

# Computer Vision – TP6

## Spatial Filters

*Miguel Coimbra, Hélder Oliveira*

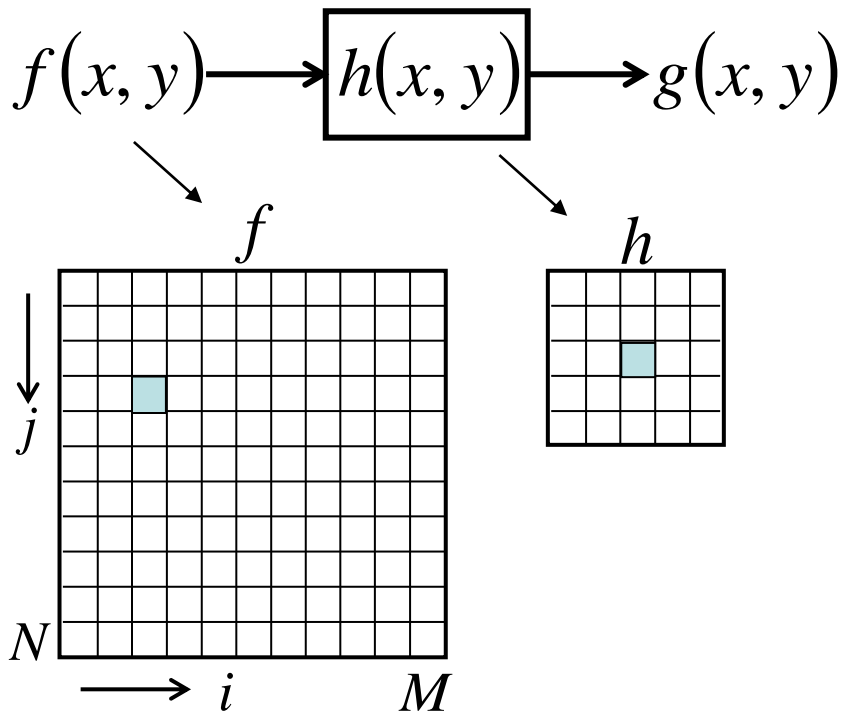
# Outline

- Spatial filters
- Frequency domain filtering
- Edge detection
- Morphological filters

# Topic: Spatial filters

- Spatial filters
- Frequency domain filtering
- Edge detection
- Morphological filters

# Images are Discrete and Finite



## Convolution

$$g(i, j) = \sum_{m=1}^M \sum_{n=1}^N f(m, n) h(i - m, j - n)$$

## Fourier Transform

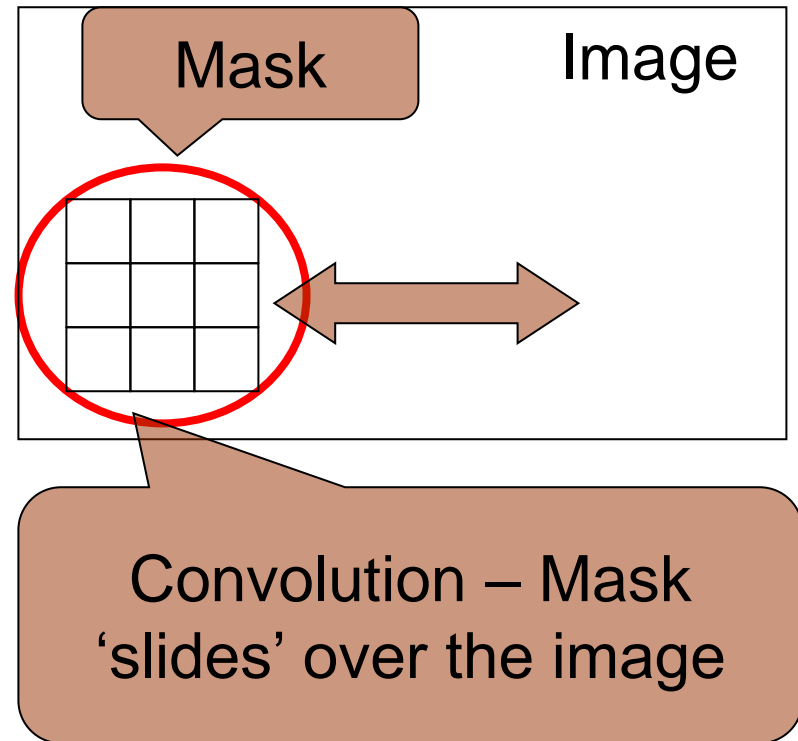
$$F(u, v) = \sum_{m=1}^M \sum_{n=1}^N f(m, n) e^{-i2\pi \left( \frac{mu}{M} + \frac{nv}{N} \right)}$$

## Inverse Fourier Transform

$$f(k, l) = \frac{1}{MN} \sum_{u=1}^M \sum_{v=1}^N F(u, v) e^{i2\pi \left( \frac{ku}{M} + \frac{lv}{N} \right)}$$

# Spatial Mask

- Simple way to process an image
- Mask defines the processing function
- Corresponds to a multiplication in frequency domain



# Example

- Each mask position has weight **w**
- The result of the operation for each pixel is given by:

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

Mask

2	2	2
4	4	4
4	5	6

Image

$$g(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x + s, y + t)$$

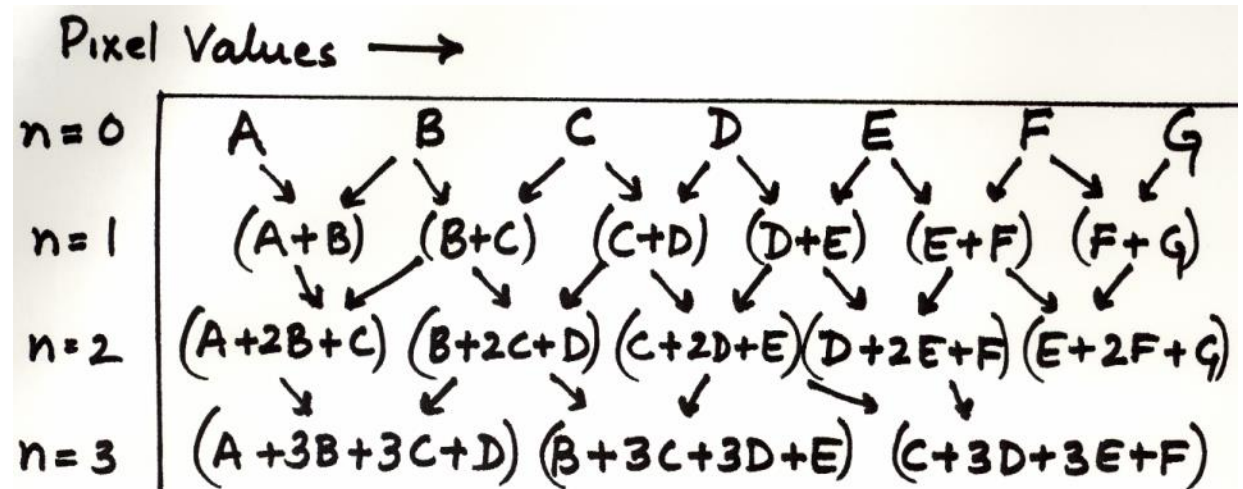
$$\begin{aligned} &= 1*2 + 2*2 + 1*2 + \dots \\ &= 8 + 0 - 20 \\ &= -12 \end{aligned}$$

# Definitions

- **Spatial filters**
  - Use a **mask (kernel)** over an image region
  - Work directly with pixels
  - As opposed to: **Frequency filters**
- **Advantages**
  - Simple implementation: **convolution** with the kernel function
  - Different masks offer a **large variety of functionalities**

# Averaging

Let's think  
about  
averaging  
pixel values



For  $n=2$ , convolve pixel values with 

1	2	1
---	---	---

Which is faster?  
(a)  $O(2(n+1))$     (b)  $O((n+1)^2)$

2D images:

(a) use 

1	2	1
---	---	---

 then 

1
2
1

 or (b) use 

1	2	1
---	---	---

 $*$ 

1
2
1

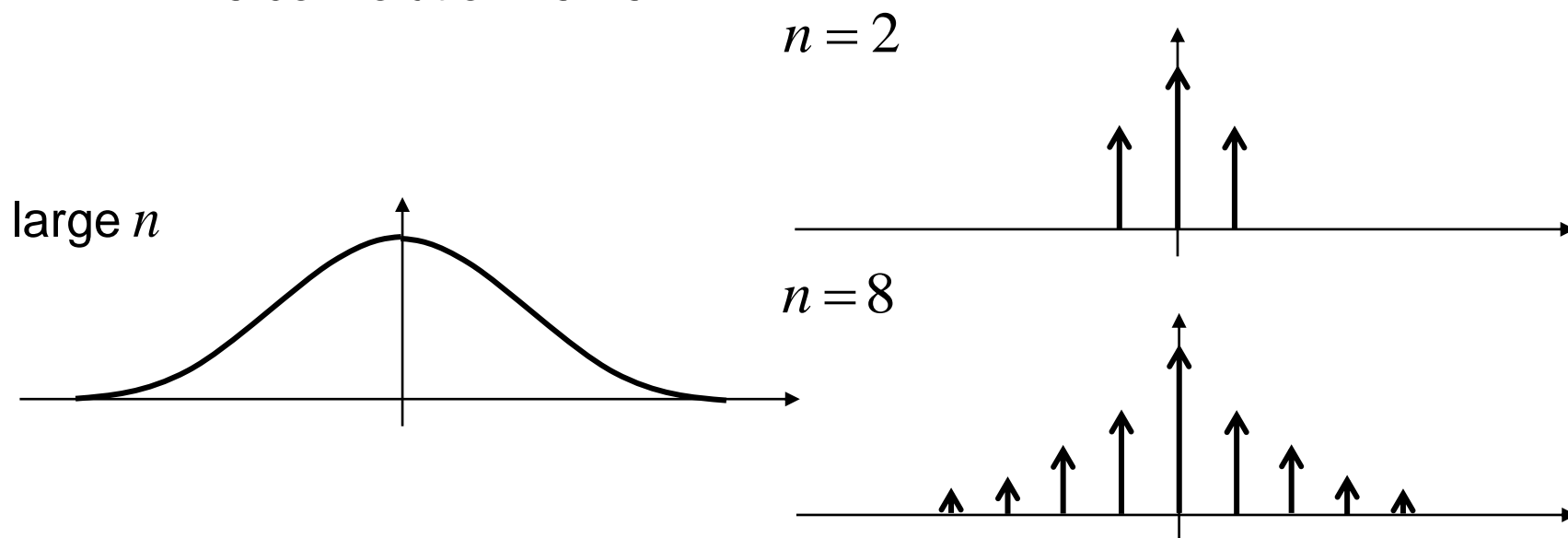
 $=$ 

1	2	1
2	4	2
1	2	1



# Averaging

The convolution kernel



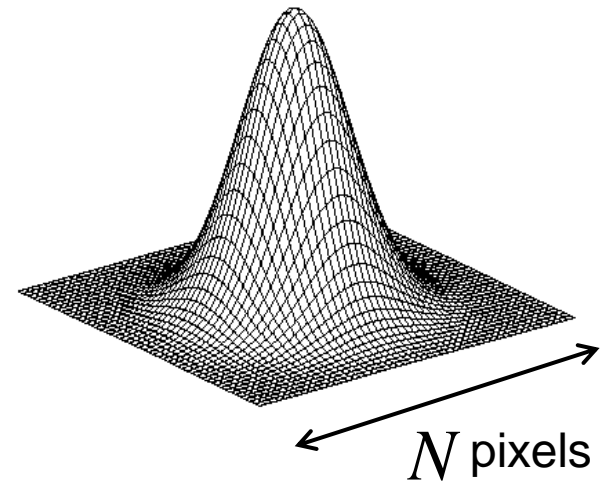
Repeated averaging  $\approx$  Gaussian smoothing

# Gaussian Smoothing

Gaussian  
kernel

$$h(i, j) = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2}\left(\frac{i^2+j^2}{\sigma^2}\right)}$$

Filter size  $N \propto \sigma$  ...can be very large  
(truncate, if necessary)



$$g(i, j) = \frac{1}{2\pi\sigma^2} \sum_{m=1} \sum_{n=1} e^{-\frac{1}{2}\left(\frac{m^2+n^2}{\sigma^2}\right)} f(i-m, j-n)$$

2D Gaussian is separable!

$$g(i, j) = \frac{1}{2\pi\sigma^2} \sum_{m=1} e^{-\frac{1}{2}\frac{m^2}{\sigma^2}} \sum_{n=1} e^{-\frac{1}{2}\frac{n^2}{\sigma^2}} f(i-m, j-n)$$

Use two 1D  
Gaussian  
Filters!

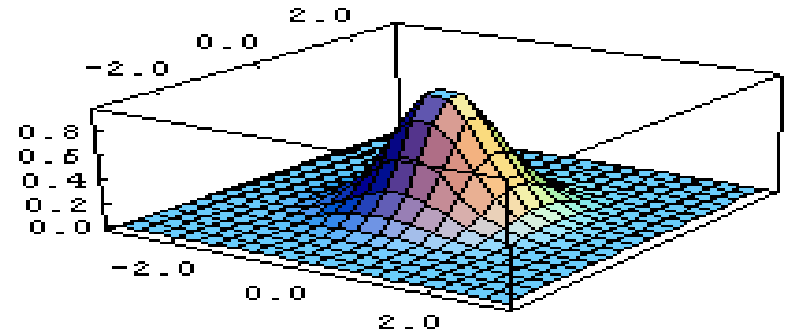
# Gaussian Smoothing

- A Gaussian kernel gives less weight to pixels further from the center of the window

$$H[u, v] = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

- This kernel is an approximation of a Gaussian function:

$$F[x, y]$$
$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$



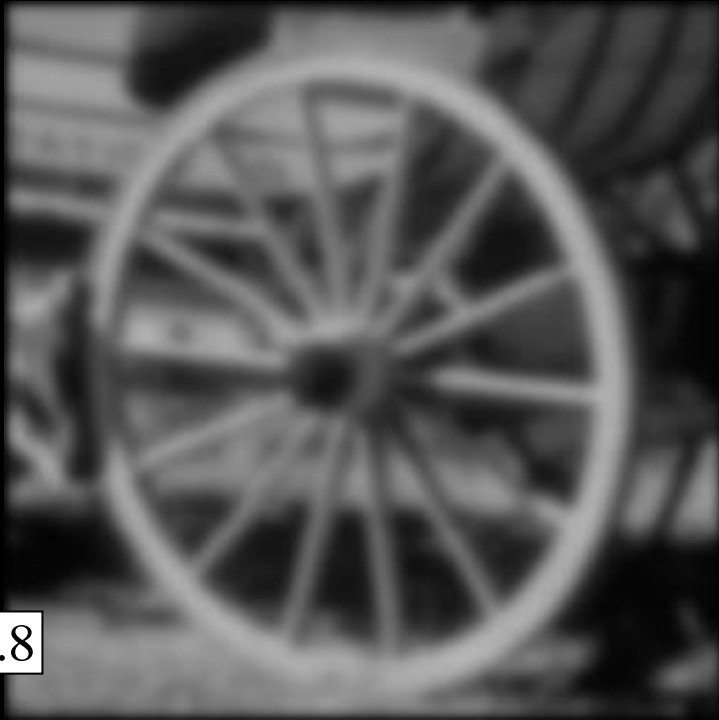
original



$\sigma = 2$



$\sigma = 2.8$

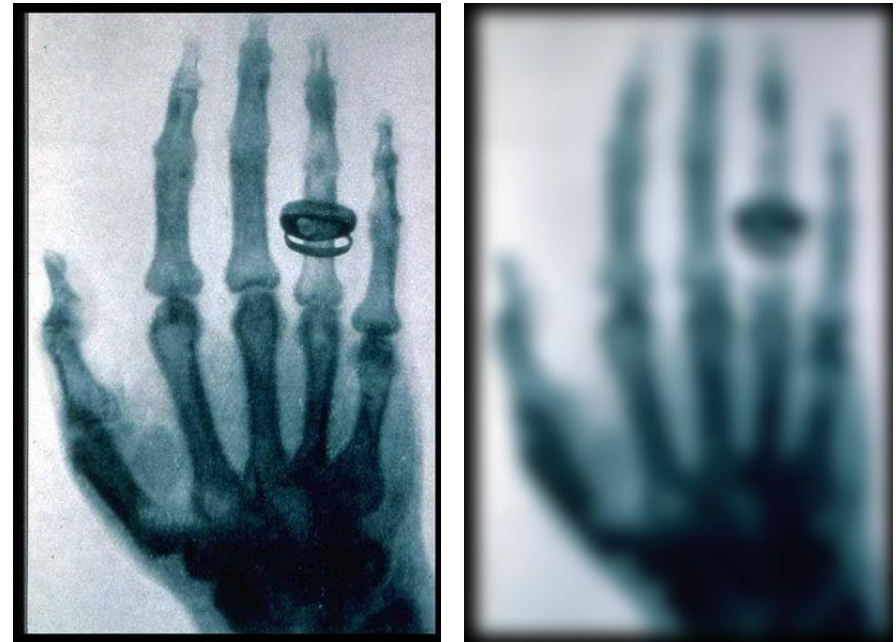


$\sigma = 4$



# Mean Filtering

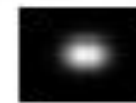
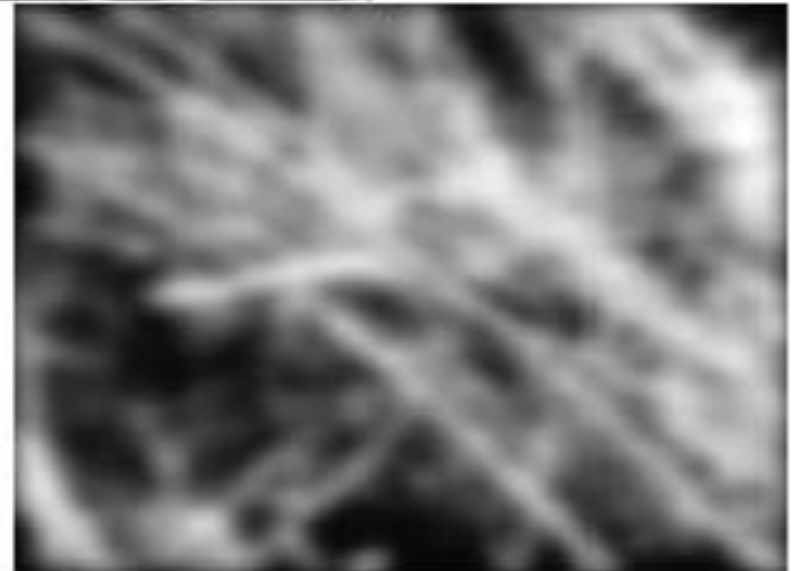
- We are degrading the energy of the high spatial frequencies of an image (**low-pass filtering**)
  - Makes the image 'smoother'
  - Used in noise reduction
- Can be implemented with spatial masks or in the frequency domain



1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9



Mean filter



Gaussian filter

# Median Filter

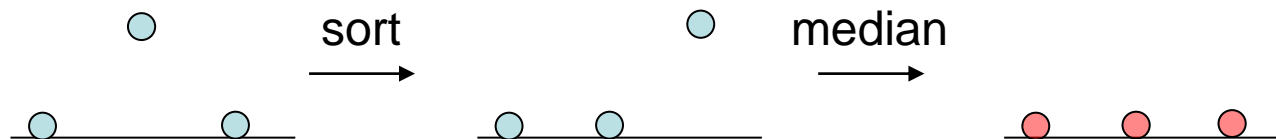
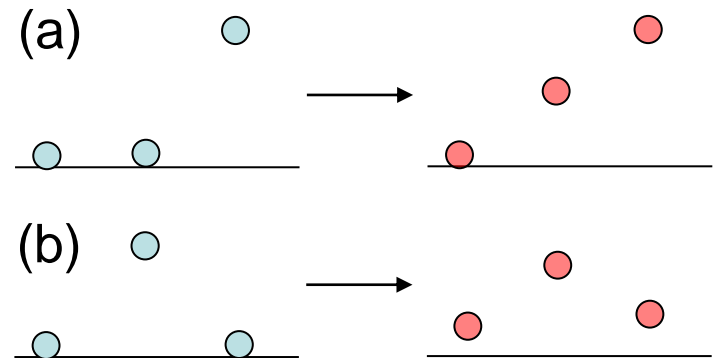
- **Smoothing is averaging**

- (a) Blurs edges

- (b) Sensitive to outliers

- Median filtering

- Sort  $N$  values around the pixel (including itself)
  - Select middle value (median)



- Non-linear (Cannot be implemented with convolution)



## Salt and pepper noise

Gaussian

Median

3x3



5x5



7x7



## Gaussian noise

Gaussian

Median





# Border Problem

$$\frac{1}{16}$$

1	2	1
2	4	2
1	2	1

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

How do we apply  
our mask to this  
pixel?

What a computer sees

# Border Problem

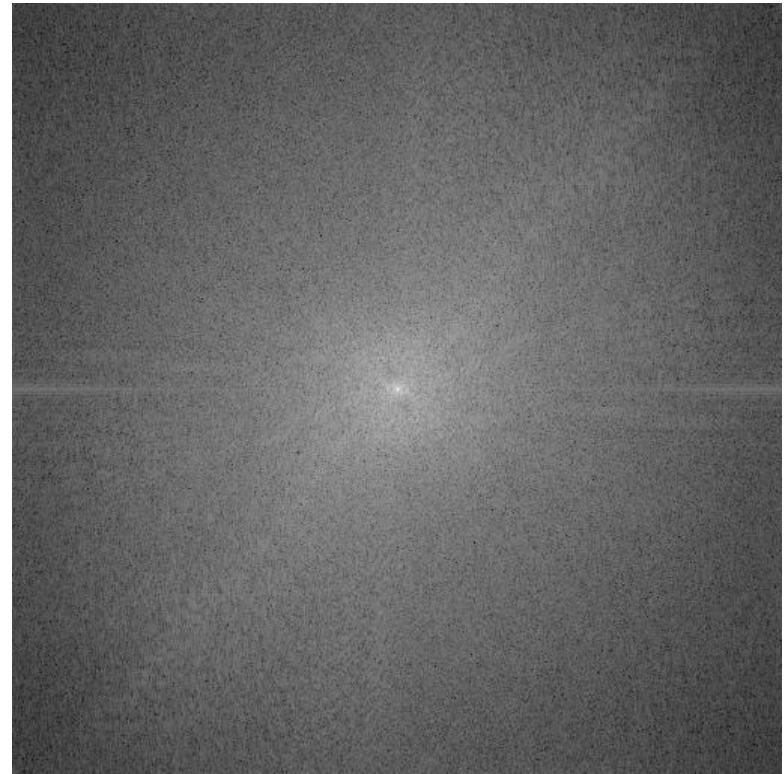
- Ignore
  - Output image will be smaller than original
- Pad with constant values
  - Can introduce substantial 1<sup>st</sup> order derivative values
- Pad with reflection
  - Can introduce substantial 2<sup>nd</sup> order derivative values

# Topic: Frequency domain filtering

- Spatial filters
- **Frequency domain filtering**
- Edge detection
- Morphological filters

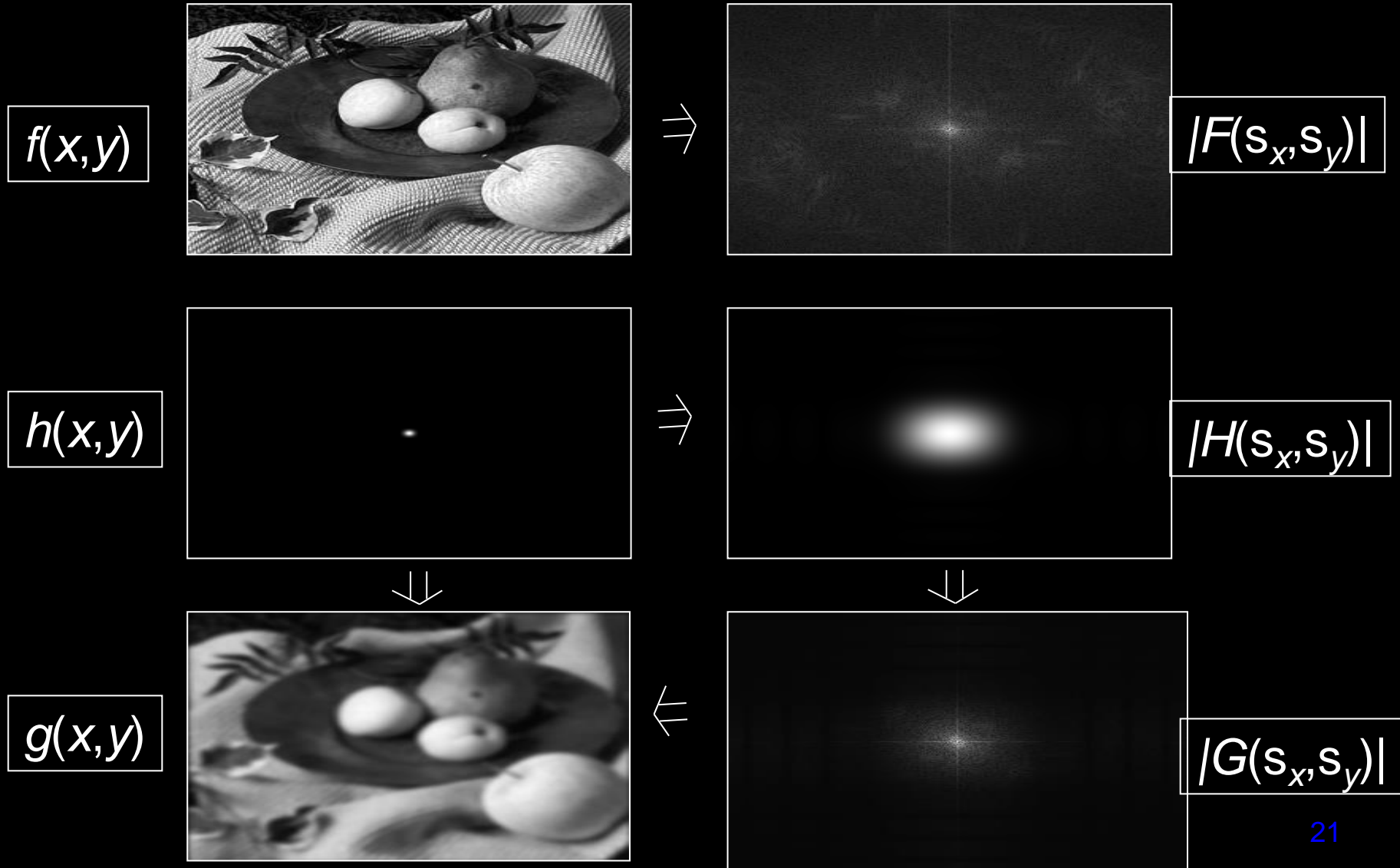
# Image Processing in the Fourier Domain

Magnitude of the FT



Does not look anything like what we have seen

# Convolution in the Frequency Domain

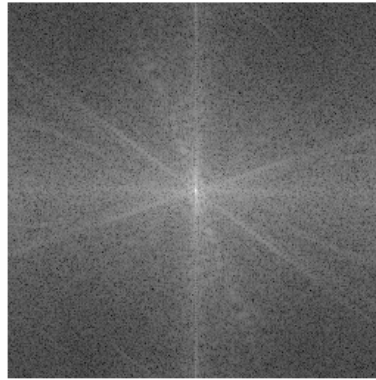


# Low-pass Filtering

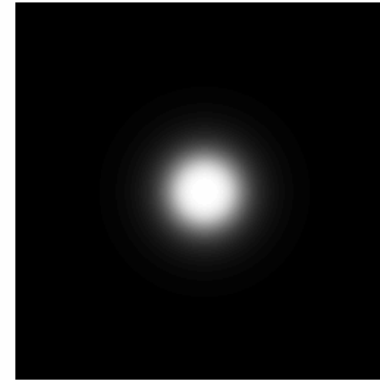
Original image



FFT of original image



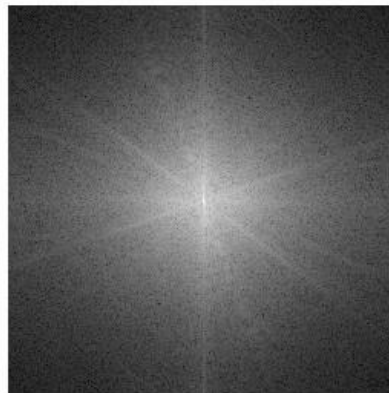
Low-pass filter



Low-pass image



FFT of low-pass image



Lets the low frequencies pass and eliminates the high frequencies.

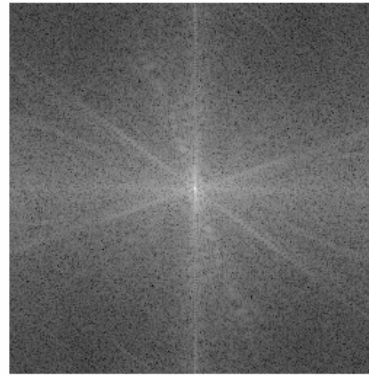
Generates image with overall shading, but not much detail

# High-pass Filtering

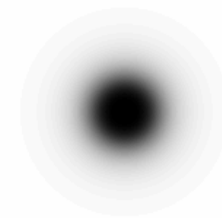
Original image



FFT of original image



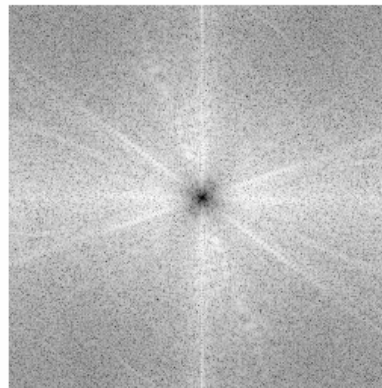
High-pass filter



High-pass image



FFT of high-pass image



Lets through the high frequencies (the detail), but eliminates the low frequencies (the overall shape). It acts like an edge enhancer.

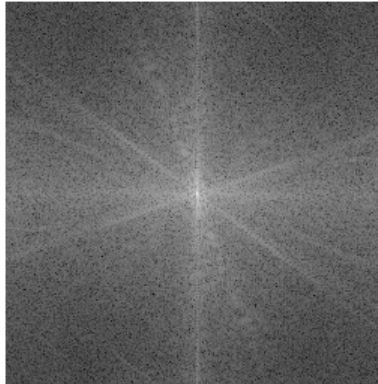


# Boosting High Frequencies

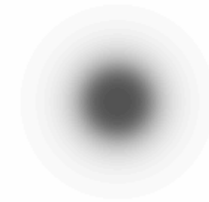
Original image



FFT of original image



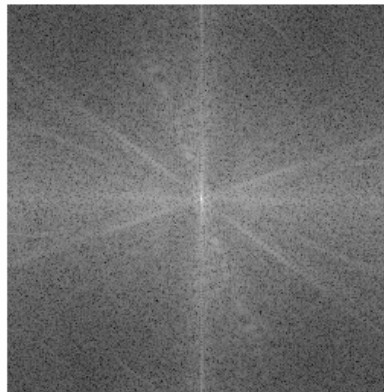
High-boost filter



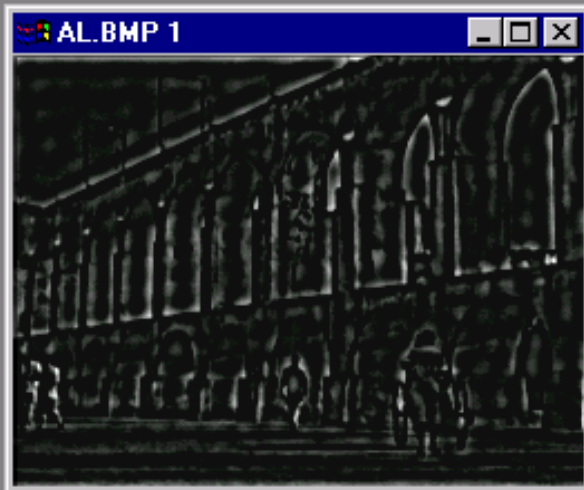
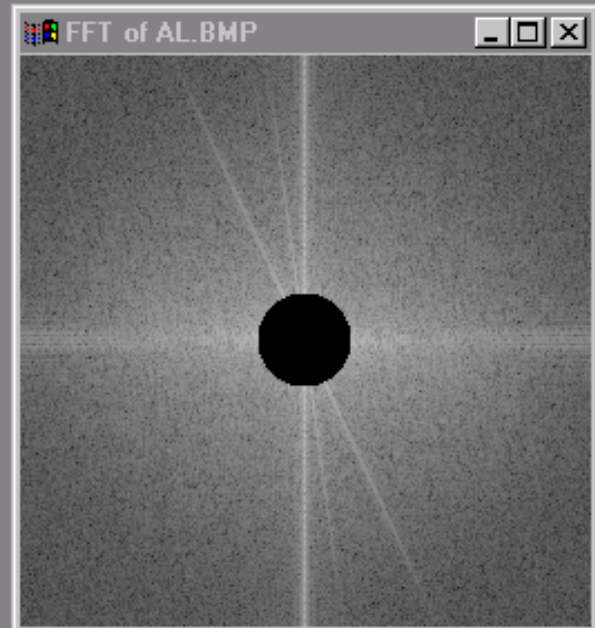
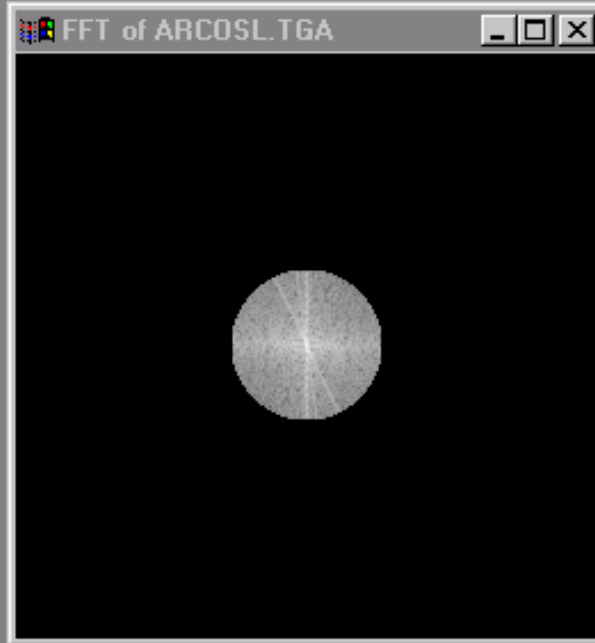
High boosted image

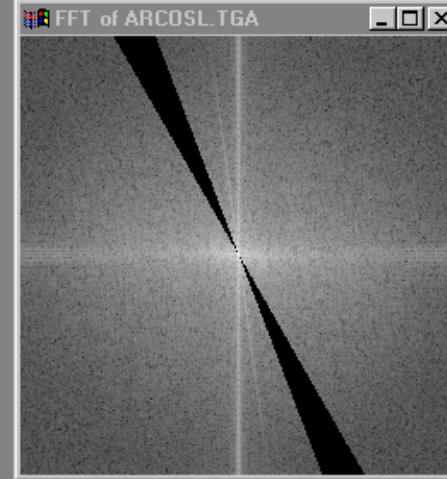
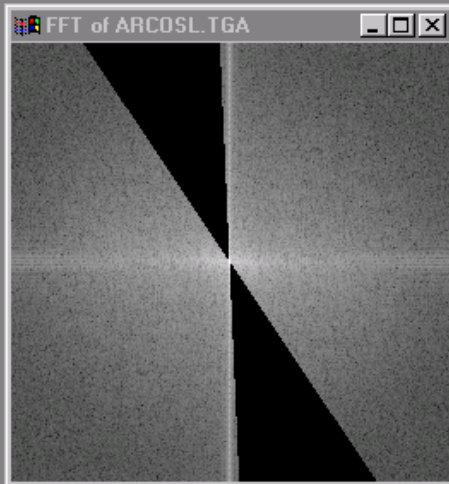
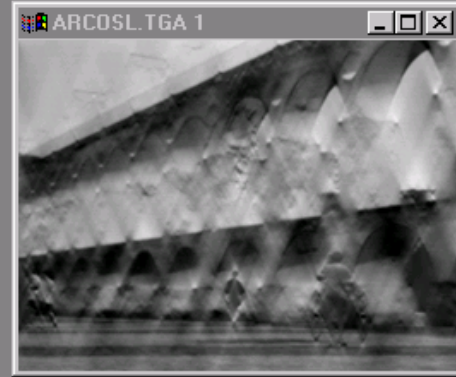
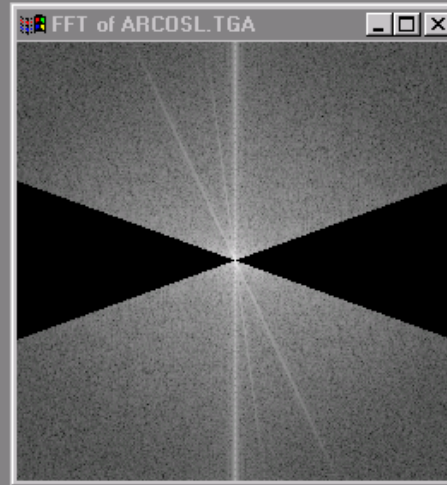
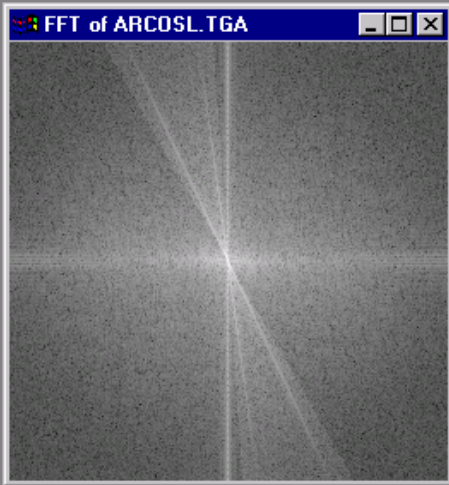


FFT of high boosted image

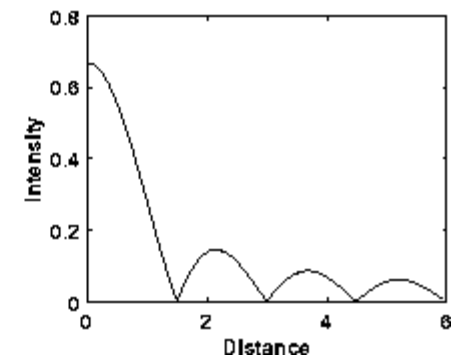
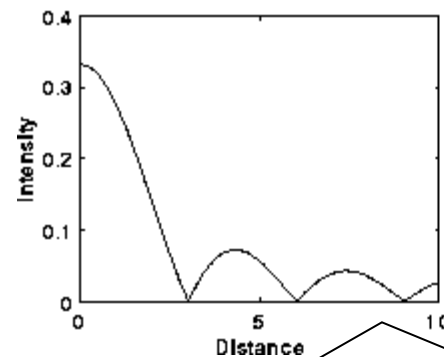
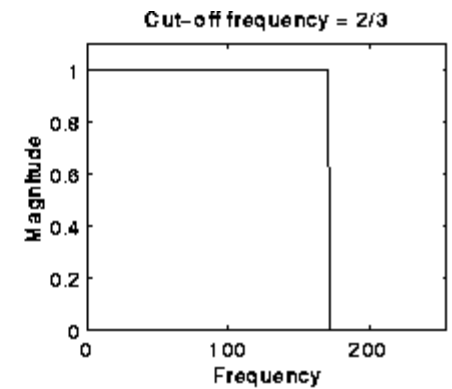
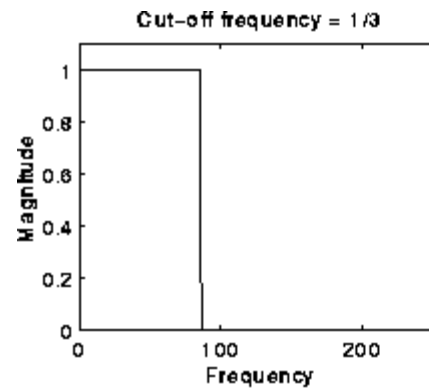








# The Ringing Effect



An ideal low-pass filter causes 'rings' in the spatial domain!

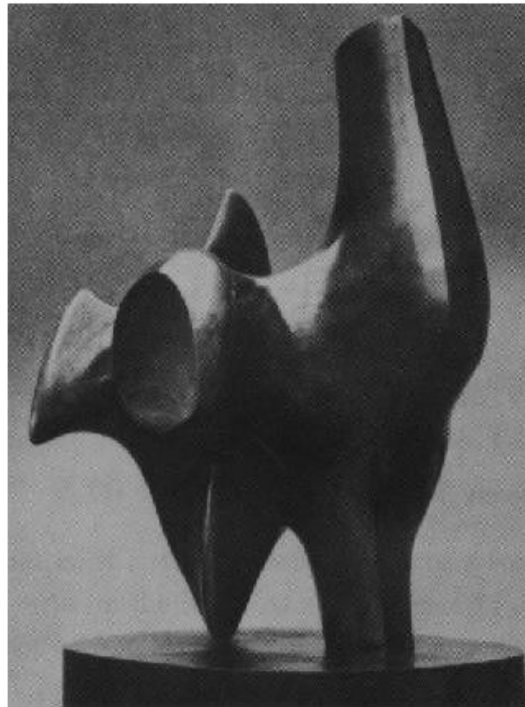
# Topic: Edge detection

- Spatial filters
- Frequency domain filtering
- **Edge detection**
- Morphological filters

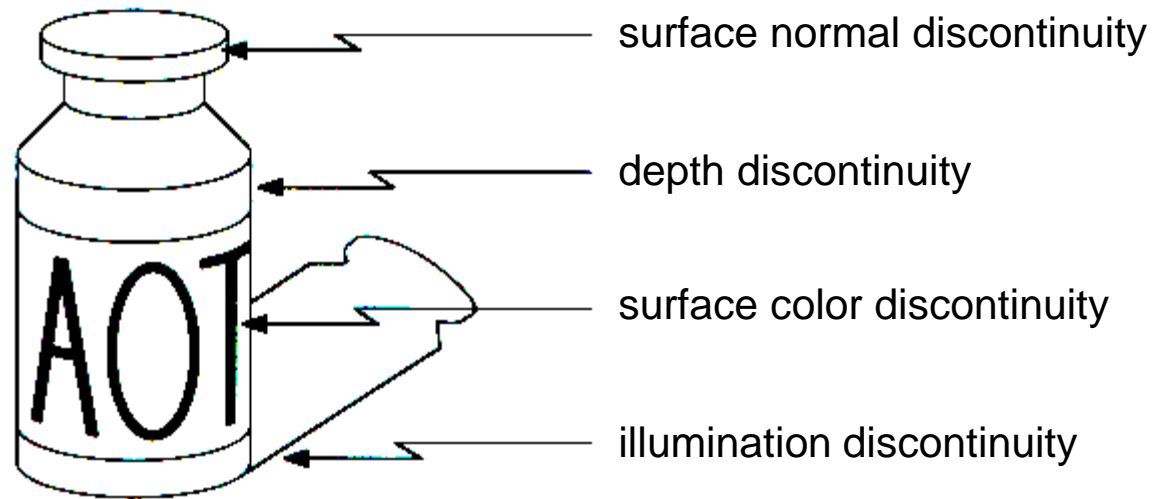


# Edge Detection

- Convert a 2D image into a set of curves
  - Extracts salient features of the scene
  - More compact than pixels

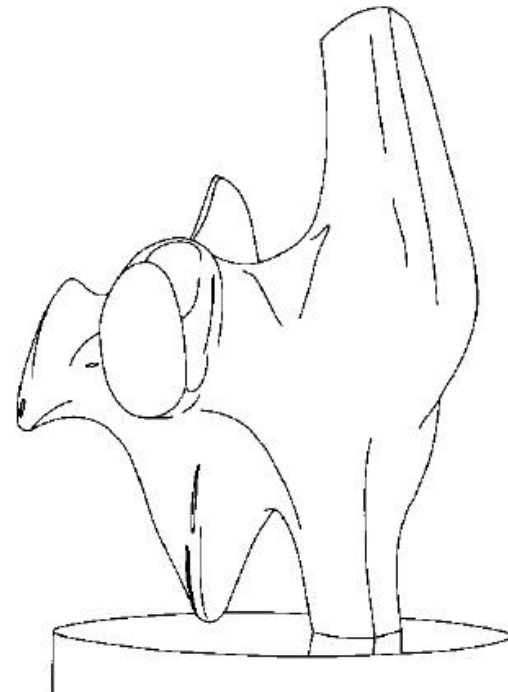
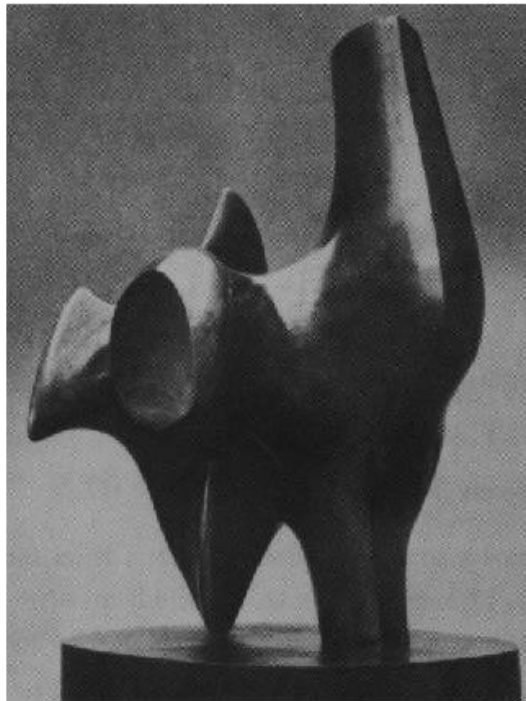


# Origin of Edges

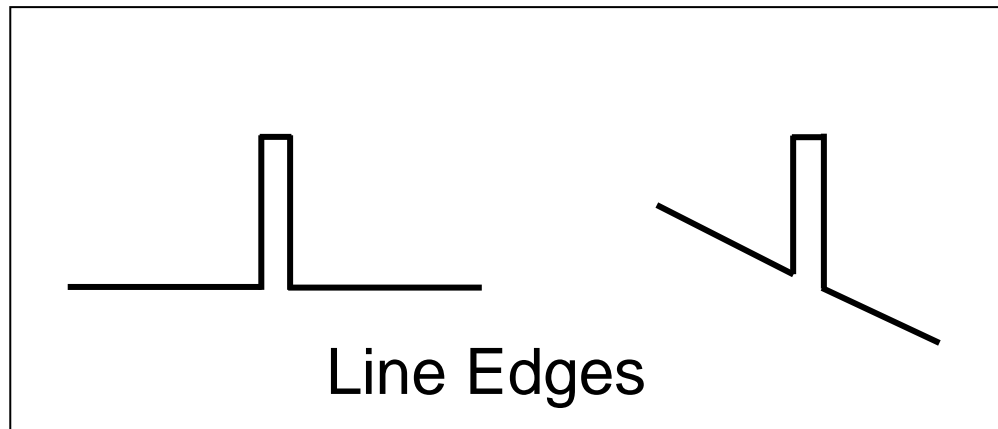
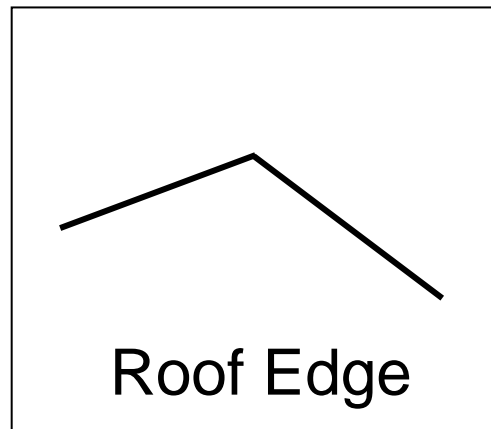
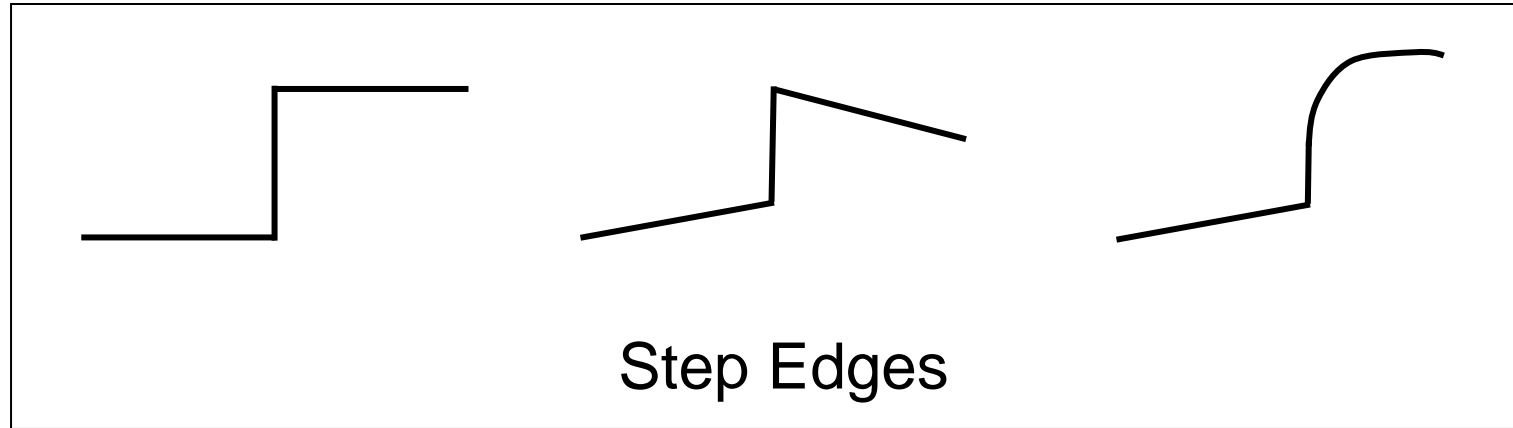


- Edges are caused by a variety of factors

# How can you tell that a pixel is on an edge?

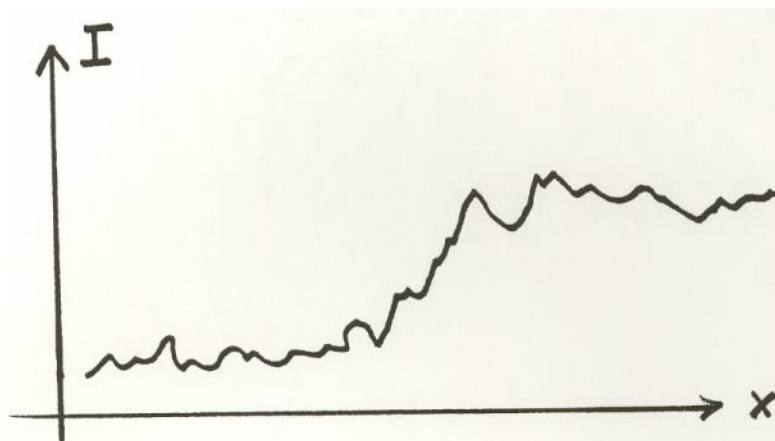


# Edge Types





# Real Edges



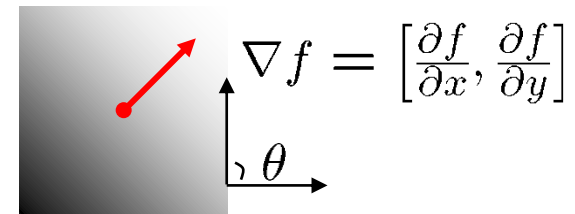
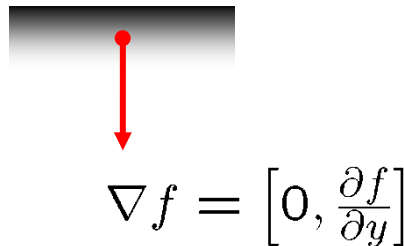
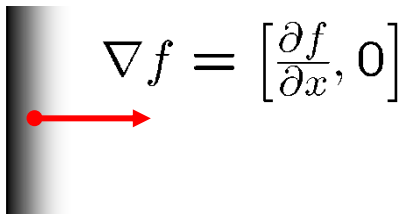
Noisy and Discrete!

We want an **Edge Operator** that produces:

- Edge **Magnitude**
- Edge **Orientation**
- High **Detection Rate** and Good **Localization**

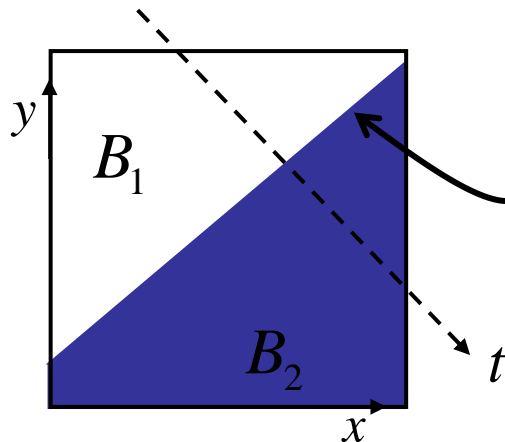
# Gradient

- Gradient equation:  $\nabla f = \left[ \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$
- Represents direction of most rapid change in intensity



- Gradient direction:  $\theta = \tan^{-1} \left( \frac{\partial f}{\partial y} / \frac{\partial f}{\partial x} \right)$
- The *edge strength* is given by the gradient magnitude  $\|\nabla f\| = \sqrt{\left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2}$

# Theory of Edge Detection



Unit step function:

Ideal edge

$$L(x, y) = x \sin \theta - y \cos \theta + \rho = 0$$

$$B_1 : L(x, y) < 0$$

$$B_2 : L(x, y) > 0$$

$$u(t) = \begin{cases} 1 & \text{for } t > 0 \\ 1/2 & \text{for } t = 0 \\ 0 & \text{for } t < 0 \end{cases} \quad u(t) = \int_{-\infty}^t \delta(s) ds$$

Image intensity (brightness):

$$I(x, y) = B_1 + (B_2 - B_1)u(x \sin \theta - y \cos \theta + \rho)$$

# Theory of Edge Detection

- Partial derivatives (gradients):

$$\frac{\partial I}{\partial x} = +\sin \theta (B_2 - B_1) \delta(x \sin \theta - y \cos \theta + \rho)$$

$$\frac{\partial I}{\partial y} = -\cos \theta (B_2 - B_1) \delta(x \sin \theta - y \cos \theta + \rho)$$

- Squared gradient:

$$s(x, y) = \left( \frac{\partial I}{\partial x} \right)^2 + \left( \frac{\partial I}{\partial y} \right)^2 = [(B_2 - B_1) \delta(x \sin \theta - y \cos \theta + \rho)]^2$$

Edge Magnitude:  $\sqrt{s(x, y)}$

Edge Orientation:  $\arctan\left(\frac{\partial I}{\partial y} / \frac{\partial I}{\partial x}\right)$  (normal of the edge)

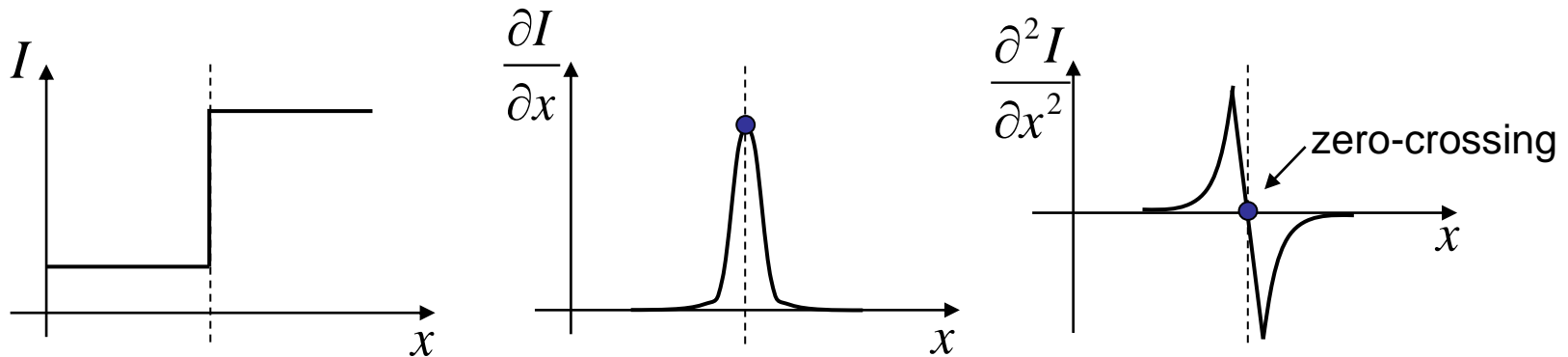
Rotationally symmetric, non-linear operator

# Theory of Edge Detection

- Laplacian:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} = (B_2 - B_1) \delta'(x \sin \theta - y \cos \theta + \rho)$$

Rotationally symmetric, linear operator



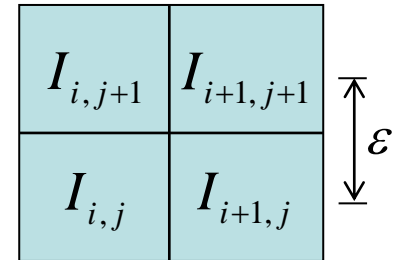
# Discrete Edge Operators

- How can we differentiate a **discrete** image?

Finite difference approximations:

$$\frac{\partial I}{\partial x} \approx \frac{1}{2\varepsilon} \left( (I_{i+1,j+1} - I_{i,j+1}) + (I_{i+1,j} - I_{i,j}) \right)$$

$$\frac{\partial I}{\partial y} \approx \frac{1}{2\varepsilon} \left( (I_{i+1,j+1} - I_{i+1,j}) + (I_{i,j+1} - I_{i,j}) \right)$$



Convolution masks :

$$\frac{\partial I}{\partial x} \approx \frac{1}{2\varepsilon} \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix}$$

$$\frac{\partial I}{\partial y} \approx \frac{1}{2\varepsilon} \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}$$

# Discrete Edge Operators

- Second order partial derivatives:

$$\frac{\partial^2 I}{\partial x^2} \approx \frac{1}{\varepsilon^2} (I_{i-1,j} - 2I_{i,j} + I_{i+1,j})$$

$$\frac{\partial^2 I}{\partial y^2} \approx \frac{1}{\varepsilon^2} (I_{i,j-1} - 2I_{i,j} + I_{i,j+1})$$

$I_{i-1,j+1}$	$I_{i,j+1}$	$I_{i+1,j+1}$
$I_{i-1,j}$	$I_{i,j}$	$I_{i+1,j}$
$I_{i-1,j-1}$	$I_{i,j-1}$	$I_{i+1,j-1}$

- Laplacian :**

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

Convolution masks :

$$\nabla^2 I \approx \frac{1}{\varepsilon^2} \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$\text{or } \frac{1}{6\varepsilon^2} \begin{bmatrix} 1 & 4 & 1 \\ 4 & -20 & 4 \\ 1 & 4 & 1 \end{bmatrix}$$

(more accurate)

# The Sobel Operators

- Better approximations of the gradients exist
  - The *Sobel* operators below are commonly used

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

$s_x$

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

$s_y$



# Comparing Edge Operators

Gradient:  $\nabla f = \left[ \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$

Good Localization  
Noise Sensitive  
Poor Detection

Roberts (2 x 2):

0	1
-1	0

1	0
0	-1

Sobel (3 x 3):

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

1	2	1
0	0	0
-1	-2	1

Sobel (5 x 5):

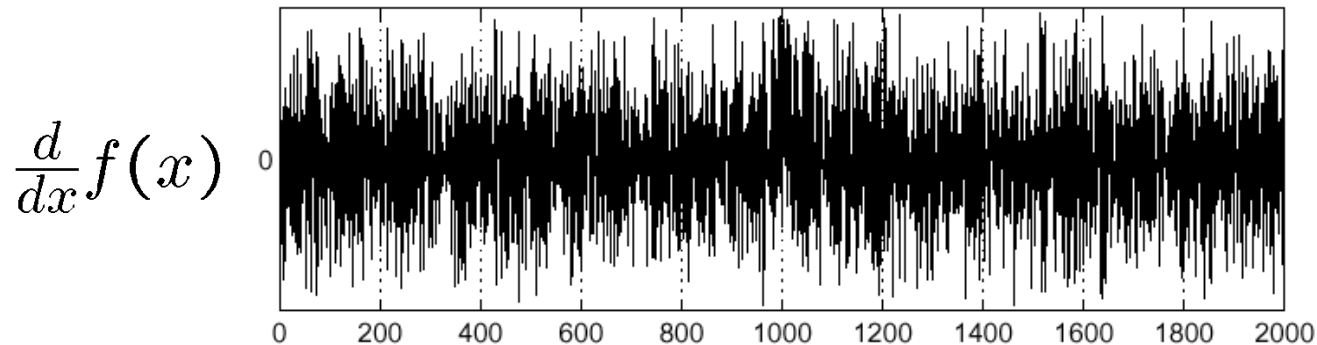
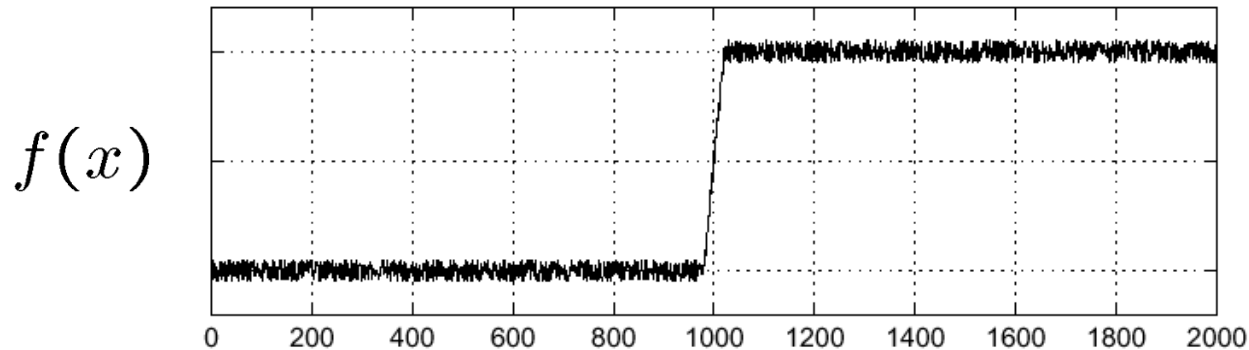
-1	-2	0	2	1
-2	-3	0	3	2
-3	-5	0	5	3
-2	-3	0	3	2
-1	-2	0	2	1

1	2	3	2	1
2	3	5	3	2
0	0	0	0	0
-2	-3	-5	-3	-2
-1	-2	-3	-2	-1

Poor Localization  
Less Noise Sensitive  
Good Detection

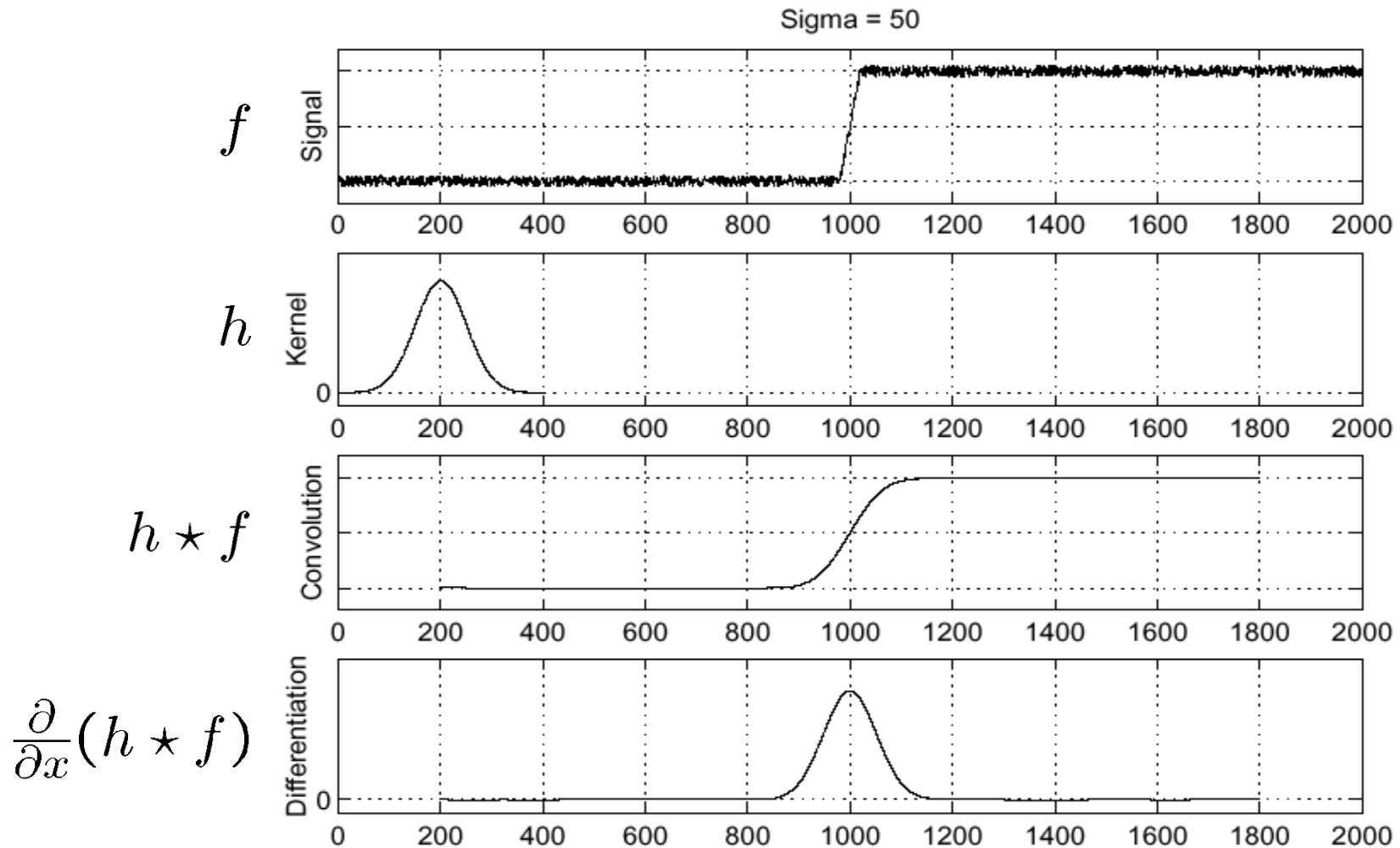
# Effects of Noise

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



Where is  
the edge??

# Solution: Smooth First



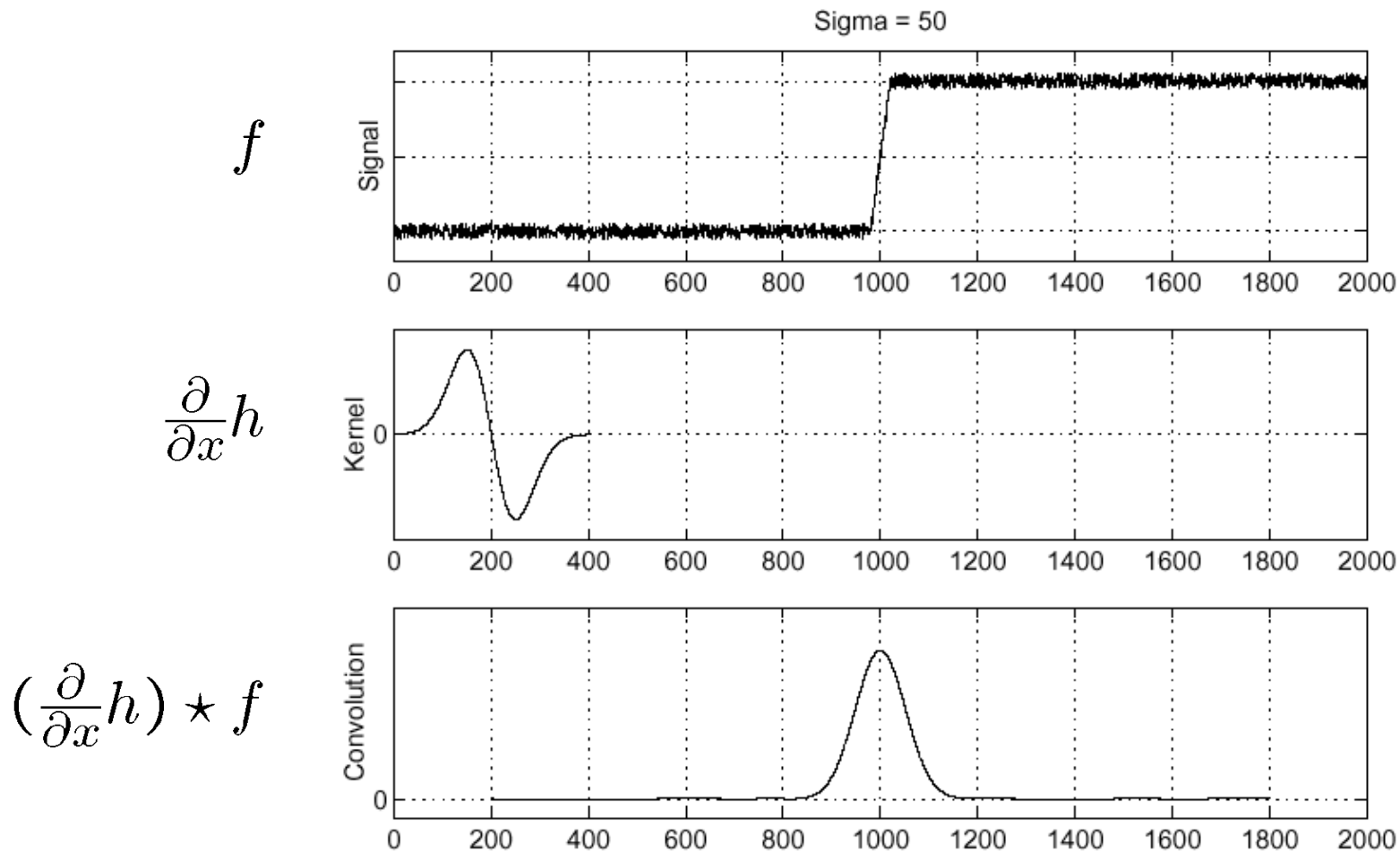
Where is the edge?

Look for peaks in  $\frac{\partial}{\partial x}(h \star f)$

# Derivative Theorem of Convolution

$$\frac{\partial}{\partial x}(h \star f) = \left(\frac{\partial}{\partial x}h\right) \star f$$

...saves us one operation.

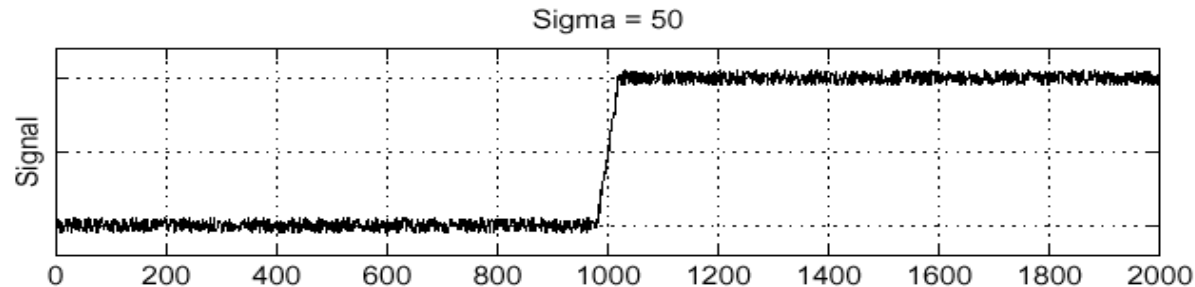


# Laplacian of Gaussian (LoG)

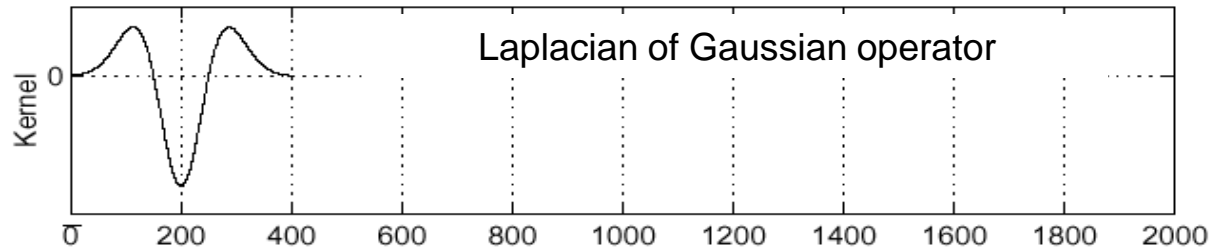
$$\frac{\partial^2}{\partial x^2} (h * f) = \left( \frac{\partial^2}{\partial x^2} h \right) * f$$

Laplacian of Gaussian

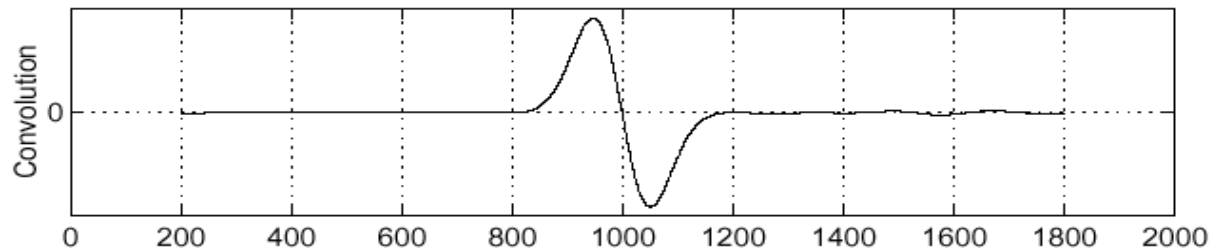
$f$



$\frac{\partial^2}{\partial x^2} h$



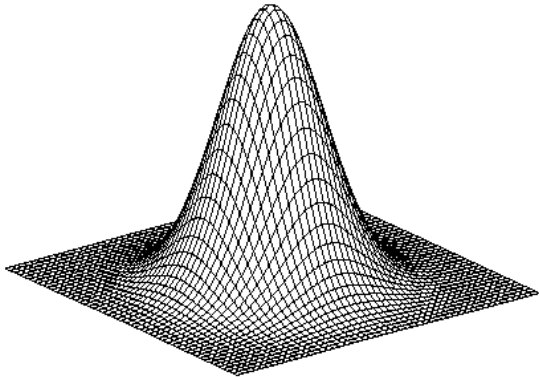
$\left( \frac{\partial^2}{\partial x^2} h \right) * f$



Where is the edge?

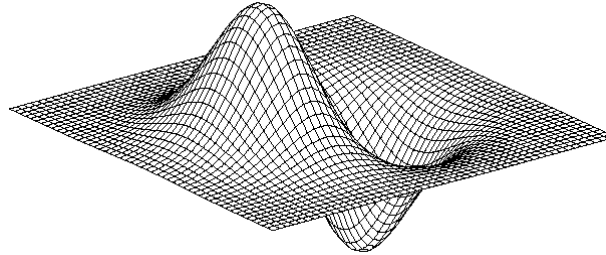
Zero-crossings of bottom graph !

# 2D Gaussian Edge Operators



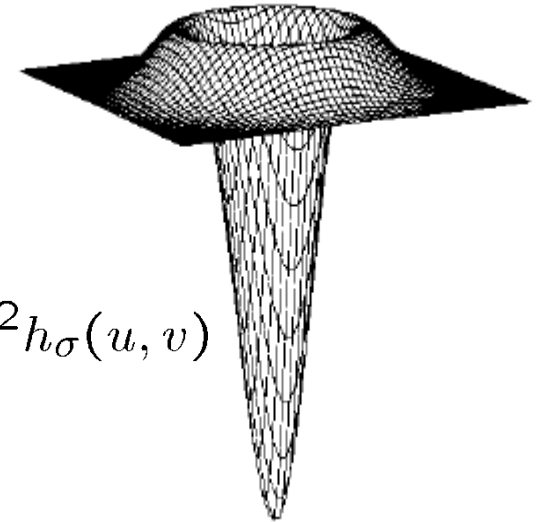
$$h_{\sigma}(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$

Gaussian



$$\frac{\partial}{\partial x} h_{\sigma}(u, v)$$

Derivative of Gaussian (DoG)



$$\nabla^2 h_{\sigma}(u, v)$$

Laplacian of Gaussian  
Mexican Hat (Sombrero)

- $\nabla^2$  is the **Laplacian** operator:  $\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$

# Canny Edge Operator

- Smooth image  $I$  with 2D Gaussian:  $G * I$
- Find local edge normal directions for each pixel

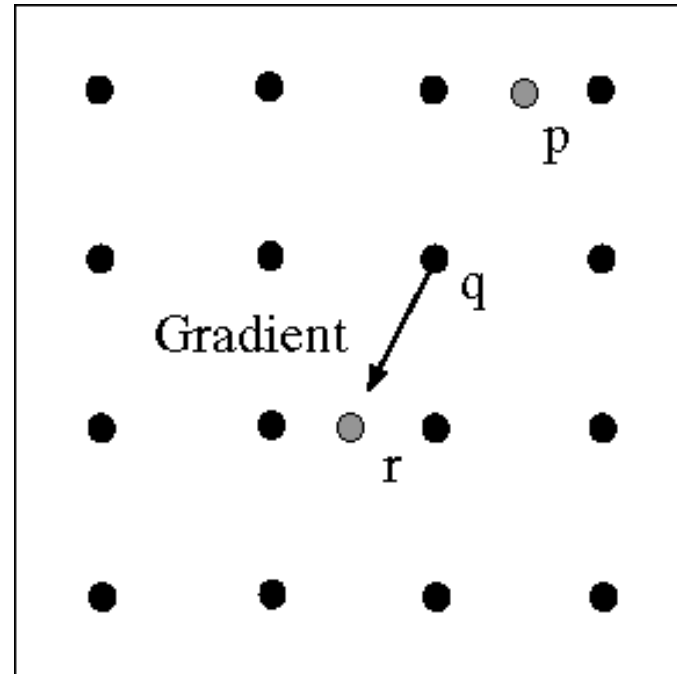
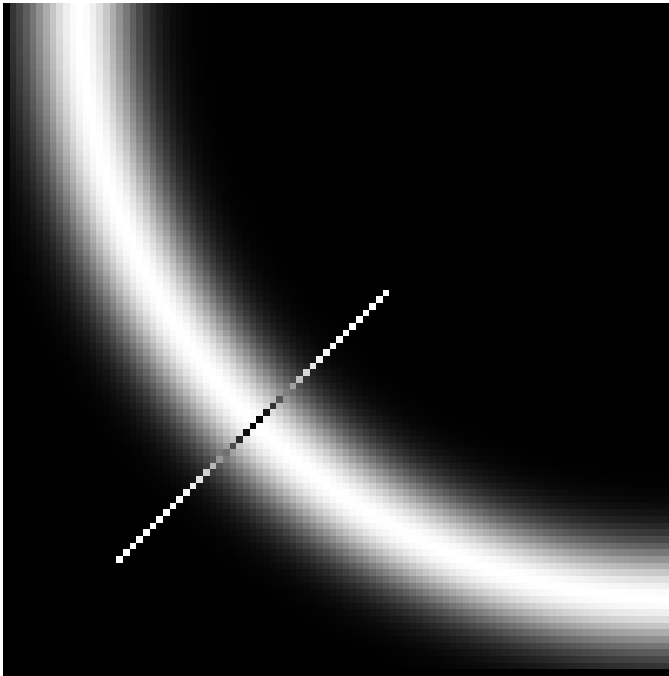
$$\bar{\mathbf{n}} = \frac{\nabla(G * I)}{|\nabla(G * I)|}$$

- Compute edge magnitudes  $|\nabla(G * I)|$
- Locate edges by finding zero-crossings along the edge normal directions (**non-maximum suppression**)

$$\frac{\partial^2(G * I)}{\partial \bar{\mathbf{n}}^2} = 0$$

# Non-maximum Suppression

- Check if pixel is local maximum along gradient direction
  - requires checking interpolated pixels  $p$  and  $r$







original image



magnitude of the gradient



After non-maximum suppression

# Canny Edge Operator



original



Canny with  $\sigma = 1$

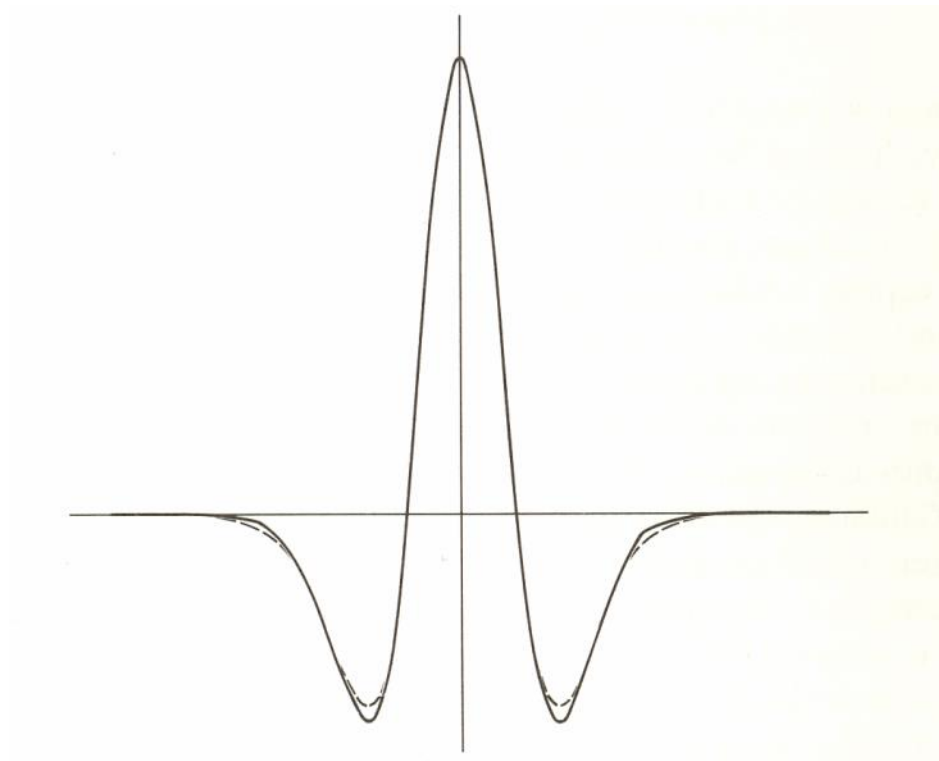


Canny with  $\sigma = 2$

- The choice of  $\sigma$  depends on desired behavior
  - large  $\sigma$  detects large scale edges
  - small  $\sigma$  detects fine features

# Difference of Gaussians (DoG)

- Laplacian of Gaussian can be approximated by the difference between two different Gaussians



# DoG Edge Detection



(a)  $\sigma = 1$

(b)  $\sigma = 2$

(b)-(a)



# Unsharp Masking

---



-



=



+ a



=



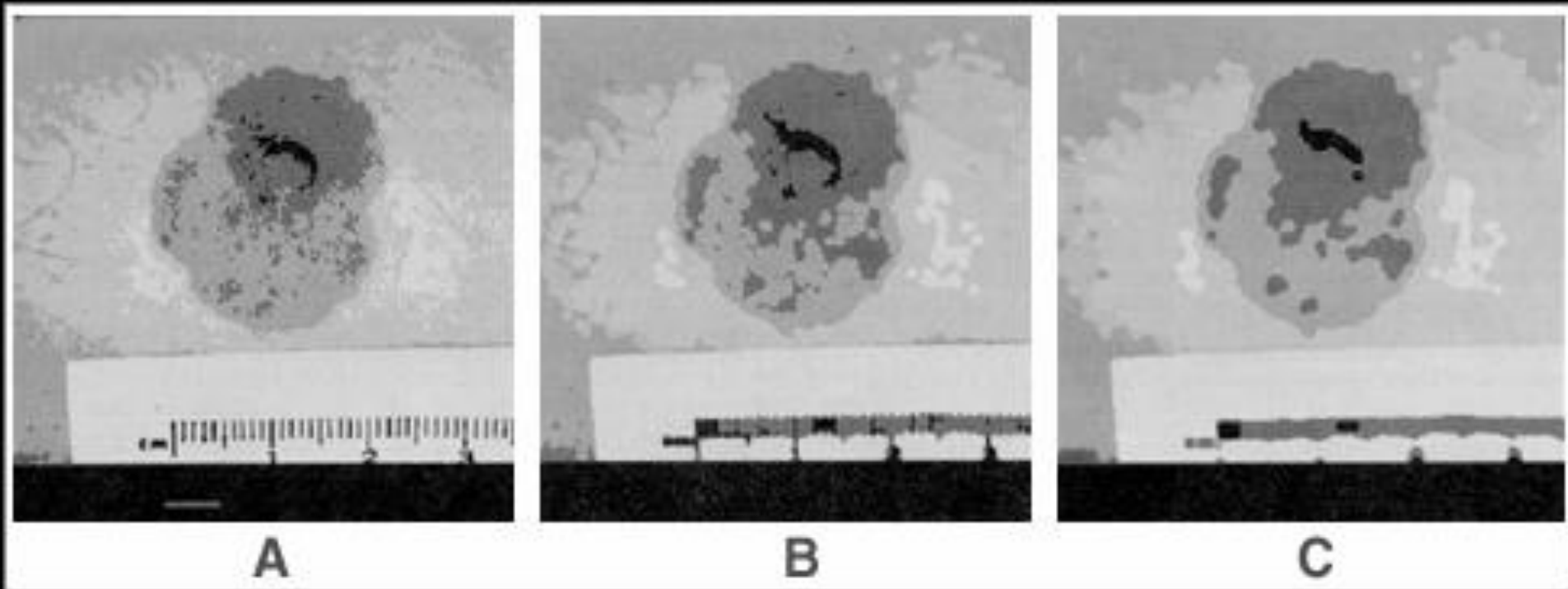
# Topic: Morphological Filters

- Spatial filters
- Frequency domain filtering
- Edge detection
- **Morphological filters**



# Mathematical Morphology

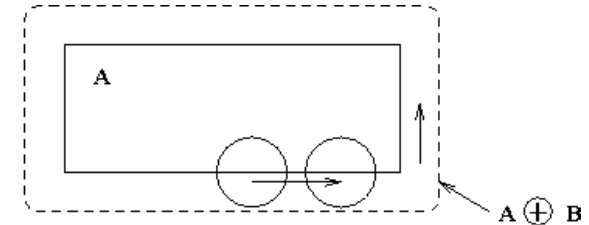
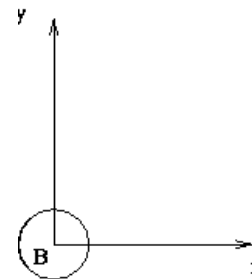
- Provides a mathematical description of geometric structures
- Based on *sets*
  - Groups of pixels which define an image region
- What is this used for?
  - Binary images
  - Can be used for **post-processing** segmentation results!
- Core techniques
  - Erosion, Dilation
  - Open, Close



Tumor Segmentation using Morphologic Filtering

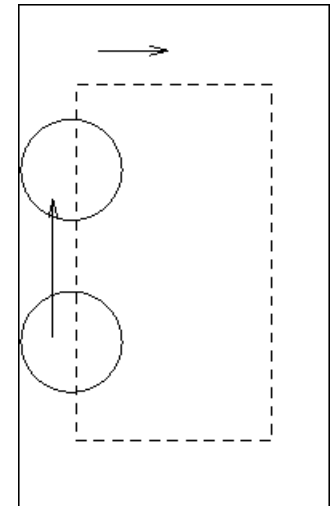
# Dilation, Erosion

- Two sets:
  - Image
  - Morphological **kernel**
- Dilation (D)
  - Union of the **kernel** with the **image** set
  - Increases resulting area
- Erosion (E)
  - Intersection
  - Decreases resulting area



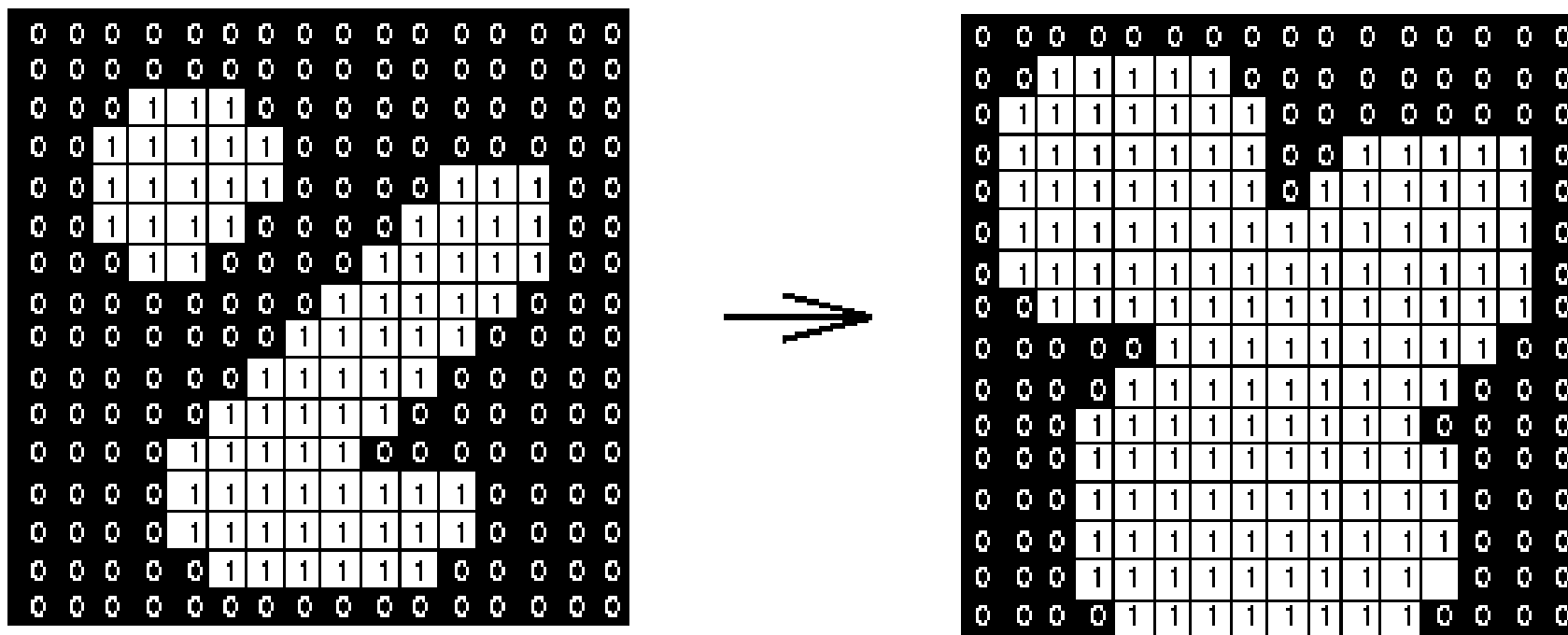
$$D(A, B) = A \oplus B = \bigcup_{\beta \in B} (A + \beta)$$

$$E(A, B) = A \ominus B = \bigcap_{\beta \in B} (A - \beta)$$



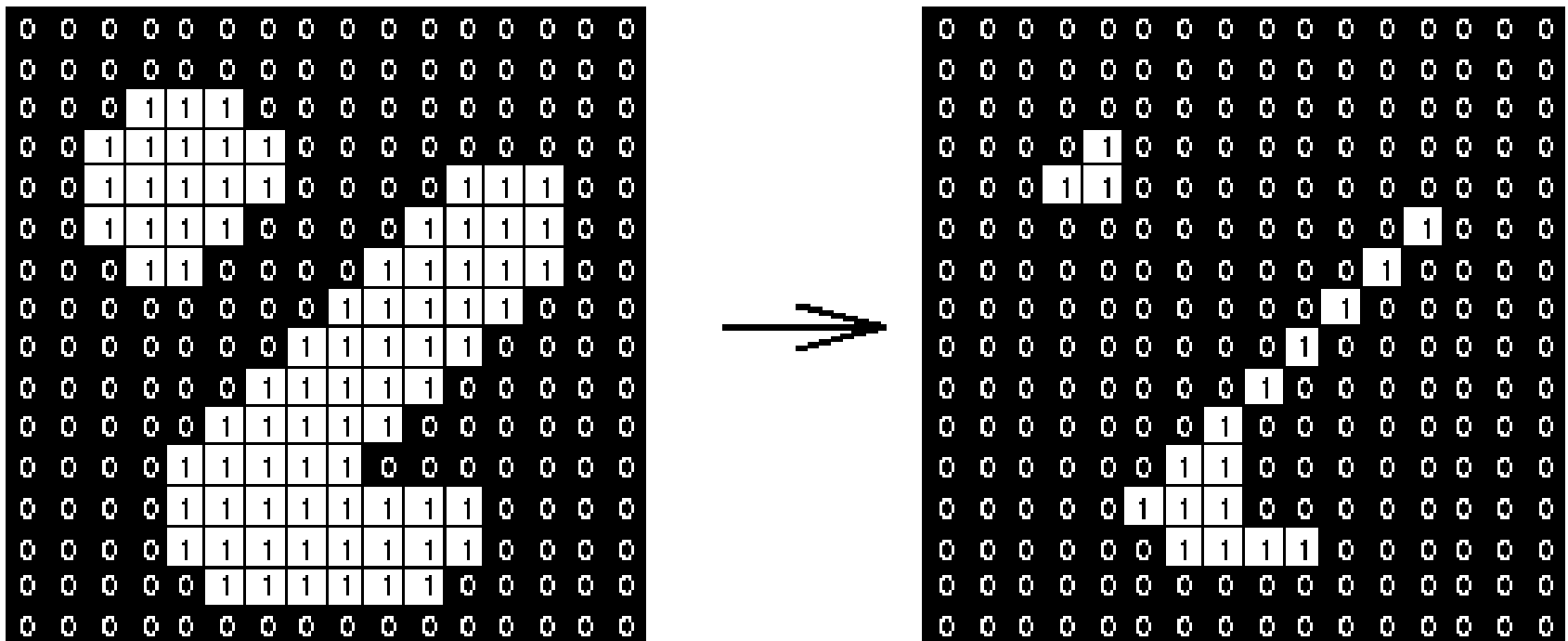
# Dilation

- Example using a 3x3 morphological kernel



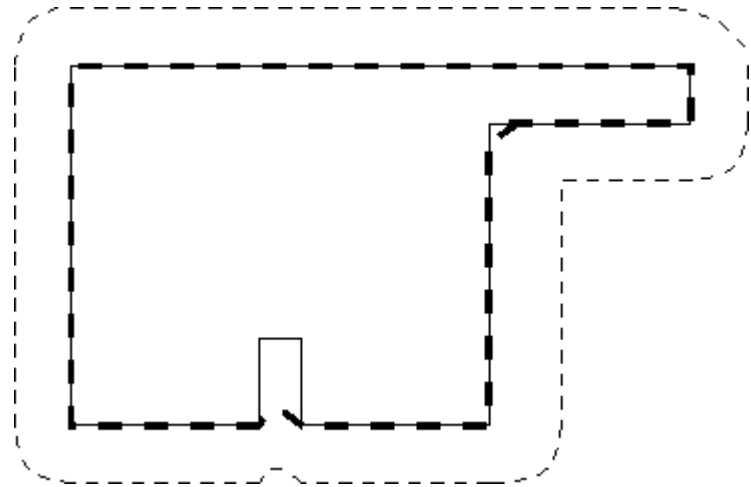
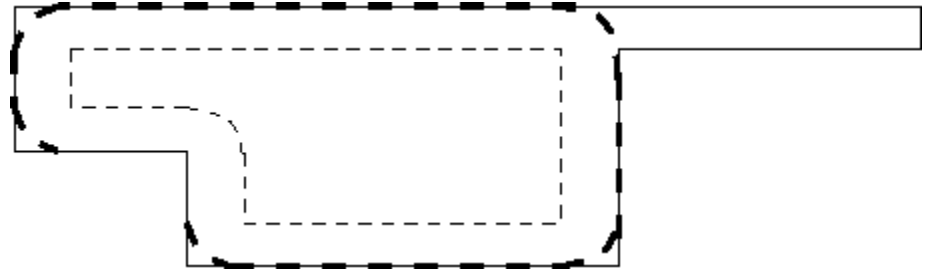
# Erosion

- Example using a 3x3 morphological kernel



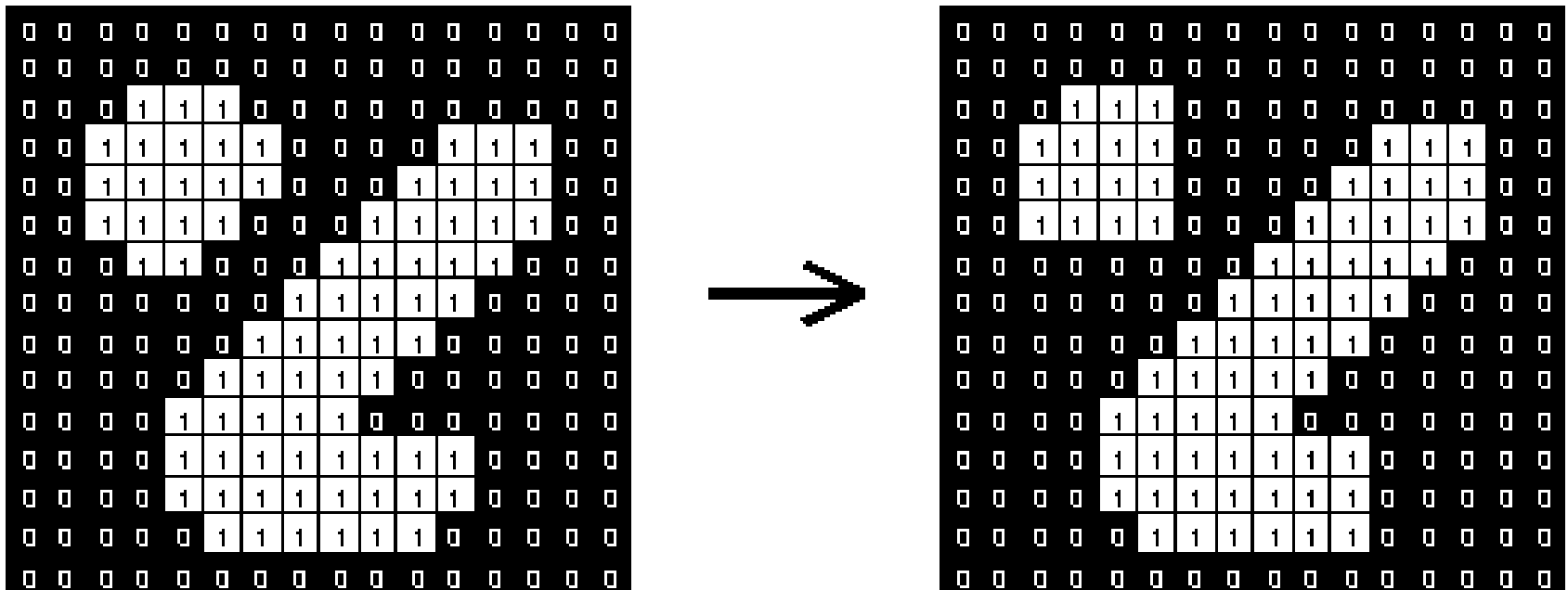
# Opening, Closing

- **Opening**
  - **Erosion**, followed by **dilation**
  - Less destructive than an erosion
  - **Adapts** image shape to kernel shape
- **Closing**
  - **Dilation**, followed by **erosion**
  - Less destructive than a dilation
  - Tends to **close** shape irregularities



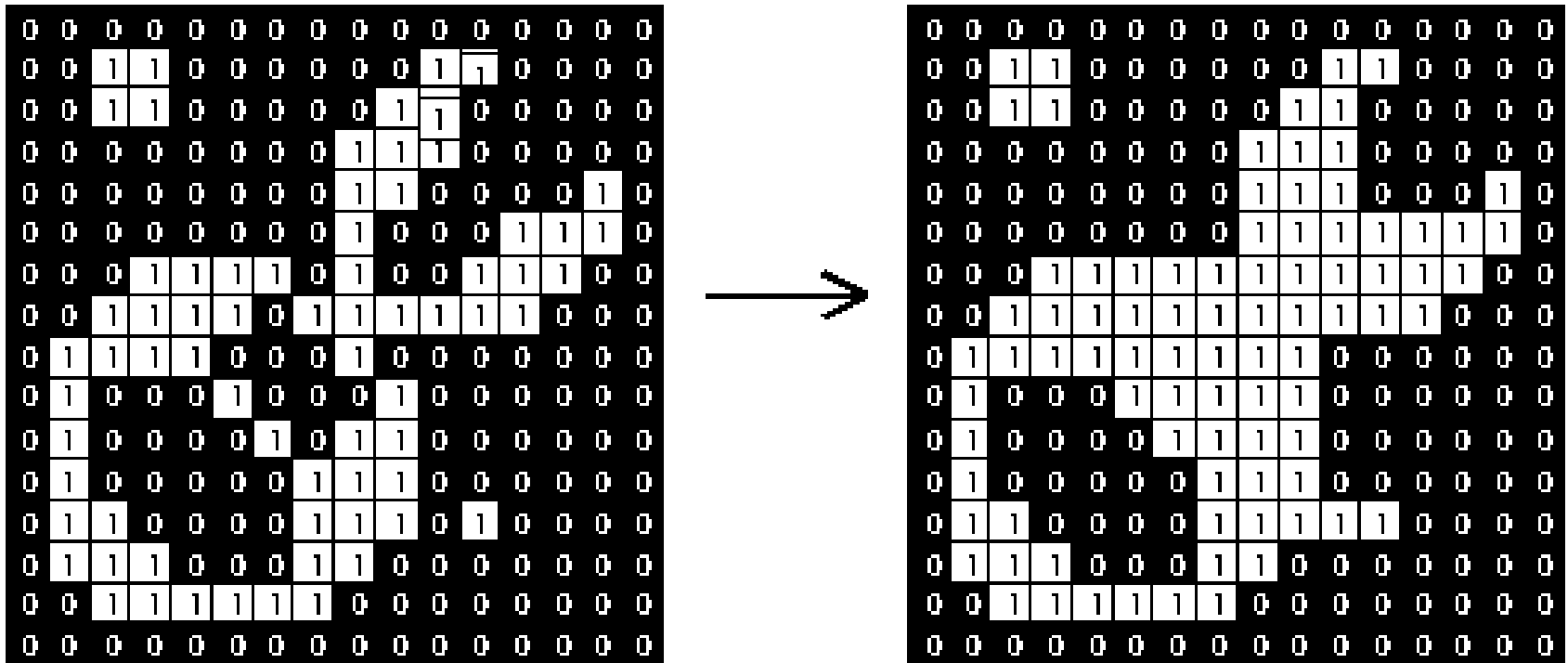
# Opening

- Example using a 3x3 morphological kernel



# Closing

- Example using a 3x3 morphological kernel





# Core morphological operators



Dilation



Erosion

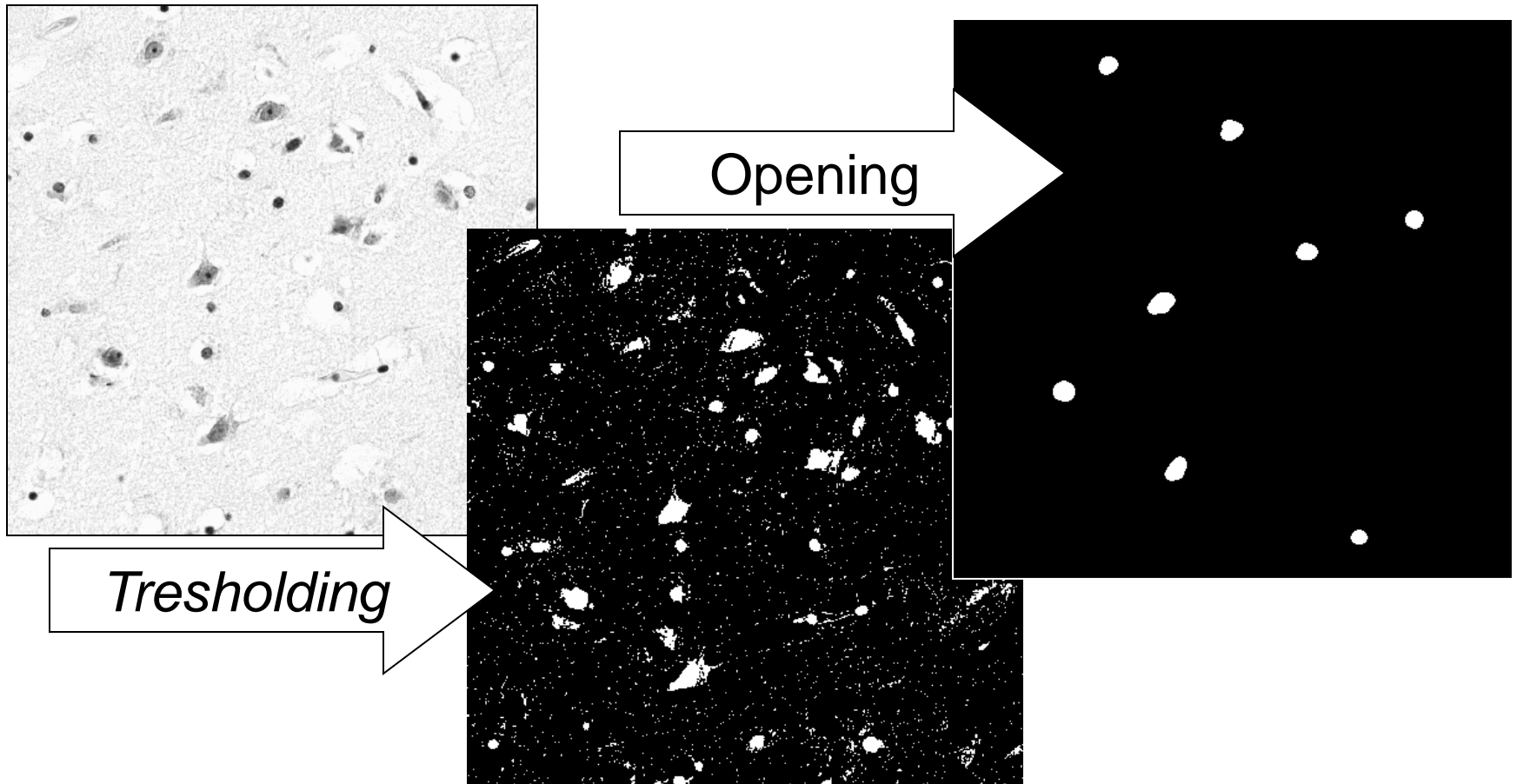


Closing

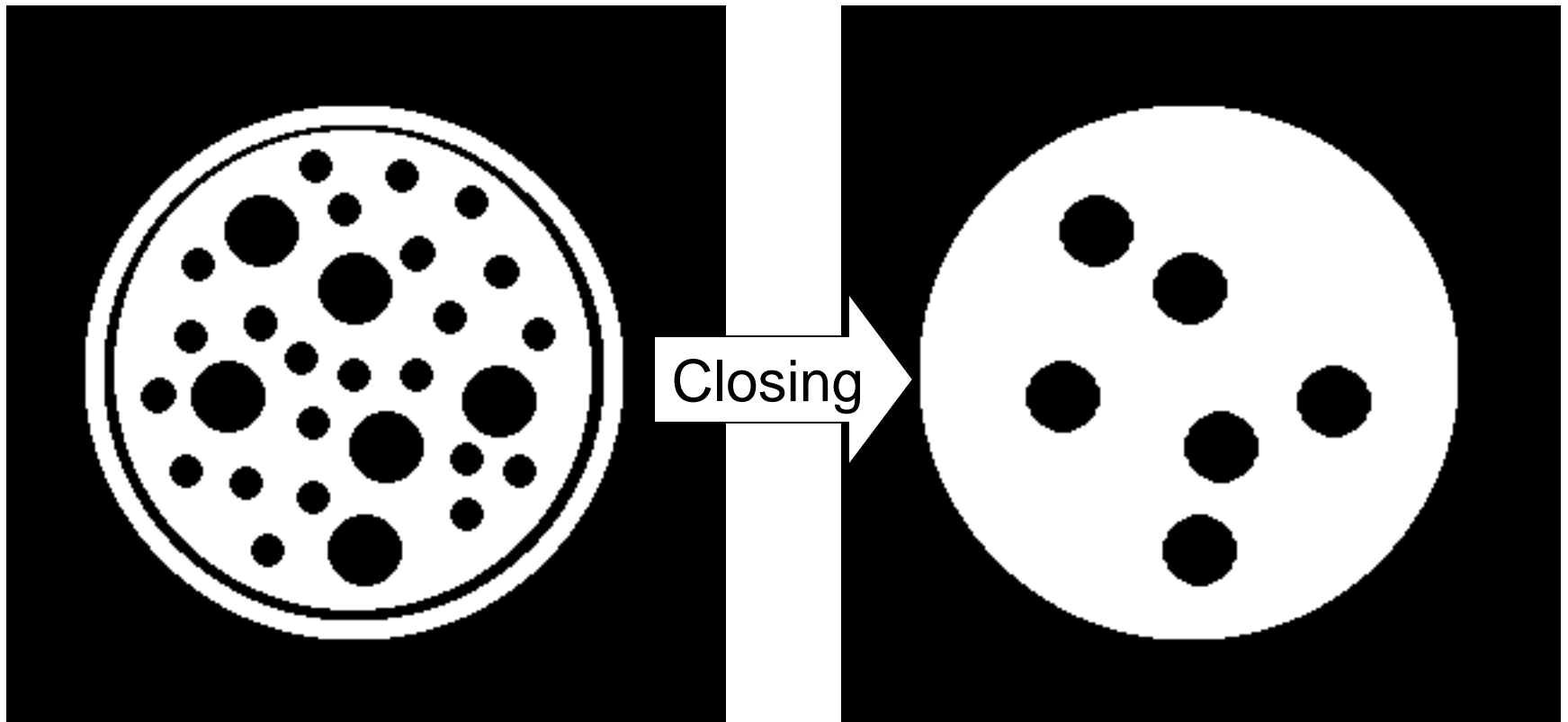


Opening

# Example: Opening



# Example: Closing



# Connected Component Analysis

- Define '**connected**'
  - 4 neighbors.
  - 8 neighbors.
- Search the image for **seed points**
- Recursively obtain all **connected points** of the seeded region

