# Lecture 07

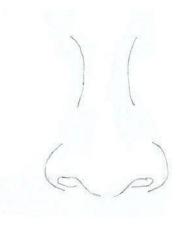
### Outline

- What is edge detection?
- Why do we need edge detection?
- Challenges
  - Noise
- How to detect edges?
  - Prewit
  - Sobel
  - Laplacian
  - Canny

## Why edge detection?

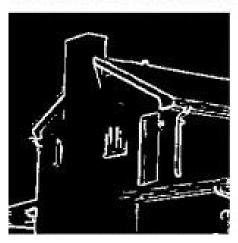
- Extract useful information from images
  - Recognizing objects











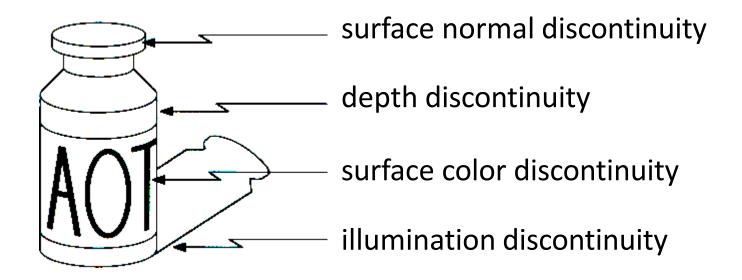
### Edge Detection

- Identify sudden changes in an image
  - Semantic and shaped information
  - Marks the border of an object
  - More compact than pixels



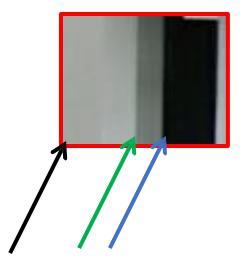
### Origins of Edges

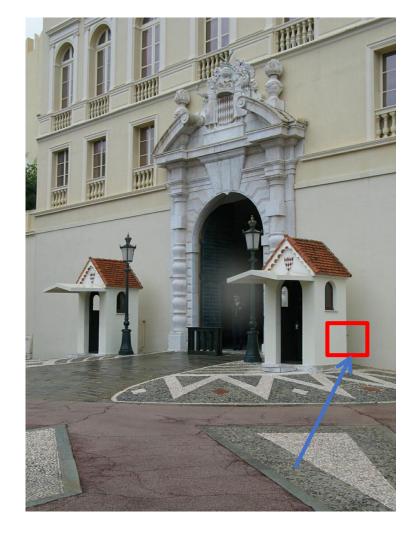
Edges are caused by a variety of factors

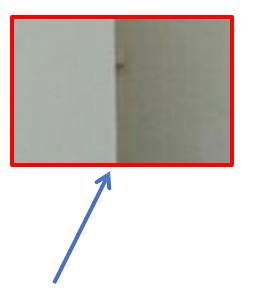










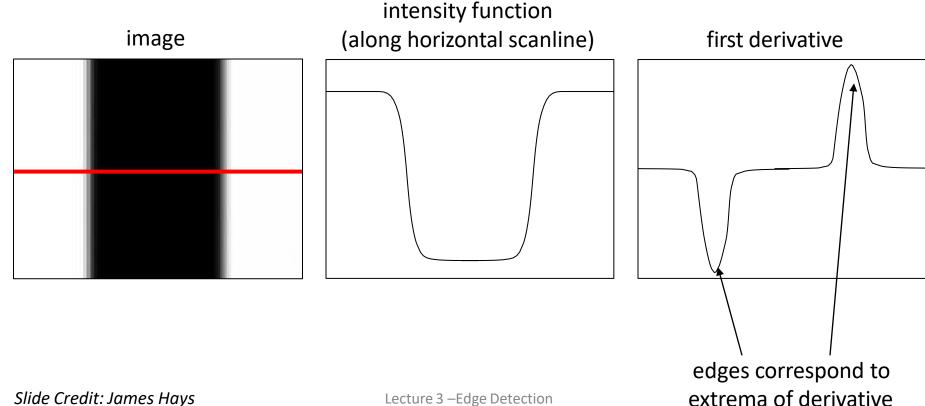


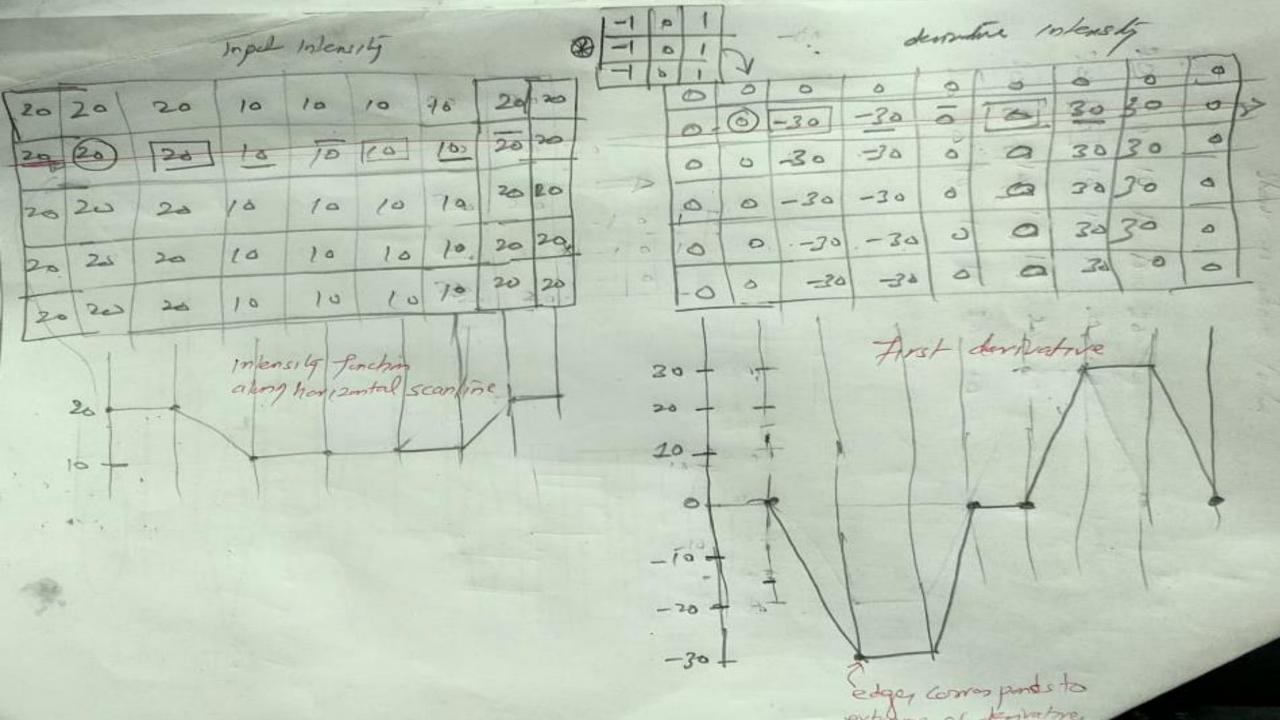




### Characterizing edges

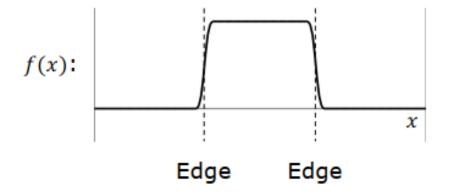
An edge is a place of rapid change in the image intensity function





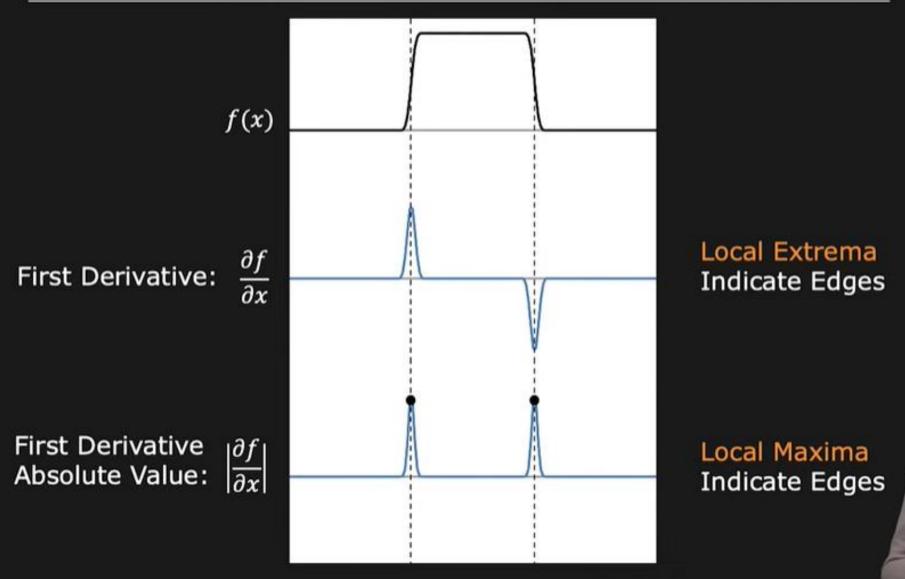
### 1D Edge Detection

Edge is a rapid change in image intensity in a small region.



Basic Calculus: Derivative of a continuous function represents the amount of change in the function.

### Edge Detection Using 1st Derivative



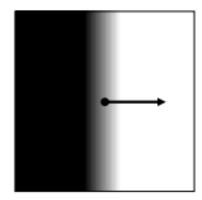
Provides Both Location and Strength of an Edge

### Gradient (♥)

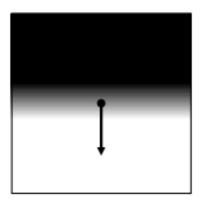
Gradient (Partial Derivatives) represents the direction of most rapid change in intensity

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

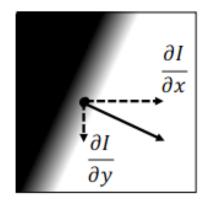
Pronounced as "Del I"



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

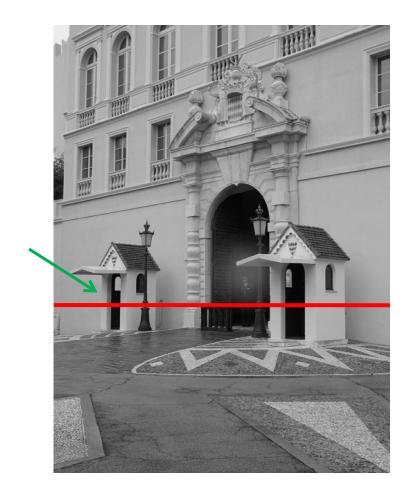


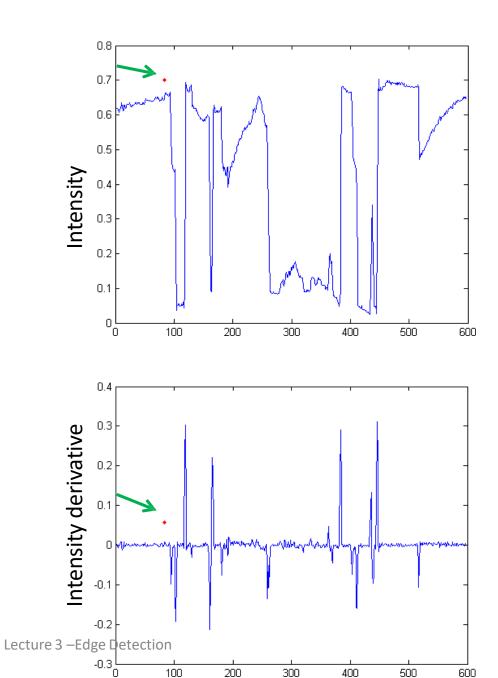
$$\nabla I = \left[0, \frac{\partial I}{\partial y}\right]$$



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

## Intensity profile



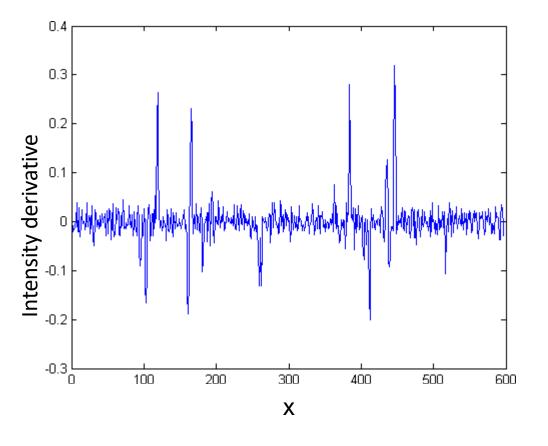


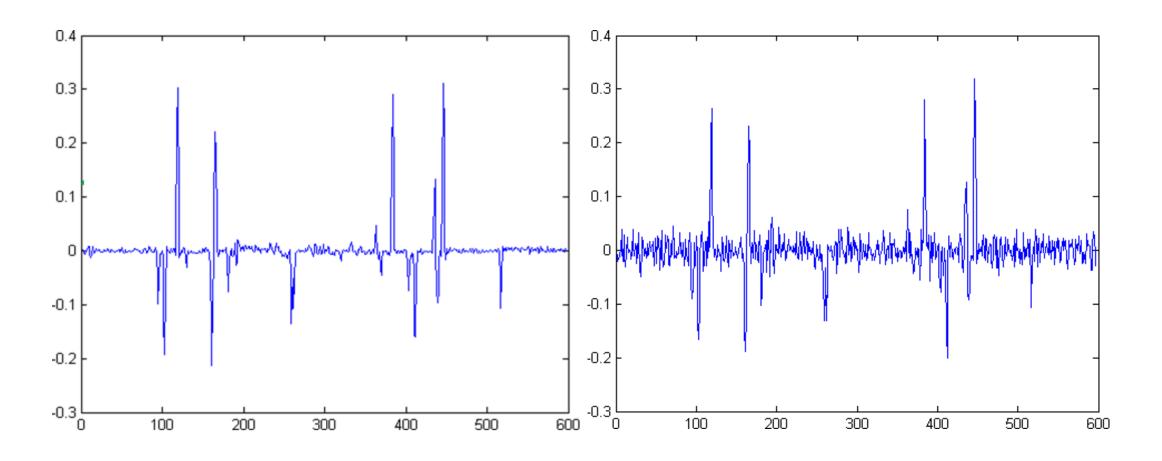
9/14/2021

Source: D. Hoiem

### With a little Gaussian noise

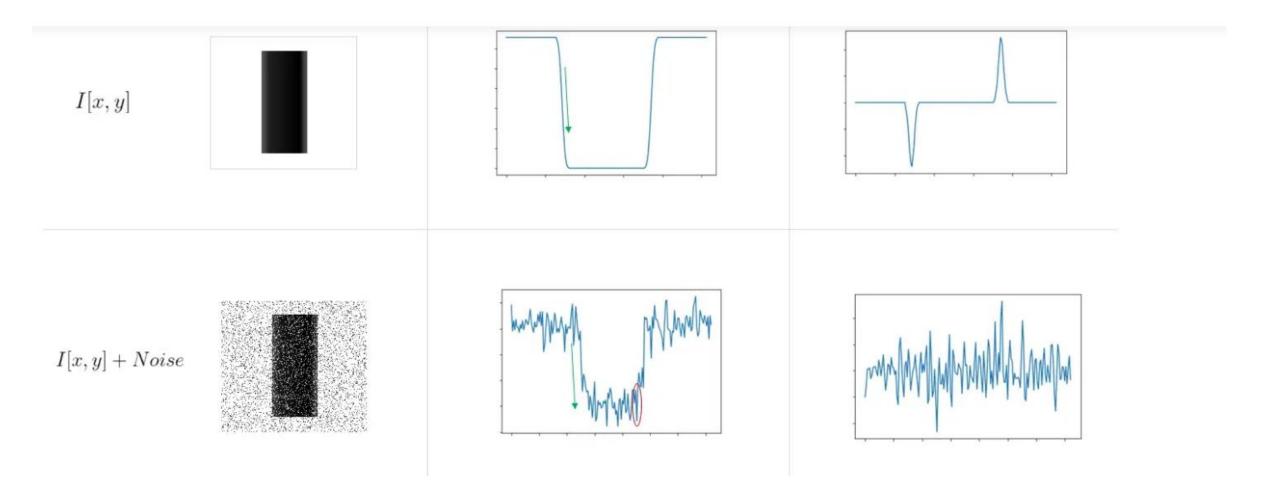






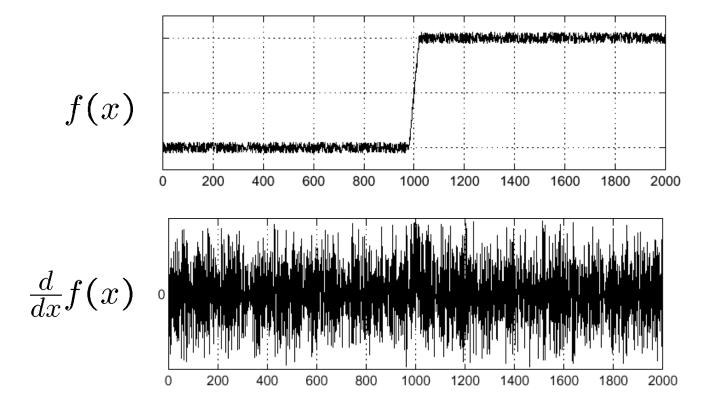
a) Intensity derivatives of clean image

b) Intensity derivative of Image with gaussian noise

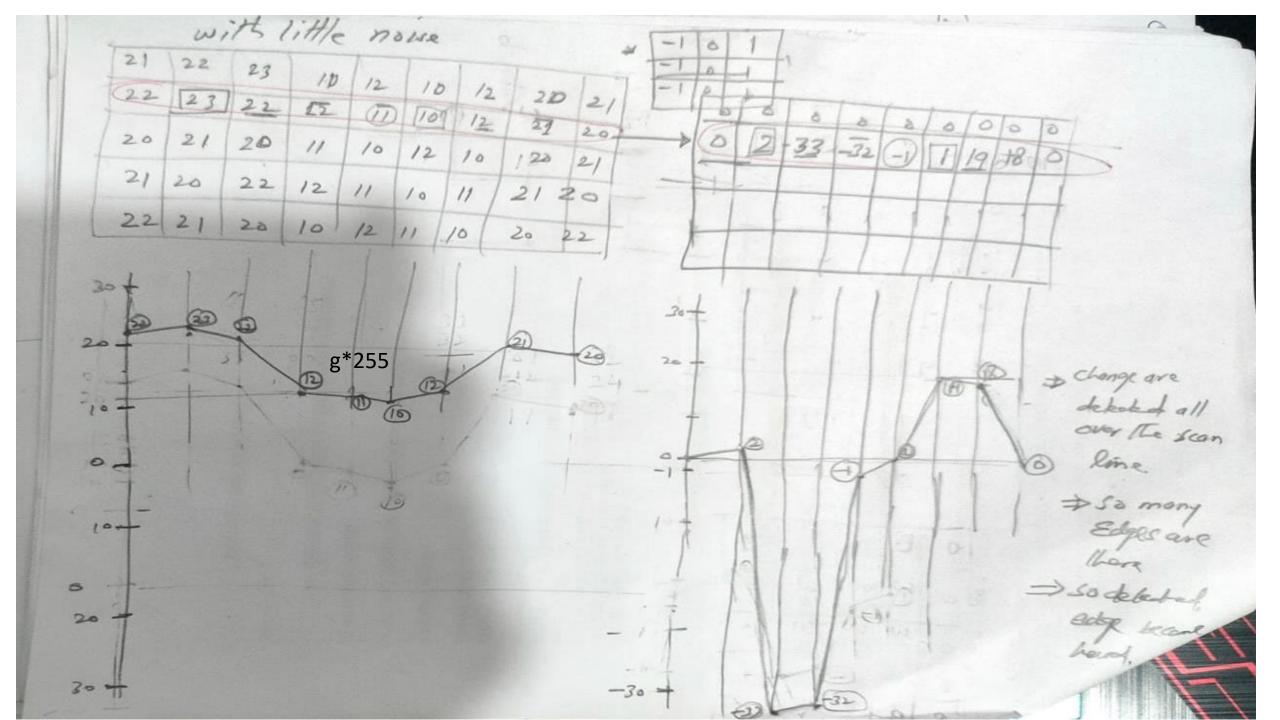


### Effects of Noise

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



Where is the edge?



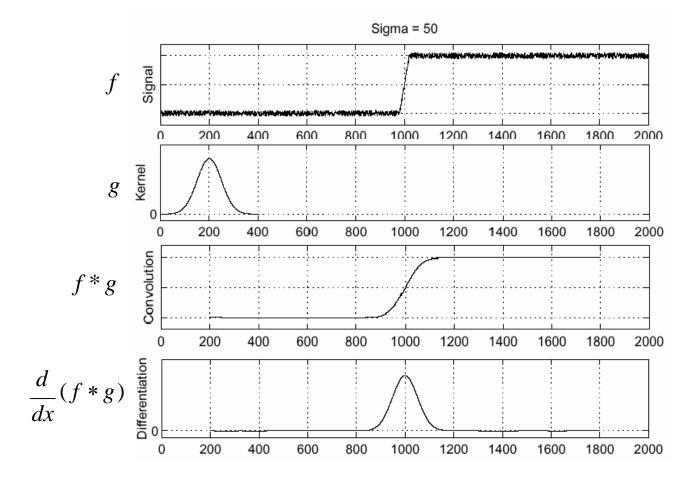
### Effects of noise

- 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?

9/14/2021 Lecture 3 –Edge Detection Source: D. Forsyth

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### Solution: smooth first



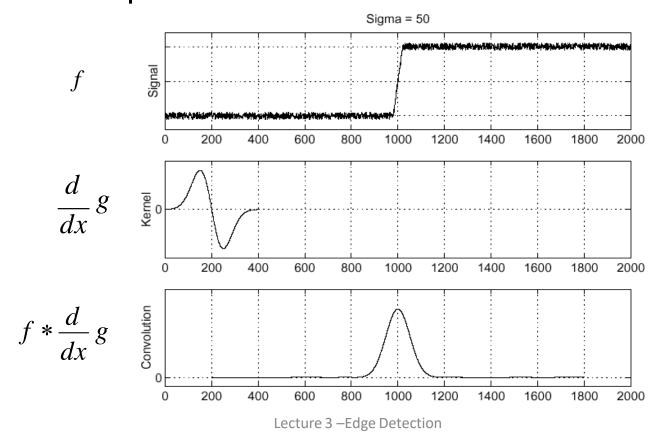
To find edges, look for peaks in

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

### Derivative theorem of convolution

- Convolution is differentiable:
- This saves us one operation:

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



### Prewitt and Sobel Edge Detector

- Compute derivatives
  - In *x* and *y* directions
- Find gradient magnitude
- Threshold gradient magnitude

# Prewitt Edge Detector

- 1. Convert image to grey-scale
- 2. Compute derivatives in x and y directions ( $f_x$  and  $f_y$  using horizontal and vertical Prewitt filter respectively)
- 3. Find gradient magnitude at every pixel

$$\sqrt{f_x^2+f_y^2}$$

4. Threshold gradient magnitude image

## Prewitt Filter

Prewitt Filter

► Horizontal Prewitt Filter

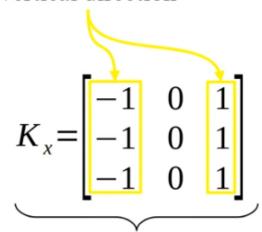
$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

Vertical Prewitt Filter

$$egin{bmatrix} -1 & -1 & -1 \ 0 & 0 & 0 \ 1 & 1 & 1 \end{bmatrix}$$

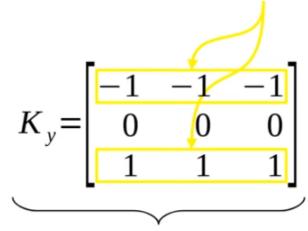
#### Note that these kernels are separable

Here, these columns smooth in vertical direction



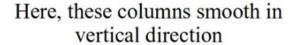
First order derivative estimator for horizontal direction

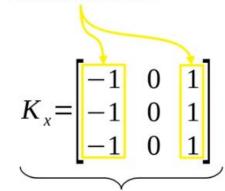
And these rows smooth in horizontal direction



First order derivative estimator for vertical direction

#### Note that these kernels are separable

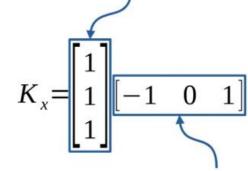




First order derivative estimator for horizontal direction

2D kernel

Vertical smoothing filter (Averaging filter)

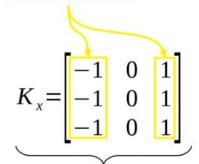


1D first order derivative estimator for horizontal direction

Product of two 1D kernels

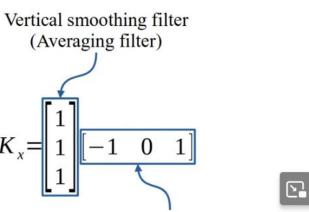
### Note that these kernels are separable Instead of 2D, two 1D kernels can be convolved with image sequentially

Here, these columns smooth in vertical direction



First order derivative estimator for horizontal direction

2D kernel



1D first order derivative estimator for horizontal direction

Product of two 1D kernels

#### These kernels are separable too, as in Prewitt

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

First order derivative estimator for horizontal direction

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

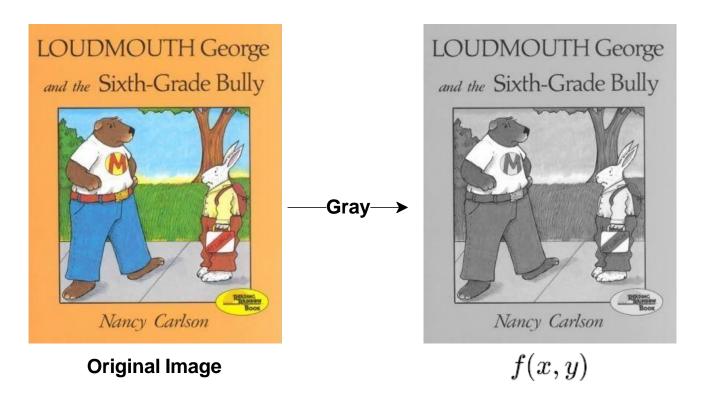
1D first order derivative estimator for horizontal direction

2D kernel

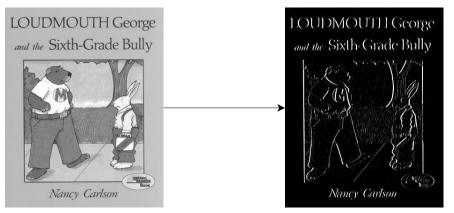
Product of two 1D kernels



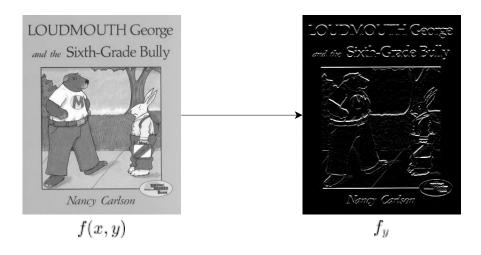
#### Convert image to grey-scale



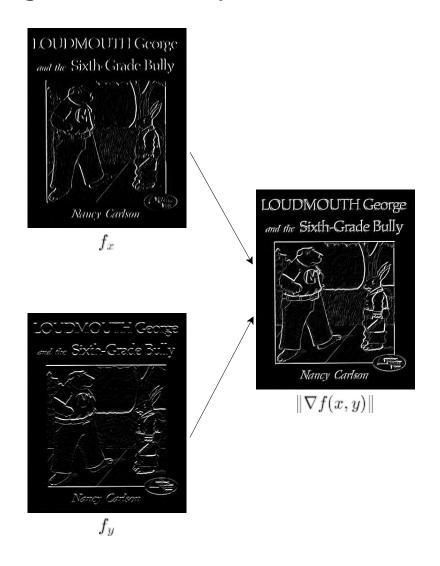
Compute  $f_X$  i.e. convolve gray image with horizontal Prewitt filter



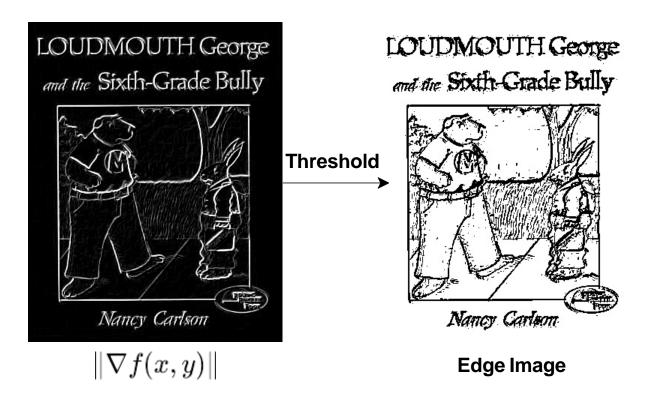
Compute  $f_y$  i.e. convolve gray image with vertical Prewitt filter



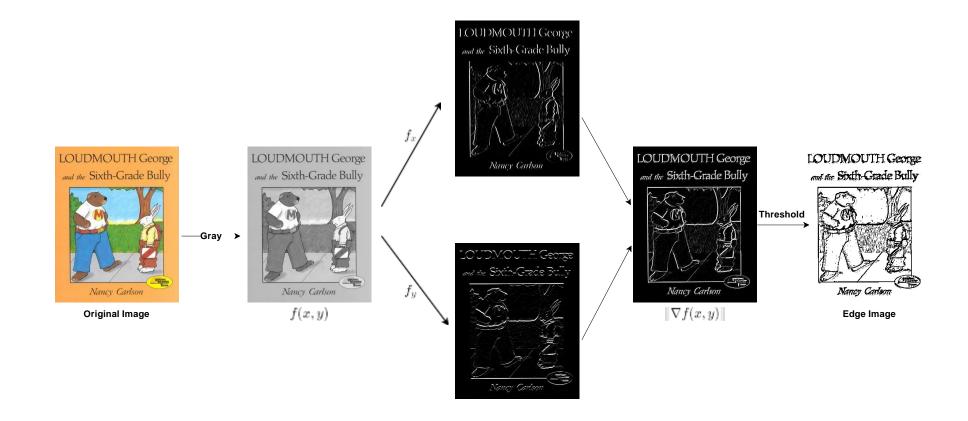
Find gradient magnitude at each pixel



Threshold gradient magnitude image



### Prewitt Edge Detector Complete Pipeline



# Sobel Edge Detector

- 1. Convert image to grey-scale
- 2. Compute derivatives in x and y directions ( $f_x$  and  $f_y$  using horizontal and vertical Sobel filter respectively)
- 3. Find gradient magnitude at every pixel

$$\sqrt{f_x^2+f_y^2}$$

4. Threshold gradient magnitude image

# Sobel Filter

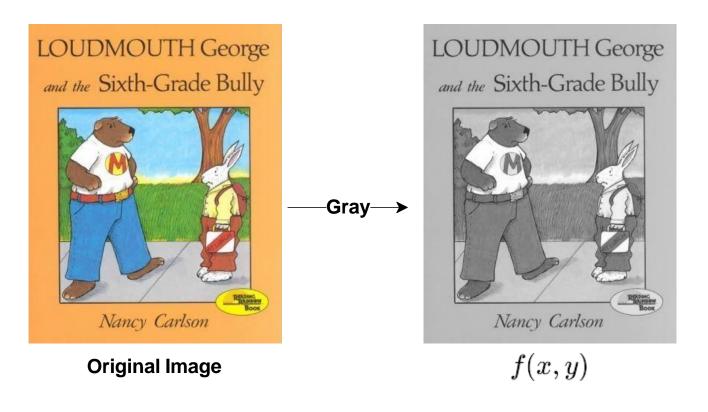
Horizontal Sobel Filter

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

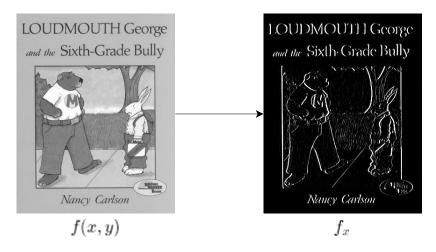
Vertical Sobel Filter

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

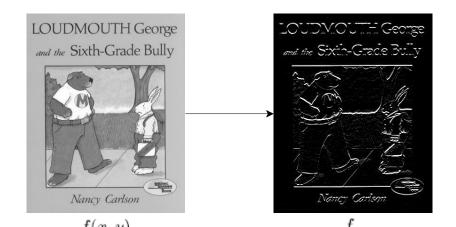
#### Convert image to grey-scale



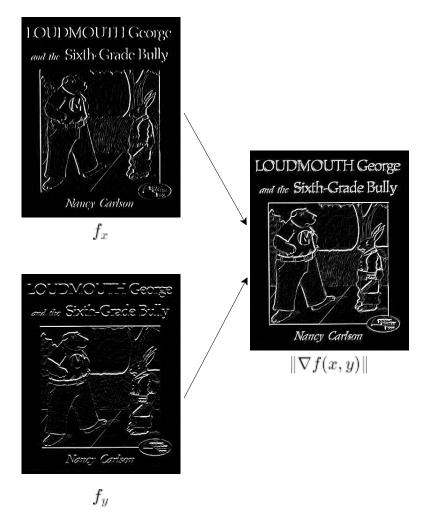
Compute  $f_X$  i.e. convolve gray image with horizontal Sobel filter



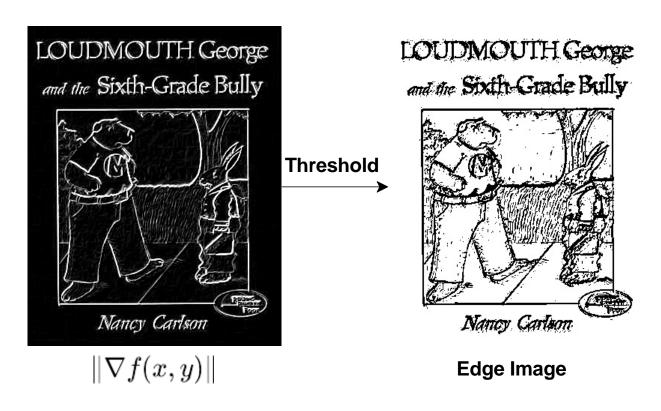
Compute  $f_V$  i.e. convolve gray image with vertical Sobel filter



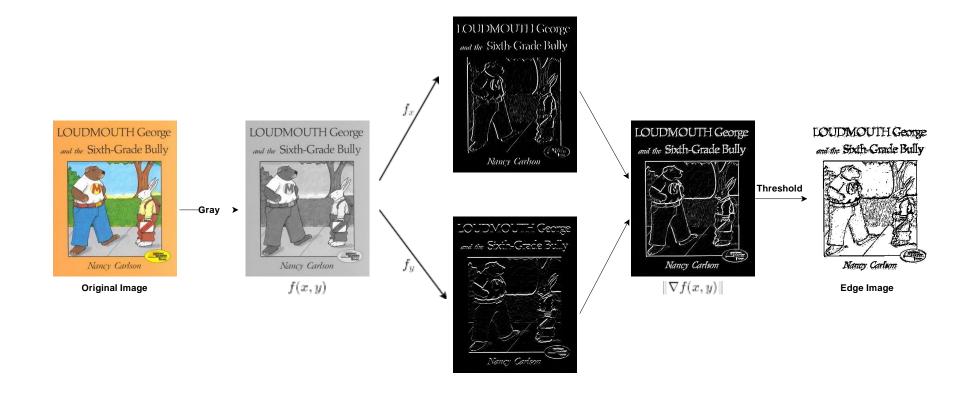
Find gradient magnitude at each pixel



Threshold gradient magnitude image

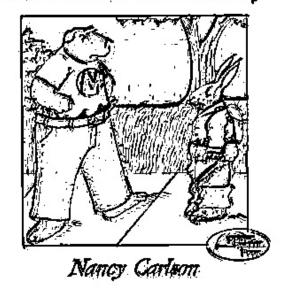


### Sobel Edge Detector Complete Pipeline



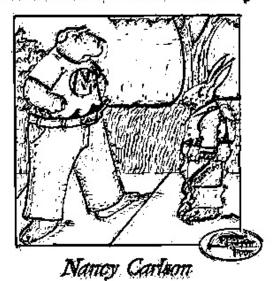
#### Prewitt vs. Sobel Results

LOUDMOUTH George
and the Sixth-Grade Bully



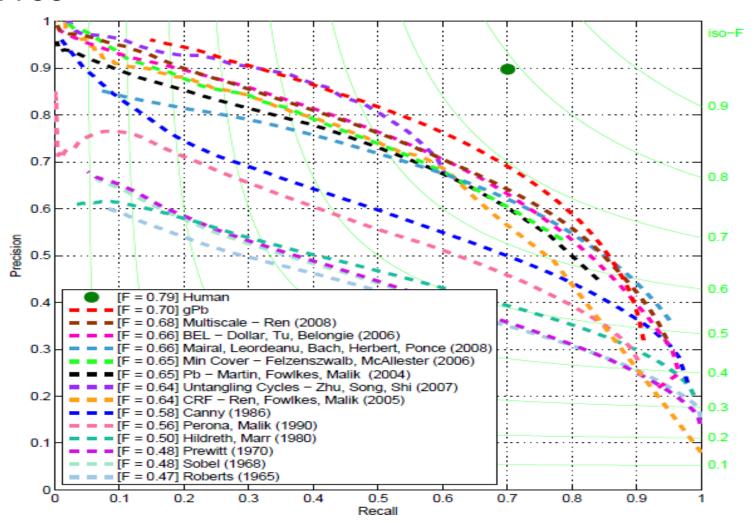
Prewitt

LOUDMOUTH George
and the Sixth-Grade Bully



Sobel

### Sobel vs Prewitt



### Source: Dr Rawat(AP UCF)

# Questions?

Sources for this lecture include materials from works by Mubarak Shah, Abhijit Mahalanobis, and D. Lowe

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