# CAP 5415 Computer Vision Fall 2011

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www.cs.ucf.edu/~vision/courses/cap5415/fall2012

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# **Filtering**

Lecture-2

#### **General**

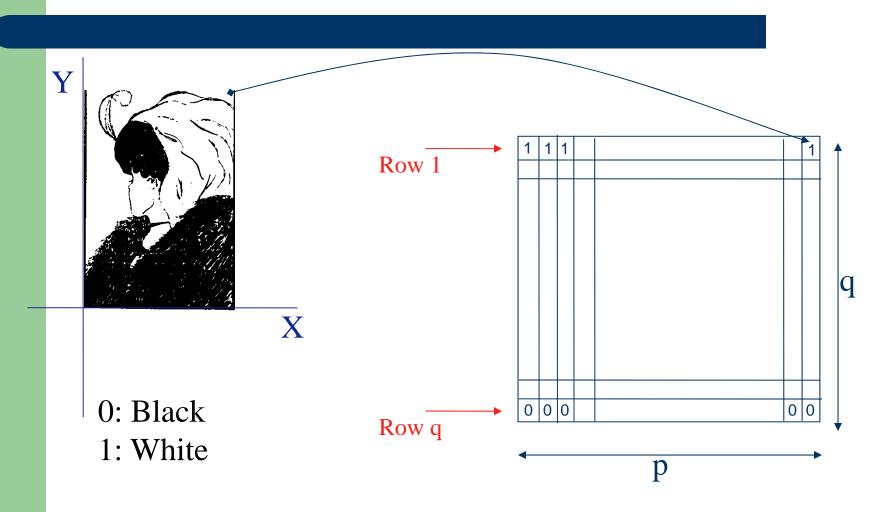
- Binary
- Gray Scale
- Color



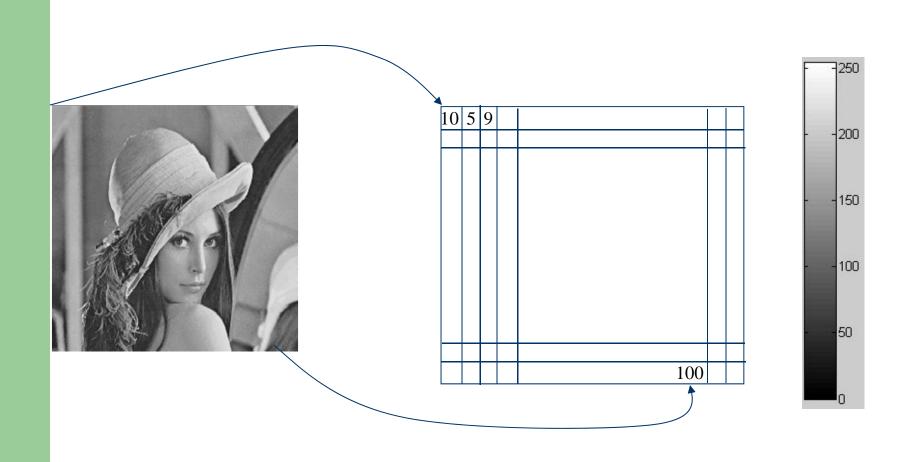




# **Binary Images**



## **Gray Level Image**



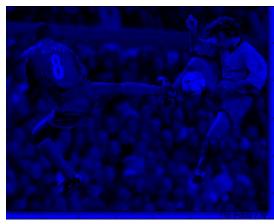
# **Gray Scale Image**





# **Color Image Red, Green, Blue Channels**

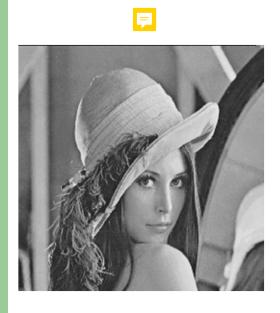


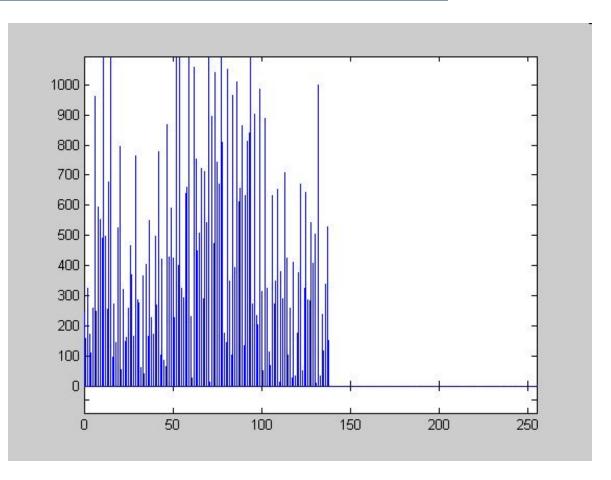






# **Image Histogram**





## **Image Noise**

- Light Variations
- Camera Electronics
- Surface Reflectance
- Lens

## **Image Noise**

- I(x,y): the true pixel values
- n(x,y): the noise at pixel (x,y)

$$\hat{I}(x, y) = I(x, y) + n(x, y)$$



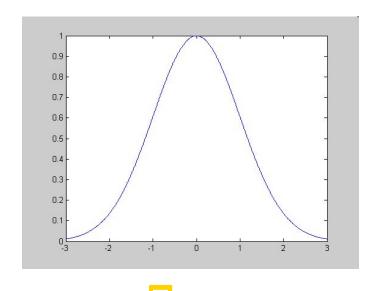




#### **Gaussian Noise**

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





## **Image Derivatives & Averages**

#### **Definitions**

- Derivative: Rate of change
  - Speed is a rate of change of a distance
  - Acceleration is a rate of change of speed
- Average (Mean)
  - Dividing the sum of N values by N

#### **Derivative**

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

$$v = \frac{ds}{dt}$$
 speed  $a = \frac{dv}{dt}$  acceleration

### **Examples**

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

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

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

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

#### **Discrete Derivative**

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

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

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

# **Discrete Derivative Finite Difference**

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

Backward difference

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

Forward difference

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

Central difference

### **Example**

$$f(x) = 10$$
 15 10 10 25 20 20 20  $f'(x) = 0$  5 -5 0 15 -5 0 0  $f''(x) = 0$  5 -10 5 15 20 5

#### **Derivative Masks**

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

#### **Derivatives in 2 Dimensions**

Given function

**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

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

Gradient direction

$$\theta = \tan^{-1} \frac{f_x}{f_y}$$

## **Derivatives of Images**

Derivative masks

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

$$f_x \Rightarrow \frac{1}{3} \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad f_y \Rightarrow \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

## **Derivatives of Images**

### Correlation

 $\otimes$ 

$$f \otimes h = \sum_{k} \sum_{l} f(k,l) h(i+k,j+l)$$

f = Image

f = Kernel

f

$f_1$	$f_2$	$f_3$
$f_4$	$f_5$	$f_6$
f <sub>7</sub>	f <sub>8</sub>	$f_9$

h

$h_1$	h <sub>2</sub>	h <sub>3</sub>	
$h_4$	$h_5$	$h_6$	
h <sub>7</sub>	h <sub>8</sub>	h <sub>9</sub>	

 $f * h = f_1 h_1 + f_2 h_2 + f_3 h_3 + f_4 h_4 + f_5 h_5 + f_6 h_6$ 

$$+f_7h_7+f_8h_8+f_9h_9$$

## Convolution

$$f * h = \sum_{k} \sum_{l} f(k,l)h(i-k,j-l)$$

f = Image

h = Kernel

h <sub>7</sub>	h <sub>8</sub>	h <sub>9</sub>
$h_4$	$h_5$	$h_6$
$h_1$	$h_2$	$h_3$

Y-flip

X - flip

	$h_1$	$h_2$	$h_3$
_	$h_4$	$h_5$	$h_6$
	h <sub>7</sub>	h <sub>8</sub>	h <sub>9</sub>

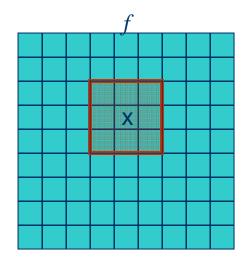
$f_1$	$f_2$	$f_3$
$f_4$	$f_5$	$f_6$
$f_7$	$f_8$	$f_9$

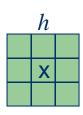
$$\begin{array}{c|cccc} h_9 & h_8 & h_7 \\ h_6 & h_5 & h_4 \\ h_3 & h_2 & h_1 \\ \end{array}$$

 $f * h = f_1 h_0 + f_2 h_8 + f_3 h_7$  $+ f_4 h_6 + f_5 h_5 + f_6 h_4$  $+ f_7 h_3 + f_8 h_2 + f_9 h_1$ 

#### Convolution

$$f(x,y) * h = f(x+1,y+1)h(-1,-1) + f(x,y+1)h(0,-1) + f(x-1,y+1)h(1,-1) + f(x+1,y)h(-1,0) + f(x,y)h(0,0) + f(x-1,y)h(1,0)$$
$$f(x+1,y-1)h(-1,1) + f(x,y-1)h(0,1) + f(x-1,y-1)h(1,1)$$





$$f * h = \sum_{i=-1}^{1} \sum_{j=-1}^{1} f(x-i, y-i)h(i, j)$$

Coordinates

-1,0	0,1	1,1
-1,0	0,0	1,0
-1,-1	0,-1	1,-1

## **Averages**

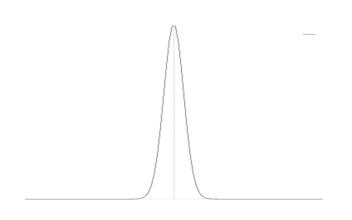
#### Mean

$$I = \frac{I_1 + I_2 + \dots I_n}{n} = \frac{\sum_{i=1}^{n} I_i}{n}$$

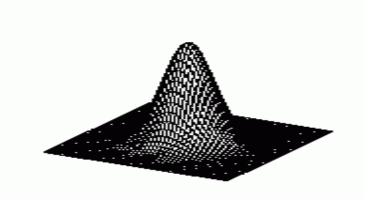
#### Weighted mean

$$I = \frac{w_1 I_1 + w_2 I_2 + \ldots + w_n I_n}{n} = \frac{\sum_{i=1}^{n} w_i I_i}{n}$$

#### **Gaussian Filter**



$$g(x) = e^{\frac{-x^2}{2o^2}}$$



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

$$g(x) = [.011 \quad .13 \quad .6 \quad 1 \quad .6 \quad .13 \quad .011]$$

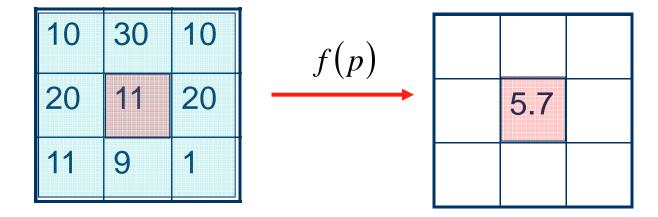
$$\sigma = 1$$

## **Properties of Gaussian**

- Most common natural model
- Smooth function, it has infinite number of derivatives
- Fourier Transform of Gaussian is Gaussian.
- Convolution of a Gaussian with itself is a Gaussian.
- There are cells in eye that perform Gaussian filtering.

## **Filtering**

 Modify pixels based on some function of the neighborhood

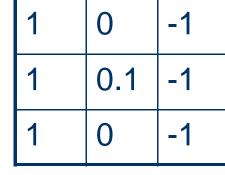


## **Linear Filtering**

 The output is the linear combination of the neighborhood pixels

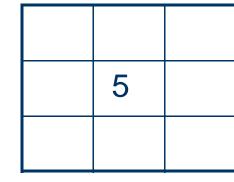
1	3	0
2	10	2
4	1	1

Image



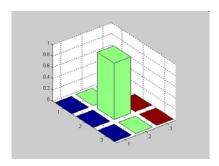
 $\otimes$ 

Kernel



Filter Output



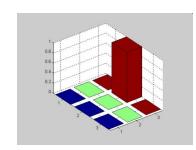


0	0	0
0	1	0
0	0	0



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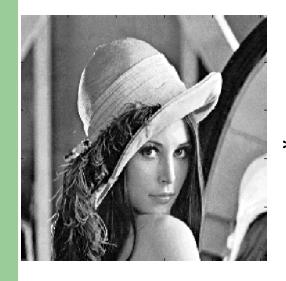


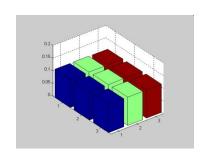


0	0	0
0	0	1
0	0	0



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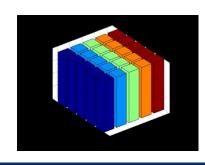


1	1	1
1	1	1
1	1	1



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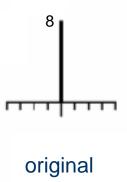


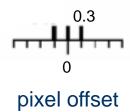
	1	1	1	1	1
5	1	1	1	1	1
	1	1	1	1	1
	1	1	1	1	1
	1	1	1	1	1

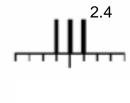


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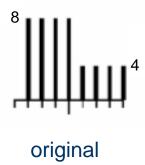
# **Blurring Examples**

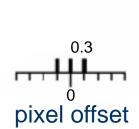


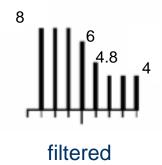




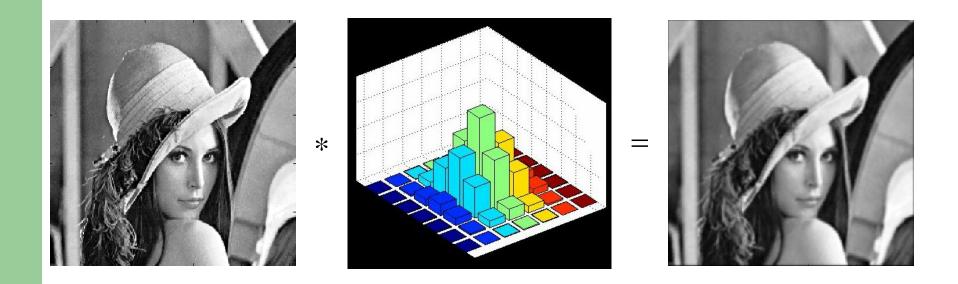
filtered







## Filtering Gaussian



## Gaussian vs. Smoothing



Gaussian Smoothing



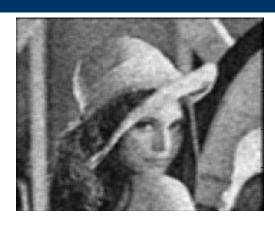
Smoothing by Averaging

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# **Noise Filtering**



Gaussian Noise



After Averaging



After Gaussian Smoothing Alper Yilmaz, Mubarak Shah, UCF

- conv: 1-D Convolution.
  - C = conv(A, B) convolves vectors A and B.
- conv2: Two dimensional convolution.
  - C = conv2(A, B) performs the 2-D convolution of matrices A and B.

- filter2: Two-dimensional digital filter.
  - Y = filter2(B,X) filters the data in X with the 2-D FIR filter in the matrix B.
  - The result, Y, is computed using 2-D correlation and is the same size as X.
  - filter2 uses CONV2 to do most of the work. 2-D correlation is related to 2-D convolution by a 180 degree rotation of the filter matrix.

- gradient: Approximate gradient.
  - [FX,FY] = gradient(F) returns the numerical gradient of the matrix F. FX corresponds to dF/dx,
     FY corresponds to dF/dy.
- mean: Average or mean value.
  - For vectors, mean(X) is the mean value (average) of the elements in X.

- special: Create predefined 2-D filters
  - H = fspecial(TYPE) creates a two-dimensional filter H of the specified type. Possible values for TYPE are:
  - 'average' averaging filter;
  - 'gaussian' Gaussian lowpass filter
  - 'laplacian' filter approximating the 2-D Laplacian operator
  - 'log' Laplacian of Gaussian filter
  - 'prewitt' Prewitt horizontal edge-emphasizing filter
  - 'sobel'
     Sobel horizontal edge-emphasizing filter
  - Example: H=fspecial('gaussian',7,1) creates a 7x7 Gaussian filter with variance 1.