Computer Vision – TP6
Spatial Filters

Miguel Coimbra, Hélder Oliveira

U.PORTO FC

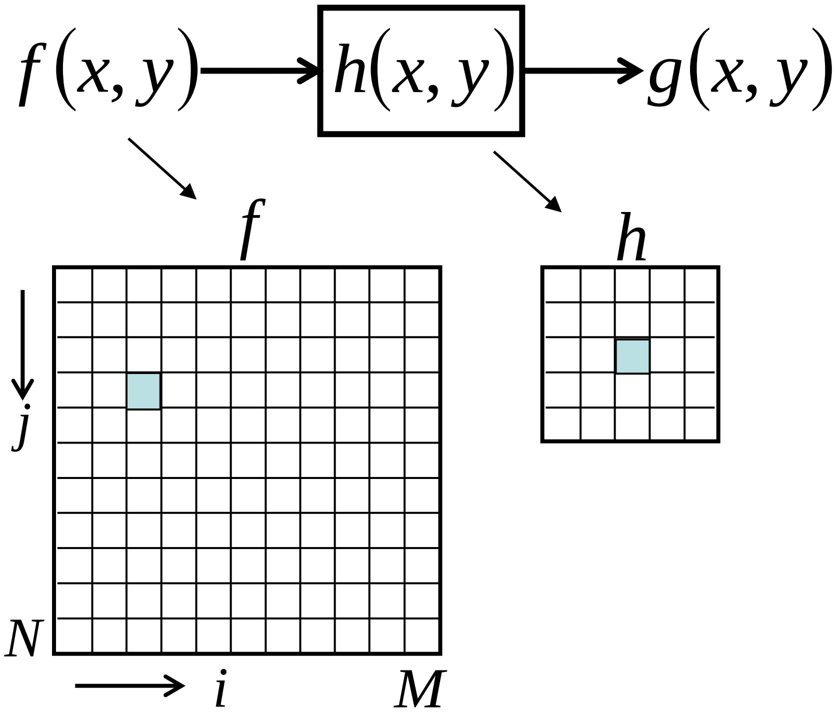
Outline

- 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

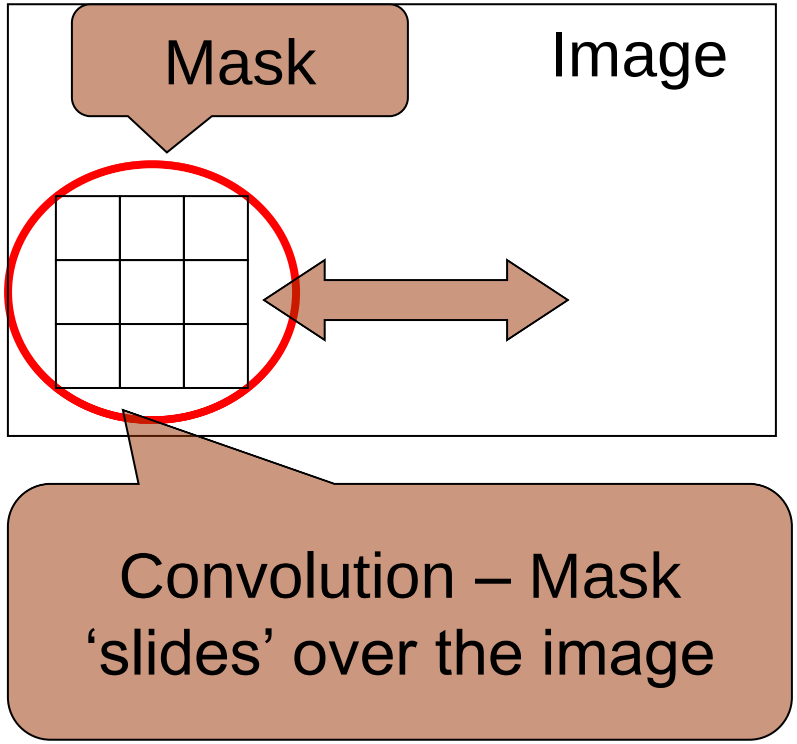
$$F(u,v) = \sum_{m=1}^{M} \sum_{n=1}^{N} f(m,n)\, e^{-i2\pi\left(\frac{mu}{M}+\frac{nv}{N}\right)}$$

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:

Mask

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

Image

2	2	2
4	4	4
4	5	6

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

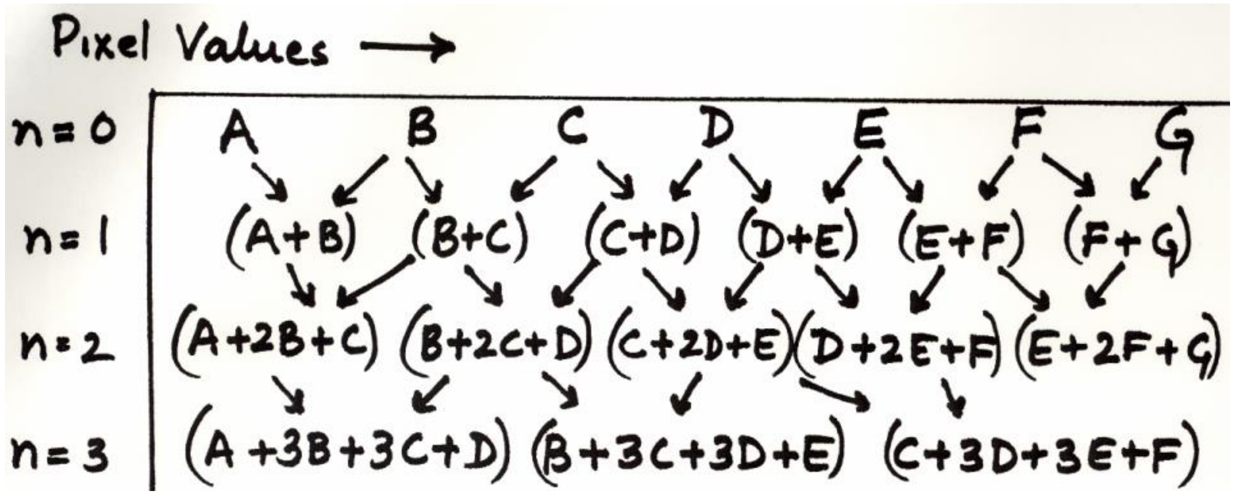
=1*2+2*2+1*2+…
=8+0-20
=-12

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 $\boxed{1 \,|\, 2 \,|\, 1}$

Which is faster?

$(a)\, O(2(n+1)) \qquad (b)\, O((n+1)^2)$

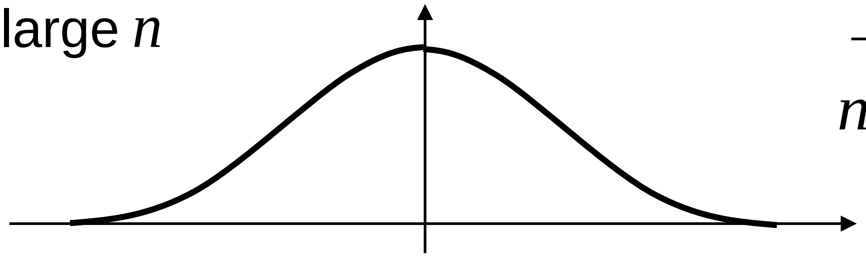
2D images:

(a) use $\begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$ then $\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$ or (b) use $\begin{bmatrix} 1 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$

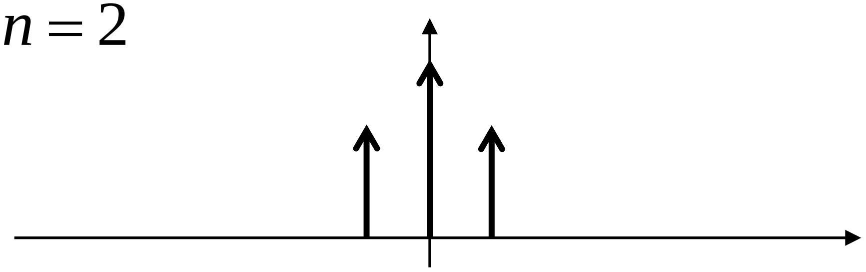
Averaging

The convolution kernel

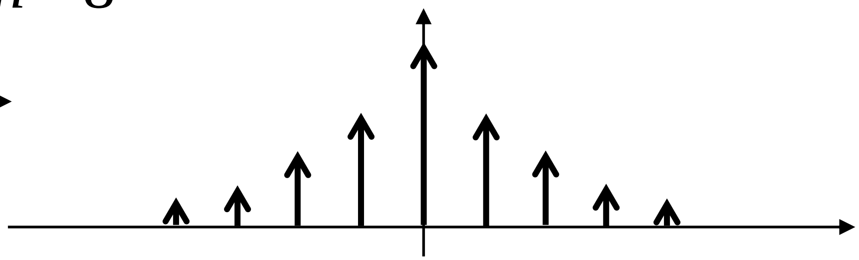
large n



$n = 2$



$n = 8$

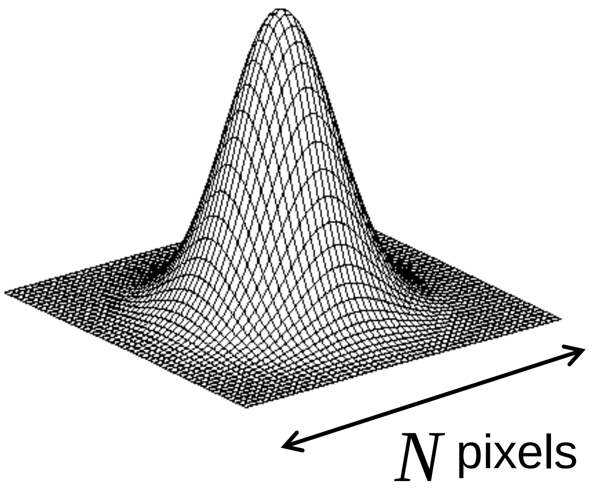


Repeated averaging $\approx$ Gaussian smoothing

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

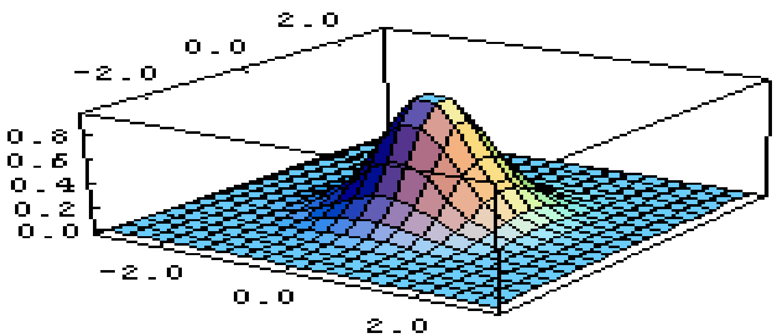
$$H[u, v] \qquad \frac{1}{16}$$

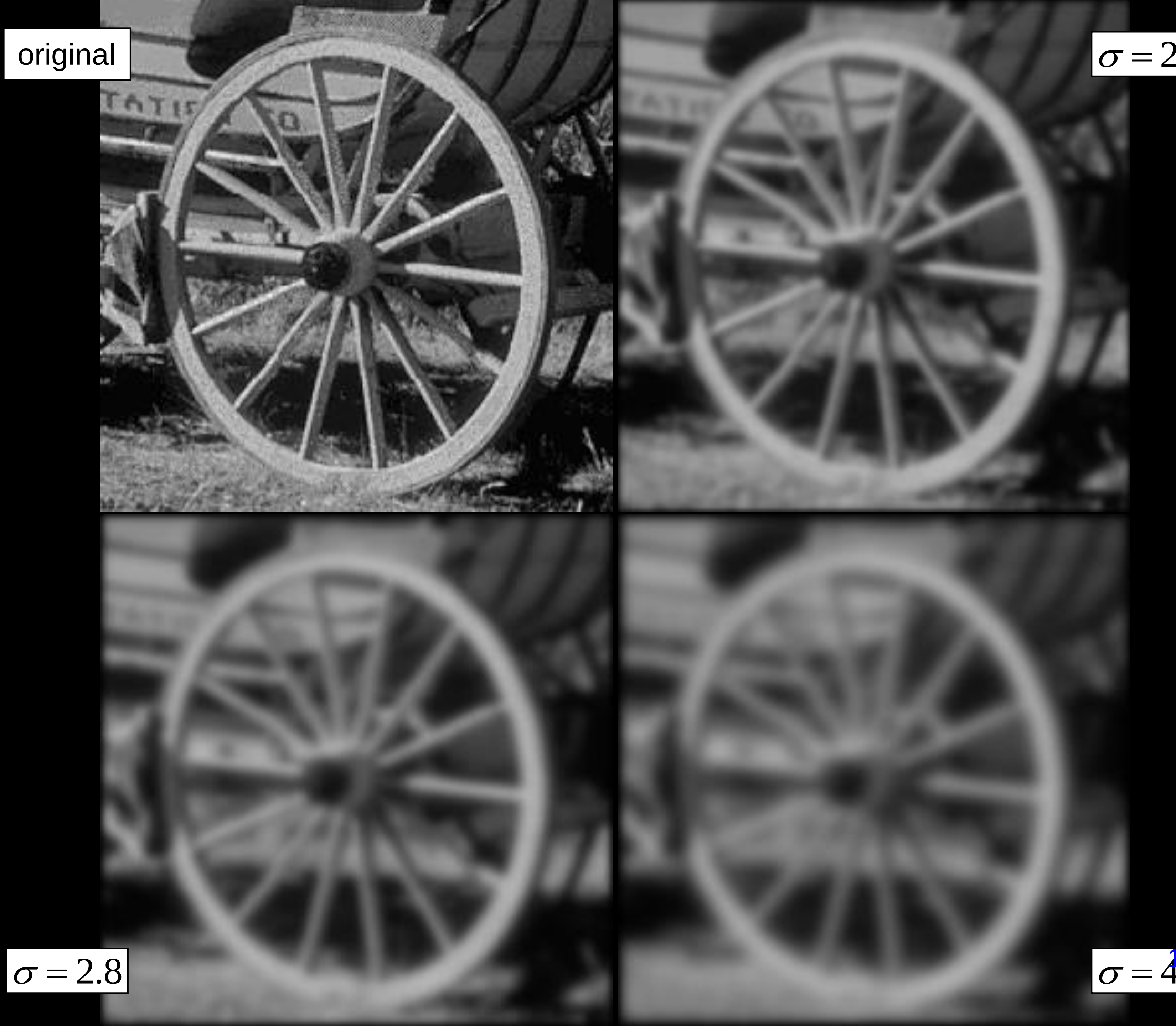
1	2	1
2	4	2
1	2	1

- This kernel is an approximation of a Gaussian function:

$$F[x, y]$$

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

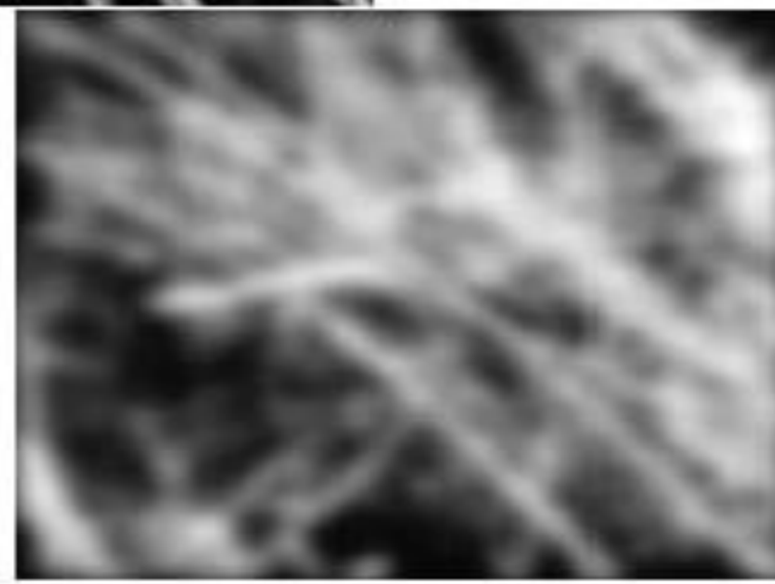



original
$\sigma = 2$
$\sigma = 2.8$
$\sigma = 4$

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

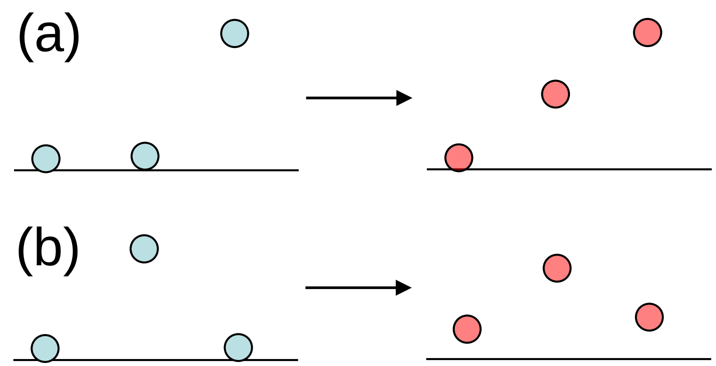


Mean filter

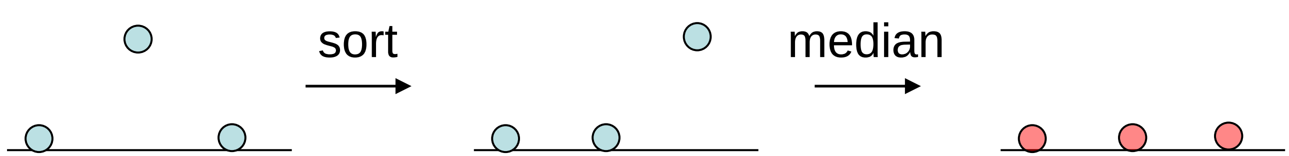
Gaussian filter

Median Filter

- Smoothing is averaging
  - (a) Blurs edges
  - (b) Sensitive to outliers



- Median filtering
  - Sort $N^2 - 1$ values around the pixel
  - Select middle value (median)



  - Non-linear (Cannot be implemented with convolution)

Salt and pepper noise

Gaussian noise

Border Problem

$$\frac{1}{16}\begin{bmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{bmatrix}$$

How do we apply our mask to this pixel?

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

What a computer sees

Border Problem

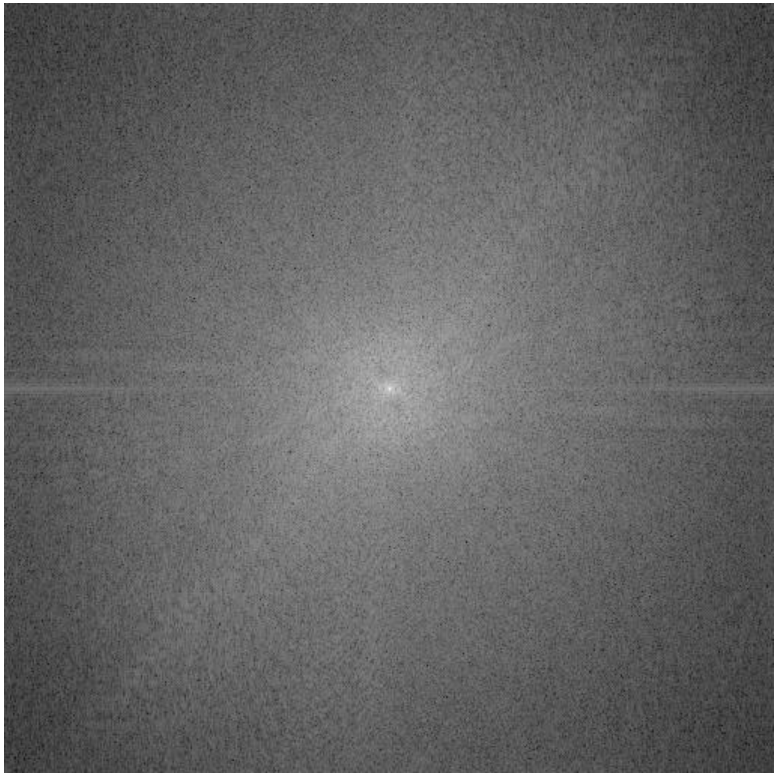
- Ignore
  - Output image will be smaller than original
- Pad with constant values
  - Can introduce substantial 1st order derivative values
- Pad with reflection
  - Can introduce substantial 2nd order derivative values

Topic: Frequency domain filtering

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

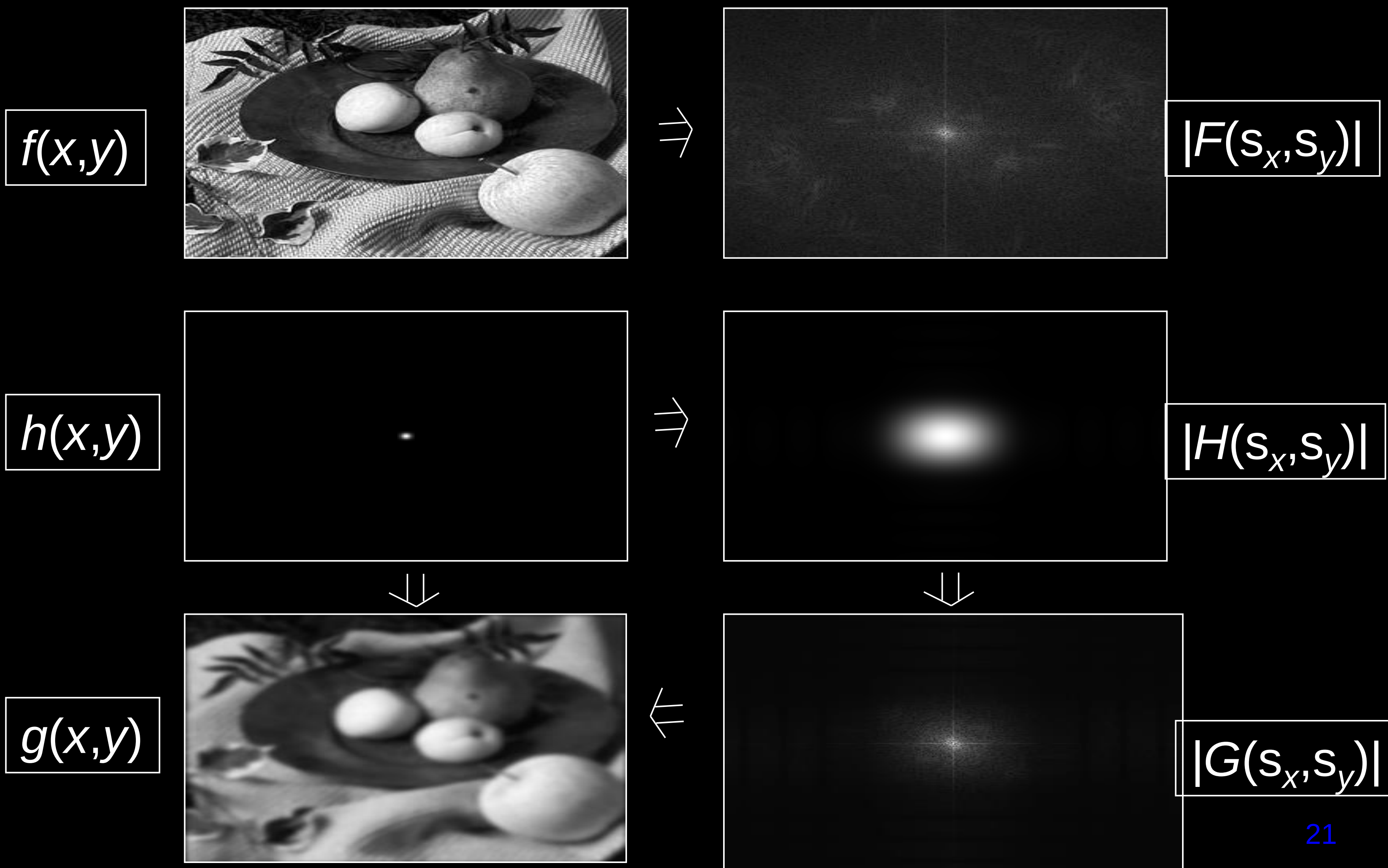
Image Processing in the Fourier Domain

Magnitude of the FT



Does not look anything like what we have seen

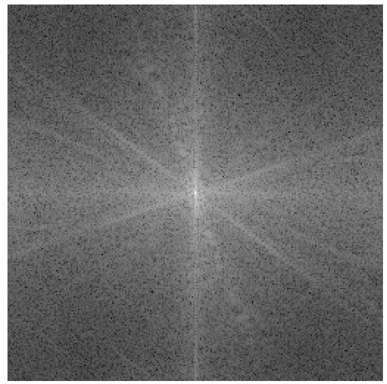
Convolution in the Frequency Domain



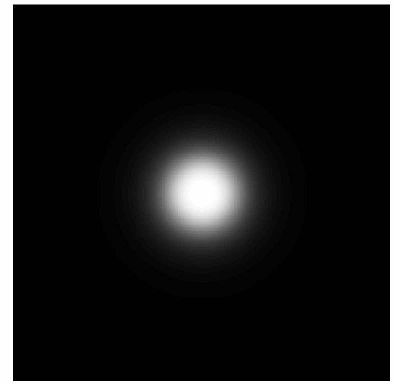
Low-pass Filtering

Original image

FFT of original image

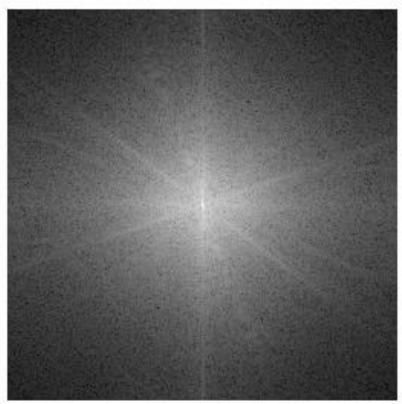


Low–pass filter



Low–pass image

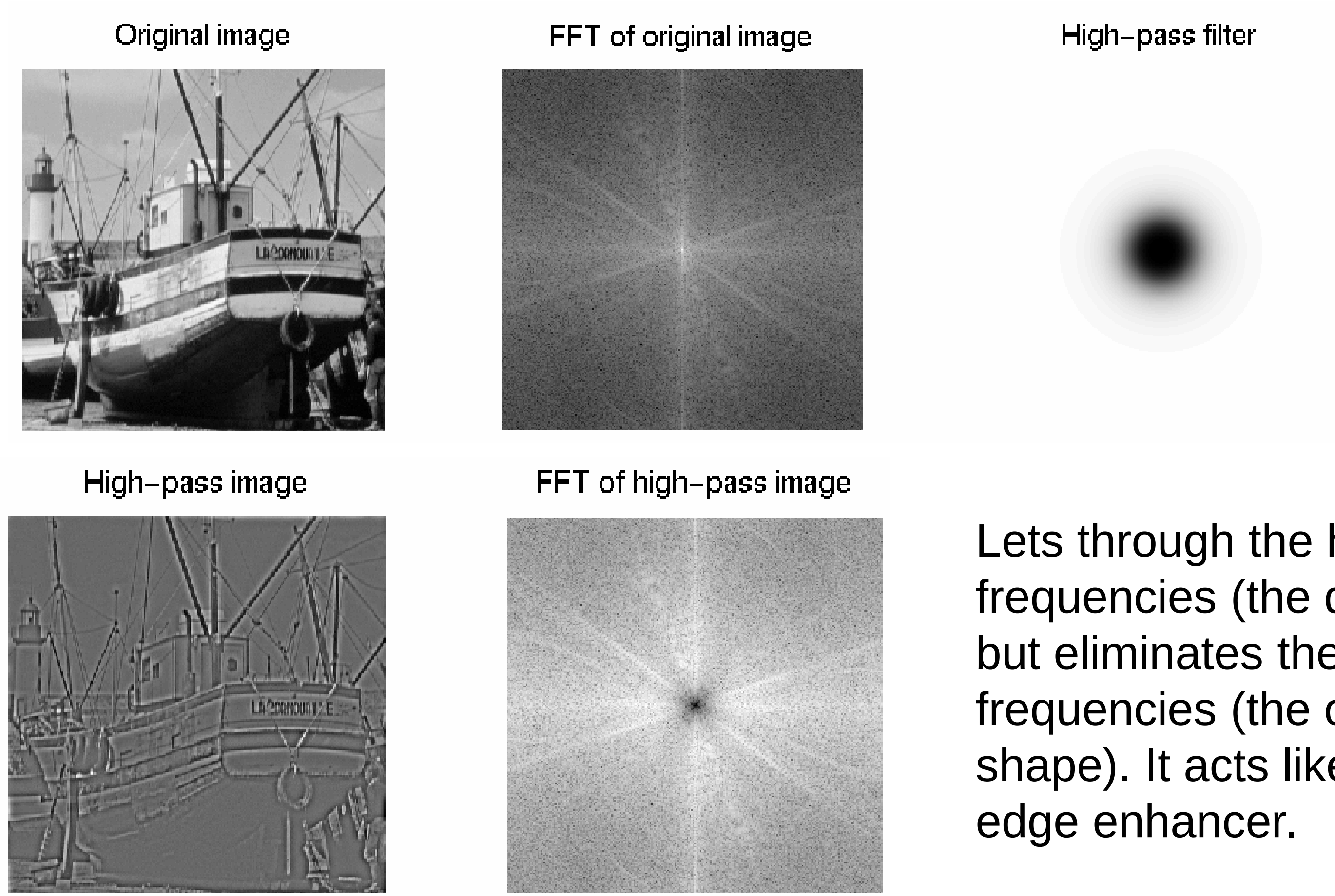
FFT of low–pass image



Lets the low frequencies pass and eliminates the high frequencies.

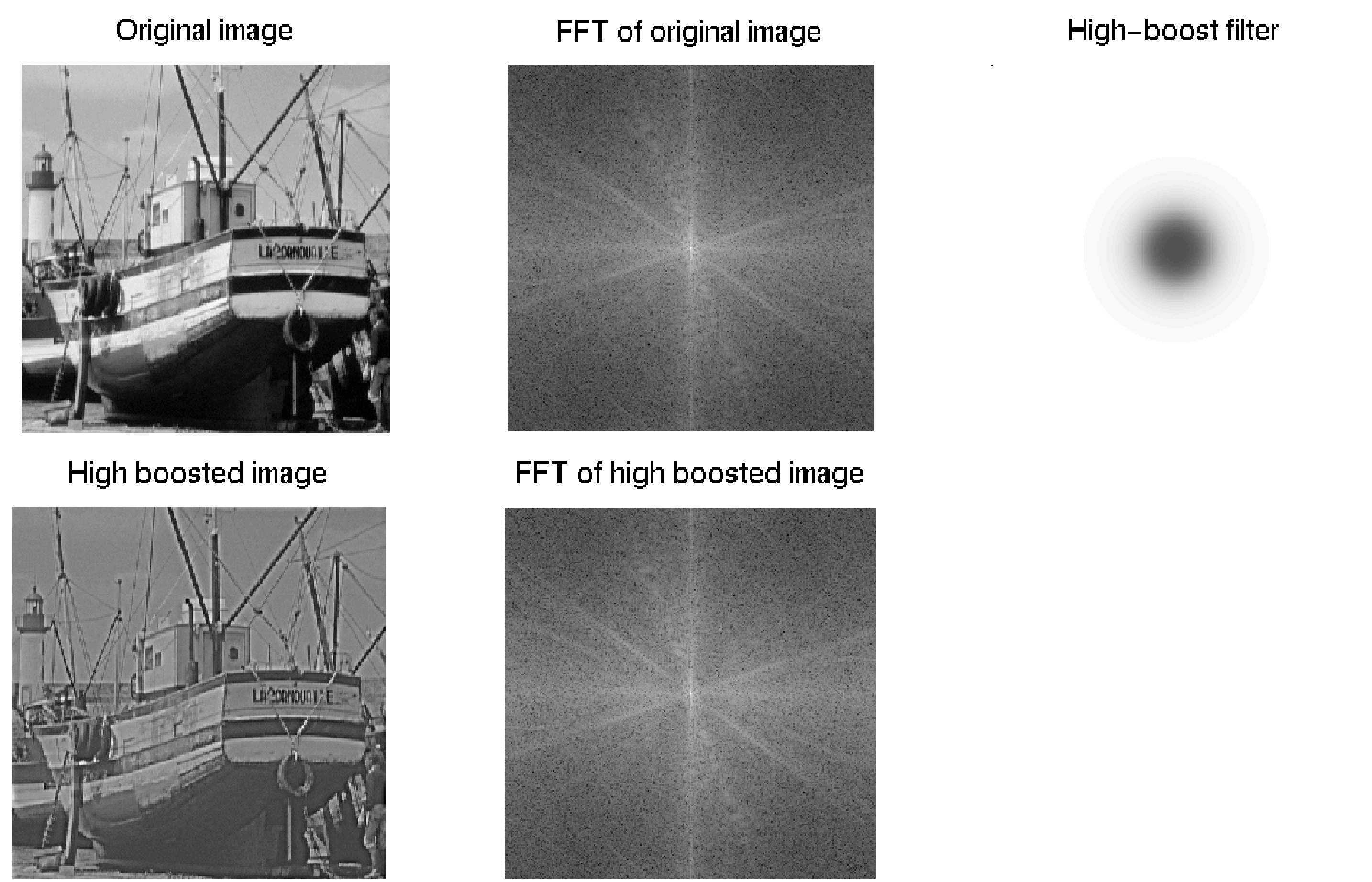
Generates image with overall shading, but not much detail

High-pass Filtering



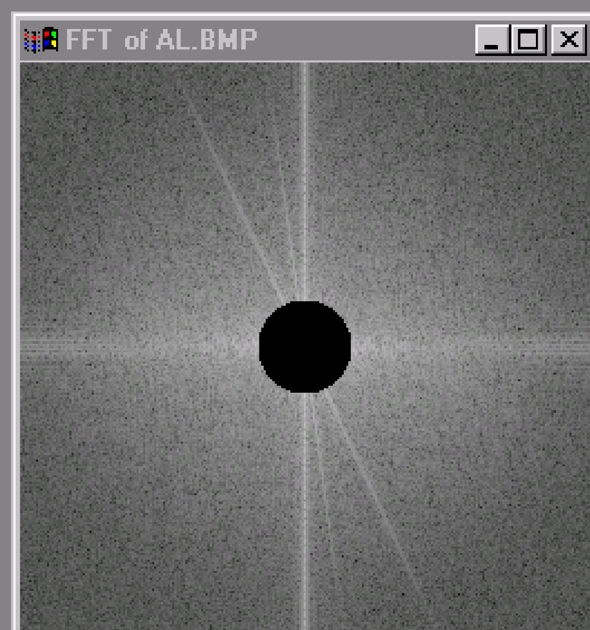
Lets through the high frequencies (the detail), but eliminates the low frequencies (the overall shape). It acts like an edge enhancer.

Boosting High Frequencies

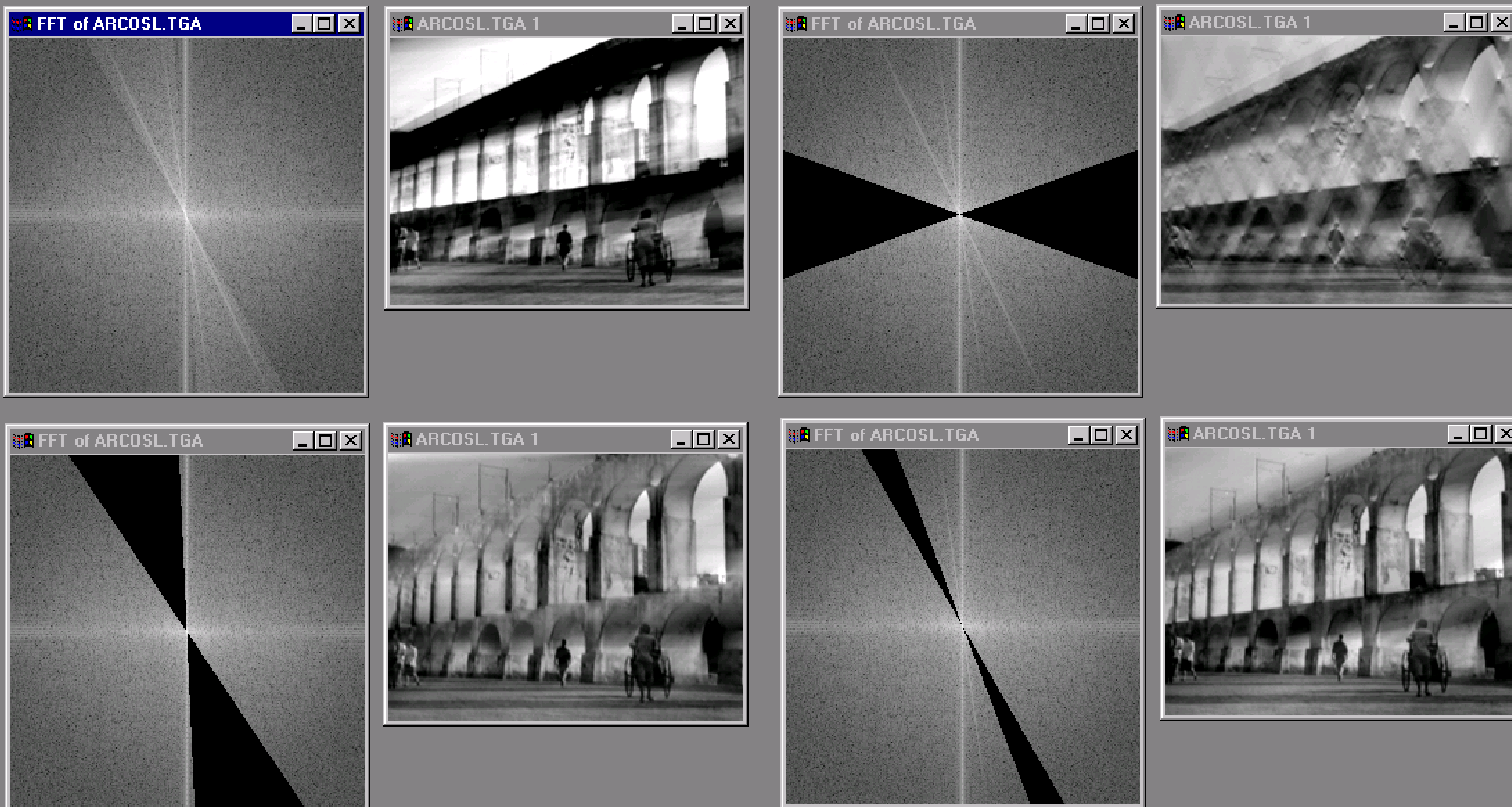



ARCOSL.TGA
FFT of ARCOSL.TGA
ARCOSL.TGA 1

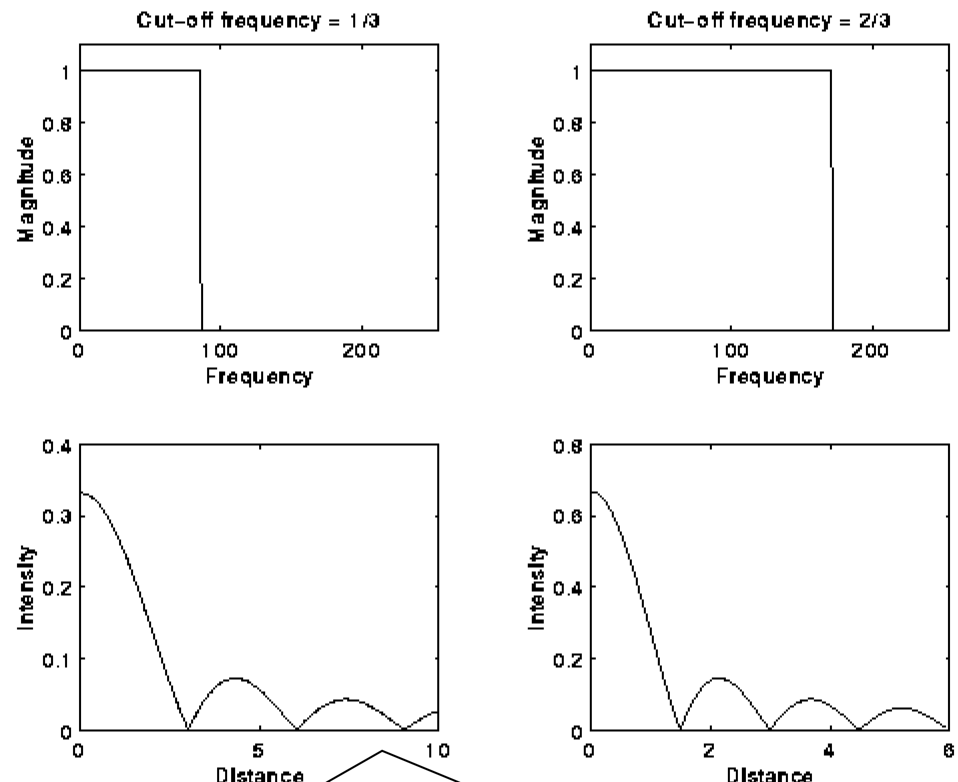

AL.BMP


FFT of AL.BMP


AL.BMP 1


FFT of ARCOSL.TGA
ARCOSL.TGA 1
FFT of ARCOSL.TGA
ARCOSL.TGA 1
FFT of ARCOSL.TGA
ARCOSL.TGA 1
FFT of ARCOSL.TGA
ARCOSL.TGA 1

The Ringing Effect



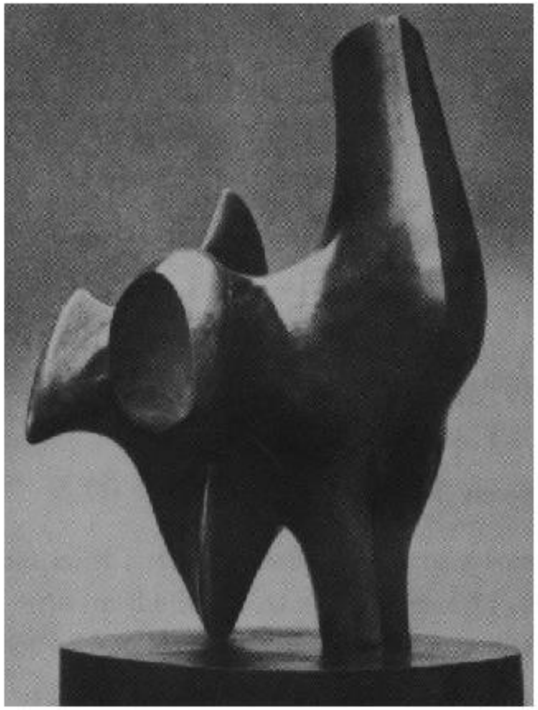
An ideal low-pass filter causes ‘rings’ in the spatial domain!

Topic: Edge detection

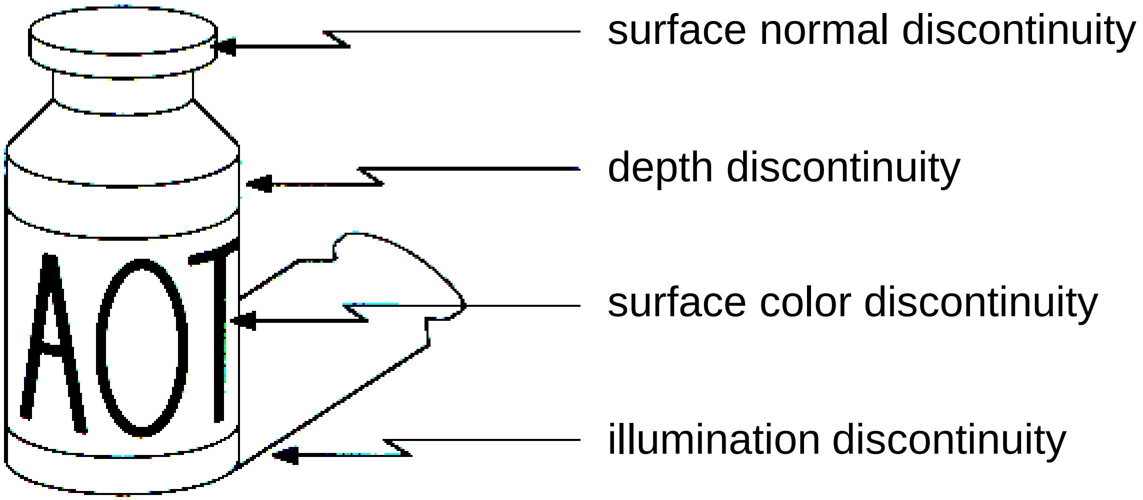
- Spatial filters
- Frequency domain filtering
- Edge detection
- Morphological filters

Edge Detection

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

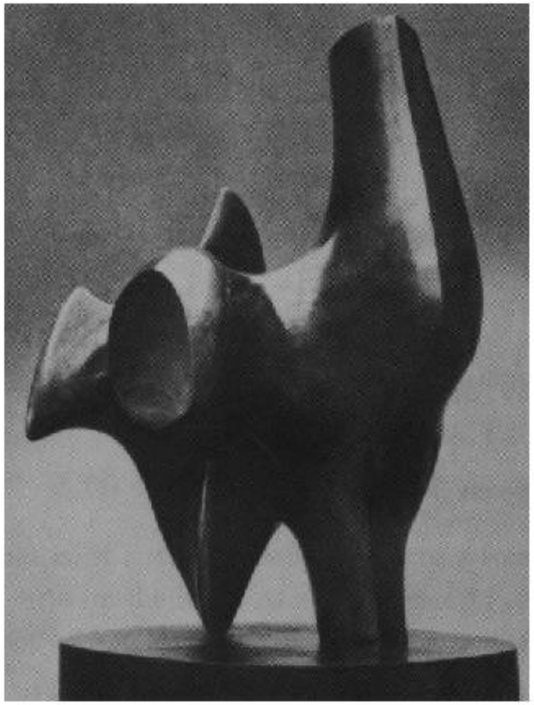


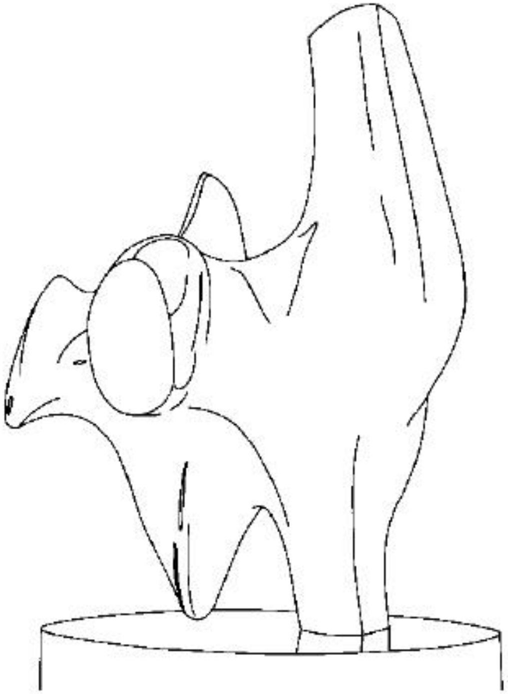
Origin of Edges



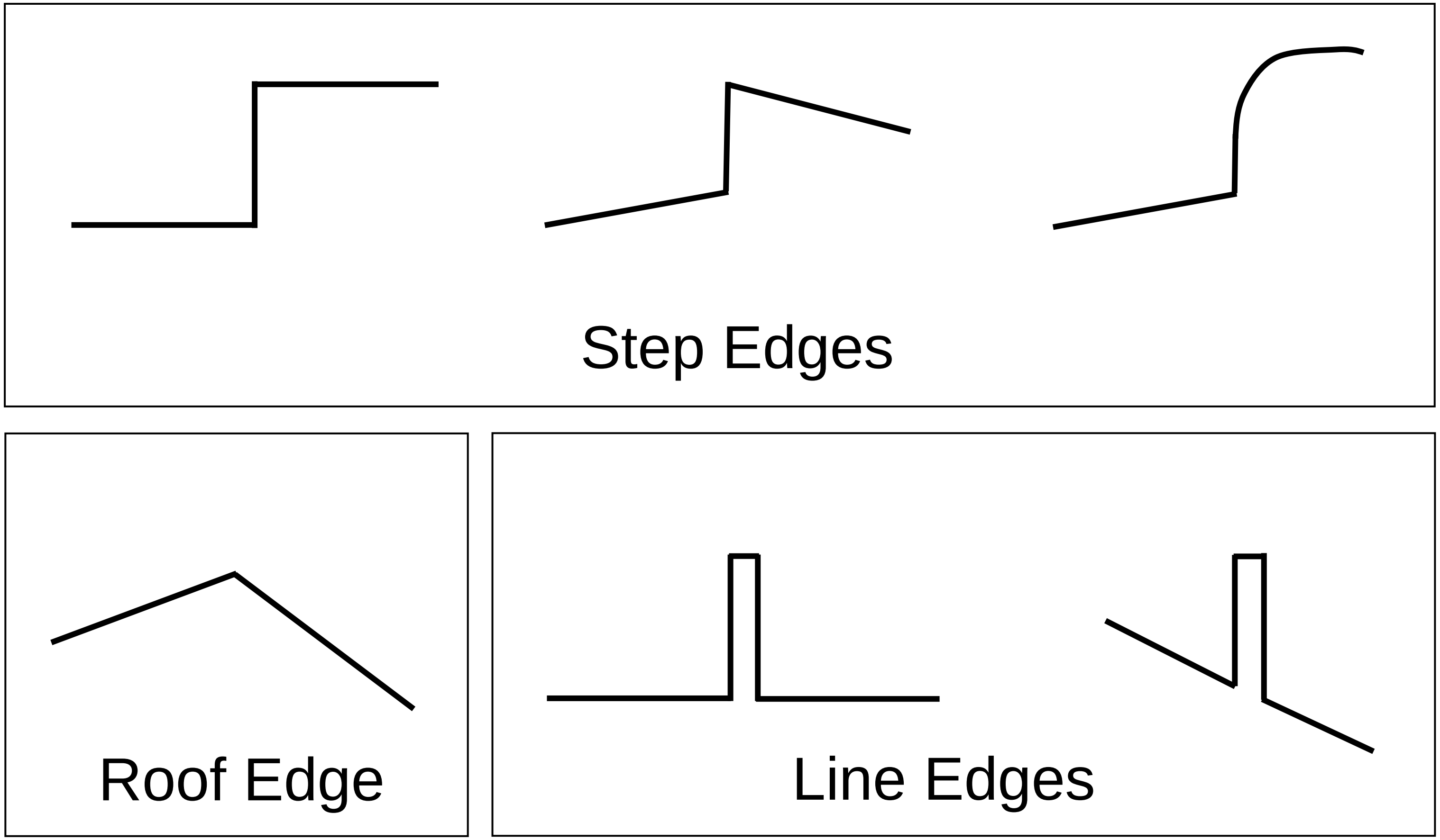
- Edges are caused by a variety of factors

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

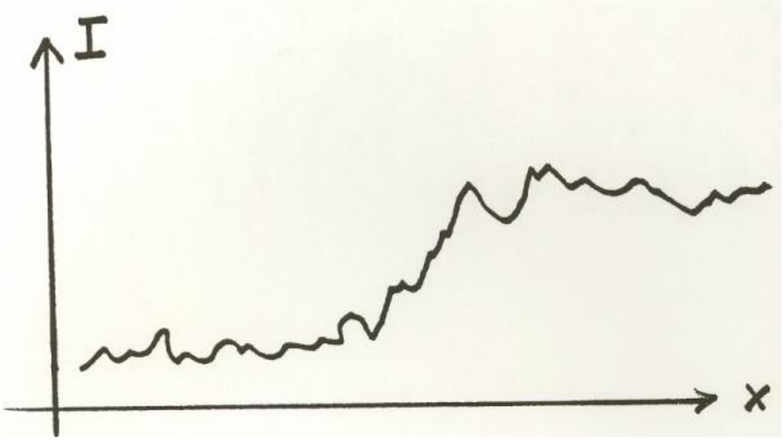




Edge Types



Real Edges



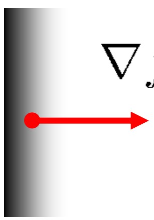
Noisy and Discrete!

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

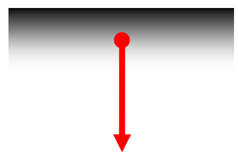
- Edge Magnitude
- Edge Orientation
- High Detection Rate and Good Localization

Gradient

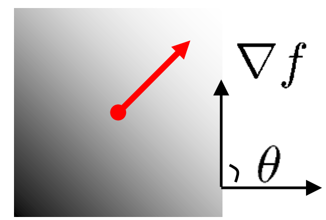
- Gradient equation: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$
- Represents direction of most rapid change in intensity



$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$



$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$

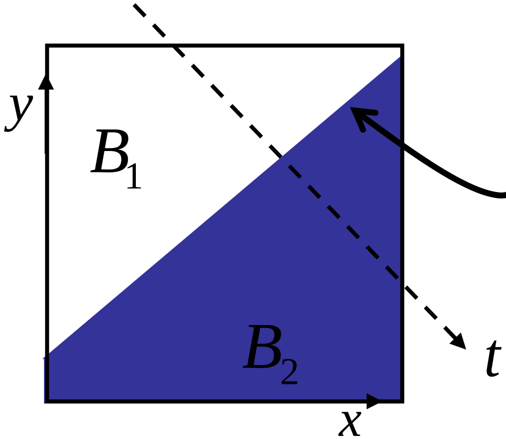


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

- 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



Ideal edge

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

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

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

Unit step function:

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

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):

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

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

- Squared gradient:

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

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)

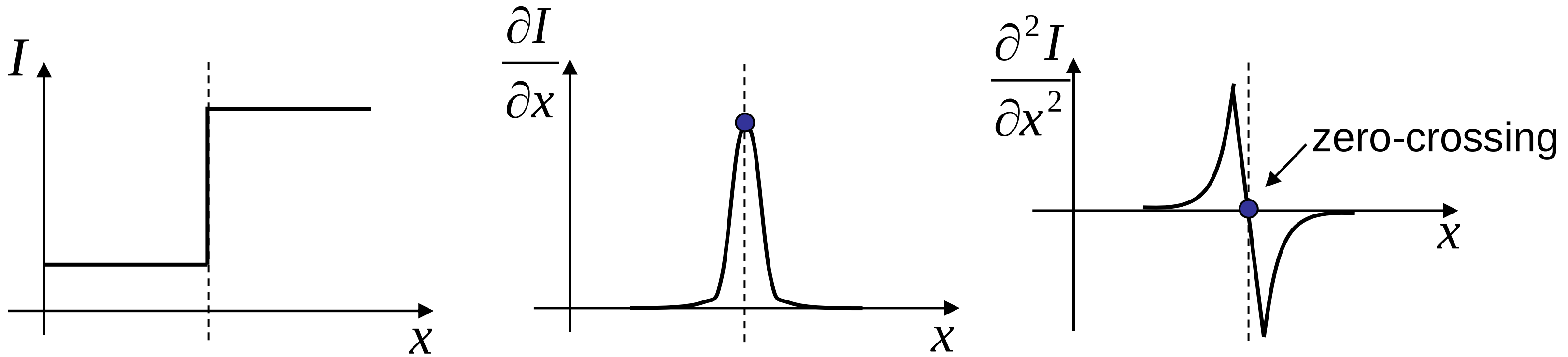
Rotationally symmetric, non-linear operator

Theory of Edge Detection

- Laplacian:

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

Rotationally symmetric, linear operator



Discrete Edge Operators

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

Finite difference approximations:

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

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

$$\begin{array}{|c|c|}\hline I_{i,j+1} & I_{i+1,j+1} \\ \hline I_{i,j} & I_{i+1,j} \\ \hline \end{array} \;\updownarrow \varepsilon$$

Convolution masks :

$$\frac{\partial I}{\partial x} \approx \frac{1}{2\varepsilon}\begin{array}{|c|c|}\hline -1 & 1 \\ \hline -1 & 1 \\ \hline \end{array} \qquad \frac{\partial I}{\partial y} \approx \frac{1}{2\varepsilon}\begin{array}{|c|c|}\hline 1 & 1 \\ \hline -1 & -1 \\ \hline \end{array}$$

Discrete Edge Operators

- Second order partial derivatives:

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

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

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

- **Laplacian** :

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

Convolution masks :

$$\nabla^2 I \approx \frac{1}{\varepsilon^2}\begin{array}{|c|c|c|}\hline 0 & 1 & 0 \\ \hline 1 & -4 & 1 \\ \hline 0 & 1 & 0 \\ \hline\end{array} \quad \text{or} \quad \frac{1}{6\varepsilon^2}\begin{array}{|c|c|c|}\hline 1 & 4 & 1 \\ \hline 4 & -20 & 4 \\ \hline 1 & 4 & 1 \\ \hline\end{array}$$

(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

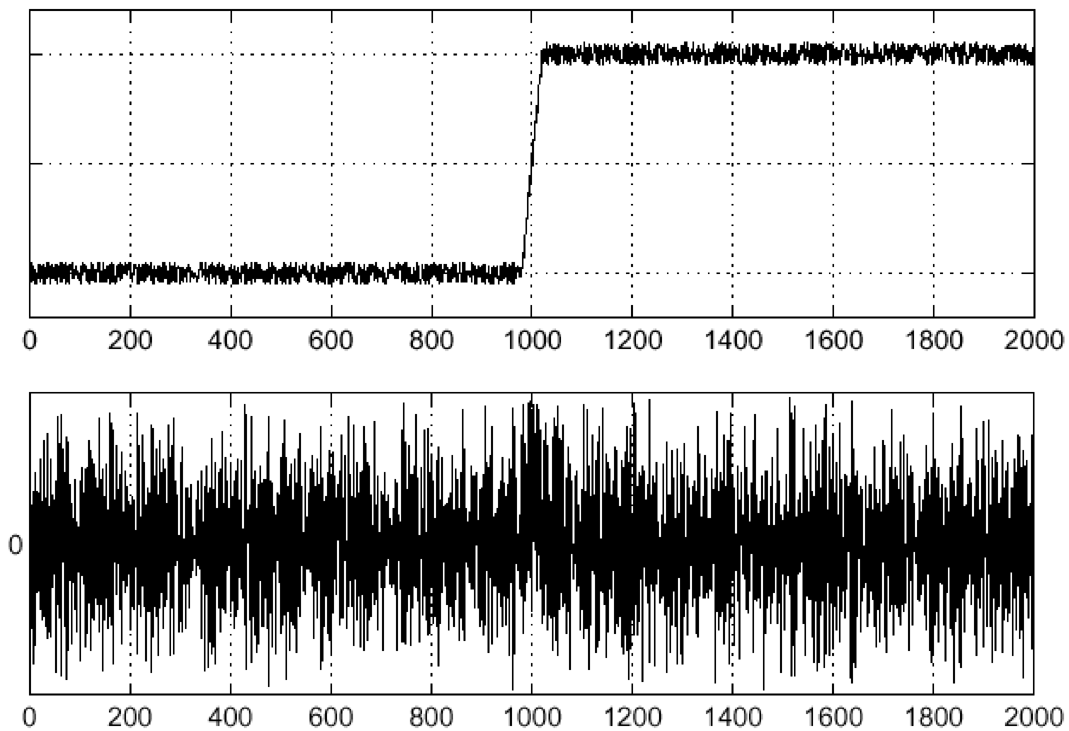
Poor Localization
Less Noise Sensitive
Good Detection

Effects of Noise

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

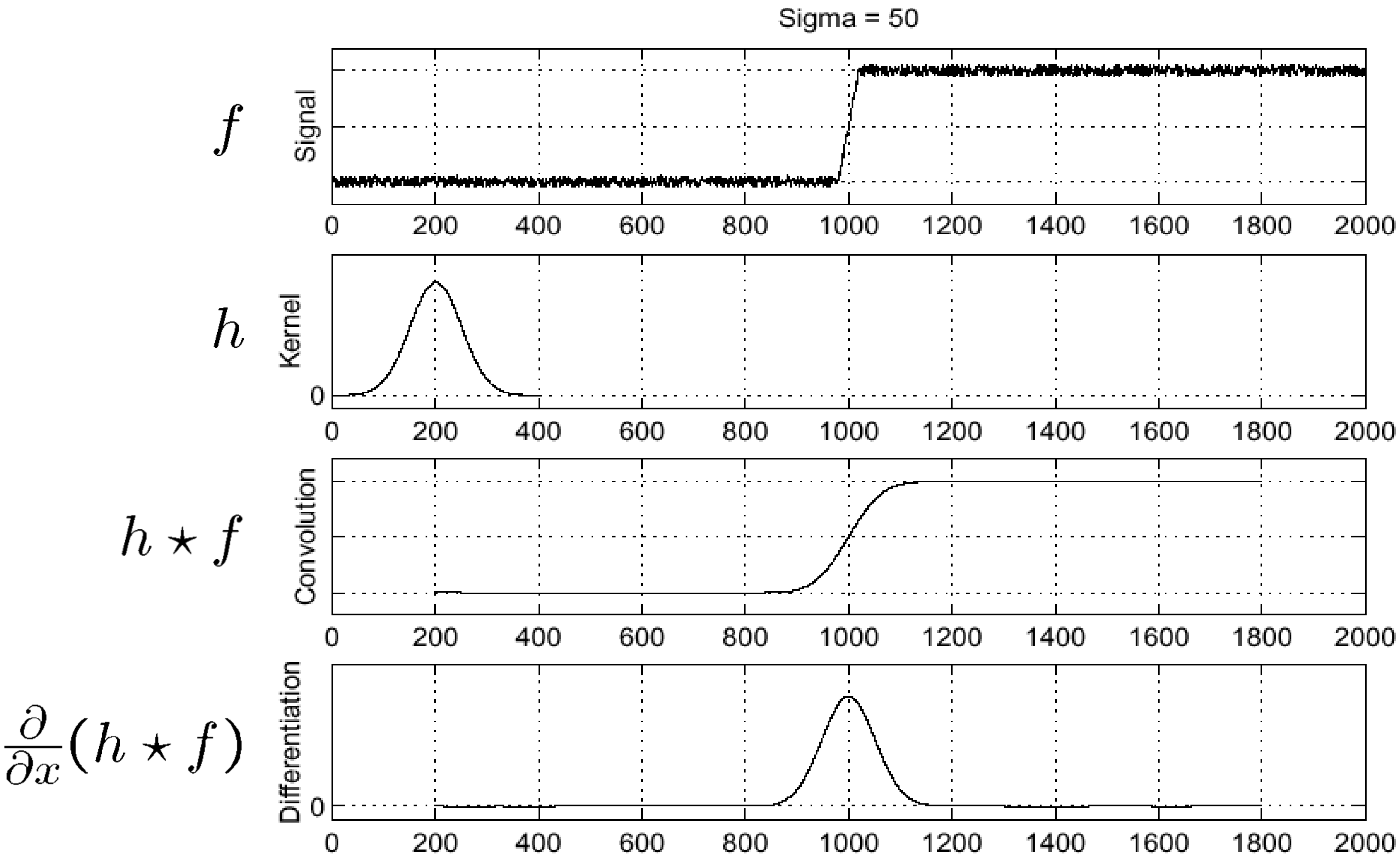
$f(x)$

$\frac{d}{dx}f(x)$



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

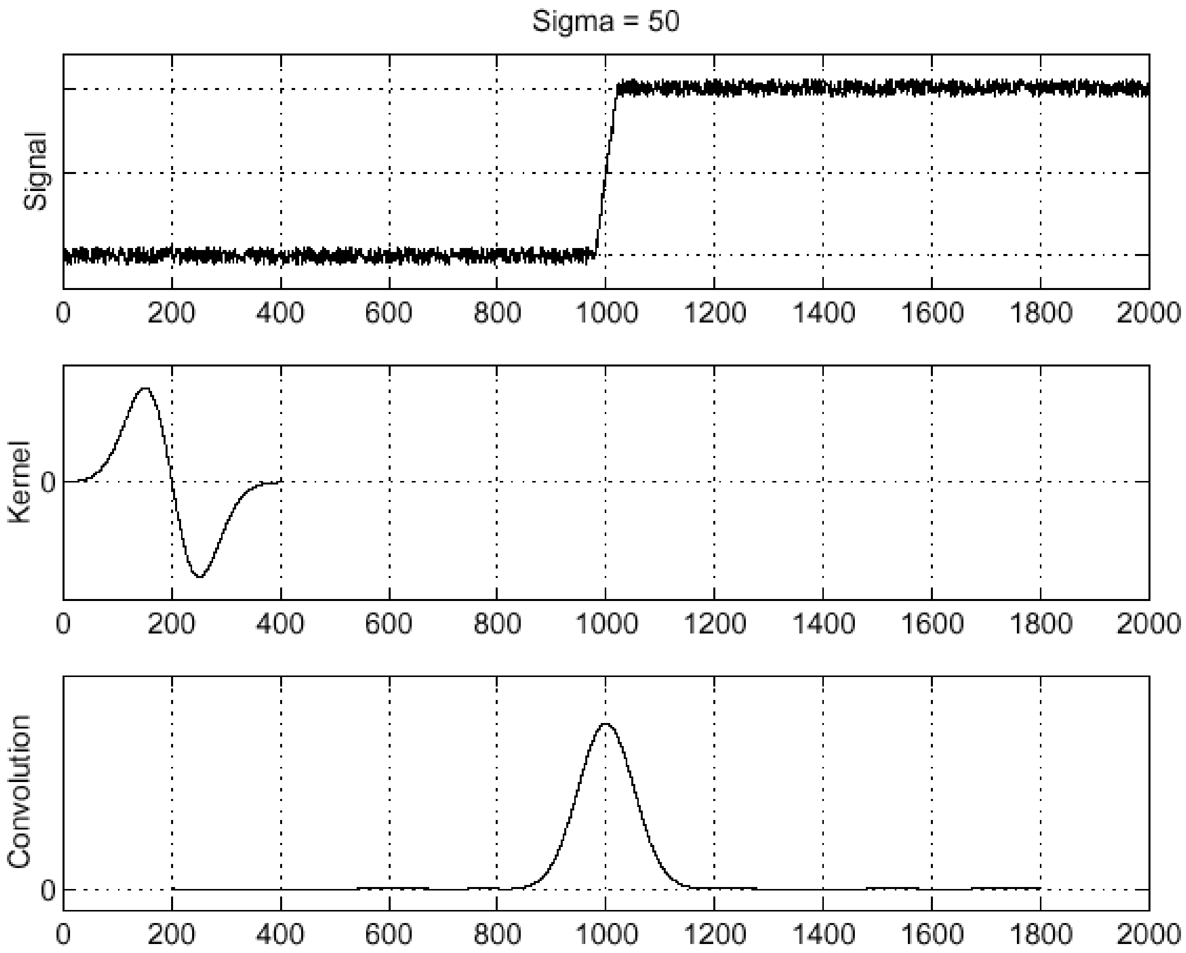
$$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$$

…saves us one operation.

f

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

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



Laplacian of Gaussian (LoG)

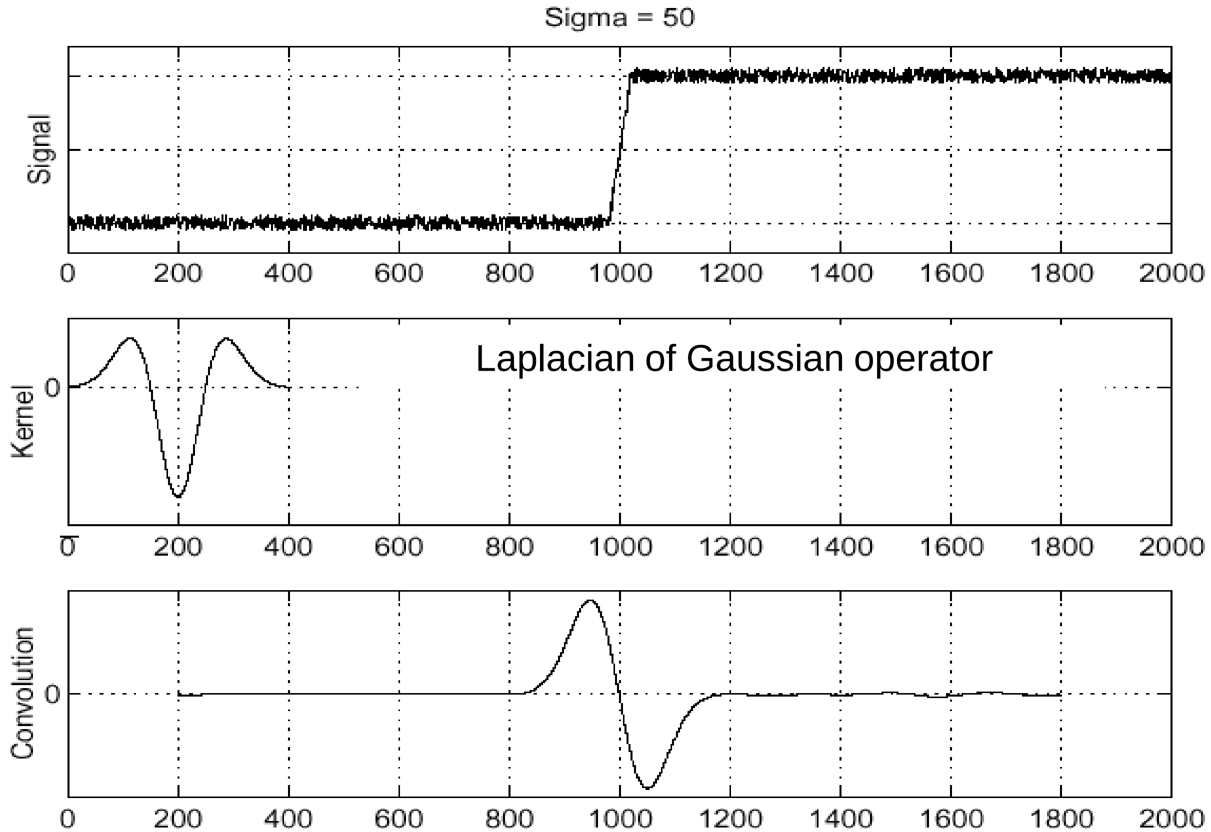
$$\frac{\partial^2}{\partial x^2}(h * f) = \boxed{\left(\frac{\partial^2}{\partial x^2} h\right)} * f$$

Laplacian of Gaussian

f

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

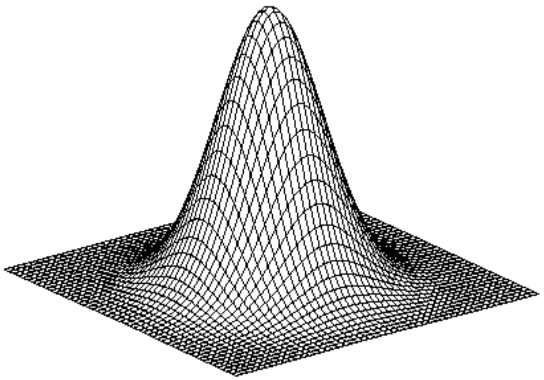
$(\frac{\partial^2}{\partial x^2} h) \star f$

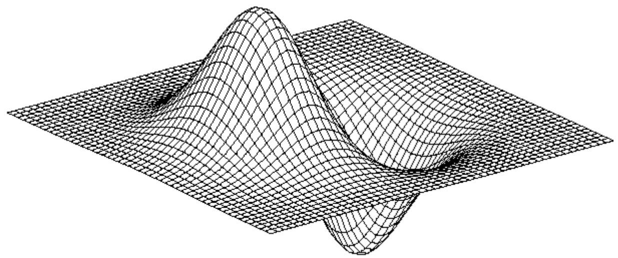


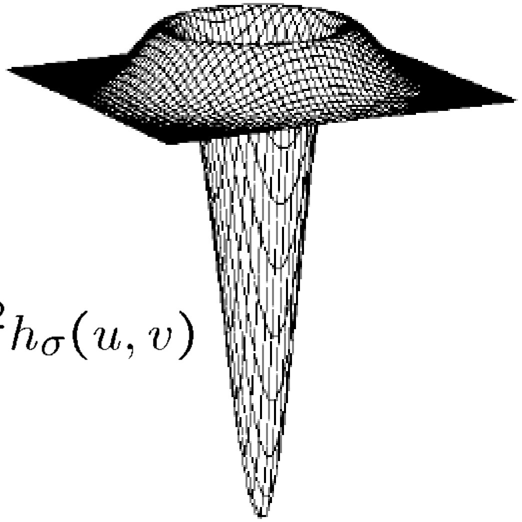
Where is the edge?

Zero-crossings of bottom graph !

2D Gaussian Edge Operators







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

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

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

Gaussian

Derivative of Gaussian (DoG)

Laplacian of Gaussian

Mexican Hat (Sombrero)

- ∇^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

$$\overline{\mathbf{n}} = \frac{\nabla(G * I)}{\left|\nabla(G * I)\right|}$$

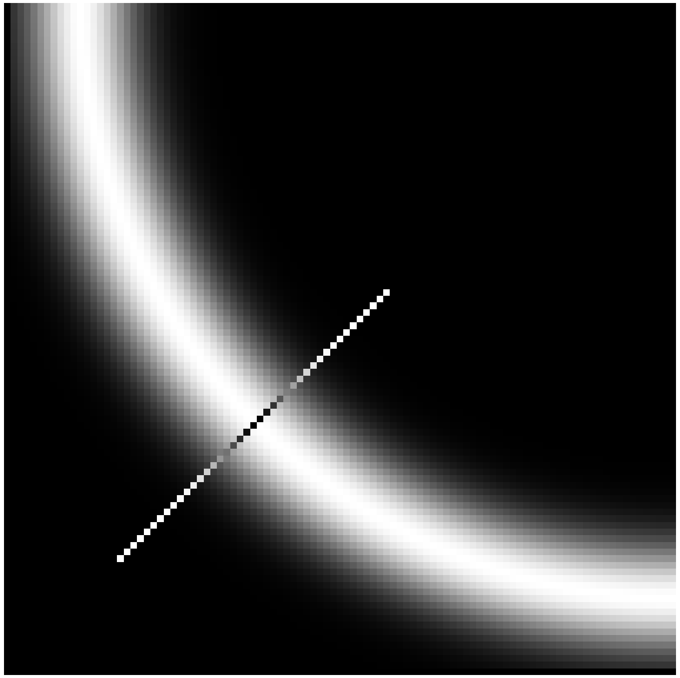
- Compute edge magnitudes $\left|\nabla(G * I)\right|$

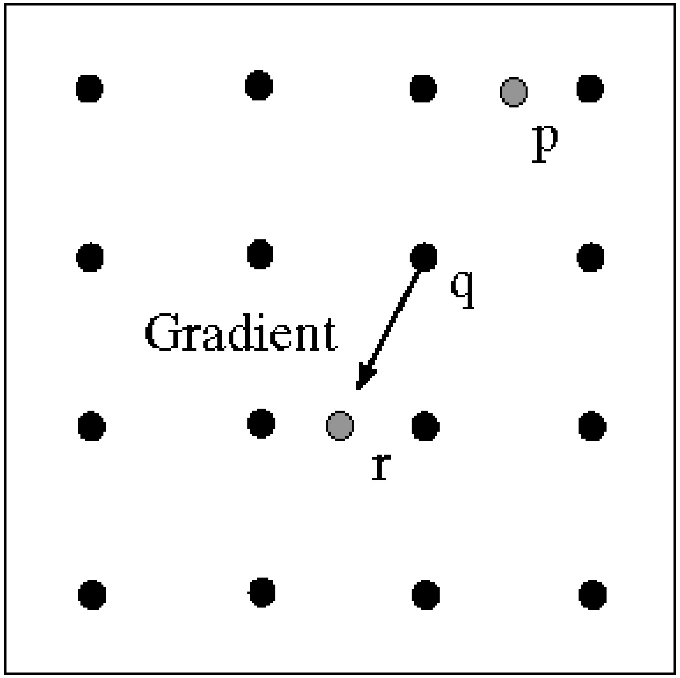
- Locate edges by finding zero-crossings along the edge normal directions (**non-maximum suppression**)

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

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

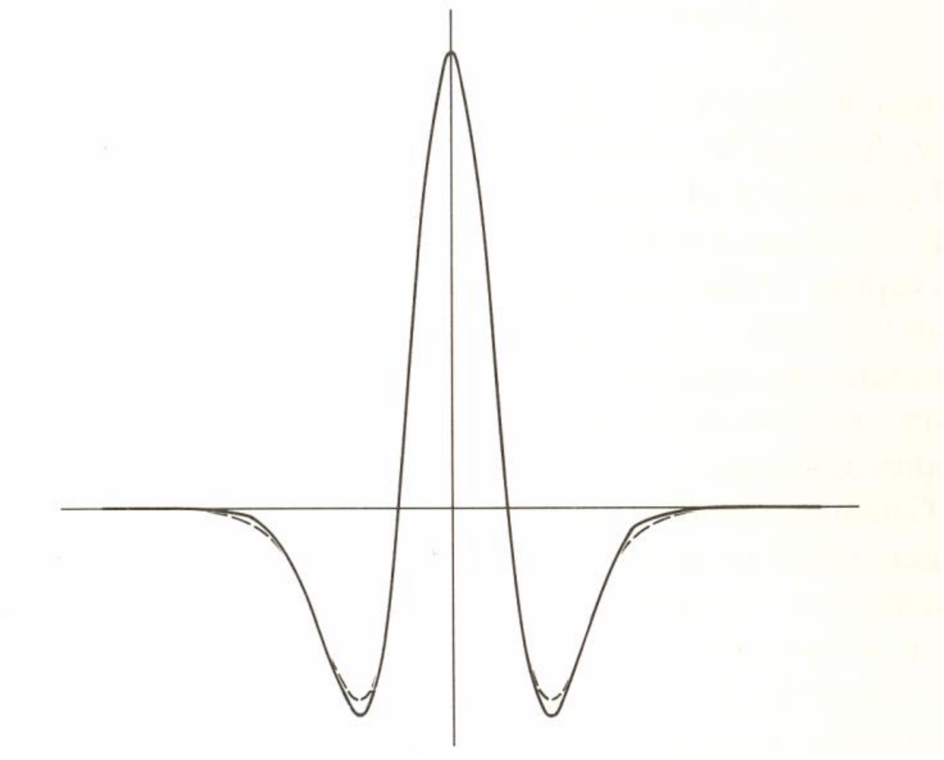
Canny with $\sigma = 1$

Canny with $\sigma = 2$

- The choice of σ depends on desired behavior
  - large σ detects large scale edges
  - small σ 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

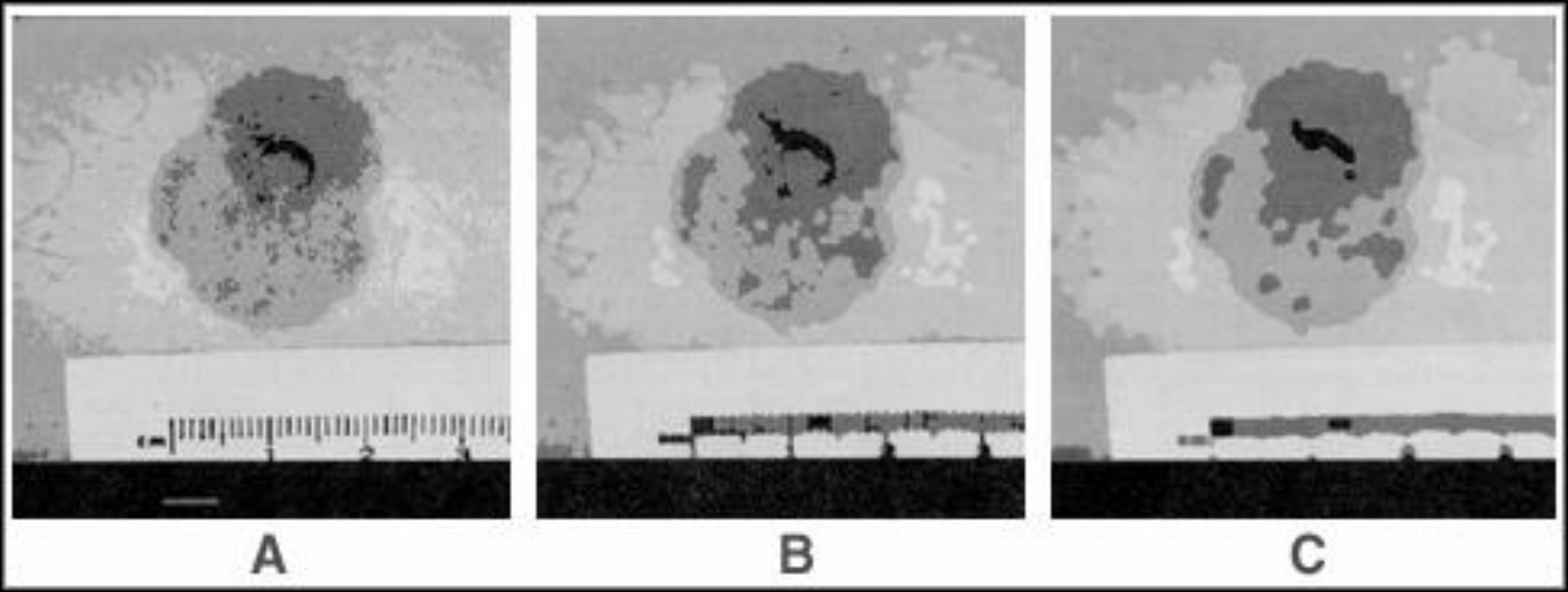
=

Topic: Morphological Filters

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

Mathematical Morphology

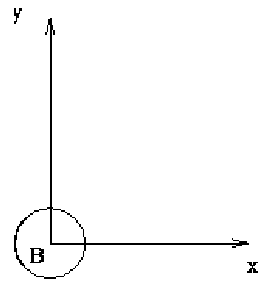
- Provides a mathematical description of geometric structures
- Based on *sets*
  - Groups of pixels which define an image region
- What is this used for?
  - Binary images
  - Can be used for **post-processing** segmentation results!
- Core techniques
  - Erosion, Dilation
  - Open, Close

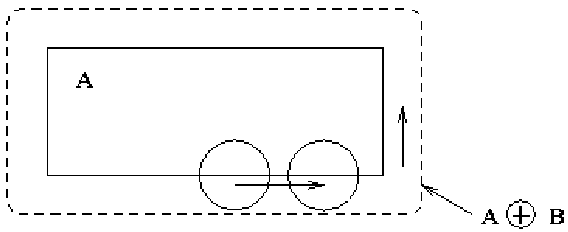


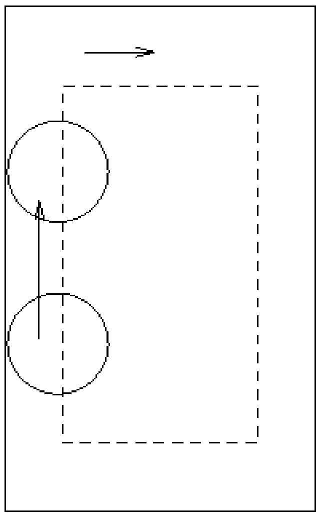
Tumor Segmentation using Morphologic Filtering

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





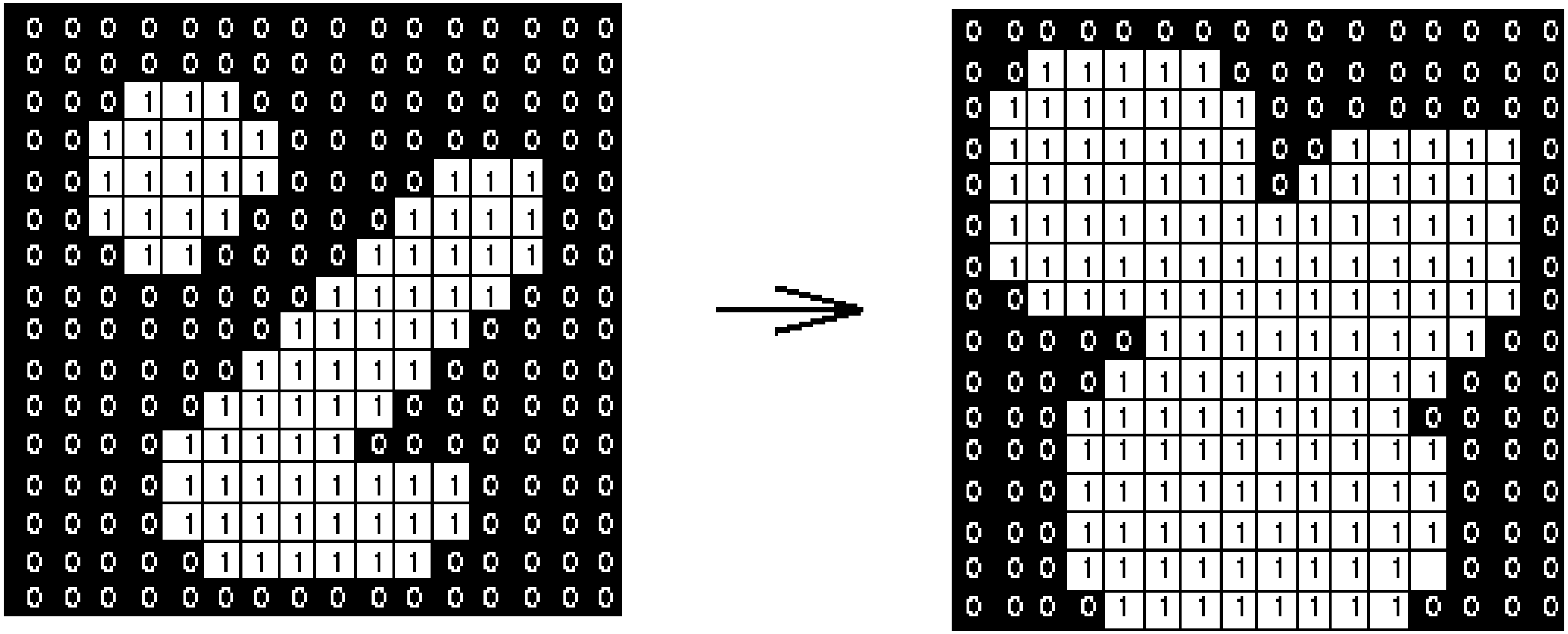


$$D(A,B) = A \oplus B = \bigcup_{\beta \in B} (A + \beta)$$

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

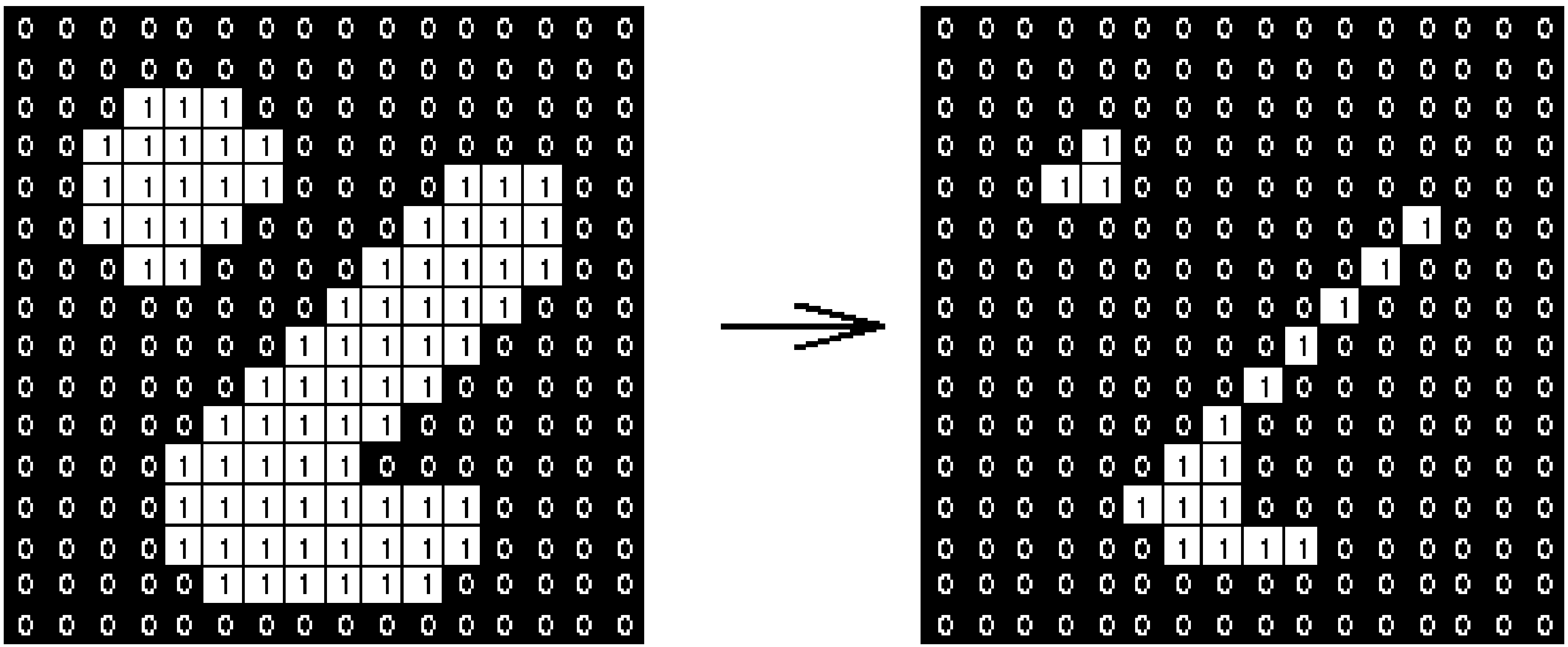
Dilation

- Example using a 3x3 morphological kernel



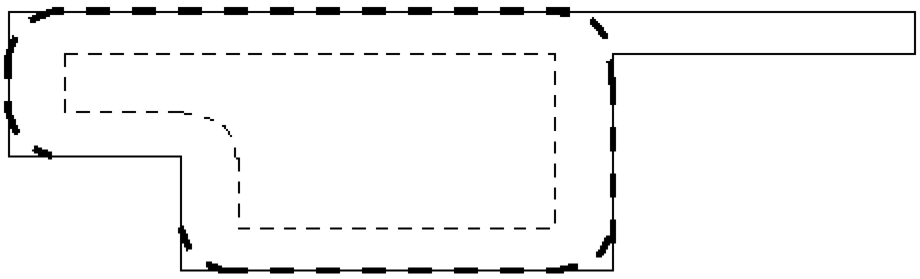
Erosion

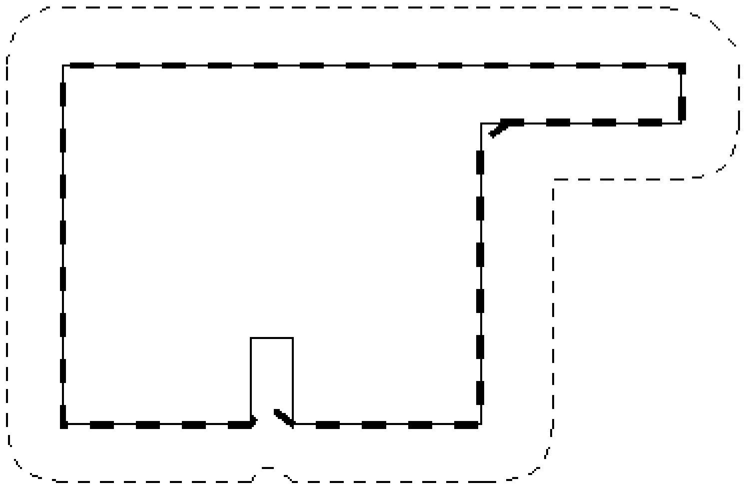
- Example using a 3x3 morphological kernel



Opening, Closing

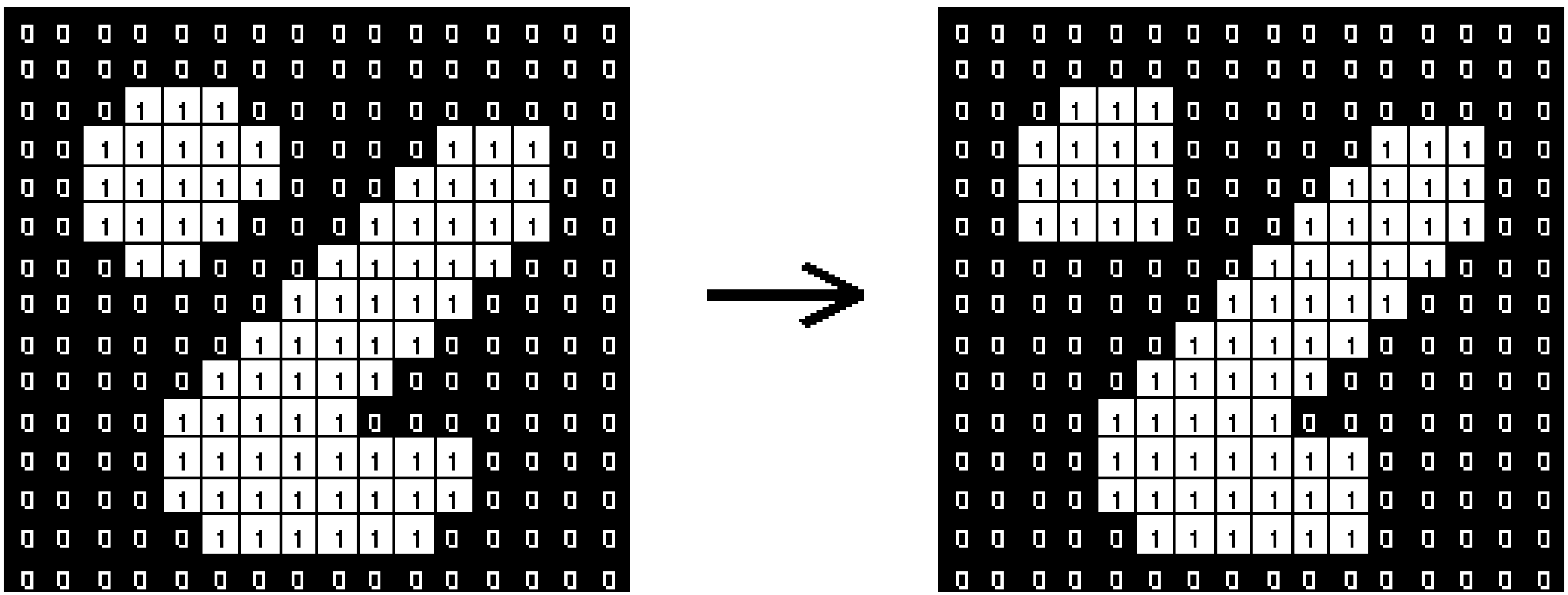
- Opening
  - **Erosion**, followed by **dilation**
  - Less destructive than an erosion
  - **Adapts** image shape to kernel shape
- Closing
  - **Dilation**, followed by **erosion**
  - Less destructive than a dilation
  - Tends to **close** shape irregularities





Opening

- Example using a 3x3 morphological kernel



Closing

- Example using a 3x3 morphological kernel

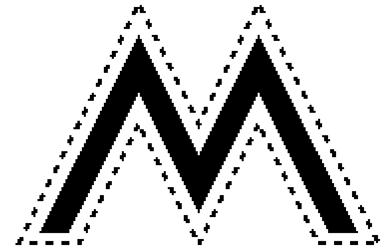
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0
0	0	1	1	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0
0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0
0	0	0	1	1	1	1	0	1	0	0	1	1	1	0	0
0	0	1	1	1	1	0	1	1	1	1	1	1	0	0	0
0	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0
0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0
0	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0
0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	1	1	0	0	0	0	1	1	1	0	1	0	0	0	0
0	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0
0	0	1	1	1	1	1	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

$\rightarrow$

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0
0	0	1	1	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	0
0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0
0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
0	1	0	0	0	1	1	1	1	1	0	0	0	0	0	0
0	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0
0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0
0	1	1	0	0	0	0	1	1	1	1	1	0	0	0	0
0	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0
0	0	1	1	1	1	1	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

Core morphological operators

Dilation

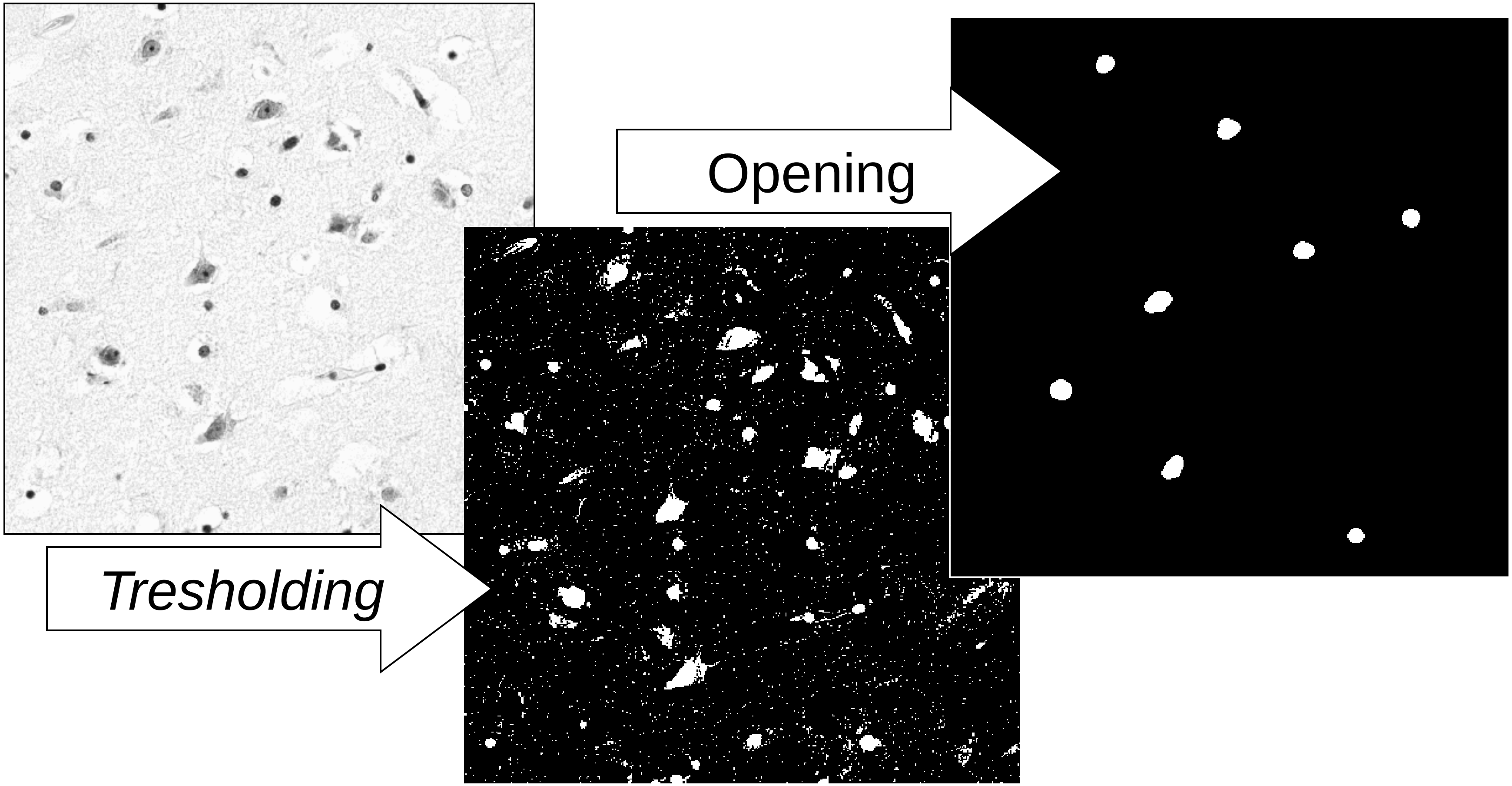


Erosion

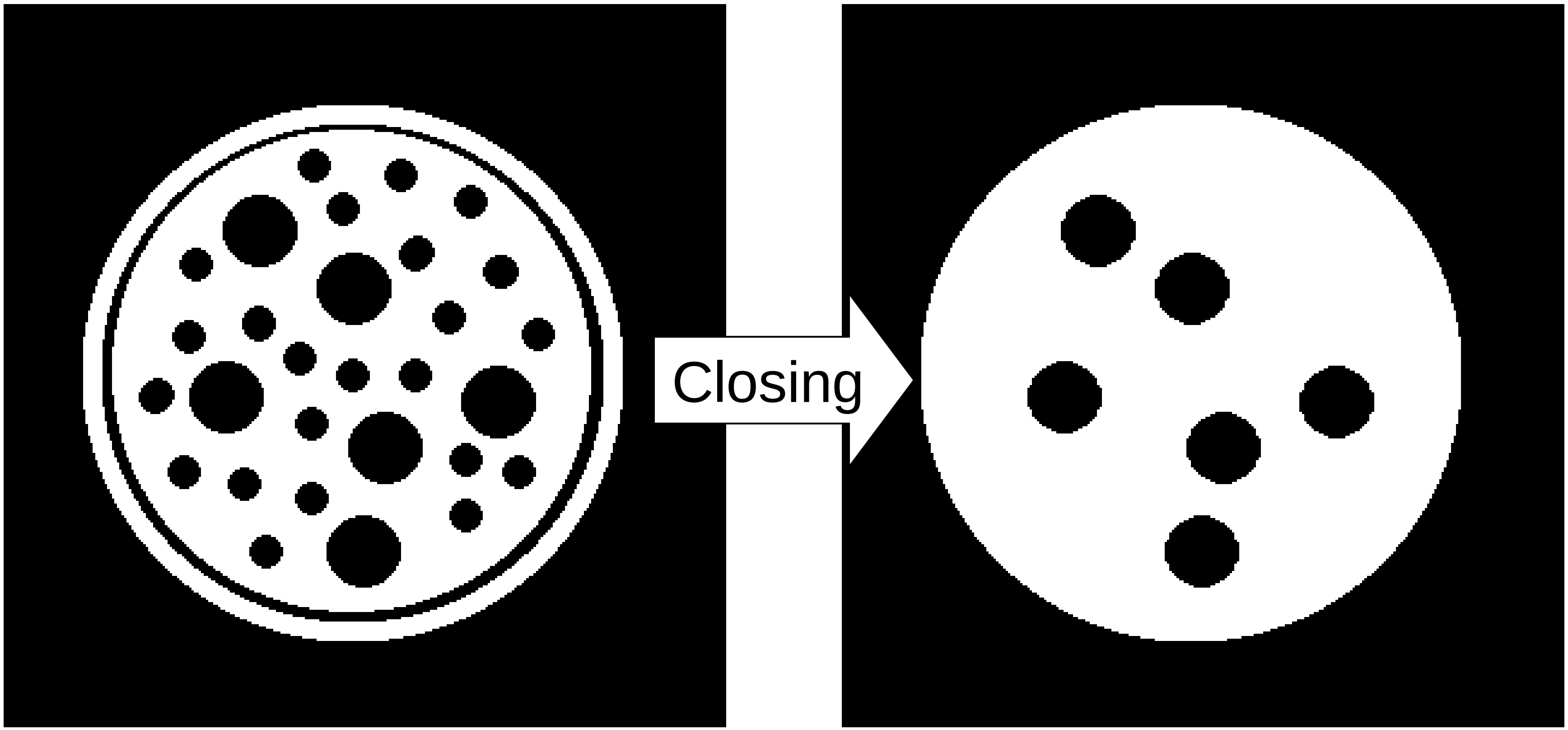
Closing

Opening

Example: Opening

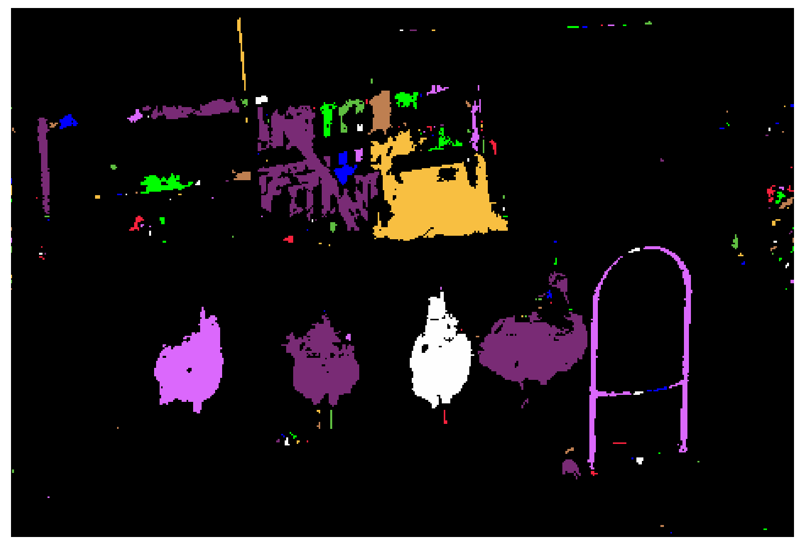


Example: Closing



Connected Component Analysis

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



Resources

- Szeliski, “Computer Vision: Algorithms and Applications”, Springer, 2011
  - Chapter 3 – “Image Processing”
  - Chapter 4 – “Feature Detection and Matching”