CAP 5415 Computer Vision
Fall 2005

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www.cs.ucf.edu/courses/cap5415/fall2005
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Recap (Filtering)

- Modify pixels based on the neighborhood

10	30	10
20	11	20
11	9	1

$\xrightarrow{f(p)}$

	5.7	

Linear Filtering

- The output is the linear combination of the neighborhood pixels

1	3	0
2	10	2
4	1	1

Image

$\otimes$

1	0	-1
1	0.1	-1
1	0	-1

Kernel

=

	5	

Filter Output

convolution

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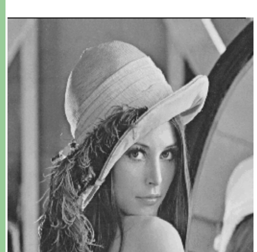
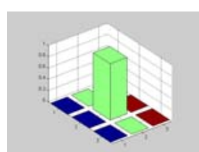
Filtering Examples



$*$



0	0	0
0	1	0
0	0	0

=

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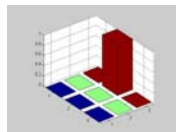
Filtering Examples



$*$

0	0	0
0	0	1
0	0	0

$=$

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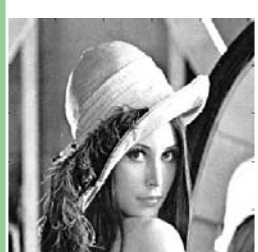
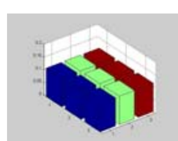
Filtering Examples

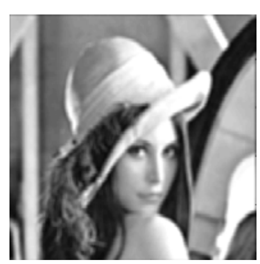




$*\frac{1}{9}$

1	1	1
1	1	1
1	1	1

$=$



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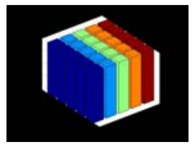
Filtering Examples



$$* \frac{1}{25} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} =$$

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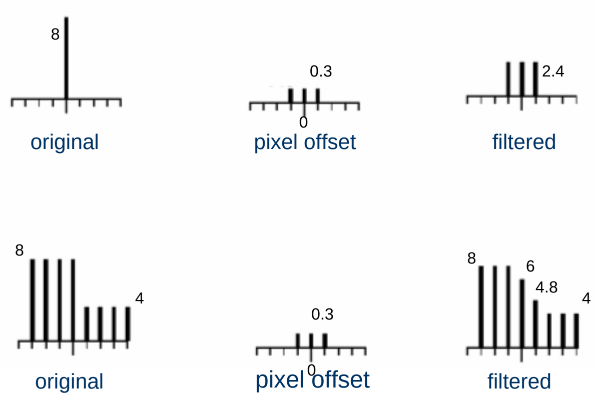
Blurring Examples



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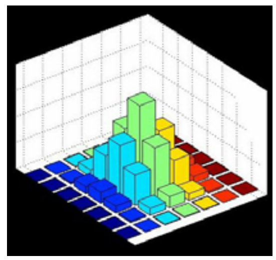
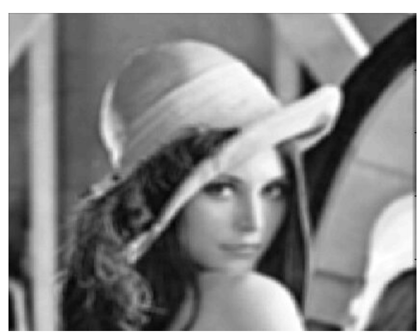
Filtering Gaussian


*

=


Gaussian vs. Smoothing

Gaussian Smoothing



Smoothing by Averaging

Noise Filtering

Gaussian Noise

After Averaging

After Gaussian Smoothing

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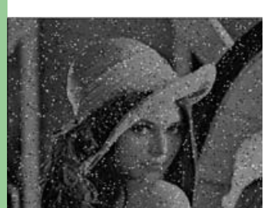
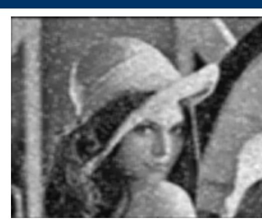
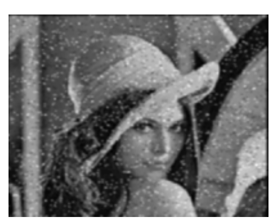
Noise Filtering



Salt & Pepper Noise



After Averaging



After Gaussian Smoothing

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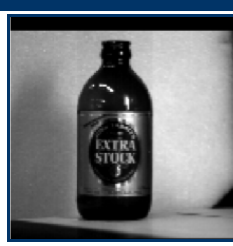
Edge Detection

Example



An Application

- What is an object?
- How can we find it?

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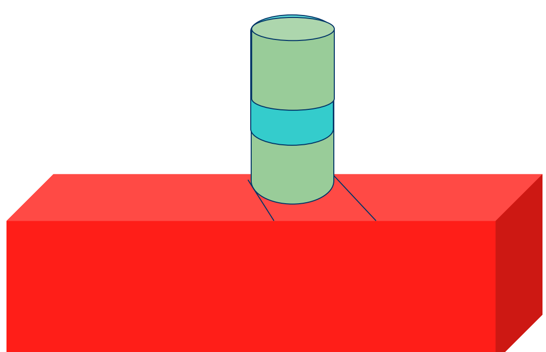
Edge Detection in Images

- Can occur due to different sources
  - Shadows
  - Texture



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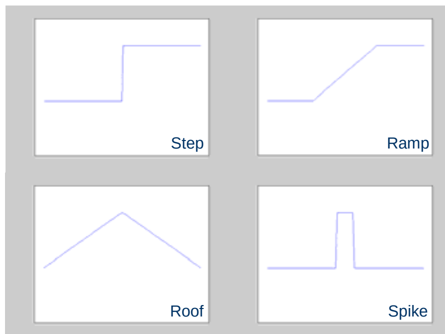
What is an Edge?

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



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Detecting Discontinuities

- Image derivatives

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

- Convolve image with derivative filters

Backward difference	[-1 1]
Forward difference	[1 -1]
Central difference	[-1 0 1]

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Derivative in Two-Dimensions

- Definition

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

- Approximation

$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x_{n+1},y_m)-f(x_n,y_m)}{\Delta x} \qquad \frac{\partial f(x,y)}{\partial y} \approx \frac{f(x_n,y_{m+1})-f(x_n,y_m)}{\Delta x}$$

- Convolution kernels

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

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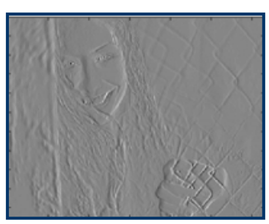
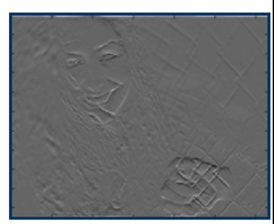
Image Derivatives

Image I



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



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

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Derivatives and Noise

- Strongly affected by noise
  - obvious reason: pixels look very different from their neighbors
- The larger the noise is the stronger the response

- What is to be done?
  - Neighboring pixels look alike
  - Pixel along an edge look alike
  - Image smoothing should help
    - Force pixels different to their neighbors (possibly noise) to look like neighbors

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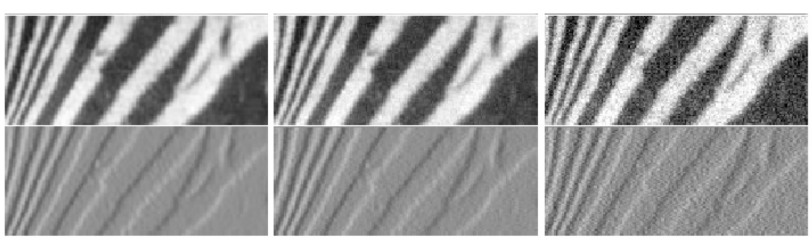
Derivatives and Noise



Increasing noise →

Zero mean additive gaussian noise

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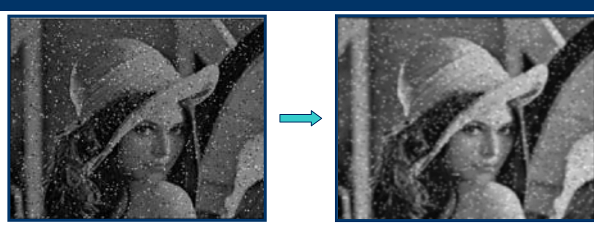
Image Smoothing

- Expect pixels to “**be like**” their neighbors
  - Relatively few reflectance changes
- Generally expect noise to be independent from pixel to pixel
  - Smoothing suppresses noise

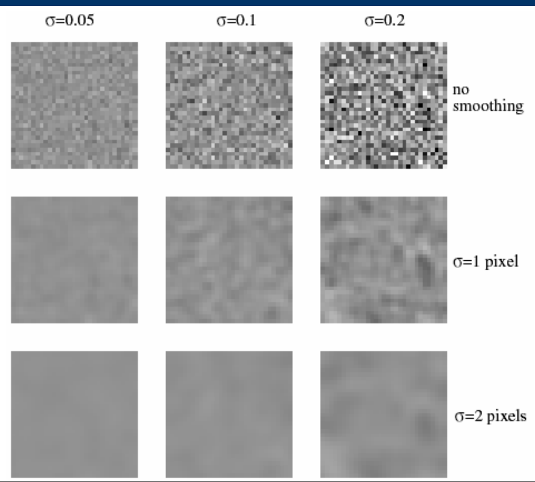
Gaussian Smoothing



$$g(x,y) = e^{\frac{-(x^2+y^2}{2\sigma^2}}$$

- Scale of Gaussian σ
  - As σ increases, more pixels are involved in average
  - As σ increases, image is more blurred
  - As σ increases, noise is more effectively suppressed

Gaussian Smoothing (Examples)



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Edge Detectors

- Gradient operators
  - Prewit
  - Sobel
- Laplacian of Gaussian (Marr-Hildreth)
- Gradient of Gaussian (Canny)
- Facet Model Based Edge Detector (Haralick)

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Prewitt and Sobel Edge Detector

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

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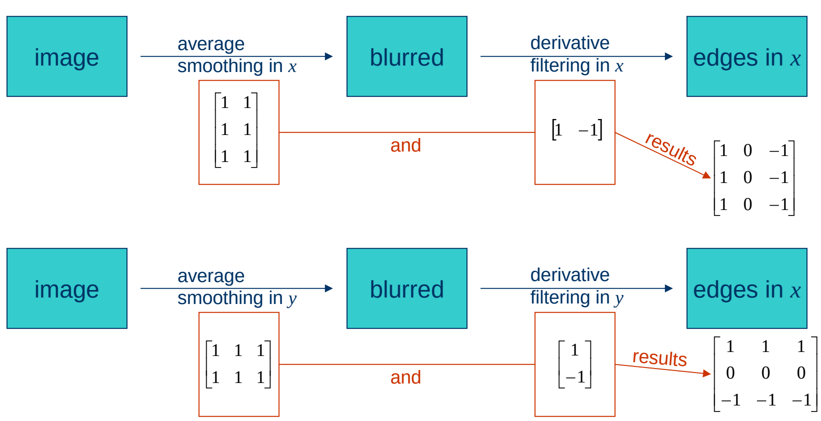
Prewitt Edge Detector



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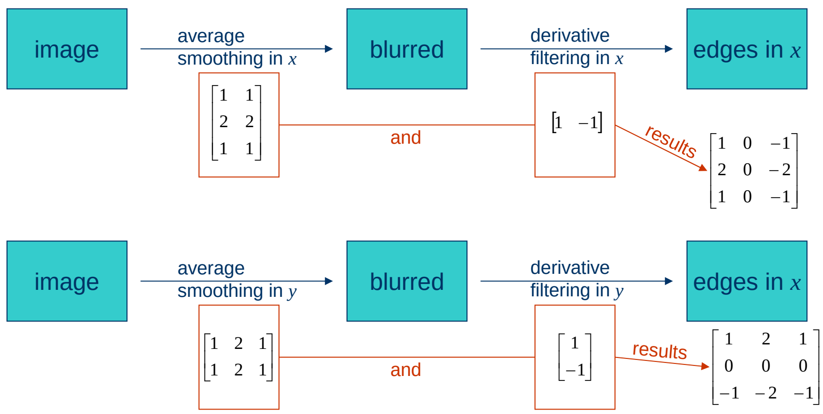
Sobel Edge Detector



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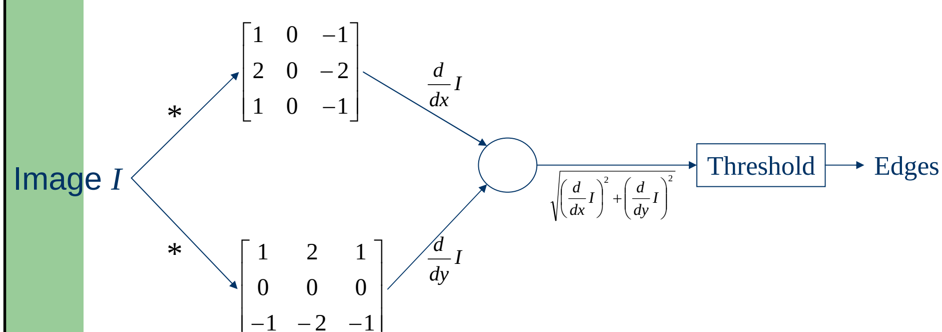
Sobel Edge Detector



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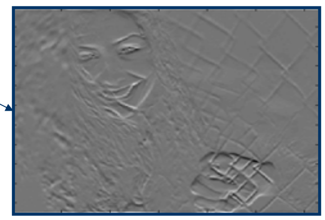
Sobel Edge Detector

$\frac{d}{dx}I$

$\frac{d}{dy}I$



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Sobel Edge Detector

$\Delta = \sqrt{\left(\frac{d}{dx}I\right)^2 + \left(\frac{d}{dy}I\right)^2}$

$\Delta \geq Threshold = 100$

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Exercise

- Code Sobel and Prewitt edge detectors.
  - Reading images
  - Use of convolution
    - Gradient computation
  - Thresholding

Suggested Reading

- Chapter 4, Emanuele Trucco, Alessandro Verri, "Introductory Techniques for 3-D Computer Vision"
- Chapter 2, Mubarak Shah, “Fundamentals of Computer Vision”