## **Edge Detection**

Most of the slides in this lecture are either from or adapted from Dr. Mubarak Shah's slides (Uni. Of Central Florida)

#### **Contents**

- Gradient operators
  - Prewit
  - Sobel
- Laplacian of Gaussian (Marr-Hildreth)
- Gradient of Gaussian (Canny)

This lecture

Next lecture

## 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)











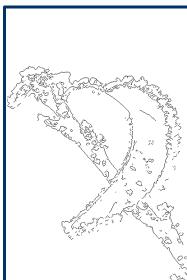






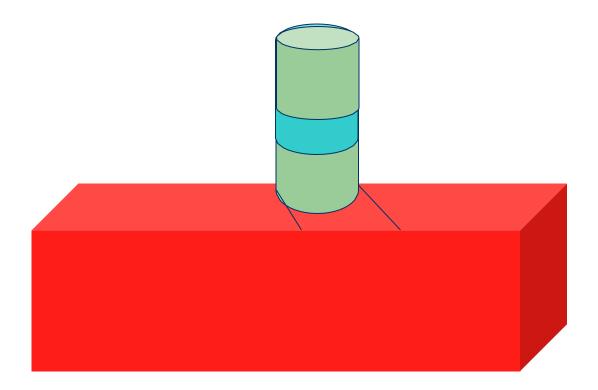




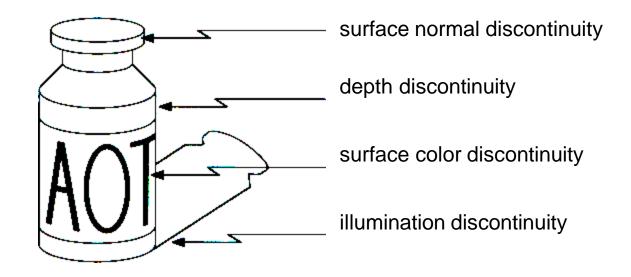


## **Edge Detection in Images**

At edges intensity or color changes

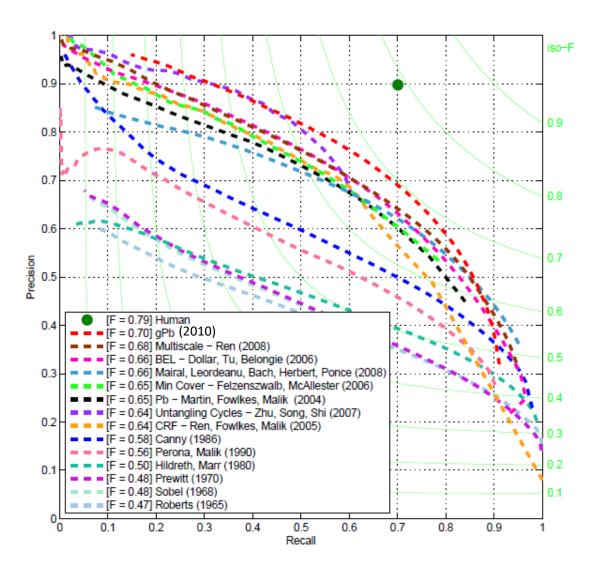


## Origin of Edges

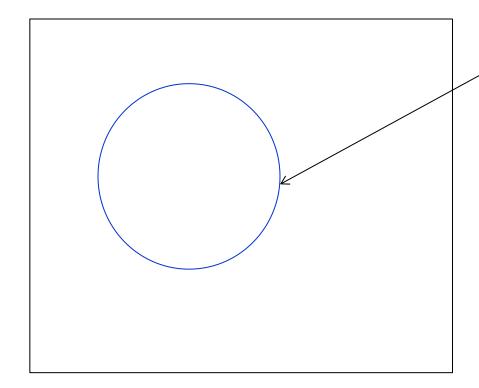


Edges are caused by a variety of factors

# 45 years of boundary detection

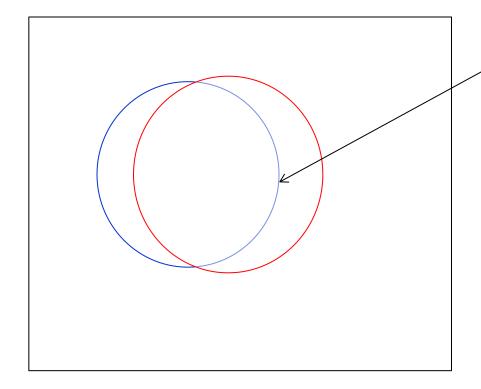






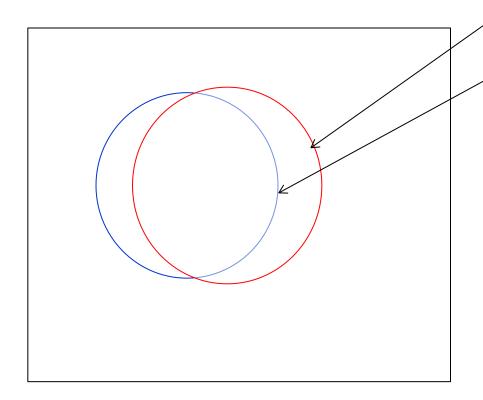
Results of Method (RM)





Results of Method (RM)

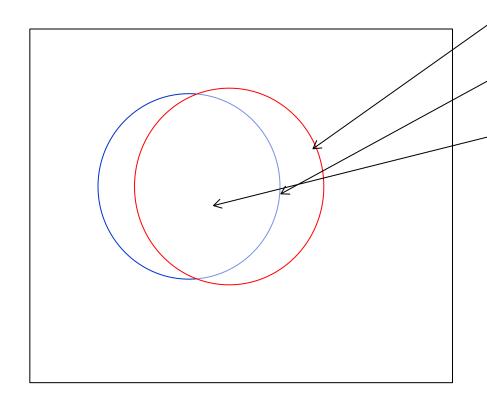




#### Ground Truth (GT)

Results of Method (RM)



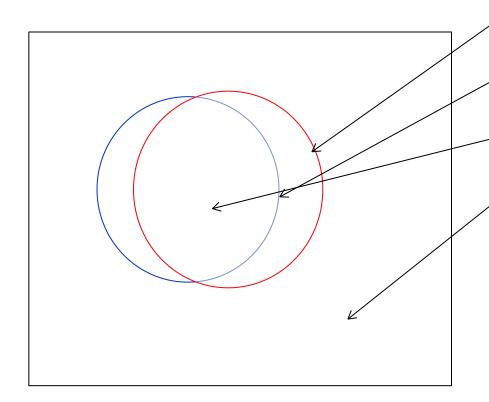


#### Ground Truth (GT)

Results of Method (RM)

True Positives (TP)





#### Ground Truth (GT)

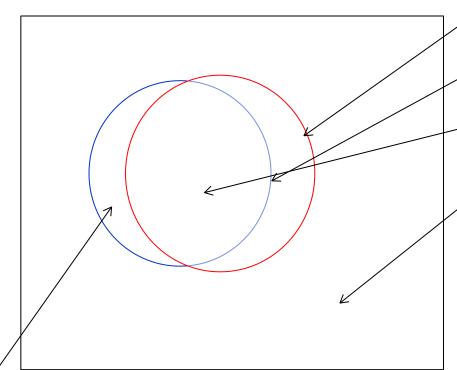
Results of Method (RM)

True Positives (TP)

True Negatives (TN)



## **Evaluation Metrics**



Ground Truth (GT)

Results of Method (RM)

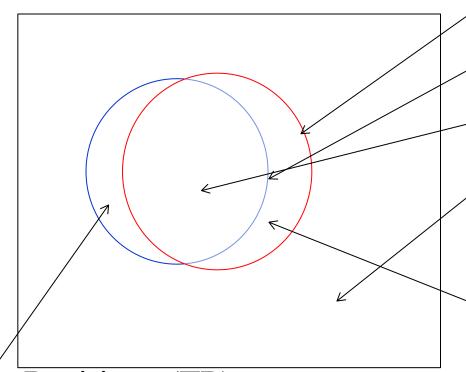
True Positives (TP)

True Negatives (TN)

False Positives (FP)



## **Evaluation Metrics**



Ground Truth (GT)

Results of Method (RM)

True Positives (TP)

True Negatives (TN)

False Negatives (FN)

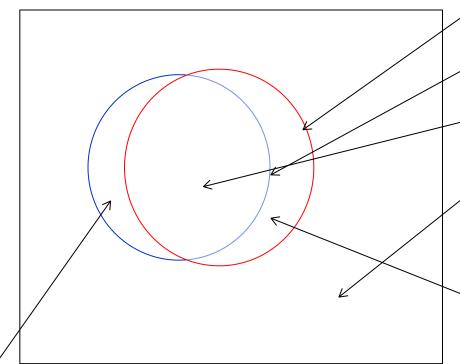
False Positives (FP)



## **Evaluation Metrics**

$$precision = \frac{GT \bigcap RM}{RM} = \frac{TP}{RM}$$

$$recall = \frac{GT \bigcap RM}{GT} = \frac{TP}{GT}$$



#### Ground Truth (GT)

Results of Method (RM)

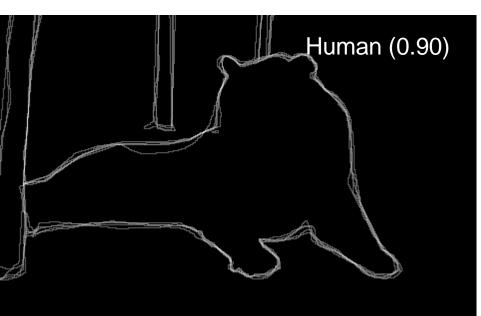
True Positives (TP)

True Negatives (TN)

False Negatives (FN)

False Positives (FP)







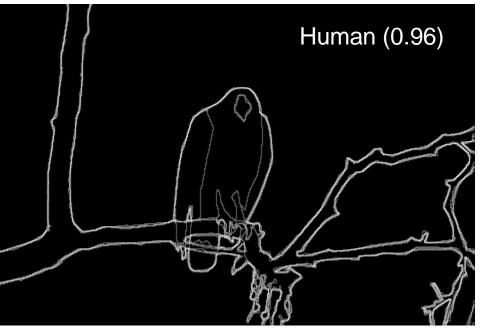
Slide Credit: James Hays

#### For more:

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

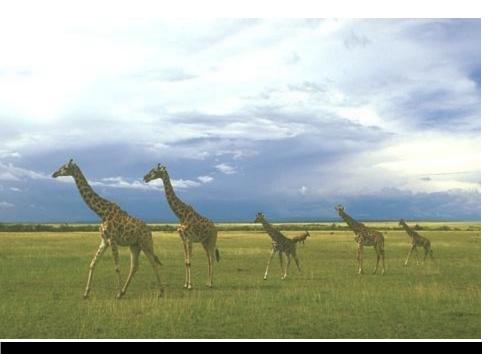
#### Results

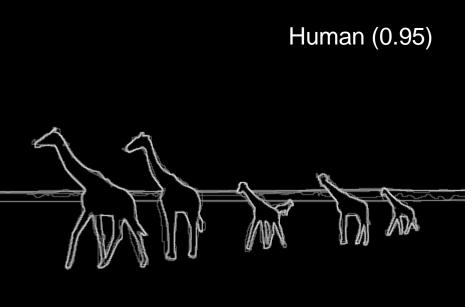






Slide Credit: James Hays



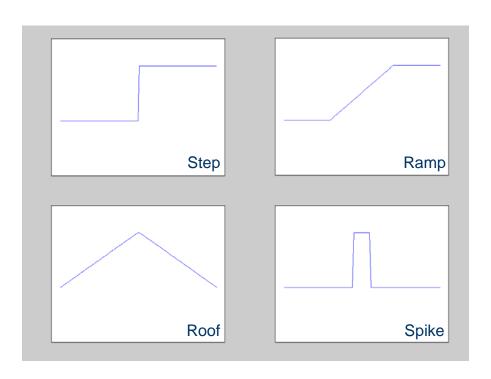




Slide Credit: James Hays

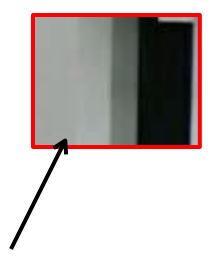
## What is an Edge?

- Discontinuity of intensities in the image
- Edge models
  - Step
  - Roof
  - Ramp
  - Spike

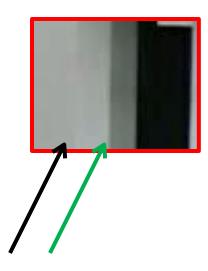




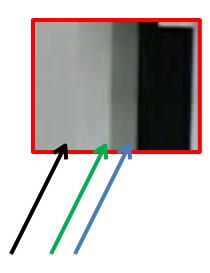




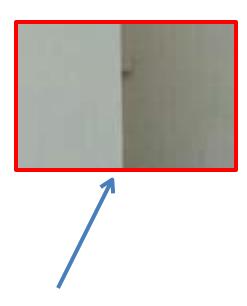




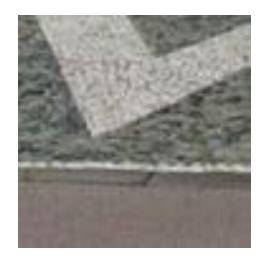




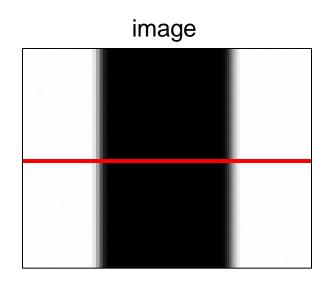




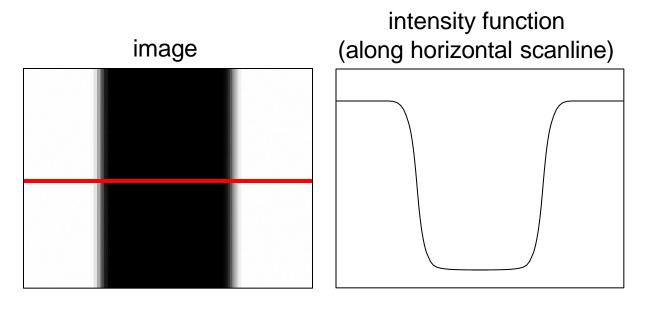




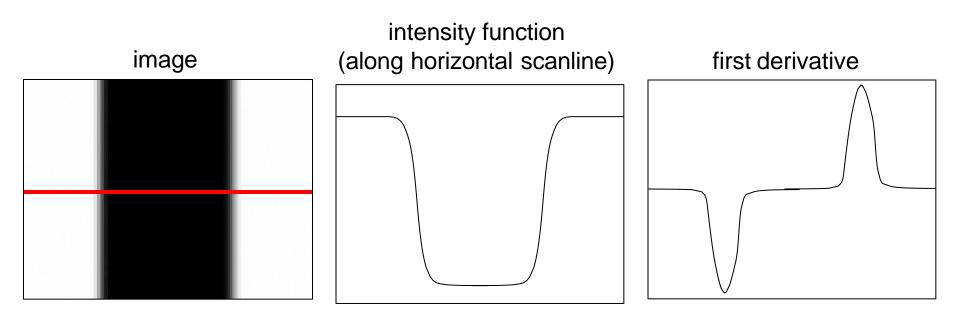
 An edge is a place of rapid change in the image intensity function



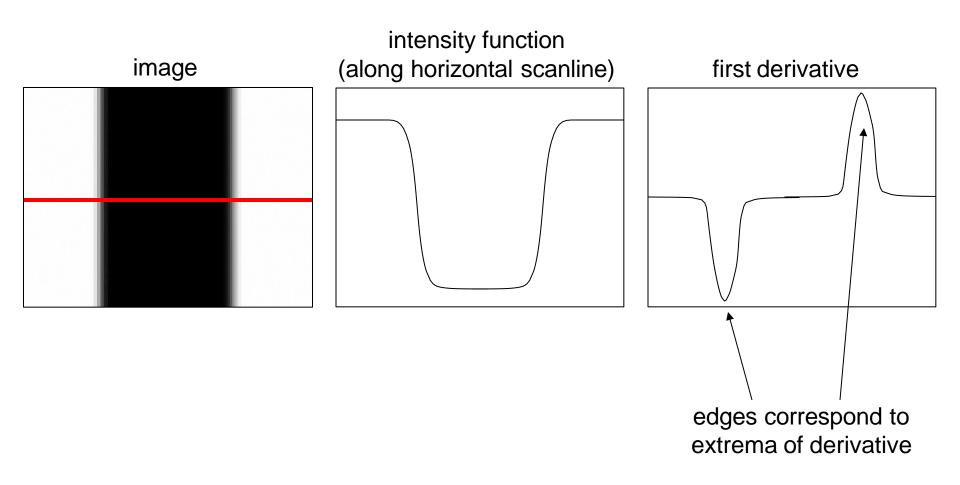
 An edge is a place of rapid change in the image intensity function



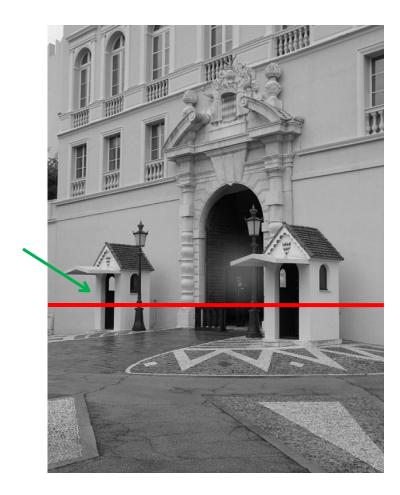
 An edge is a place of rapid change in the image intensity function



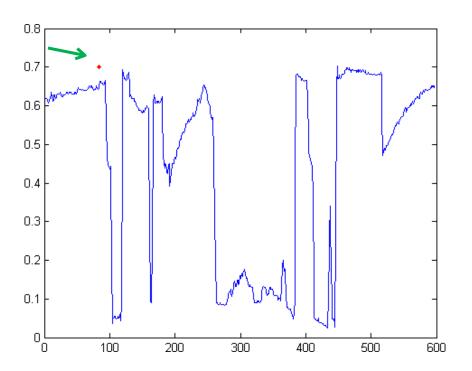
An edge is a place of rapid change in the image intensity function



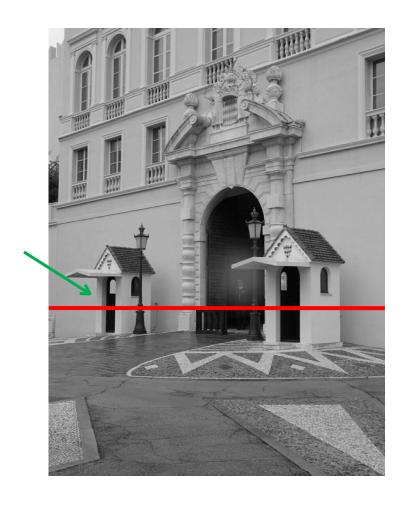
# Intensity profile

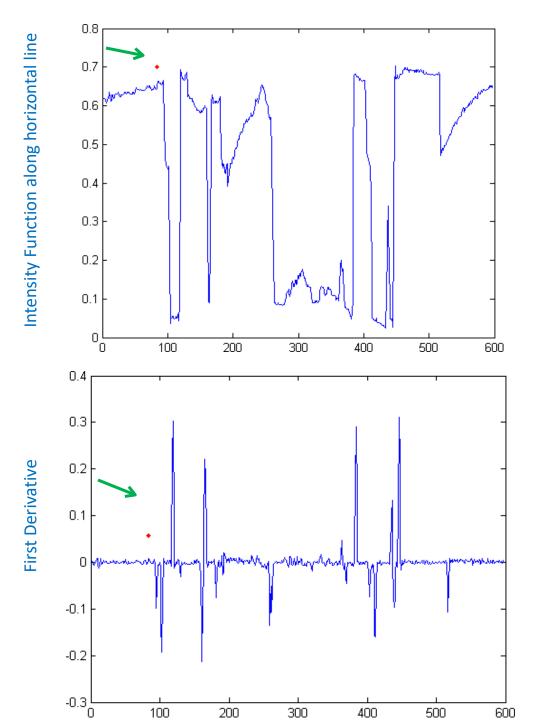


# Intensity Function along horizontal line



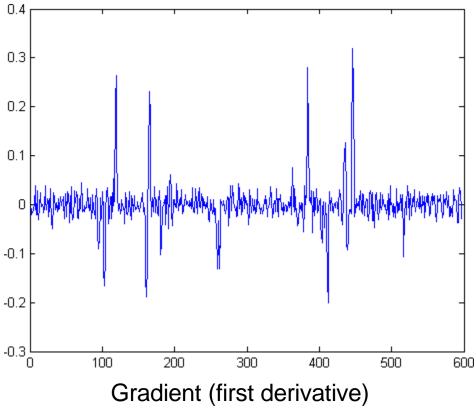
# Intensity profile





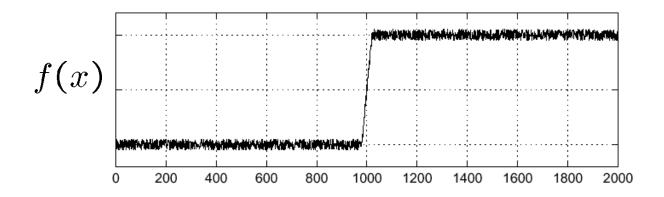
## Intensity Profile of a little noisy image





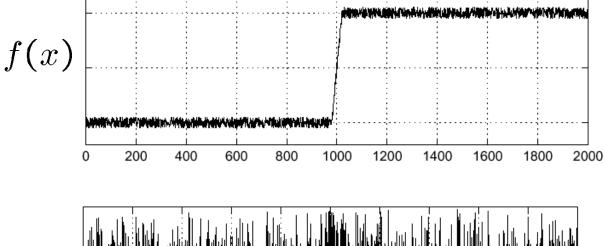
#### Effects of noise

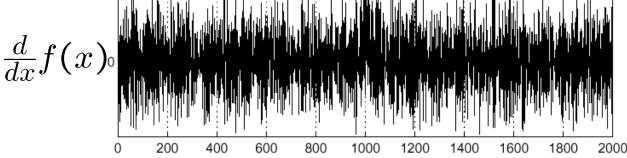
- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal



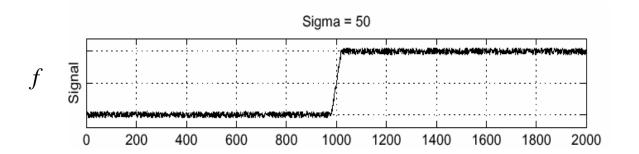
#### Effects of noise

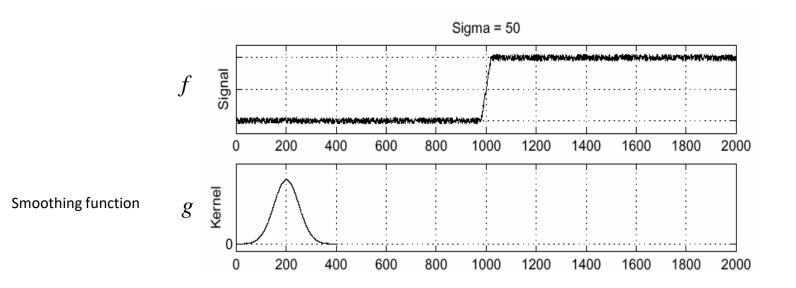
- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal

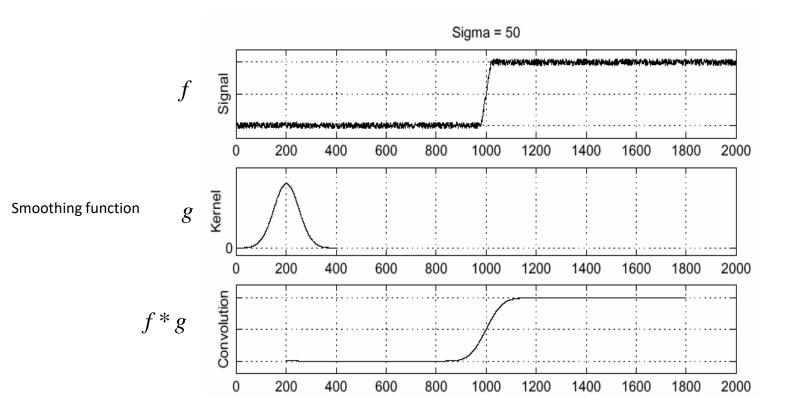


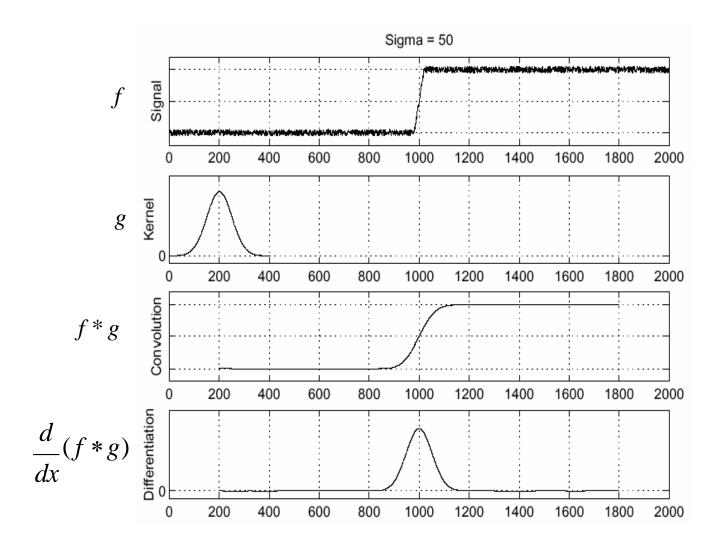


Where is the edge?









• To find edges, look for peaks in  $\frac{d}{dx}(f*g)$ 

#### Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative:  $\frac{d}{dx}(f*g) = f*\frac{d}{dx}g$
- This saves us one operation:

#### Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative:  $\frac{d}{dx}(f*g) = f*\frac{d}{dx}g$
- This saves us one operation:

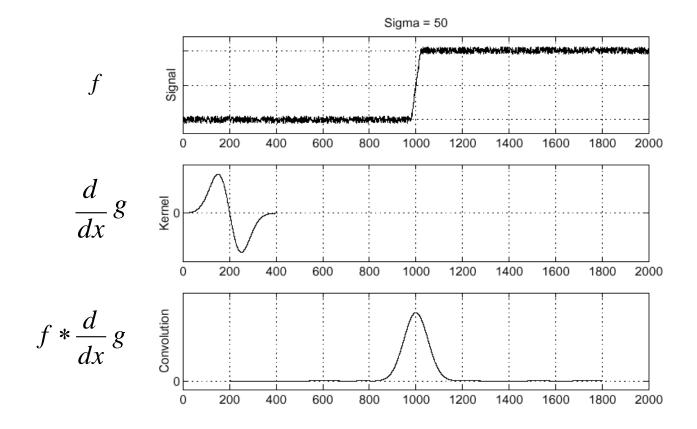


Image derivatives

$$\frac{\partial f}{\partial x} = \lim_{\varepsilon \to 0} \left( \frac{f(x+\varepsilon) - f(x)}{\varepsilon} \right) \longrightarrow \frac{\partial f}{\partial x} \approx \frac{f(x_{n+1}) - f(x)}{\partial x}$$

Convolve image with derivative filters

Image derivatives

$$\frac{\partial f}{\partial x} = \lim_{\varepsilon \to 0} \left( \frac{f(x+\varepsilon) - f(x)}{\varepsilon} \right) \longrightarrow \frac{\partial f}{\partial x} \approx \frac{f(x_{n+1}) - f(x)}{\partial x}$$

Convolve image with derivative filters

Backward difference [-1 1]

Image derivatives

$$\frac{\partial f}{\partial x} = \lim_{\varepsilon \to 0} \left( \frac{f(x+\varepsilon) - f(x)}{\varepsilon} \right) \longrightarrow \frac{\partial f}{\partial x} \approx \frac{f(x_{n+1}) - f(x)}{\partial x}$$

Convolve image with derivative filters

Backward difference [-1 1]

Forward difference [1 -1]

Image derivatives

$$\frac{\partial f}{\partial x} = \lim_{\varepsilon \to 0} \left( \frac{f(x+\varepsilon) - f(x)}{\varepsilon} \right) \longrightarrow \frac{\partial f}{\partial x} \approx \frac{f(x_{n+1}) - f(x)}{\partial x}$$

Convolve image with derivative filters

Backward difference [-1 1]

Forward difference [1 -1]

Central difference [-1 0 1]

Definition

Definition

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

**Definition** 

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

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

Definition

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

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

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

#### **Definition**

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

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

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

$$f_{y} = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Image I

$$I_{x} = I * \begin{bmatrix} 1 & -1 \end{bmatrix}$$

$$I_{y} = I * \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



Image I

$$I_x = I * \begin{bmatrix} 1 & -1 \end{bmatrix}$$

$$I_{y} = I * \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



Image I



$$I_{x} = I * \begin{bmatrix} 1 & -1 \end{bmatrix}$$

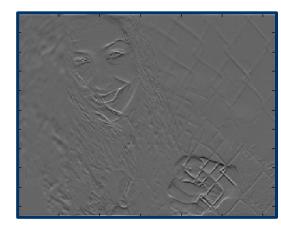
$$I_{y} = I * \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$



Image I



 $I_x = I * \begin{bmatrix} 1 & -1 \end{bmatrix}$ 



$$I_{y} = I * \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

# **Edge Detectors**

### **Edge Detectors**

- Gradient operators
  - Prewit
  - Sobel
- Laplacian of Gaussian (Marr-Hildreth)
- Gradient of Gaussian (Canny)

- Compute derivatives
  - In x and y directions

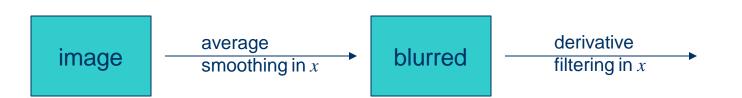
- Compute derivatives
  - In x and y directions
- Find gradient magnitude

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

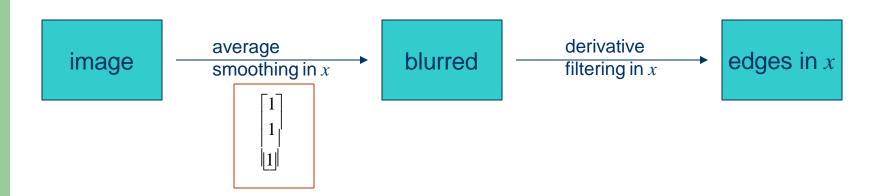
image

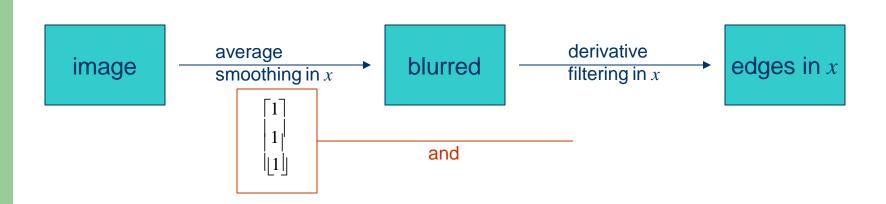
image average smoothing in x

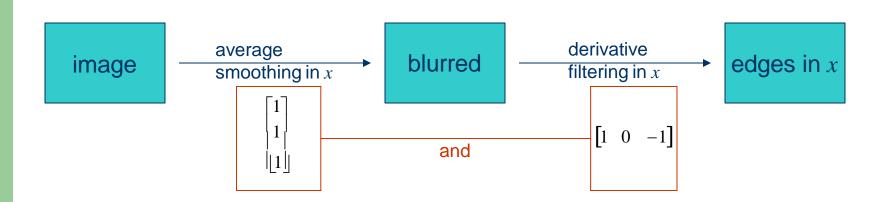


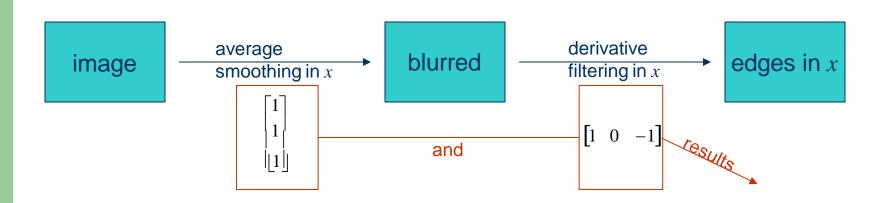


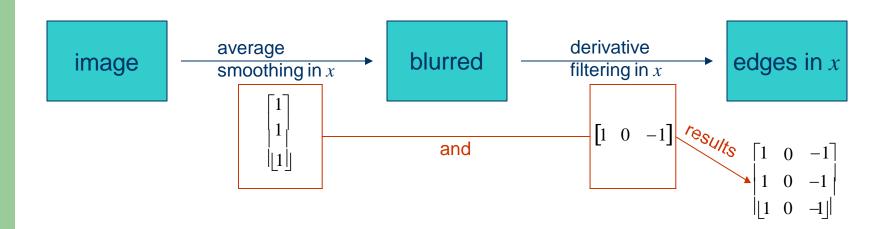


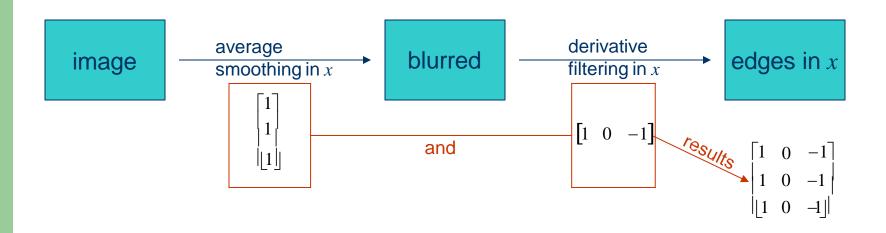




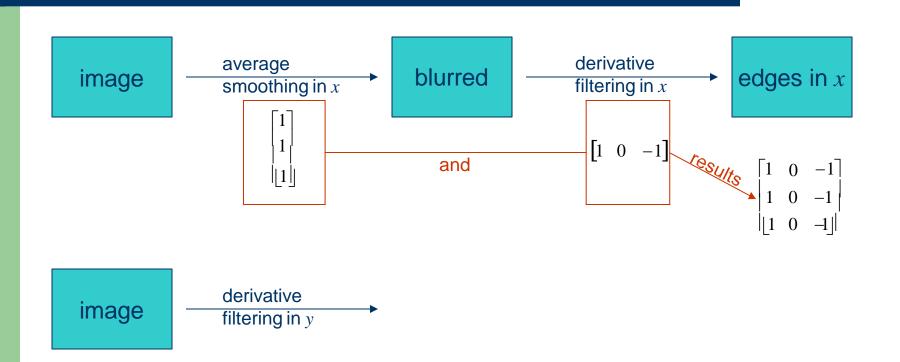


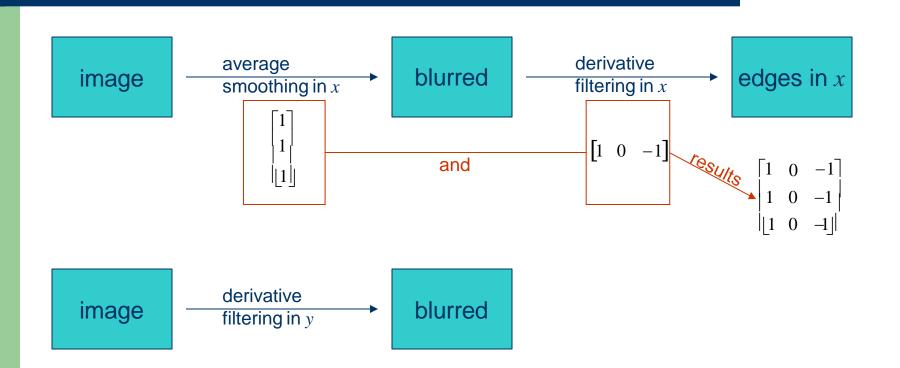


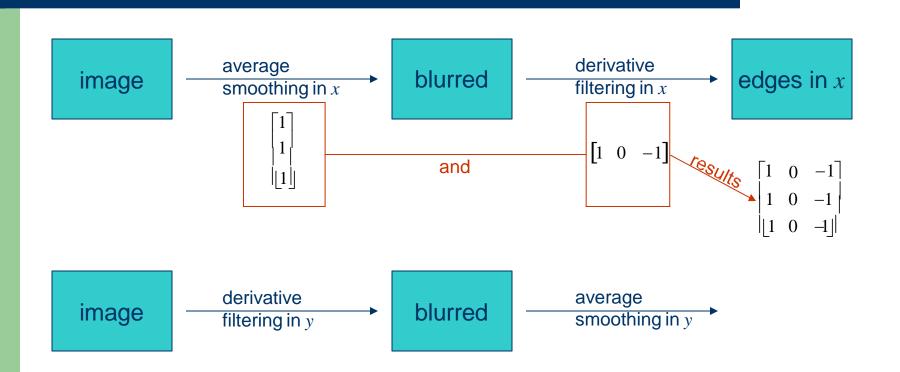


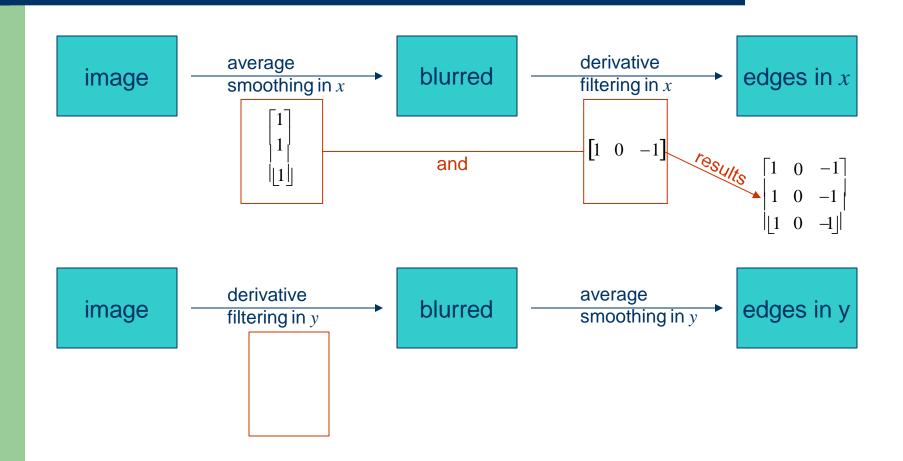


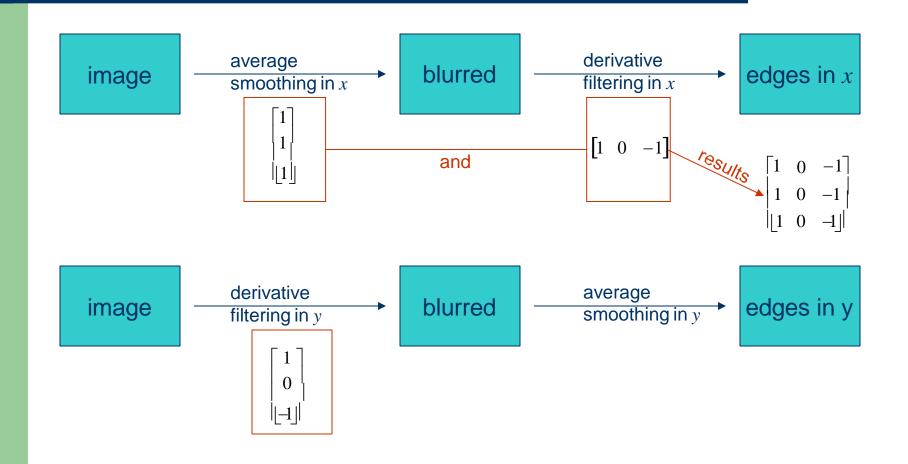
image

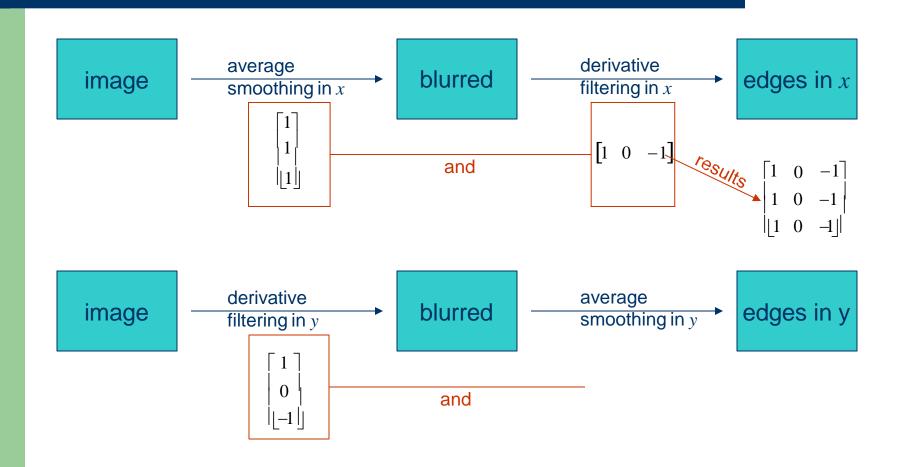


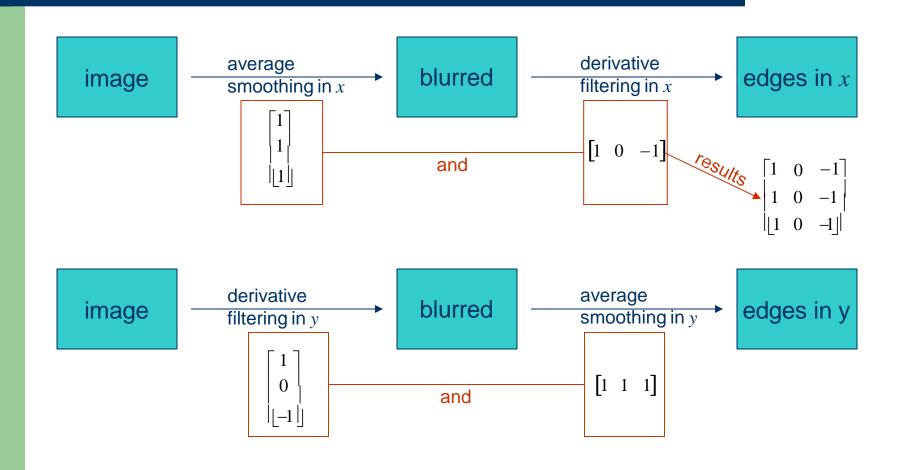


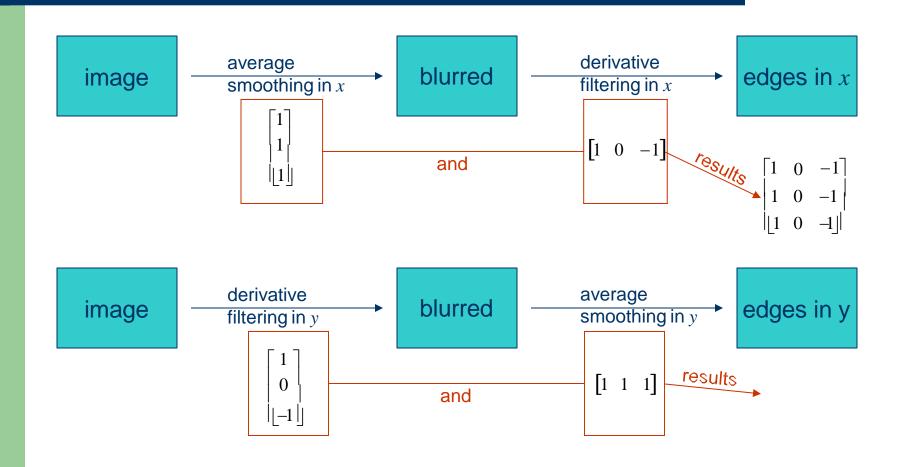


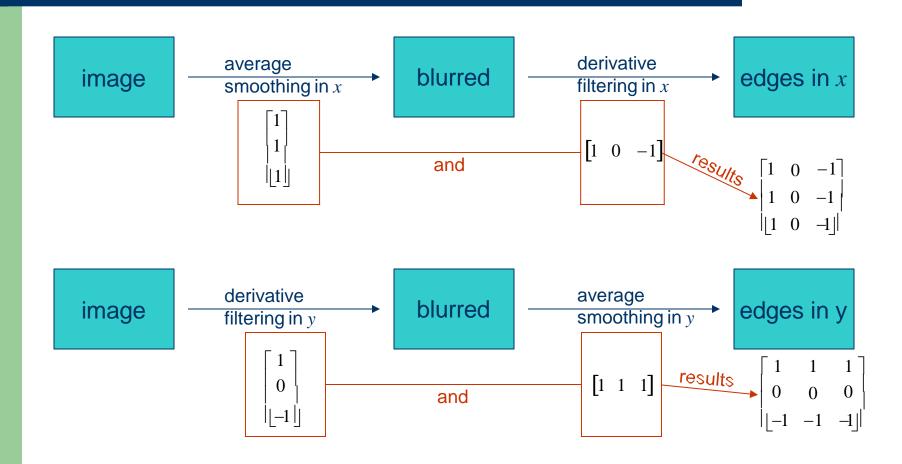








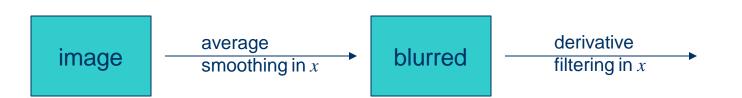




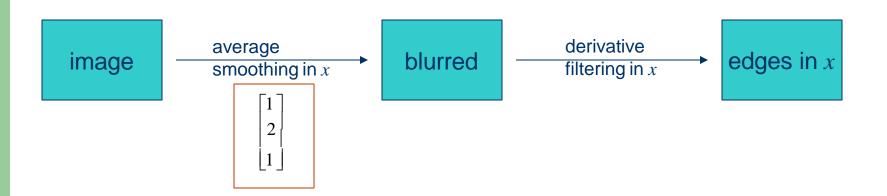
image

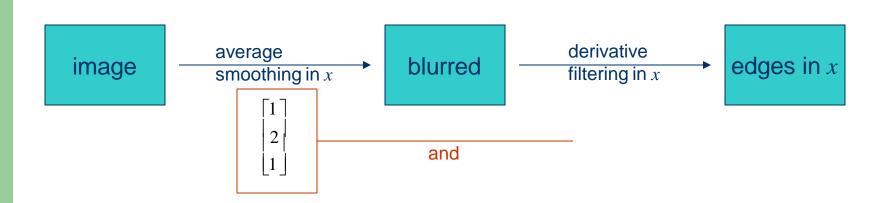
image average smoothing in x

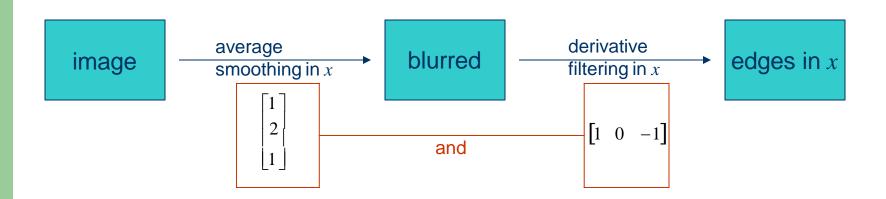


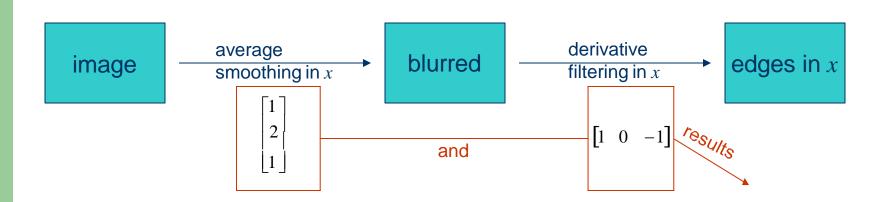


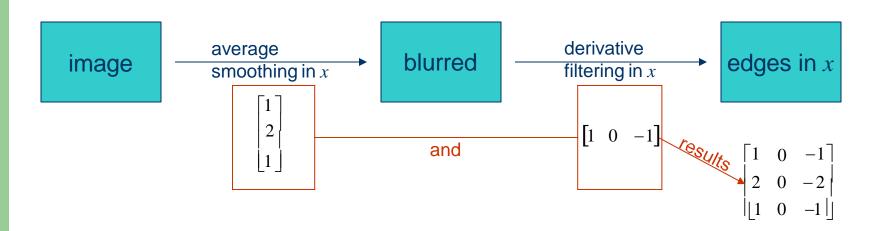


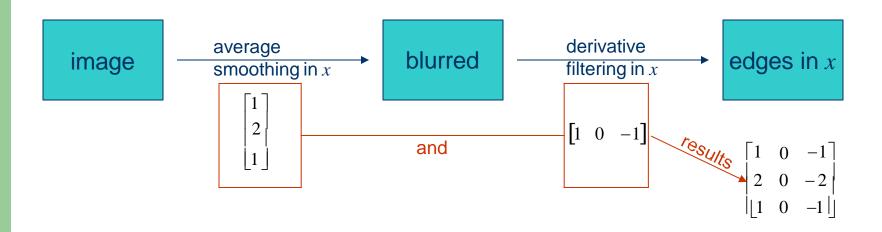












image

