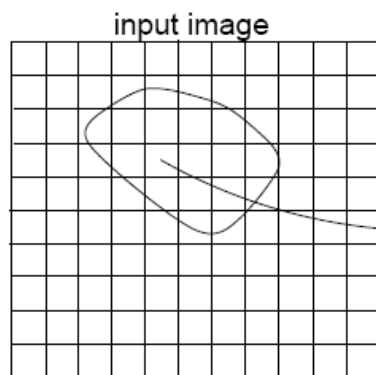
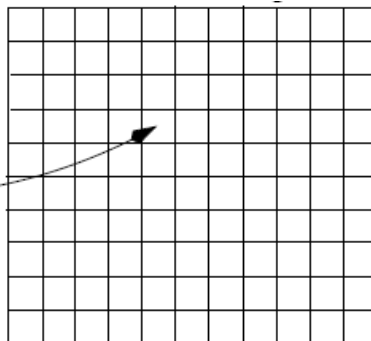


Spatial Filtering Methods (or Mask Processing Methods)

Area or Mask Processing Methods



T



$$g(x,y) = T[f(x,y)]$$

T operates on a
neighborhood of pixels

Spatial Filtering

- The word “filtering” has been borrowed from the frequency domain.
- Filters are classified as:
 - Low-pass (i.e., preserve low frequencies)
 - High-pass (i.e., preserve high frequencies)
 - Band-pass (i.e., preserve frequencies within a band)
 - Band-reject (i.e., reject frequencies within a band)

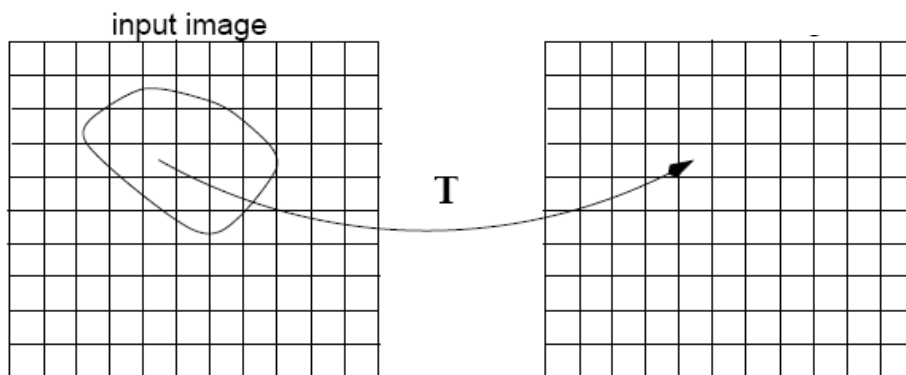
Spatial Filtering (cont'd)

- Spatial filtering are defined by:

A neighborhood

An operation that is performed on the pixels inside the neighborhood

Area or Mask Processing Methods

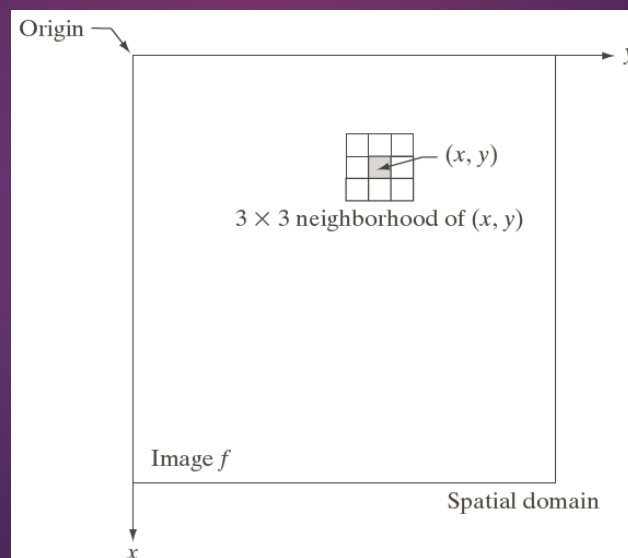


$$g(x,y) = T[f(x,y)]$$

T operates on a neighborhood of pixels

Spatial Filtering (cont'd)

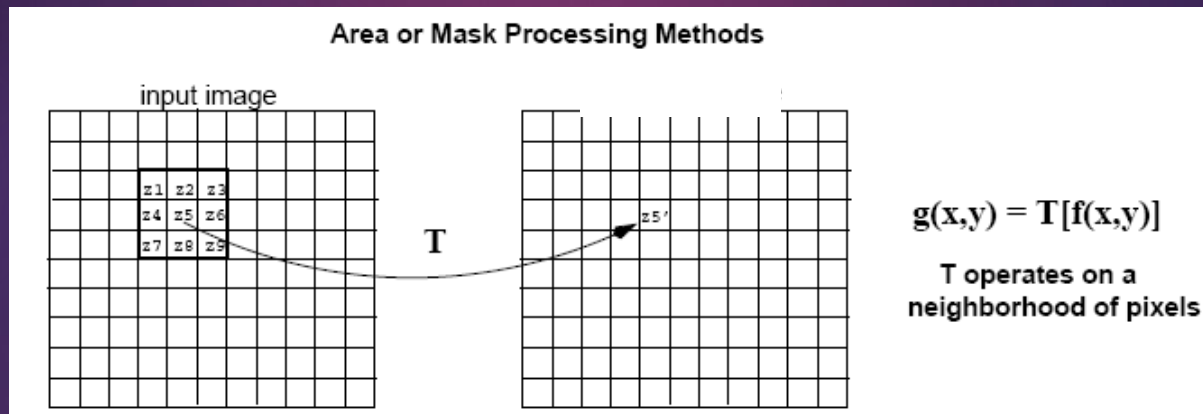
- Typically, the neighborhood is rectangular and its size is much smaller than that of $f(x,y)$
 - e.g., 3x3 or 5x5



Spatial filtering (cont'd)

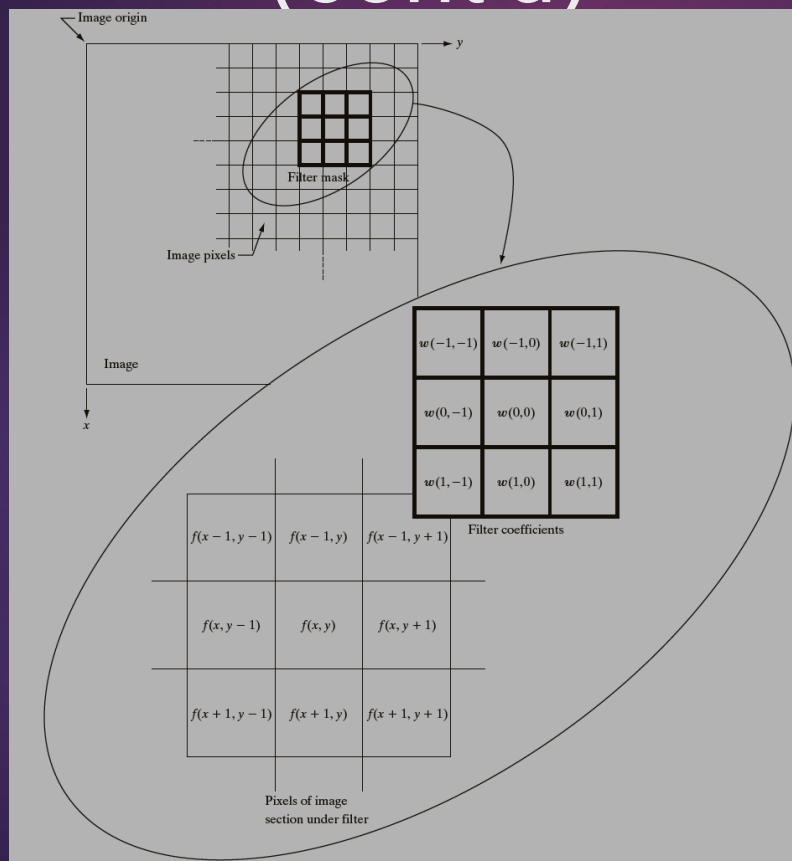
- **Example:** apply a “mask” of weights

w1	w2	w3
w4	w5	w6
w7	w8	w9



$$z_5' = R = w_1z_1 + w_2z_2 + \dots + z_9w_9$$

Spatial filtering (cont'd)



Assume the origin of the mask is the center of the mask.

for a 3 x 3 mask:

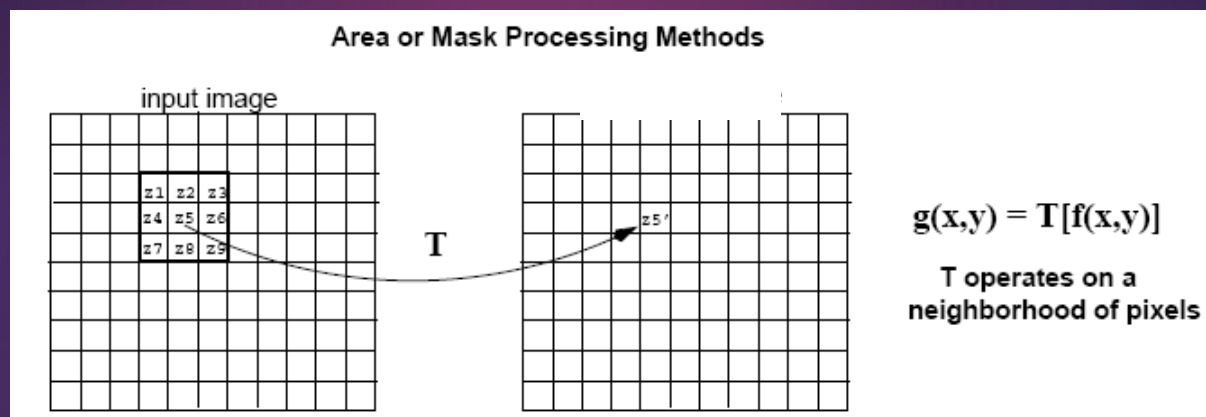
$$g(x, y) = \sum_{s=-1}^1 \sum_{t=-1}^1 w(s, t) f\left(\left\lfloor \frac{x}{2} \right\rfloor + s, \left\lfloor \frac{y}{2} \right\rfloor + t\right)$$

for a K x K mask:

$$g(x, y) = \sum_{s=-K/2}^{K/2} \sum_{t=-K/2}^{K/2} w(s, t) f\left(\left\lfloor \frac{x}{2} \right\rfloor + s, \left\lfloor \frac{y}{2} \right\rfloor + t\right)$$

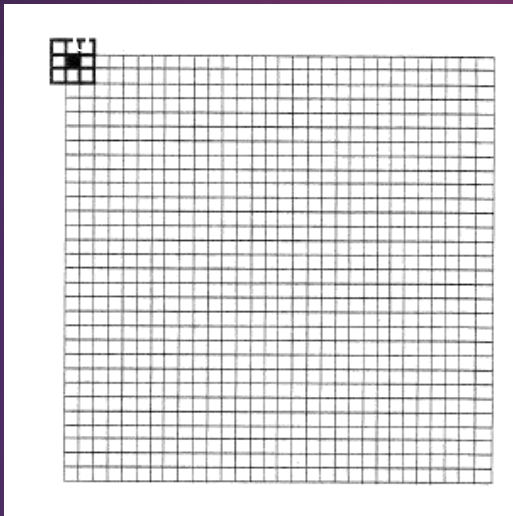
Spatial Filtering (cont'd)

- A **filtered image** is generated as the center of the mask moves to every pixel in the input image.



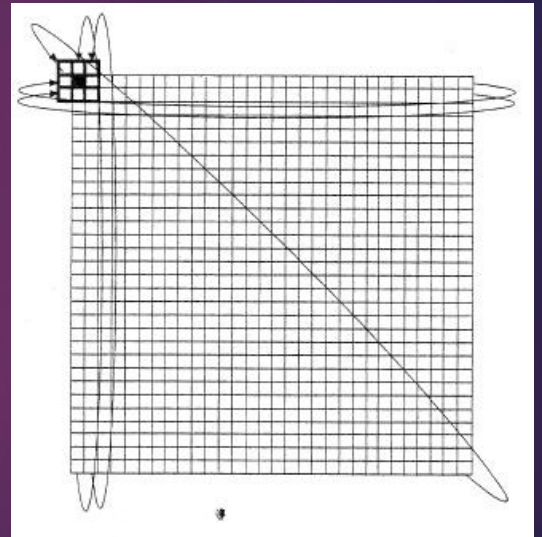
Handling Pixels Close to Boundaries

pad with zeroes



...
.0

or



Handling Pixels Close to Boundaries (cont'd)

↙ Origin	$f(x, y)$							
0	0	0	0	0				
0	0	0	0	0				
0	0	1	0	0	$w(x, y)$	1	2	3
0	0	0	0	0		4	5	6
0	0	0	0	0		7	8	9

Padded f									
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	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	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	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	0	0
0	0	0	0	0	0	0	0
0	0	0	0	1	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	0	0
0	0	0	0	0	0	0	0

Linear vs Non-Linear Spatial Filtering Methods

- A filtering method is **linear** when the output is a weighted sum of the input pixels.

w1	w2	w3
w4	w5	w6
w7	w8	w9

$$z_5' = R = w_1 z_1 + w_2 z_2 + \dots + z_9 w_9$$

- Methods that do not satisfy the above property are called **non-linear**.

– e.g.,

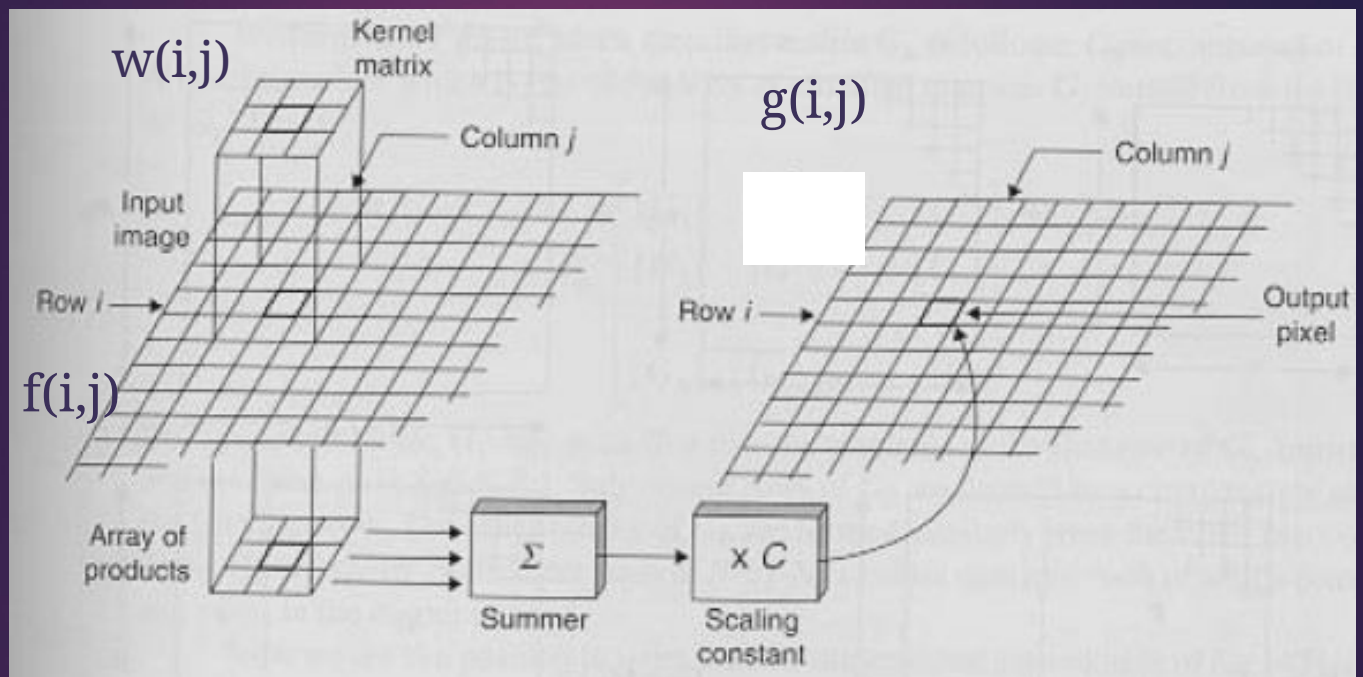
$$z_5' = \max(z_k, k = 1, 2, \dots, 9)$$



Linear Spatial Filtering Methods

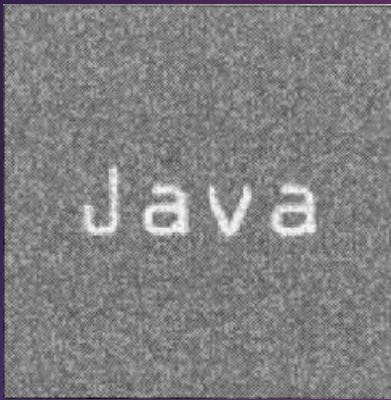
- Two main linear spatial filtering methods:
 - Correlation
 - Convolution

Correlation



$$g(x,y) = \sum h(x,y) \cdot f(x,y)$$

Correlation (cont'd)



Often used in applications where we need to measure the similarity between images or parts of images (e.g., pattern matching).



Convolution

- ၎ Convolution is a mathematical way of combining two signals to form a third signal.
- ၎ It is the single most important technique in Digital Signal Processing.
- ၎ Using the strategy of impulse decomposition, systems are described by a signal called the *impulse response*.
- ၎ Convolution is important because it relates the three signals of interest: the input signal, the output signal, and the impulse response.

Convolution

- Similar to correlation except that the mask is first flipped both horizontally and vertically.

$$g(x, y) = w(x, y) * f(x, y) = \sum_{s=-K/2}^{K/2} \sum_{t=-K/2}^{K/2} w(s, t) f(x-s, y-t)$$

Note: if $w(x, y)$ is symmetric, that is $w(x, y) = w(-x, -y)$, then convolution is equivalent to correlation!

Example

Correlation:

Convolution:

Figure 1 illustrates the steps of 2D correlation. The diagram is divided into eight sub-figures labeled (a) through (h).

- (a) Original image $f(x, y)$ and kernel $w(x, y)$. The image is a 5x5 grid of zeros. The kernel is a 3x3 grid with values 1, 2, 3 in the first row and 4, 5, 6 in the second row, with zeros elsewhere.
- (b) Padded f . The original image is padded with a border of 1. The padding value is 1, which is the value at the center of the kernel.
- (c) Initial position for w . The kernel is positioned at the top-left corner of the padded image.
- (d) Full correlation result. The result is a 7x7 grid where each element is the dot product of the kernel and the corresponding 3x3 region of the padded image. The values are:

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	9	8	7	0
0	0	0	6	5	4	0
0	0	0	3	2	1	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
- (e) Cropped correlation result. The result is a 3x3 grid of values:

0	0	0
0	9	8
0	6	5
- (f) Rotated w . The kernel is rotated 90 degrees clockwise. The values are:

9	8	7
6	5	4
3	2	1
- (g) Full convolution result. The result is a 7x7 grid where each element is the dot product of the rotated kernel and the corresponding 3x3 region of the padded image. The values are:

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	2	3	0
0	0	0	4	5	6	0
0	0	0	7	8	9	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
- (h) Cropped convolution result. The result is a 3x3 grid of values:

0	0	0
0	1	2
0	4	5

How do we choose the elements of a mask?

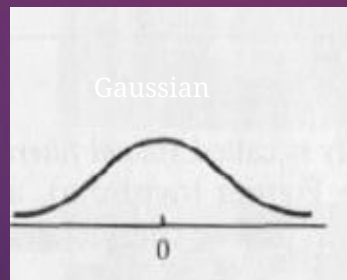
- Typically, by sampling certain functions.

w1	w2	w3
w4	w5	w6
w7	w8	w9



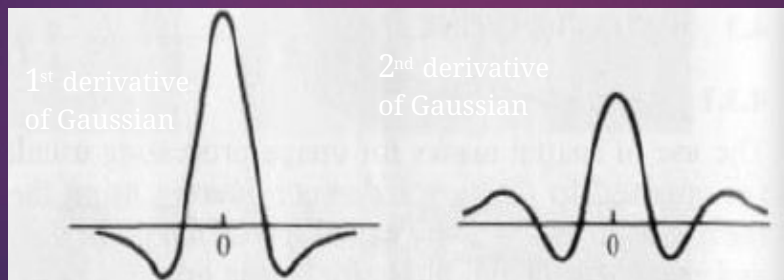
Filters

- **Smoothing** (i.e., low-pass filters)
 - Reduce noise and small details.
 - The elements of the mask must be positive.
 - Sum of mask elements is 1



Filters

- **Sharpening** (i.e., high-pass filters)
 - Highlight fine detail or enhance detail that has been blurred.
 - The elements of the mask contain both positive and negative weights.
 - Sum of the mask weights is 0



Smoothing Filters (Low Pass Filter)

- ၁ Averaging Filter

- ၂ Median Filter

- ၃ Gaussian Filter

Linear Filter

- ✧ In linear filter, output values are the linear combinations of the pixels in the original image.
- ✧ Linear methods are far more amenable to mathematical analysis than are nonlinear ones, and are consequently far better understood.
- ✧ For example, if a linear filter is applied to the output from another linear filter, then the result is a third linear filter.

Linear Filters

🌀 Linear Filters

🌀 **GaussianFilter** — Gaussian and Gaussian derivatives filtering of images and arrays

🌀 **DerivativeFilter** — general-order derivative filter

🌀 **MeanFilter** ▪ **GradientFilter** ▪ **LaplacianFilter** ▪ **WienerFilter** ▪ **Moving Average**

🌀 **LowpassFilter** ▪ **HighpassFilter** ▪ **BandpassFilter** ▪ **BandstopFilter** ▪ **HilbertFilter** ▪ **Differentiator Filter**

🌀 **ListConvolve**, **ListCorrelate** — convolve, correlate with any kernel

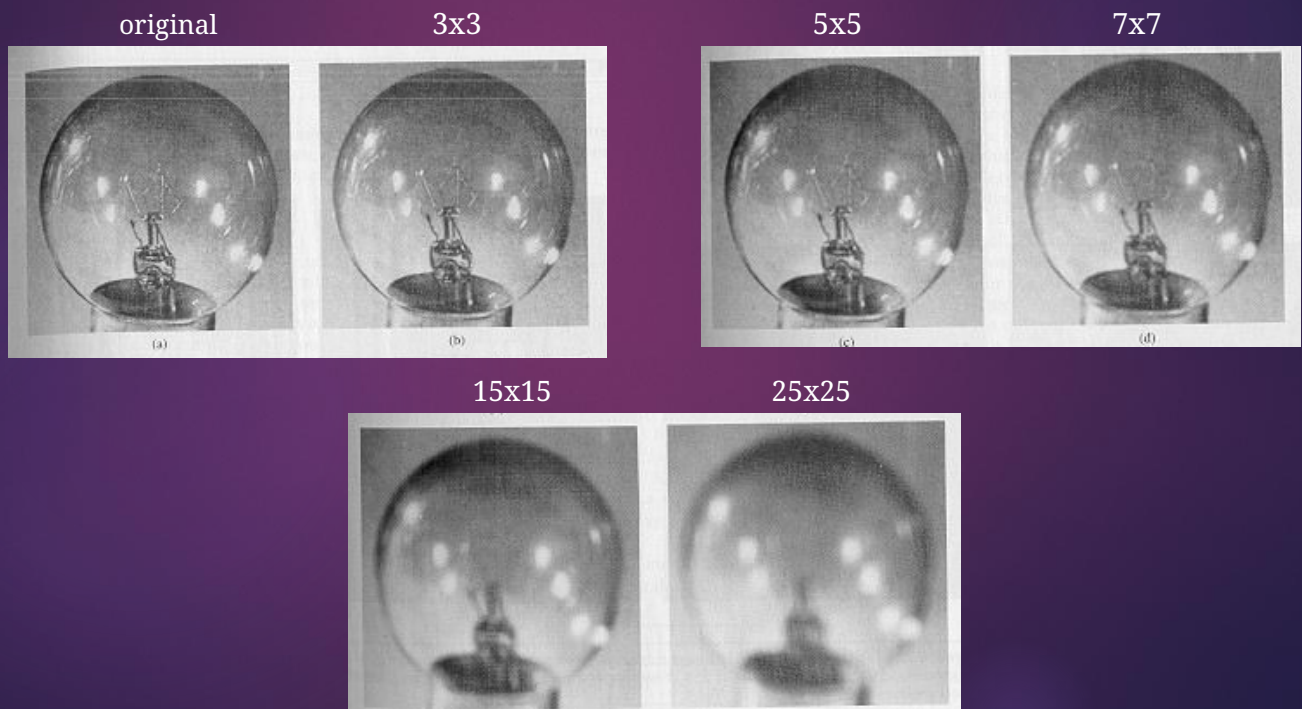
Non Linear Filters

- ၍ Median Filter ▪
- ၍ Min Filter ▪
- ၍ Max Filter ▪
- ၍ MeanShift Filter ▪
- ၍ Entropy Filter▪
- ၍ Corner Filter ▪
- ၍ Ridge Filter ▪
- ၍ Kuwahara Filter ▪
- ၍ Bilateral Filter

Smoothing Filters:

Averaging (cont'd)

- Mask size determines the degree of smoothing and loss of detail.



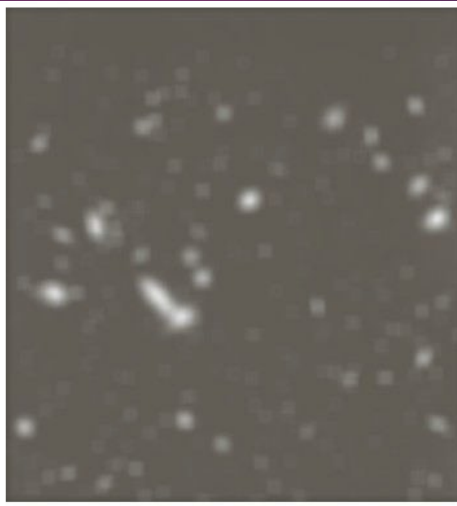
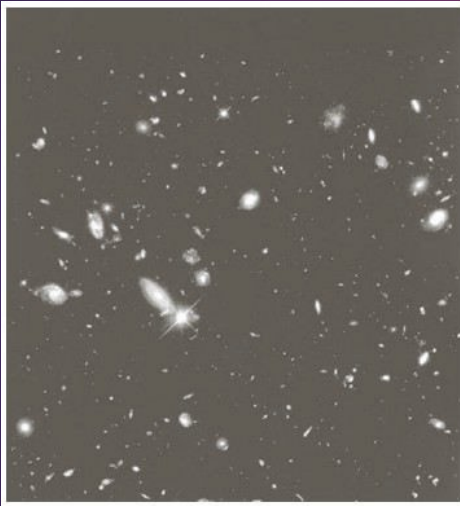
Smoothing Filters:

Averaging (cont'd)

Example: extract, largest, brightest objects

15 x 15 averaging

image thresholding

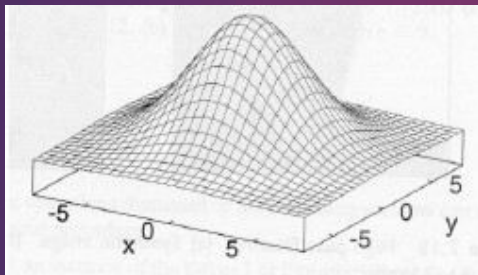


Smoothing filters:

Gaussian

- The weights are samples of the Gaussian function

$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} \exp -\frac{x^2 + y^2}{2\sigma^2}$$



7 × 7 Gaussian mask

1	1	2	2	2	1	1
1	2	2	4	2	2	1
2	2	4	8	4	2	2
2	4	8	16	8	4	2
2	2	4	8	4	2	2
1	2	2	4	2	2	1
1	1	2	2	2	1	1

$\sigma = 1.4$

mask size:

height = width = 5σ (subtends 98.76% of the area)

Smoothing filters:

Gaussian (cont'd)

- As σ increases, more samples must be obtained to represent the Gaussian function accurately.
- Therefore, σ controls the amount of smoothing

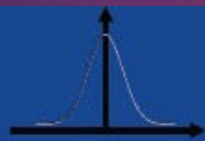
$\sigma = 3$

15 × 15 Gaussian mask

2	2	3	4	5	5	6	6	6	5	5	4	3	2	2
2	3	4	5	7	7	8	8	8	7	7	5	4	3	2
3	4	6	7	9	10	10	11	10	10	9	7	6	4	3
4	5	7	9	10	12	13	13	13	12	10	9	7	5	4
5	7	9	11	13	14	15	16	15	14	13	11	9	7	5
5	7	10	12	14	16	17	18	17	16	14	12	10	7	5
6	8	10	13	15	17	19	19	19	17	15	13	10	8	6
6	8	11	13	16	18	19	20	19	18	16	13	11	8	6
6	8	10	13	15	17	19	19	19	17	15	13	10	8	6
5	7	10	12	14	16	17	18	17	16	14	12	10	7	5
5	7	9	11	13	14	15	16	15	14	13	11	9	7	5
4	5	7	9	10	12	13	13	13	12	10	9	7	5	4
3	4	6	7	9	10	10	11	10	10	9	7	6	4	3
2	3	4	5	7	7	8	8	8	7	7	5	4	3	2
2	2	3	4	5	5	6	6	6	5	5	4	3	2	2

Smoothing filters:

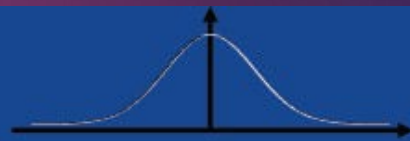
Gaussian (cont'd)



small σ



limited smoothing



large σ



strong smoothing

Averaging vs Gaussian Smoothing



Averaging



Gaussian

Smoothing Filters: Median Filtering (non-linear)

- Very effective for removing “salt and pepper” noise (i.e., random occurrences of black and white pixels).



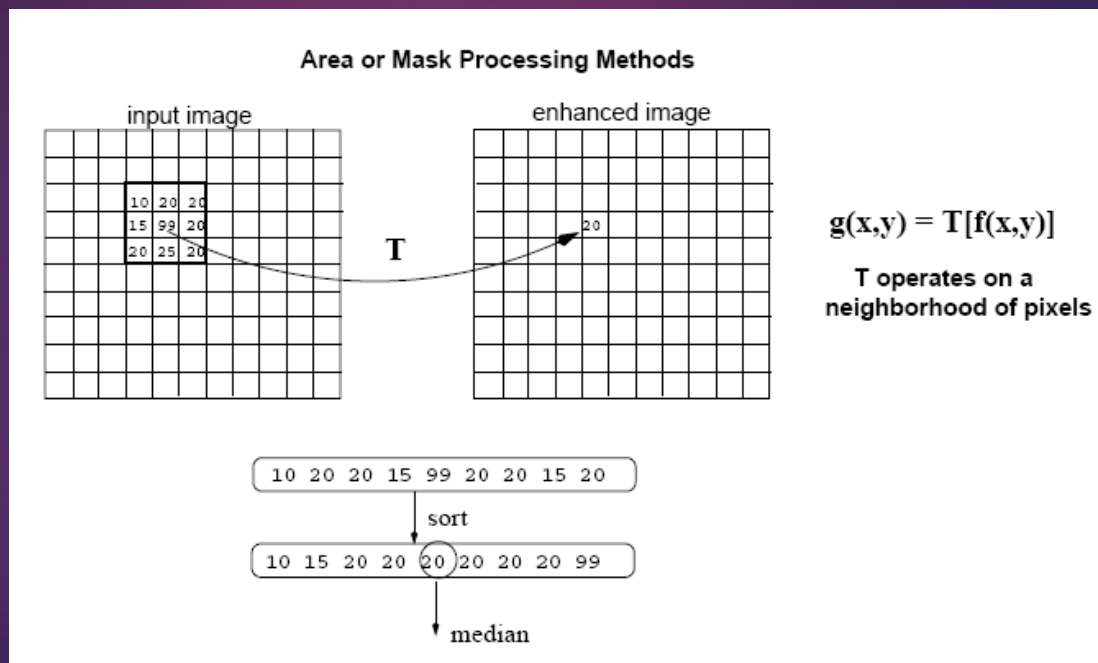
averaging



median
filtering

Smoothing Filters: Median Filtering (cont'd)

- Replace each pixel by the median in a neighborhood around the pixel.



Sharpening Filters (High Pass filtering)

- Useful for emphasizing transitions in image intensity (e.g., edges).

input image

10	10	10	10	10	10	80	80	80	
10	10	10	10	10	10	80	80	80	
10	10	10	10	10	10	80	80	80	
10	10	10	10	10	10	80	80	80	
10	10	10	10	10	10	80	80	80	

mask

1/9 x

-1	-1	-1
-1	8	-1
-1	-1	-1

$1/9 (-10 - 10 - 10 - 10 + 80 - 10 - 10 - 10 - 10) = 0$
 (there is no variation in the gray-levels)
 • $1/9 (-10 - 80 - 80 - 10 + 640 - 80 - 10 - 80 - 80) = 210/9 > 0$
 (there is variation in the gray-levels)

Sharpening Filters (cont'd)

- Note that the response of high-pass filtering might be negative.
- Values must be re-mapped to $[0, 255]$

original image



sharpened images



Unsharp Masking

🌀 **Idea: Sharpen images using low-pass filters! How?**

🌀 **1. Blur the original image**

🌀 **2. Subtract the blurred image from the original**

🌀 **3. Add the previous result to the original.**

Sharpening Filters:

Unsharp Masking

- Obtain a sharp image by subtracting a lowpass filtered (i.e., smoothed) image from the original image:

$$\textit{Highpass} = \textit{Original} - \textit{Lowpass}$$



Sharpening Filters: High Boost

- Image sharpening emphasizes edges but details (i.e., low frequency components) might be lost.
- **High boost filter:** amplify input image, then subtract a lowpass image.

$$\begin{aligned} \text{Highboost} &= A \text{ Original} - \text{Lowpass} \\ &= (A - 1) \text{ Original} + \text{Original} - \text{Lowpass} \\ &= (A - 1) \text{ Original} + \text{Highpass} \end{aligned}$$

(A-1)  +  = 

Sharpening Filters: Unsharp Masking (cont'd)

- If $A=1$, we get a high pass filter
- If $A>1$, part of the original image is added back to the high pass filtered image.

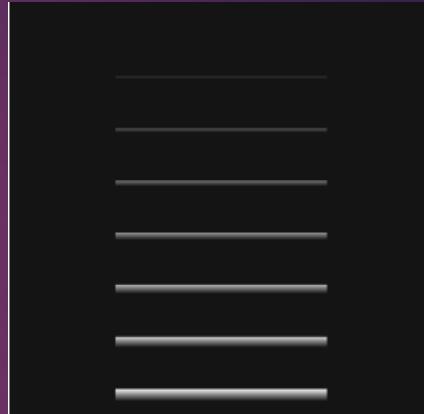
$$A \geq 1$$
$$w = 9A - 1$$

-1	-1	-1
-1	w	-1
-1	-1	-1

$$A=2$$
$$w = 17$$

-1	-1	-1
-1	17	-1
-1	-1	-1

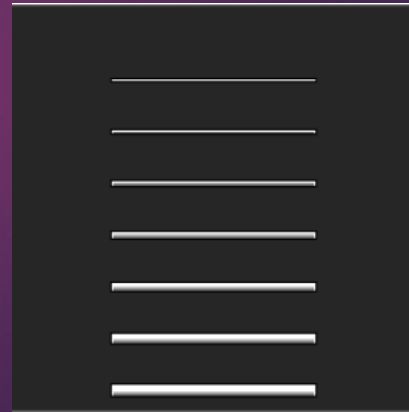
Sharpening Filters: Unsharp Masking (cont'd)



A=1.4



A=1.9



Sharpening Filters:

Derivatives

- Taking the derivative of an image results in sharpening the image.
- The derivative of an image can be computed using the gradient.

∇f

$$\text{grad}(f) = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix}$$

Sharpening Filters:

Derivatives (cont'd)

- The gradient is a **vector** which has magnitude and direction:

$$\text{magnitude}(\text{grad}(f)) = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

$$\text{direction}(\text{grad}(f)) = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

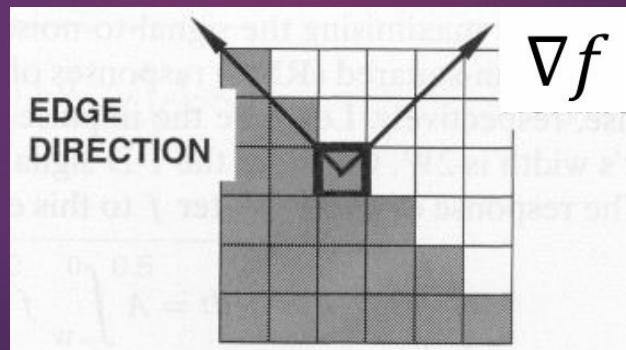
or $\left\| \frac{\partial f}{\partial x} \mathbf{i} + \frac{\partial f}{\partial y} \mathbf{j} \right\|_2$

(approximation)

Sharpening Filters:

Derivatives (cont'd)

- **Magnitude:** provides information about edge strength.
- **Direction:** perpendicular to the direction of the edge.



Sharpening Filters: Gradient Computation

- Approximate gradient using finite differences.

$$f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} \approx f(x+1) - f(x) \quad (h=1)$$

$$\frac{\partial f}{\partial x} = \frac{f(x + \Delta x, y) - f(x, y)}{\Delta x} = f(x + 1, y) - f(x, y), \quad (\Delta x=1)$$

$$\frac{\partial f}{\partial y} = \frac{f(x, y + \Delta y) - f(x, y)}{-\Delta y} = f(x, y) - f(x, y + 1), \quad (\Delta y=1)$$

Sharpening Filters: Gradient Computation (cont'd)

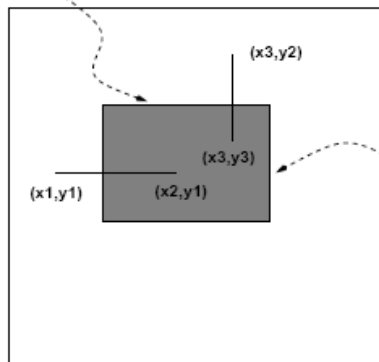
$$\frac{f(x_3, y_2) - f(x_3, y_3)}{y_2 - y_3}$$

or $\frac{f(x, y+Dy) - f(x, y)}{-Dy} = \boxed{f(x, y) - f(x, y+1)}$ (grad in the y-direction)

($y_3 = y_2 + Dy$, $y_2 = y$, $x_3 = x$, $Dy = 1$)

edge in the x-direction

(0,0)



edge in the y-direction

$$\frac{f(x_2, y_1) - f(x_1, y_1)}{x_2 - x_1}$$

or $\frac{f(x+Dx, y) - f(x, y)}{Dx} =$

$\boxed{f(x+1, y) - f(x, y)}$
(grad in the x-direction)

($x_2 = x + Dx$, $x_1 = x$, $y_1 = y_2 = y$, $Dx = 1$)

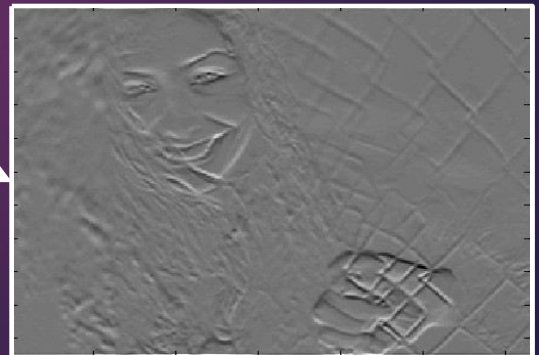
Example



$$\frac{\partial f}{\partial x}$$

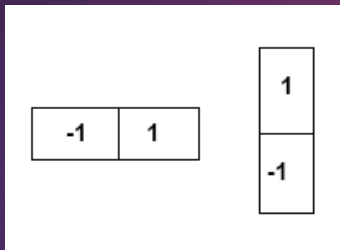


$$\frac{\partial f}{\partial y}$$



Sharpening Filters: Gradient Computation (cont'd)

- We can implement $\frac{\partial f}{\partial x}$ using the mask:

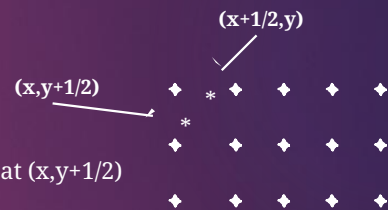


$$\frac{\partial f}{\partial x}$$

good approximation
at $(x+1/2, y)$

$$\frac{\partial f}{\partial y}$$

good approximation at $(x, y+1/2)$



- Example: approximate gradient at

z_5

z1	z2	z3
z4	z5	z6
z7	z8	z9

$$\frac{\partial f}{\partial x} = z_6 - z_4$$

$$\frac{\partial f}{\partial y} = z_5 - z_8$$

$$mag(grad(f)) = \sqrt{(z_6 - z_4)^2 + (z_5 - z_8)^2}$$

Sharpening Filters: Gradient Computation (cont'd)

- A different approximation of the gradient:

$$\frac{\partial f}{\partial x}(x, y) = f(x, y) - f(x + 1, y + 1)$$

$$\frac{\partial f}{\partial y}(x, y) = f(x + 1, y) - f(x, y + 1),$$

good approximation
(x+1/2, y+1/2)



- We can implement $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$ using the following masks:

1	0	0	1
0	-1	-1	0

(b) Roberts

Sharpening Filters: Gradient Computation (cont'd)

- Example: approximate gradient at

z_5

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

$$\frac{\partial f}{\partial x} = z_5 - z_9$$

$$\frac{\partial f}{\partial y} = z_6 - z_8$$

$$\text{mag}(\text{grad}(f)) = \sqrt{(z_5 - z_9)^2 + (z_6 - z_8)^2}$$

- Other approximations

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

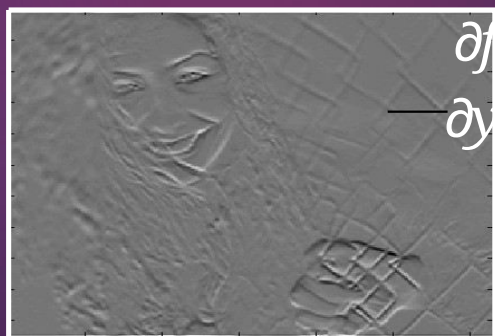
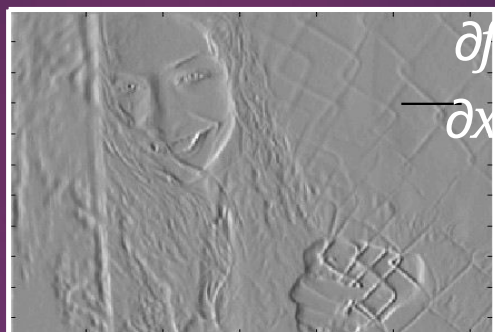
(c) Prewitt

-1	-2	-1
0	0	0
1	2	1

Sobel

-1	0	1
-2	0	2
-1	0	1

Example



$$\sqrt{\frac{\partial f^2}{\partial x} + \frac{\partial f^2}{\partial y}}$$



Sharpening Filters: Laplacian

The Laplacian (2nd derivative) is defined as:

$$\nabla^2 = \nabla \cdot \nabla = \begin{bmatrix} \frac{\partial}{\partial x} \\ \frac{\partial}{\partial y} \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial}{\partial x} \\ \frac{\partial}{\partial y} \end{bmatrix} = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$$

(dot product)

Approximate
derivatives:

$$\frac{\partial^2 f}{\partial x^2} = f(i, j+1) - 2f(i, j) + f(i, j-1)$$

$$\frac{\partial^2 f}{\partial y^2} = f(i+1, j) - 2f(i, j) + f(i-1, j)$$

$$\nabla^2 f = -4f(i, j) + f(i, j+1) + f(i, j-1) + f(i+1, j) + f(i-1, j)$$

Sharpening Filters: Laplacian (cont'd)

Laplacian Mask

$$\begin{bmatrix} 0 & 0 & 0 \\ 1 & -2 & 1 \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 \\ 0 & -2 & 0 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

5	5	5	5	5	5
5	5	5	5	5	5
5	5	10	10	10	10
5	5	10	10	10	10
5	5	5	10	10	10
5	5	5	5	10	10

detect zero-crossings

-	-	-	-	-	-
-	0	-5	-5	-5	-
-	-5	10	5	5	-
-	-5	10	0	0	-
-	0	-10	10	0	-
-	-	-	-	-	-

Sharpening Filters: Laplacian (cont'd)



Laplacian



Sobel

