

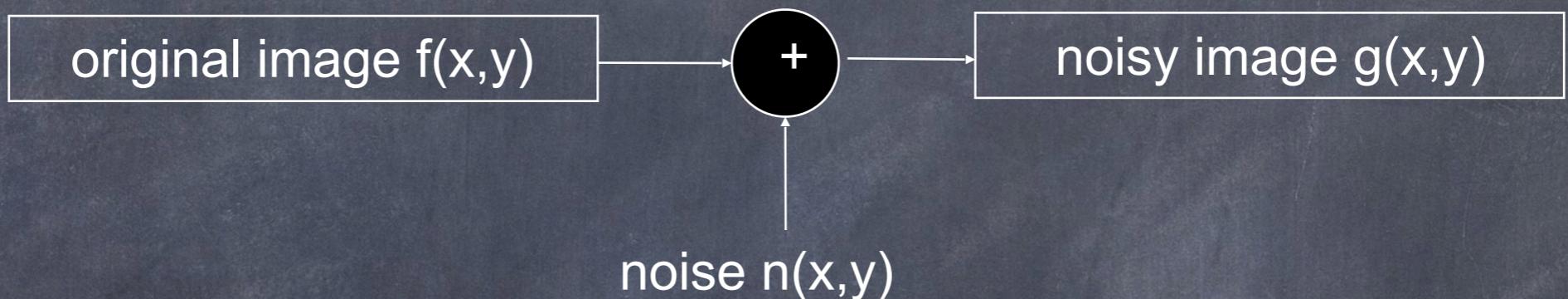
Computer Vision

CSE/ECE 344/544

Filter an image

What do you understand by
image filtering?

Image Enhancement - Point Processing



$$g(x, y) = f(x, y) + n(x, y)$$

$$\sum_{i=1}^N g_i(x, y) = \sum_{i=1}^N f(x, y) + \sum_{i=1}^N n(x, y)$$

$$\bar{g}(x, y) = \bar{f}(x, y) + \bar{n}(x, y)$$

Noisy Image



Original image



Noised image (Gaussian)

Image Enhancement

Objective of enhancement is to process image so that result is more suitable than original image for specific application.

Enhancement approaches fall into two broad categories

spatial domain : direct manipulation of pixels in an image

frequency domain : manipulation of Fourier transform of an image.

Basics of Spatial Filtering - Linear

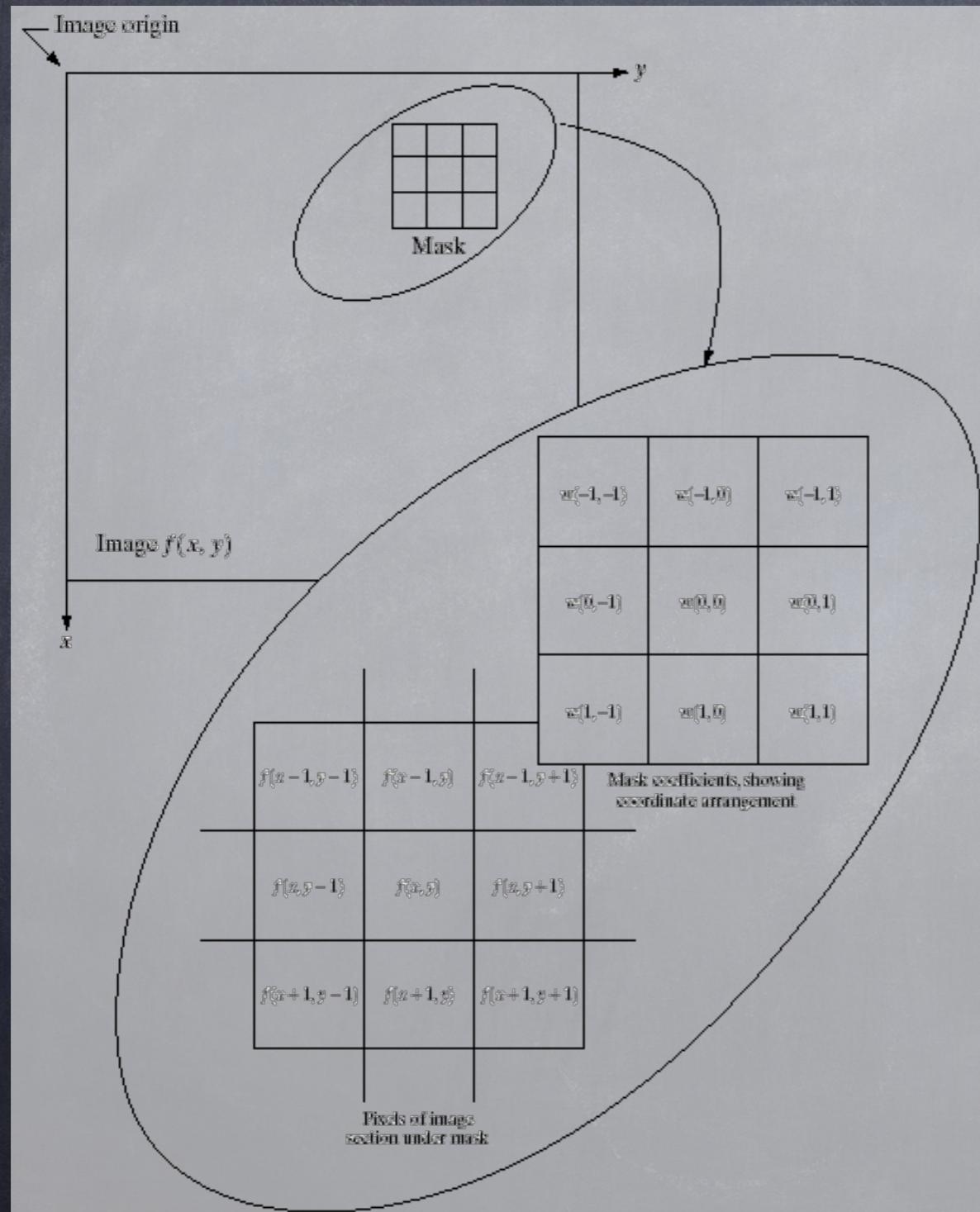


FIGURE 3.32 The mechanics of spatial filtering. The magnified drawing shows a 3×3 mask and the image section directly under it; the image section is shown displaced out from under the mask for ease of readability.

Spatial filtering are filtering operations performed on the pixel intensities of an image.

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

$$a = (m - 1) / 2$$

$$b = (n - 1) / 2$$

Basic of spatial filtering

- Linear spatial filtering often is referred to as "convolving a mask with an image"

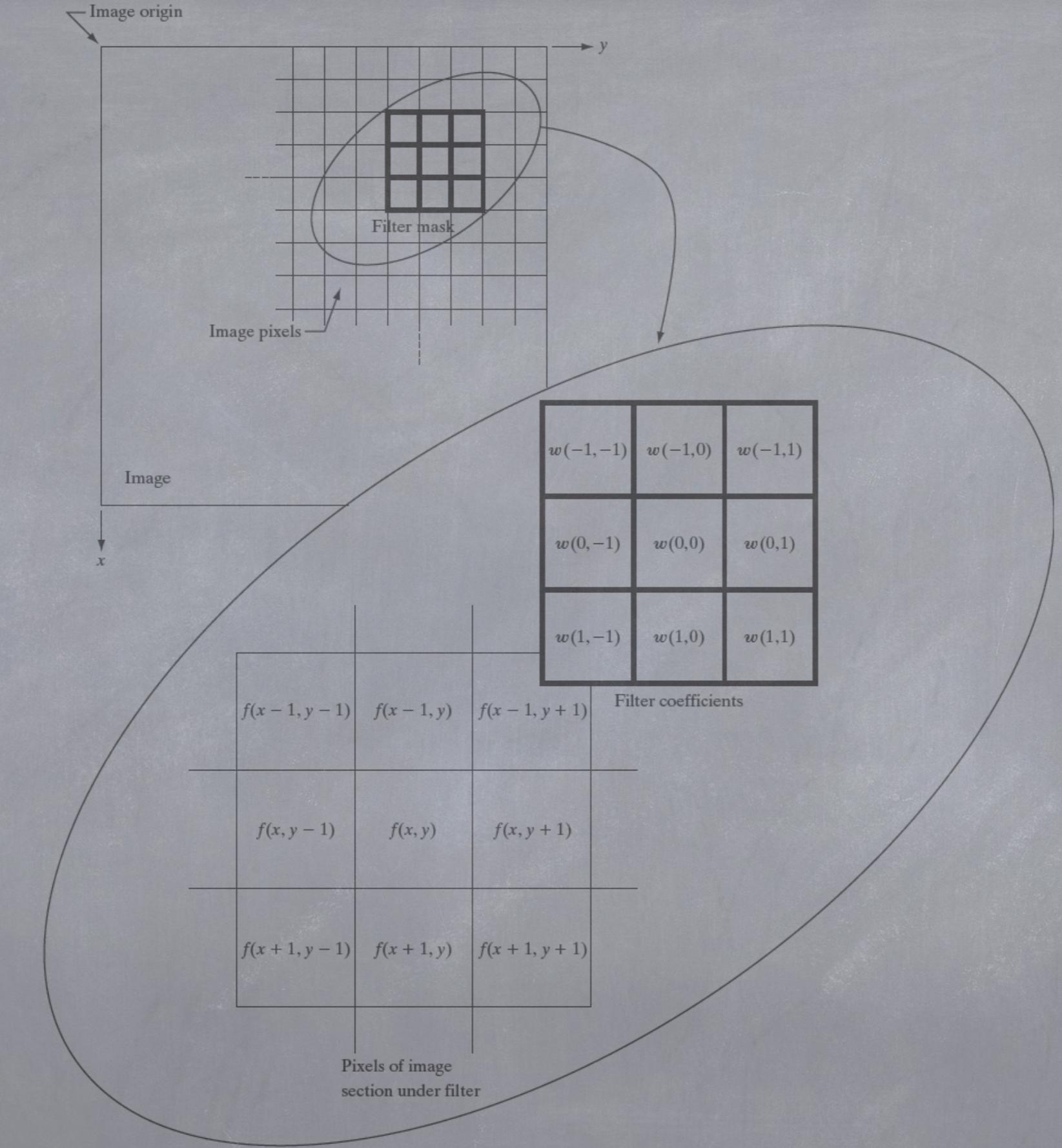


FIGURE 3.28 The mechanics of linear spatial filtering using a 3×3 filter mask. The form chosen to denote the coordinates of the filter mask coefficients simplifies writing expressions for linear filtering.

Linear spatial filtering

Pixels of image

	$w(-1,-1)$ $f(x-1,y-1)$	$w(-1,0)$ $f(x-1,y)$	$w(-1,1)$ $f(x-1,y+1)$
	$w(0,-1)$ $f(x,y-1)$	$w(0,0)$ $f(x,y)$	$w(0,1)$ $f(x,y+1)$
	$w(1,-1)$ $f(x+1,y-1)$	$w(1,0)$ $f(x+1,y)$	$w(1,1)$ $f(x+1,y+1)$

The result is the sum of products of the mask coefficients with the corresponding pixels directly under the mask

Mask coefficients

$w(-1,-1)$	$w(-1,0)$	$w(-1,1)$
$w(0,-1)$	$w(0,0)$	$w(0,1)$

$$f(x, y) = w(-1, -1)f(x - 1, y - 1) + w(-1, 0)f(x - 1, y) + w(-1, 1)f(x - 1, y + 1) + \\ w(0, -1)f(x, y - 1) + w(0, 0)f(x, y) + w(0, 1)f(x, y + 1) + \\ w(1, -1)f(x + 1, y - 1) + w(1, 0)f(x + 1, y) + w(1, 1)f(x + 1, y + 1)$$

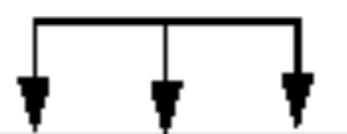
Image Enhancement

Operation Steps

- Select a single pixel.
- Determine the pixel's neighborhood.
- Apply a function to the values of the pixels in the neighborhood. This function must return a scalar.
- Find the pixel in the output image whose position corresponds to that of the center pixel in the input image. Set this output pixel to the value returned by the function.
- Repeat steps 1 through 4 for each pixel in the input image.

Image Enhancement

Outside pixels are assumed to be 0.



0	8	0
17	24	1
23	5	7

3	5	8	15
4	6	13	20
10	12	19	21
11	18	25	2
9			

Center of kernel

These pixel values are replicated from boundary pixels.



1	8	8	15	6
17	24	1	8	15
23	5	7	14	16
4	6	13	20	22
10	12	19	21	3
11	18	25	2	9

Center of kernel

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

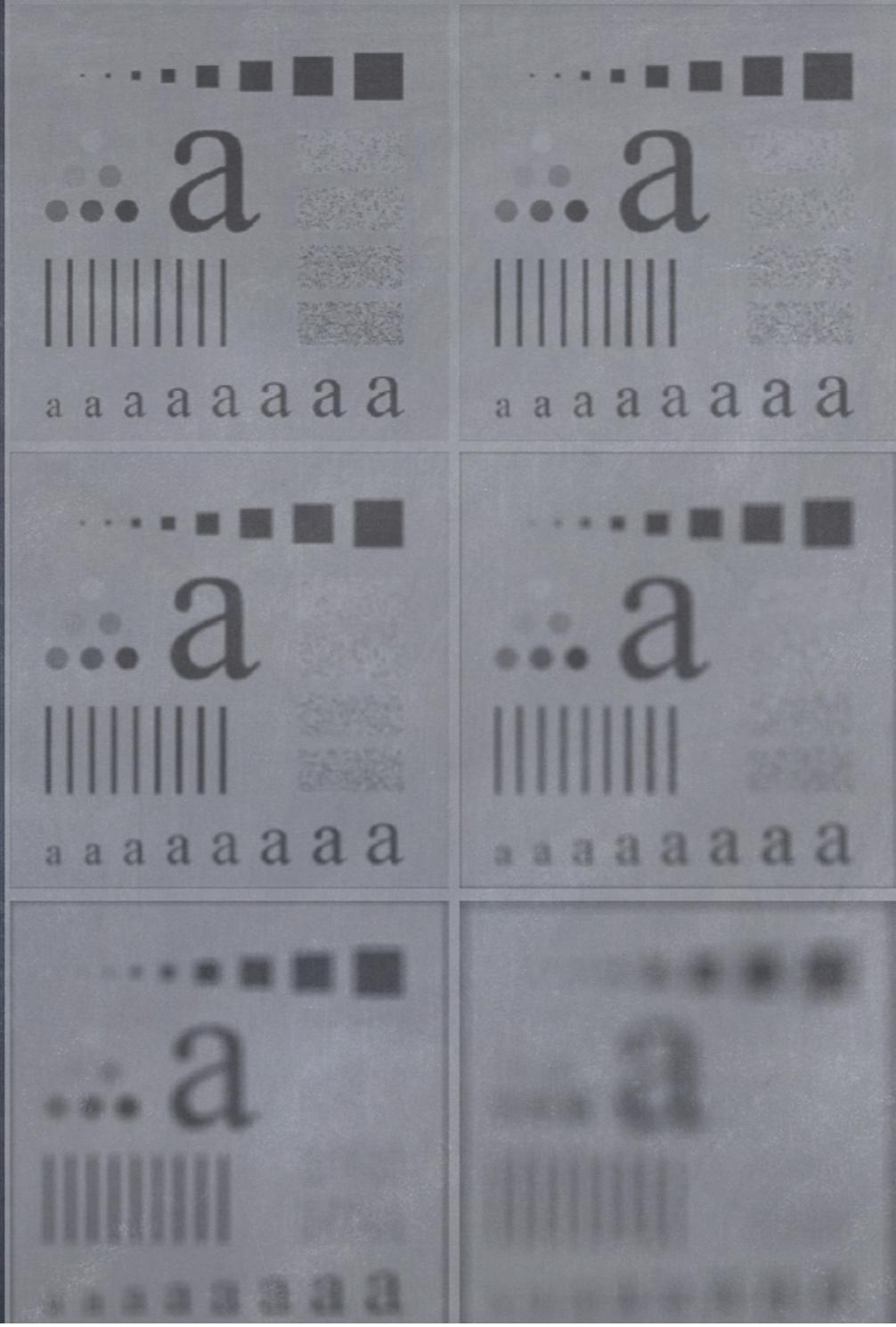
FIGURE 3.31
Another representation of a general 3×3 filter mask.

Square Averaging Filter Mask

$\frac{1}{9} \times$	<table border="1"><tr><td>1</td><td>1</td><td>1</td></tr><tr><td>1</td><td>1</td><td>1</td></tr><tr><td>1</td><td>1</td><td>1</td></tr></table>	1	1	1	1	1	1	1	1	1
1	1	1								
1	1	1								
1	1	1								
$\frac{1}{16} \times$	<table border="1"><tr><td>1</td><td>2</td><td>1</td></tr><tr><td>2</td><td>4</td><td>2</td></tr><tr><td>1</td><td>2</td><td>1</td></tr></table>	1	2	1	2	4	2	1	2	1
1	2	1								
2	4	2								
1	2	1								

a b

FIGURE 3.32 Two 3×3 smoothing (averaging) filter masks. The constant multiplier in front of each mask is equal to 1 divided by the sum of the values of its coefficients, as is required to compute an average.



a b
c d
e f

FIGURE 3.33 (a) Original image, of size 500×500 pixels. (b)–(f) Results of smoothing with square averaging filter masks of sizes $m = 3, 5, 9, 15$, and 35 , respectively. The black squares at the top are of sizes $3, 5, 9, 15, 25, 35, 45$, and 55 pixels, respectively; their borders are 25 pixels apart. The letters at the bottom range in size from 10 to 24 points, in increments of 2 points; the large letter at the top is 60 points. The vertical bars are 5 pixels wide and 100 pixels high; their separation is 20 pixels. The diameter of the circles is 25 pixels, and their borders are 15 pixels apart; their intensity levels range from 0% to 100% black in increments of 20%. The background of the image is 10% black. The noisy rectangles are of size 50×120 pixels.

Order-Statistics Filters

- Order-statistics filters are nonlinear spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter, and then replacing the value of the center pixel with the value determined by the ranking result.
- Best-known “median filter”

Order-Statistics Filters

Median filter examines the neighborhood pixel values and sort them, replace the current pixel value by the median value.

Example:

37	41	39
40	234	38
42	38	44

Sorted sequence:

37, 38, 38, 39, 40, 41, 42, 44, 234

Result of median filter



Noise from Glass effect



Remove noise by median filter

Sharpening Spatial Filters

- The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as an natural effect of a particular method of image acquisition.

Sharpening Spatial Filters

- The image blurring is accomplished in the spatial domain by pixel averaging in a neighborhood.
- Averaging is analogous to integration.
- Sharpening could be accomplished by spatial differentiation.

Definition of the 1st-order derivative

- A basic definition of the first-order derivative of a one-dimensional function $f(x)$ is

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

Definition of the 2nd-order derivative

- We define a second-order derivative as the difference

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

The Laplacian (2nd order derivative)

- Shown by Rosenfeld and Kak[1982] that the simplest isotropic derivative operator is the Laplacian, defined as

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

Discrete form of derivative

$f(x-1, y)$	$f(x, y)$	$f(x+1, y)$
-------------	-----------	-------------

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

$f(x, y-1)$
$f(x, y)$
$f(x, y+1)$

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

2-Dimensional Laplacian

- The digital implementation of the 2-Dimensional Laplacian is obtained by summing 2 components

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

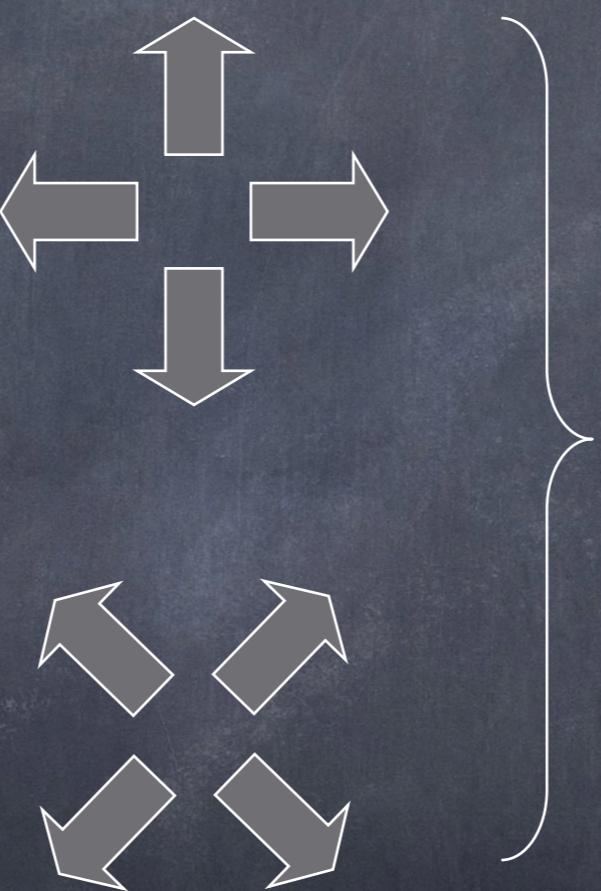
$$\nabla^2 f = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y)$$

	1	
1	-4	1
	1	

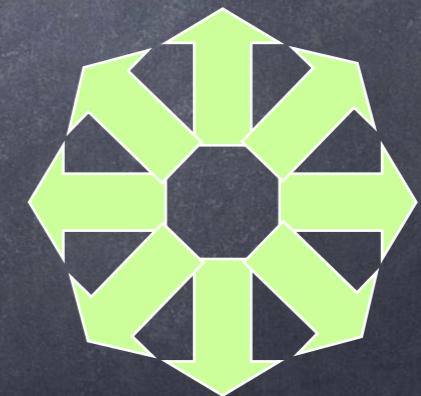
Laplacian

0	1	0
1	-4	1
0	1	0

1	0	1
0	-4	0
1	0	1



1	1	1
1	-8	1
1	1	1



Laplacian

- Applying the Laplacian to an image we get a new image that highlights edges and other discontinuities

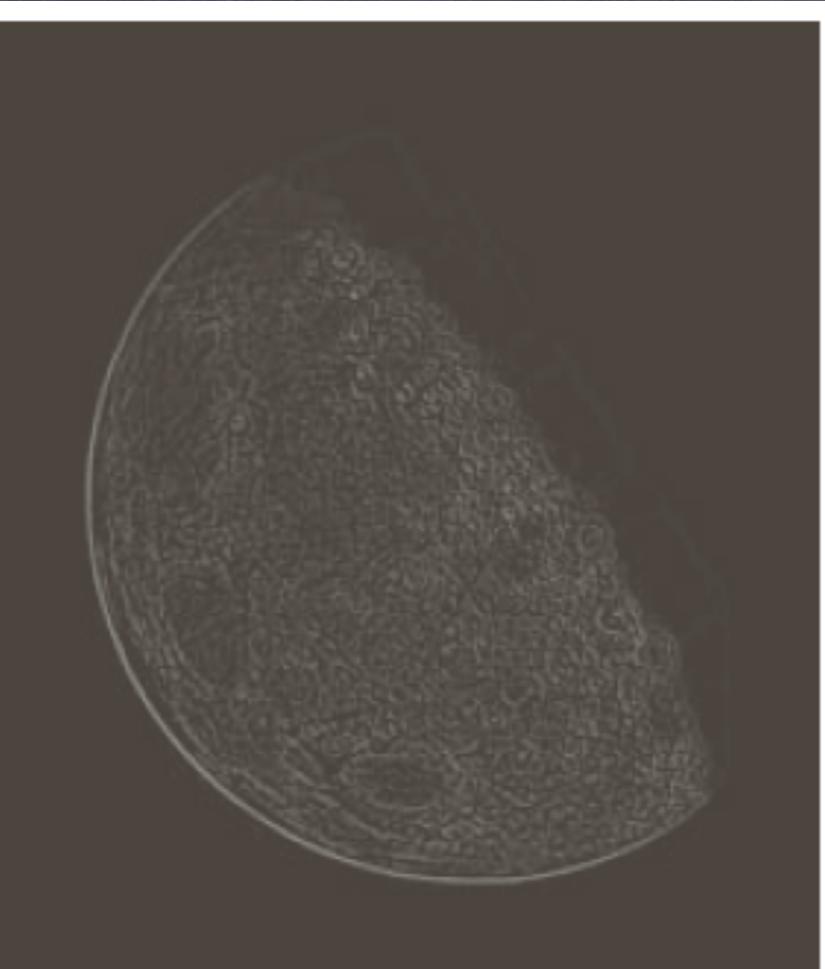


Original
Image

Laplacian
Filtered Image

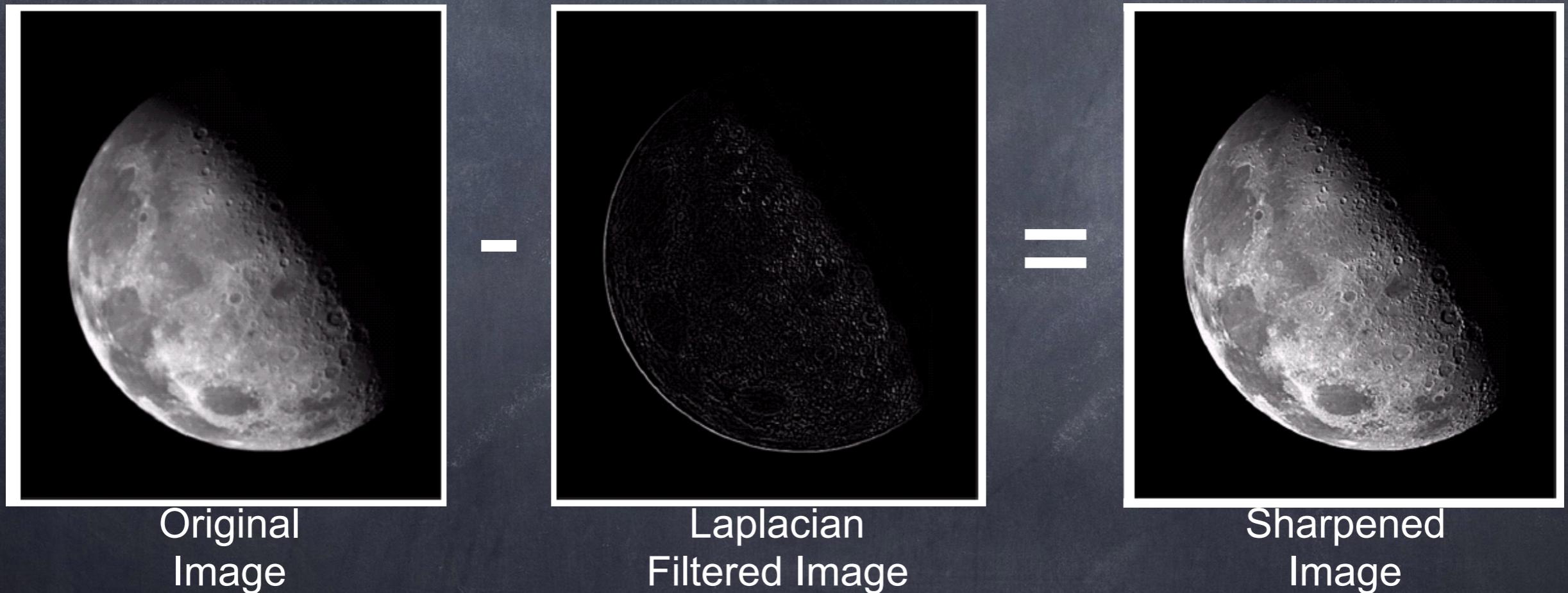
Question

- If I have an image ... and I want to make it sharp and clear ... based on filtering technique, how can we deblur/sharp it?



Laplacian Image Enhancement

- In the final sharpened image edges and fine detail are much more obvious



$$g(x, y) = f(x, y) - \nabla^2 f$$

Laplacian Image Enhancement



Simplified Image Enhancement

$$\begin{aligned}g(x, y) &= f(x, y) - \nabla^2 f \\&= f(x, y) - [f(x+1, y) + f(x-1, y) \\&\quad + f(x, y+1) + f(x, y-1) \\&\quad - 4f(x, y)] \\&= 5f(x, y) - f(x+1, y) - f(x-1, y) \\&\quad - f(x, y+1) - f(x, y-1)\end{aligned}$$

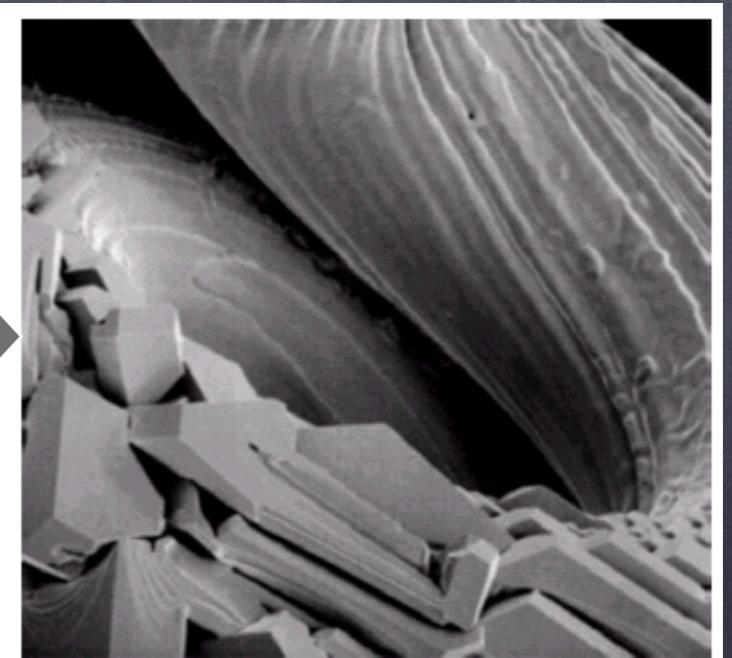
Simplified Image Enhancement

- This gives us a new filter which does the whole job for us in one step

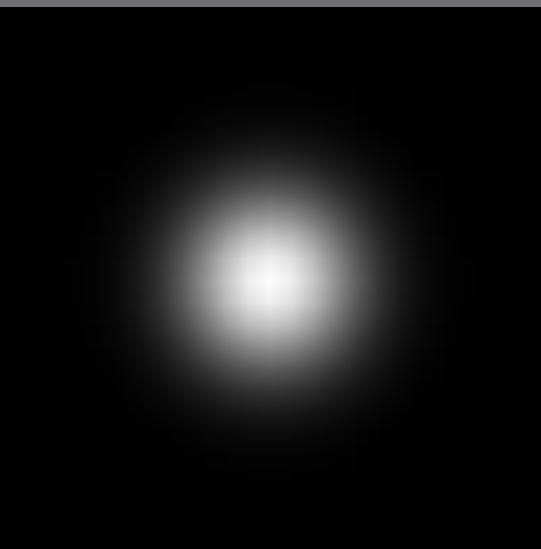
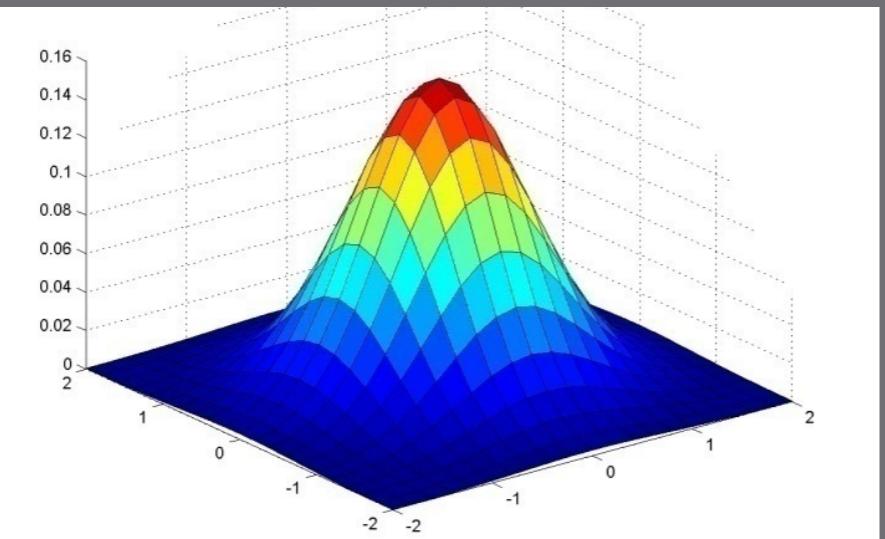


$$\begin{matrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{matrix}$$

A 3x3 kernel matrix used for image enhancement. The central value is 5, indicating it is a sharpening filter. The other values are -1, suggesting they are used to reduce the intensity of the surrounding pixels relative to the center.



Gaussian Filter

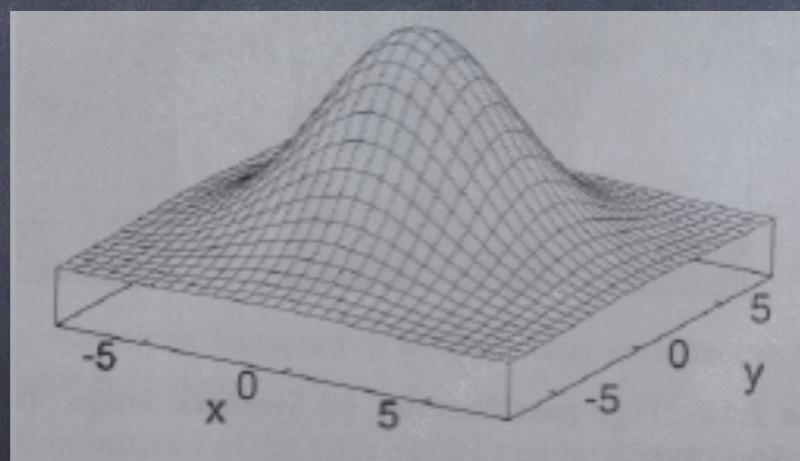


$$G_{\sigma} = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

Gaussian Filter

- 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

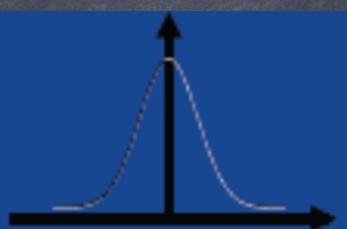
1	1	2	2	2	1	1
1	2	2	4	2	2	1
2	2	4	8	4	2	2
2	4	8	16	8	4	2
2	2	4	8	4	2	2
1	2	2	4	2	2	1
1	1	2	2	2	1	1

Gaussian Filter

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

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

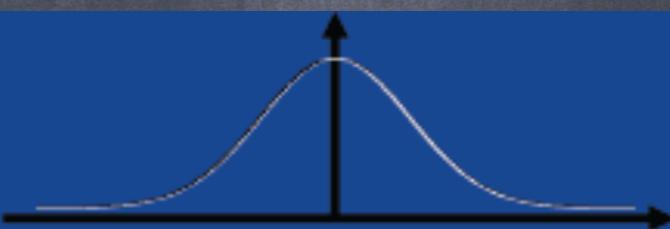
Gaussian Filter



small σ



limited smoothing

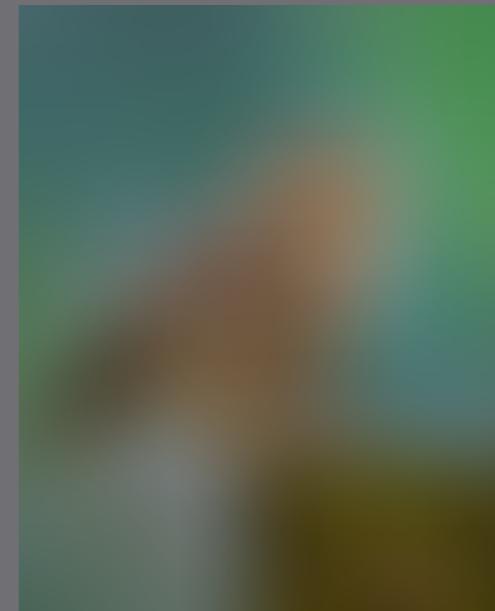
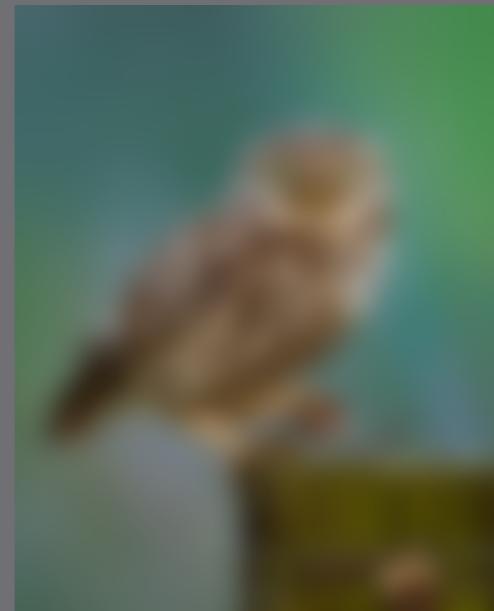
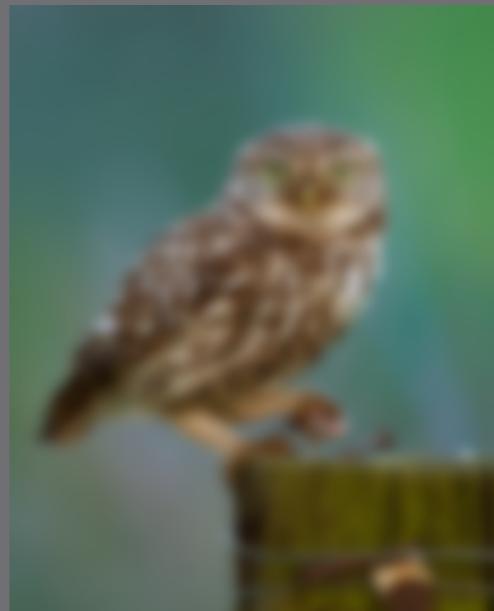


large σ



strong smoothing

Gaussian filters



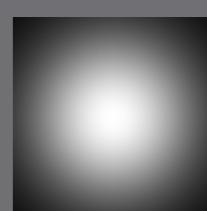
$\sigma = 1$ pixel



$\sigma = 5$ pixels



$\sigma = 10$ pixels



$\sigma = 30$ pixels

Averaging vs Gaussian Smoothing



box average

Averaging



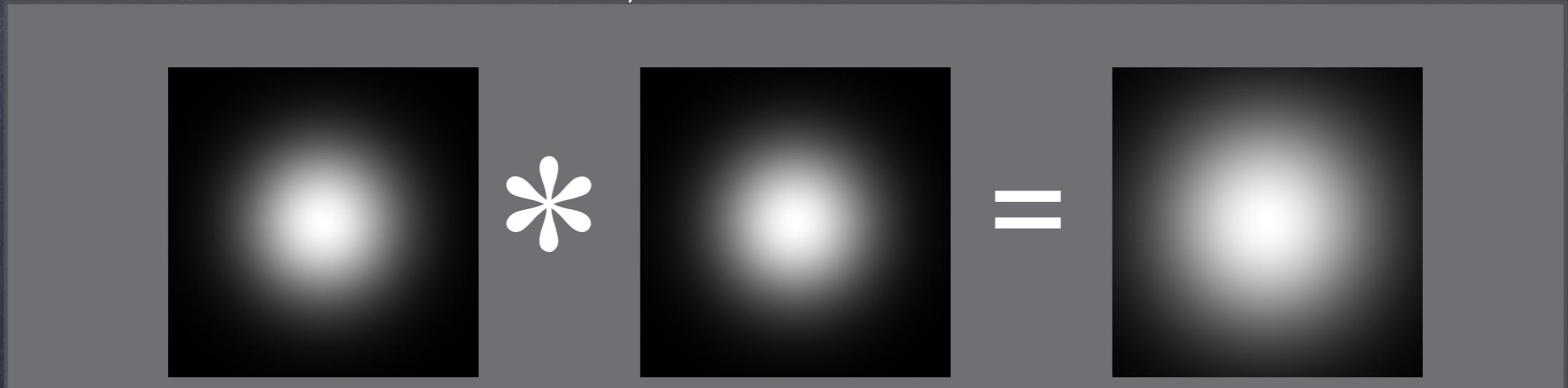
Gaussian blur

Gaussian



Gaussian filter

- Removes “high-frequency” components from the image (low-pass filter)
- Convolution with self is another Gaussian



- Convolving two times with Gaussian kernel of width $\sigma =$ convolving once with kernel of width $\sigma\sqrt{2}$

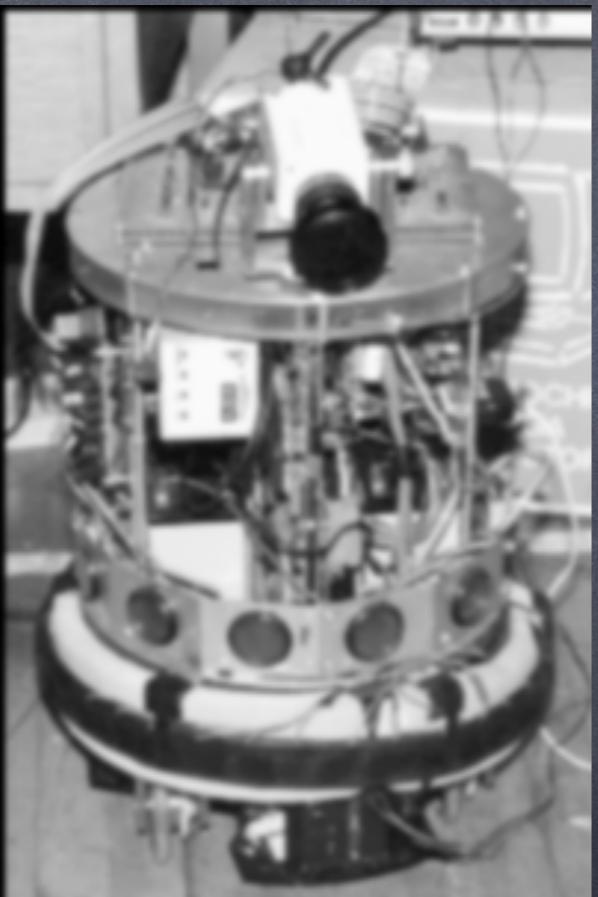
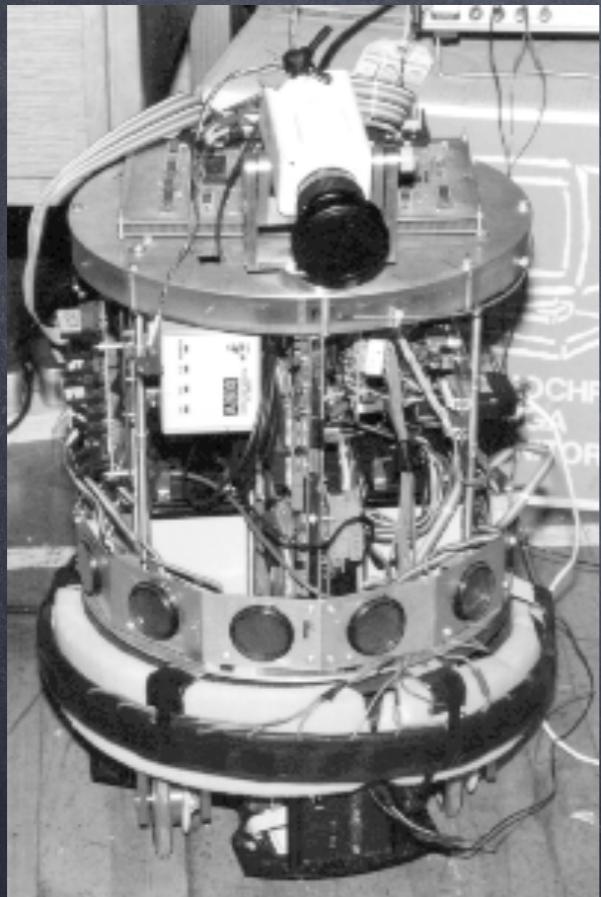
More on Gaussian Filters

- What are two parameters in Gaussian Filter?

1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

$$\frac{1}{273}$$

What happens with varying kernel size and Gaussian parameter



Filtering Revisited

Linear spatial filtering

Pixels of image

	$w(-1,-1)$ $f(x-1,y-1)$	$w(-1,0)$ $f(x-1,y)$	$w(-1,1)$ $f(x-1,y+1)$
	$w(0,-1)$ $f(x,y-1)$	$w(0,0)$ $f(x,y)$	$w(0,1)$ $f(x,y+1)$
	$w(1,-1)$ $f(x+1,y-1)$	$w(1,0)$ $f(x+1,y)$	$w(1,1)$ $f(x+1,y+1)$

The result is the sum of products of the mask coefficients with the corresponding pixels directly under the mask

Mask coefficients

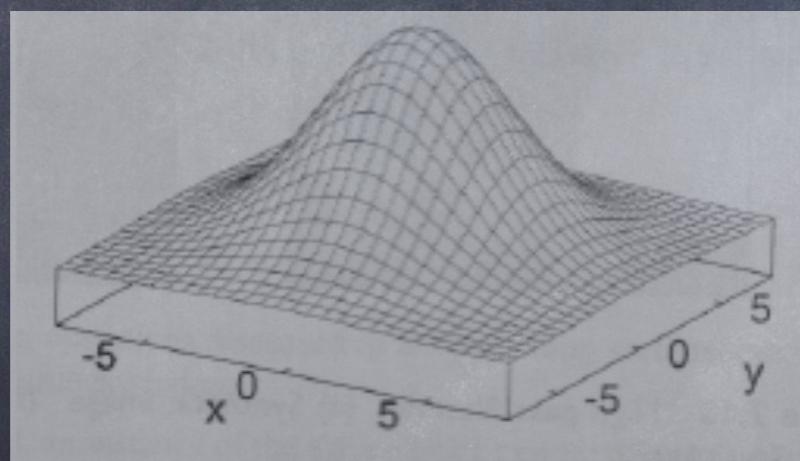
$w(-1,-1)$	$w(-1,0)$	$w(-1,1)$
$w(0,-1)$	$w(0,0)$	$w(0,1)$

$$f(x, y) = w(-1, -1)f(x - 1, y - 1) + w(-1, 0)f(x - 1, y) + w(-1, 1)f(x - 1, y + 1) + \\ w(0, -1)f(x, y - 1) + w(0, 0)f(x, y) + w(0, 1)f(x, y + 1) + \\ w(1, -1)f(x + 1, y - 1) + w(1, 0)f(x + 1, y) + w(1, 1)f(x + 1, y + 1)$$

Gaussian Filter

- The weights are samples of the Gaussian function

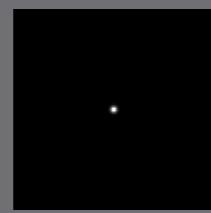
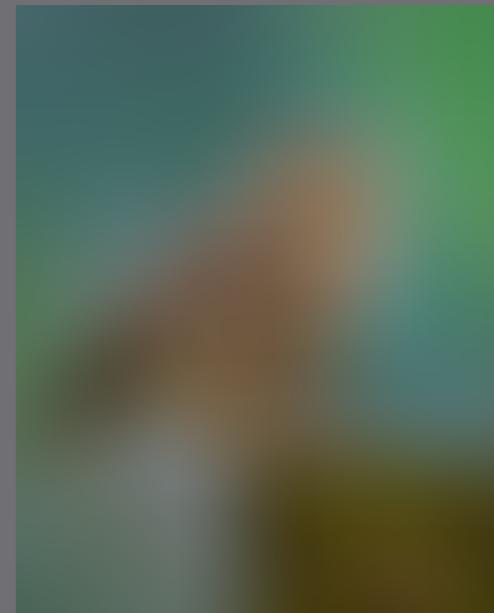
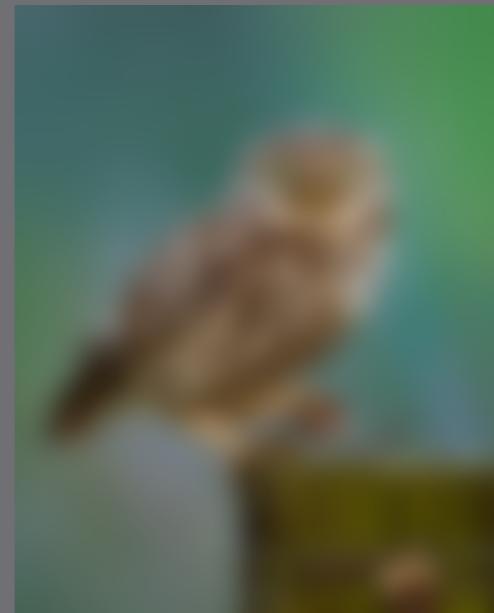
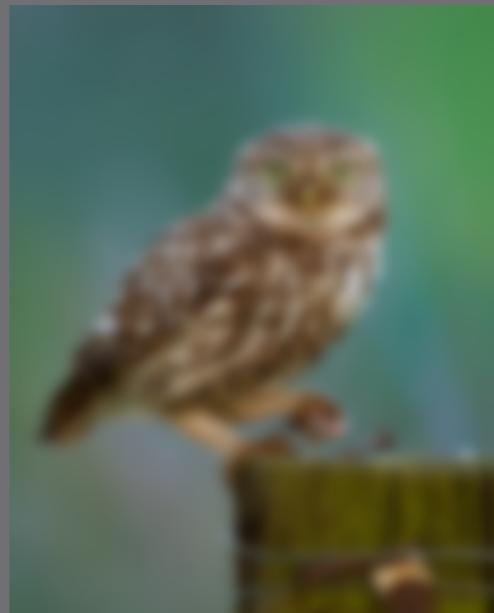
$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{x^2 + y^2}{2\sigma^2}}$$



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

Gaussian filters



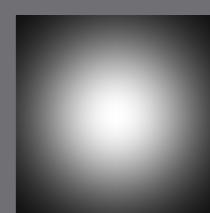
$\sigma = 1$ pixel



$\sigma = 5$ pixels

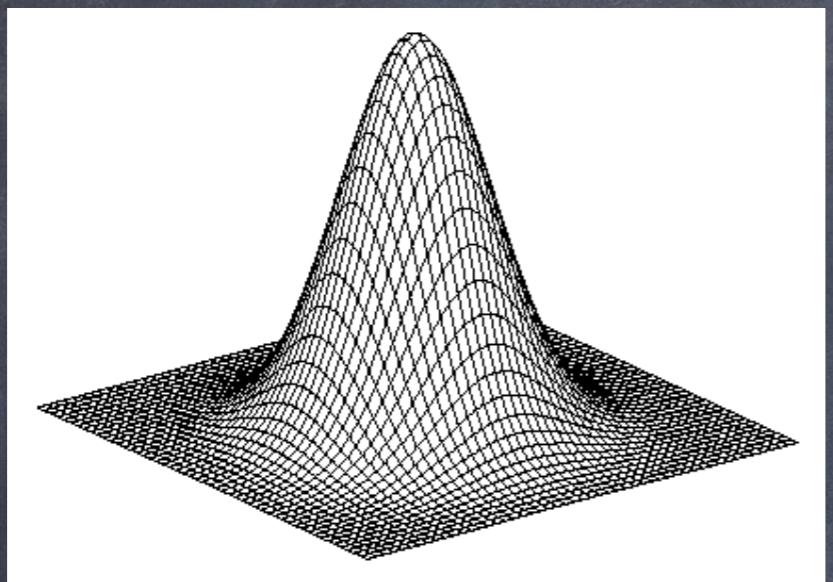


$\sigma = 10$ pixels



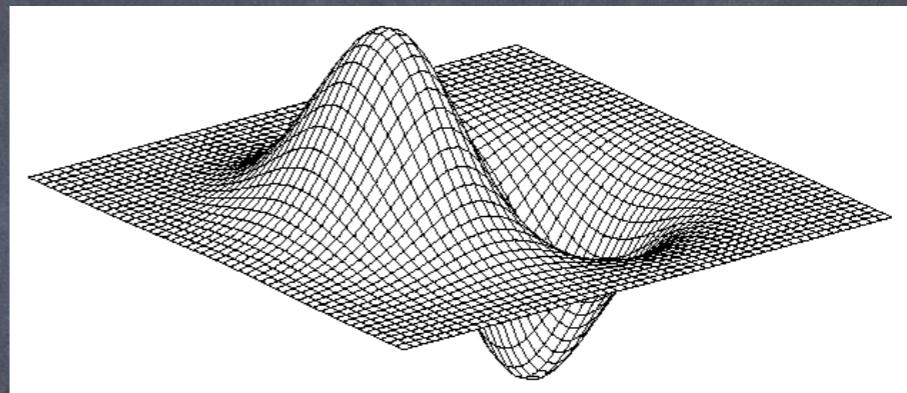
$\sigma = 30$ pixels

2D edge detection filters



Gaussian

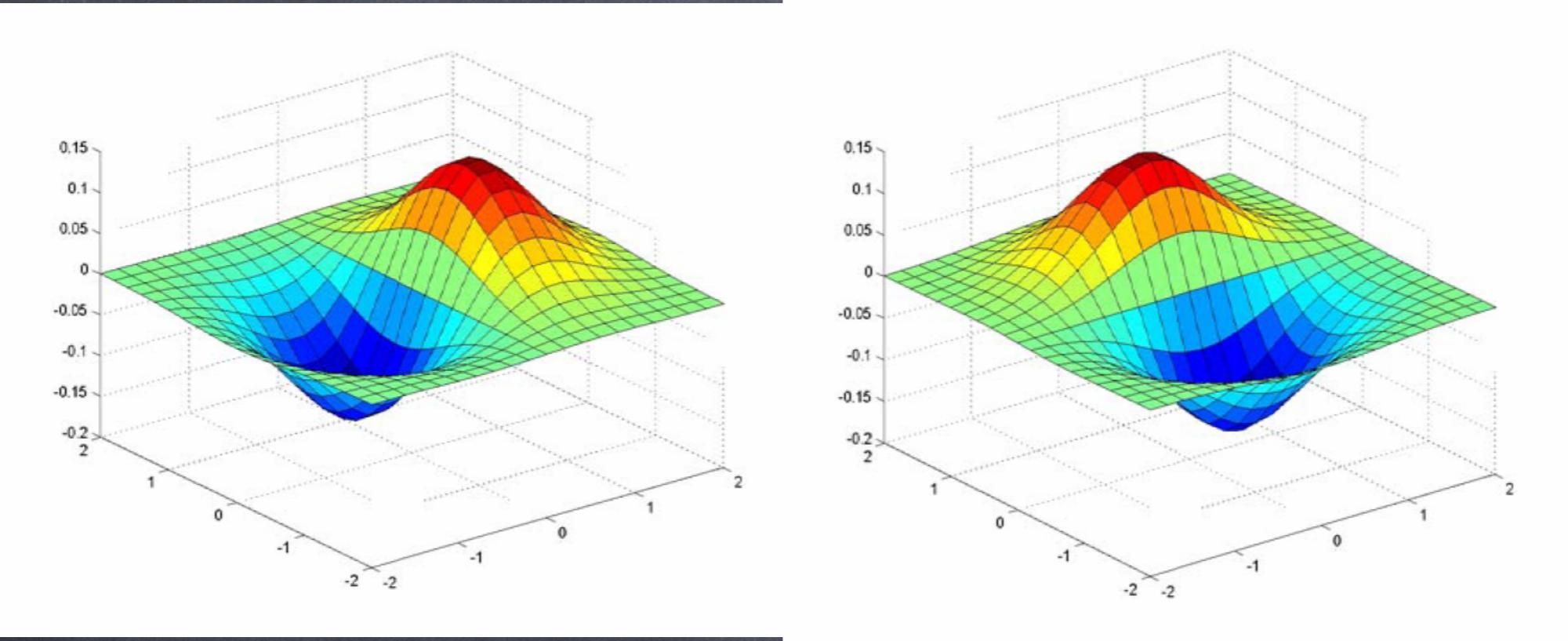
$$h_\sigma(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



derivative of Gaussian (x)

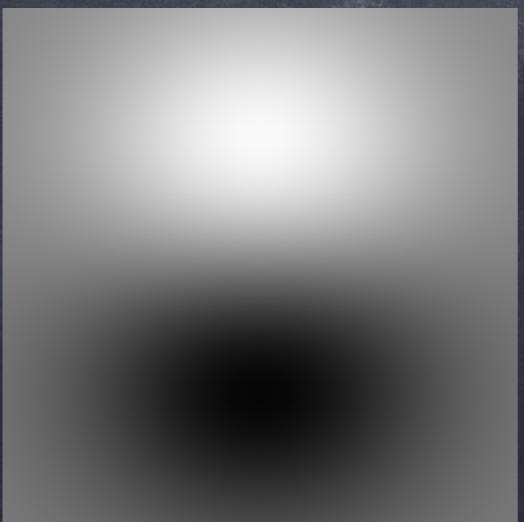
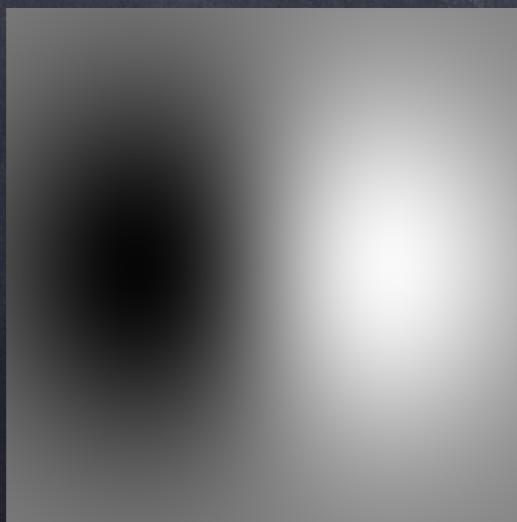
$$\frac{\partial}{\partial x} h_\sigma(u, v)$$

Derivative of Gaussian filter



x-direction

y-direction



THE SOBEL OPERATOR

Common approximation of derivative of Gaussian

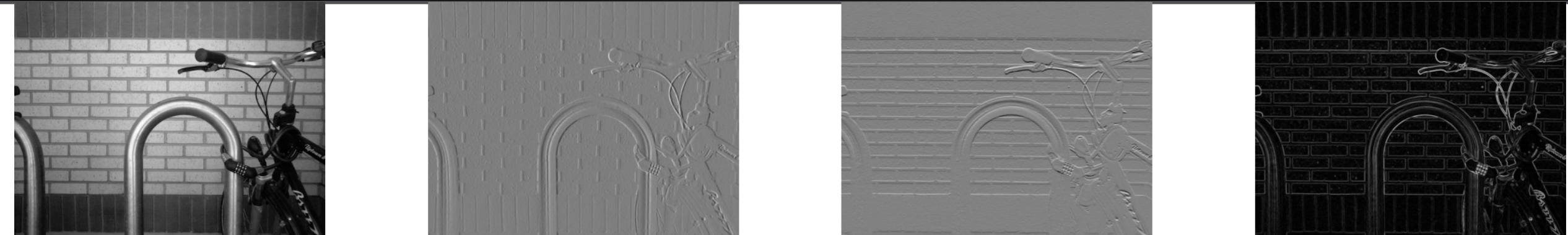
$$\frac{1}{8} \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

s_x

$$\frac{1}{8} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

s_y

SOBEL OPERATOR: EXAMPLE



Source: Wikipedia

EXAMPLE



original image (Lena)

FINDING EDGES



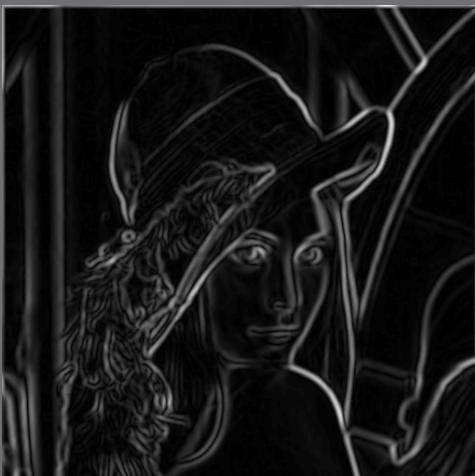
gradient magnitude

Finding edges



Thresholding and thinning

CANNY EDGE DETECTOR



1. Filter image with derivative of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression
4. Linking and thresholding

CANNY EDGE DETECTOR

Still one of the most widely used edge detectors in computer vision

J. Canny, [*A Computational Approach To Edge Detection*](#), IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

Depends on several parameters:

σ : width of the Gaussian blur
threshold

CANNY EDGE DETECTOR



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 edges

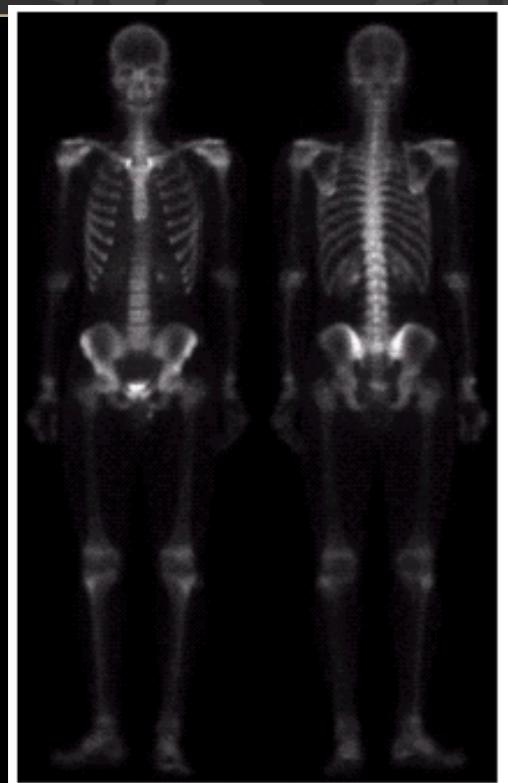
COMBINING SPATIAL ENHANCEMENT METHODS

Successful image enhancement is typically not achieved using a single operation

Rather we combine a range of techniques in order to achieve a final result



COMBINING SPATIAL ENHANCEMENT METHODS

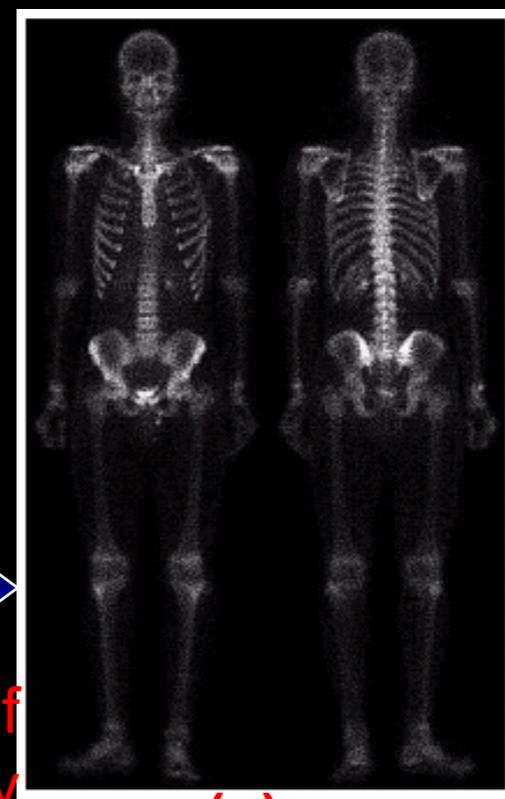


(a)



(b)

Laplacian filter of bone
scan (a)



(c)

Sharpened version of
bone scan achieved by
subtracting (a) and (b)

Sobel filter of bone
scan (a)



(d)



COMBINING SPATIAL ENHANCEMENT METHODS

The product of (c) and (e) which will be used as a mask

(e)

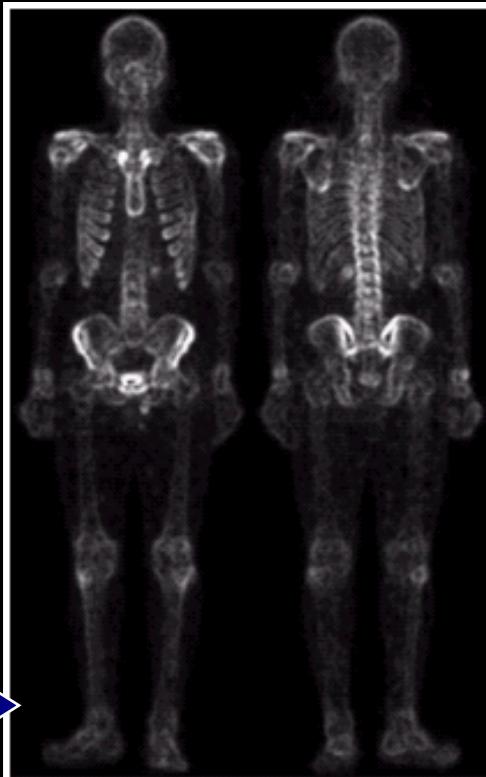


Image (d) smoothed with a
5*5 averaging filter

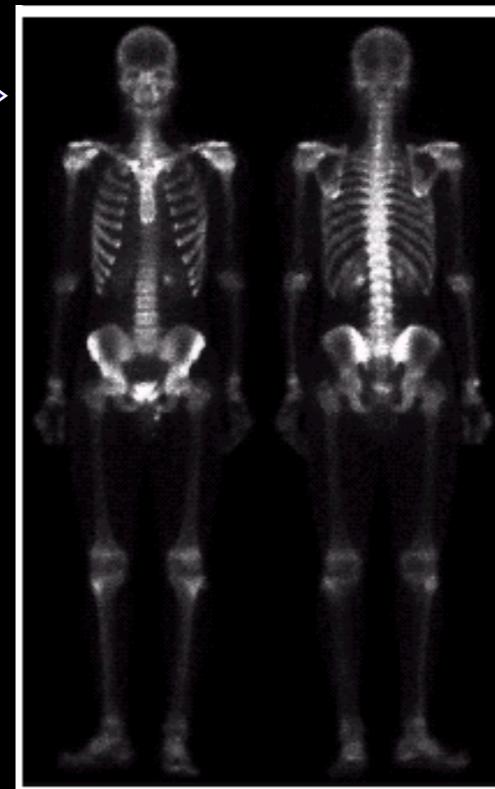
Sharpened image
which is sum of (a)
and (f)

(f)

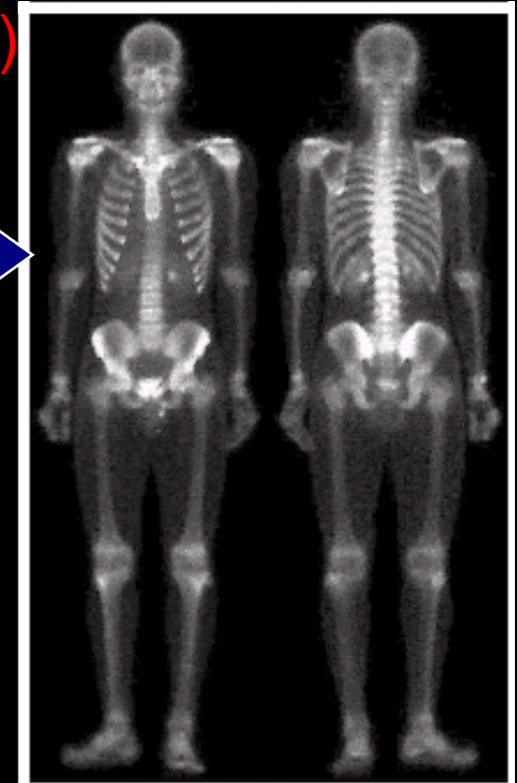


Result of applying a
power-law trans. to (g)

(g)

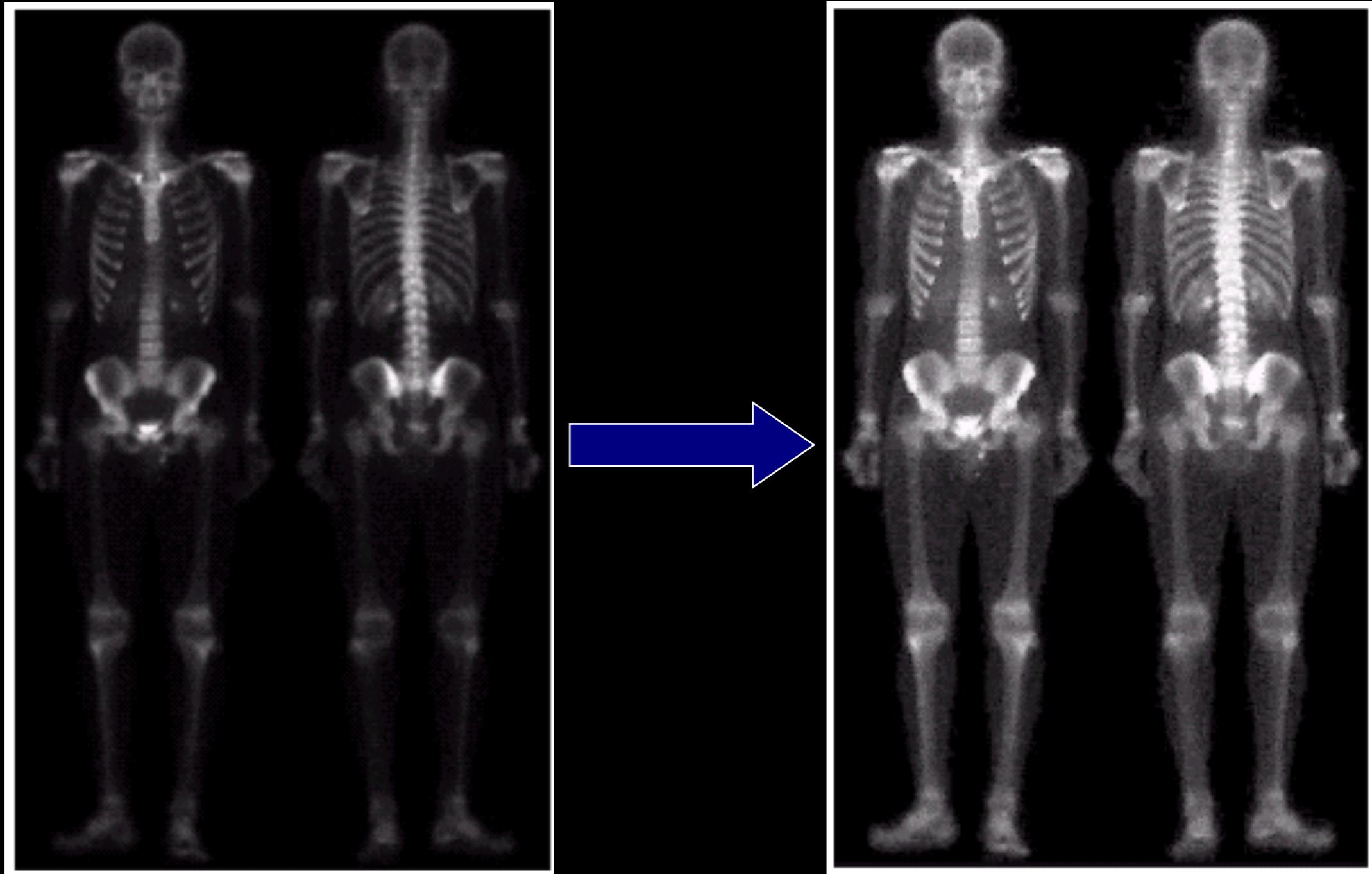


(h)



COMBINING SPATIAL ENHANCEMENT METHODS

Compare the original and final images



OTHER SPATIAL FILTERS

- Read from the book (will not cover all in lectures but may come in the exam)

Image Pyramids

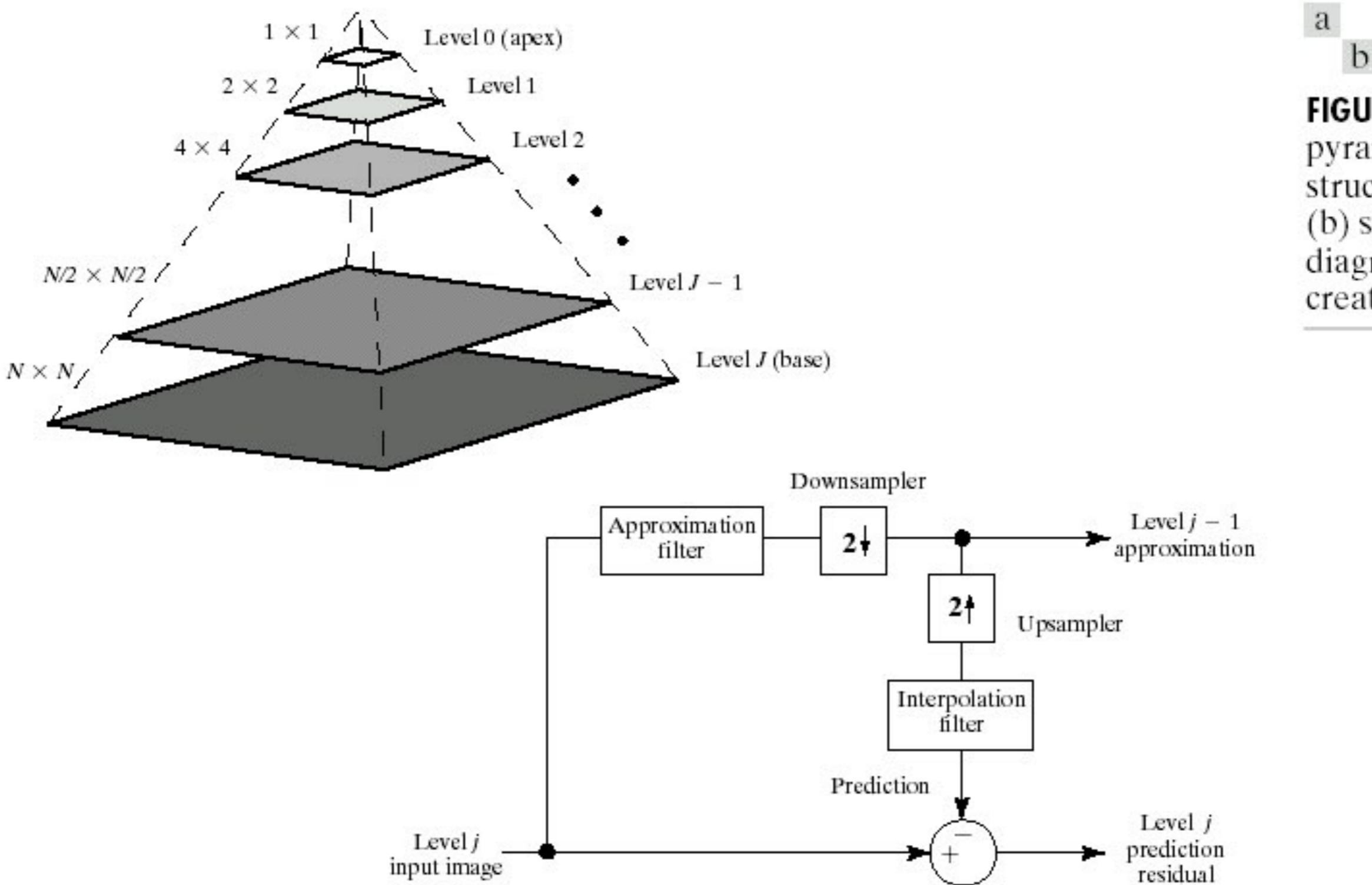


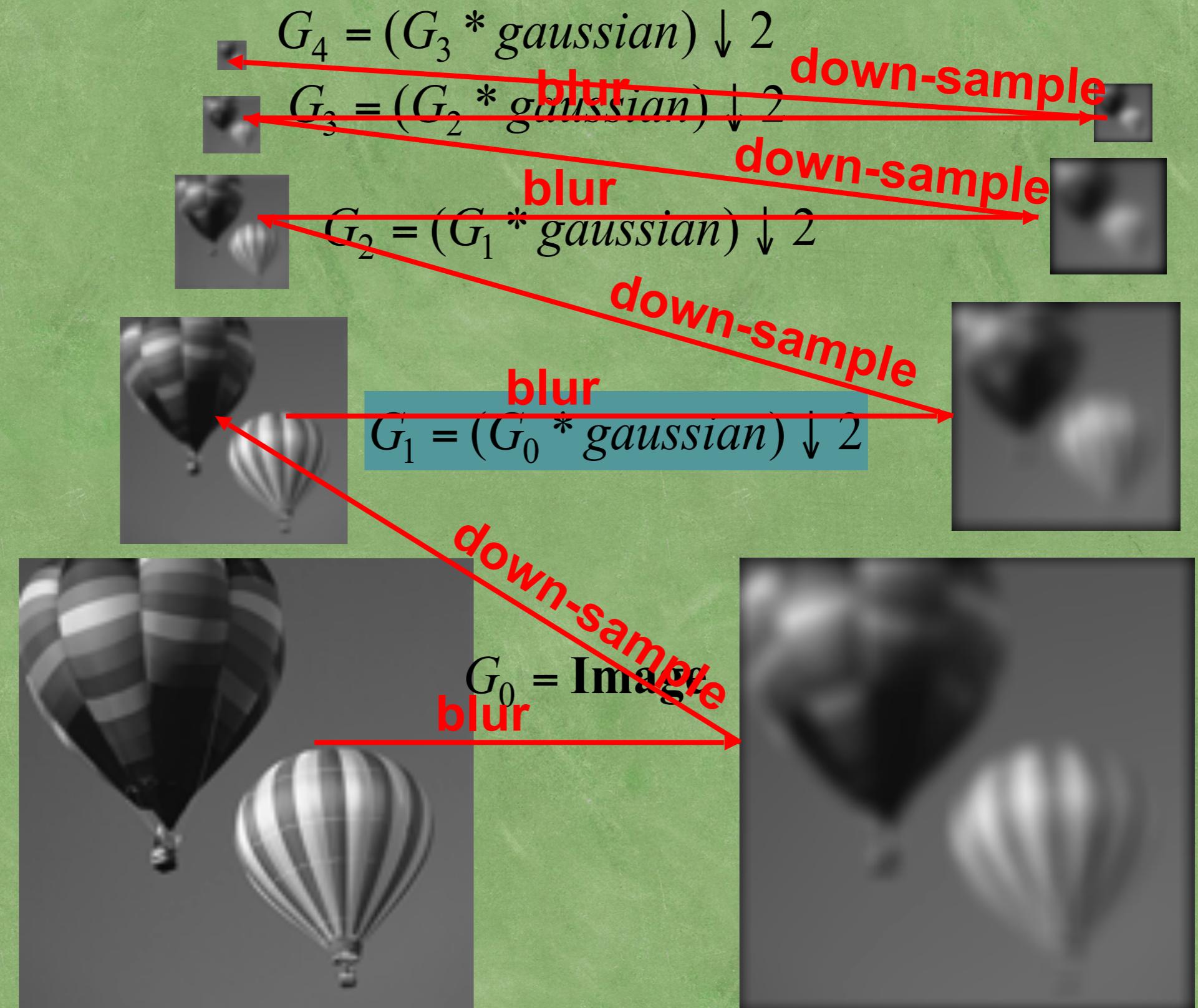
FIGURE 7.2 (a) A pyramidal image structure and (b) system block diagram for creating it.

The Gaussian Pyramid

Low resolution



High resolution



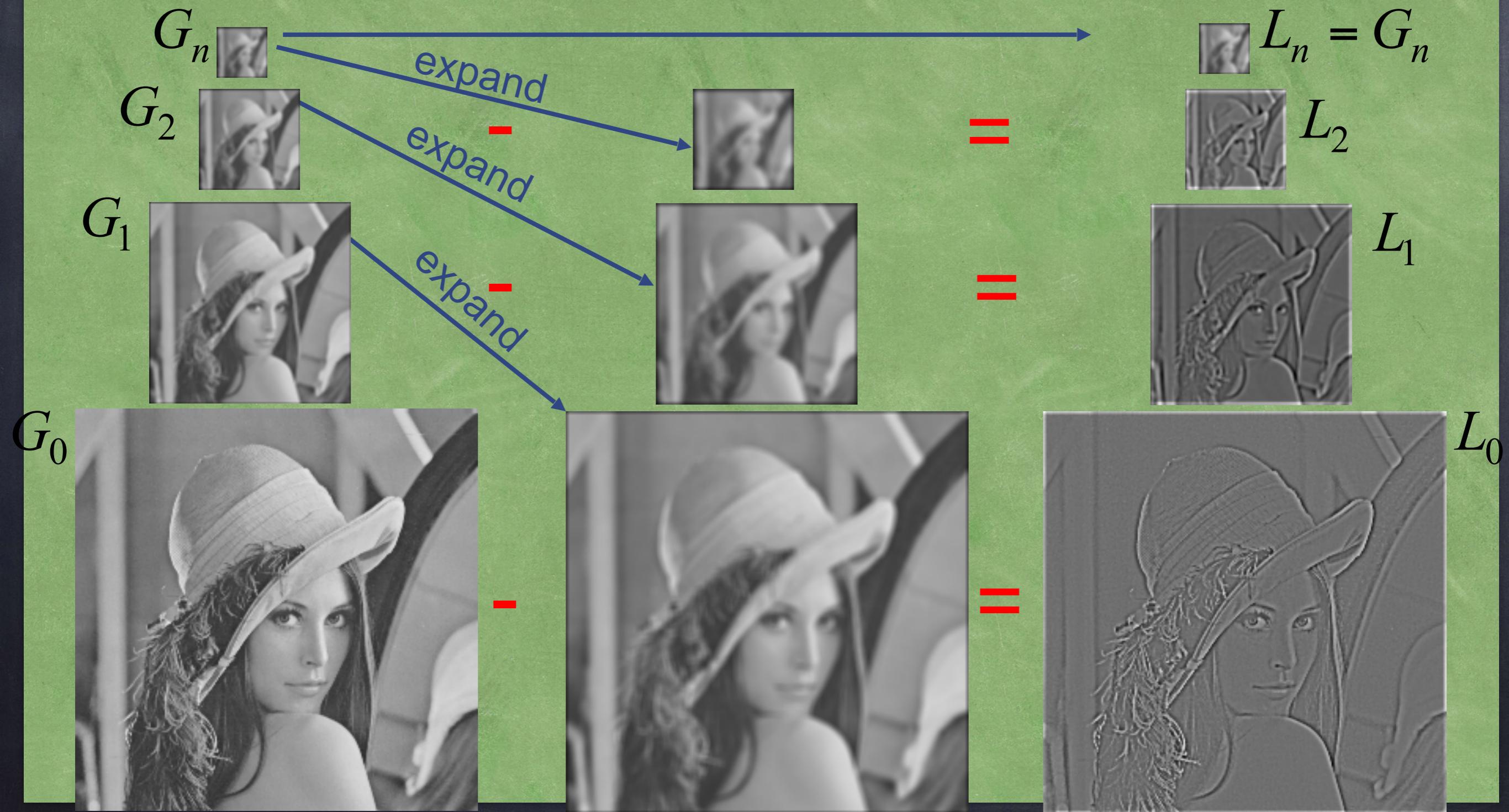
The Laplacian Pyramid

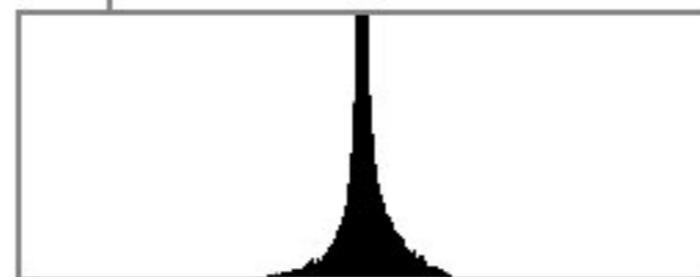
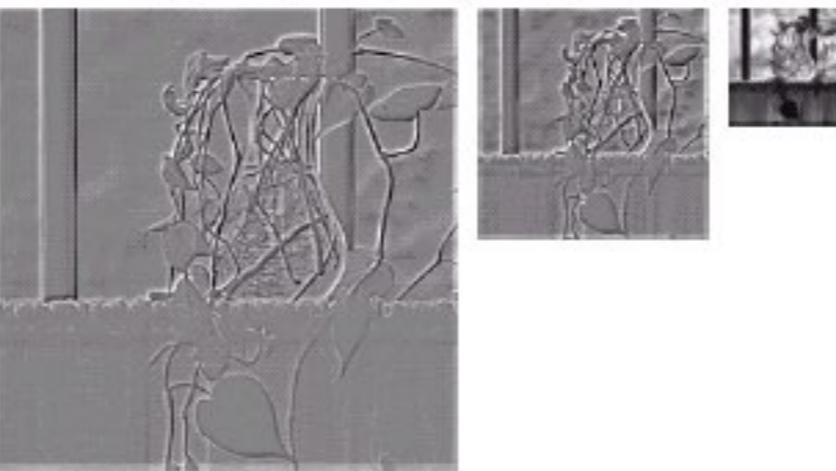
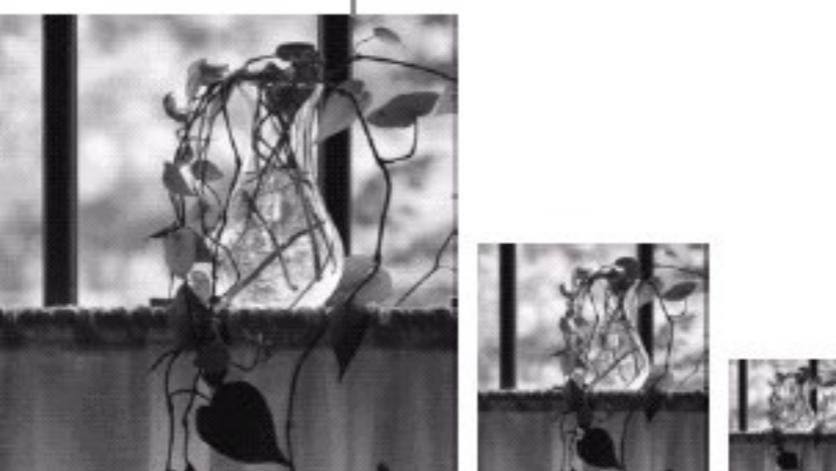
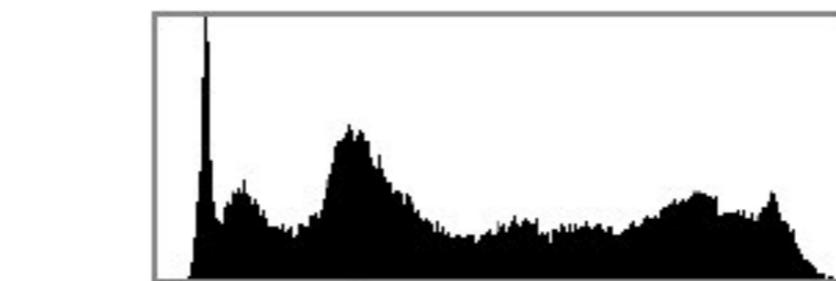
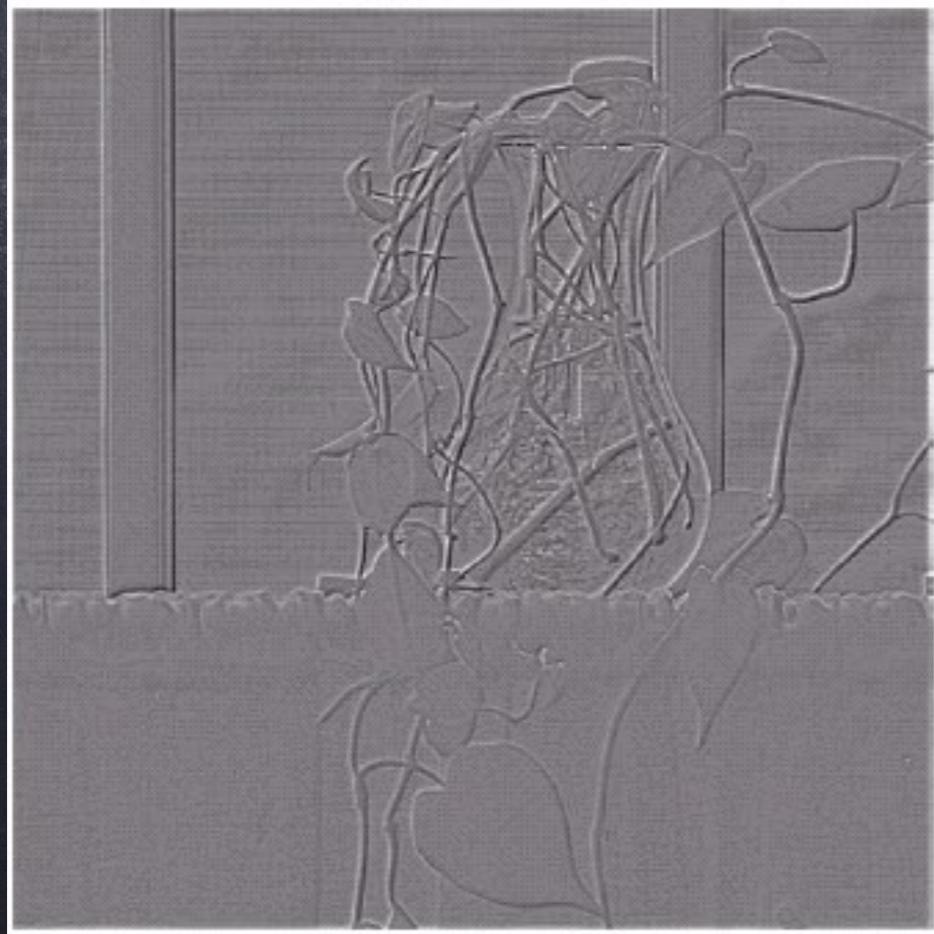
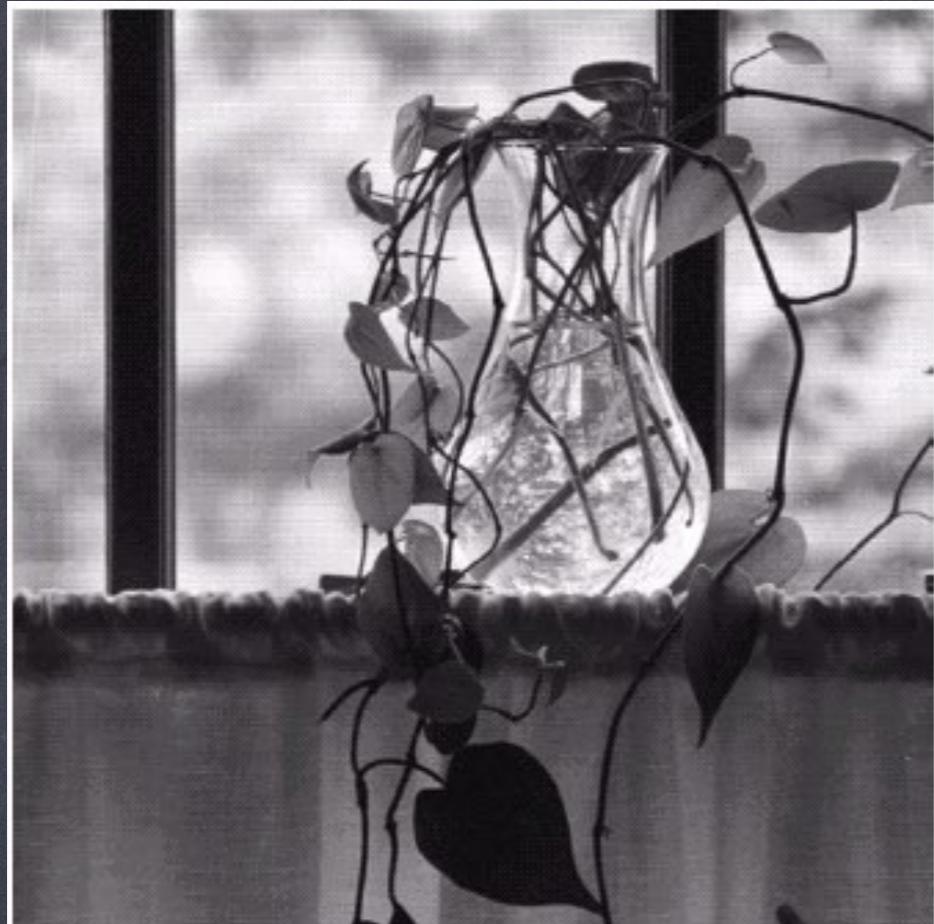
$$L_i = G_i - \text{expand}(G_{i+1})$$

Gaussian Pyramid

$$G_i = L_i + \text{expand}(G_{i+1})$$

Laplacian Pyramid





a
b

FIGURE 7.3 Two image pyramids and their statistics: (a) a Gaussian (approximation) pyramid and (b) a Laplacian (prediction residual) pyramid.

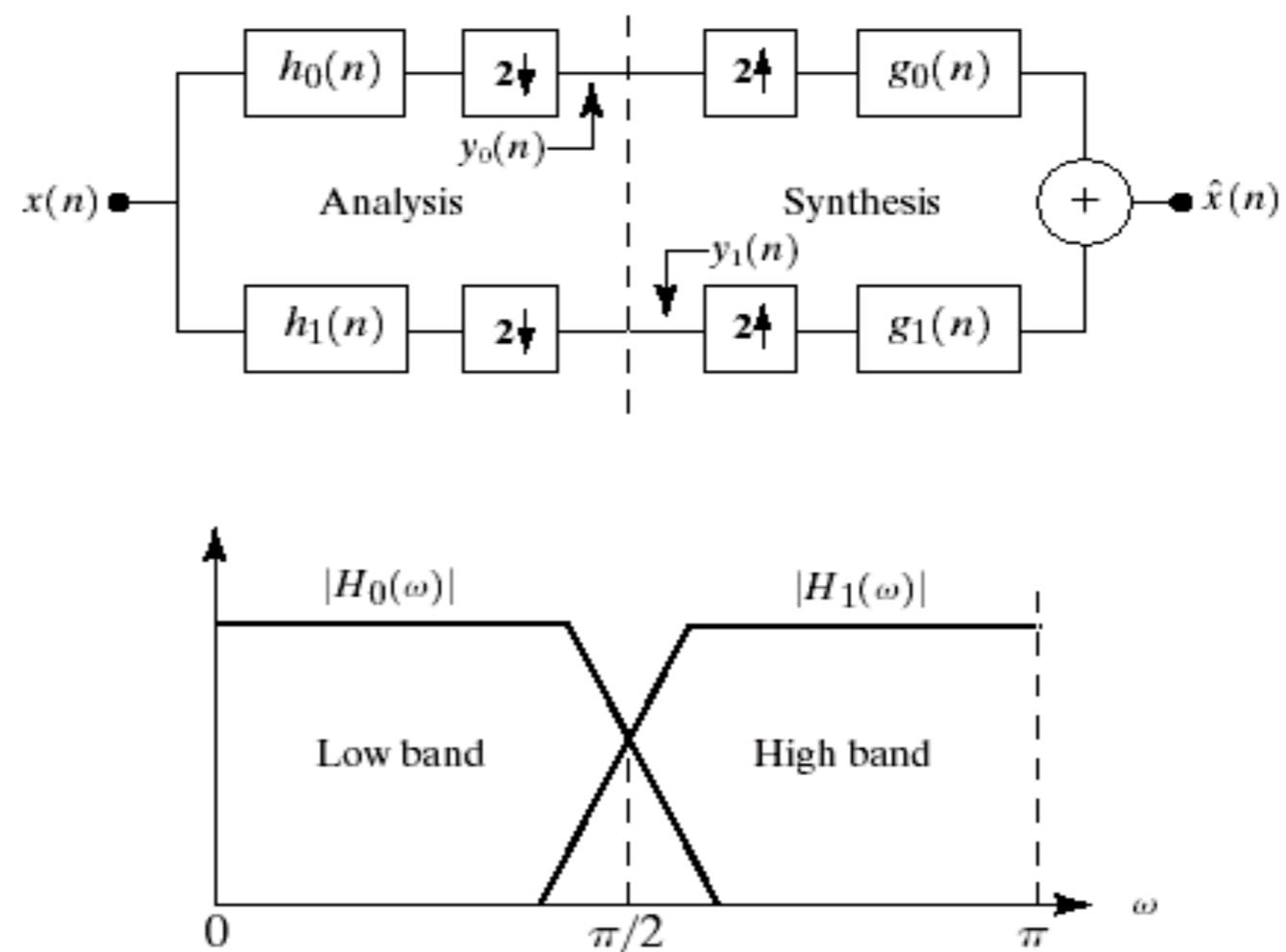
From Image Pyramids to Wavelet Transforms

Subband coding

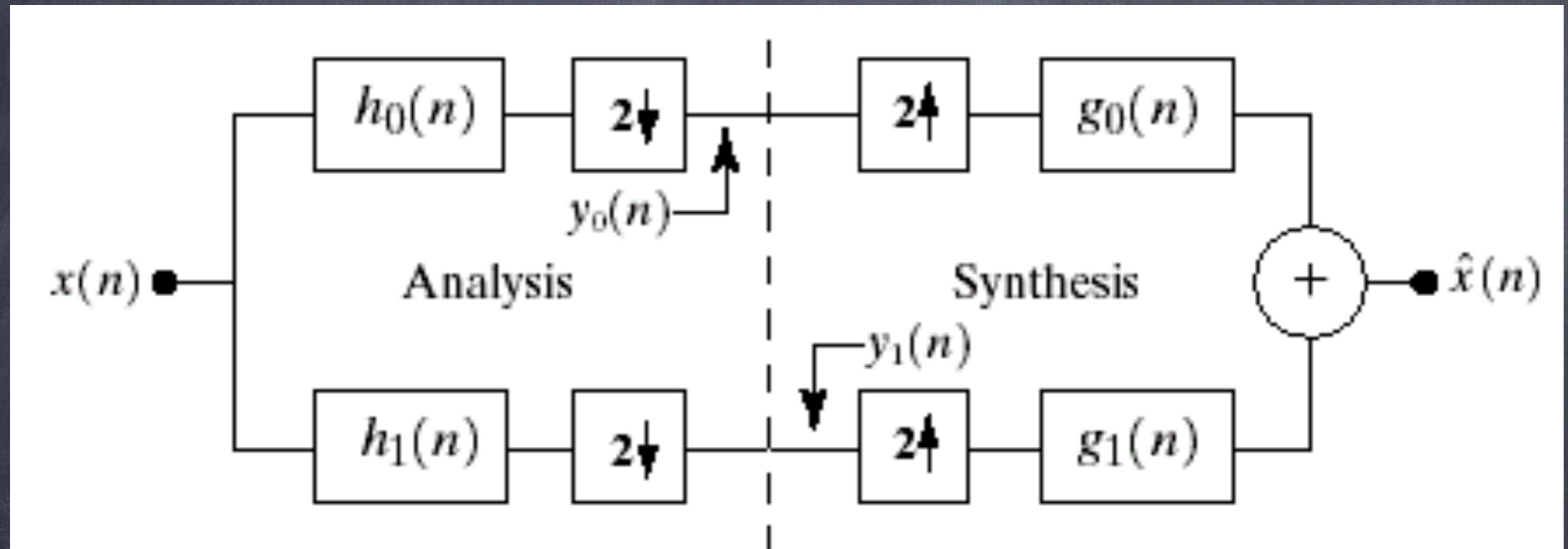
- In subband coding, an image is decomposed into a set of bandlimited components, called subbands.
- Since the bandwidth of the resulting subbands is smaller than that of the original image, the subbands can be downsampled without loss of information.

a
b

FIGURE 7.4 (a) A two-band filter bank for one-dimensional subband coding and decoding, and (b) its spectrum splitting properties.

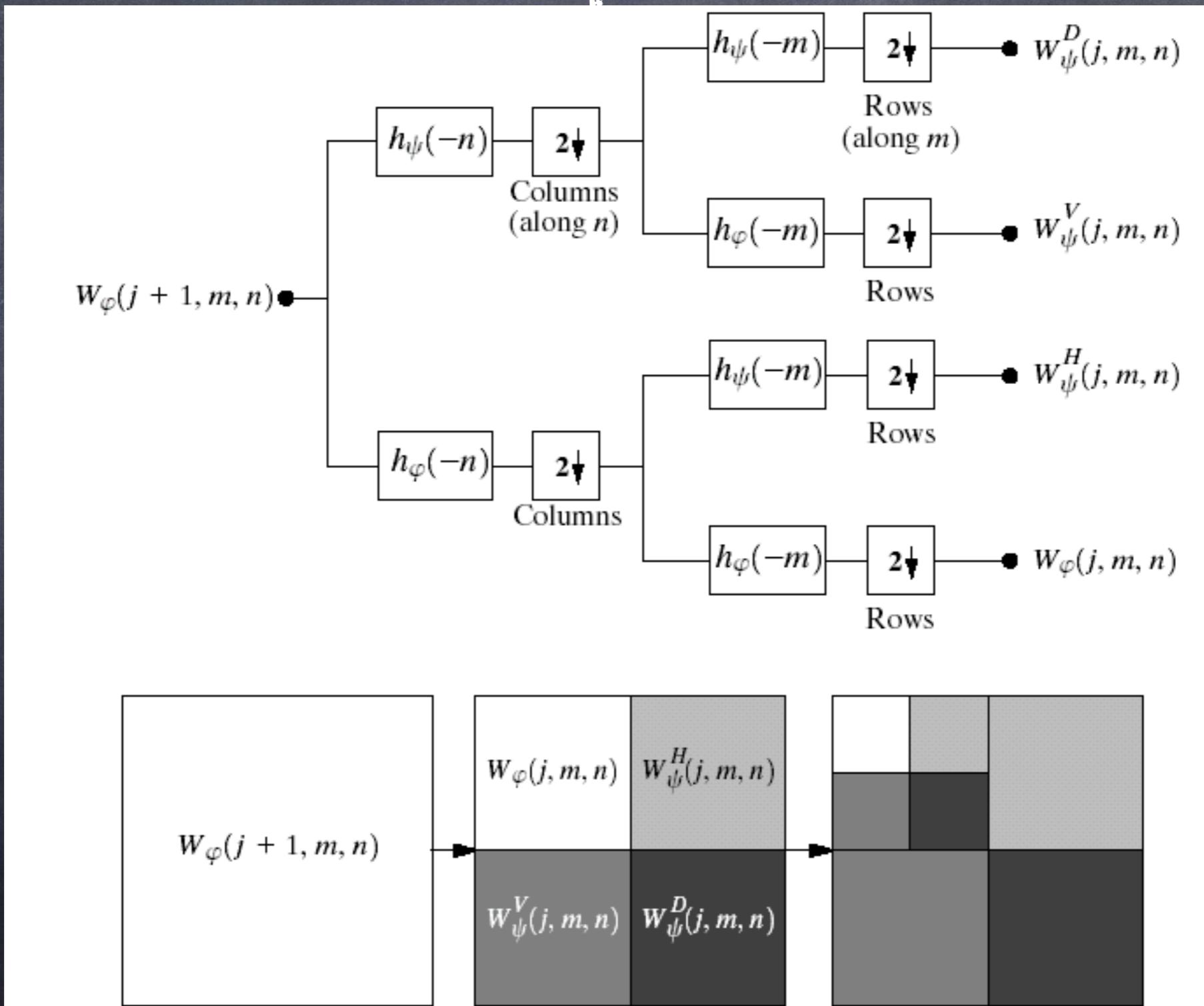


Perfect Reconstruction Filter

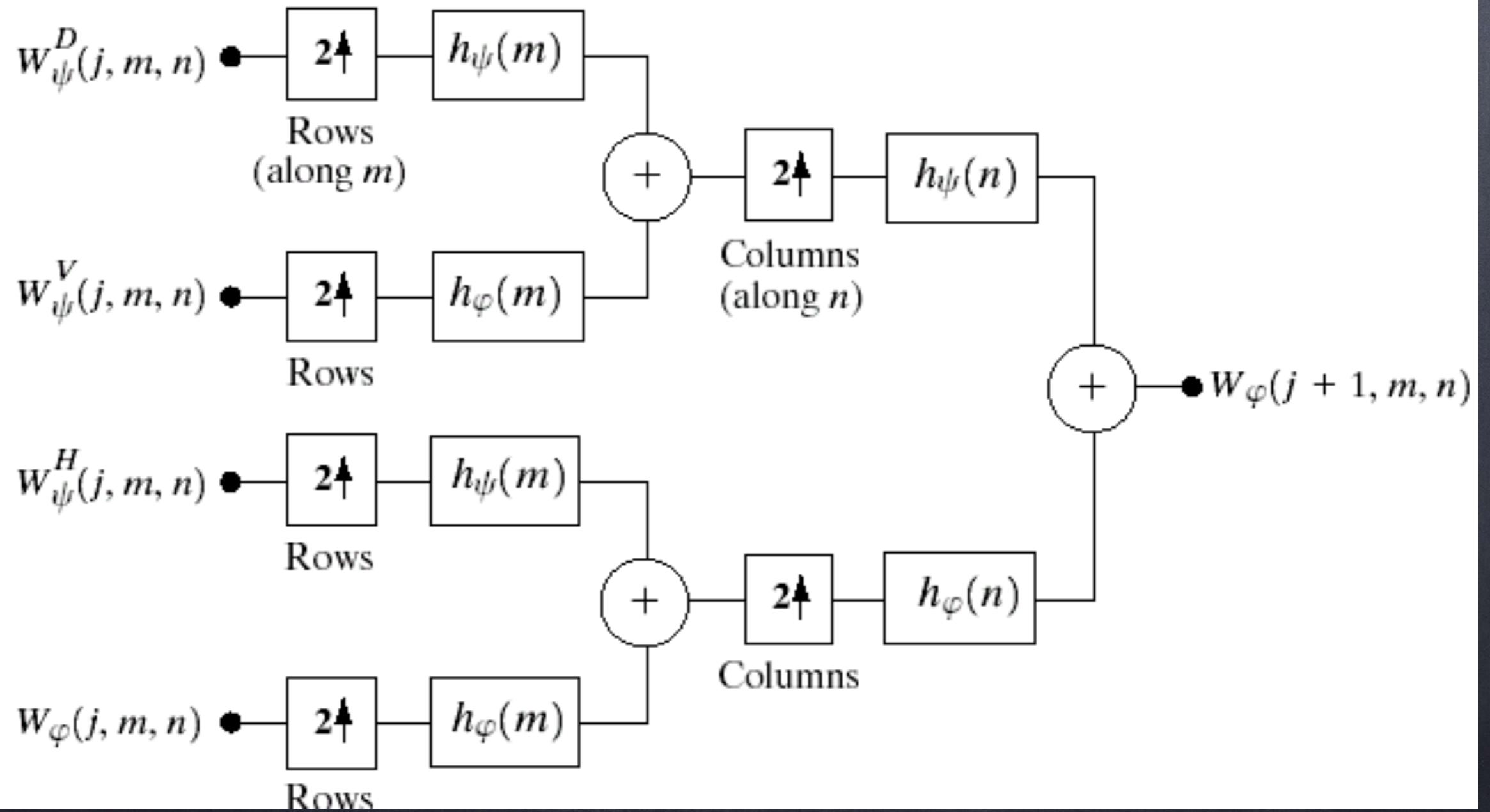


Goal: find filters so that $x(n) = \hat{x}(n)$

2-D Wavelet Transform: Decomposition

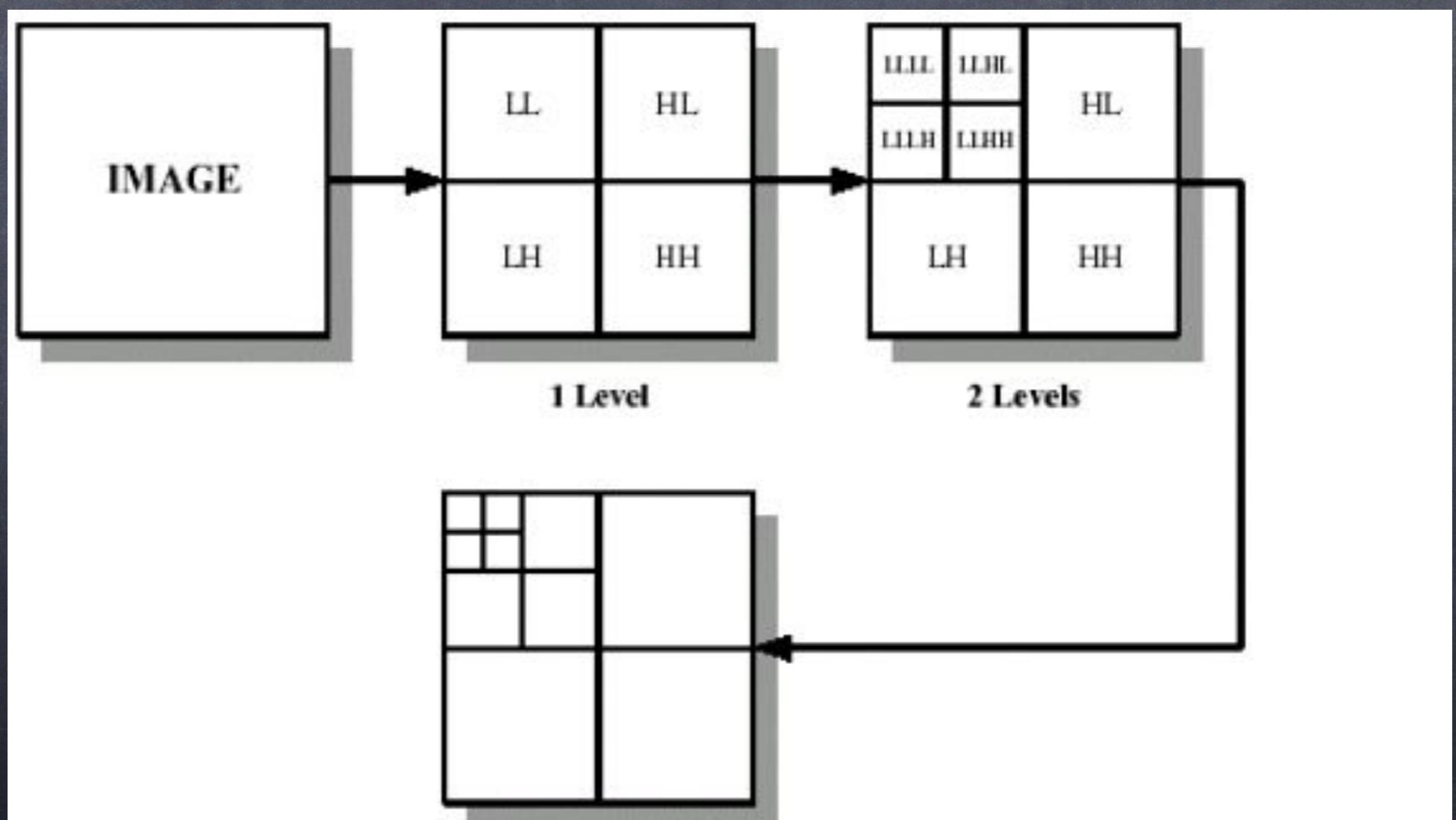


2-D Wavelet Transform: Reconstruction (IDWT)



Discrete Wavelet Transform

- 2-D DWT for Image

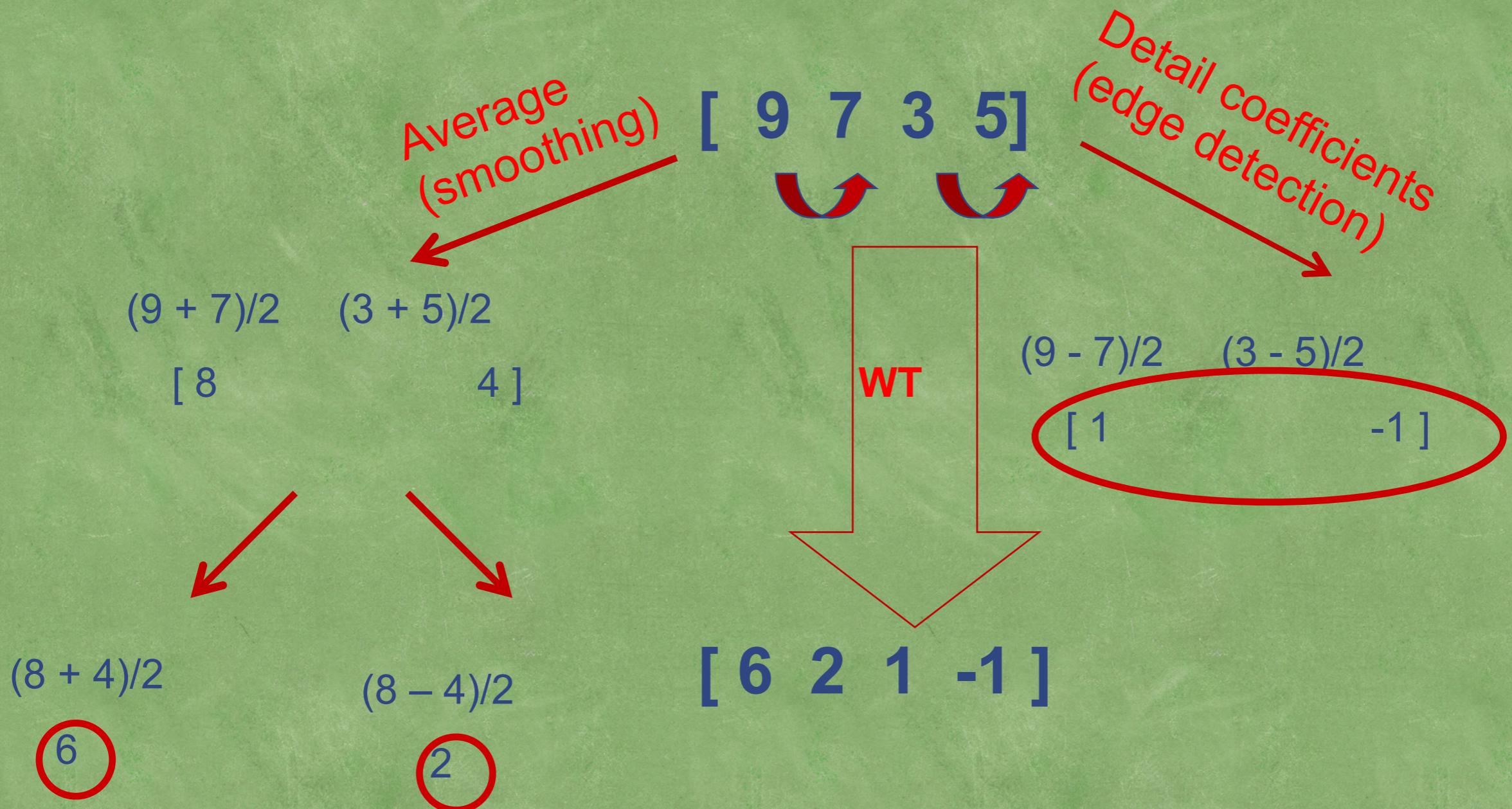


Common Wavelet Filters

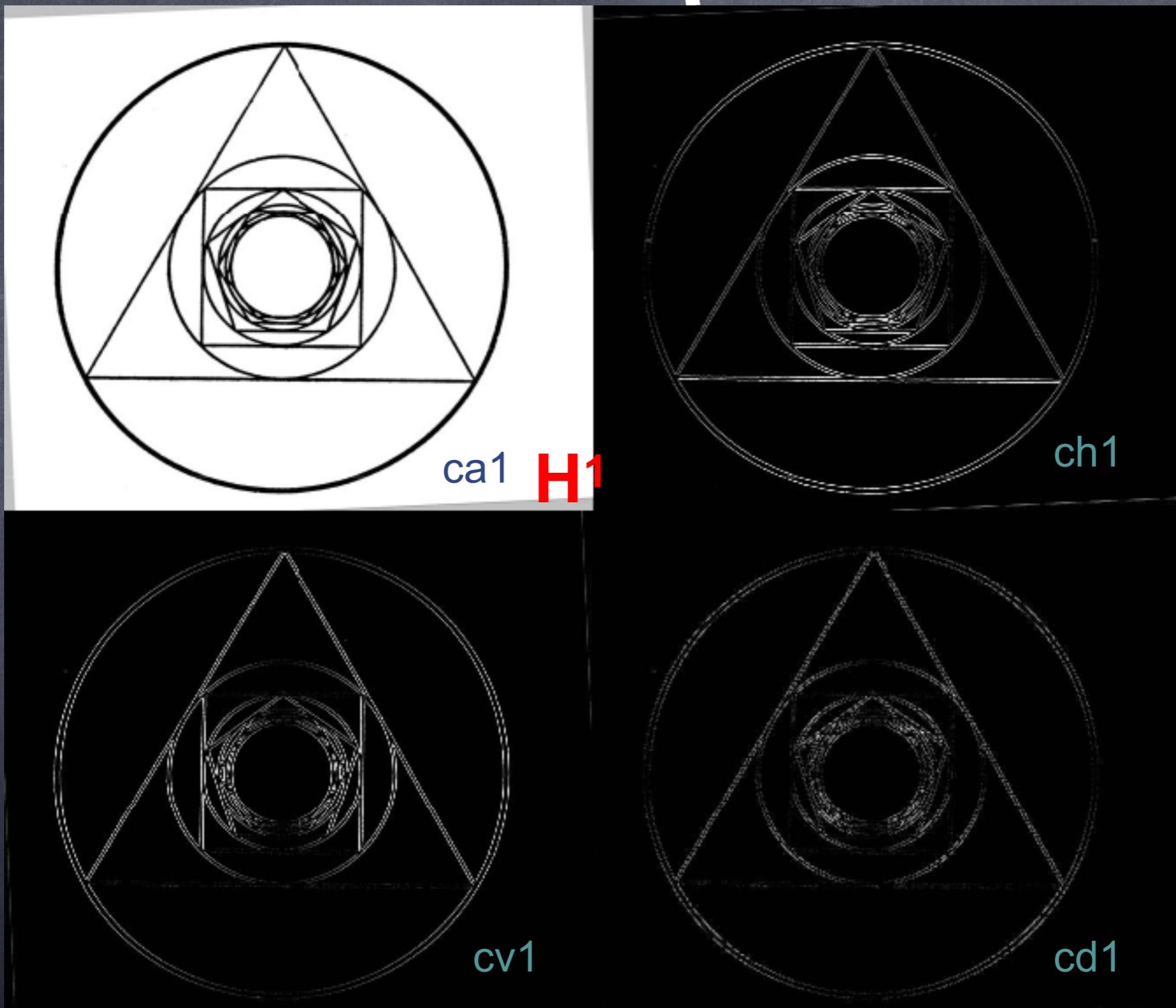
- Haar: simplest, orthogonal, not very good
- Daubechies 8/8: orthogonal
- Daubechies 9/7: bi-orthogonal
most commonly used if numerical reconstruction errors are acceptable
- LeGall 5/3: bi-orthogonal, integer operation,
can be implemented with integer operations only, used for lossless image coding

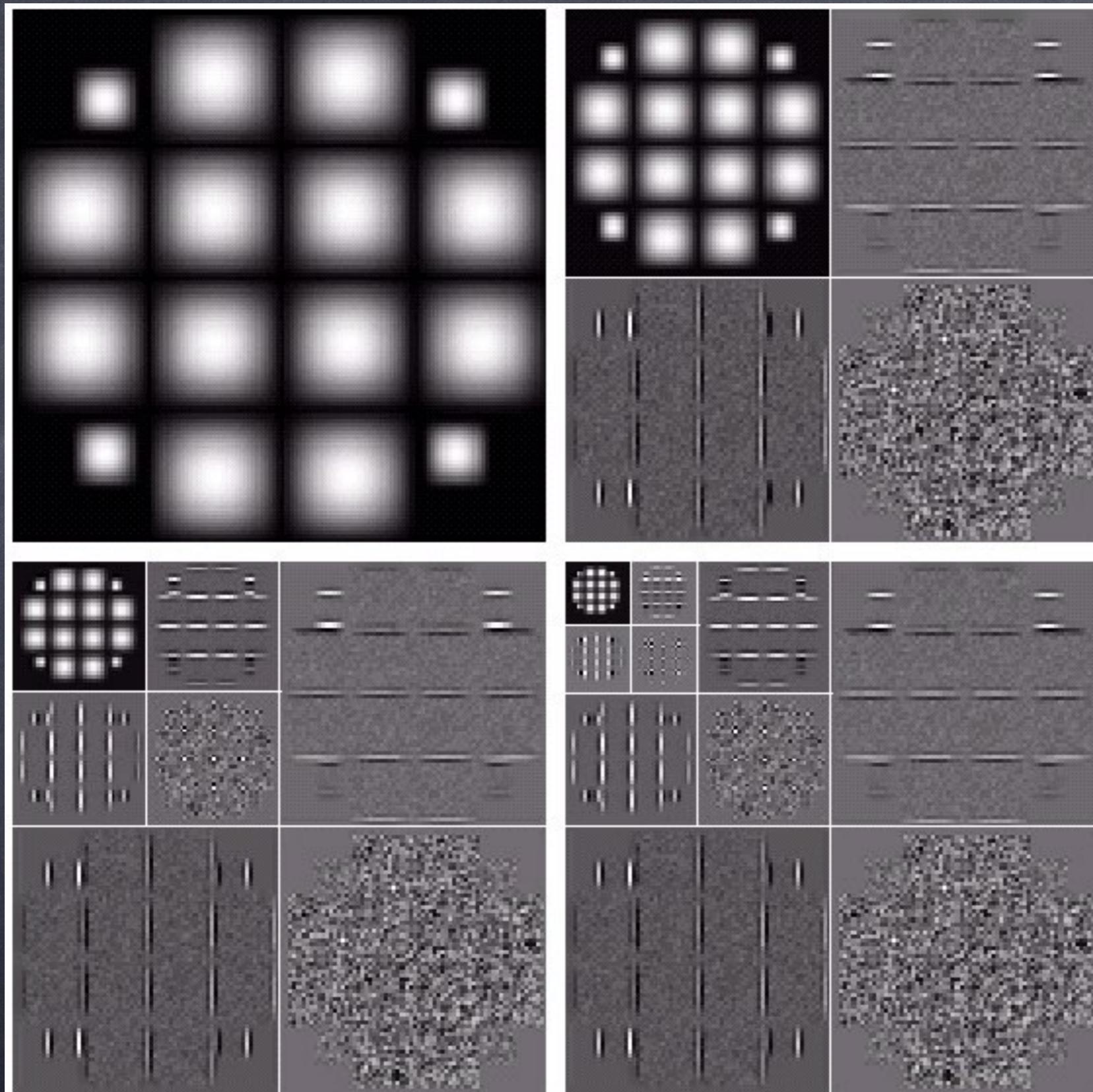
Example of DWT (Haar Basis)

Let's consider a 1D 4-pixel Image [9 7 3 5]



Example





a
b
c
d

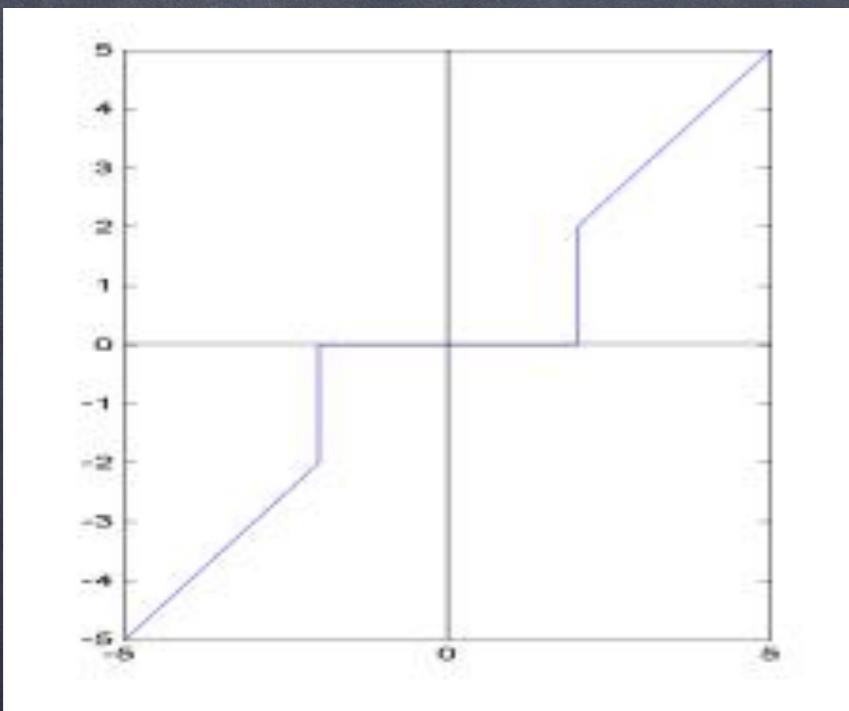
FIGURE 7.23 A three-scale FWT.

Image Denoising Using Wavelets

- Calculate DWT of the image.
- Threshold the wavelet coefficients. The threshold may be universal or subband adaptive.
- Compute the IDWT to get the denoised estimate.
- Soft thresholding is used in the different thresholding methods. Visually more pleasing images.

Threshold techniques

Hard threshold



Soft threshold

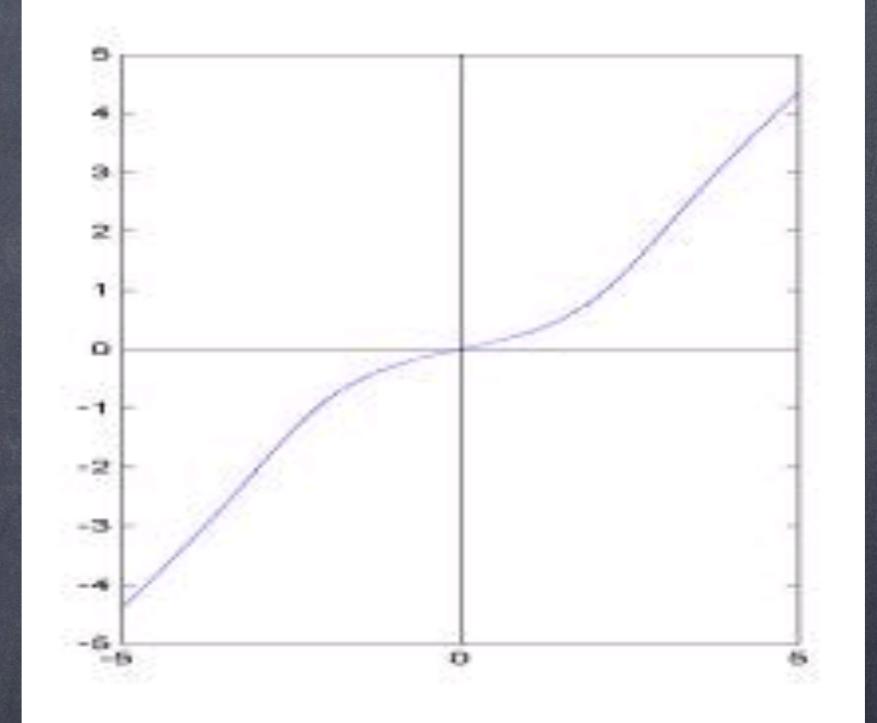


Image Enhancement

- Image contrast enhancement with wavelets, especially important in medical imaging
- Make the small coefficients very small and the large coefficients very large.
- Apply a nonlinear mapping function to the coefficients.

Enhancement



(a) Original Image



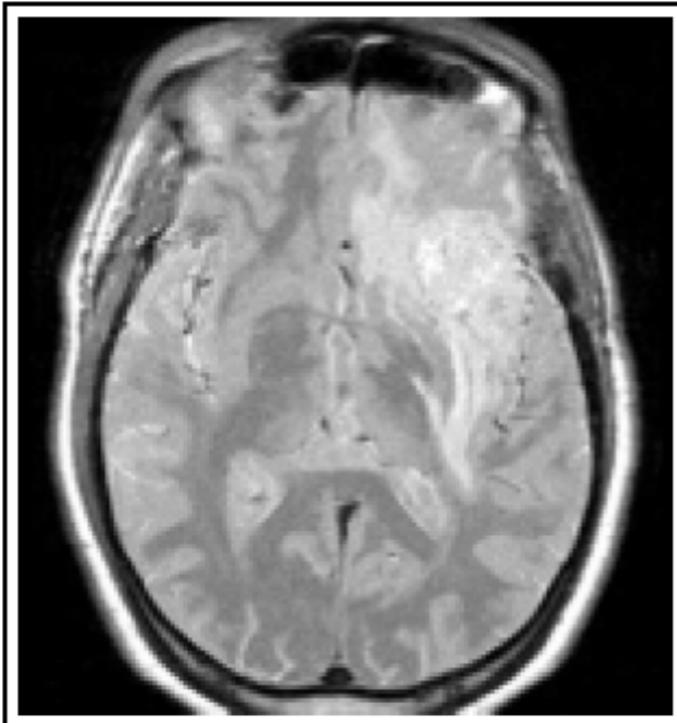
(c) Proposed Method

Denoising and Enhancement

- Apply DWT
- Shrink transform coefficients in finer scales to reduce the effect of noise
- Emphasize features within a certain range using a nonlinear mapping function
- Perform IDWT to reconstruct the image.

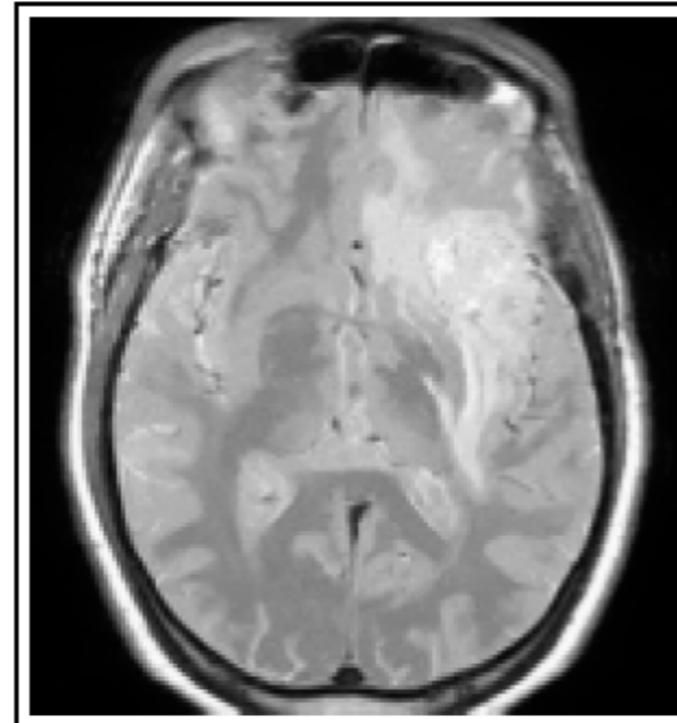
Examples

Original



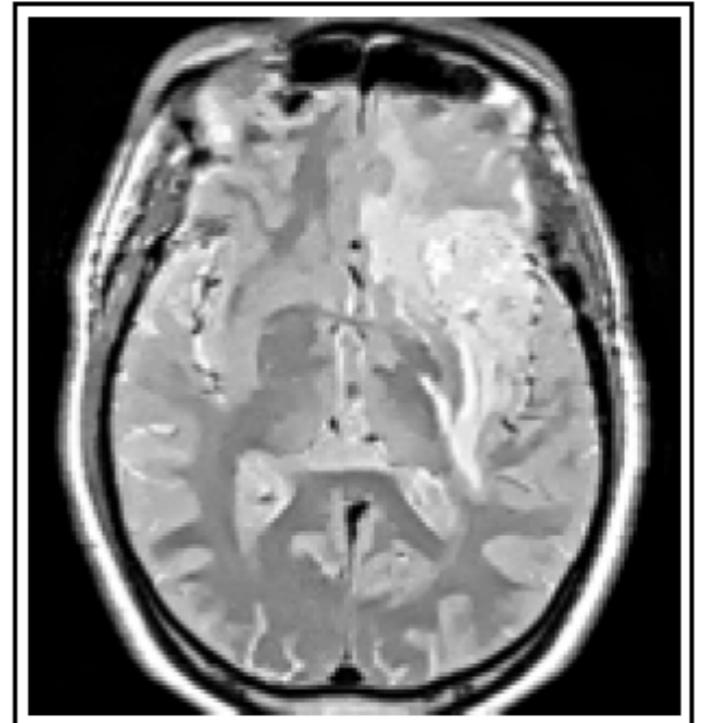
(a)

Denoised



(b)

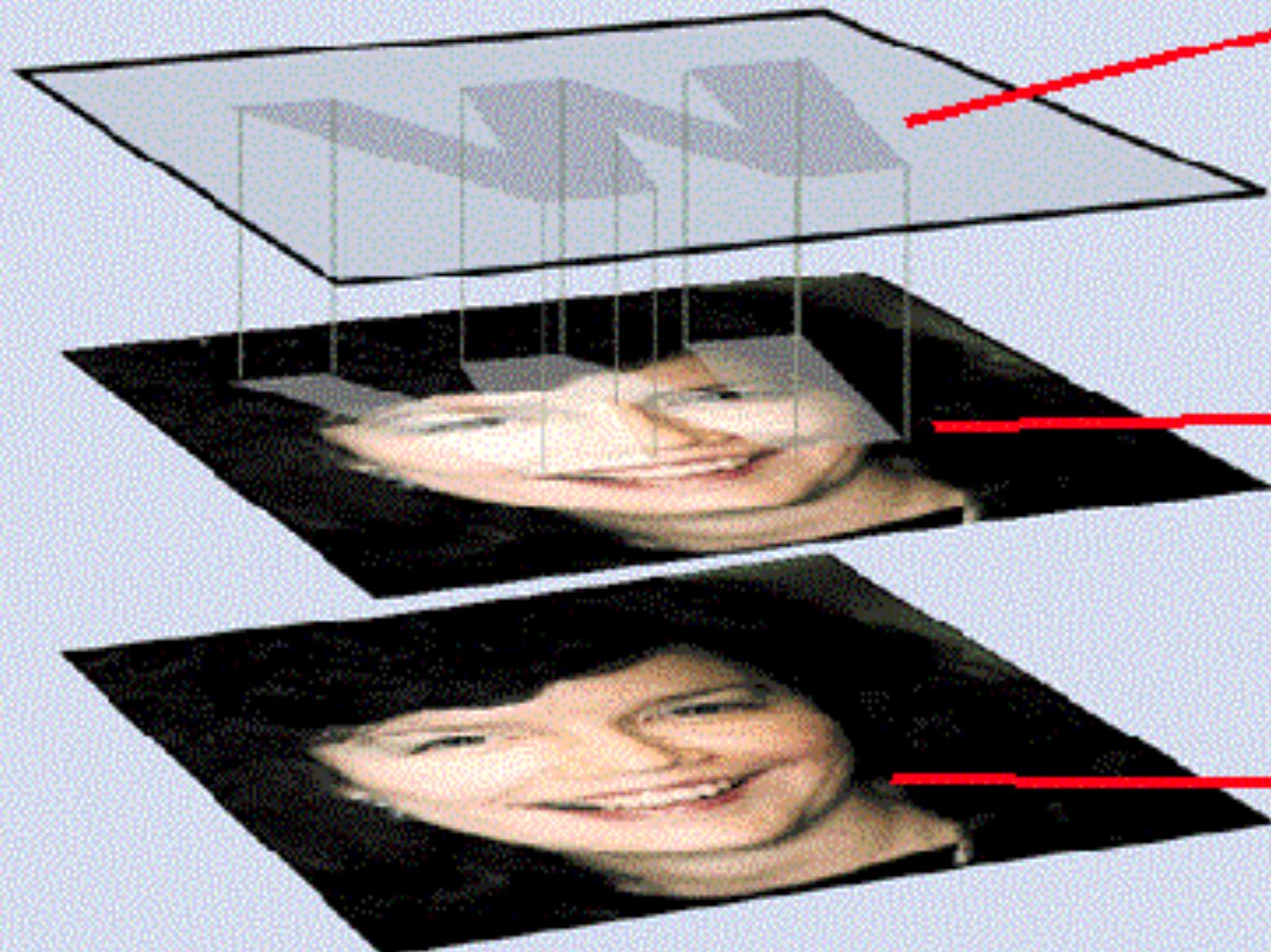
Denoising with Enhancement



(c)

Watermarking

Watermarks: Secret Code for Protection



1 Depending on the chosen technique, noise is added to every data element or just to a pseudo-random subset

2 Hidden information (watermark) is embedded in the noise signal of the original.

3 Watermark is invisible and can be retrieved only by extraction software.

Watermarking



Fusion: How do we combine two images?



Assignment 1

1. Spatial filtering
2. Image pyramid
3. Edge detection
4. Wavelet processing