

Edge and Line Detection

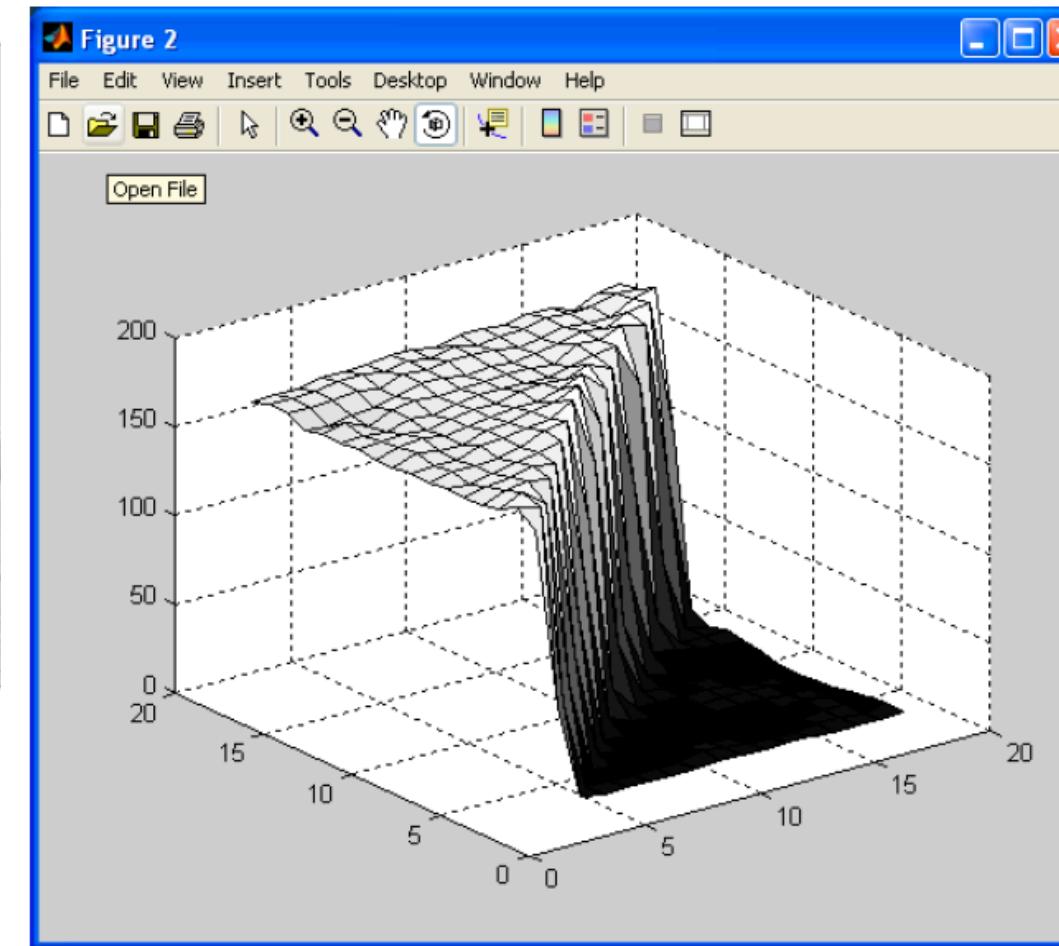
Chetan Arora

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What are Edges?

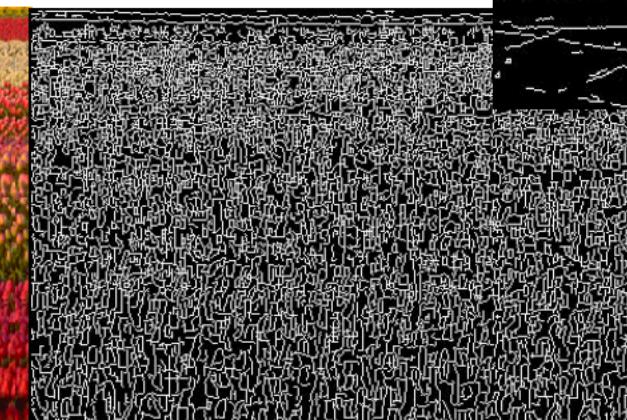
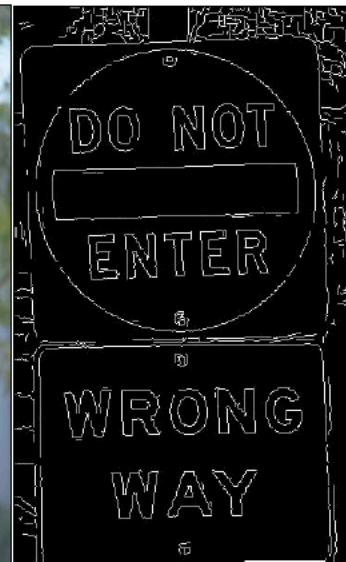
- Mathematically: discontinuity in intensity or color.





What are Edges?

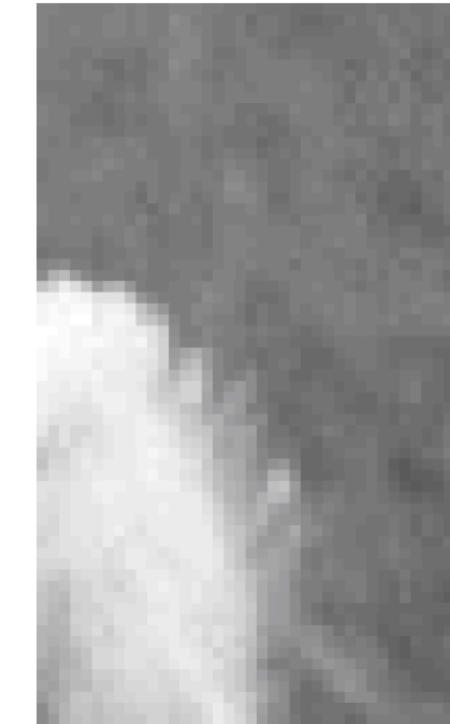
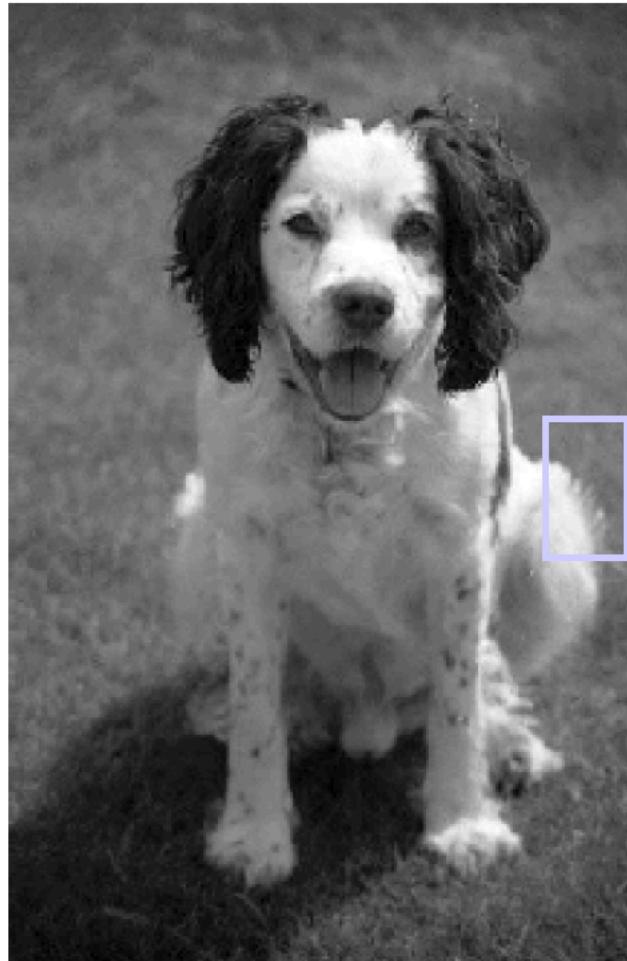
- Mathematically: discontinuity in intensity or color.





What are Edges?

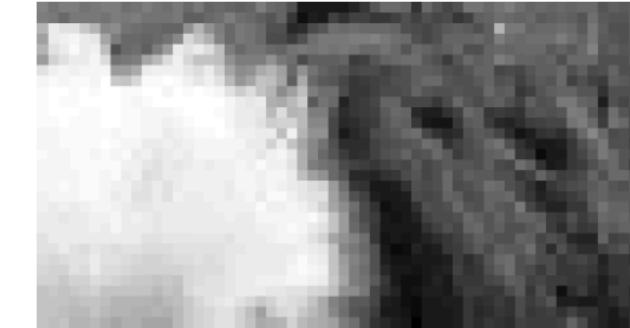
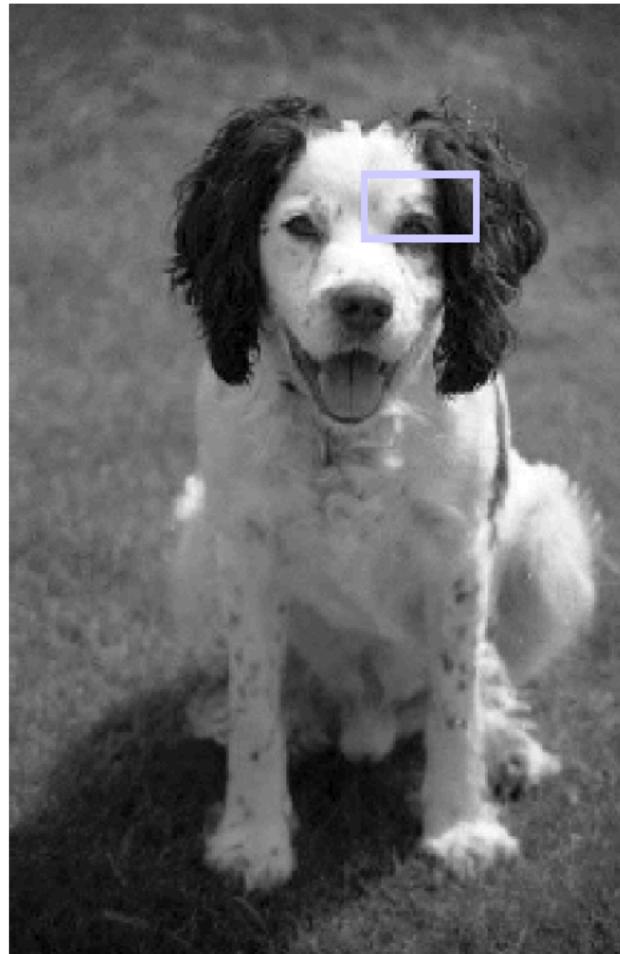
- Semantically: object boundaries





What are Edges?

- Semantically: boundaries of material properties



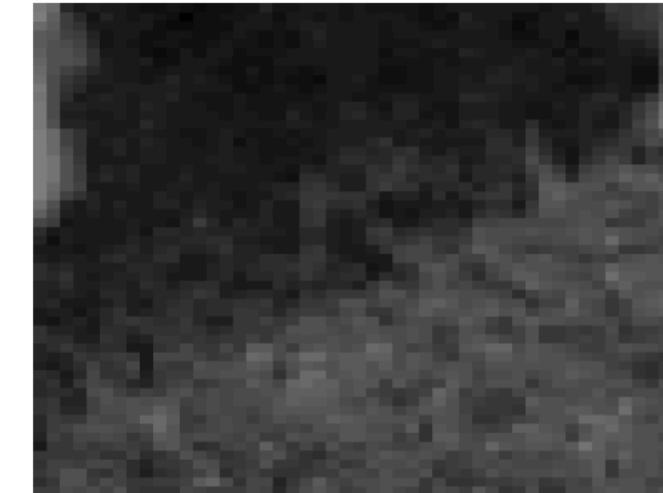


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What are Edges?

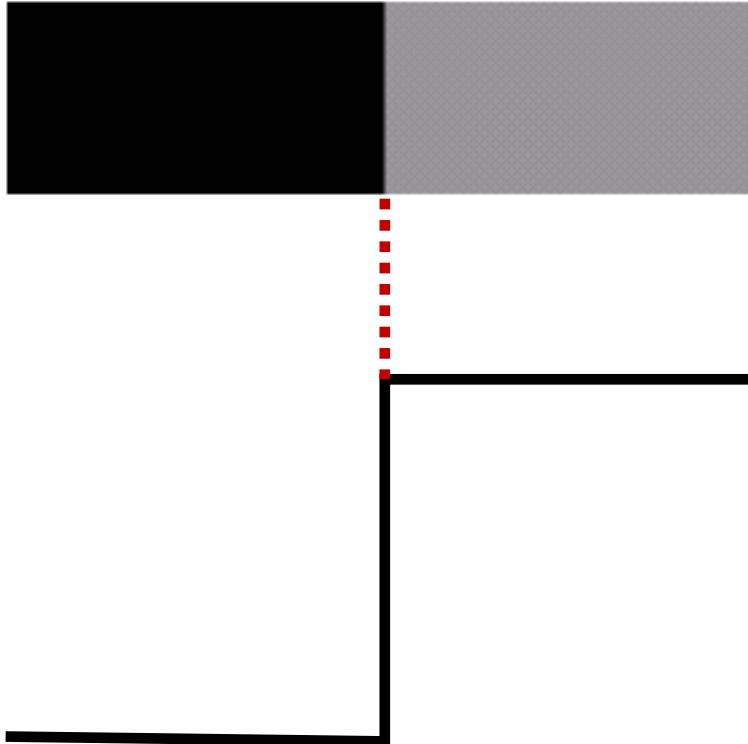
- Semantically: lighting boundary



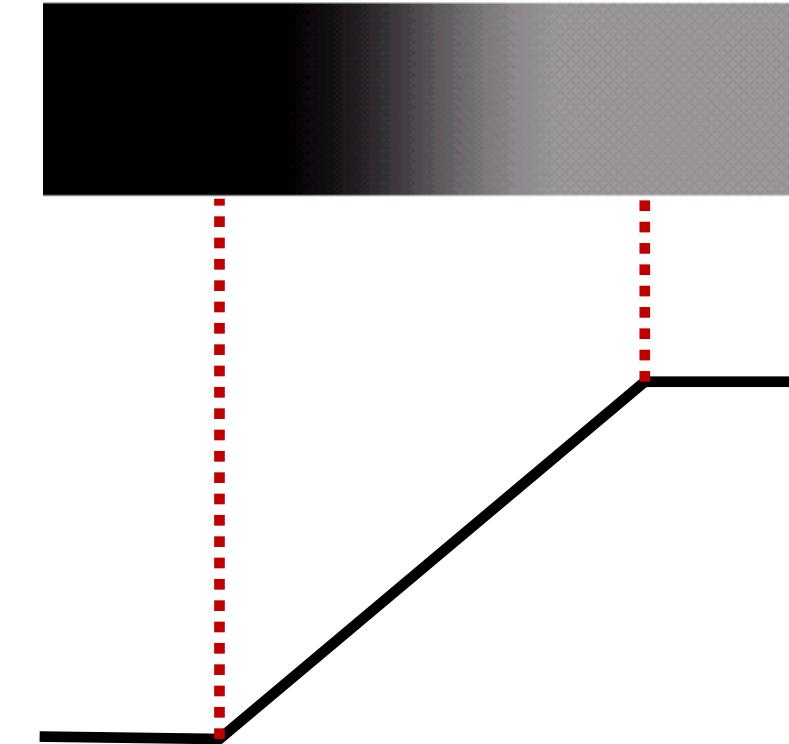


Types of Edges

Step edge



Ramp edge



Gray-level profile of the edge



Derivative Response to a Ramp Edge

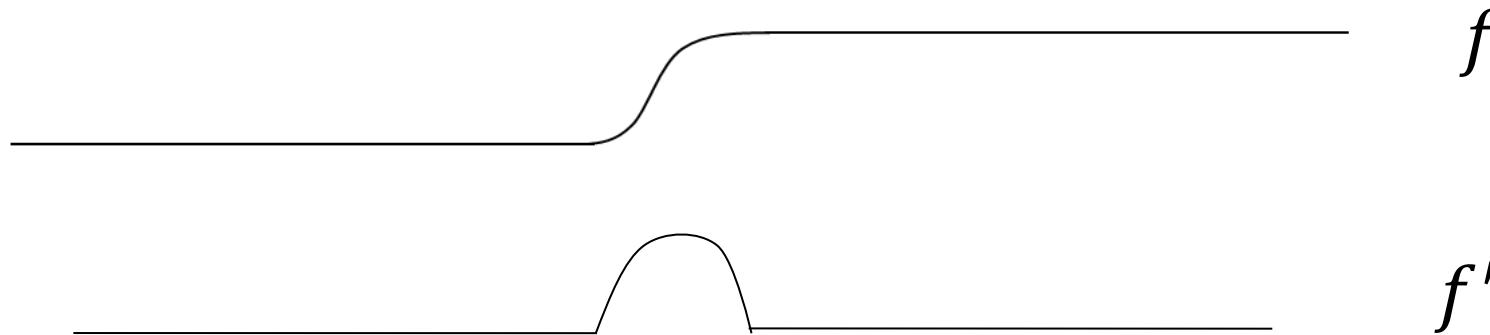
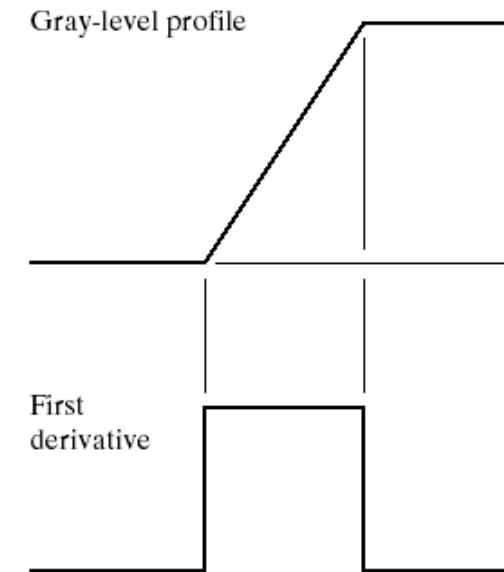
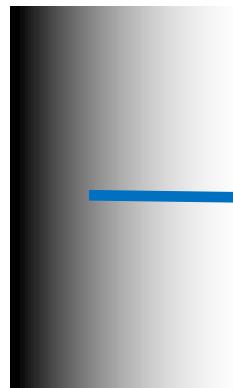




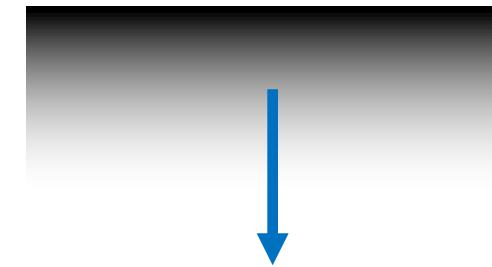
Image Gradient

- Gradient: The vector of derivatives $\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right) = (I_x, I_y)$
- Gradient: The direction of most rapid change in intensity

$$\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right)$$



$$\nabla f = \left(\frac{\partial f}{\partial x}, 0 \right)$$



$$\nabla f = \left(0, \frac{\partial f}{\partial y} \right)$$

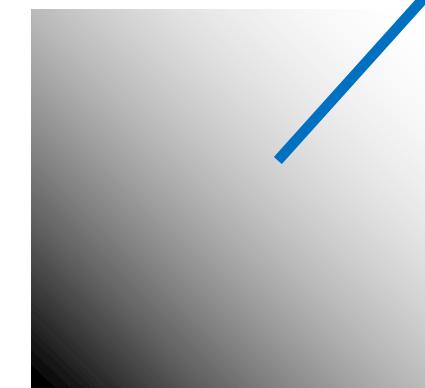




Image Gradient

$$\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right)$$

- Edge (Gradient) Magnitude: $|\nabla f| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$
- Edge (Gradient) Direction: $\alpha = \tan^{-1} \left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}} \right)$
- Directional Derivative in direction α : $\cos(\alpha) \frac{\partial f}{\partial x} + \sin(\alpha) \frac{\partial f}{\partial y}$



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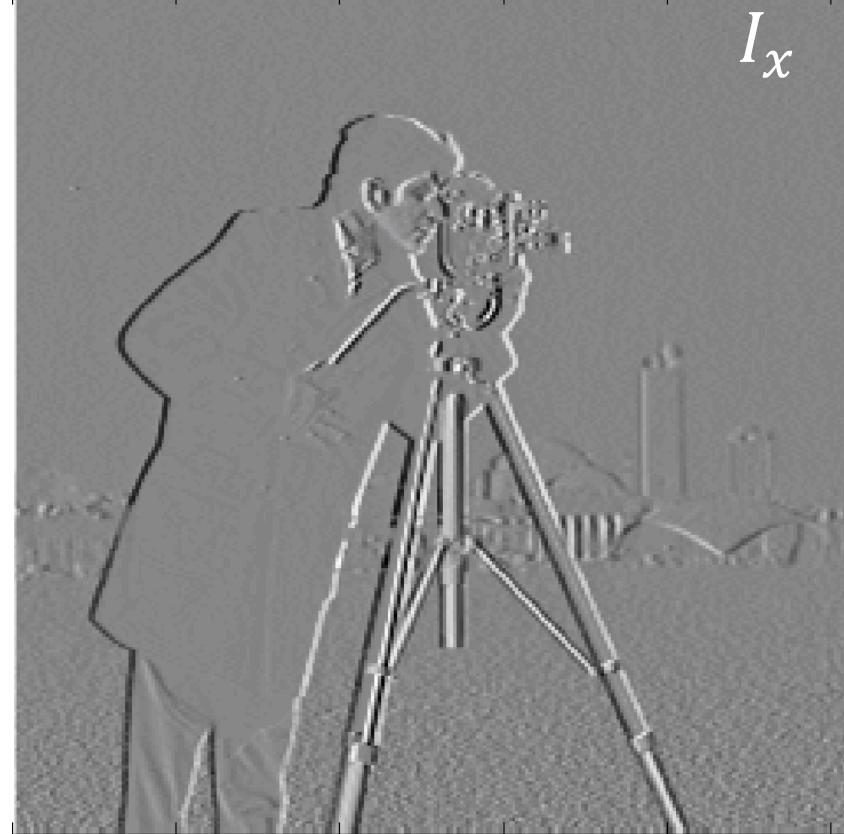
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Image Gradient

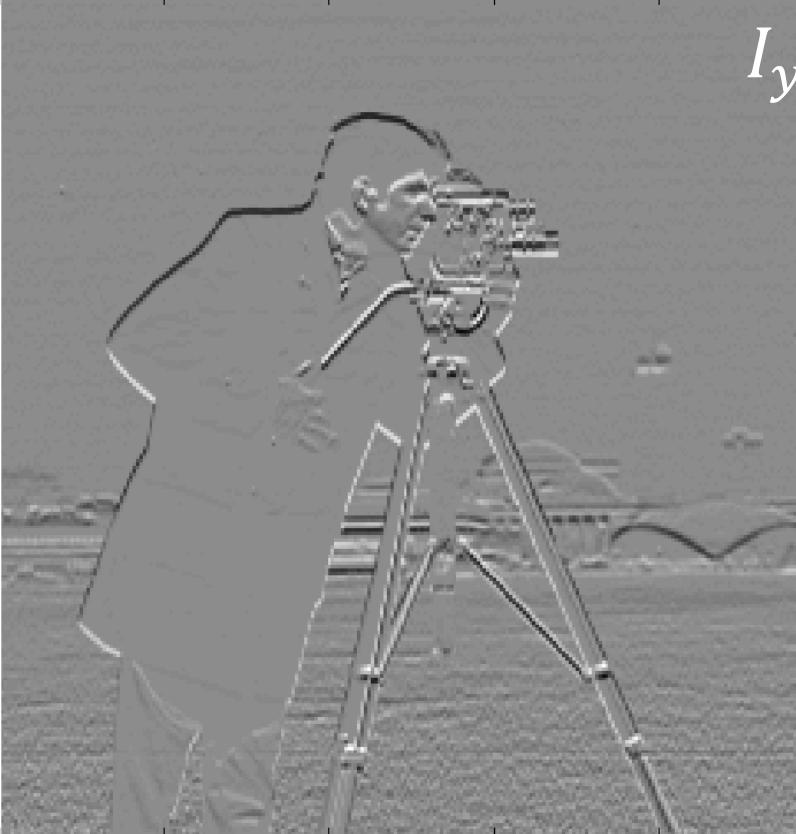


Original

I_x



I_y



$$\sqrt{I_x^2 + I_y^2}$$





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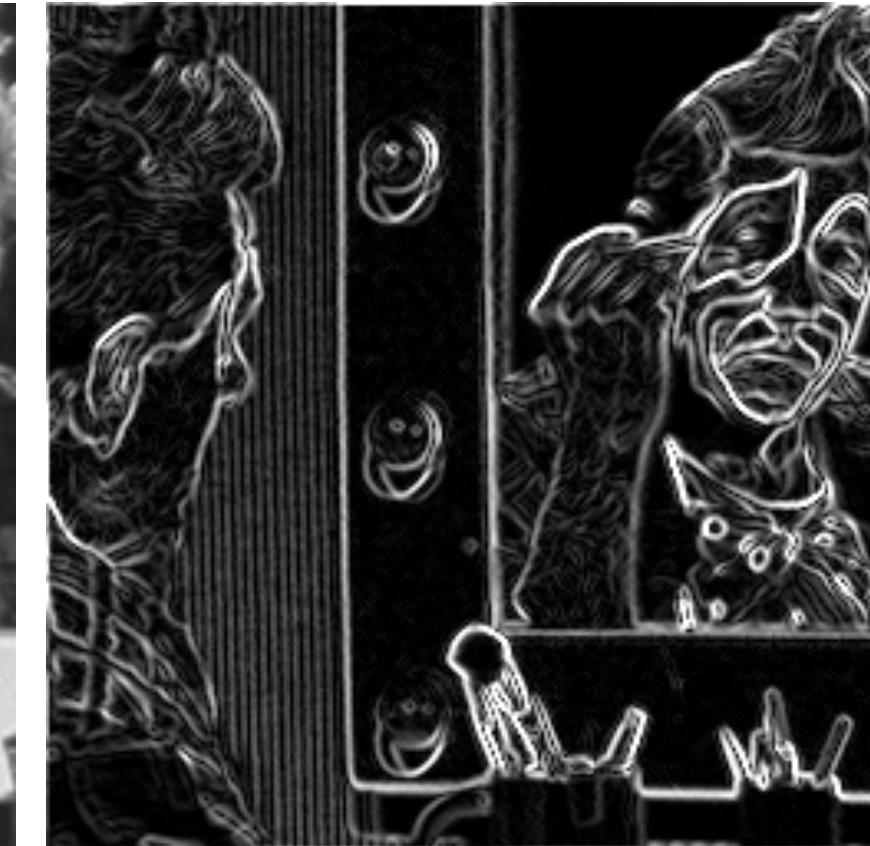
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Edge Detection using Image Gradients

Original



$|Gradient|$





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Edge Detection using Image Gradients

Original



$|\text{Gradient}|$





Image Gradients to Edges

|Gradient|



Camore-Man

|Gradient|
 > 30

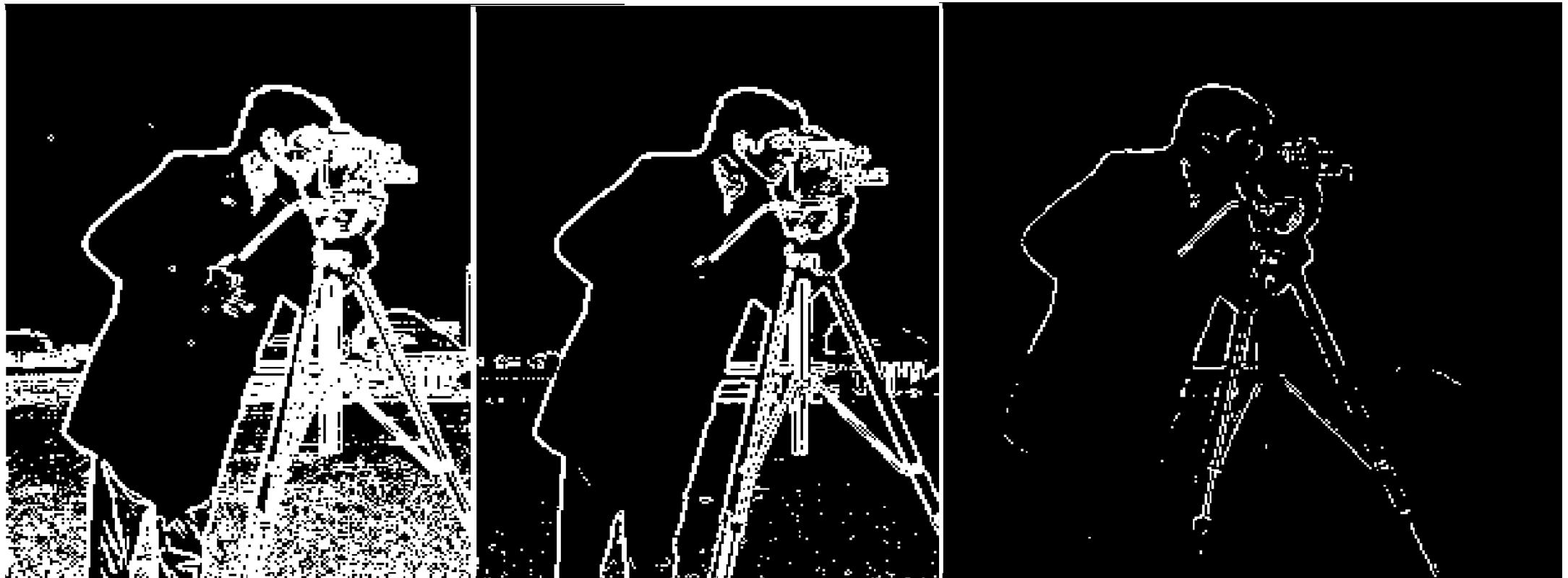
Binary Image





Image Gradients to Edges

Problem 1: How to choose the threshold



>10

>30

>80

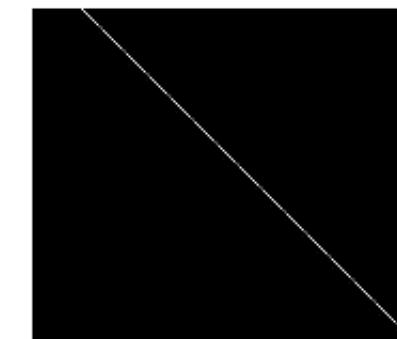


Image Gradients to Edges

- We smooth to reduce the effect noise on image gradients
- Smoothed derivative removes noise but blurs edges



Image with Edge



Edge Location

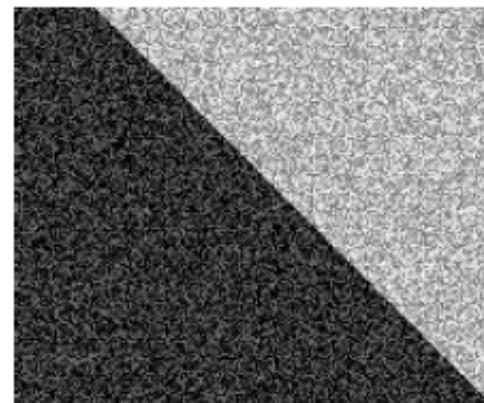
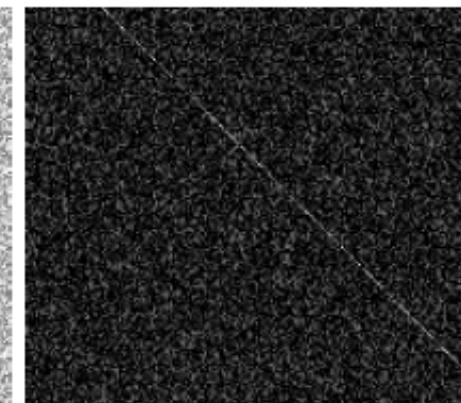
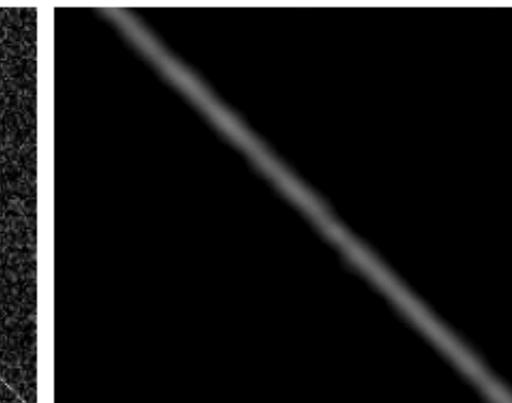


Image + Noise

Derivatives detect
edge and noiseSmoothed derivative removes
noise, but blurs edge

$$\begin{aligned} & \mathcal{I}_x \quad \mathcal{I}_y \\ & \sqrt{\mathcal{I}_x^2 + \mathcal{I}_y^2} \end{aligned}$$

A hand-drawn red diagram illustrates the calculation of edge magnitude. It shows two perpendicular vectors labeled \mathcal{I}_x and \mathcal{I}_y originating from the same point. A red bracket indicates the hypotenuse of a right triangle formed by these vectors, with the formula $\sqrt{\mathcal{I}_x^2 + \mathcal{I}_y^2}$ written next to it. A red arrow points from this formula towards the third image in the sequence.

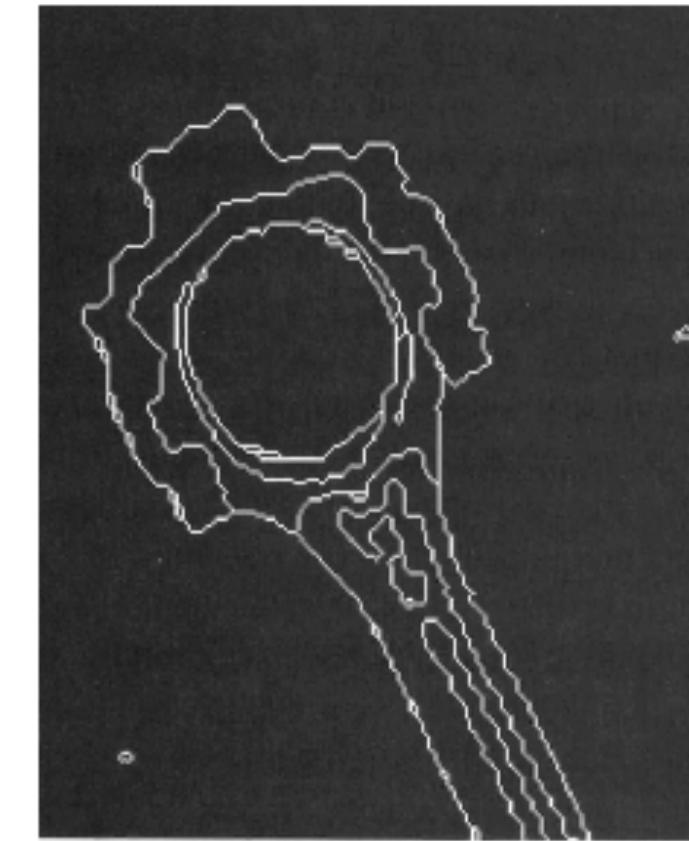


Image Gradients to Edges

Problem 2: How to get thin localized edges



Smoothing+Thresholding gives a binary mask with “thick” edges



We want thin, one-pixel wide, connected contours

Marr Hildreth Edge Detector



Second Derivative

$$\frac{\partial}{\partial x} f(i, j) \cong f(i, j) - f(i - 1, j)$$

$$\frac{\partial}{\partial y} f(i, j) \cong f(i, j) - f(i, j - 1)$$

$$\frac{\partial^2}{\partial x^2} f(i, j) \cong \frac{\partial}{\partial x} f(i + 1, j) - \frac{\partial}{\partial x} f(i, j)$$

$$= f(i - 1, j) + f(i + 1, j) - 2f(i, j)$$

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

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

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

$$= [1 \quad -2 \quad 1]$$



Laplacian

Equation:

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

 L_1 L_2

$$\begin{aligned} & I \otimes L_1 + I \otimes L_2 \\ & I \otimes (L_1 + L_2) \\ & + \\ & = \end{aligned}$$

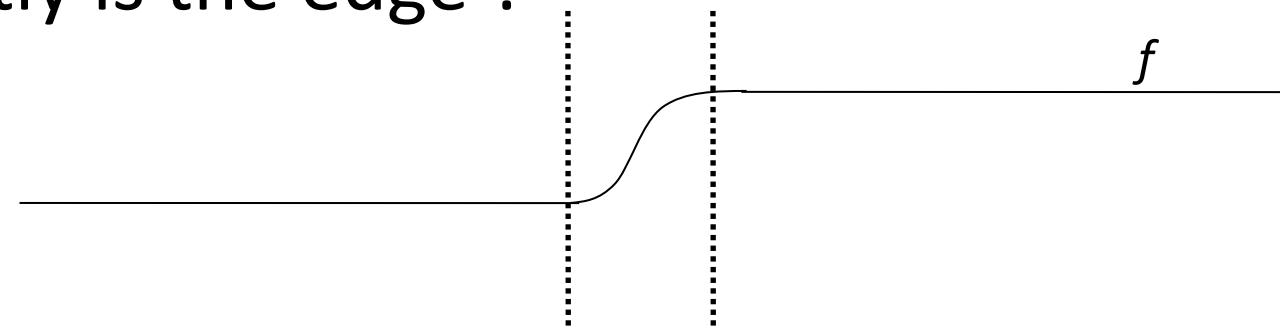
Convolution:

$$\begin{bmatrix} 1 & -2 & 1 \end{bmatrix} * \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

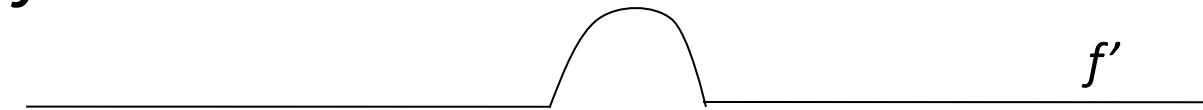


Edge Localization with Zero Crossing

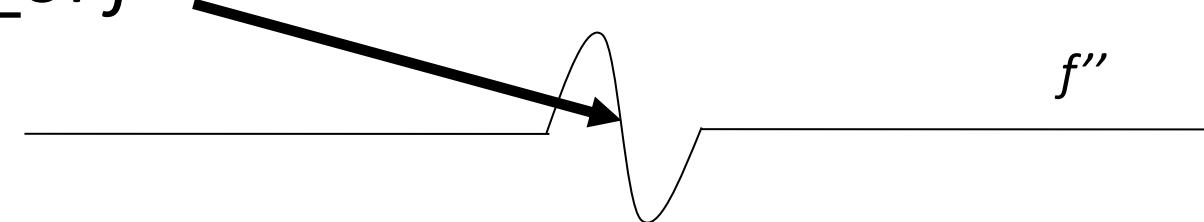
Where exactly is the edge ?



Maximum of f'

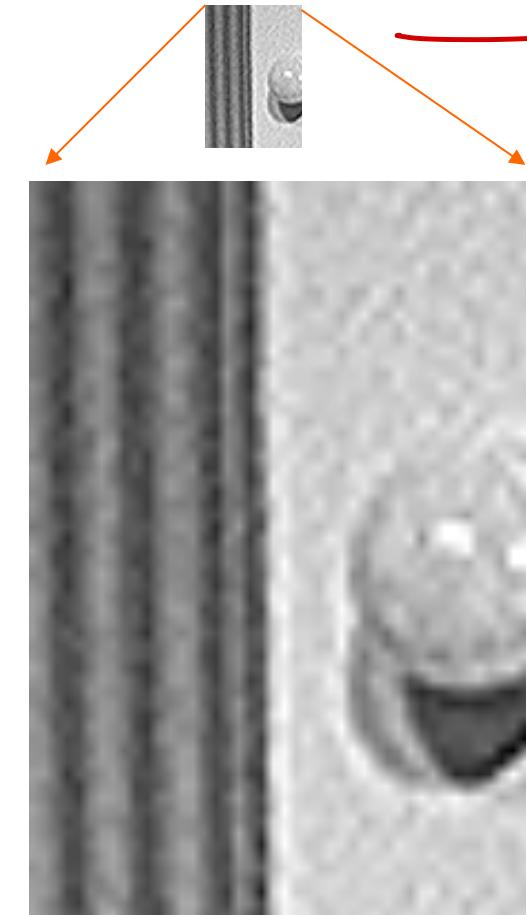
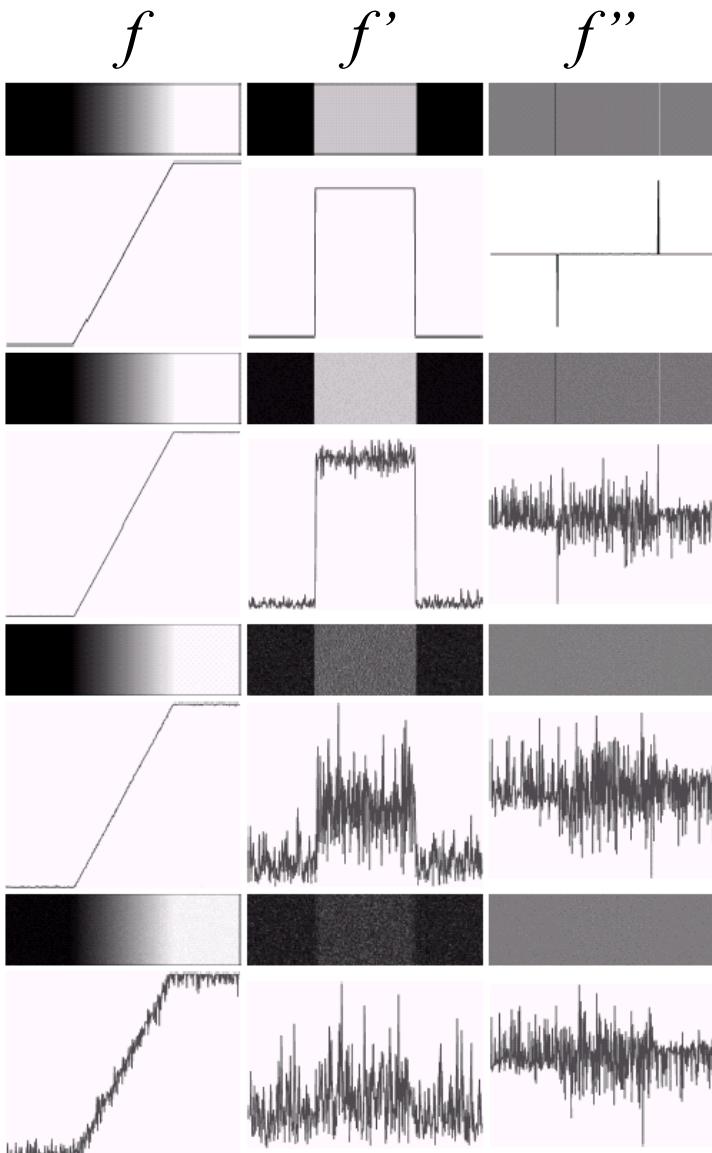
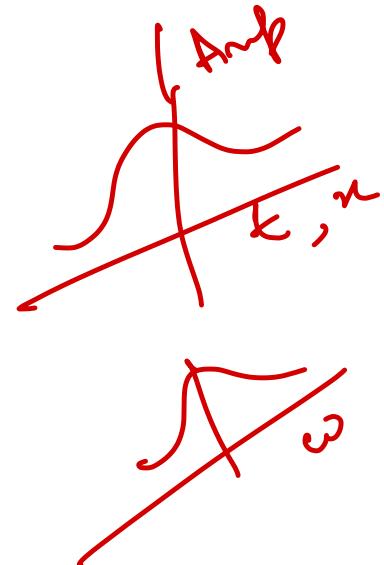


Zero crossing of f''





Effect of Noise on Derivatives



Gaussian filter~

Low Pass
filter

Derivatives
High Pass
filter

Noise
high frequency

$$A \otimes B \equiv (A' B')'$$

A' = Fourier transform



Recall: Image Derivatives

- Good derivative filters are high-pass (edge) in one direction and low-pass (blur) in the orthogonal direction.

Sobel (X)

$$\frac{1}{8} \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Laplace $\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$

I_x

Sobel (Y)

$$\frac{1}{8} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$f_{xx}'' + f_{yy}''$

I_y

I_y

(I_x, I_y)
 I_x, I_y^2
 I_x, I_y



Laplacian of Gaussian
LoG

Zero Crossing After Smoothing

Input

Laplacian after increasingly strong smoothing



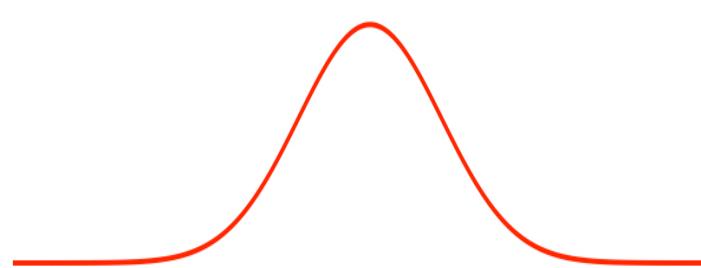
Canny Edge Detector



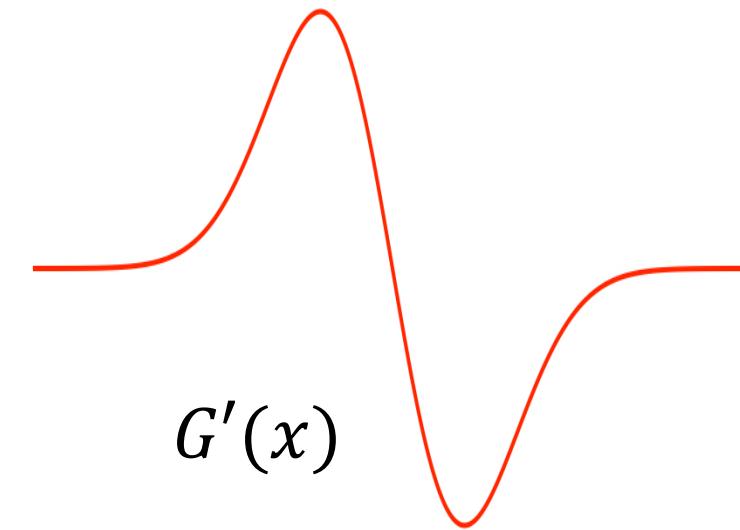
Canny Edge Detector

Step 1: Compute Edge Points

- Compute image derivatives G_x, G_y using derivative of Gaussian
 - Smooth with a Gaussian.
 - Use simple derivative kernels $[1 \ -1]$.



$G(x)$



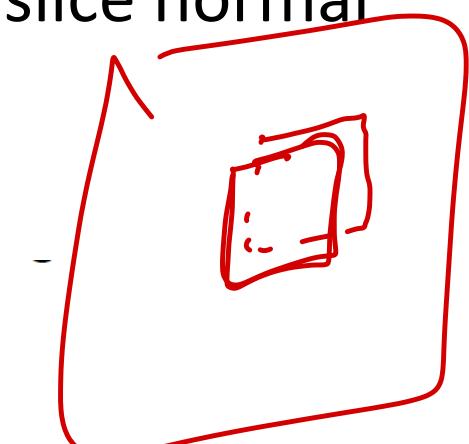
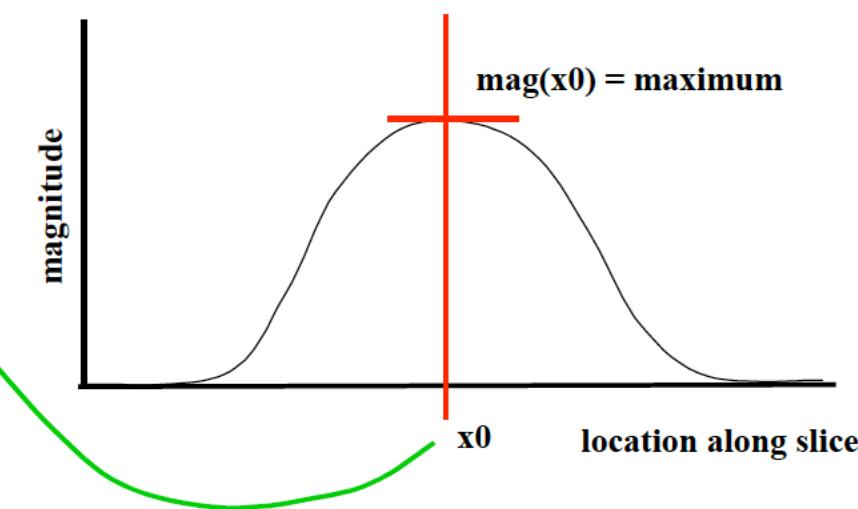
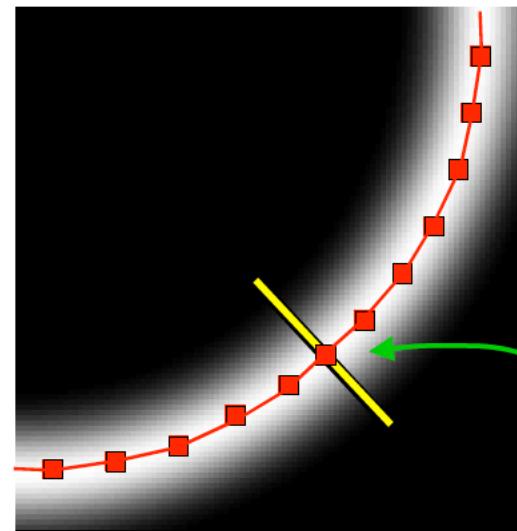
$G'(x)$



Canny Edge Detector

Step 2: Thin Edges

- We want to mark points along curve where the magnitude is largest.
- We can do this by looking for a maximum along a 1D intensity slice normal to the curve (non-maximum suppression).
- These points should form a one-pixel wide curve.





Canny Edge Detector

Step 2: Thin Edges

- Compute edge direction: $\tan(\alpha) = \frac{G_y}{G_x}$.
- Edge point is the local maxima in edge direction. Find using non maximal suppression

$$\tan(\alpha) = \frac{G_y}{G_x}$$



Canny Edge Detector

Step 3: Threshold and find connected edges

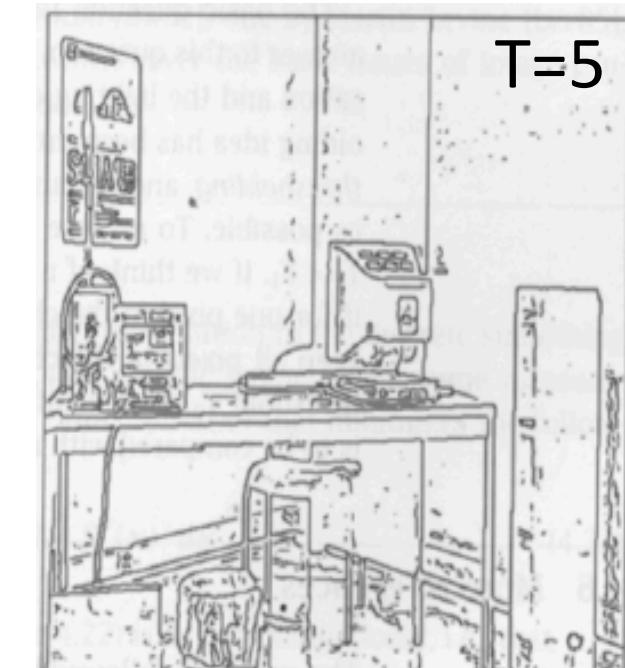
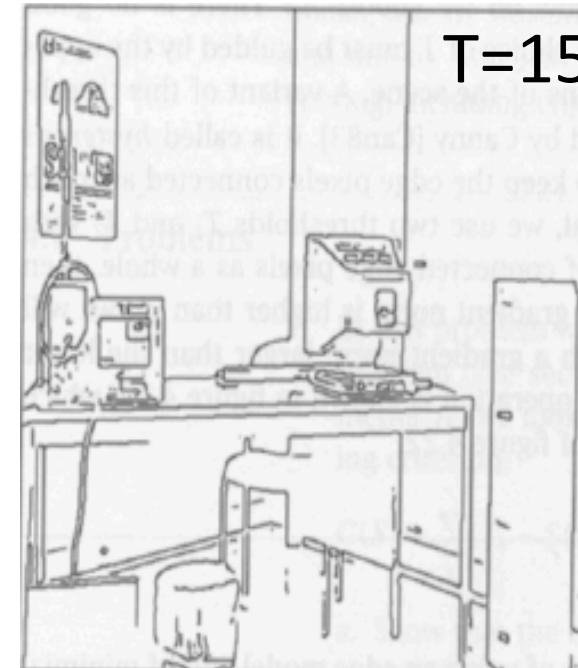
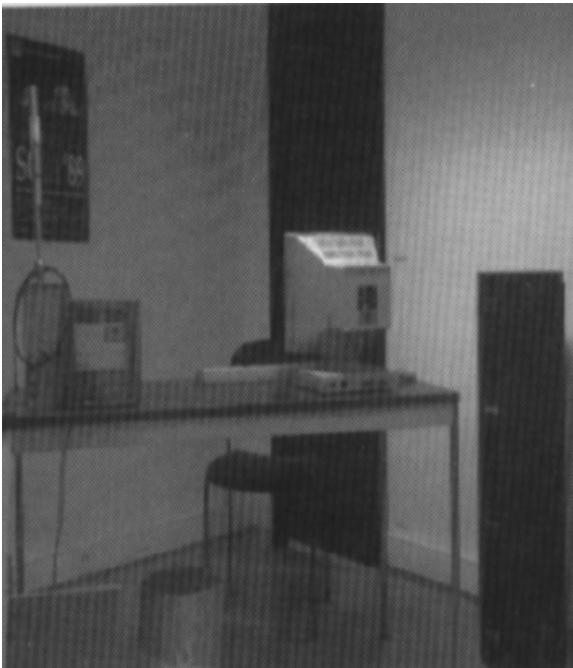
- How to pick threshold?
- How to connect edges?

Hysteresis



How to Choose the Gradient Threshold

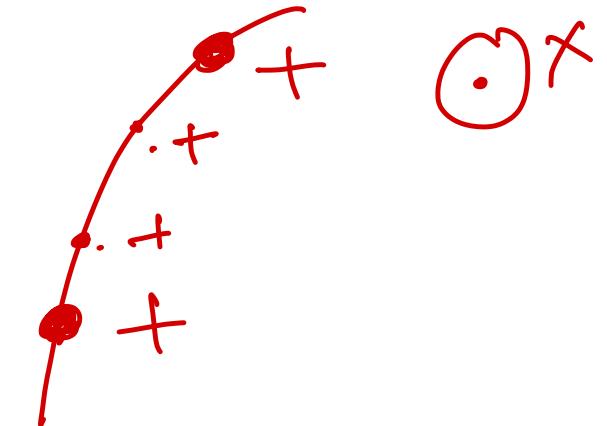
- If the threshold is too high:
 - Very few (none) edges, High MISDETECTIONS, Many gaps
- If the threshold is too low:
 - Too many (all pixels) edges, High FALSE POSITIVES, many extra edges





Hysteresis Thresholding and Edge Linking

- Keep both a high threshold H and a low threshold L .
 - Any edges with strength $< L$ are discarded.
 - Any edge with strength $> H$ are kept.
- An edge P with strength between L and H is kept only if there is a path of edges with strength $> L$ connecting P to an edge of strength $> H$.

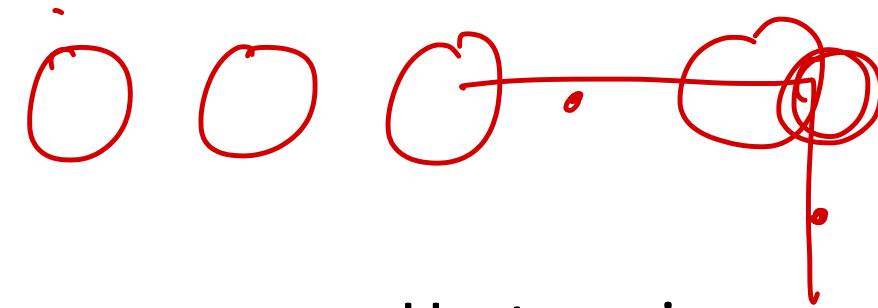


Edge Linking

- In practice, hysteresis thresholding is combined with edge linking, by choosing the neighbors only along the edge direction. This links the edge pixels along the edge direction.

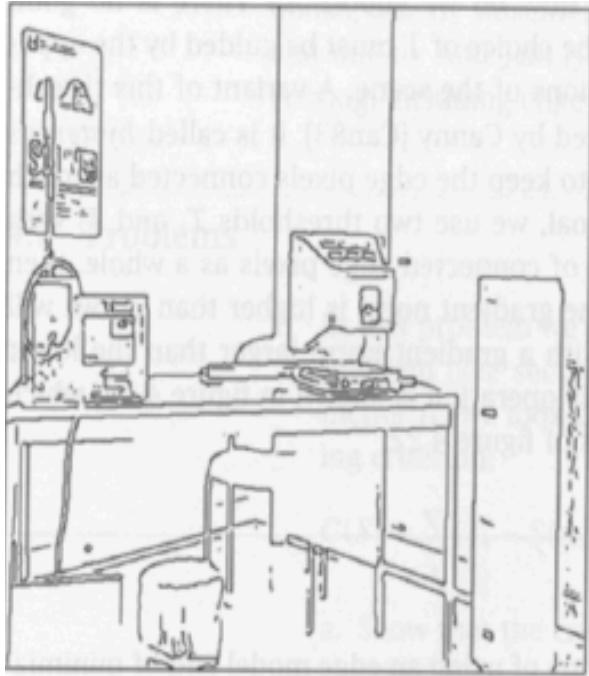


Hysteresis

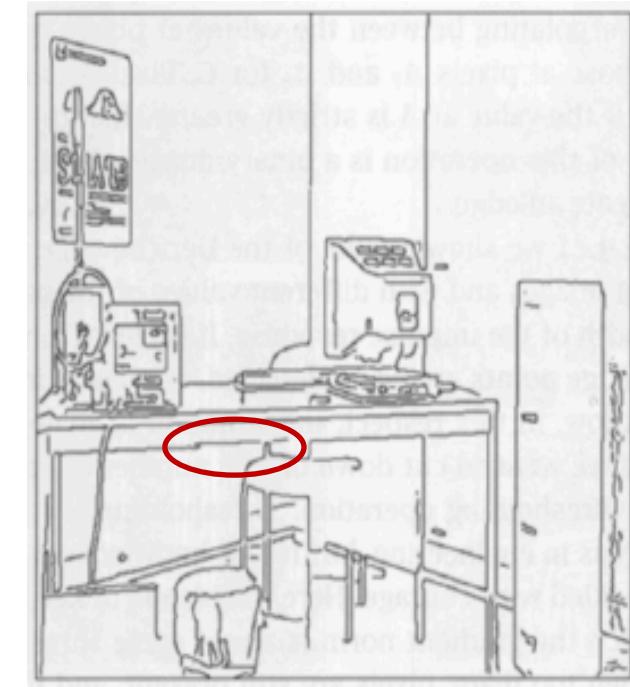
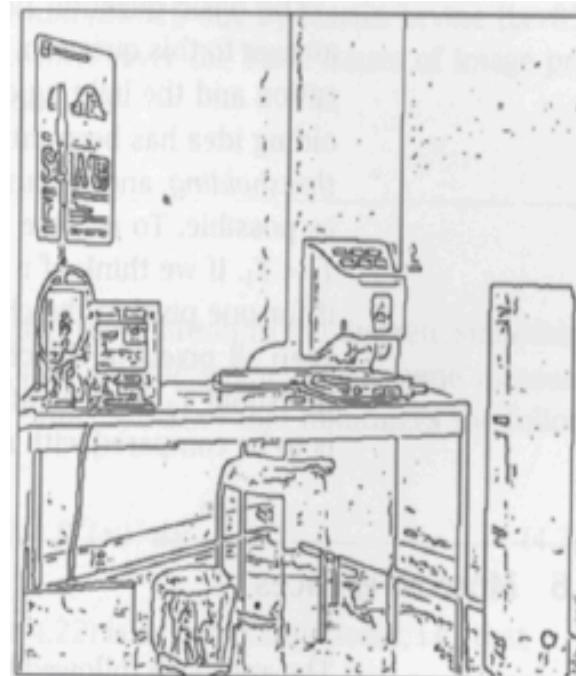


Hysteresis
 $H=15, L=5$

$T=15$



$T=5$





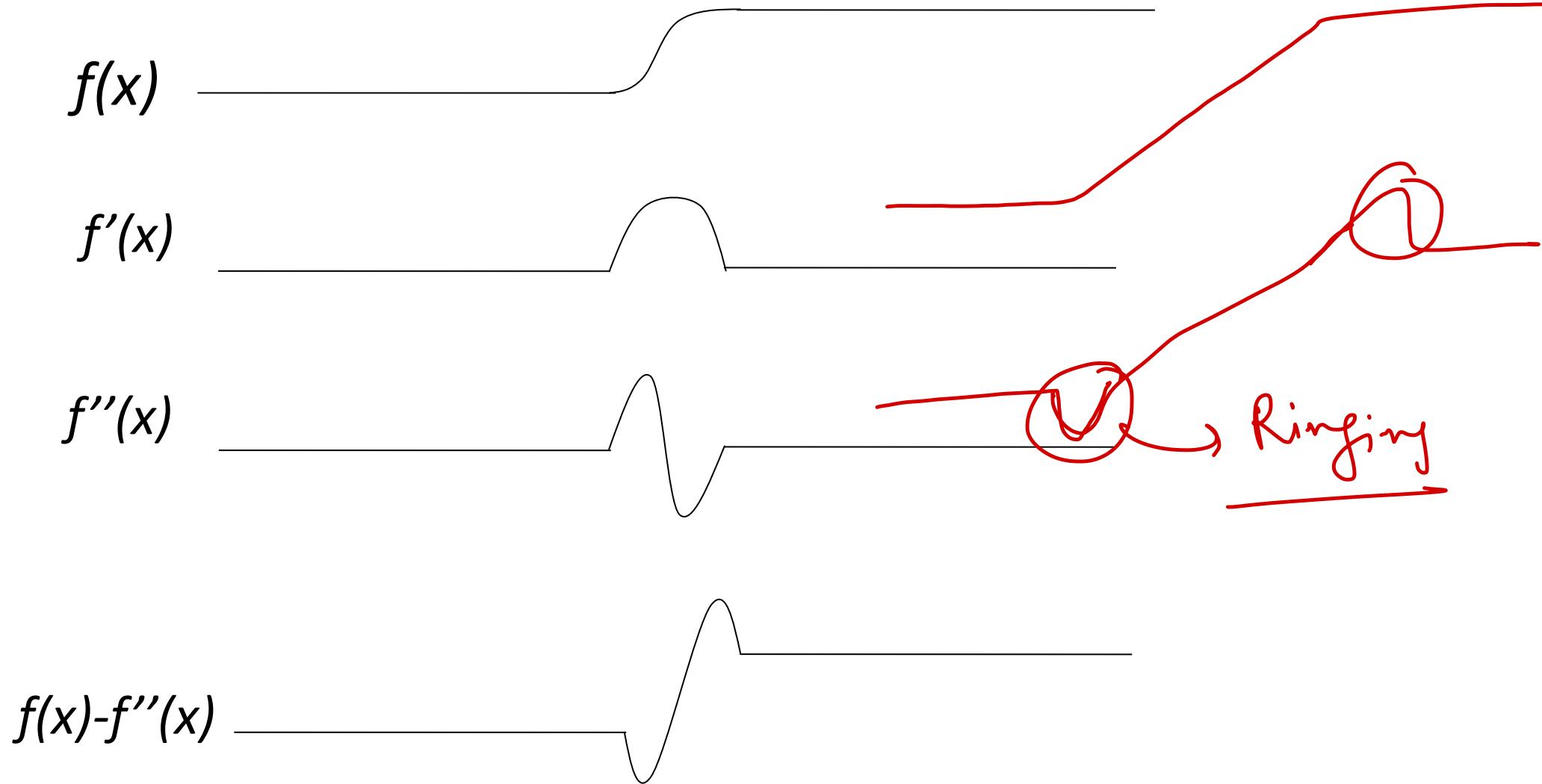
Canny Edge Detector

- Compute image derivatives G_x, G_y using derivative of Gaussian
 - Smooth with a Gaussian.
 - Use simple derivative kernels $\begin{bmatrix} 1 & -1 \end{bmatrix}$.
- Compute edge direction: $\tan(\alpha) = G_y / G_x$. Edge point is the local maxima in edge direction.
- Use only edge points with gradient above threshold. Use hysteresis based thresholding and edge linking with two thresholds. Low threshold accepted only if neighbor to high threshold

Image Sharpening



Sharpening by Subtracting the Laplacian





Sharpening by Subtracting the Laplacian

Equation:

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

Convolution:

$$\begin{bmatrix} 1 & -2 & 1 \end{bmatrix} + \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Subtracting the Laplacian from the image:

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



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Sharpening Example





Line Detection

- Why detect lines? Many objects characterized by presence of straight lines

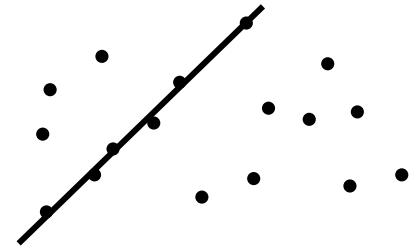
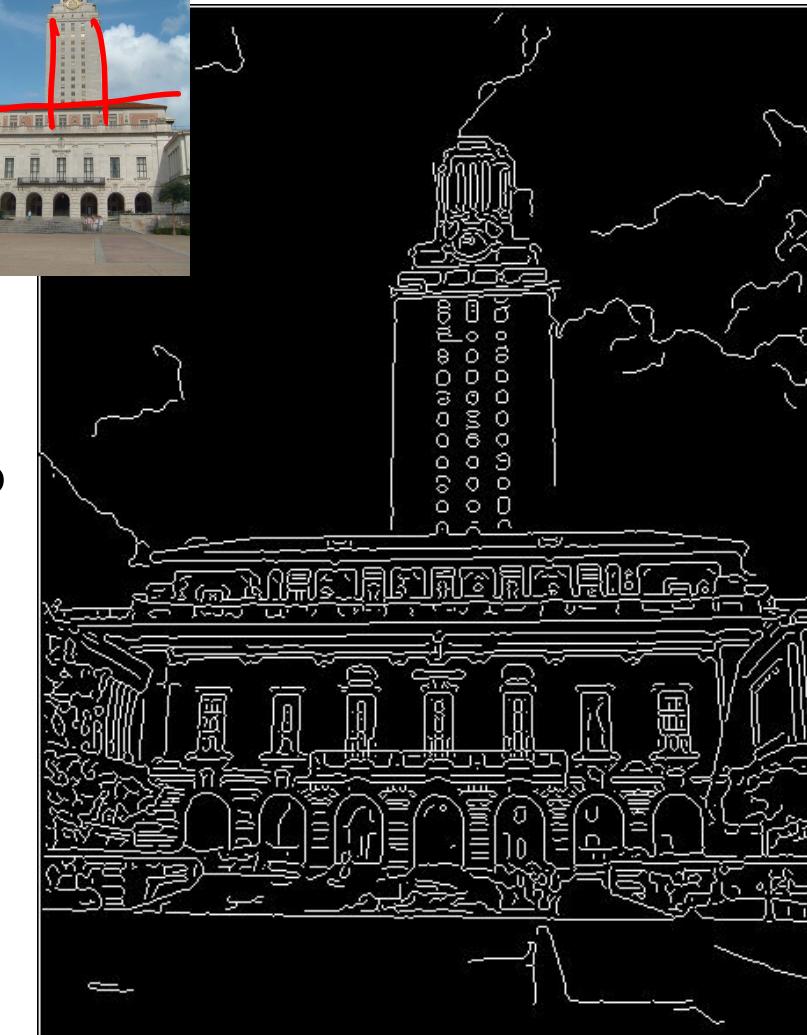
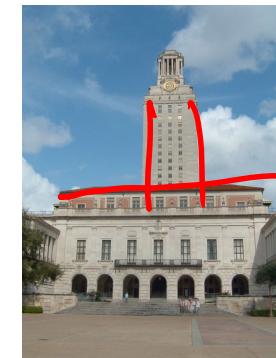


- Why aren't we done just by running edge detection?



Difficulty of Line Detection

- Extra edge points (clutter), multiple models:
 - Which points go with which line, if any?
- Only some parts of each line detected, and some parts are missing:
 - How to find a line that bridges missing evidence?
- Noise in measured edge points, orientations:
 - How to detect true underlying parameters?





Edges to Lines: Problem Statement

- 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.
- We wish to find sets of pixels that make up straight lines.





Hough Transform

- Can be used to detect lines, circles etc.
- 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. It can give robust detection under noise and partial occlusion
- **Caveat:** Hough transform can detect structures ONLY if their parametric equation is known.



Detecting Lines using Hough Transform

- 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 $y_i = ax_i + b$
 - Common to them is that they satisfy the above equation for some set of parameters (a, b)

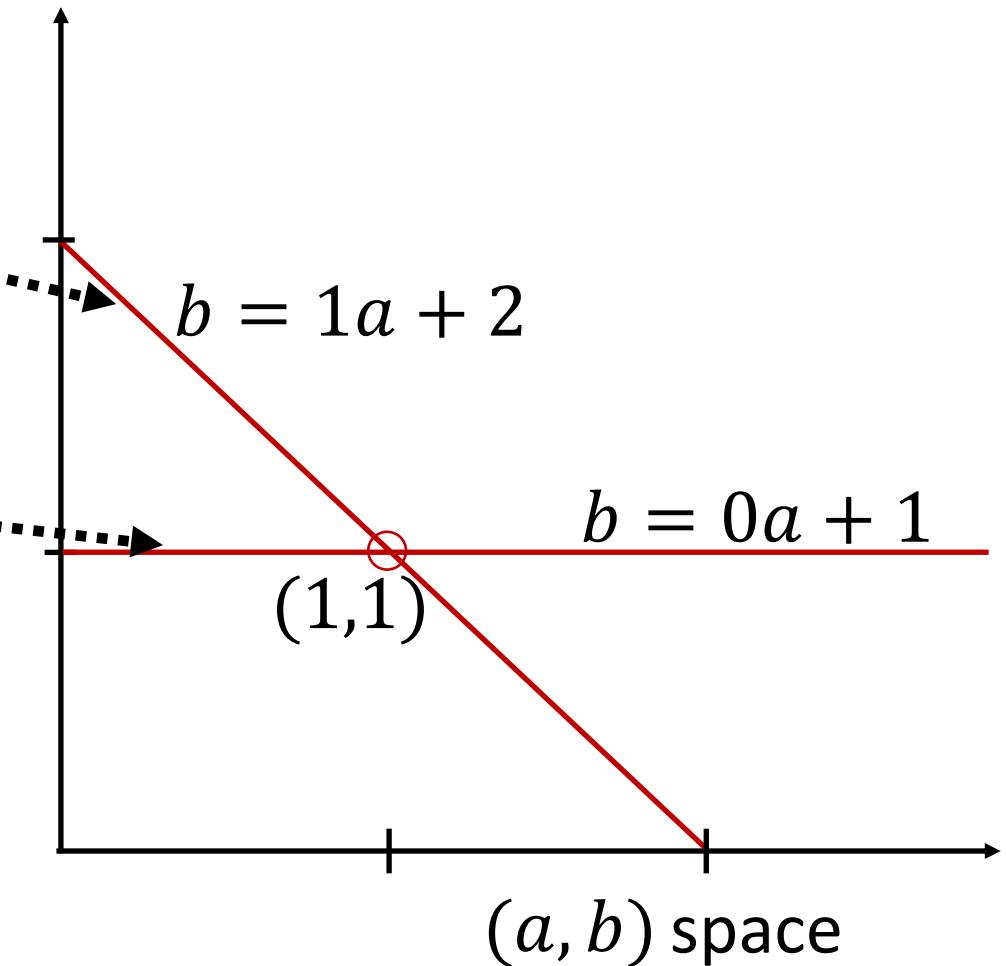
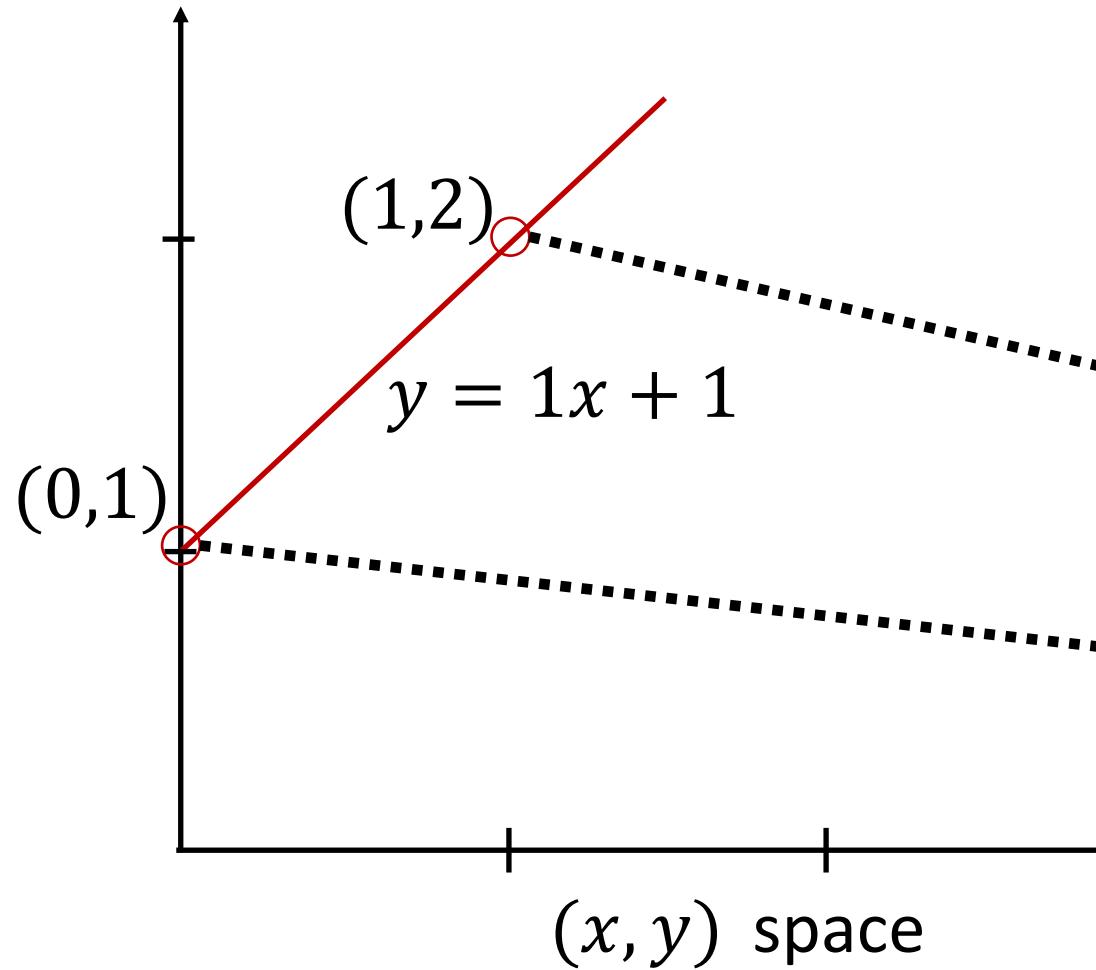


Detecting Lines using Hough Transform

- This equation can obviously be rewritten as follows:
 - $b = -ax_i + y_i$
 - 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 .
 - A single point (x_i, y_i) gives a line in (a, b) space.
 - Another point (x_j, y_j) will give rise to another line in (a, b) space.



Detecting Lines using Hough Transform





Detecting Lines using Hough Transform

- Two points (x_i, y_i) and (x_j, y_j) define a line in the (x, y) plane with parameters (a_k, b_k) .
- These two points give rise to two different lines in (a, b) space.
- In (a, b) space these lines will intersect at a point (a_k, b_k)
- All points on the line (a_k, b_k) in (x, y) space will parameterize lines that intersect at point (a_k, b_k) in (a, b) space.



Detecting Lines using Hough Transform

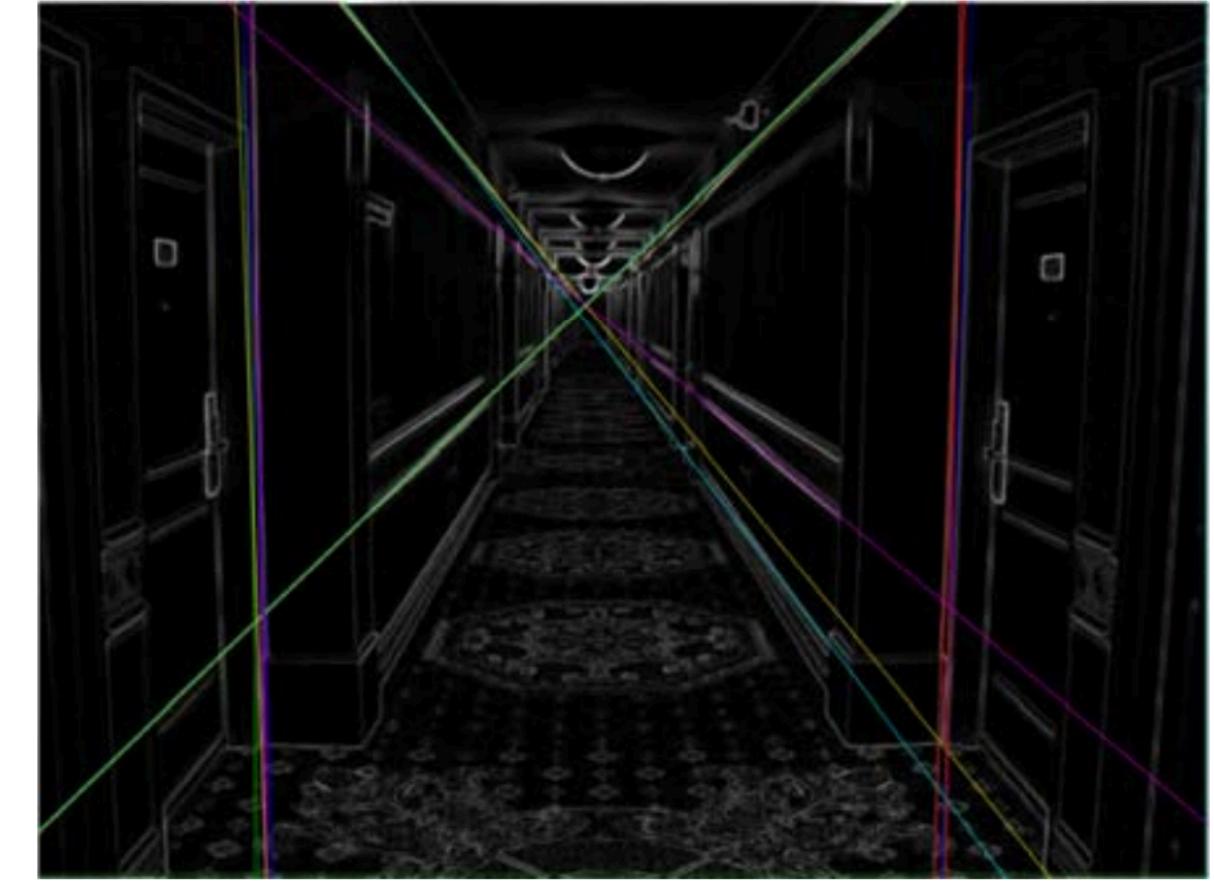
- Quantize the parameter space (a, b) by dividing it into accumulator cells
- For each pair of points (x_i, y_i) and (x_j, y_j) detected as an edge:
 - Find the intersection (a_k, b_k) in (a, b) space.
 - Increase the value of cell $[(a_{\min}, a_{\max}], [b_{\min}, b_{\max}]]$ containing (a_k, b_k)
- Cells receiving more than a certain number of counts (also called votes) are assumed to correspond to lines in (x, y) space.



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Hough Transform: Example



Top 20 most voted lines



Other Hough Transformations

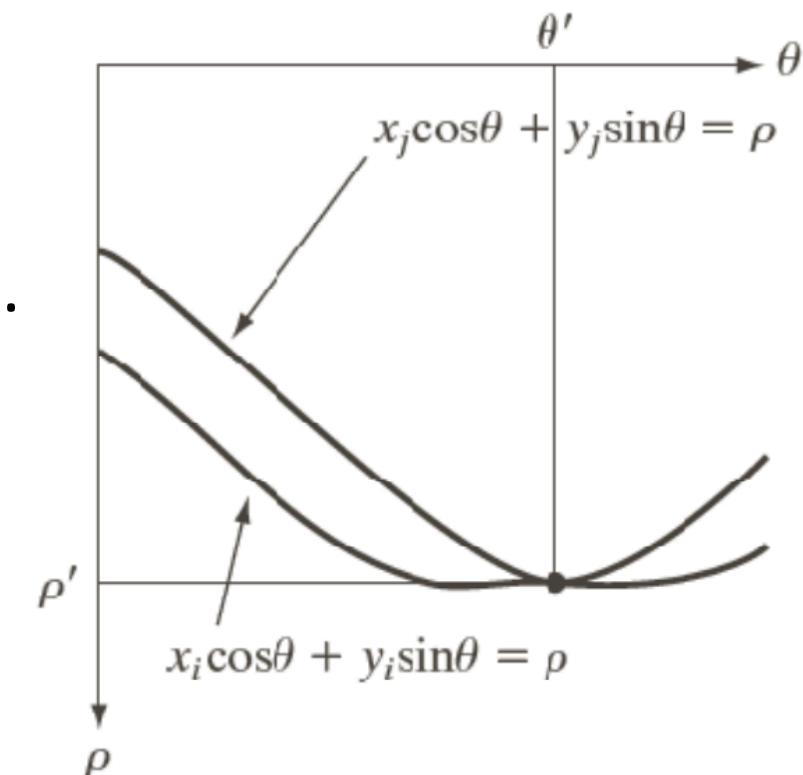
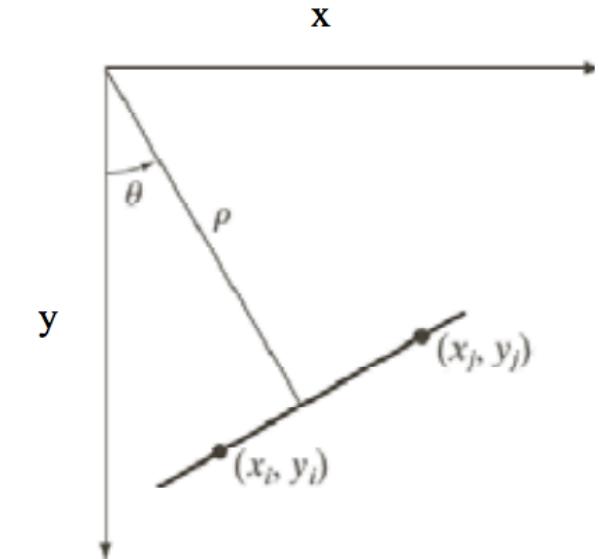
- We can represent lines as polar coordinates instead of $y = ax + b$

$$x * \cos(\theta) + y * \sin(\theta) = \rho$$

- Lines in (x, y) space are not lines in (ρ, θ) space

- Horizontal line: $\theta = 0, \rho =$ intercept with the y -axis.

- Vertical line: $\theta = 90, \rho =$ intercept with the x -axis.

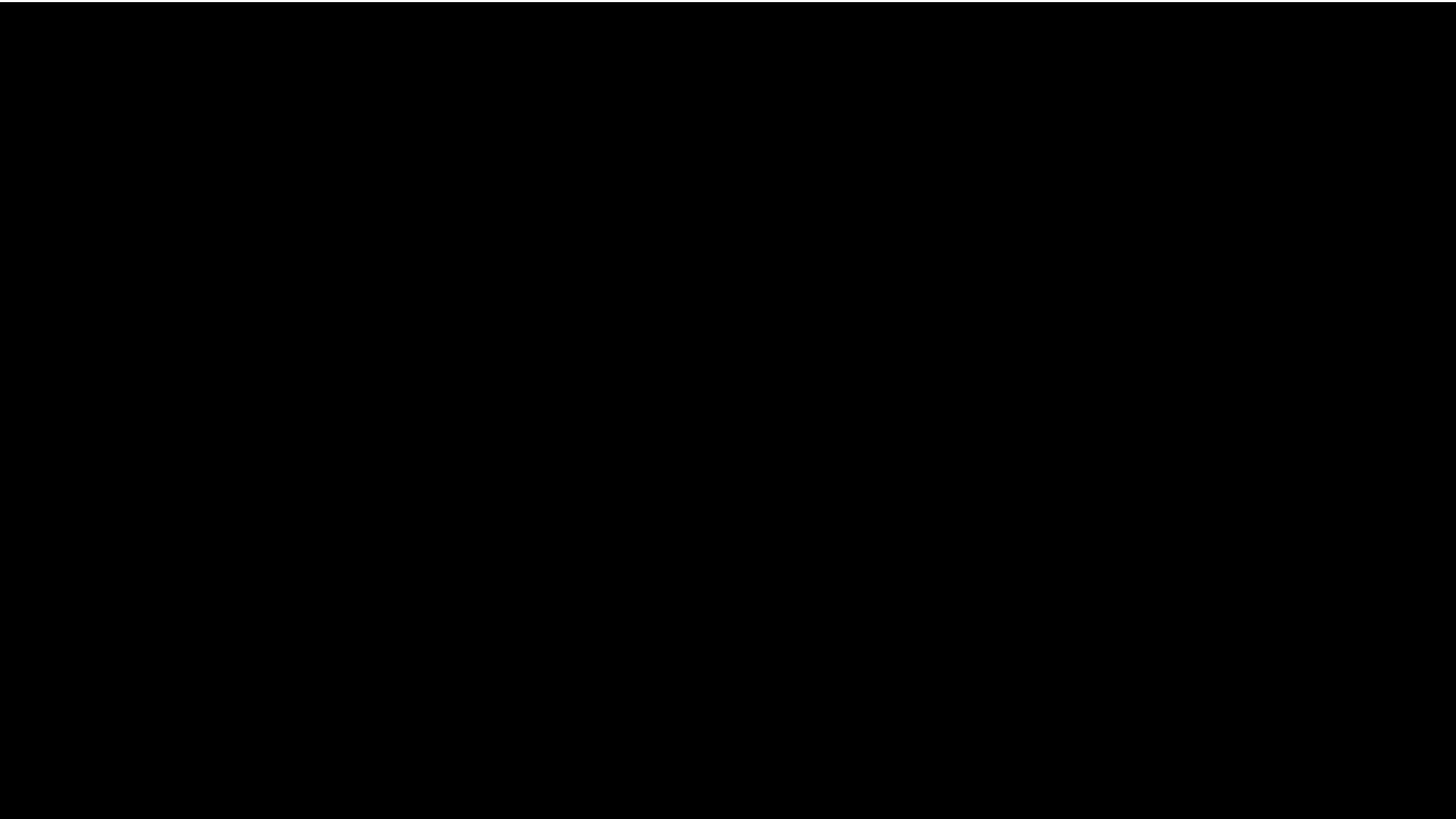




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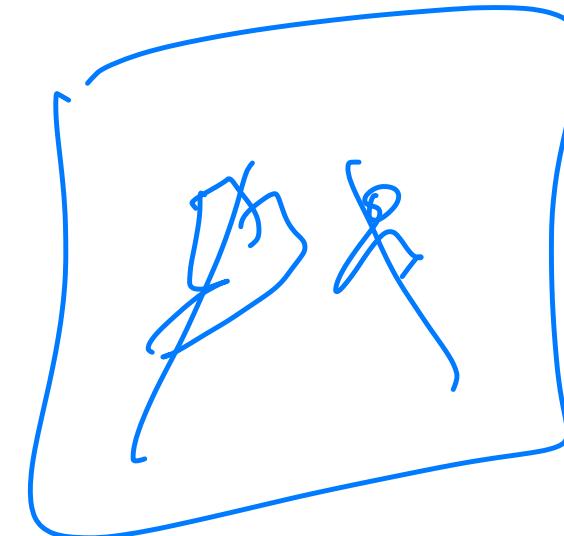
Other Hough Transformations





Hough Transform: Advantages

- Conceptually simple.
- Easy implementation
- Handles missing and occluded data very gracefully. ✓
- Can be adapted to many types of forms, not just lines





Hough Transform: Disadvantages

- Computationally complex for objects with many parameters.
- Accuracy of estimation (accumulator cell size) needs to be traded off with complexity of estimation.
- Looks for only one single type of object



Hough Transform: Disadvantages

- 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.

