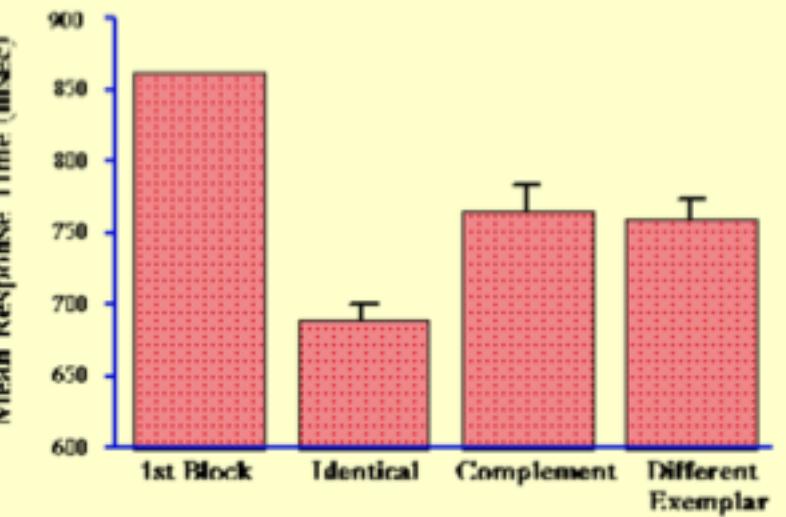
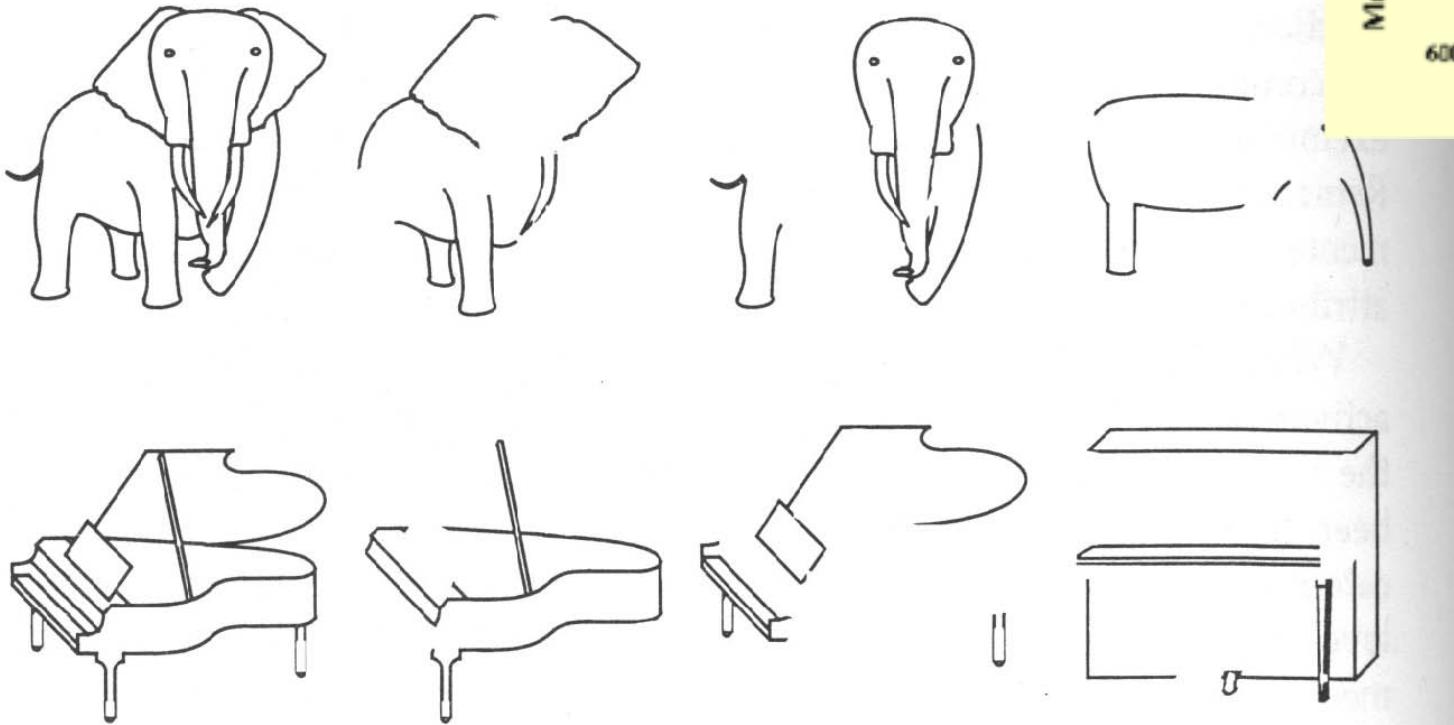


Figure 4.14

Complementary-part images. From an original intact image (left column), two complemen-

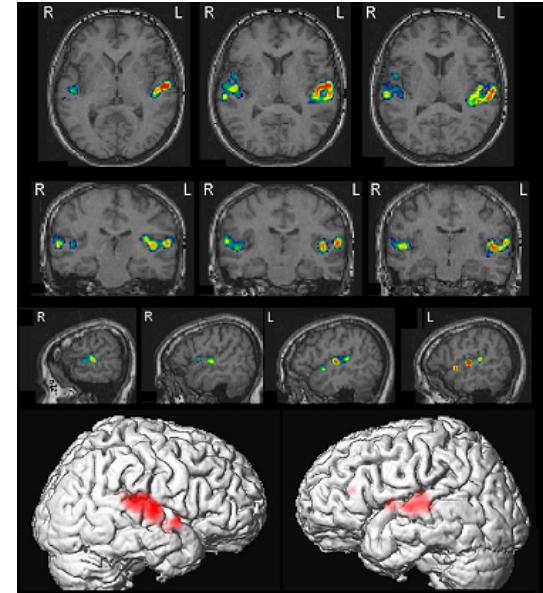
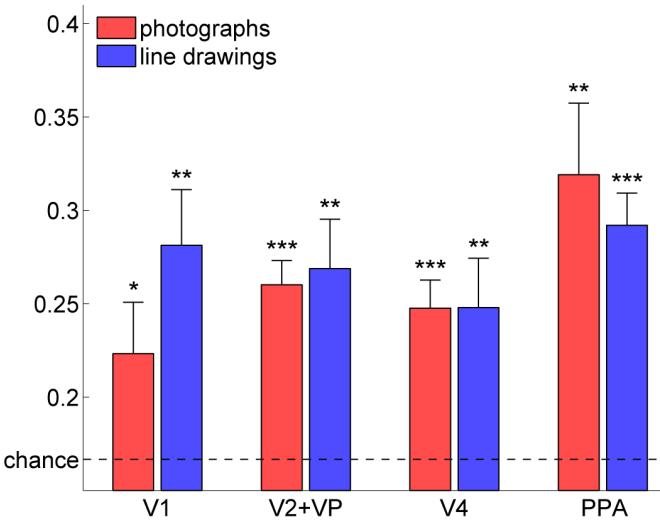


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Decoding Accuracy





Edge detection

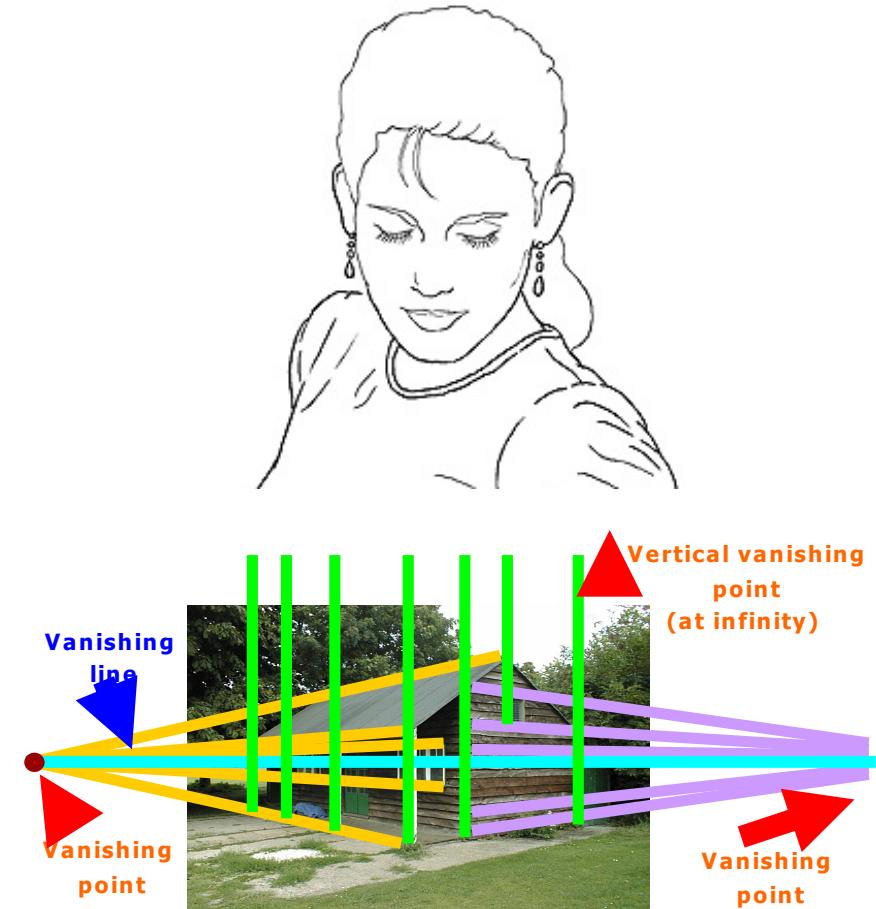
- **Goal:** Identify sudden changes (discontinuities) in an image
 - Intuitively, most semantic and shape information from the image can be encoded in the edges
 - More compact than pixels
- **Ideal:** artist's line drawing (but artist is also using object-level knowledge)



Source: D. Lowe

Why do we care about edges?

- Extract information, recognize objects
- Recover geometry and viewpoint





Origins of edges



surface normal discontinuity

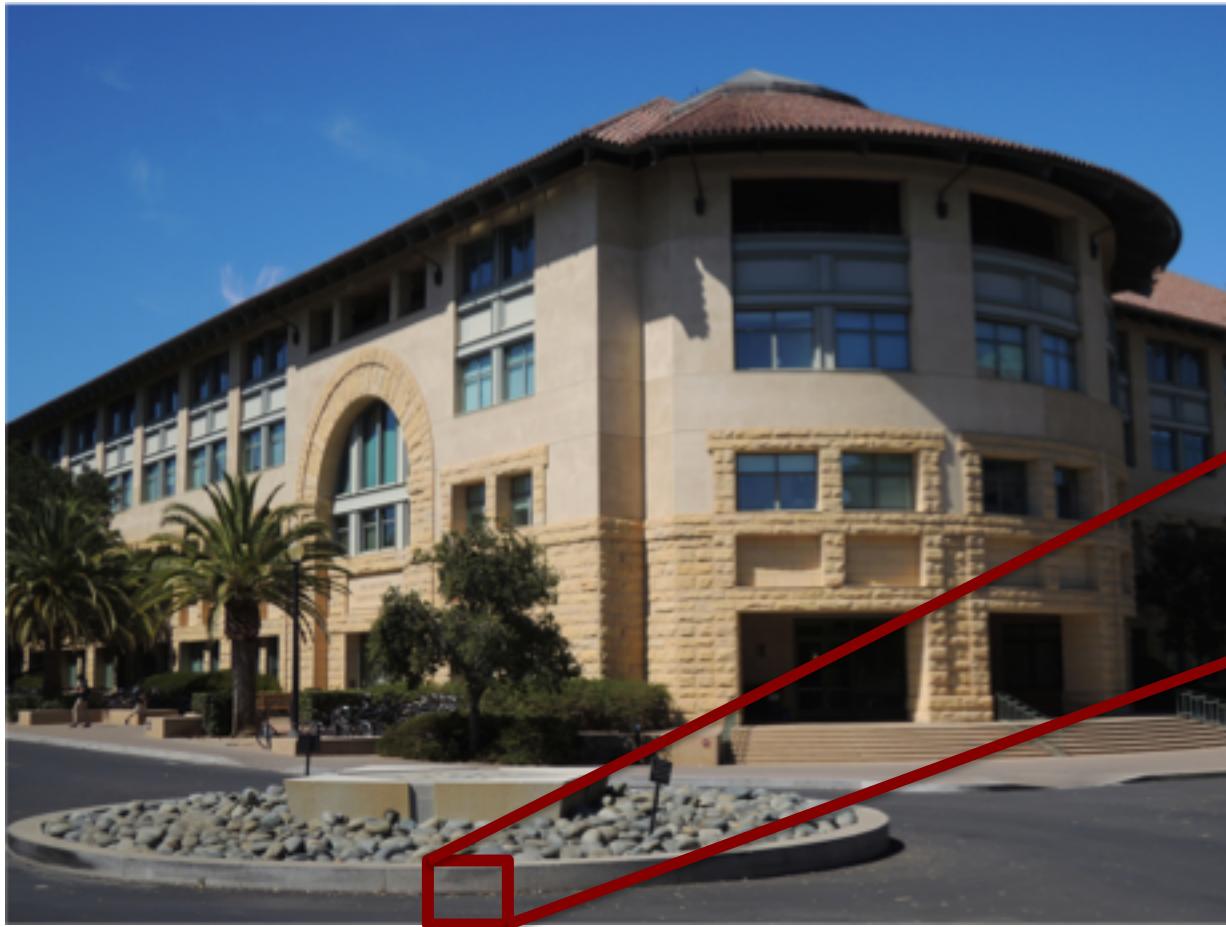
depth discontinuity

surface color discontinuity

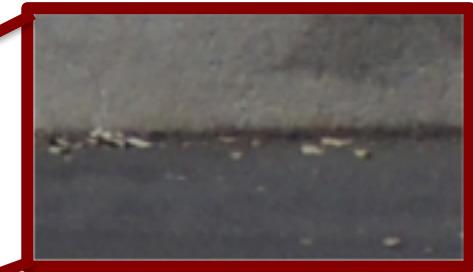
illumination discontinuity



Closeup of edges



Surface normal discontinuity

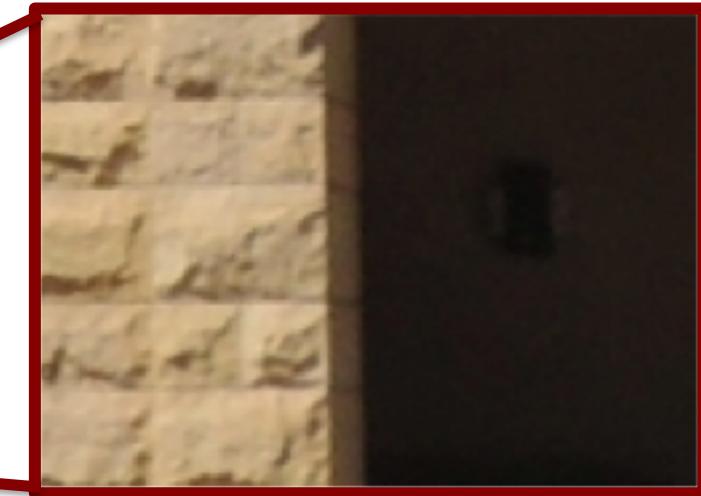




Closeup of edges



Depth discontinuity

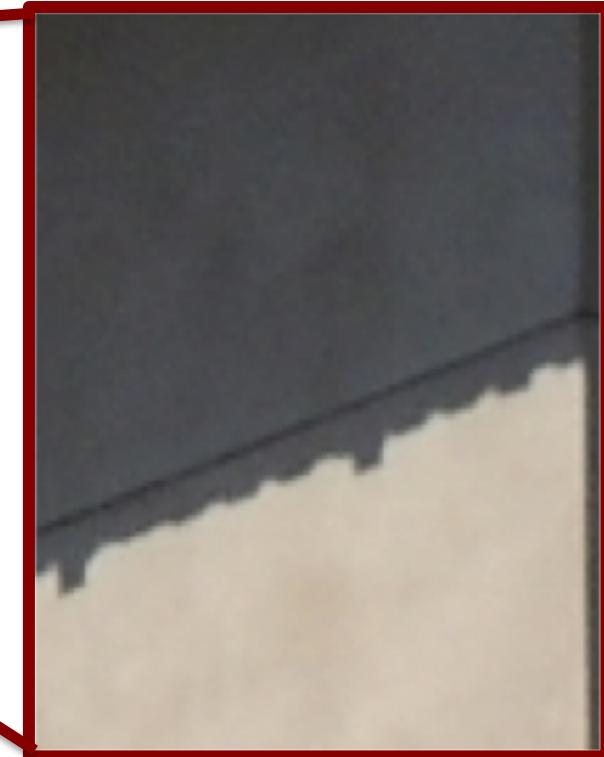




Closeup of edges



Surface color discontinuity



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Derivatives in 1D

$$\frac{df}{dx} = \lim_{\Delta x \rightarrow 0} \frac{f(x) - f(x - \Delta x)}{\Delta x} = f'(x) = f_x$$



Derivatives in 1D - example

$$y = x^2 + x^4$$

$$\frac{dy}{dx} = 2x + 4x^3$$



Derivatives in 1D - example

$$y = x^2 + x^4$$

$$\frac{dy}{dx} = 2x + 4x^3$$

$$y = \sin x + e^{-x}$$

$$\frac{dy}{dx} = \cos x + (-1)e^{-x}$$



Discrete Derivative in 1D

$$\frac{df}{dx} = \lim_{\Delta x \rightarrow 0} \frac{f(x) - f(x - \Delta x)}{\Delta x} = f'(x)$$

$$\frac{df}{dx} = \frac{f(x) - f(x - 1)}{1} = f'(x)$$

$$\frac{df}{dx} = f(x) - f(x - 1) = f'(x)$$



Types of Discrete derivative in 1D

Backward

$$\frac{df}{dx} = f(x) - f(x-1) = f'(x)$$

Forward

$$\frac{df}{dx} = f(x) - f(x+1) = f'(x)$$

Central

$$\frac{df}{dx} = f(x+1) - f(x-1) = f'(x)$$



1D discrete derivate filters

- Backward filter:

$$[0 \quad 1 \quad -1]$$

$$f(x) - f(x-1) = f'(x)$$

- Forward:

$$[-1 \quad 1 \quad 0]$$

$$f(x) - f(x+1) = f'(x)$$

- Central:

$$[1 \quad 0 \quad -1]$$

$$f(x+1) - f(x-1) = f'(x)$$



1D discrete derivate filters

- Backward filter:

$$[0 \quad 1 \quad -1]$$

$$f(x) - f(x-1) = f'(x)$$



1D discrete derivate filters

- Backward filter:

$$[0 \quad 1 \quad -1]$$

$$f(x) - f(x-1) = f'(x)$$

- Forward:

$$[-1 \quad 1 \quad 0]$$

$$f(x) - f(x+1) = f'(x)$$



1D discrete derivate example

$$f(x) = 10 \quad 15 \quad 10 \quad 10 \quad 25 \quad 20 \quad 20 \quad 20$$

$$f'(x) = \quad 0 \quad 5 \quad -5 \quad 0 \quad 15 \quad -5 \quad 0 \quad 0$$



Discrete derivate in 2D

Given function

$$f(x, y)$$



Discrete derivate in 2D

Given function

$$f(x, y)$$

Gradient vector

$$\nabla f(x, y) = \begin{bmatrix} \frac{\partial f(x, y)}{\partial x} \\ \frac{\partial f(x, y)}{\partial y} \end{bmatrix} = \begin{bmatrix} f_x \\ f_y \end{bmatrix}$$



Discrete derivate in 2D

Given function

$$f(x, y)$$

Gradient vector

$$\nabla f(x, y) = \begin{bmatrix} \frac{\partial f(x, y)}{\partial x} \\ \frac{\partial f(x, y)}{\partial y} \end{bmatrix} = \begin{bmatrix} f_x \\ f_y \end{bmatrix}$$

Gradient magnitude

$$|\nabla f(x, y)| = \sqrt{f_x^2 + f_y^2}$$

Gradient direction

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



2D discrete derivative filters

What does this filter do?

$$\frac{1}{3} \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$



2D discrete derivative filters

What about this filter?

$$\frac{1}{3} \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$



2D discrete derivative - example

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$



2D discrete derivative - example

What happens when we apply
this filter?

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$

$$\boxed{\frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}}$$



2D discrete derivative - example

What happens when we apply this filter?

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$

$$\frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

$$I_y = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$



2D discrete derivative - example

Now let's try the other filter!

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$

$$\frac{1}{3} \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$



2D discrete derivative - example

What happens when we apply this filter?

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$

$$\frac{1}{3} \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

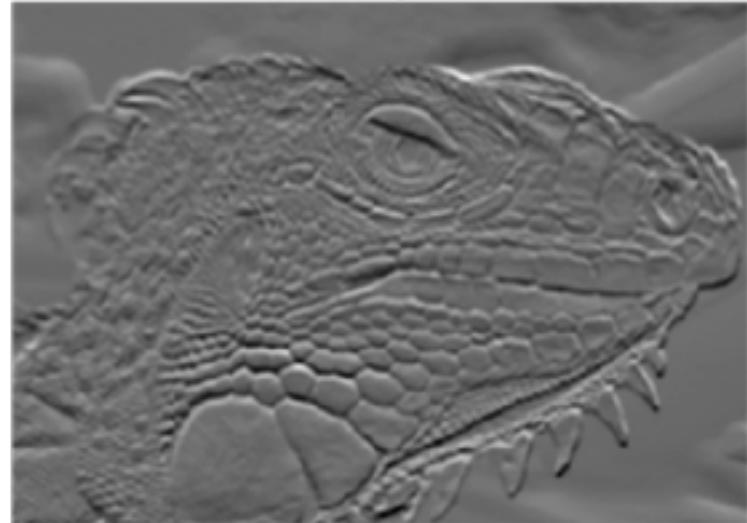
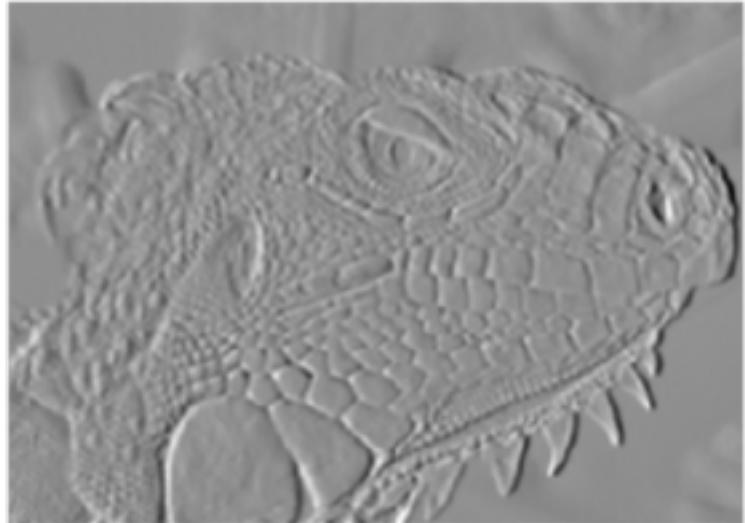
$$I_x = \begin{bmatrix} 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \end{bmatrix}$$



3x3 image gradient filters

$$\frac{1}{3} \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$





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Characterizing edges

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

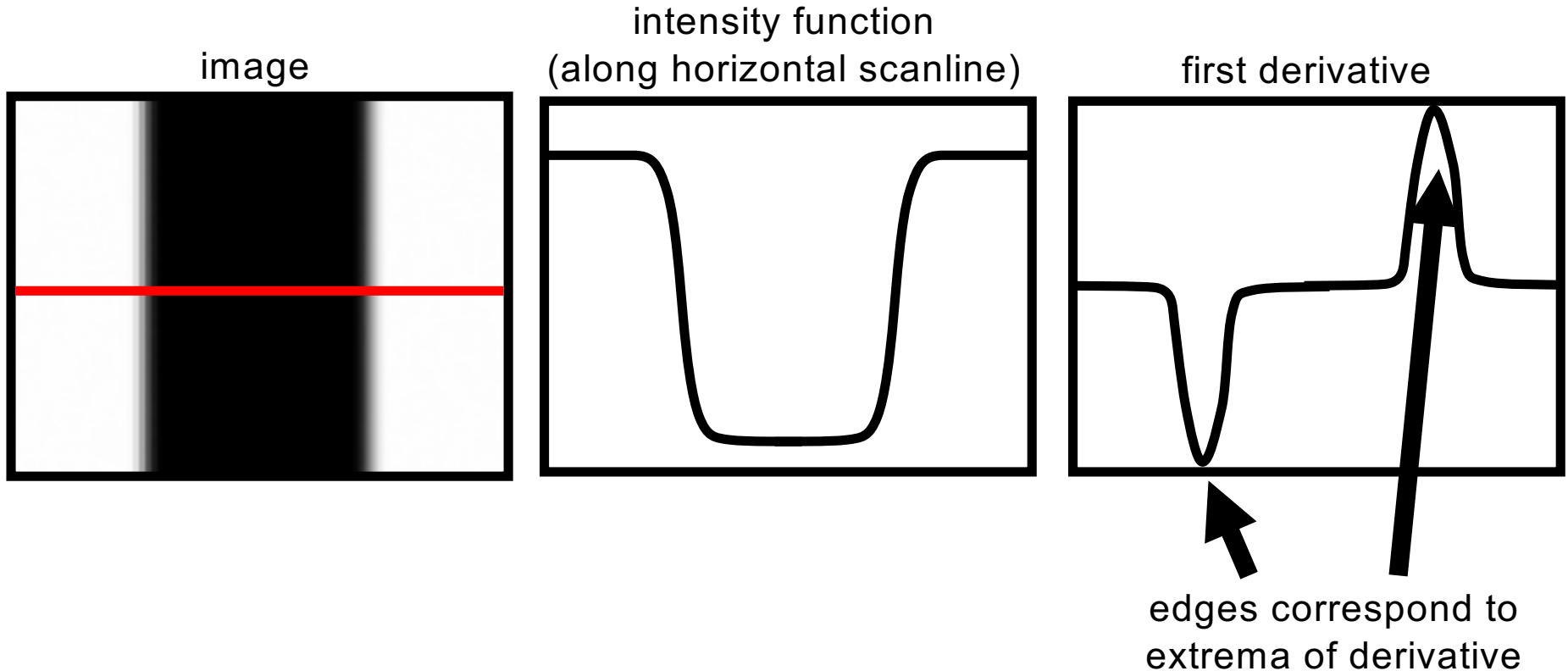
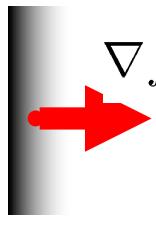




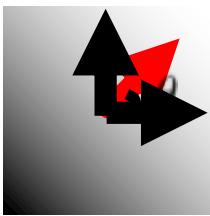
Image gradient

- The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$


$$\nabla f = \left[\frac{\partial f}{\partial x}, 0 \right]$$



$$\nabla f = \left[0, \frac{\partial f}{\partial y} \right]$$



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

The gradient vector points in the direction of most rapid increase in intensity

The gradient direction is given by $\theta = \tan^{-1} \left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x} \right)$

- how does this relate to the direction of the edge?

The *edge strength* is given by the gradient magnitude

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2}$$

Finite differences: example

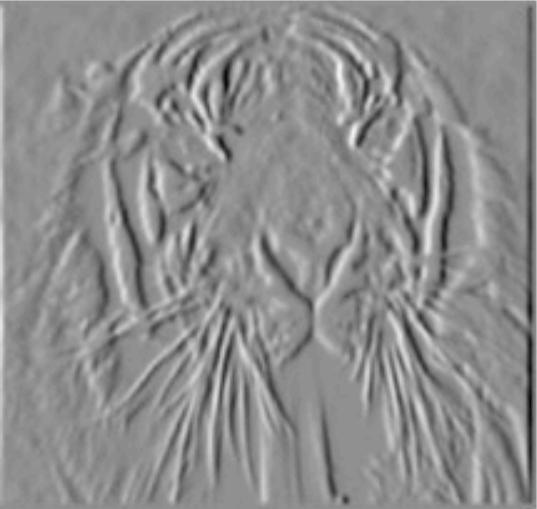
Original
Image



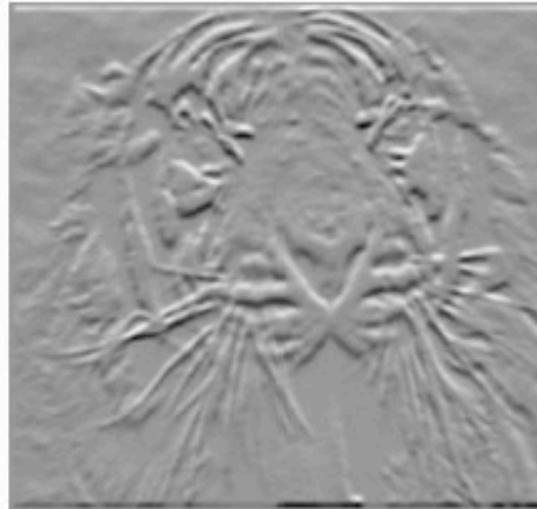
Gradient
magnitude



x-direction



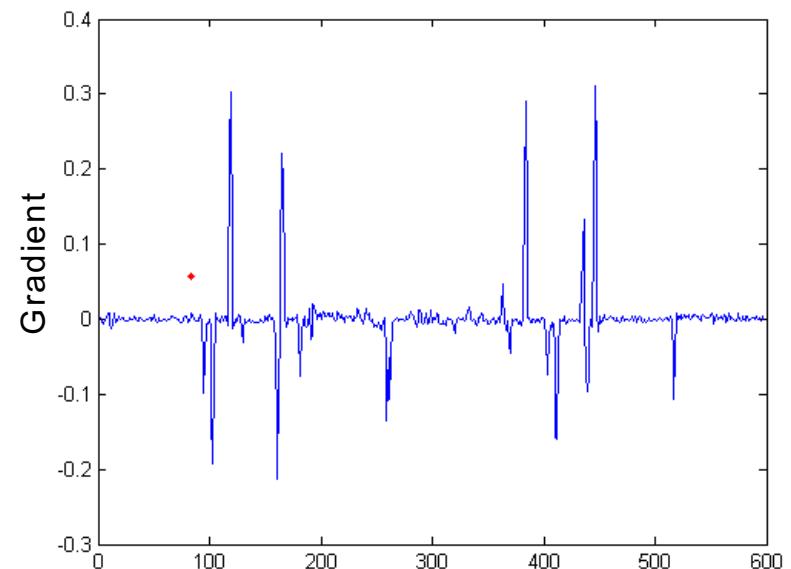
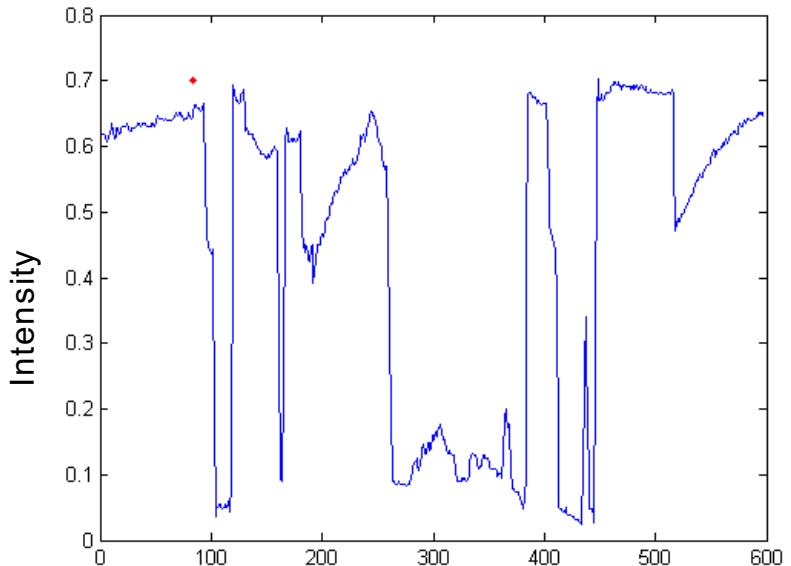
y-direction



- Which one is the gradient in the x-direction? How about y-direction?



Intensity profile



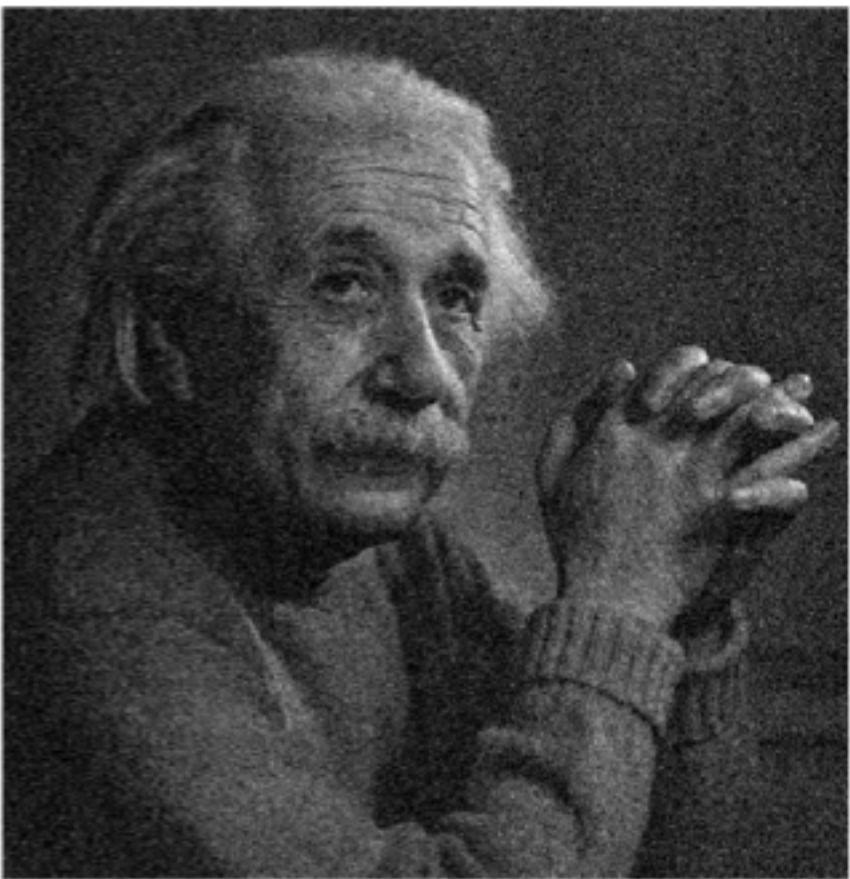
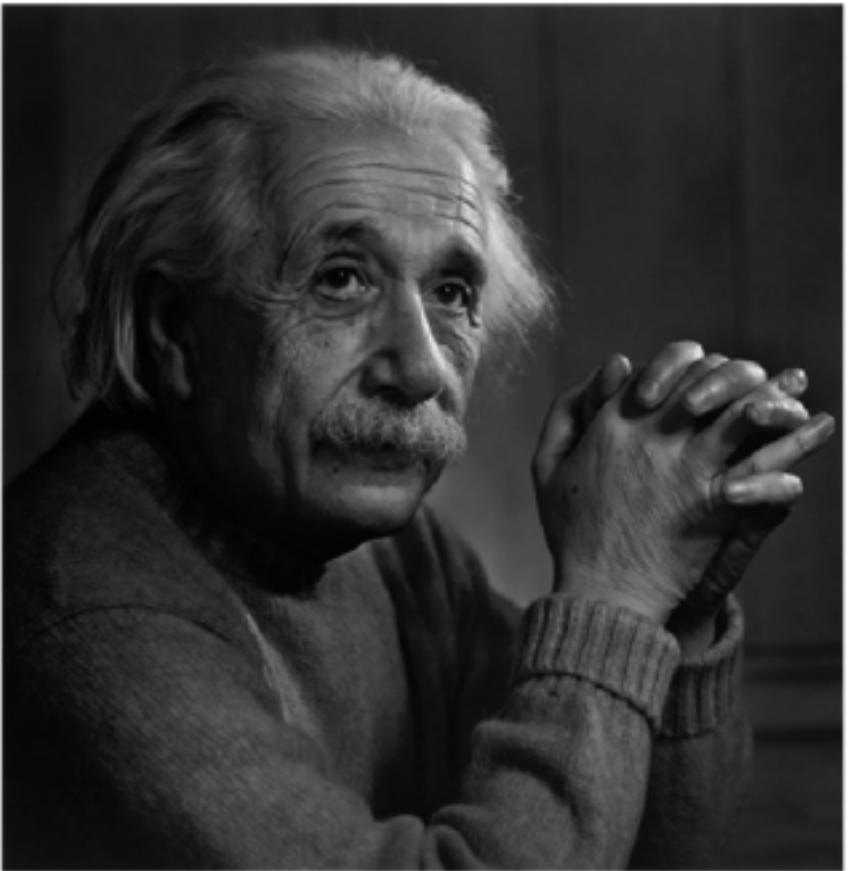


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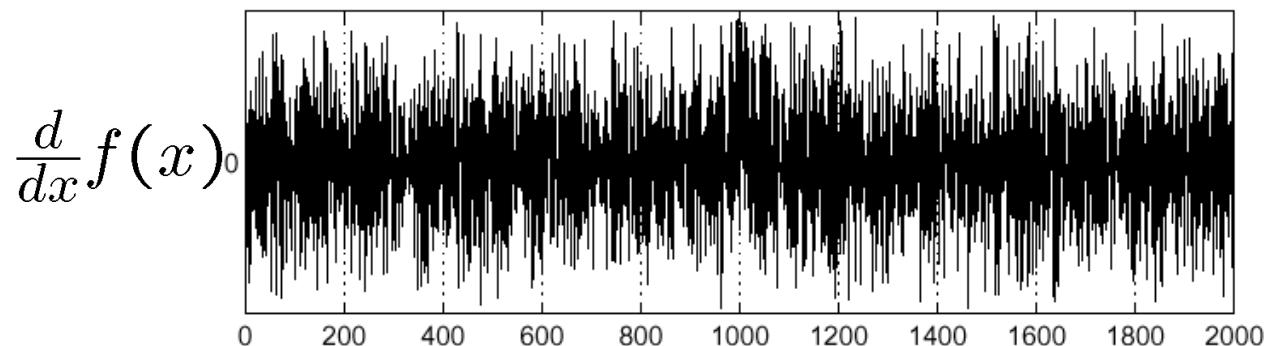
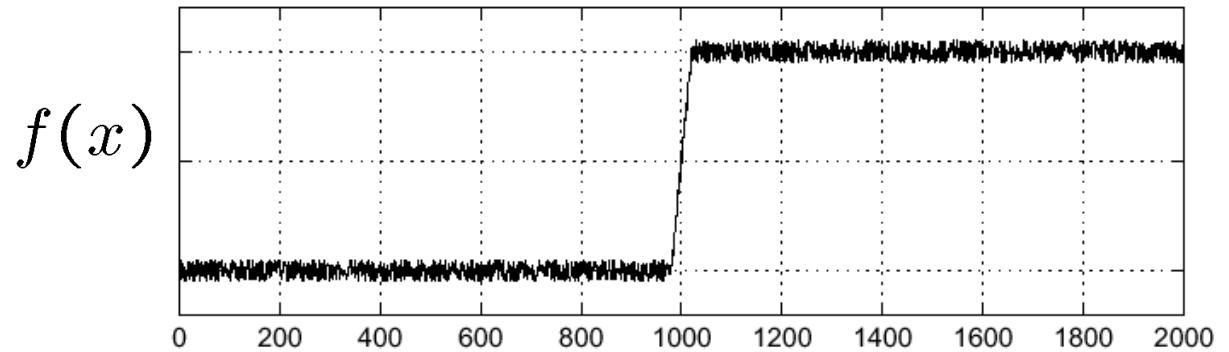
Effects of noise





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

- Finite 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 is to be done?



Effects of noise

- Finite 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 is to be done?
 - Smoothing the image should help, by forcing pixels different to their neighbors (=noise pixels?) to look more like neighbors



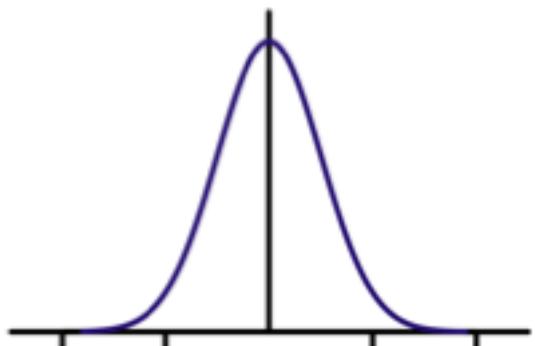
Smoothing with different filters

- Mean smoothing

$$\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$$

- Gaussian (smoothing * derivative)



$$\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

Smoothing with different filters

Mean

3x3



Gaussian

5x5



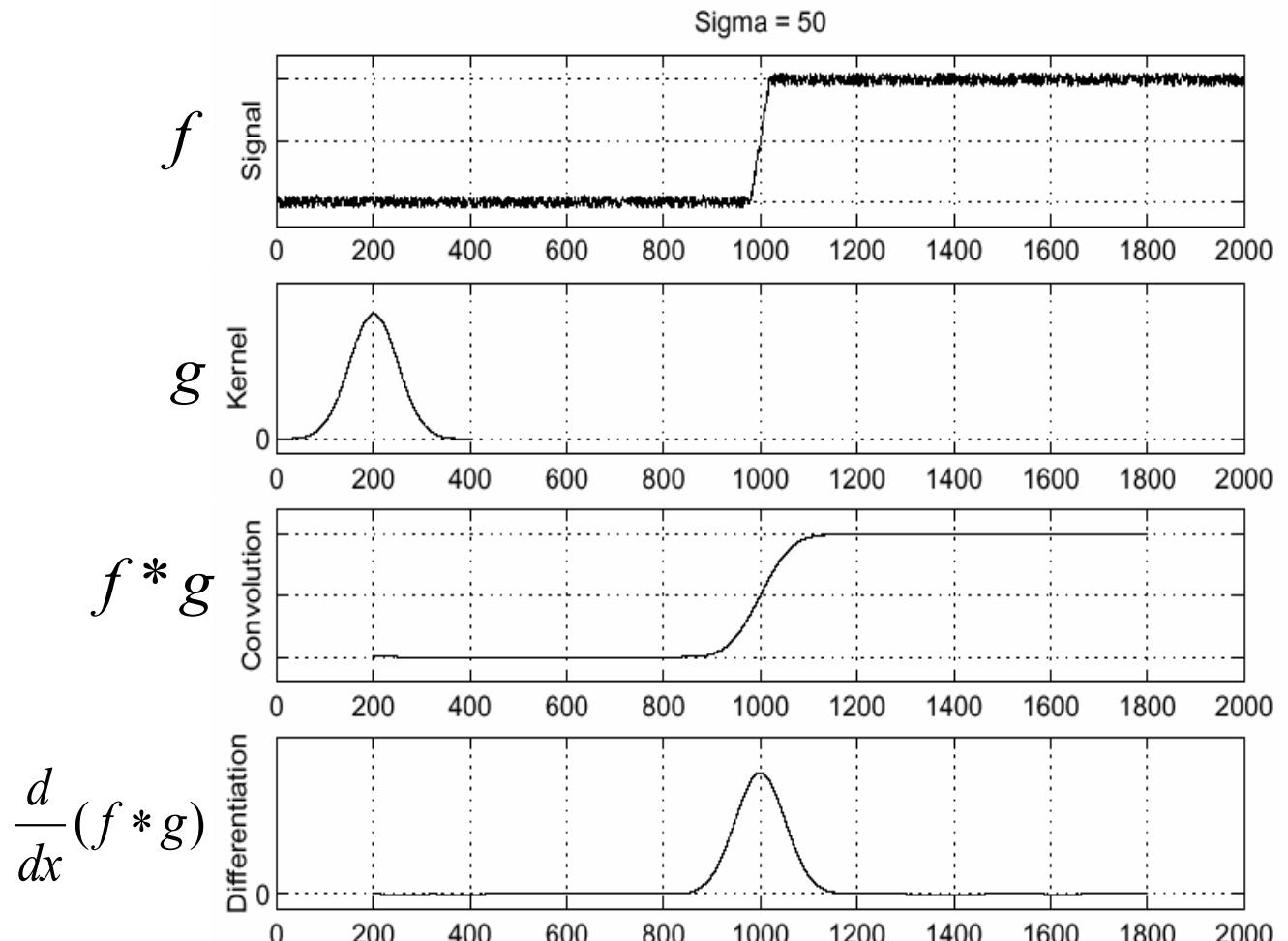
Median

7x7





Solution: smooth first



- To find edges, look for peaks in

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

Source: S. Seitz

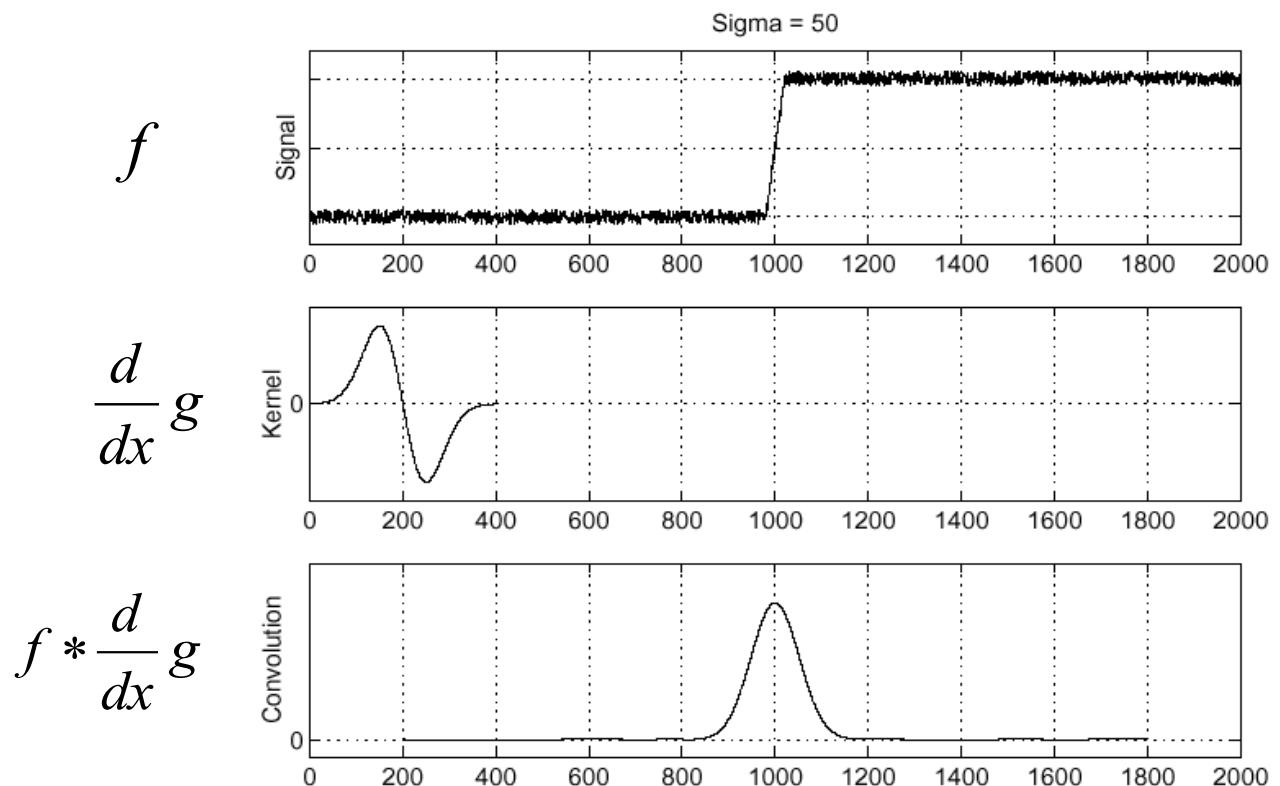


Derivative theorem of convolution

- This theorem gives us a very useful property:

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

- This saves us one operation:



Edges

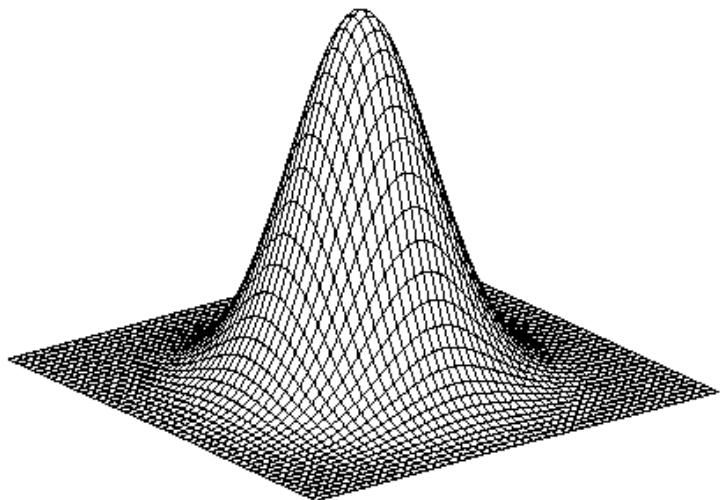
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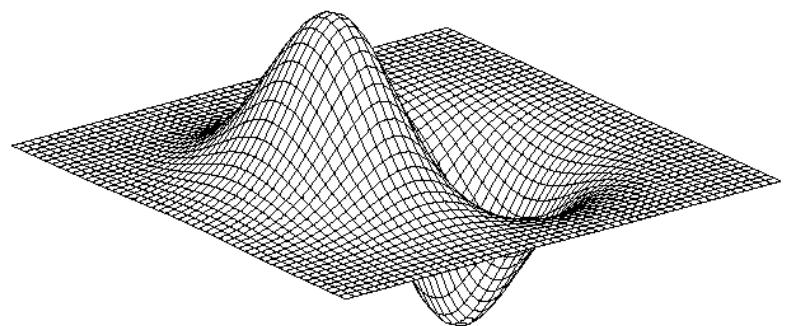
Source: S. Seitz



Derivative of Gaussian filter



$$\ast \quad [1 \ 0 \ -1] =$$

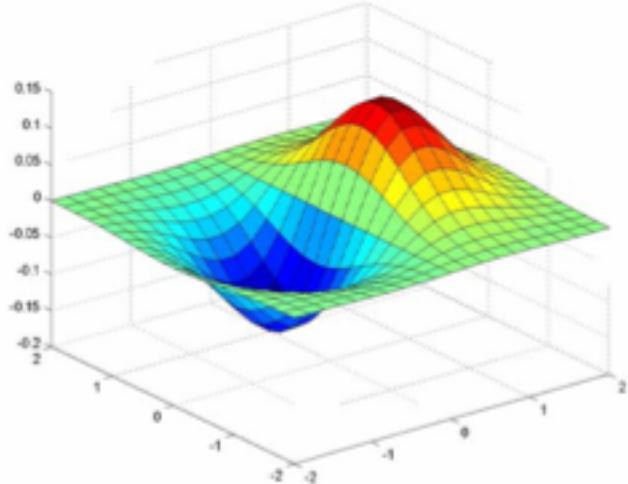


2D-gaussian

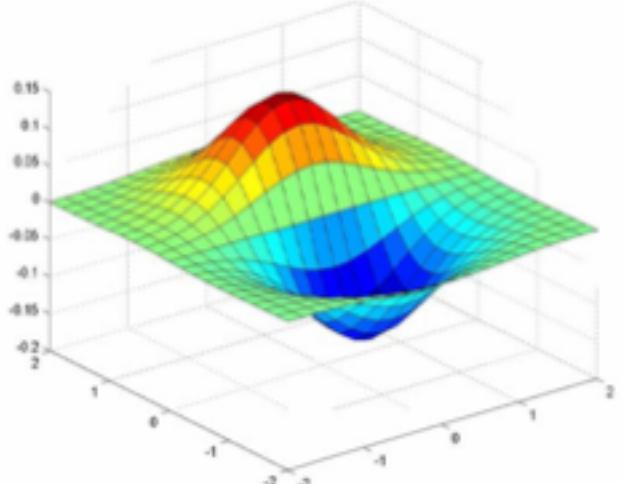
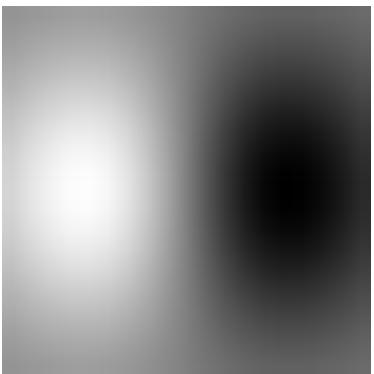
x - derivative



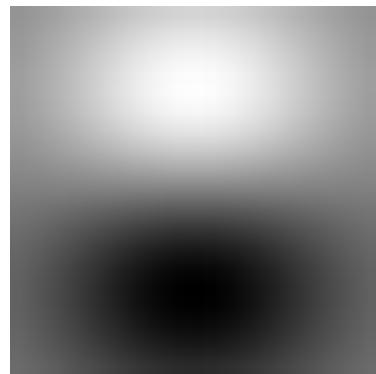
Derivative of Gaussian filter



x-direction



y-direction





Edges

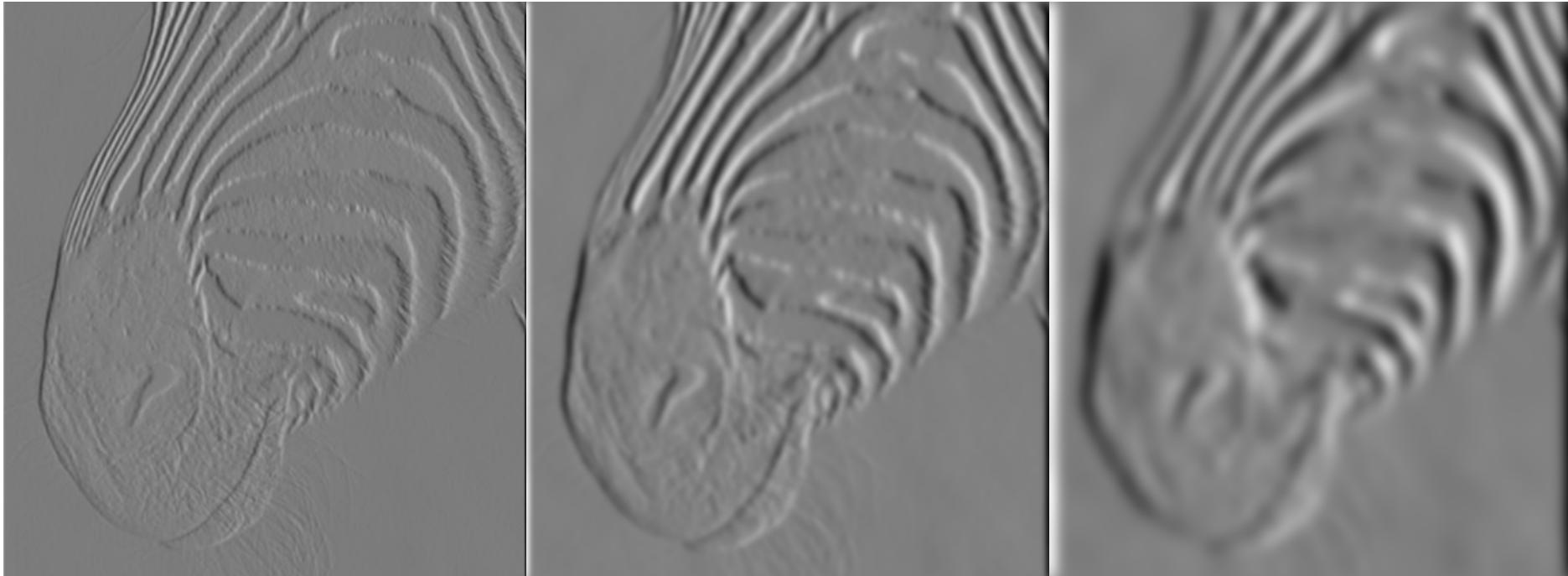
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Derivative of Gaussian filter





Tradeoff between smoothing at different scales



1 pixel

3 pixels

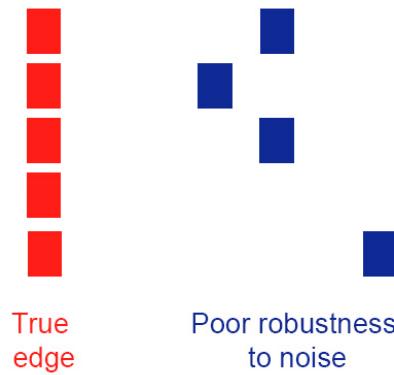
7 pixels

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



Designing an edge detector

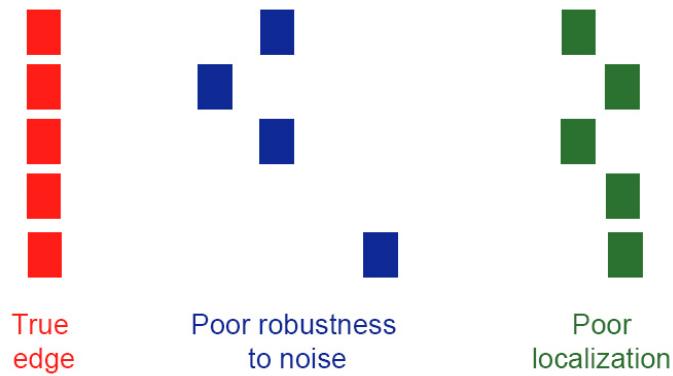
- Criteria for an “optimal” edge detector:
 - **Good detection:** the optimal detector must minimize the probability of false positives (detecting spurious edges caused by noise), as well as that of false negatives (missing real edges)





Designing an edge detector

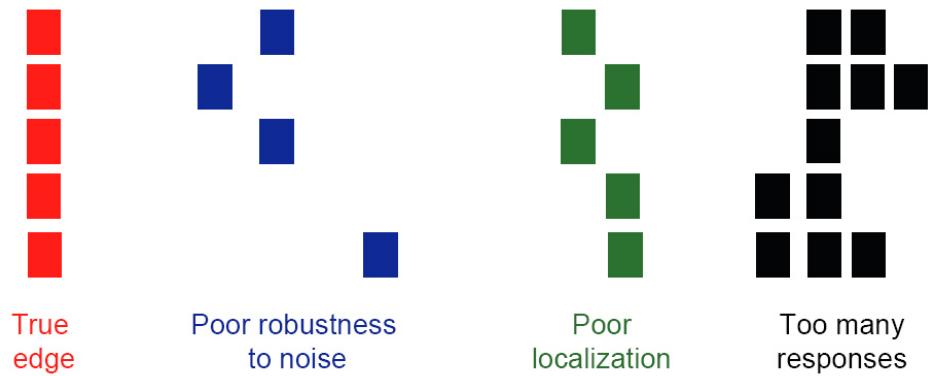
- Criteria for an “optimal” edge detector:
 - **Good detection:** the optimal detector must minimize the probability of false positives (detecting spurious edges caused by noise), as well as that of false negatives (missing real edges)
 - **Good localization:** the edges detected must be as close as possible to the true edges





Designing an edge detector

- Criteria for an “optimal” edge detector:
 - **Good detection:** the optimal detector must minimize the probability of false positives (detecting spurious edges caused by noise), as well as that of false negatives (missing real edges)
 - **Good localization:** the edges detected must be as close as possible to the true edges
 - **Single response:** the detector must return one point only for each true edge point; that is, minimize the number of local maxima around the true edge





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- **Sobel Edge detector**
- Canny edge detector
- Hough transform



Sobel Operator

- uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives
- one for horizontal changes, and one for vertical

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$



Sobel Operation

- Smoothing + differentiation

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} [+1 \quad 0 \quad -1]$$

 Gaussian smoothing  differentiation



Sobel Operation

- Magnitude:

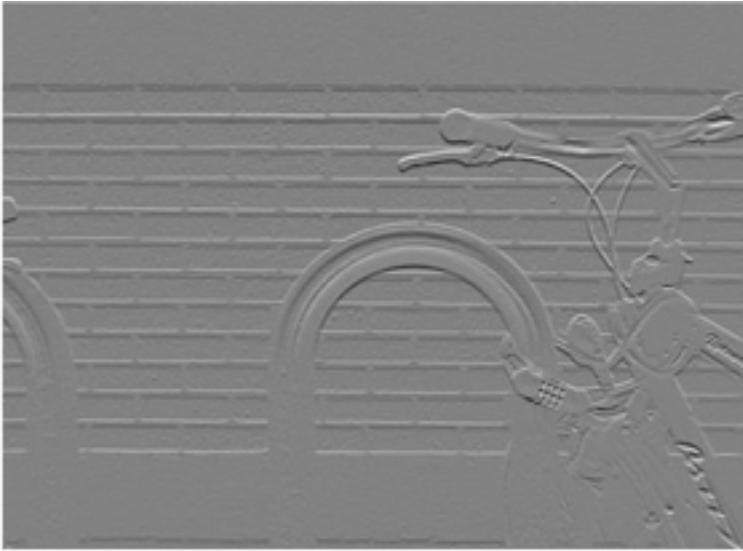
$$\mathbf{G} = \sqrt{\mathbf{G}_x^2 + \mathbf{G}_y^2}$$

- Angle or direction of the gradient:

$$\Theta = \text{atan}\left(\frac{\mathbf{G}_y}{\mathbf{G}_x}\right)$$



Sobel Filter example



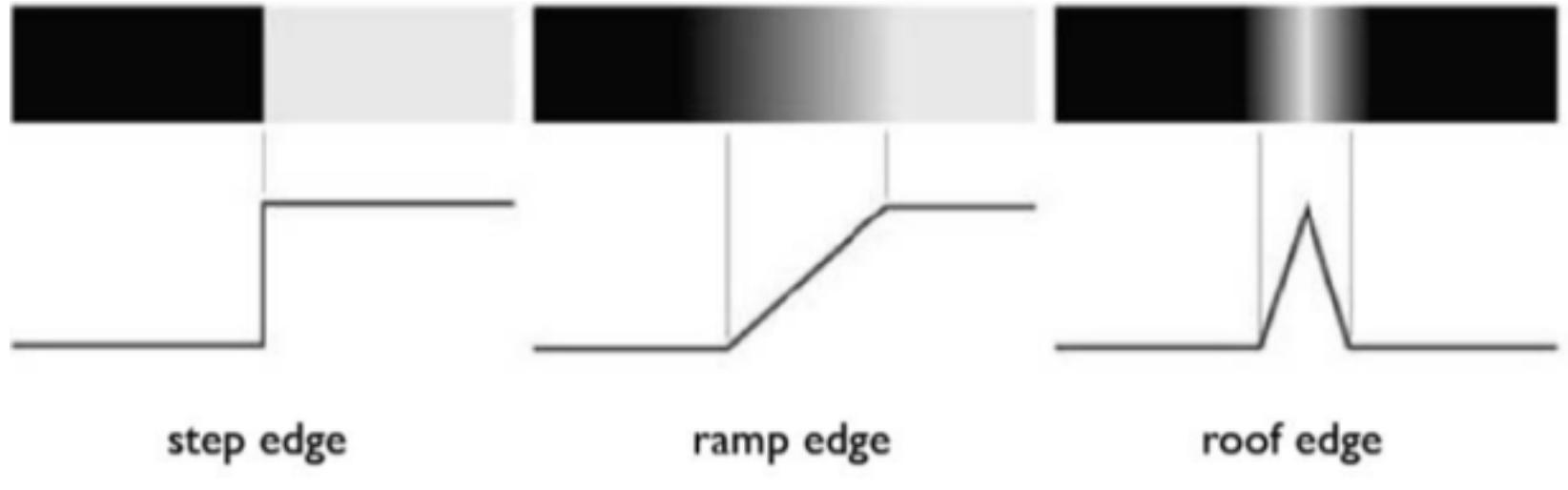
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Sobel Filter Problems



- Poor Localization (Trigger response in multiple adjacent pixels)
- Thresholding value favors certain directions over others
 - Can miss oblique edges more than horizontal or vertical edges
 - False negatives



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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.



Canny edge detector

- Suppress Noise
- Compute gradient magnitude and direction
- Apply Non-Maximum Suppression
 - Assures minimal response
- Use hysteresis and connectivity analysis to detect edges

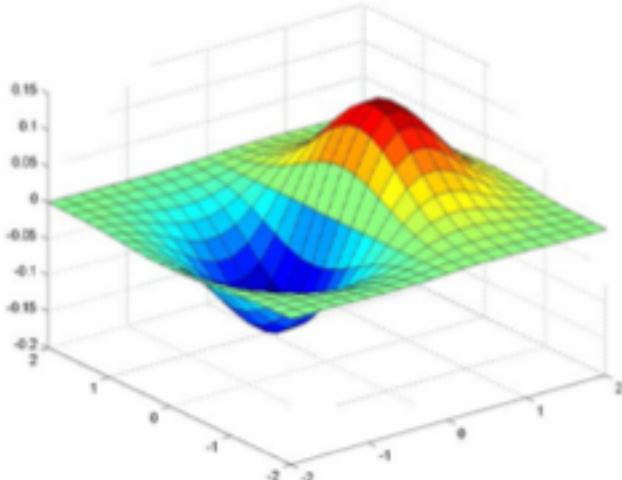
Example



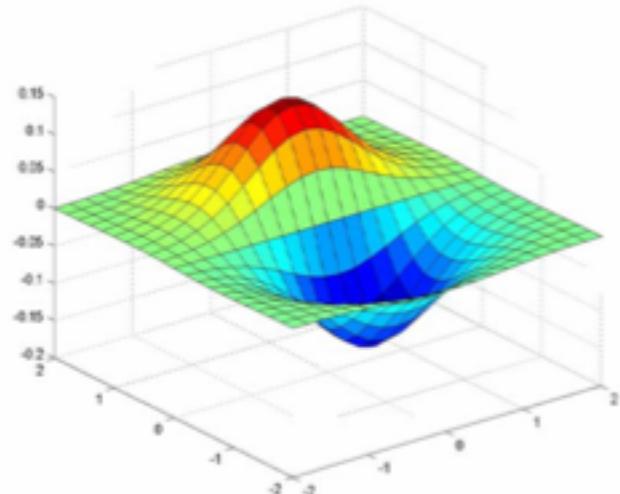
- original image



Derivative of Gaussian filter

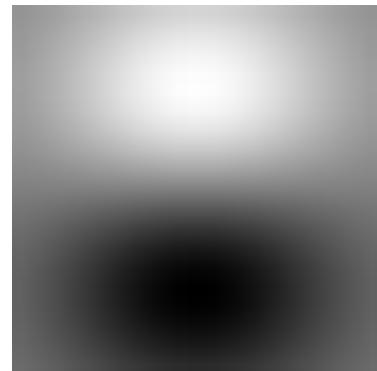
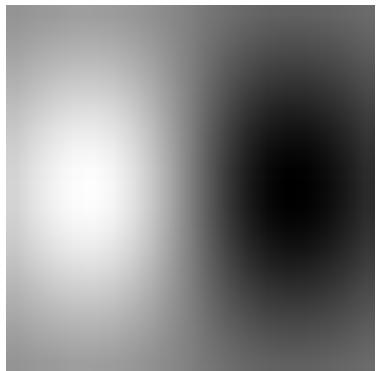


x-direction

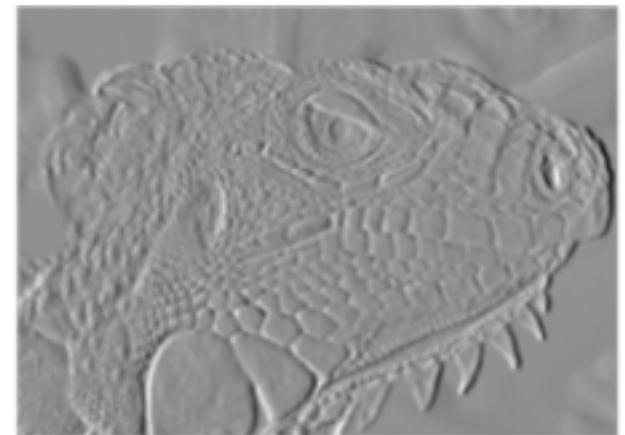


y-direction

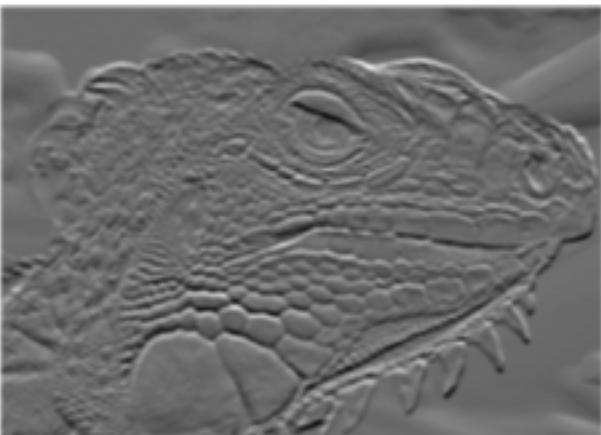
$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$



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



X-Derivative of Gaussian



Y-Derivative of Gaussian



Gradient Magnitude

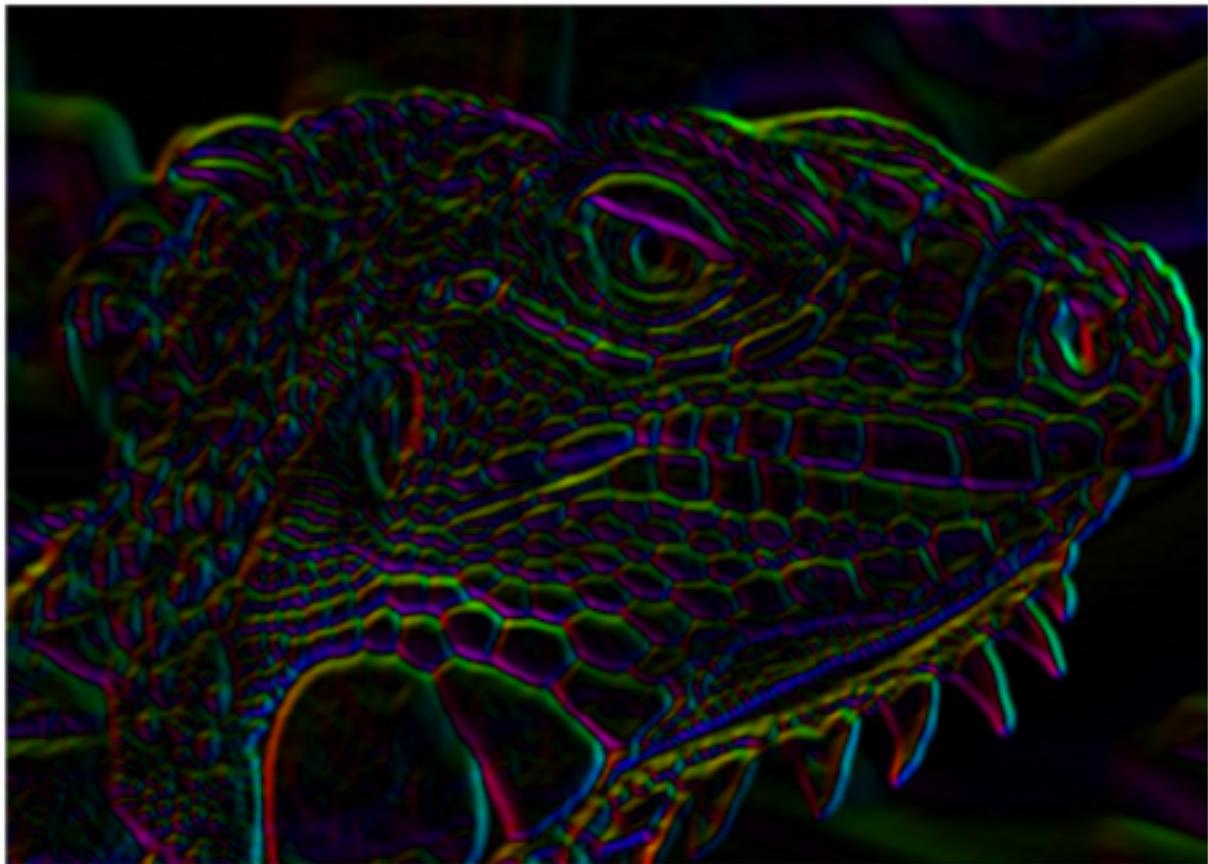
Source: J. Hayes



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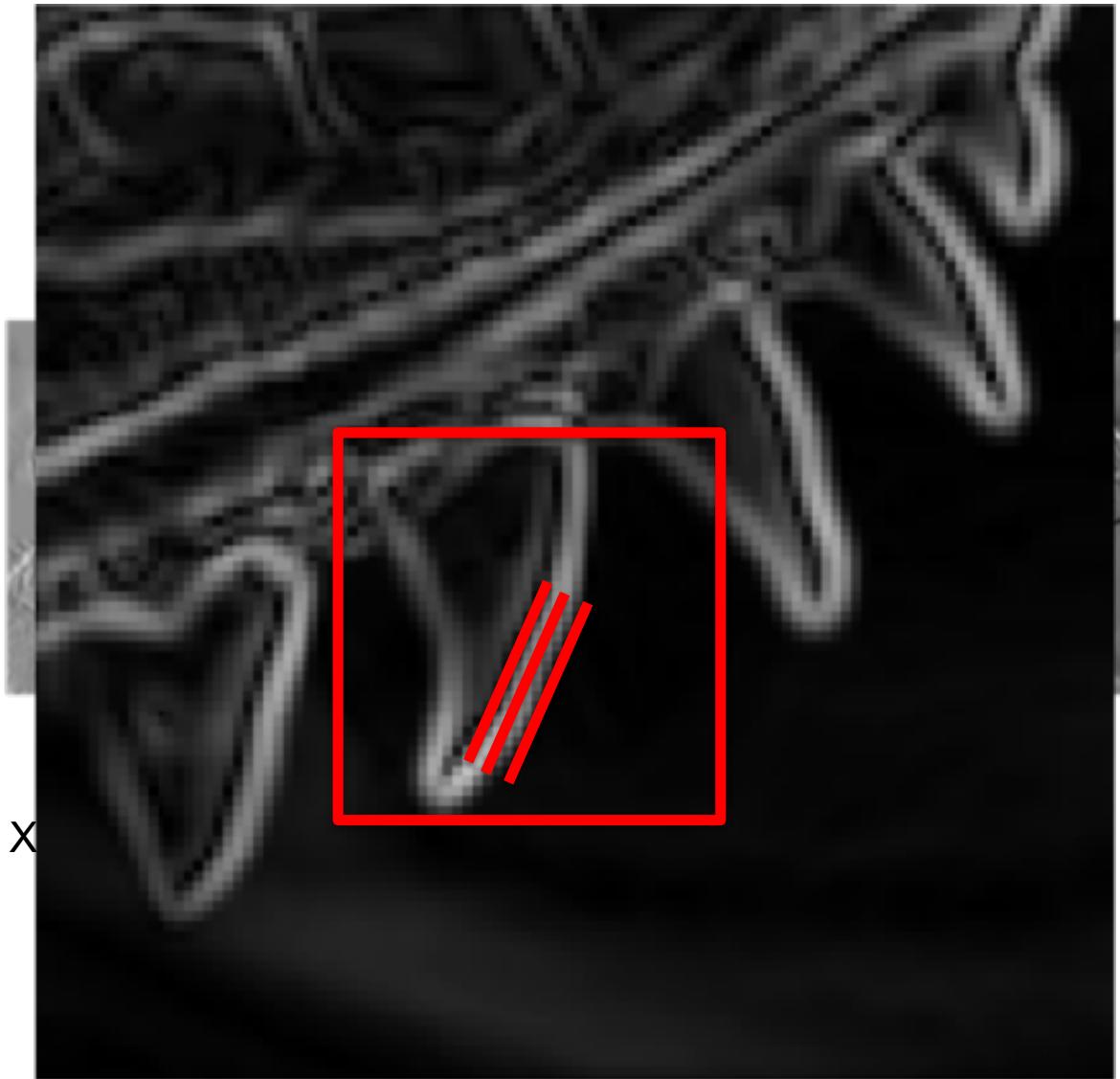
Get orientation at each pixel



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

Source: J. Hayes

Compute gradients (DoG)



Gradient Magnitude



Canny edge detector

- Suppress Noise
- Compute gradient magnitude and direction
- Apply Non-Maximum Suppression
 - Assures minimal response



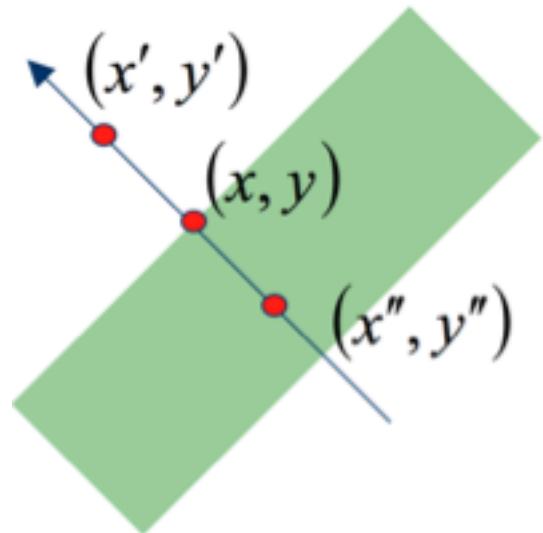
Non-maximum suppression

- Edge occurs where gradient reaches a maxima
- Suppress non-maxima gradient even if it passes threshold
- Only eight angle directions possible
 - Suppress all pixels in each direction which are not maxima
 - Do this in each marked pixel neighborhood



Remove spurious gradients

$|\nabla G|(x, y)$ is the gradient at pixel (x, y)



$$M(x, y) = \begin{cases} |\nabla G|(x, y) & \text{if } |\nabla G|(x, y) > |\nabla G|(x', y') \\ & \& |\nabla G|(x, y) > |\nabla G|(x'', y'') \\ 0 & \text{otherwise} \end{cases}$$

x' and x'' are the neighbors of x along normal direction to an edge

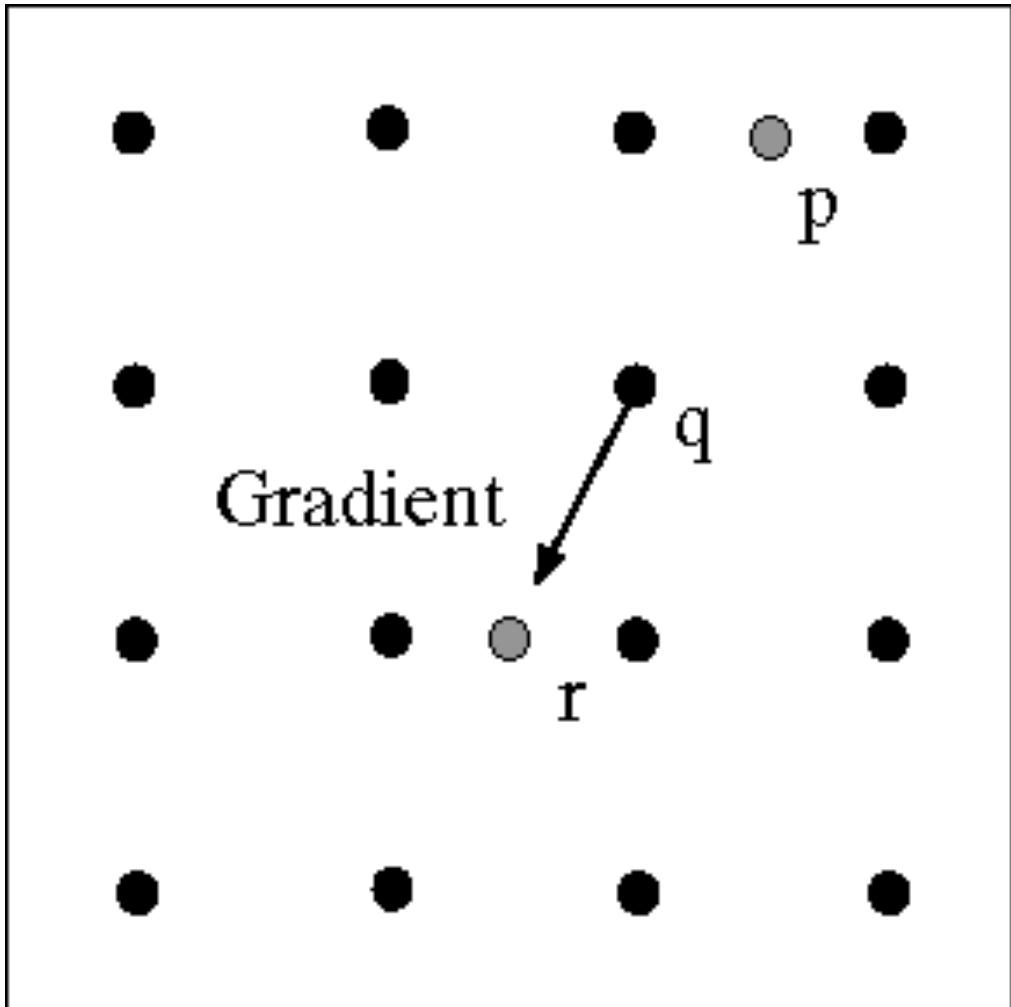


Non-maximum suppression

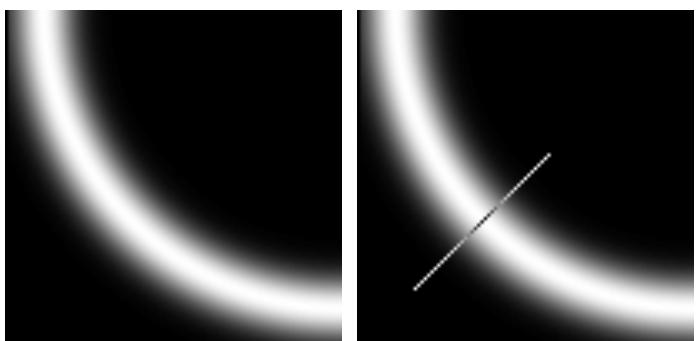
- Edge occurs where gradient reaches a maxima
- Suppress non-maxima gradient even if it passes threshold
- Only eight angle directions possible
 - Suppress all pixels in each direction which are not maxima
 - Do this in each marked pixel neighborhood



Non-maximum suppression



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





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Non-max Suppression



Before



After



Canny edge detector

- Suppress Noise
- Compute gradient magnitude and direction
- Apply Non-Maximum Suppression
 - Assures minimal response
- Use hysteresis and connectivity analysis to detect edges



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Hysteresis thresholding

- Avoid streaking near threshold value
- Define two thresholds: Low and High
 - If less than Low, not an edge
 - If greater than High, strong edge
 - If between Low and High, weak edge



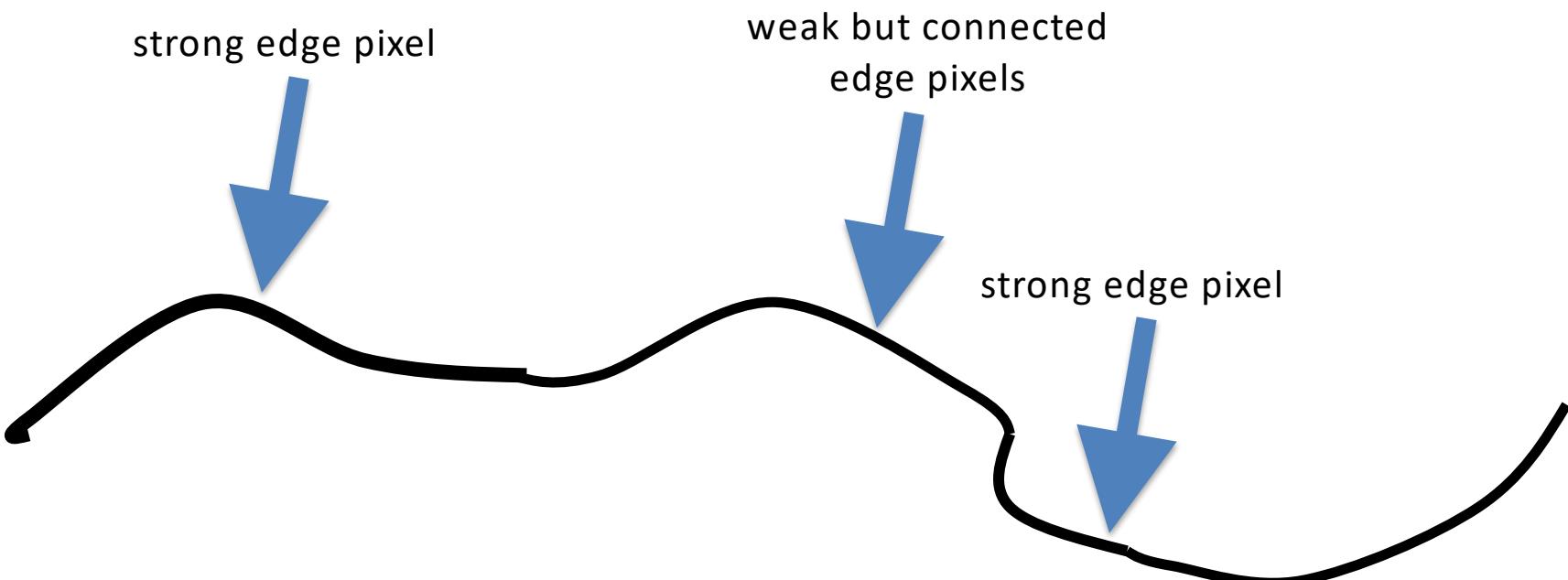
Hysteresis thresholding

If the gradient at a pixel is

- above High, declare it as an ‘strong edge pixel’
- below Low, declare it as a “non-edge-pixel”
- between Low and High
 - Consider its neighbors iteratively then declare it an “edge pixel” if it is connected to an ‘strong edge pixel’ directly or via pixels between Low and High



Hysteresis thresholding



Source: S. Seitz



Final Canny Edges

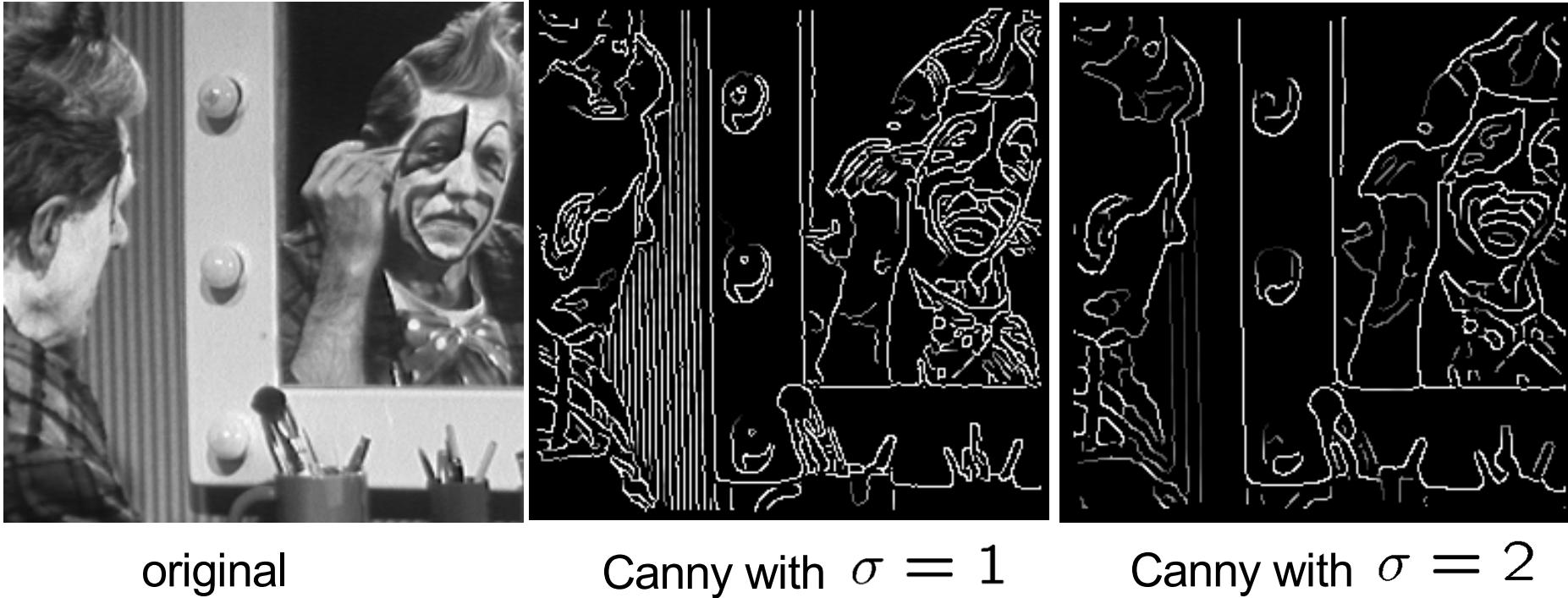




Canny edge detector

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

Effect of σ (Gaussian kernel spread/size)



The choice of σ depends on desired behavior

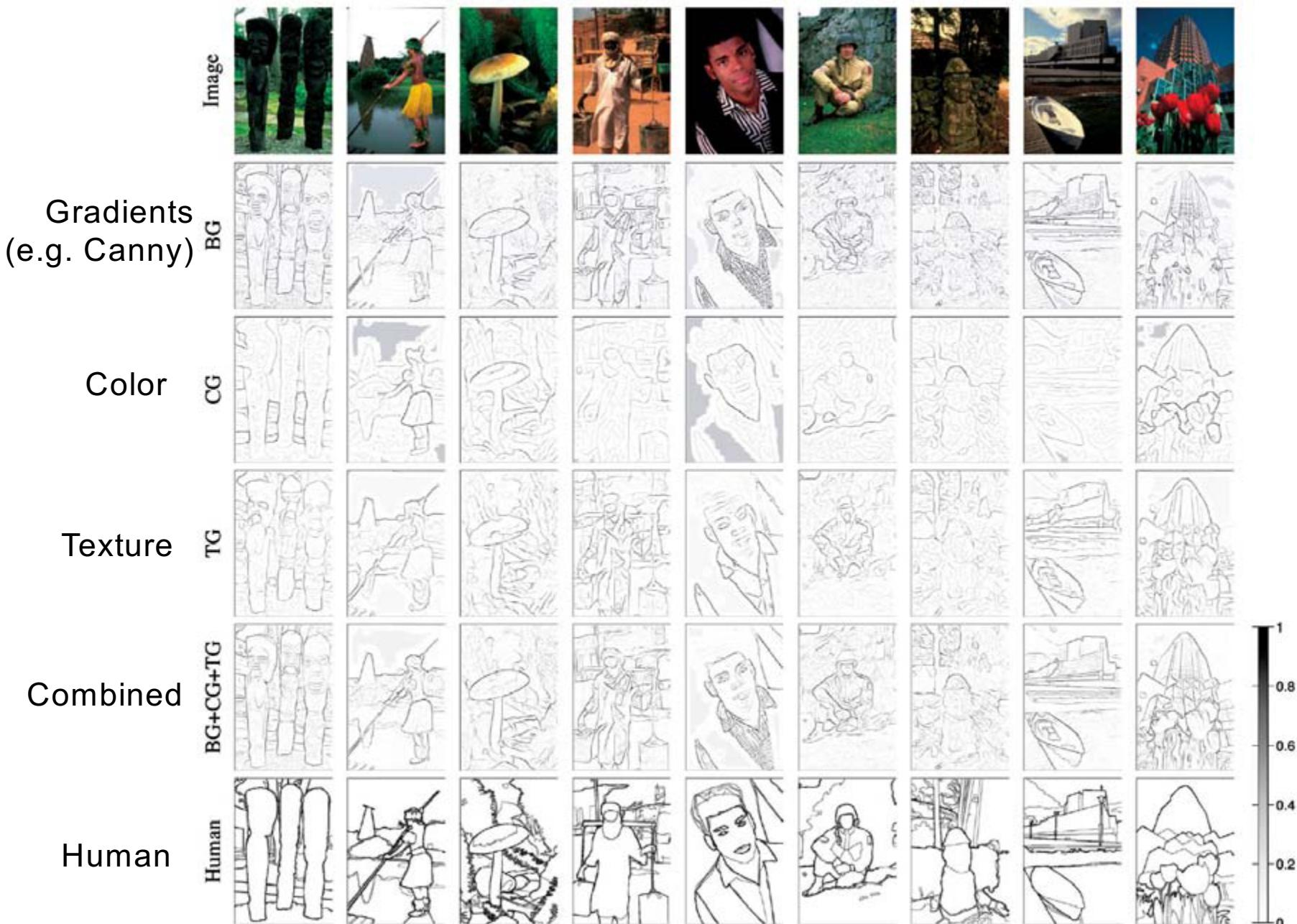
- large σ detects large scale edges
- small σ detects fine features

Source: S. Seitz



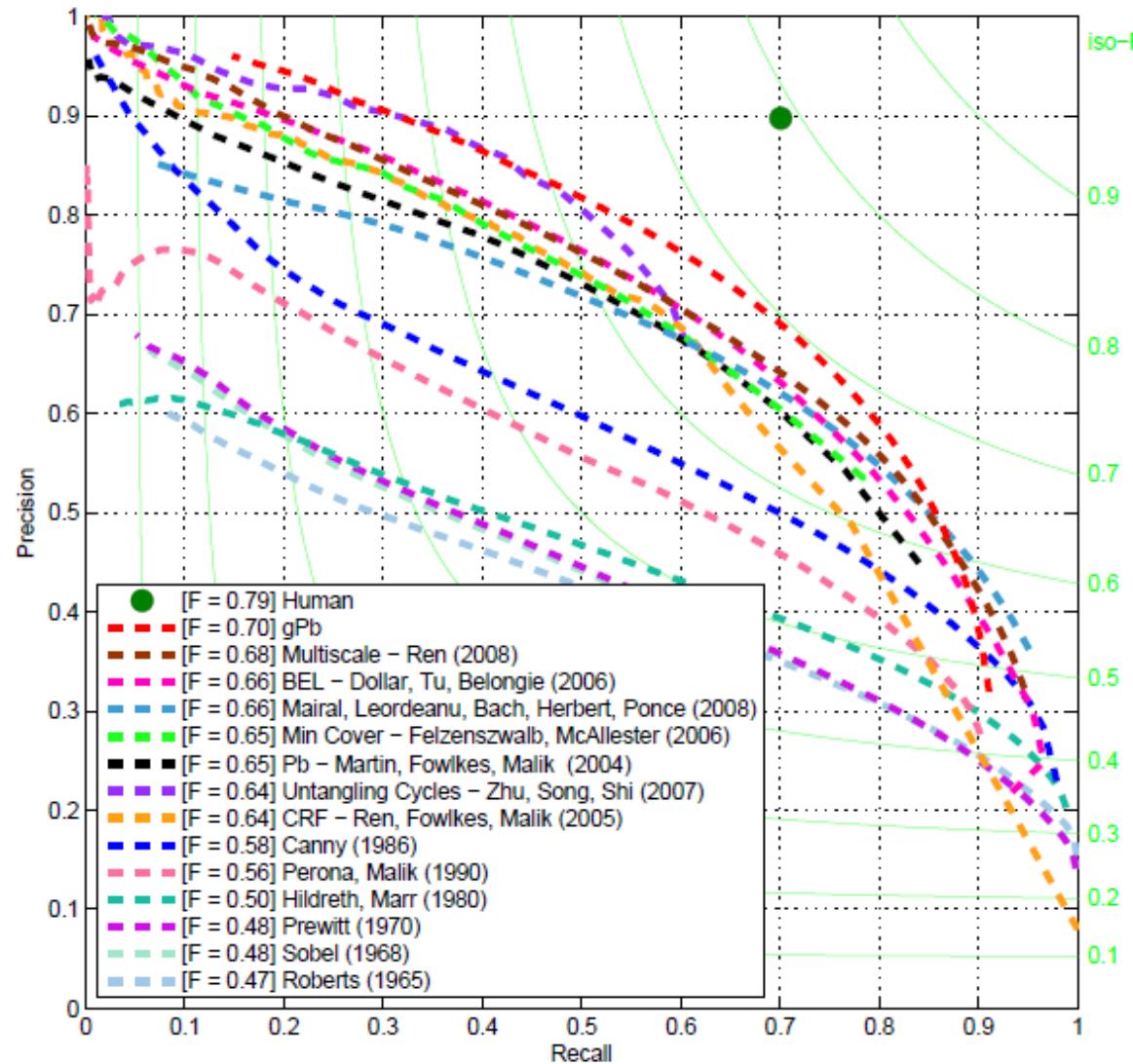
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45 years of boundary detection





What we will learn today

- Edge detection
- Image Gradients
- A simple edge detector
- Sobel Edge detector
- Canny edge detector
- Hough Transform



Intro to Hough transform

- The Hough transform (HT) can be used to detect lines.
- It was introduced in 1962 (Hough 1962) and first used to find lines in images a decade later (Duda 1972).
- The goal is to find the location of lines in images.
- **Caveat:** Hough transform can detect lines, circles and other structures ONLY if their parametric equation is known.
- It can give robust detection under noise and partial occlusion

Prior to Hough transform

- Assume that we have performed some edge detection, and a thresholding of the edge magnitude image.
- Thus, we have some pixels that may partially describe the boundary of some objects.





Detecting lines using Hough transform

- We wish to find sets of pixels that make up straight lines.
- Consider a point of known coordinates $(x_i; y_i)$
 - There are many lines passing through the point (x_i, y_i) .
- Straight lines that pass that point have the form $y_i = a * x_i + b$
 - Common to them is that they satisfy the equation for some set of parameters (a, b)

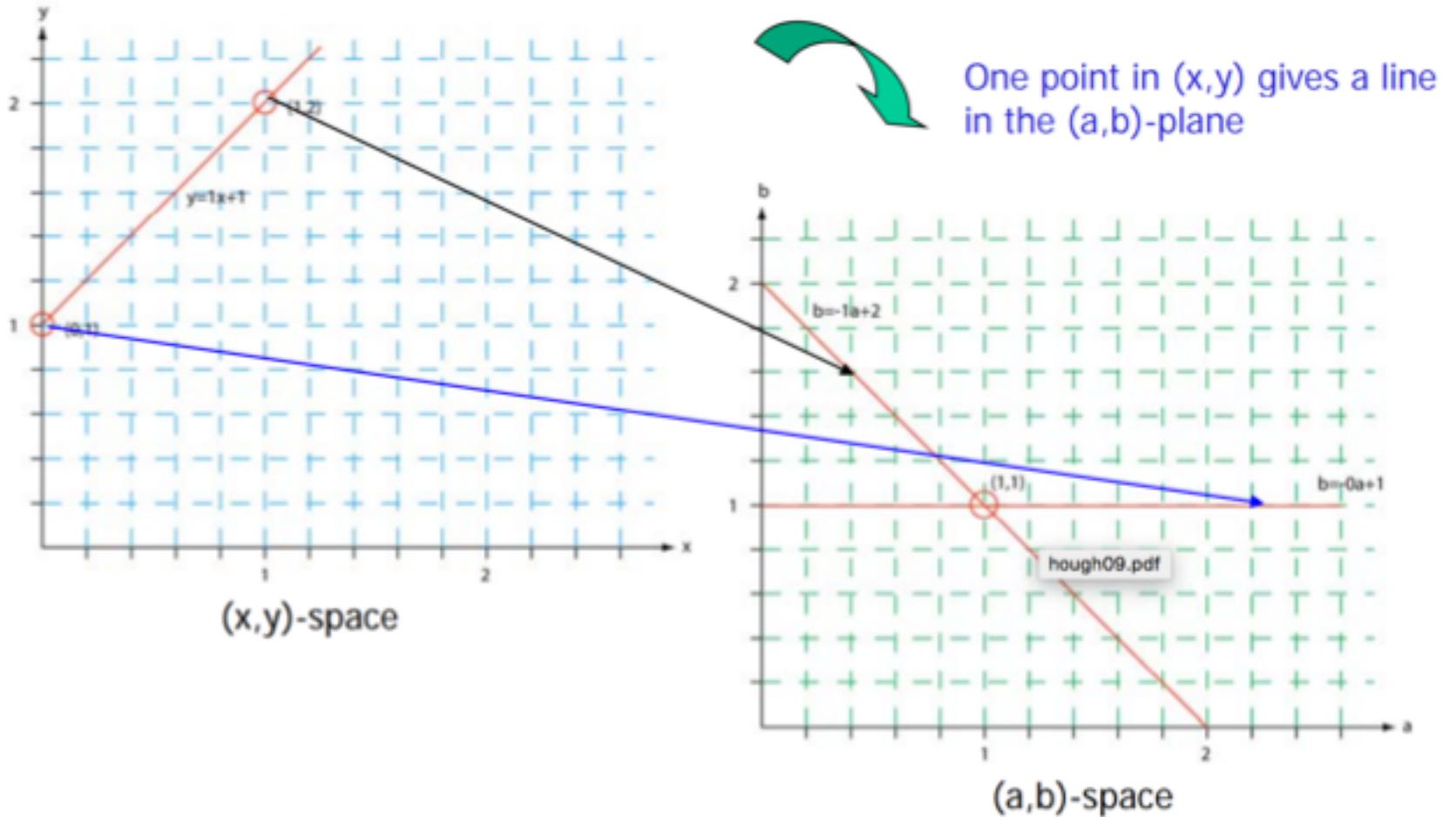


Detecting lines using Hough transform

- This equation can obviously be rewritten as follows:
 - $b = -a^*x_i + y_i$
 - We can now consider x and y as parameters
 - a and b as variables.
- This is a line in (a, b) space parameterized by x and y .
 - So: a single point in x_1, y_1 -space gives a line in (a, b) space.
 - Another point (x_2, y_2) will give rise to another line (a, b) space.

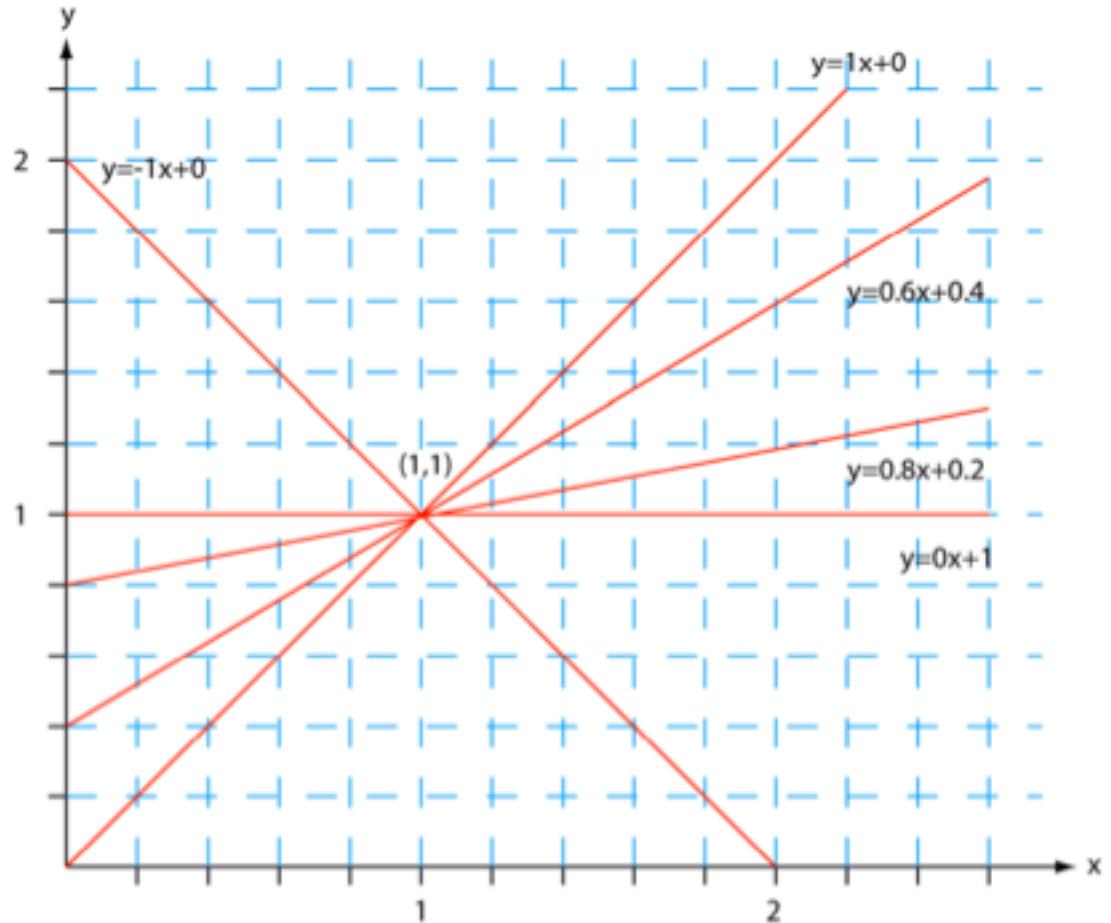


Detecting lines using Hough transform





Detecting lines using Hough transform





Detecting lines using Hough transform

- Two points (x_1, y_1) and (x_2, y_2) define a line in the (x, y) plane.
- These two points give rise to two different lines in (a, b) space.
- In (a, b) space these lines will intersect in a point (a', b')
- All points on the line defined by (x_1, y_1) and (x_2, y_2) in (x, y) space will parameterize lines that intersect in (a', b') in (a, b) space.

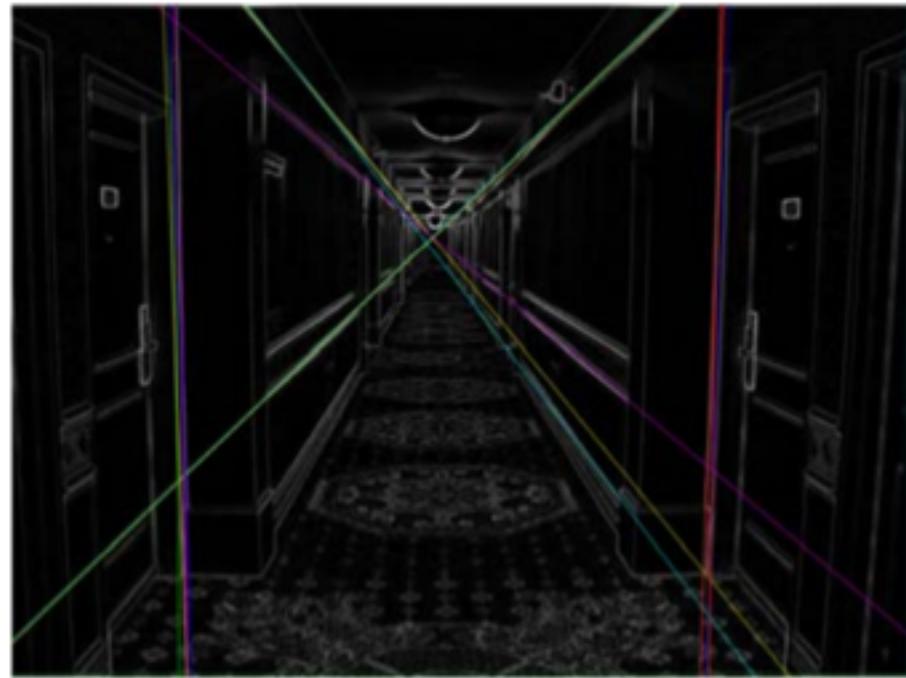


Algorithm for Hough transform

- Quantize the parameter space (a b) by dividing it into cells
- This quantized space is often referred to as the accumulator cells.
- Count the number of times a line intersects a given cell.
 - For each pair of points (x_1, y_1) and (x_2, y_2) detected as an edge, find the intersection (a', b') in (a , b)space.
 - Increase the value of a cell in the range $[[a_{\min}, a_{\max}], [b_{\min}, b_{\max}]]$ that (a', b') belongs to.
 - Cells receiving more than a certain number of counts (also called ‘votes’) are assumed to correspond to lines in (x, y) space.

Output of Hough transform

- Here are the top 20 most voted lines in the image:





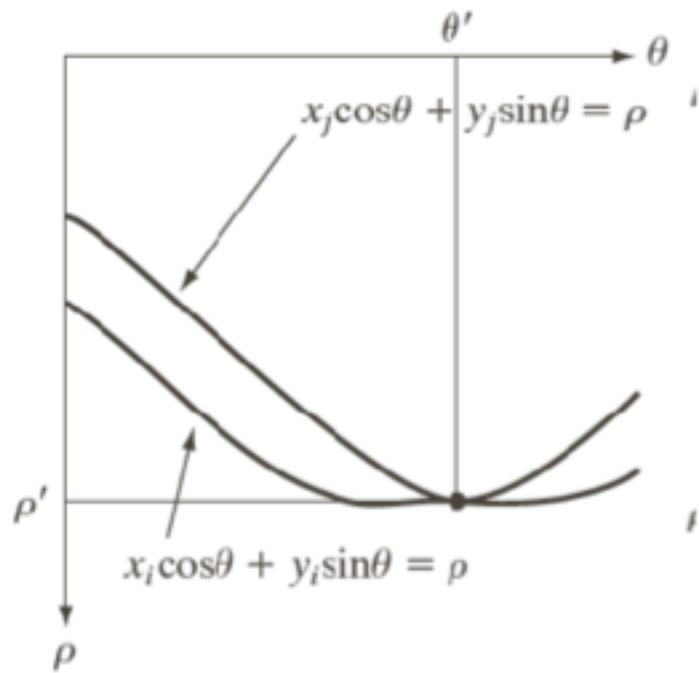
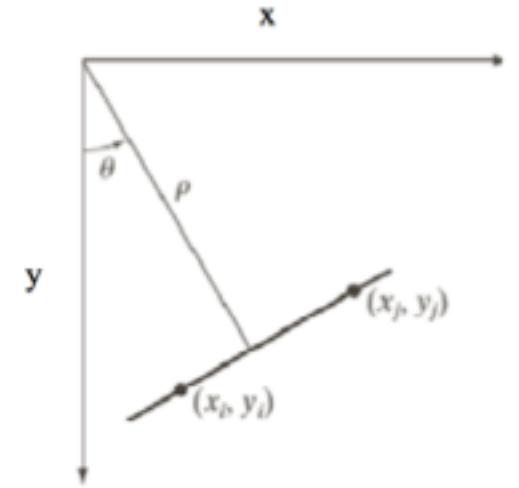
Other Hough transformations

- We can represent lines as polar coordinates instead of $y = a*x + b$
- Polar coordinate representation:
 - $x*\cos\theta + y*\sin\theta = \rho$
- Can you figure out the relationship between
 - $(x\ y)$ and $(\rho\ \theta)$?



Other Hough transformations

- Note that lines in $(x \ y)$ space are not lines in $(\rho \ \theta)$ space, unlike $(a \ b)$ space.
- A horizontal line will have $\theta=0$ and ρ equal to the intercept with the y-axis.
- A vertical line will have $\theta=90$ and ρ equal to the intercept with the x-axis.





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Example video

- <https://youtu.be/4zHbl-fFII?t=3m35s>



Concluding remarks

- Advantages:
 - Conceptually simple.
 - Easy implementation
 - Handles missing and occluded data very gracefully.
 - Can be adapted to many types of forms, not just lines
- Disadvantages:
 - Computationally complex for objects with many parameters.
 - Looks for only one single type of object
 - Can be “fooled” by “apparent lines”.
 - The length and the position of a line segment cannot be determined.
 - Co-linear line segments cannot be separated.



What we will learn today

- Edge detection
- Image Gradients
- A simple edge detector
- Sobel Edge detector
- Canny edge detector
- Hough Transform