

# Digital Image Processing

Image Enhancement - Filtering

# Derivative

- Derivative is defined as a rate of change.

# Discrete Derivative Finite Distance

$$\frac{df}{dx} = \frac{f(x) - f(x-1)}{1} = f'(x) \quad \text{Backward difference}$$

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

$$\frac{df}{dx} = \frac{f(x+1) - f(x-1)}{2} = f'(x) \quad \text{Central difference}$$

# Example

$$f(x) = \quad 10 \quad 15 \quad 10 \quad 10 \quad 25 \quad 20 \quad 20 \quad 20$$

$$f'(x) = \quad 0 \quad 5 \quad -5 \quad 0 \quad 15 \quad -5 \quad 0 \quad 0$$

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

## Derivative Masks

Backward difference      [-1 1]

Forward difference      [1 -1]

Central difference      [-1 0 1]

# Derivatives in 2-dimension

Given function

$$f(x, y)$$

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

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

Gradient direction

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

# Derivatives of Images

Derivative masks

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

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$

$$I_x = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

# Derivatives of Images

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix}$$

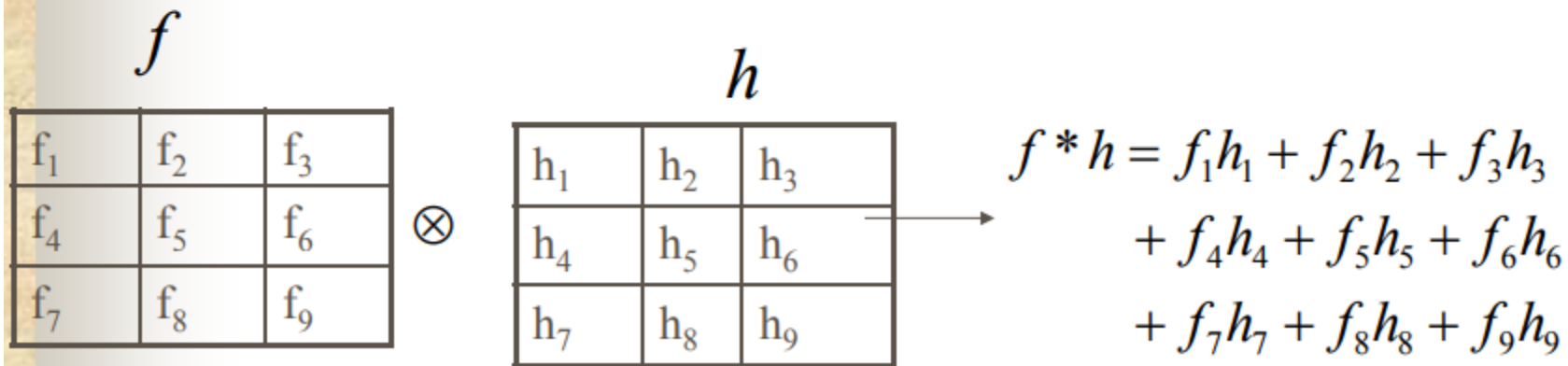
$$I_y = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

# Correlation

$$f \otimes h = \sum_k \sum_l f(k, l) h(i+k, j+l)$$

$f$  = Image

$f$  = Kernel





# Convolution

$$f * h = \sum_k \sum_l f(k, l) h(i - k, j - l)$$

$f = \text{Image}$   
 $h = \text{Kernel}$

$h_7$	$h_8$	$h_9$
$h_4$	$h_5$	$h_6$
$h_1$	$h_2$	$h_3$

$X - flip$

$h_1$	$h_2$	$h_3$
$h_4$	$h_5$	$h_6$
$h_7$	$h_8$	$h_9$

$f$

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

$Y - flip$

$h_9$	$h_8$	$h_7$
$h_6$	$h_5$	$h_4$
$h_3$	$h_2$	$h_1$

$\otimes$

$$\begin{aligned} f * h &= f_1 h_9 + f_2 h_8 + f_3 h_7 \\ &+ f_4 h_6 + f_5 h_5 + f_6 h_4 \\ &+ f_7 h_3 + f_8 h_2 + f_9 h_1 \end{aligned}$$

# Averages

- Mean

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

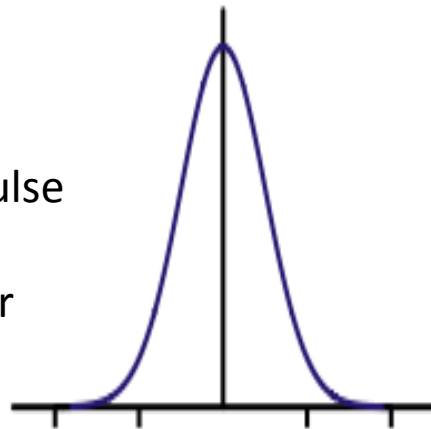
- Weighted mean

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

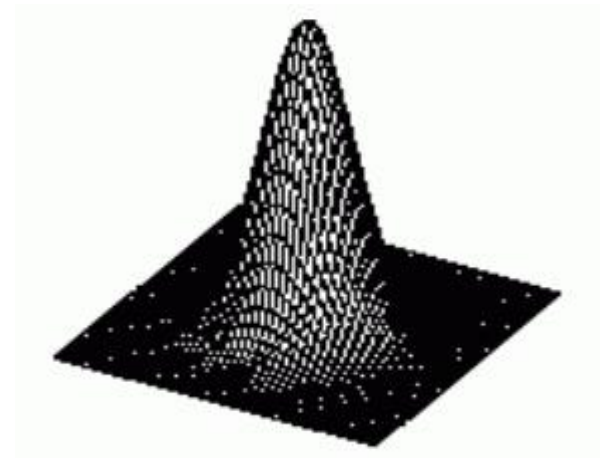
# Gaussian Filtering

- The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove detail and noise. In this sense it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian (`bell-shaped') hump.

Shape of Impulse  
Response for  
Gaussian Filter



2D Gaussian



# Scale of Gaussian

- As sigma increases, more pixels are involved in averaging
- As sigma increase, image is more blurred
- As sigma increase, noise is more effectively suppressed

# Gaussian Filter

- Gaussian smoothing

$$\begin{array}{c} \text{smoothed image} \\ \hat{S} \end{array} = \begin{array}{c} \text{Gaussian filter} \\ \hat{g} \end{array} * \begin{array}{c} \text{image} \\ \hat{I} \end{array} \quad g = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$\frac{1}{2\pi\sigma^2} \cdot e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

**Consider sigma = 0.6 and kernel size = 3x3**

$$\frac{1}{2\pi\sigma^2} = \frac{1}{2 \times 3.14 \times 0.6 \times 0.6} = \frac{1}{2.2619}$$

# Gaussian Smoothing

**Kernel width; X= 3, Kernel Height; Y = 3**

$$X = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \text{ and } Y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$e^{-\frac{(x^2+y^2)}{2\sigma^2}} = \begin{bmatrix} -2.7778 & -1.3889 & -2.7778 \\ -1.3889 & 0 & -1.3889 \\ -2.7778 & -1.3889 & -2.7778 \end{bmatrix}$$

The Gaussian kernel's center part ( Here 0.4421 ) has the highest value and intensity of other pixels decrease as the distance from the center part increases.

# Gaussian Smoothing

The Gaussian kernel takes the form as:

$$\begin{bmatrix} 0.0275 & 0.1102 & 0.0275 \\ 0.1102 & 0.4421 & 0.1102 \\ 0.0275 & 0.1102 & 0.0275 \end{bmatrix}$$

Convolve the kernel with the region in the given image

$$\begin{bmatrix} 72 & 68 & 88 & 159 \\ 69 & 66 & 87 & 162 \\ 70 & 66 & 83 & 161 \\ 70 & 66 & 78 & 154 \end{bmatrix}$$

# Gaussian Smoothing

Performing Convolution:

$$\begin{bmatrix} 68 & 88 & 159 \\ 66 & 87 & 162 \\ 66 & 83 & 161 \end{bmatrix} * \begin{bmatrix} 0.0275 & 0.1102 & 0.0275 \\ 0.1102 & 0.4421 & 0.1102 \\ 0.0275 & 0.1102 & 0.0275 \end{bmatrix} = \begin{bmatrix} 1.8692 & 9.7009 & 4.3706 \\ 7.2757 & 38.4624 & 17.8585 \\ 1.8142 & 9.1497 & 4.4256 \end{bmatrix}$$

On convolution of the local region and the Gaussian kernel gives the highest intensity value to the center part of the local region (**38.4624**) and the remaining pixels have less intensity as the distance from the center increases.

Sum up the result and store it in the current pixel location (**Intensity = 94.9269**) of the image.



# Gaussian Smoothing

$$\begin{bmatrix} [] & [] & [] & [] \\ [] & [] & 94.9269 & [] \\ [] & [] & [] & [] \\ [] & [] & [] & [] \end{bmatrix}$$

Performing calculations for each pixel, the resultant image is:

$$\begin{bmatrix} 48.7478 & 59.2645 & 79.7865 & 100.2444 \\ 57.1176 & 69.7512 & 94.9296 & 121.1870 \\ 57.1740 & 68.9526 & 92.2220 & 119.6981 \\ 47.7534 & 59.9750 & 74.1254 & 96.7113 \end{bmatrix}$$

The end