

# Image Representation

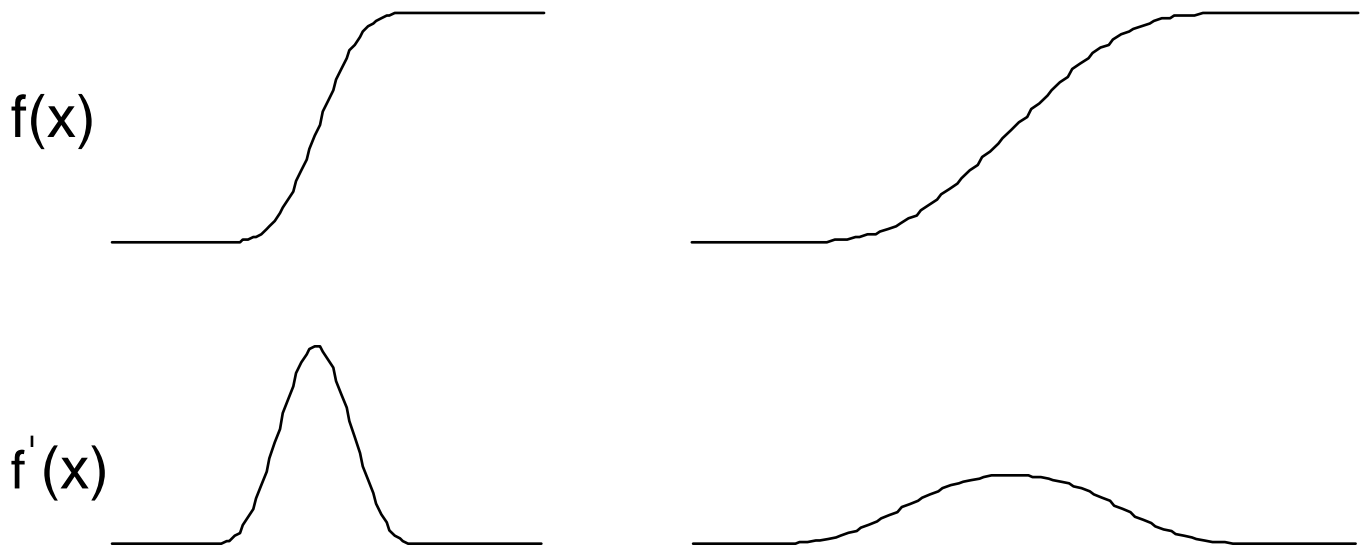
- Gaussian pyramids
- Laplacian Pyramids
- Wavelet Pyramids
- Applications



## Image Pyramids

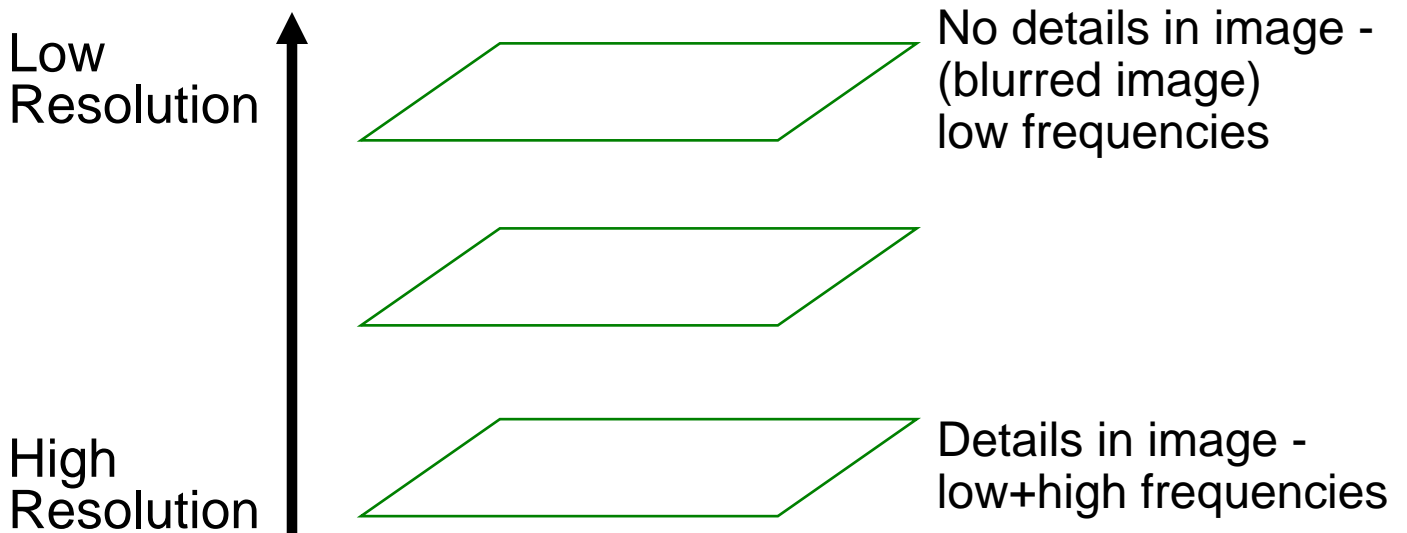
Image features at different resolutions require filters at different scales.

Edges (derivatives):



# Image Pyramids

**Image Pyramid** = Hierarchical representation of an image



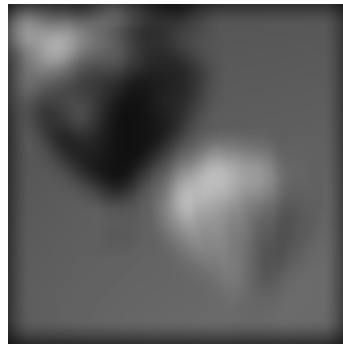
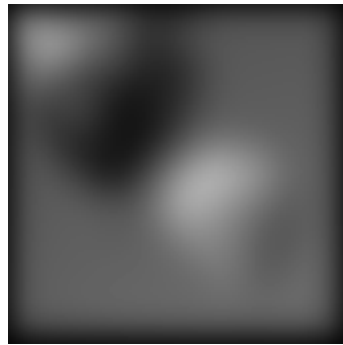
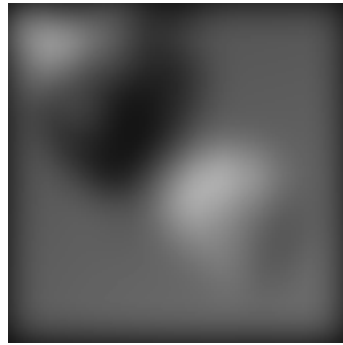
A collection of images at different resolutions.

# Image pyramids

- Gaussian Pyramids
- Laplacian Pyramids
- Wavelet/QMF

# Image Pyramid

Low resolution



High resolution

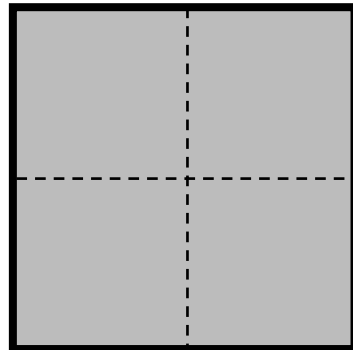
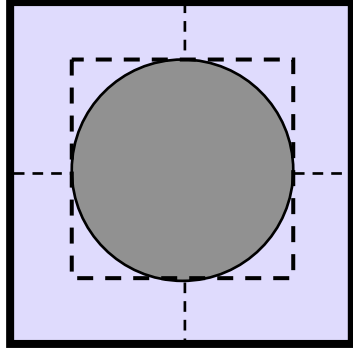
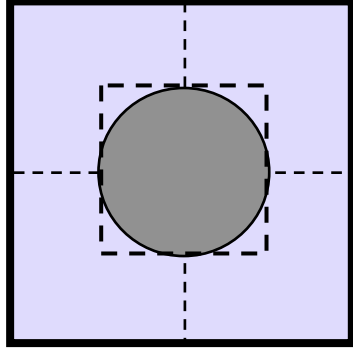
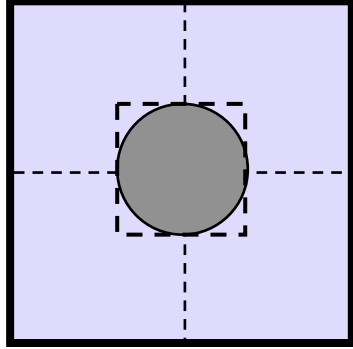
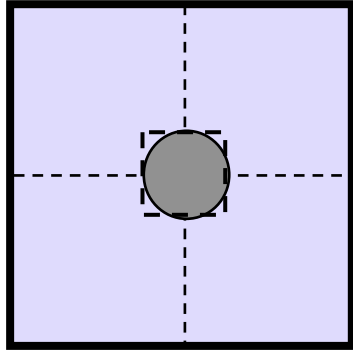


**Image Pyramid  
Frequency Domain**

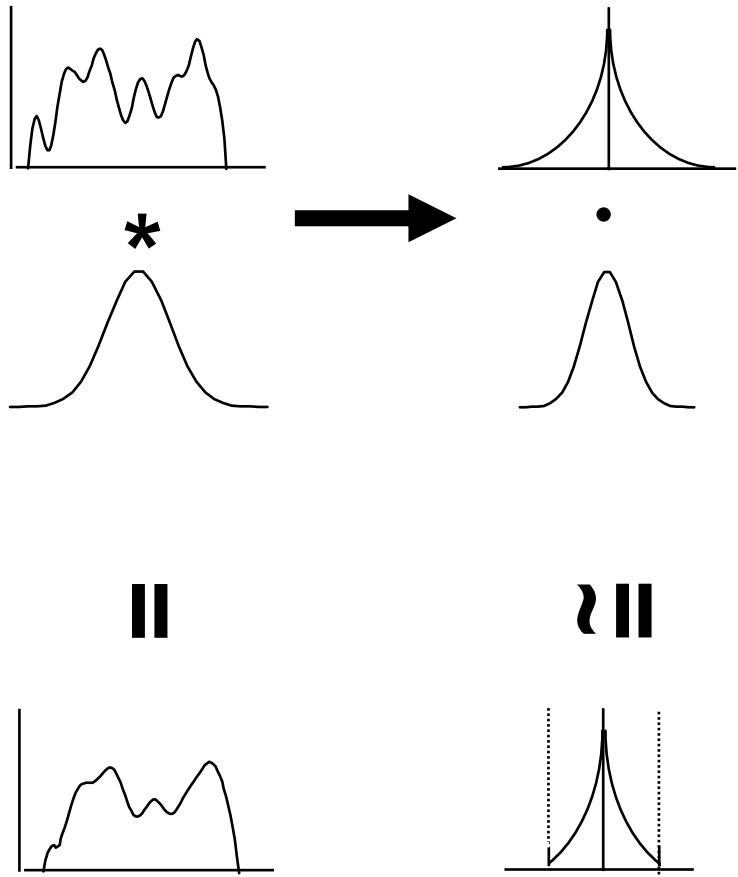
**Low resolution**

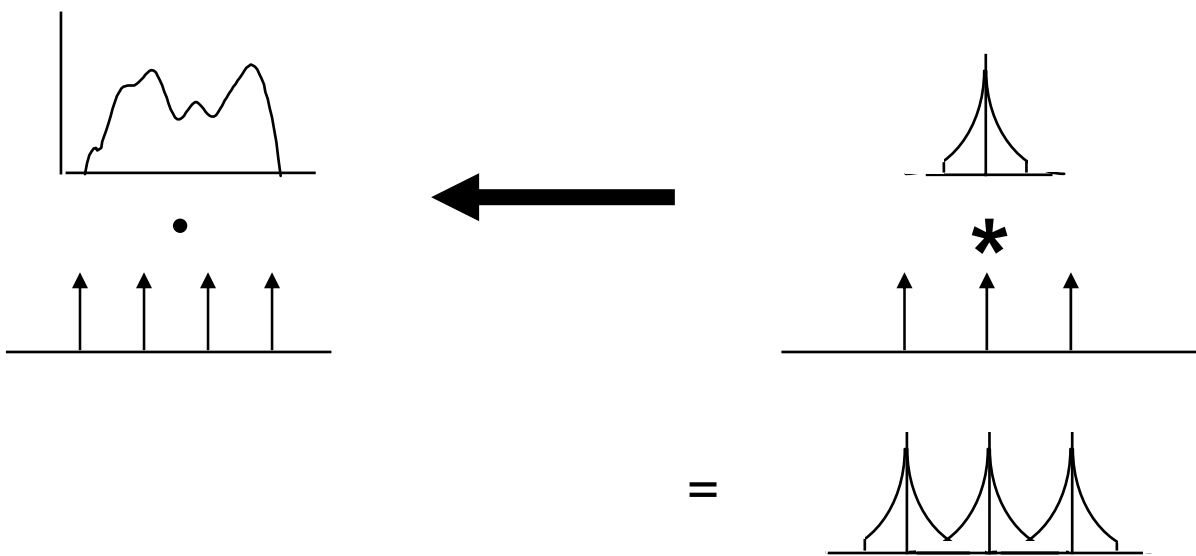
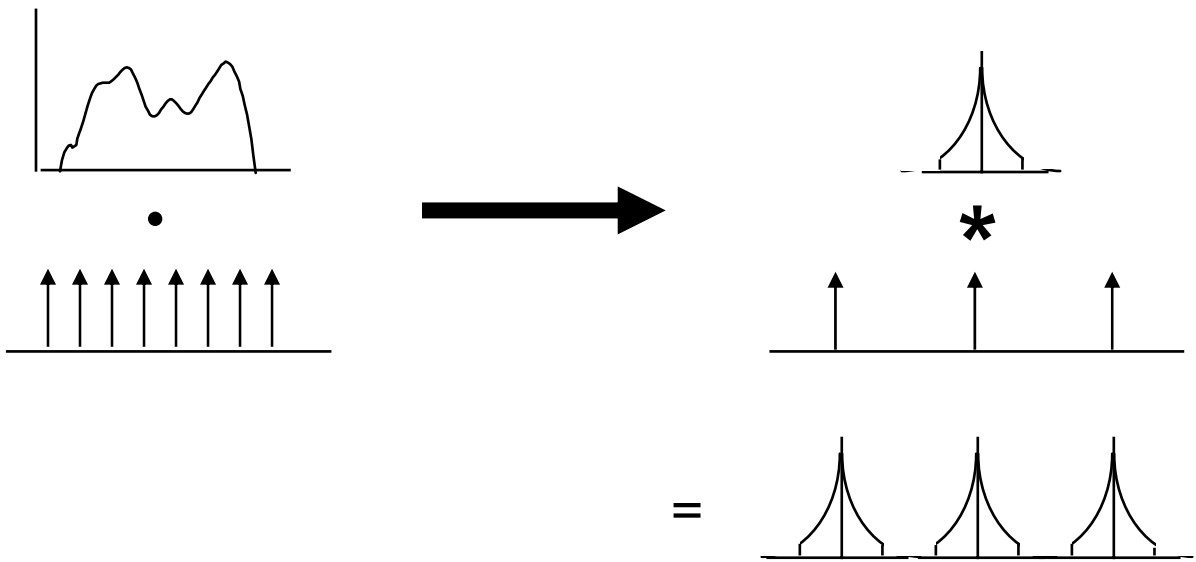
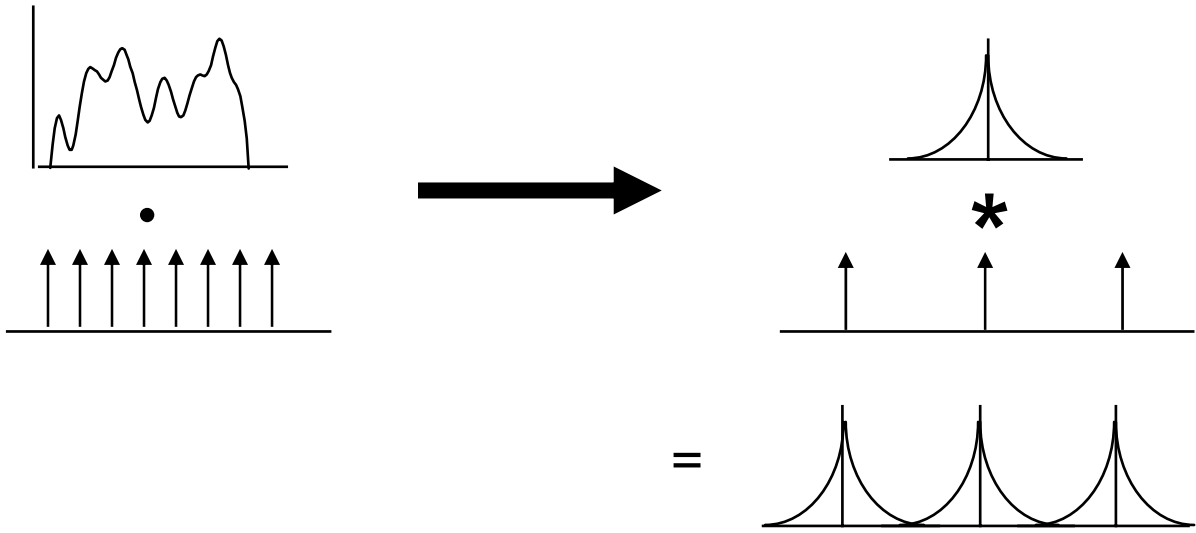


**High resolution**



**Image Blurring = low pass filtering**

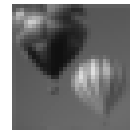






# Image Pyramid

Low resolution



High resolution

# Gaussian Pyramid



Level n  
 $1 \times 1$



Level 1  
 $2^{n-1} \times 2^{n-1}$



Level 0  
 $2^n \times 2^n$

# Gaussian Pyramid



512

256

128

64

32

16

8



# Gaussian Pyramid

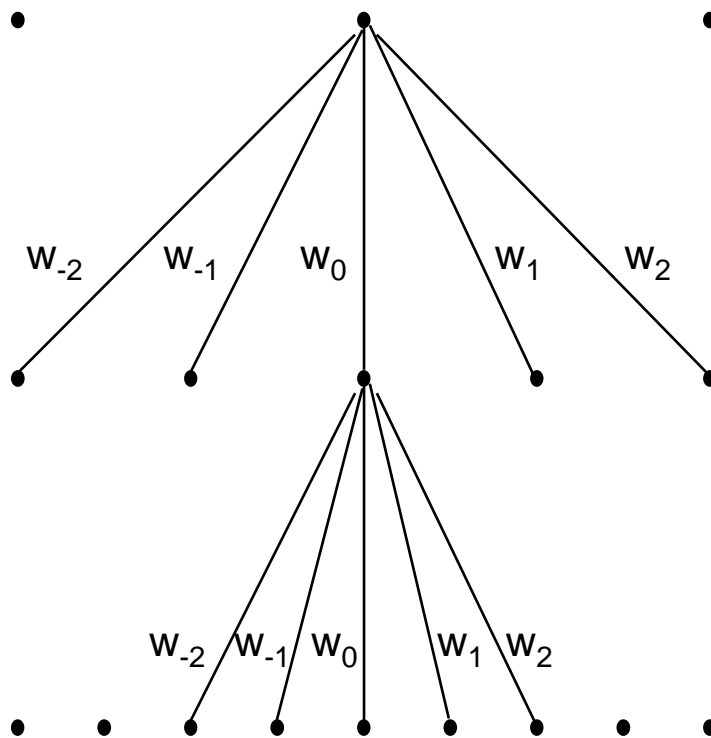
Burt & Adelson (1981)

Normalized:  $\sum w_i = 1$

Symmetry:  $w_i = w_{-i}$

Unimodal:  $w_i \geq w_j$  for  $0 < i < j$

Equal Contribution: for all  $j$   $\sum w_{j+2i} = \text{constant}$



# Gaussian Pyramid

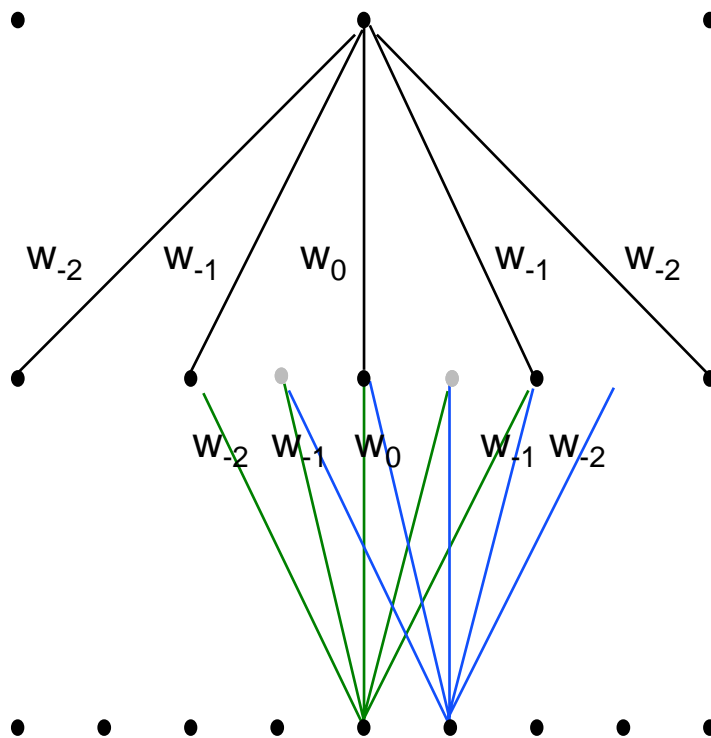
Burt & Adelson (1981)

Normalized:  $\sum w_i = 1$

Symmetry:  $w_i = w_{-i}$

Unimodal:  $w_i \geq w_j$  for  $0 < i < j$

Equal Contribution: for all  $j$   $\sum w_{j+2i} = \text{constant}$



# Gaussian Pyramid

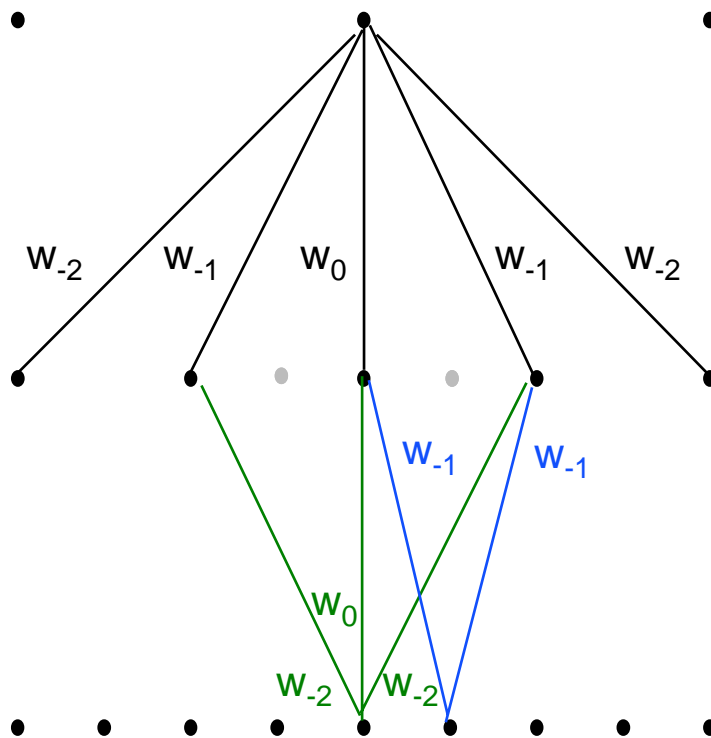
Burt & Adelson (1981)

Normalized:  $\sum w_i = 1$

Symmetry:  $w_i = w_{-i}$

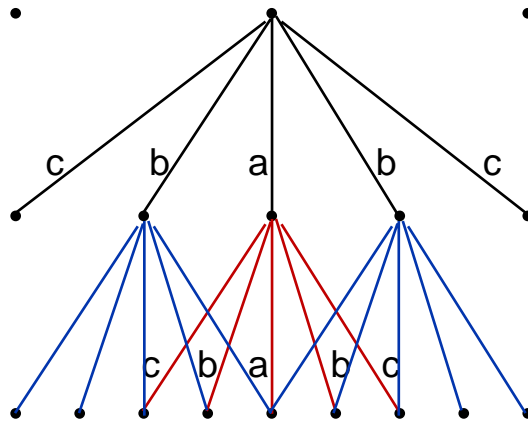
Unimodal:  $w_i \geq w_j$  for  $0 < i < j$

Equal Contribution: for all  $j$   $\sum w_{j+2i} = \text{constant}$



# Gaussian Pyramid

Burt & Adelson (1981)



$$a + 2b + 2c = 1$$

$$a + 2c = 2b$$

$$a > 0.25$$

$$b = 0.25$$

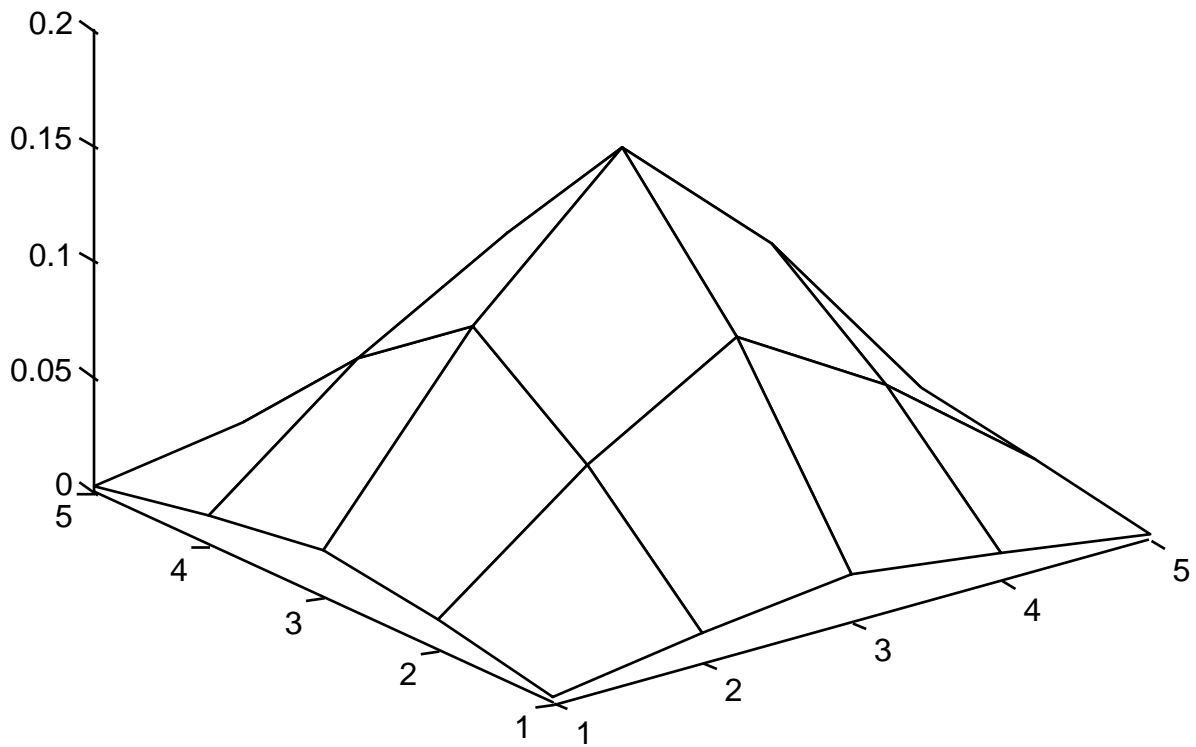
$$c = 0.25 - a/2$$

For  $a = 0.4$  most similar to a Gaussian filter

$$\mathbf{g} = [0.05 \quad 0.25 \quad 0.4 \quad 0.25 \quad 0.05]$$

$$\text{low\_pass\_filter} = \mathbf{g}' * \mathbf{g} =$$

$$\begin{bmatrix} 0.0025 & 0.0125 & 0.0200 & 0.0125 & 0.0025 \\ 0.0125 & 0.0625 & 0.1000 & 0.0625 & 0.0125 \\ 0.0200 & 0.1000 & 0.1600 & 0.1000 & 0.0200 \\ 0.0125 & 0.0625 & 0.1000 & 0.0625 & 0.0125 \\ 0.0025 & 0.0125 & 0.0200 & 0.0125 & 0.0025 \end{bmatrix}$$





# Gaussian Pyramid - Computational Aspects


Memory:

$$2^N \times 2^N (1 + 1/4 + 1/16 + \dots) = 2^N \times 2^N * 4/3$$

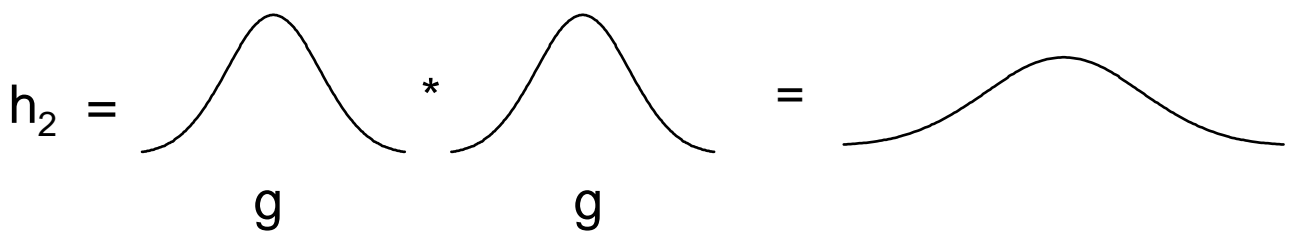
Computation:

Level  $i$  can be computed with a single convolution

with filter:  $h_i = g * g * g * \dots$

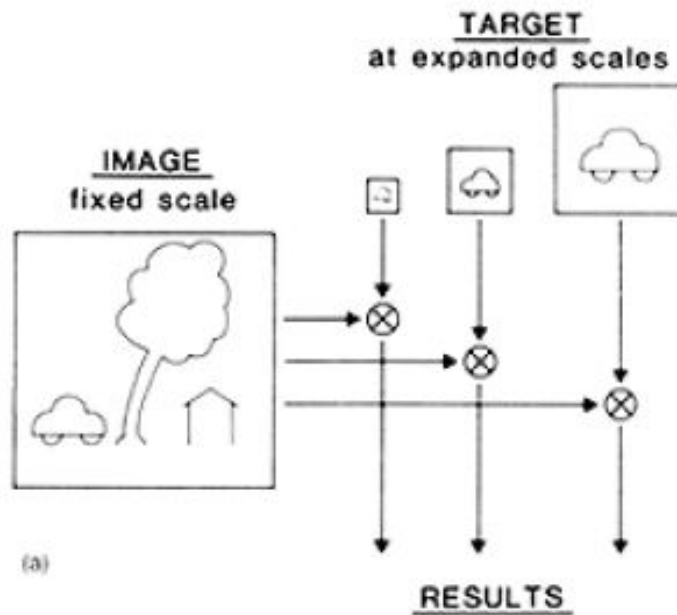
  
i times

Example:

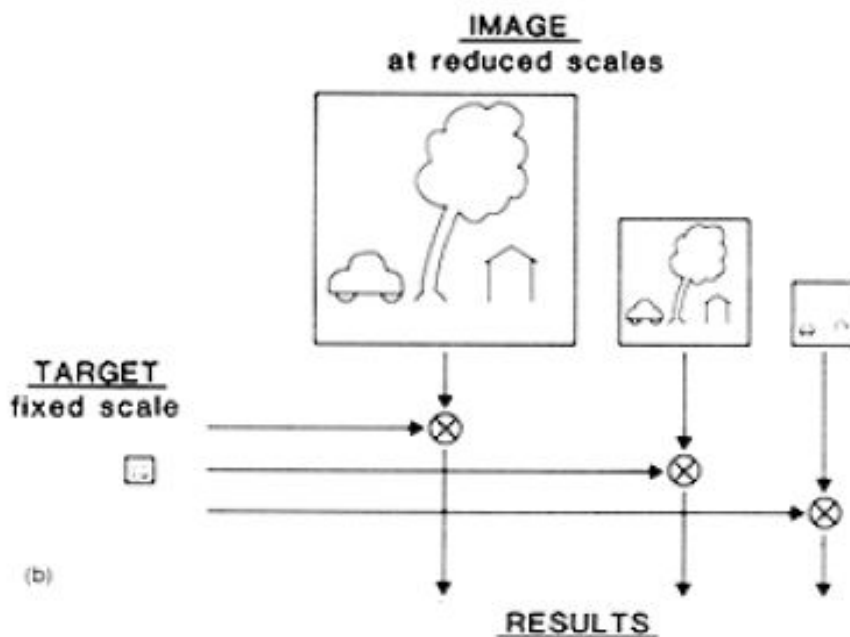
$$h_2 = \underbrace{g * g}_{g * g} = \text{wider Gaussian}$$


# MultiScale Pattern Matching

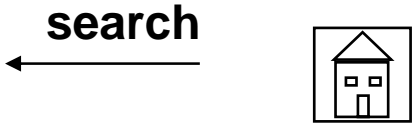
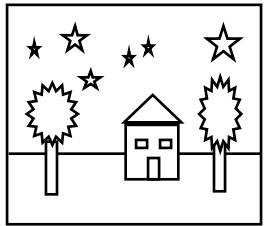
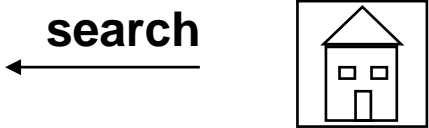
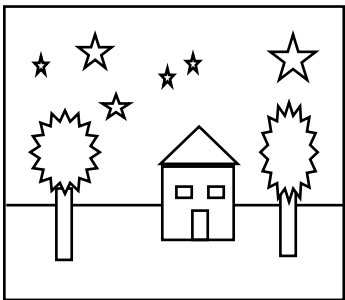
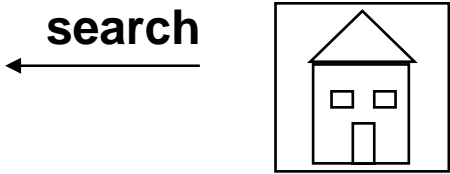
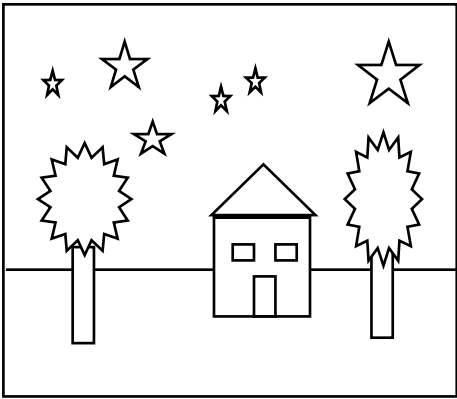
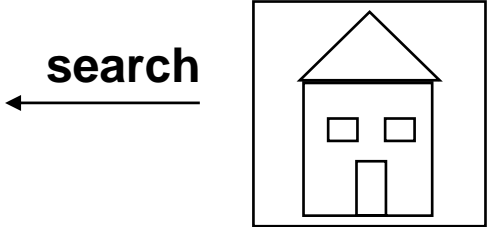
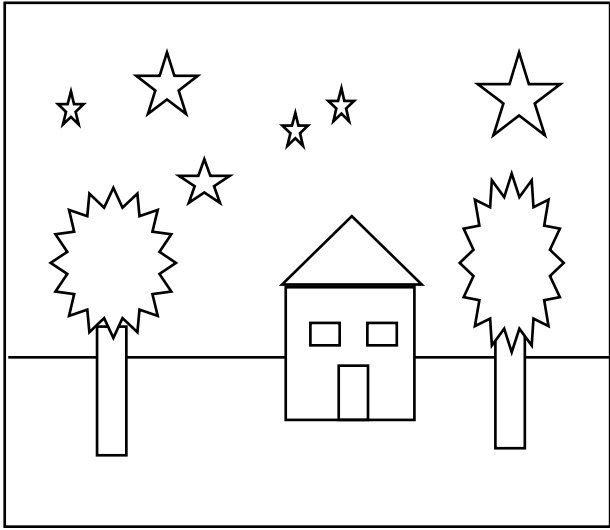
Option 1:  
Scale target and search for each in image.



Option 2:  
Search for original target in image pyramid.

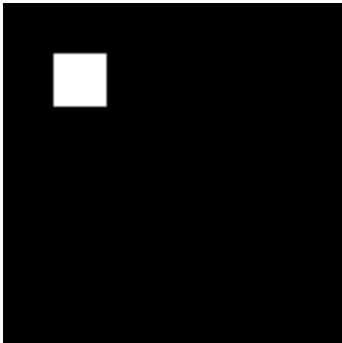


# Hierarchical Pattern Matching

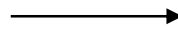


# Pattern matching using Pyramids - Example

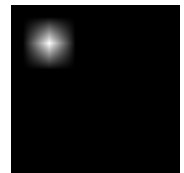
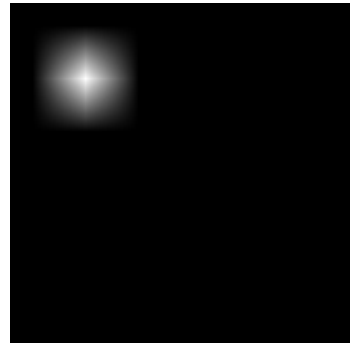
image



pattern



correlation



# Image pyramids

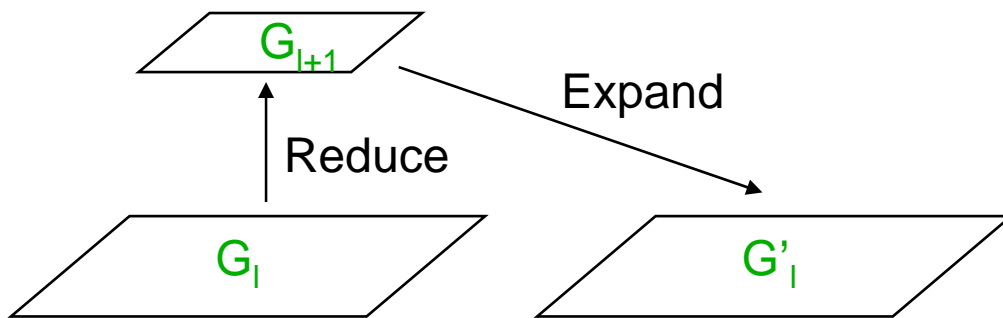
- Gaussian Pyramids
- **Laplacian Pyramids**
- Wavelet/QMF

## Laplacian Pyramid

Motivation = Compression, redundancy removal.  
compression rates are higher for predictable values.  
e.g. values around 0.

$G_0, G_1, \dots$  = the levels of a Gaussian Pyramid.

Predict level  $G_l$  from level  $G_{l+1}$  by **Expanding**  $G_{l+1}$  to  $G'_l$



Denote by  $L_l$  the error in prediction:

$$L_l = G_l - G'_l$$

$L_0, L_1, \dots$  = the levels of a **Laplacian Pyramid**.

What does blurring take away?



original

What does blurring take away?



smoothed (5x5 Gaussian)



What does blurring take away?

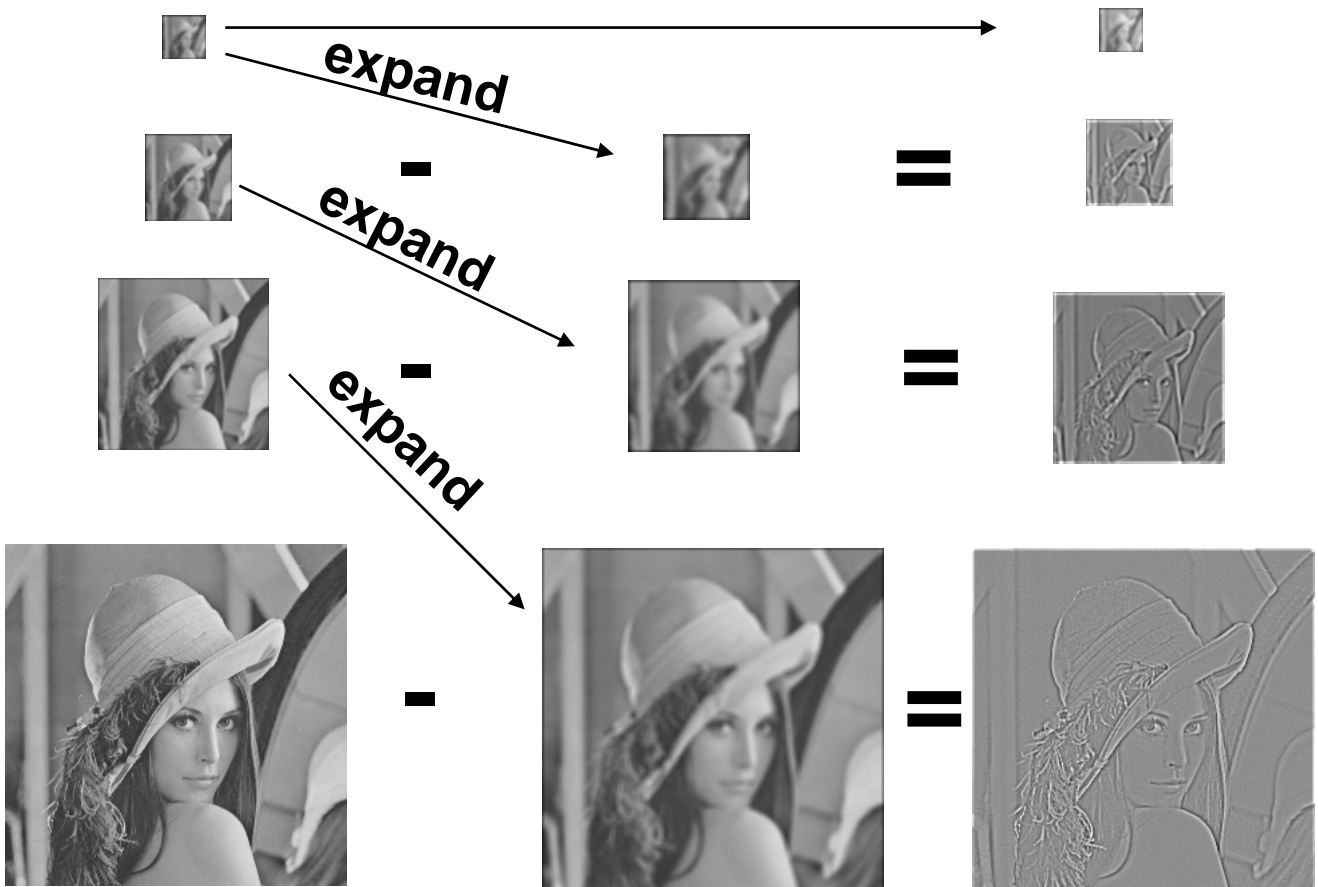


smoothed – original

# Laplacian Pyramid

**Gaussian Pyramid**

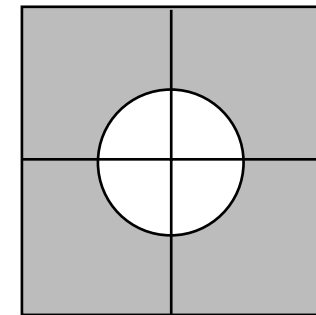
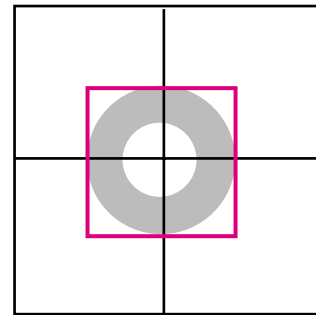
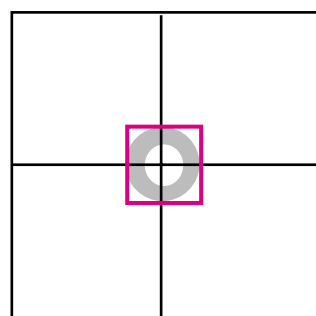
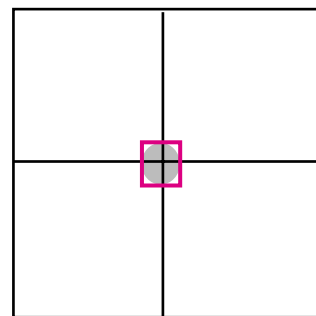
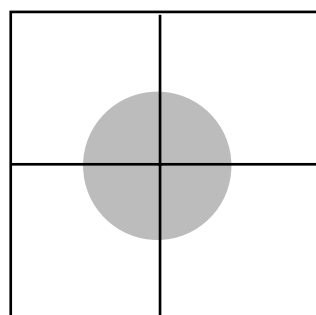
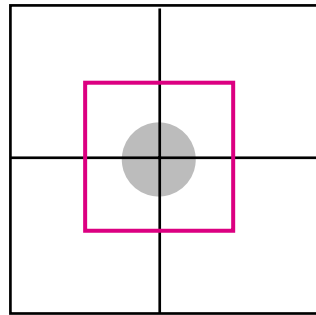
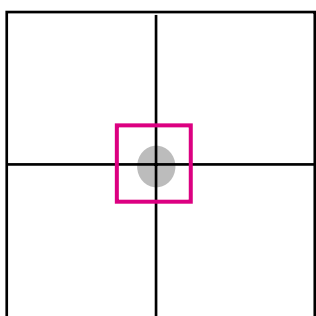
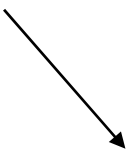
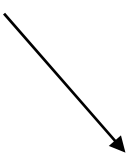
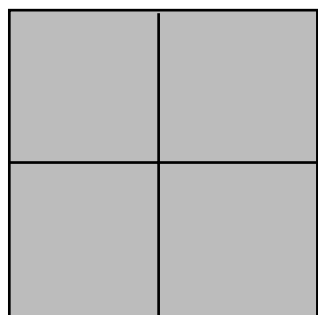
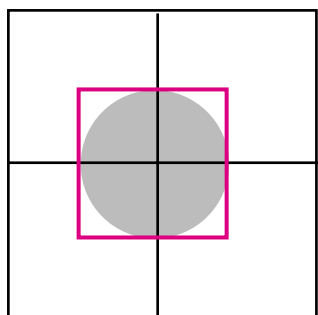
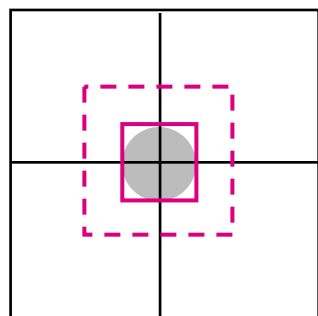
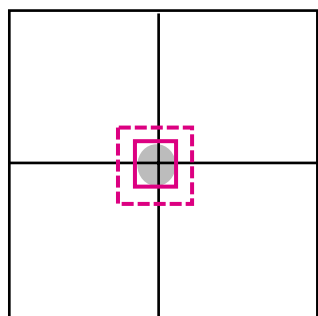
**Laplacian Pyramid**



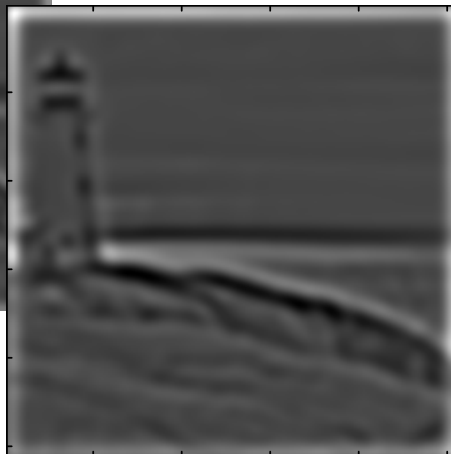
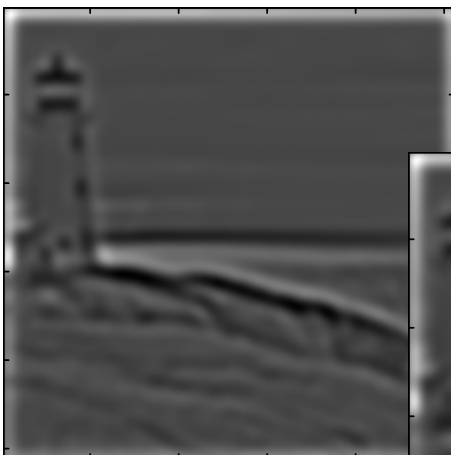
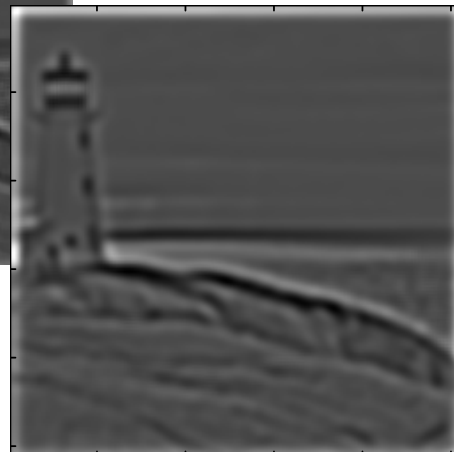
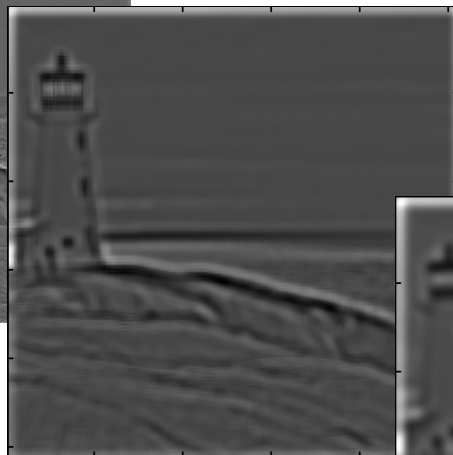
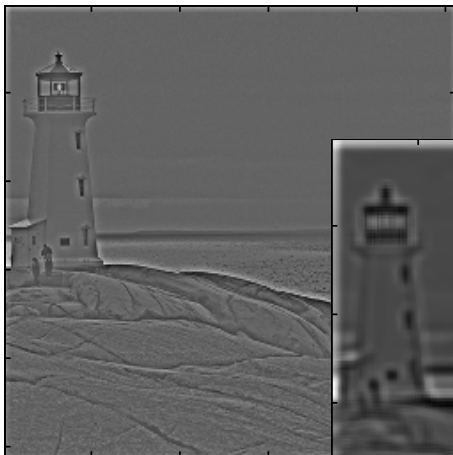
# Gaussian Pyramid

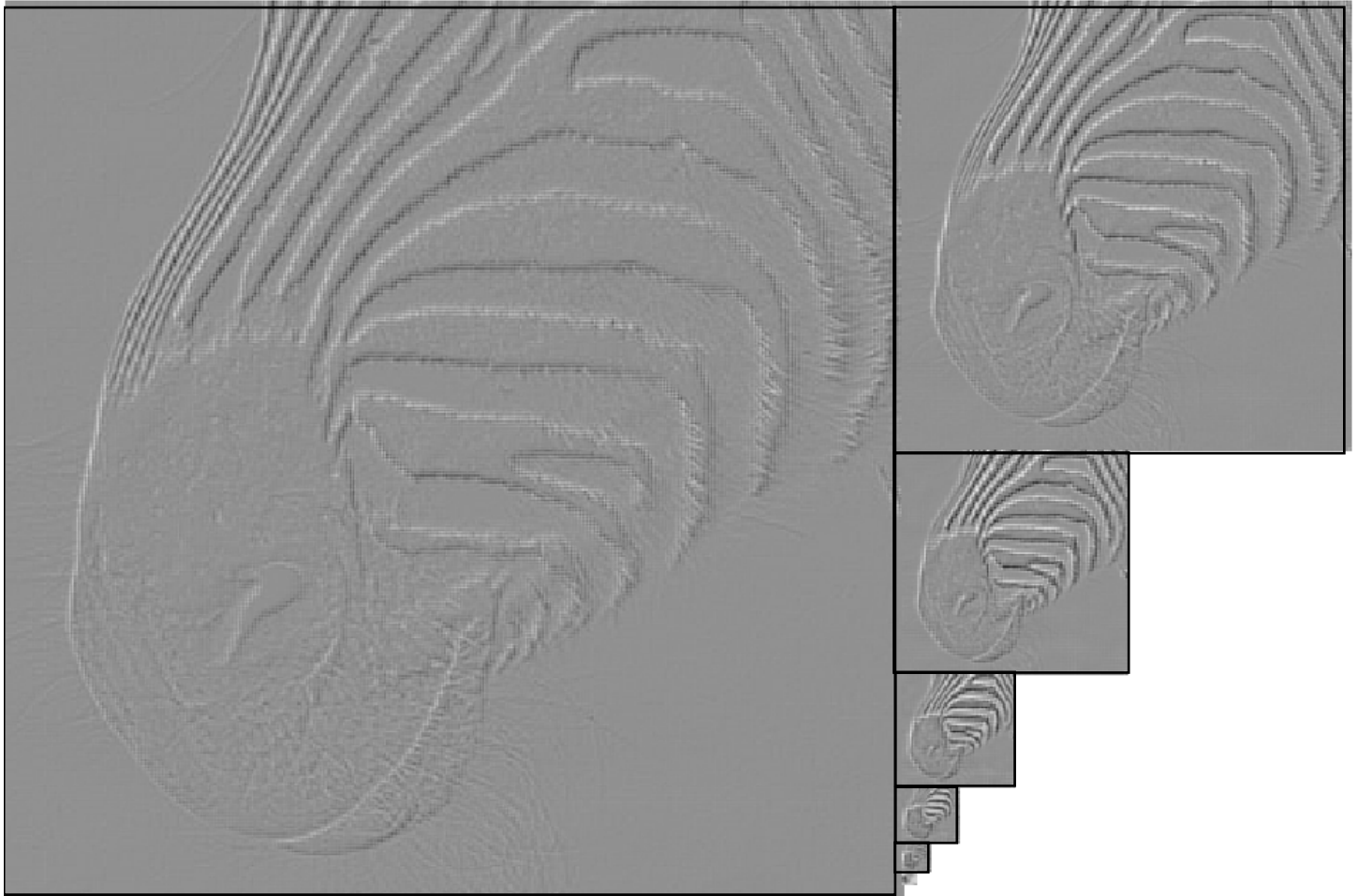
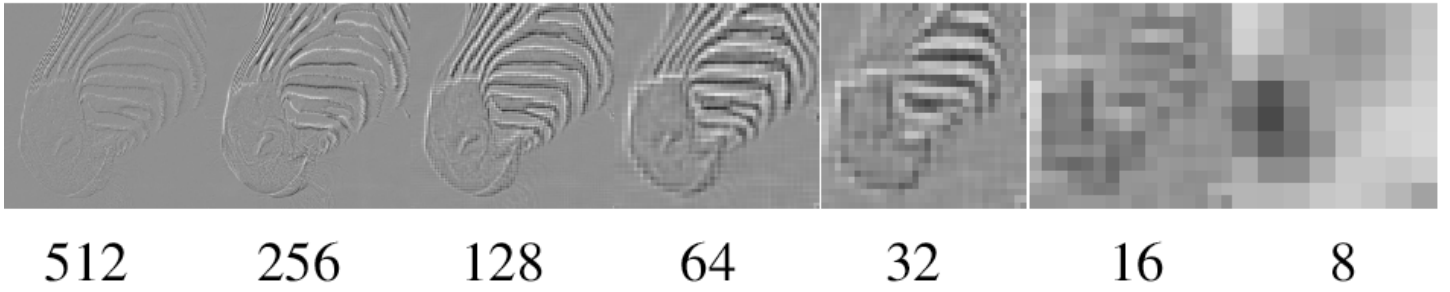
# Frequency Domain

# Laplacian Pyramid



Laplace Pyramid -  
No scaling



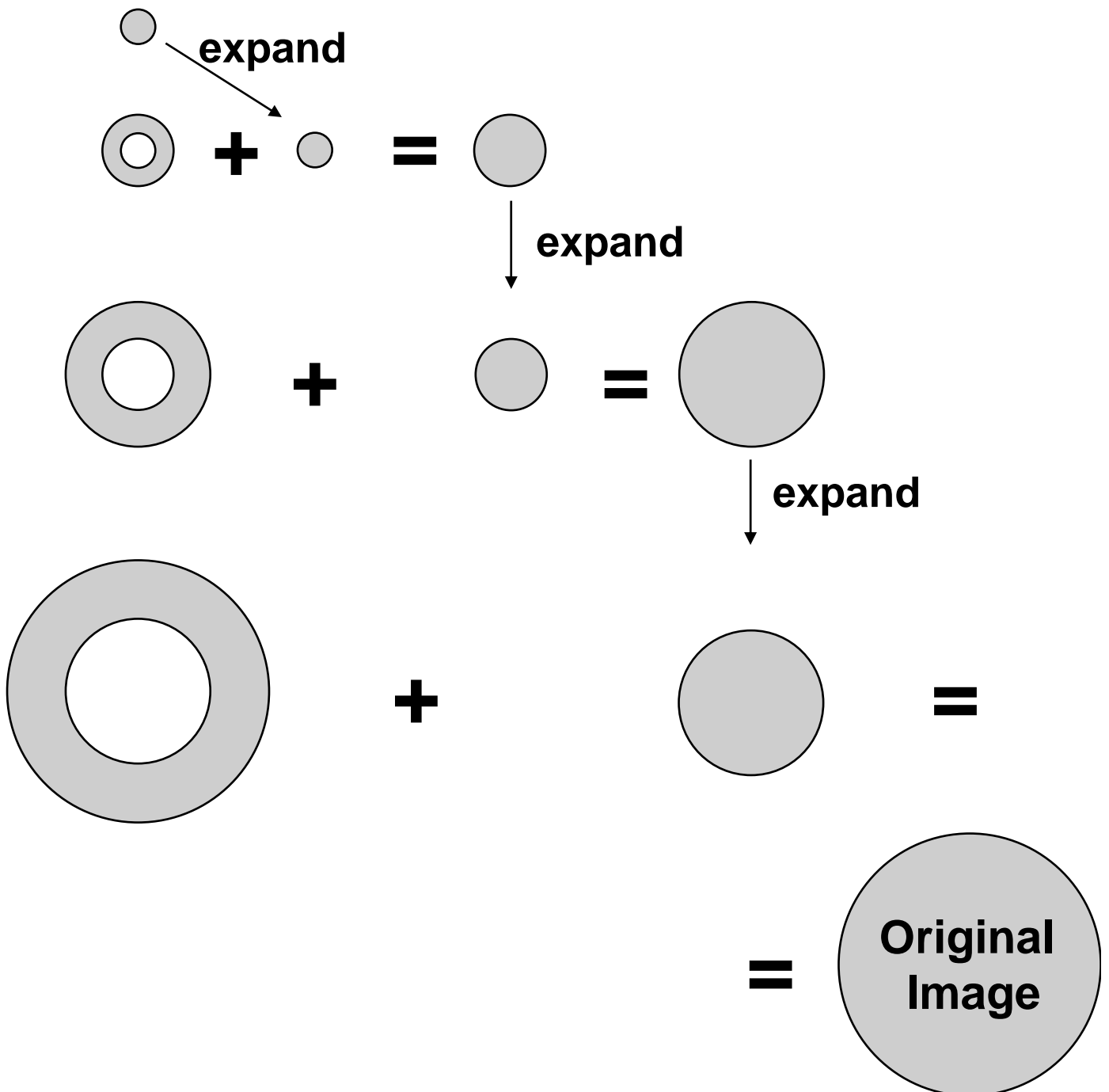


from: B.Freeman

# Reconstruction of the original image from the Laplacian Pyramid

Laplacian Pyramid

$$G_l = L_l + G'_l$$



# Laplacian Pyramid - Computational Aspects

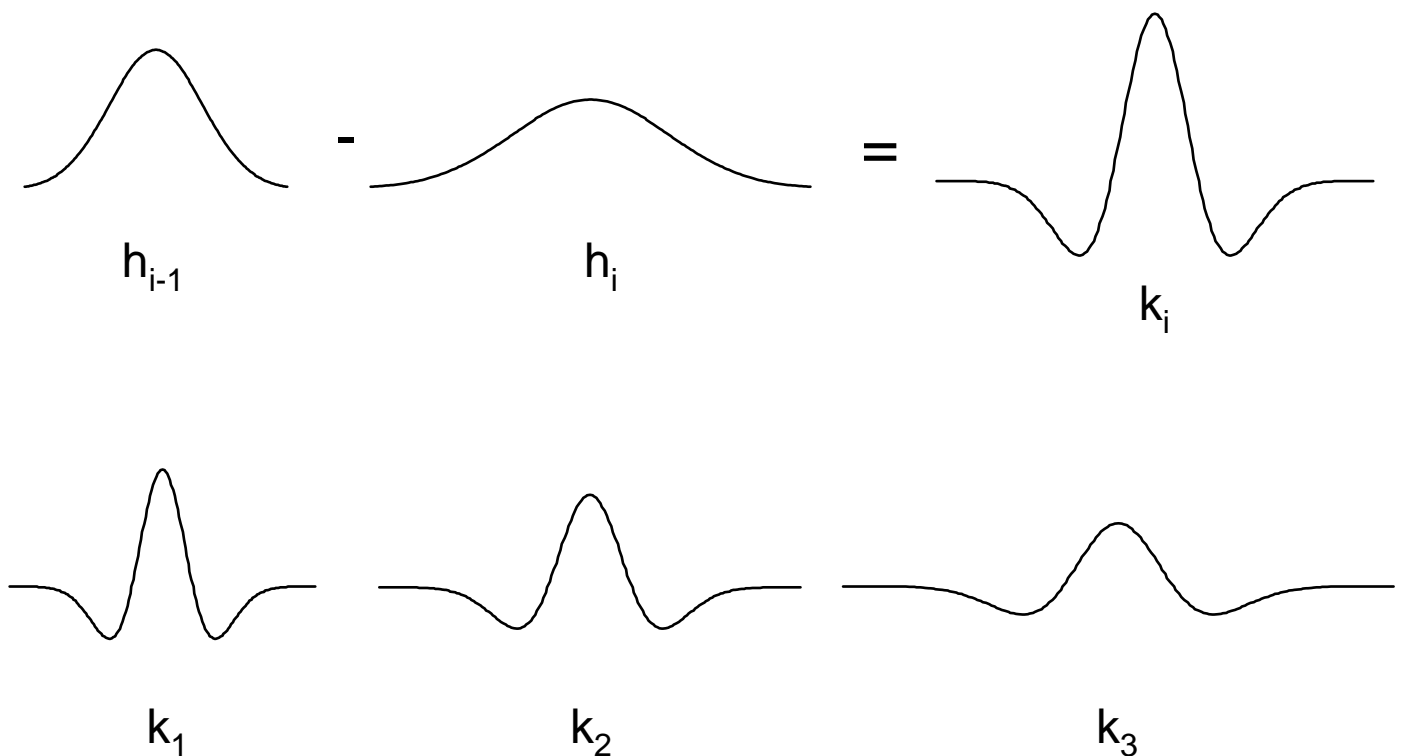
## Memory:

$$2^N \times 2^N (1 + 1/4 + 1/16 + \dots) = 2^N \times 2^N * 4/3$$

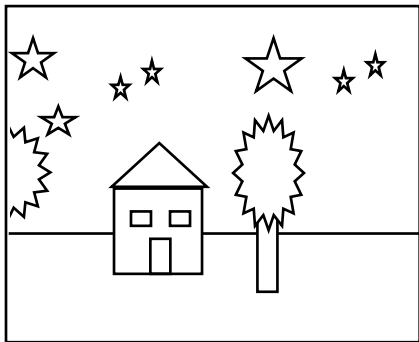
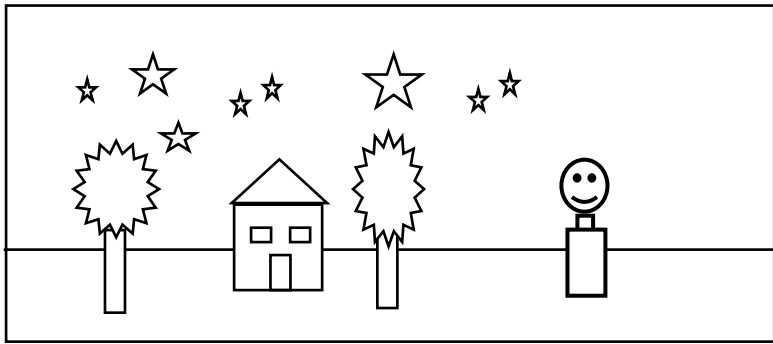
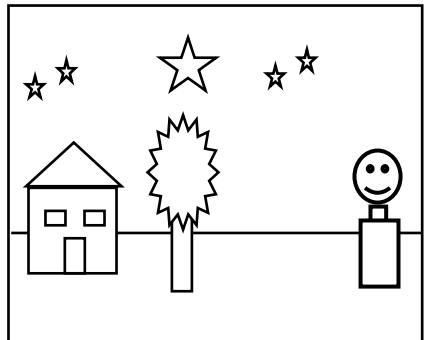
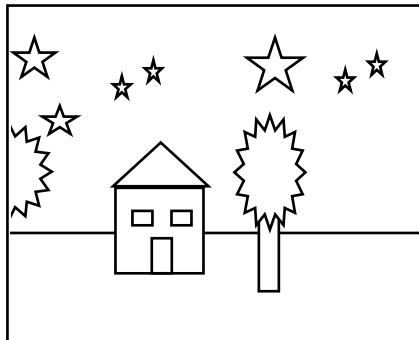
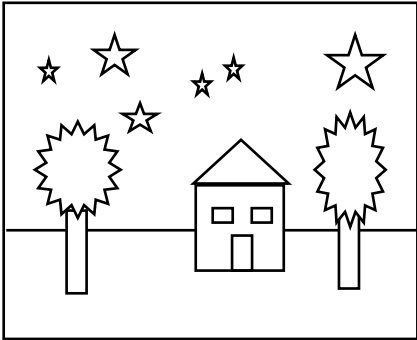
However coefficients are highly compressible.

## Computation:

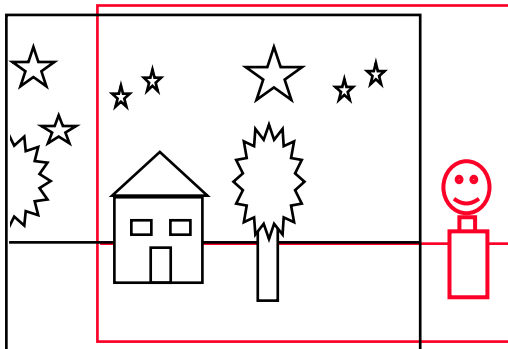
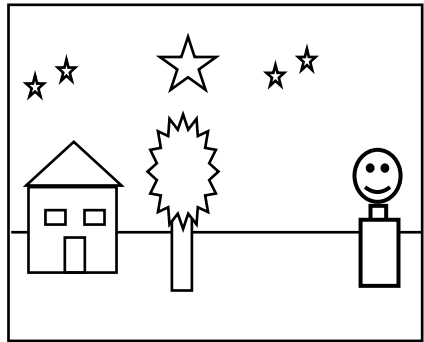
$L_i$  can be computed from  $G_0$  with a single convolution with filter:  $k_i = h_{i-1} - h_i$



# Image Mosaicing

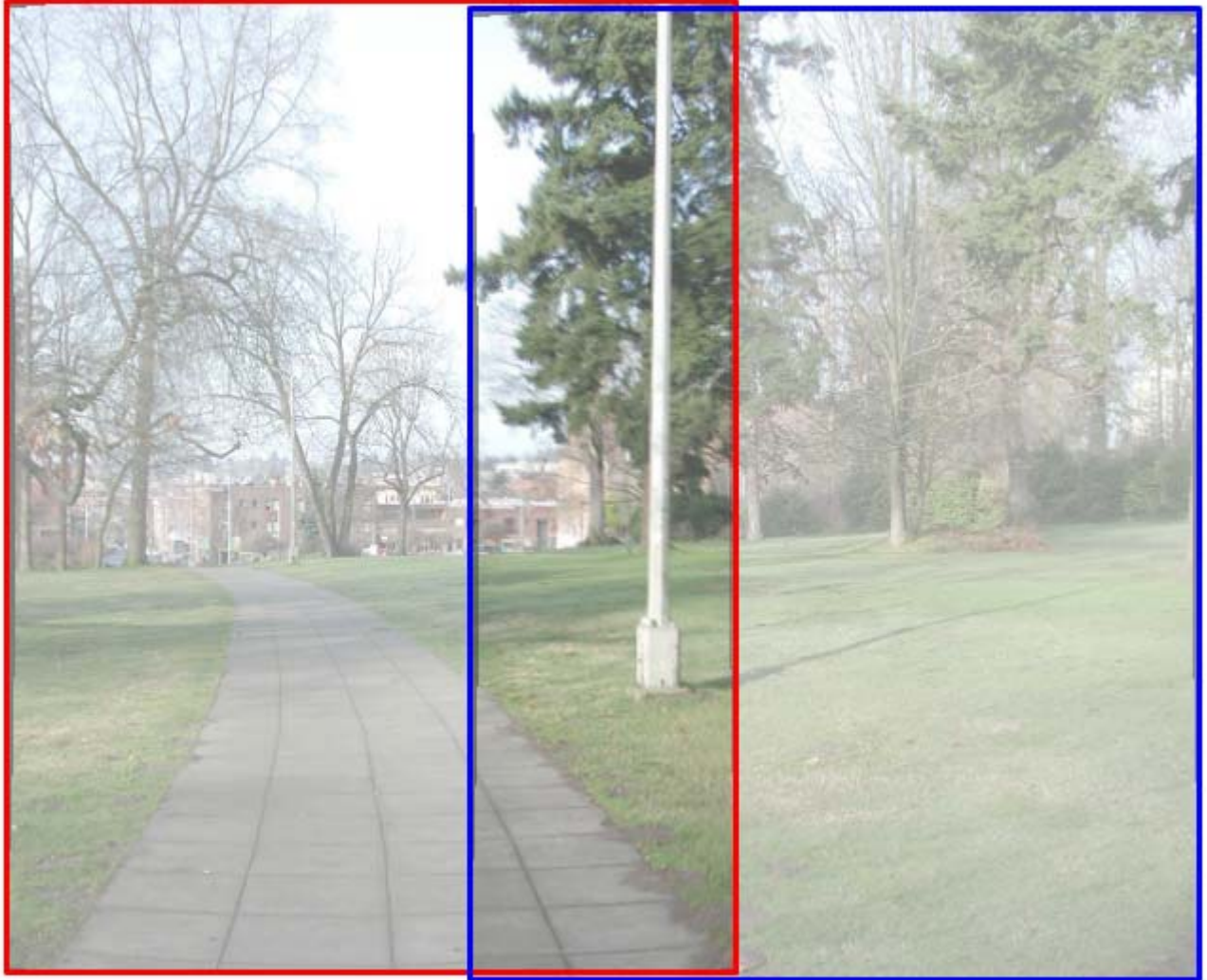


Registration





# Image Blending

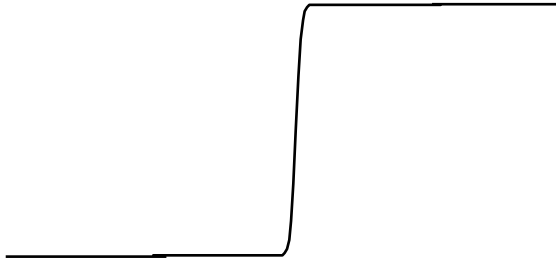


# Blending

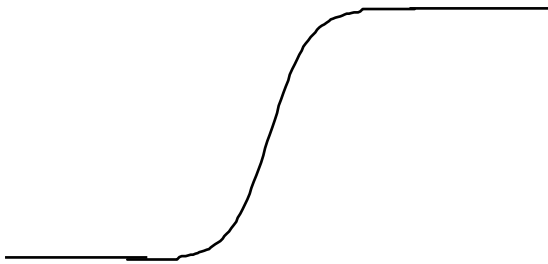


# Multiresolution Spline

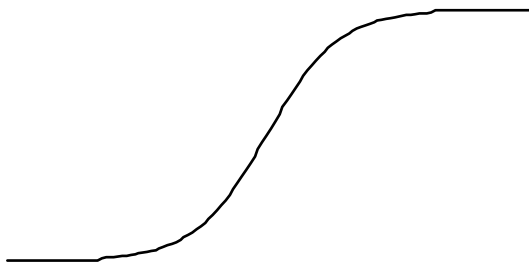
When splining two images, transition from one image to the other should behave:



High Frequencies

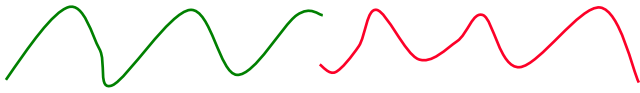


Middle Frequencies

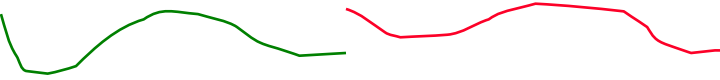
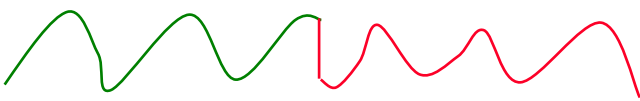


Low Frequencies

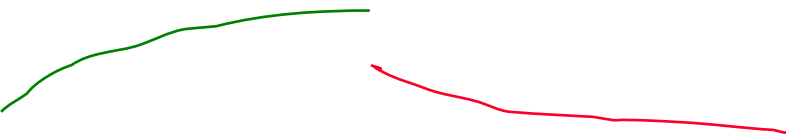
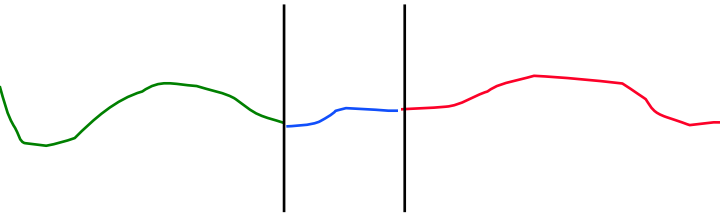
# Multiresolution Spline



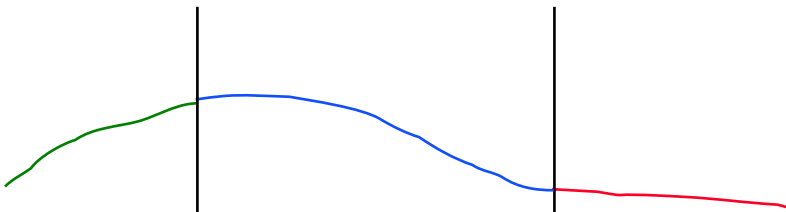
High Frequencies



Middle Frequencies

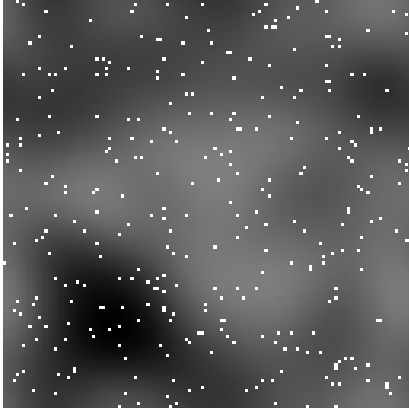


Low Frequencies

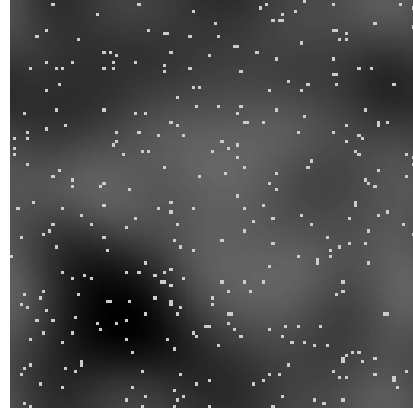


# Multiresolution Spline - Example

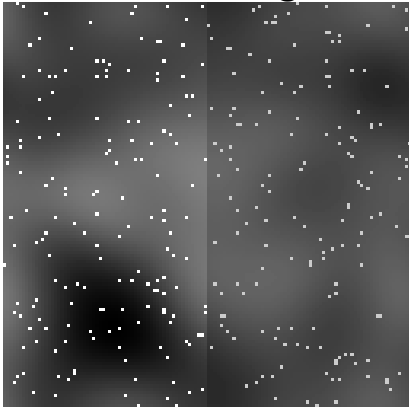
Left Image



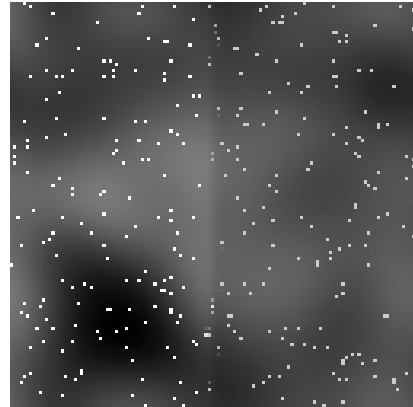
Right Image



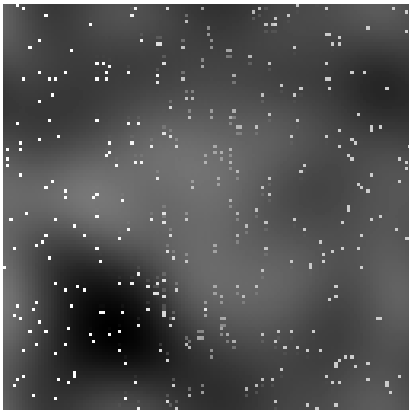
Left + Right



Narrow Transition

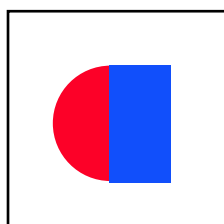
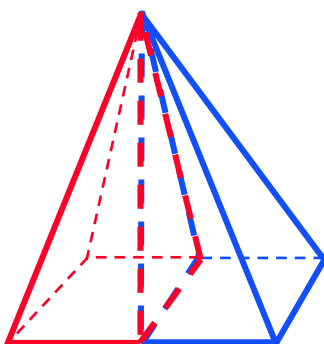
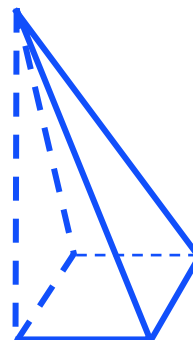
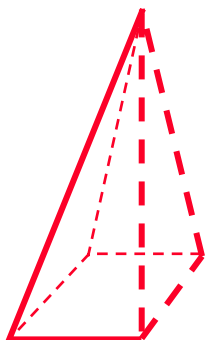
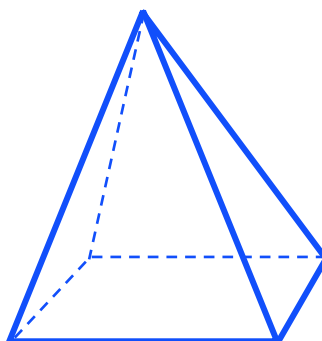
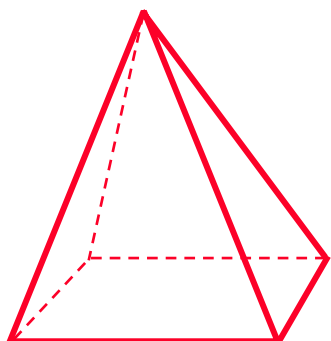
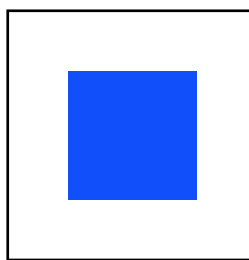
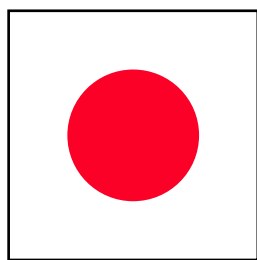


Wide Transition



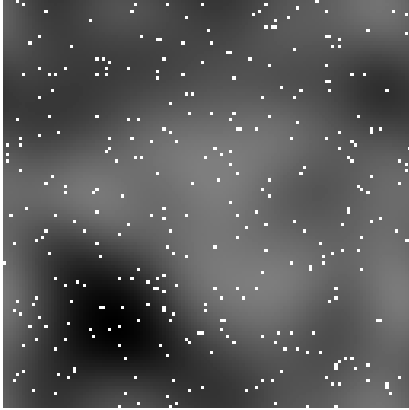
(Burt & Adelson)

# Multiresolution Spline - Using Laplacian Pyramid

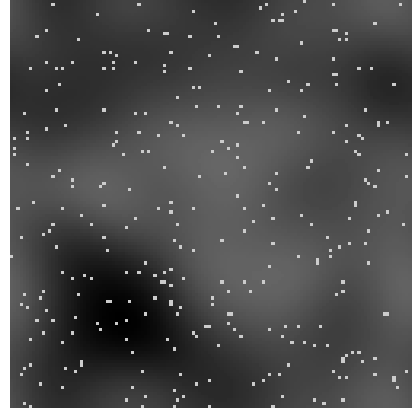


# Multiresolution Spline - Example

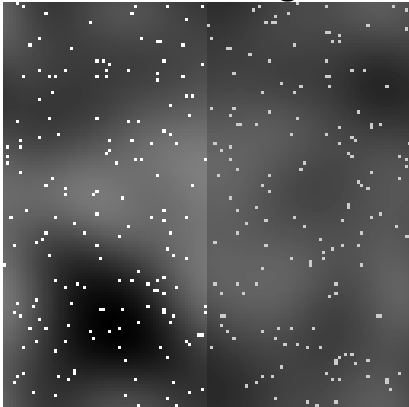
Left Image



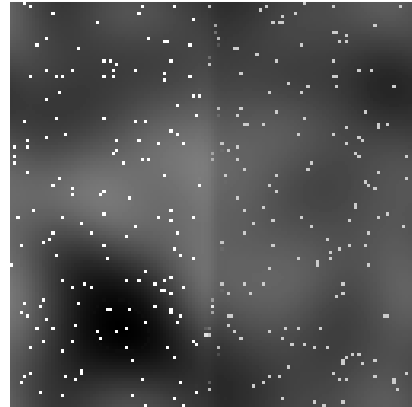
Right Image



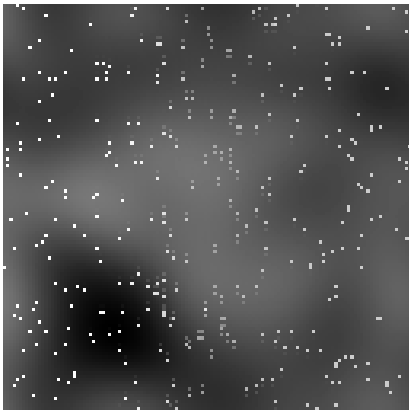
Left + Right



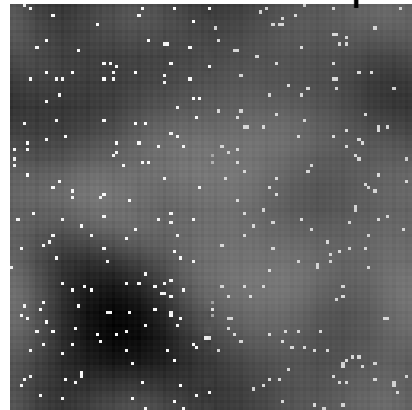
Narrow Transition



Wide Transition



Multiresolution Spline

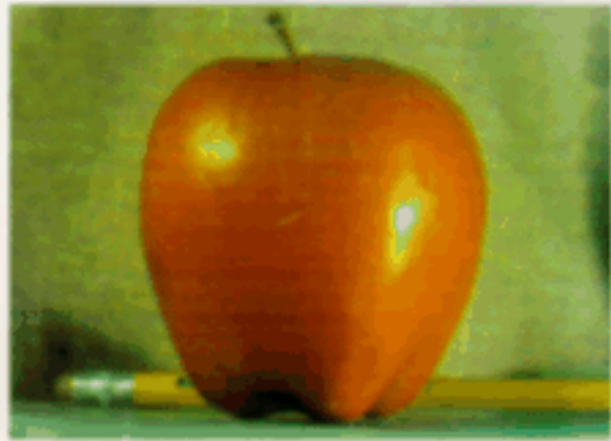


(Burt & Adelson)

## Multiresolution Spline - Example

Original - Left

Original - Right



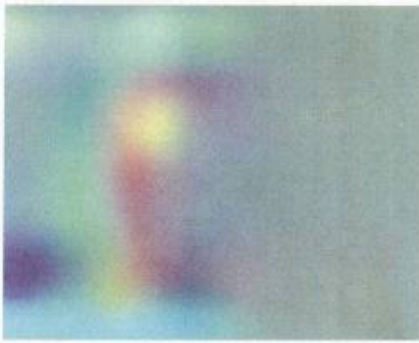
Glued



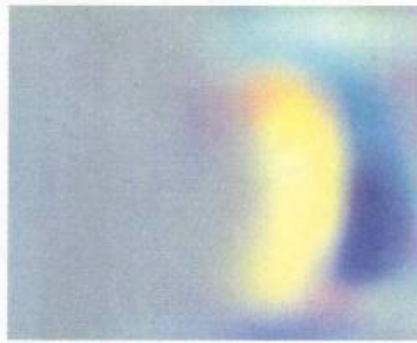
Splined



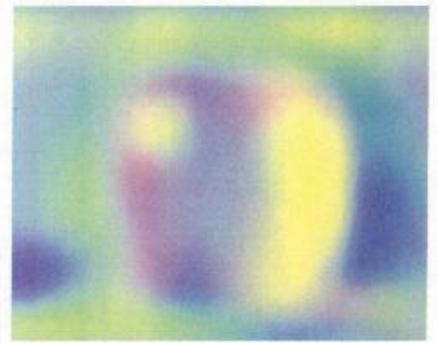
laplacian level 4



(c)

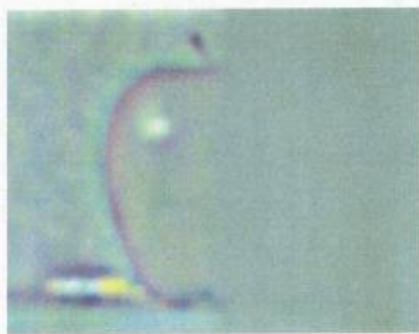


(g)

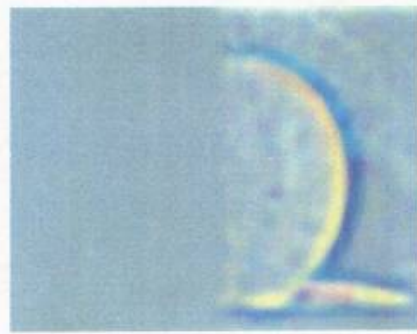


(k)

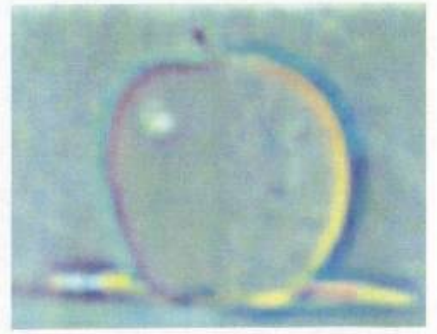
laplacian level 2



(b)

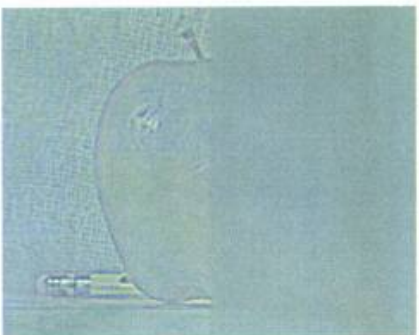


(f)

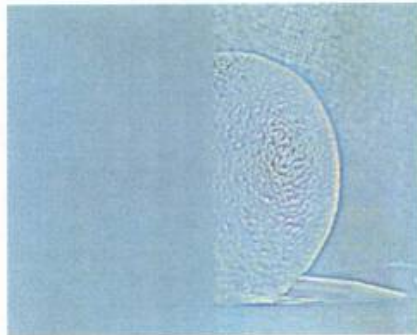


(j)

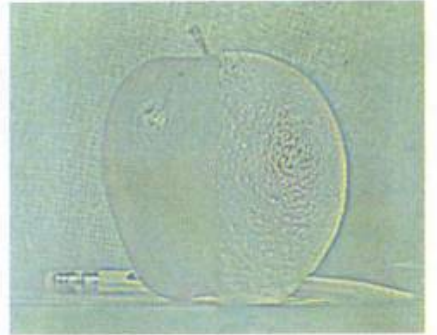
laplacian level 0



(a)



(e)



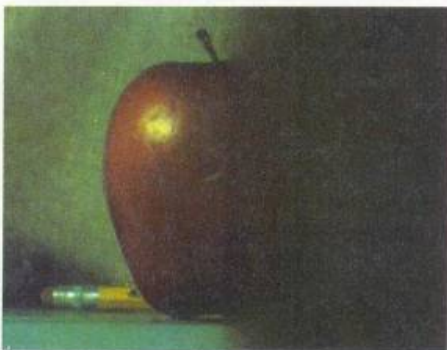
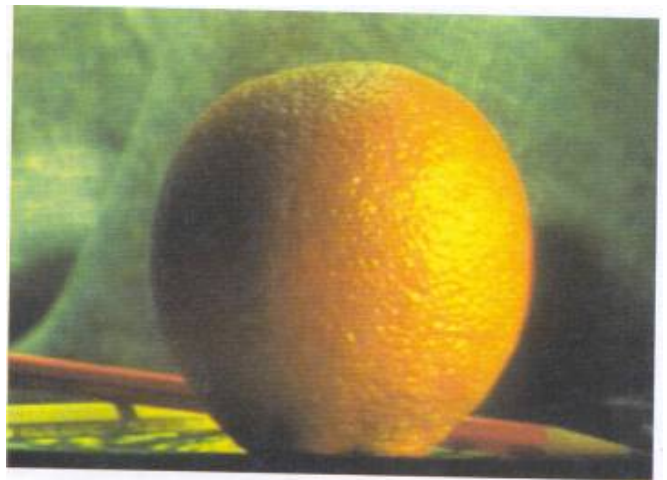
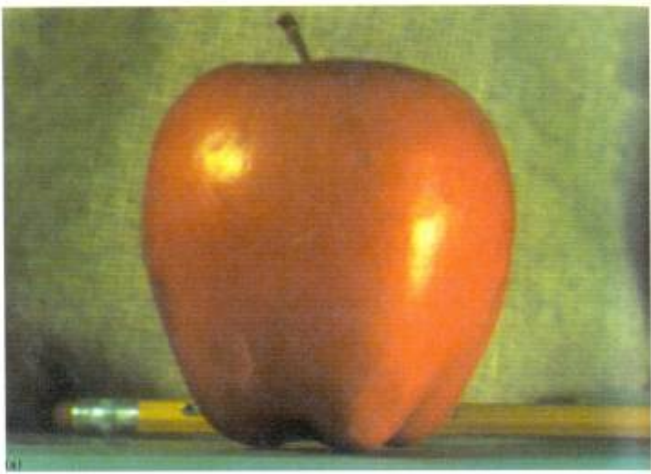
(i)

left pyramid

right pyramid

blended pyramid

# Multiresolution Spline



(d)

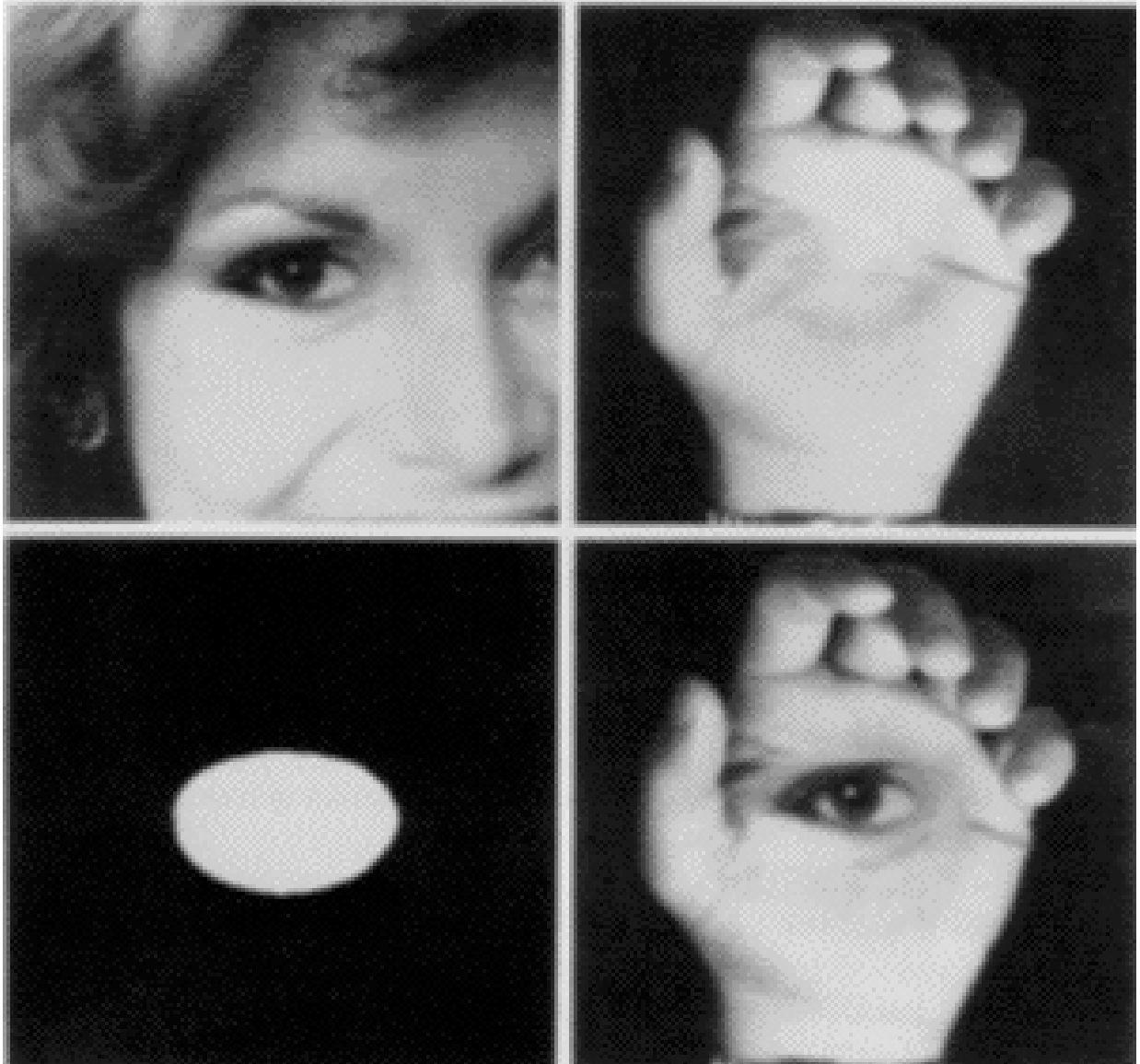


(h)

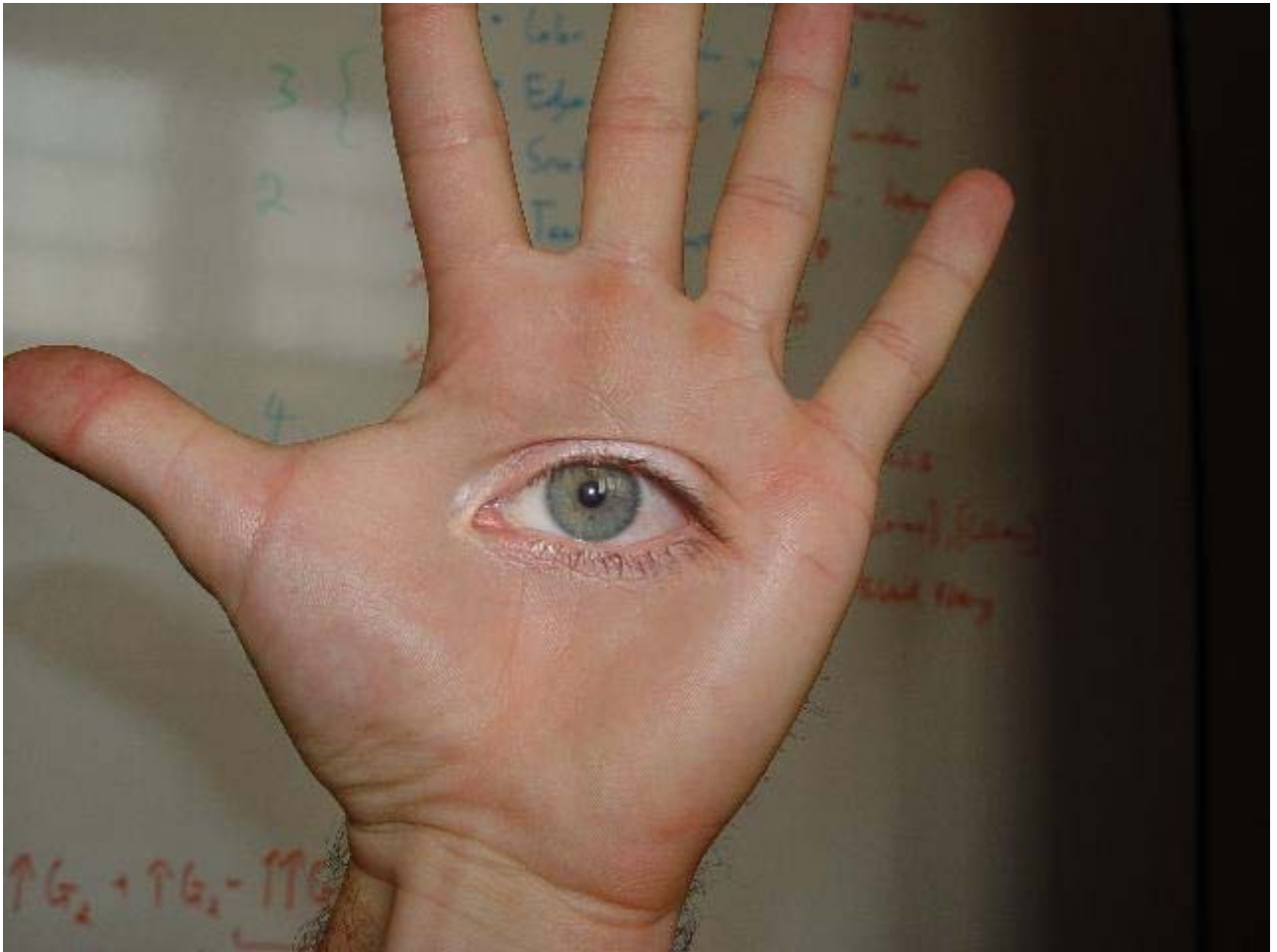


(l)

## Multiresolution Spline - Example



# Multi-Res. Blending



© prof. dmartin

# Image pyramids

- Gaussian Pyramids
- Laplacian Pyramids
- **Wavelet/QMF**

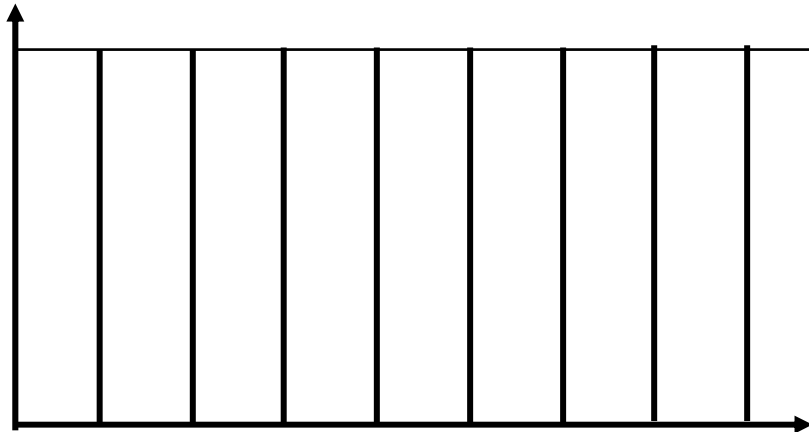
# What is a good representation for image analysis?

- Pixel domain representation tells you “where” (pixel location), but not “what”.
  - In space, this representation is too localized
- Fourier transform domain tells you “what” (textural properties), but not “where”.
  - In space, this representation is too spread out.
- Want an image representation that gives you a local description of image events—what is happening where.
  - That representation might be “just right”.

# Space-Frequency Tiling

Freq.

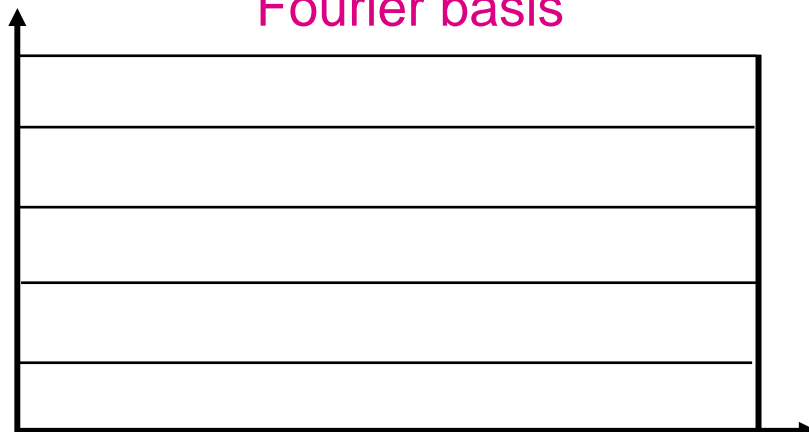
Standard basis



Spatial

Freq.

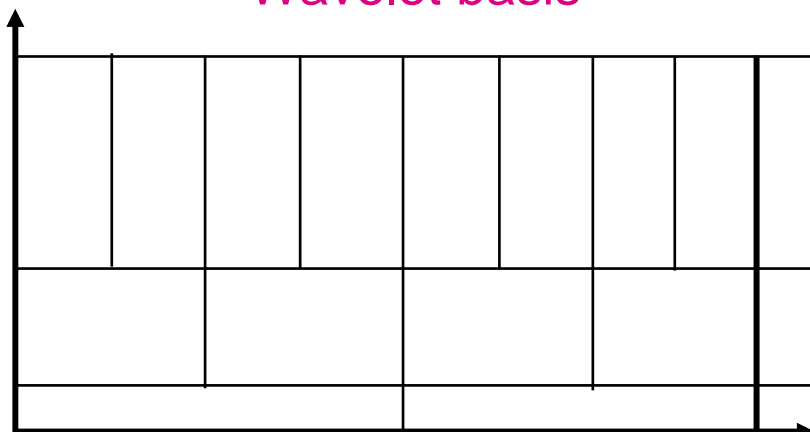
Fourier basis



Spatial

Freq.

Wavelet basis

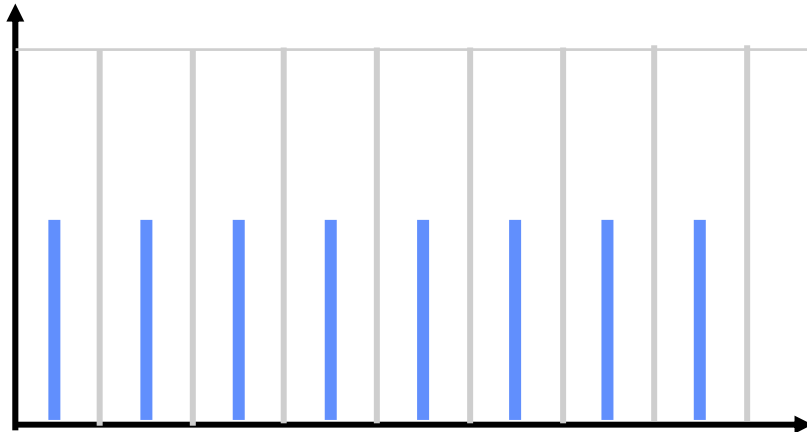


Spatial

# Space-Frequency Tiling

Freq.

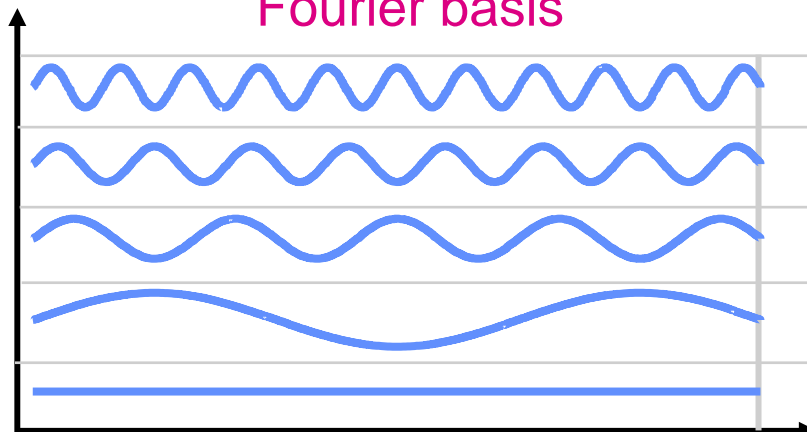
Standard basis



Spatial

Freq.

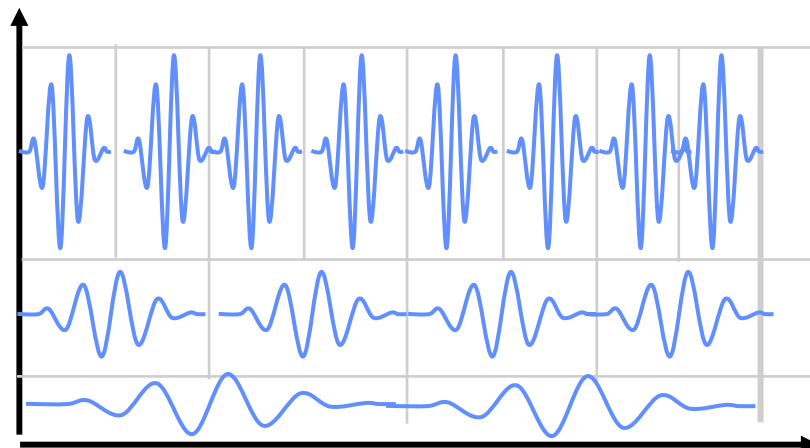
Fourier basis



Spatial

Freq.

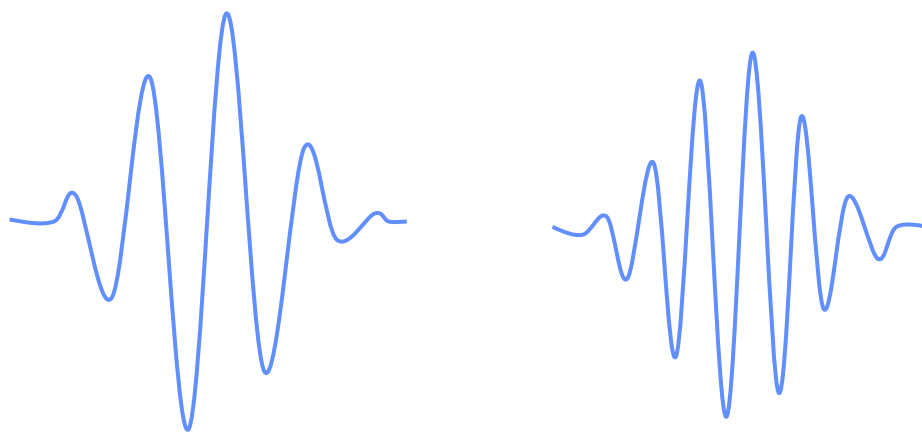
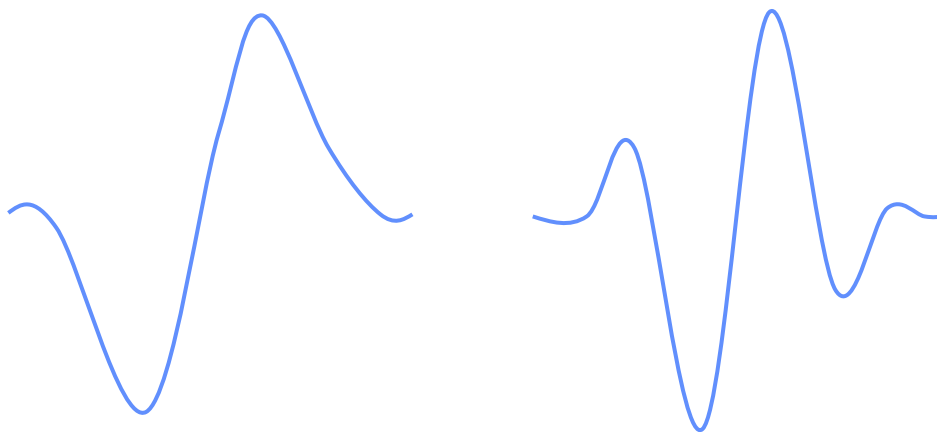
Wavelet basis



Spatial

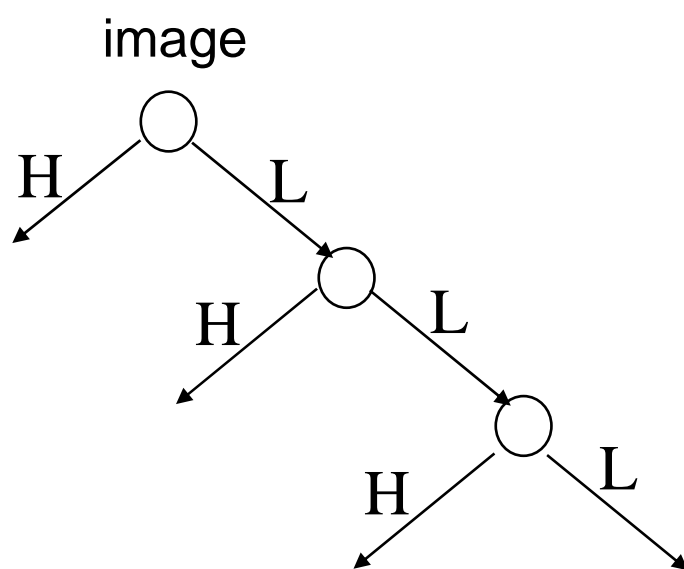


# Various Wavelet basis



# Wavelet - Frequency domain

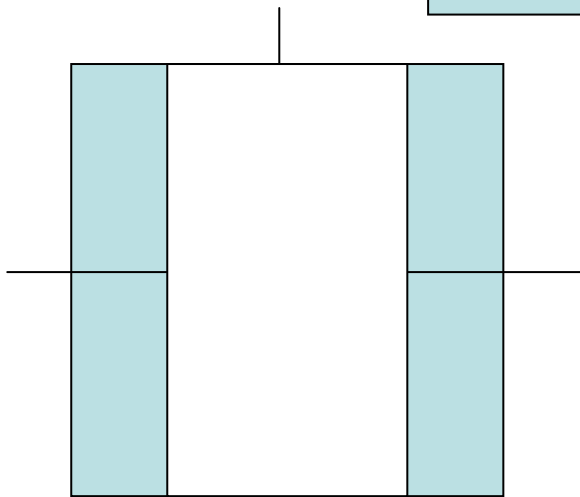
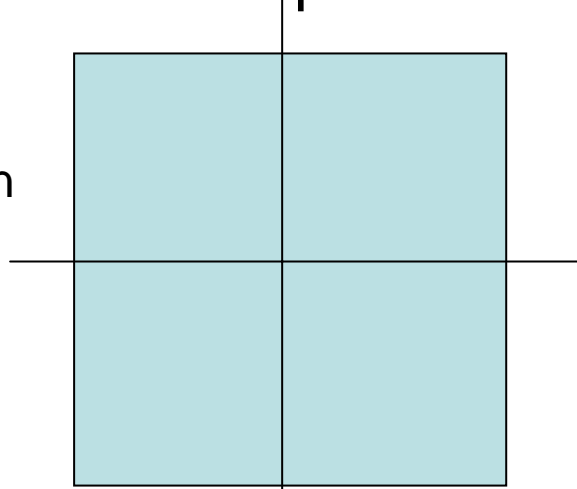
Wavelet bands are split recursively



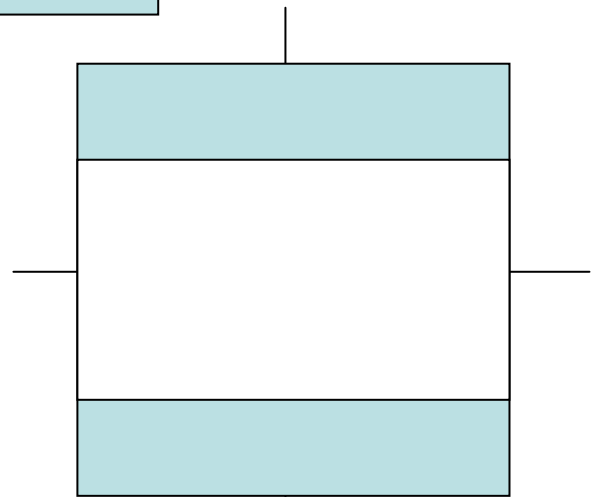
# Wavelet - Frequency domain

## Wavelet decomposition - 2D

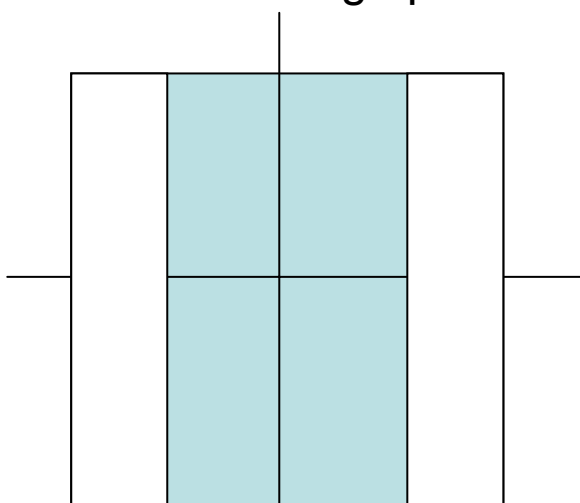
Frequency domain



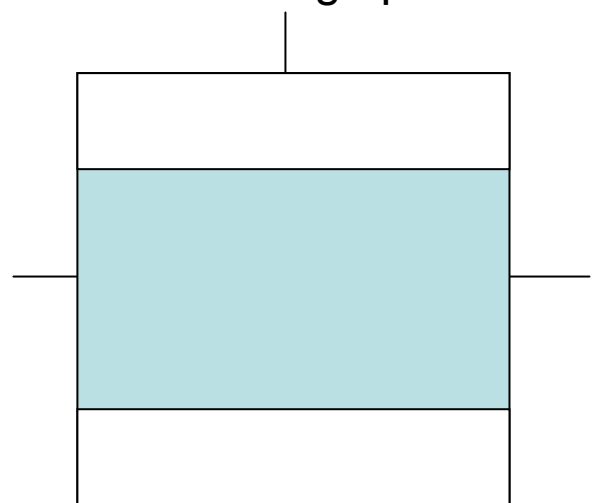
Horizontal high pass



Vertical high pass



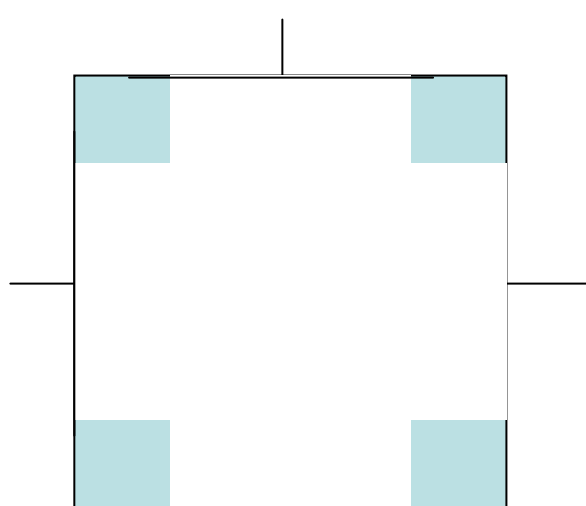
Horizontal low pass



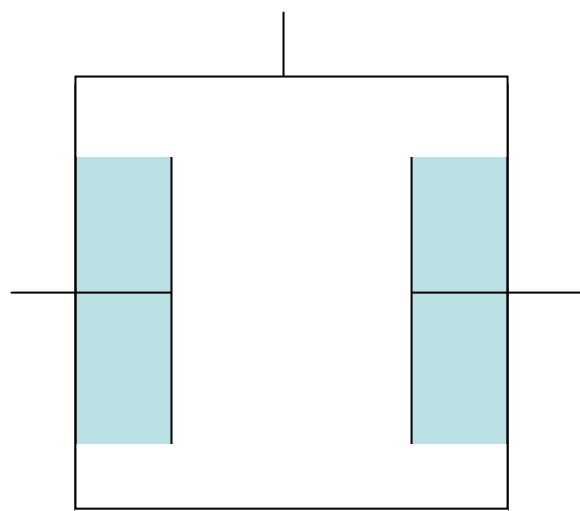
Vertical low pass

# Wavelet - Frequency domain

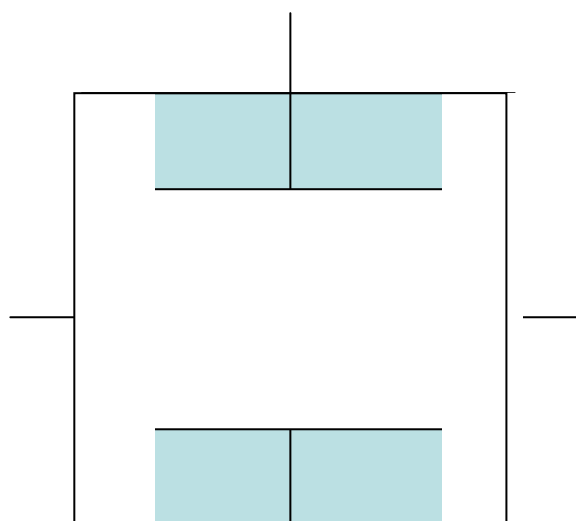
Apply the wavelet transform separably in both dimensions



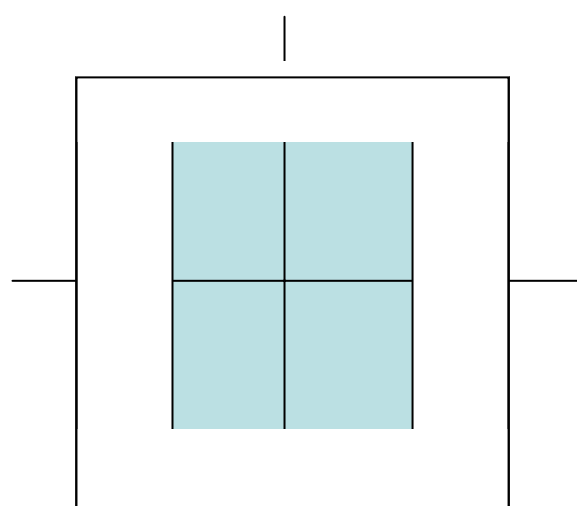
Horizontal high pass,  
vertical high pass



Horizontal high pass,  
vertical low-pass

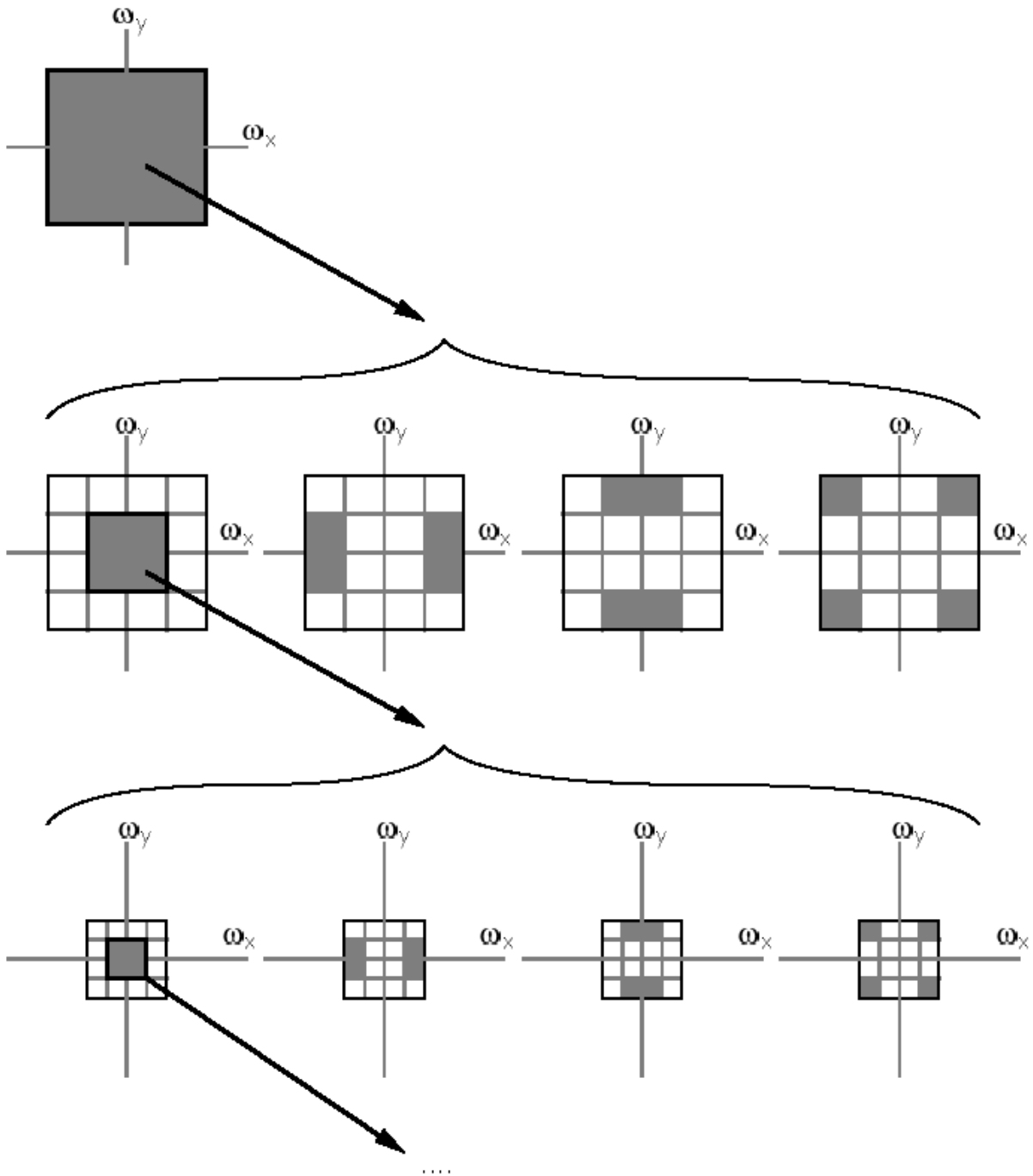


Horizontal low pass,  
vertical high-pass



Horizontal low pass,  
Vertical low-pass

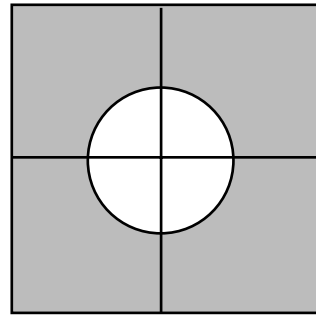
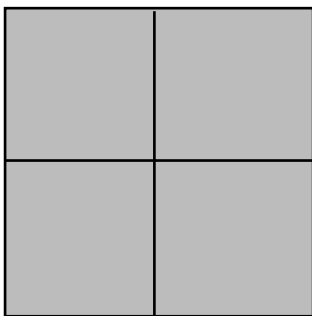
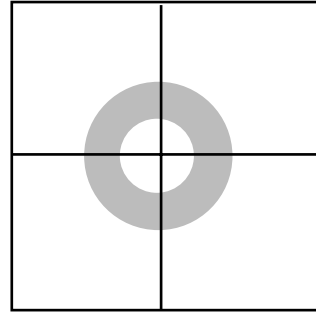
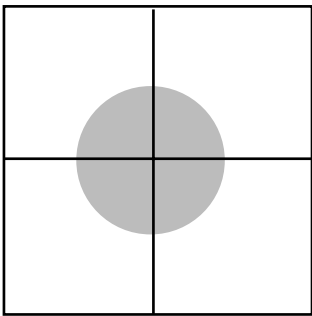
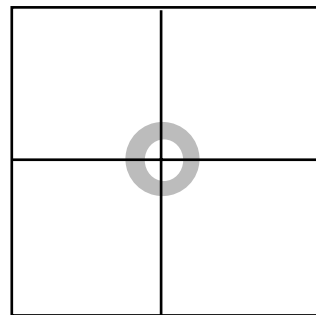
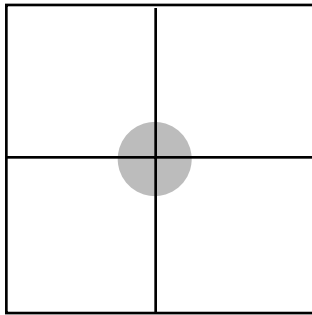
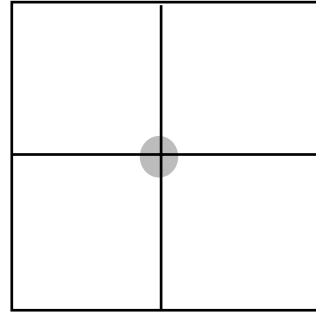
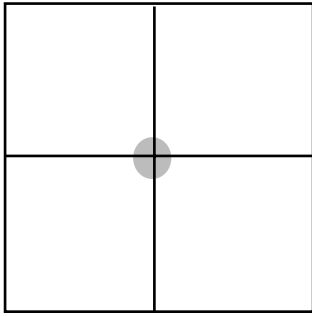
- Splitting can be applied recursively:



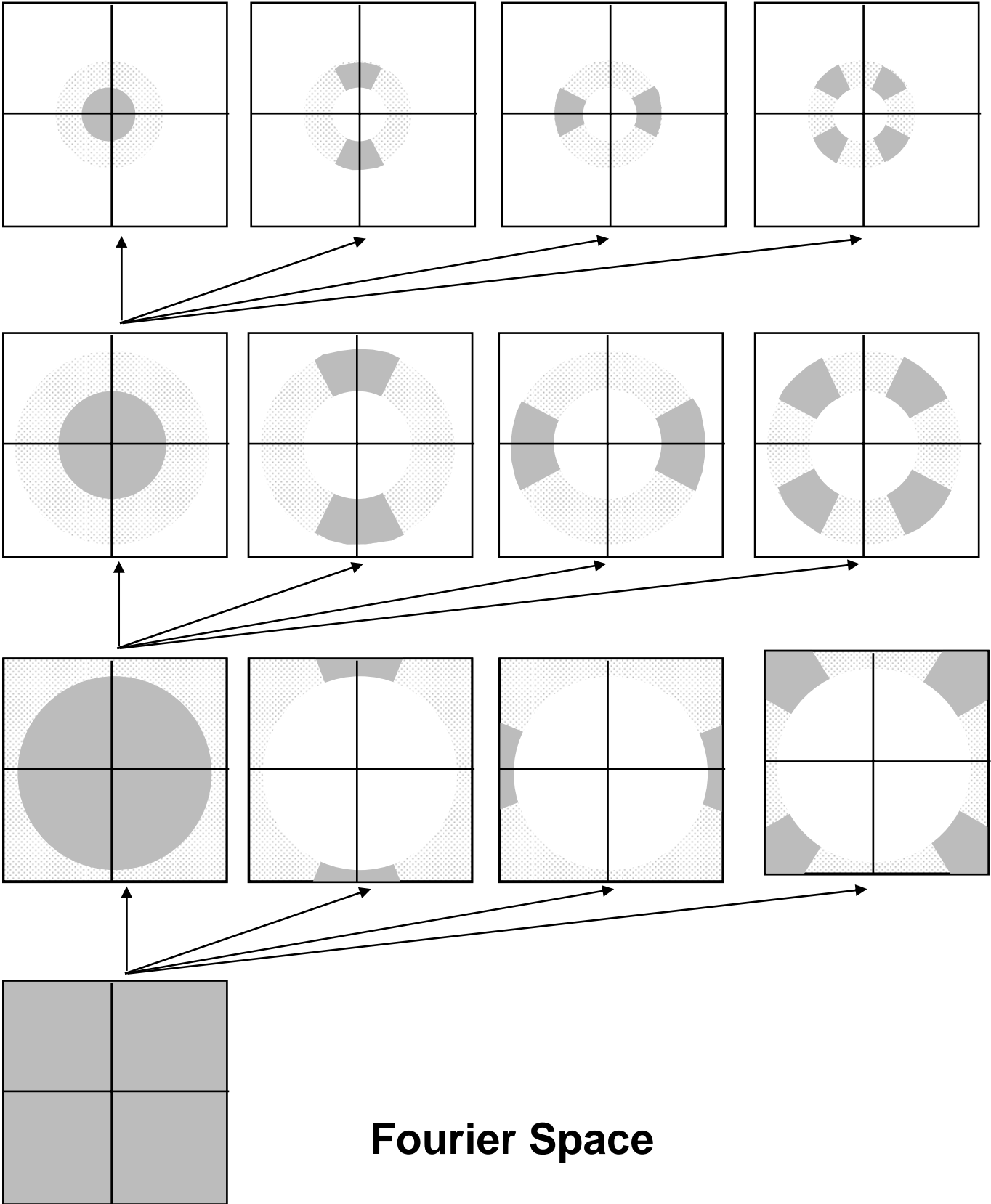
# Pyramids in Frequency Domain

## Gaussian Pyramid

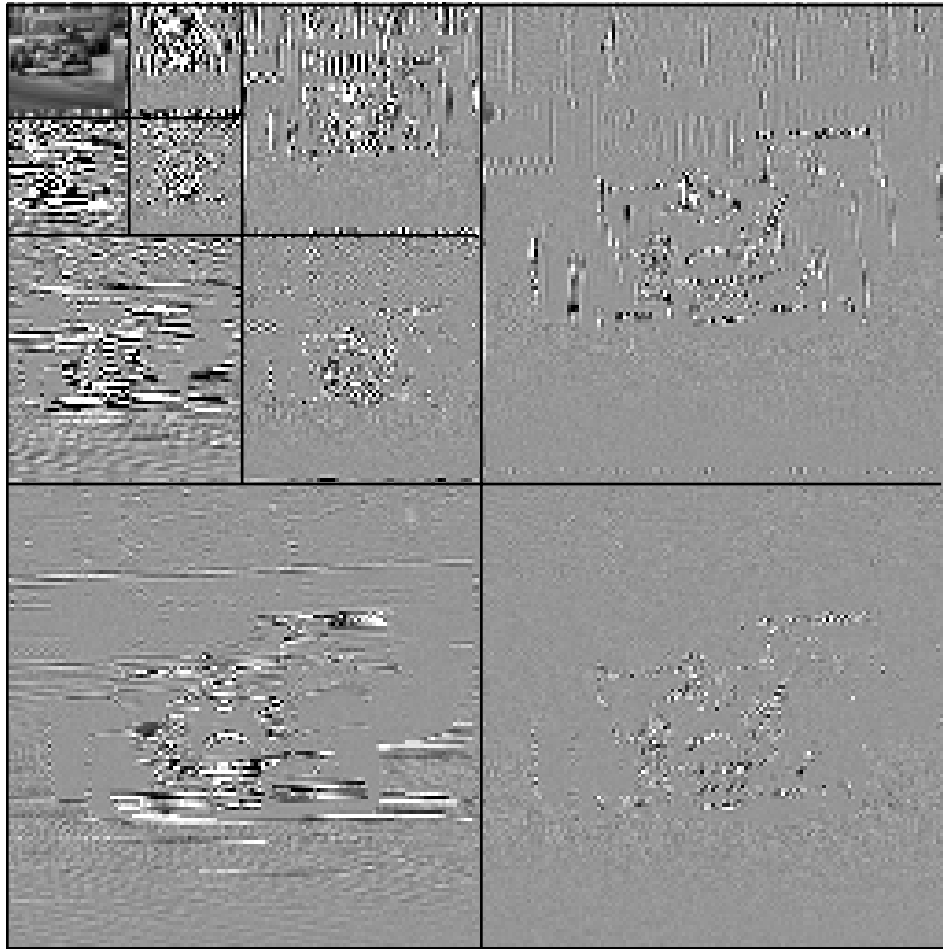
## Laplacian Pyramid



**Wavelet Decomposition**

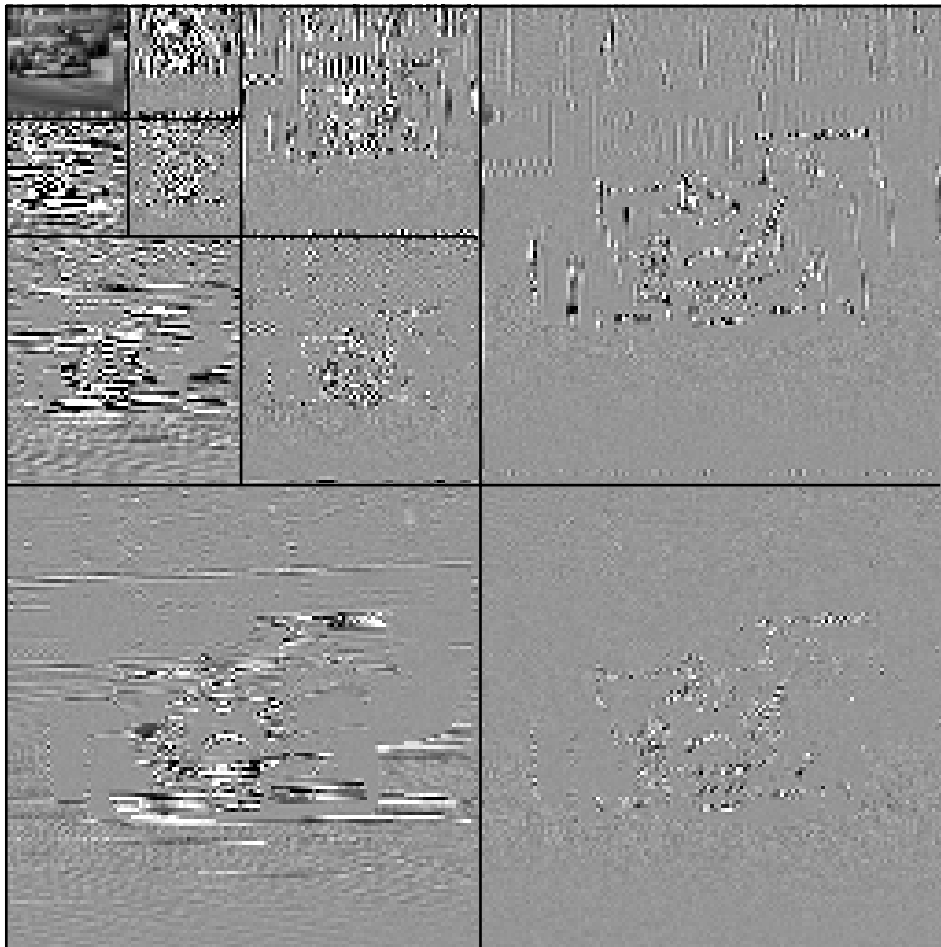


# Wavelet Transform - Step By Step Example

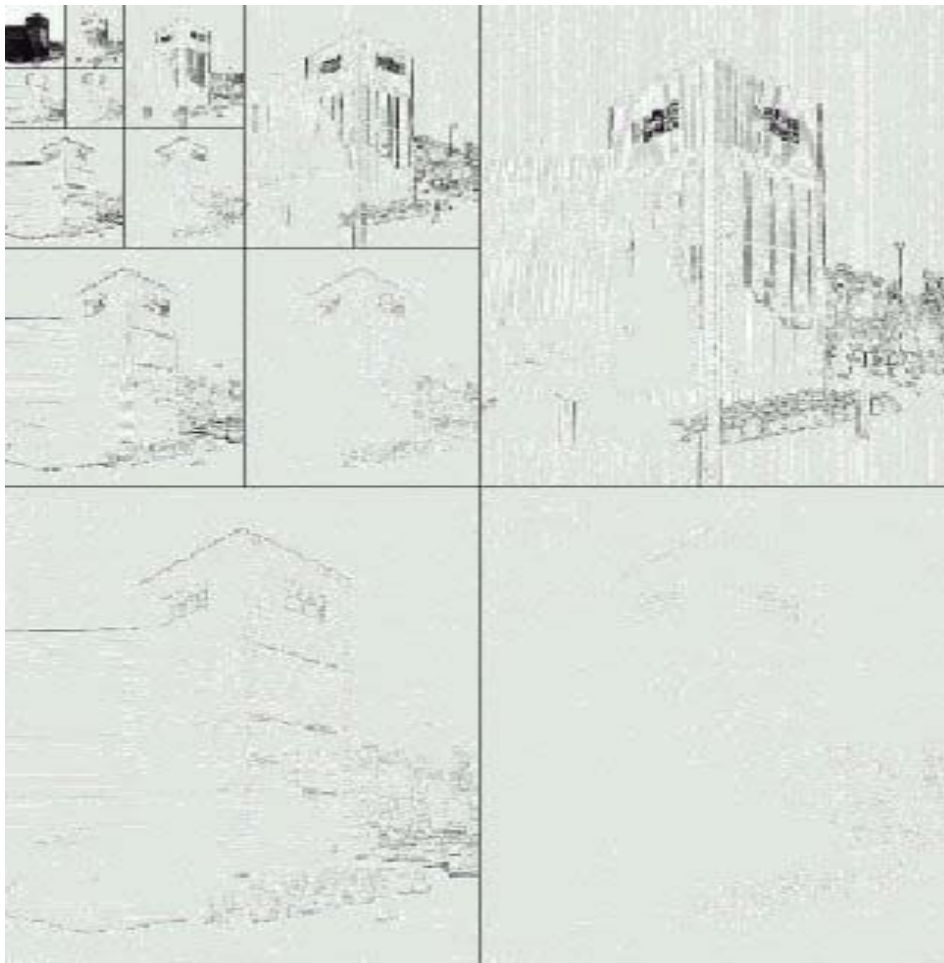




# Wavelet Transform - Example

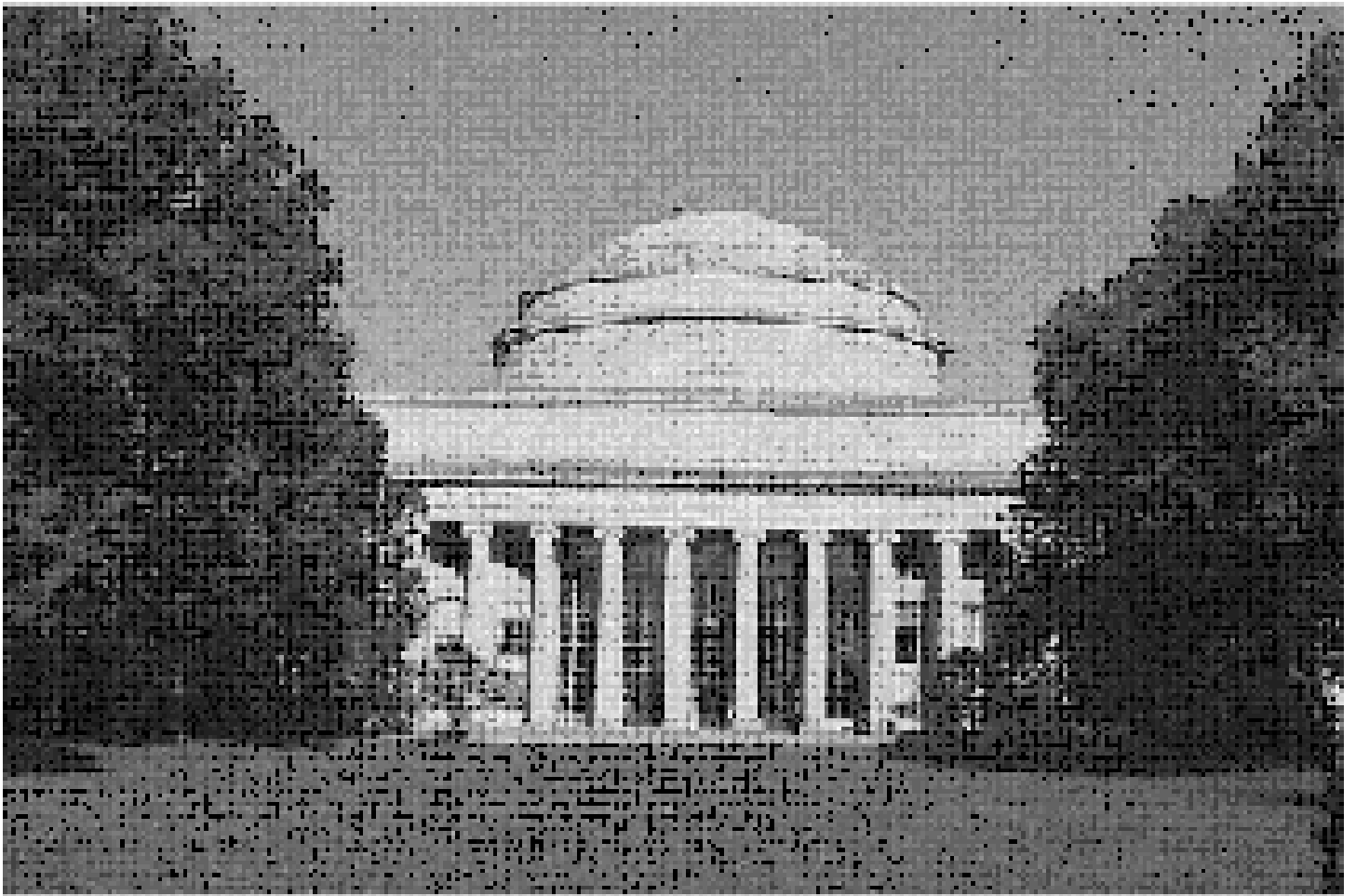


# Wavelet Transform - Example



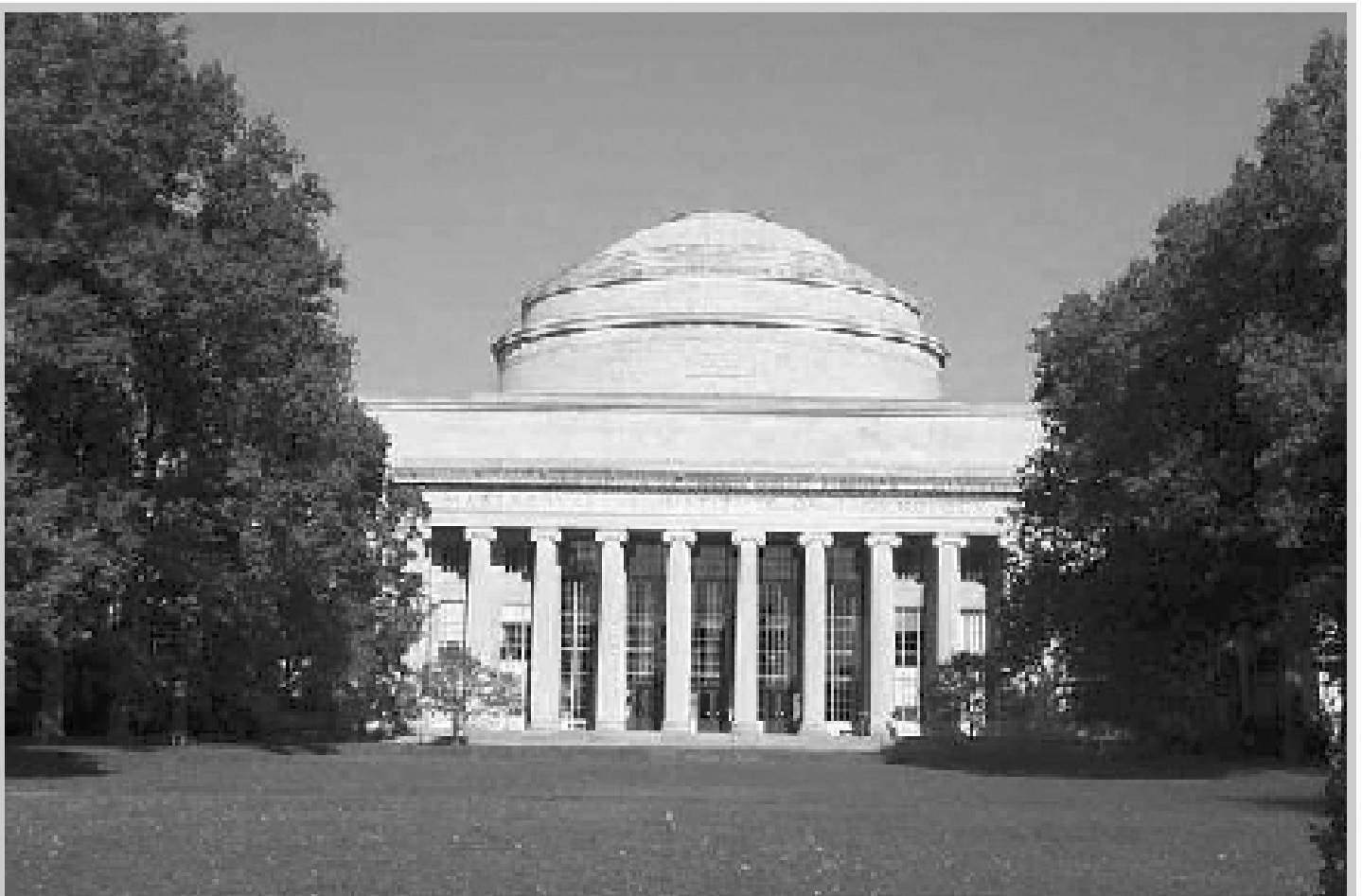
# Application: Wavelet Shrinkage Denoising

Noisy image



From: B. Freeman

Clean image

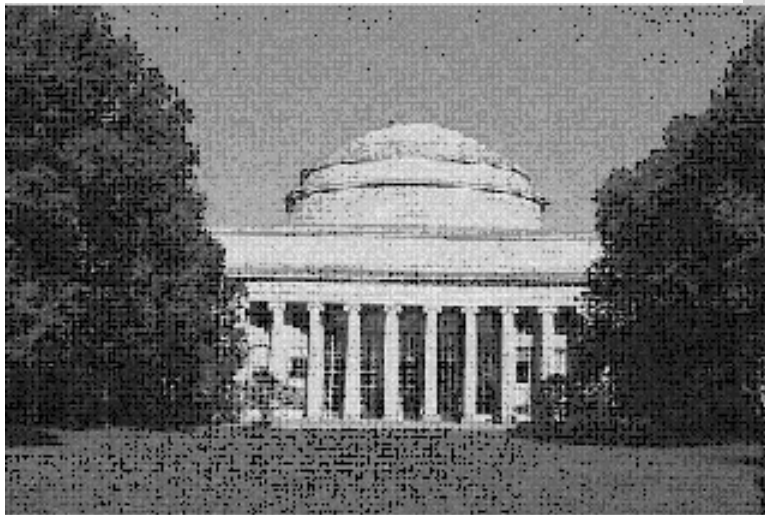


Range [0, 255]  
Dims [394, 599]

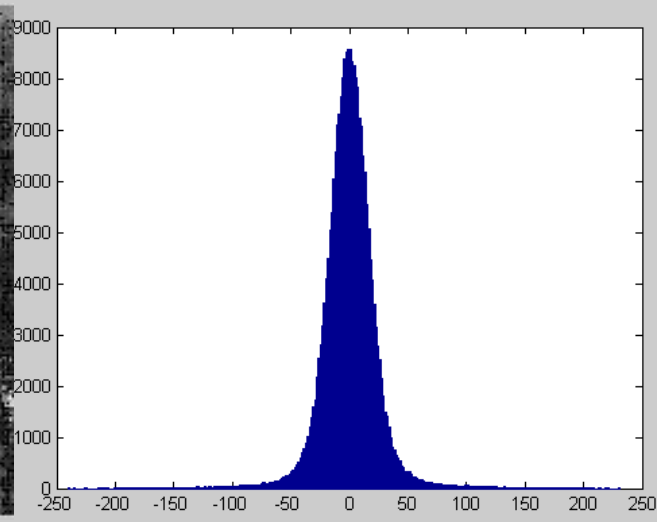
From: B. Freeman

# Wavelet Shrinkage Denoising

Noisy image



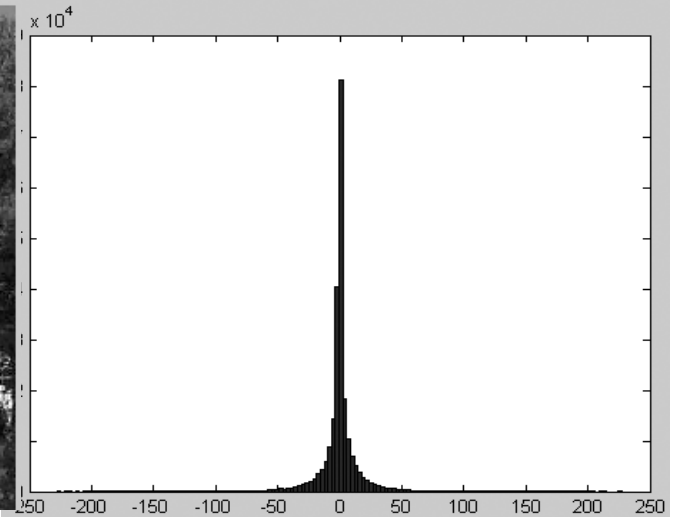
Wavelet coefficient Histogram



Clean image



Wavelet coefficient Histogram

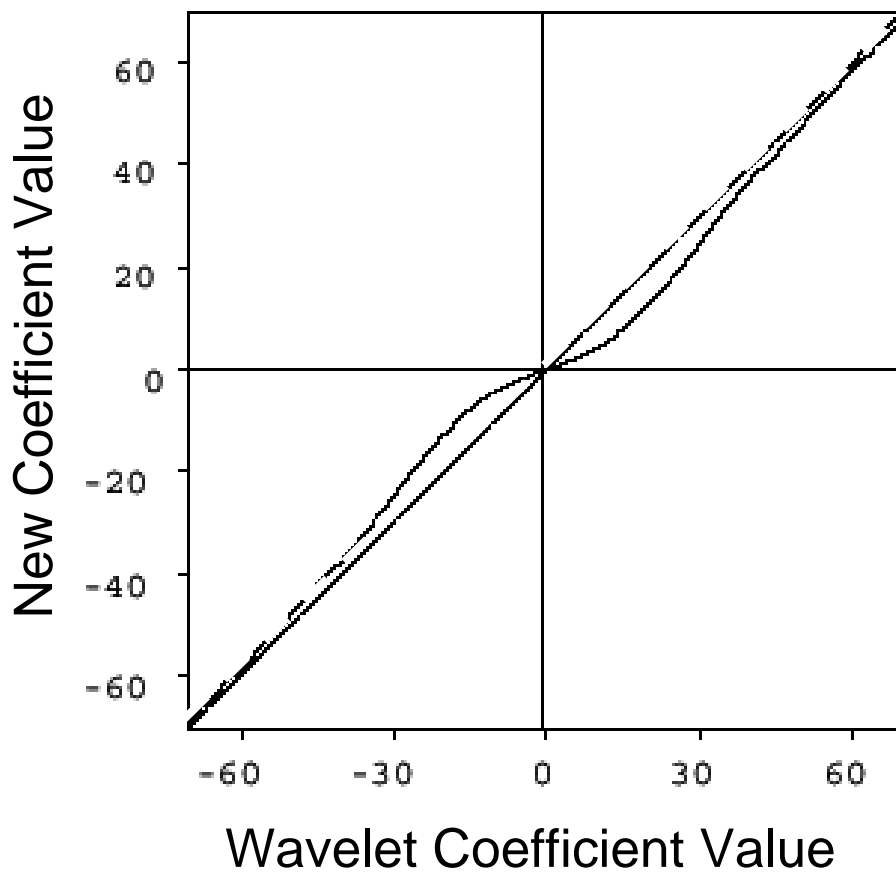


Get top histogram but want to get bottom histogram.

From: B. Freeman

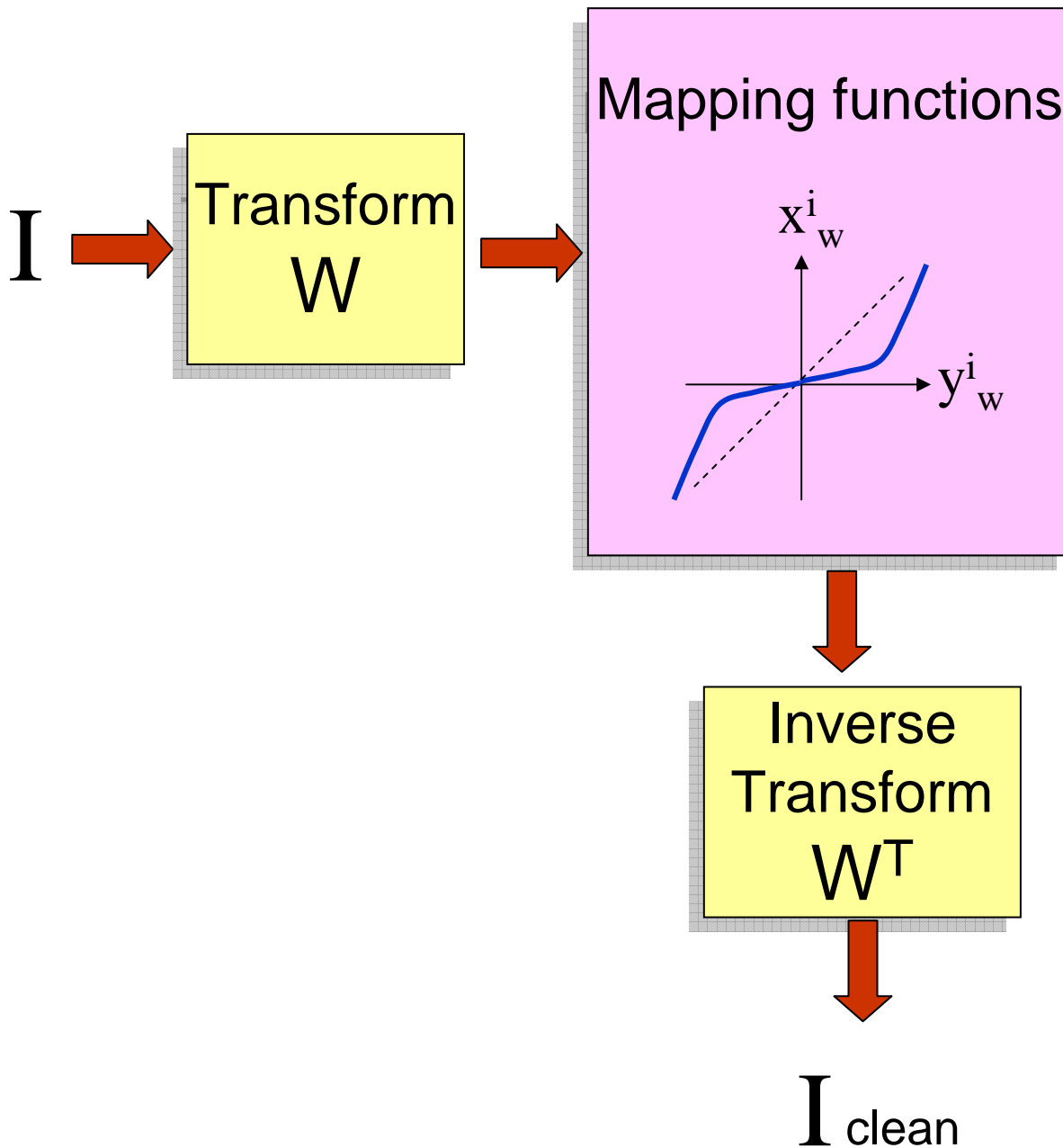
# Wavelet Shrinkage Denoising

For every Wavelet Band define  
Shrinkage function:



From: B. Freeman

# Wavelet Shrinkage Pipe-line



# More results





# More results

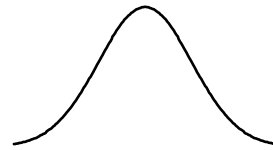


# Image Pyramids - Comparison

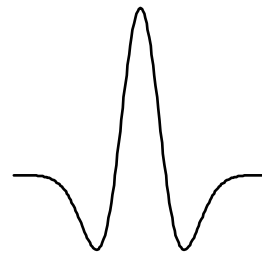
Image pyramid levels = Filter then sample.

## Filters:

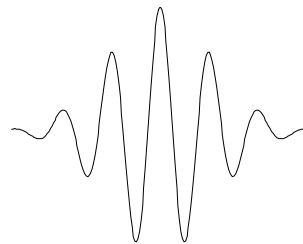
Gaussian Pyramid



Laplacian Pyramid

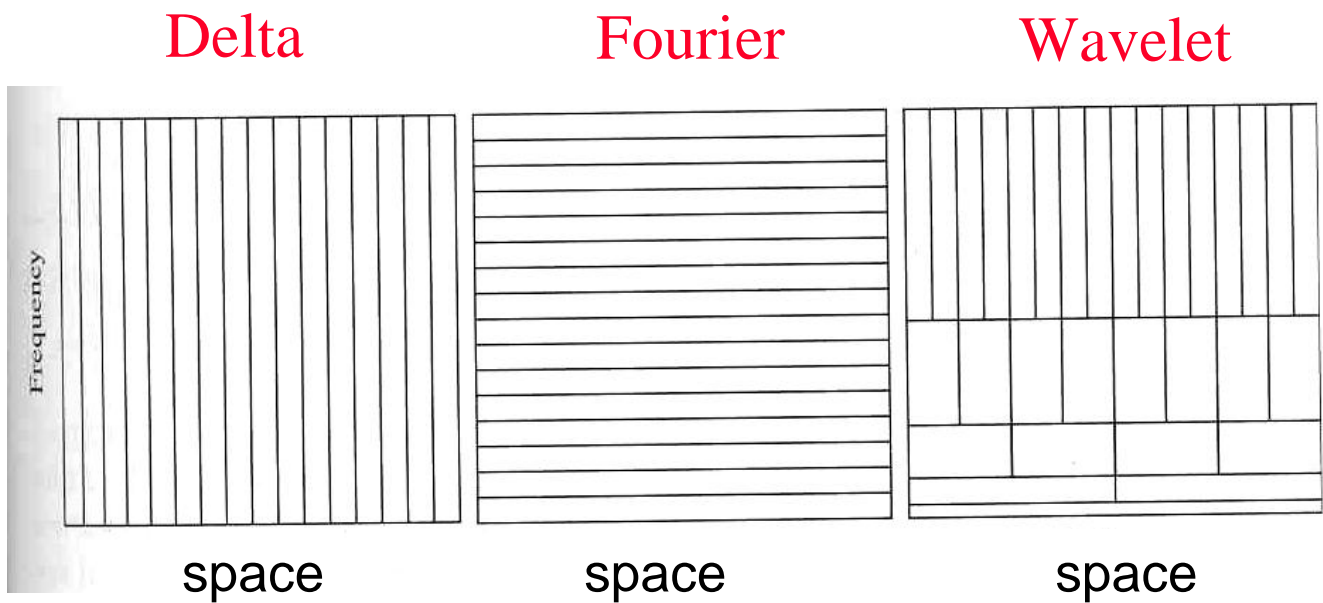


Wavelet Pyramid



# Image Linear Transforms

Transform	Basis	Characteristics
Delta	Standard	Localized in space Not localized in Frequency
Fourier	Sines+Cosines	Not localized in space Localized in Frequency
Wavelet Pyramid	Wavelet Filters	Localized in space Localized in Frequency



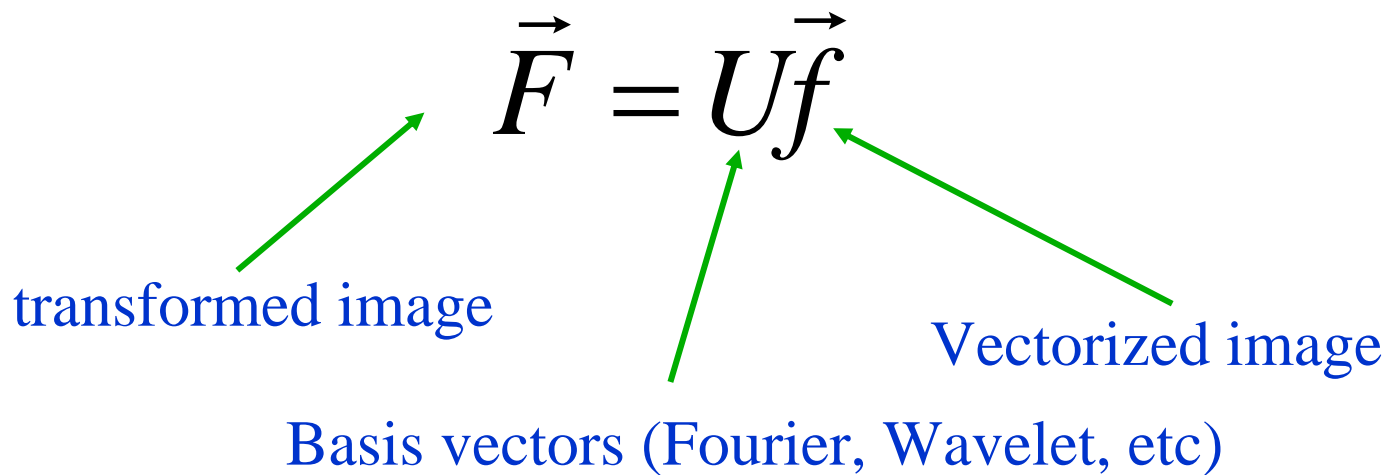
# Convolution and Transforms in matrix notation (1D case)

$$\vec{F} = U\vec{f}$$

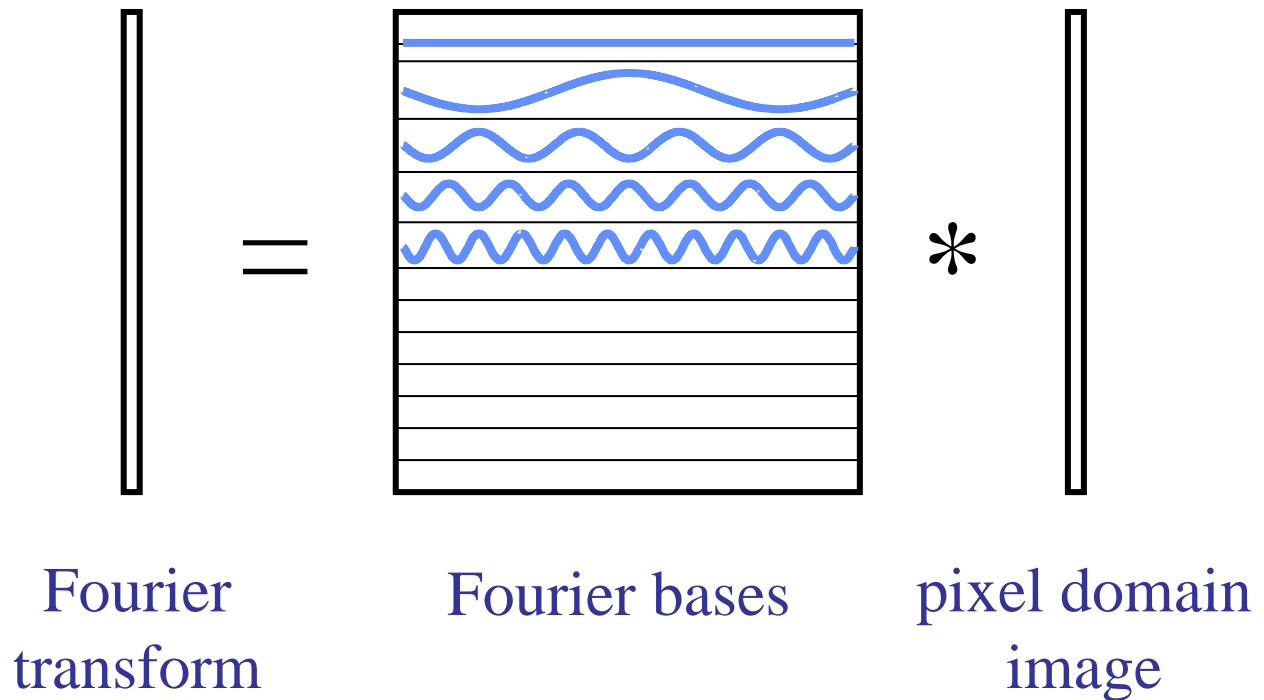
transformed image

Basis vectors (Fourier, Wavelet, etc)

Vectorized image

The diagram illustrates the matrix notation for a 1D convolution or transform. It features the equation  $\vec{F} = U\vec{f}$  in the center. Three green arrows point from labels to the terms in the equation: one from 'transformed image' to  $\vec{F}$ , one from 'Basis vectors (Fourier, Wavelet, etc)' to  $U$ , and one from 'Vectorized image' to  $\vec{f}$ .

# Fourier Transform



Fourier bases are global: each transform coefficient depends on all pixel locations.

# Transform in matrix notation (1D case)

Forward Transform:

$$\vec{F} = U\vec{f}$$

transformed image

Basis vectors (Fourier, Wavelet, etc)

Vectorized image

Detailed description: The diagram shows the equation  $\vec{F} = U\vec{f}$ . Three green arrows point from labels below to terms in the equation: one from 'transformed image' to  $\vec{F}$ , one from 'Basis vectors (Fourier, Wavelet, etc)' to  $U$ , and one from 'Vectorized image' to  $\vec{f}$ .

Inverse Transform:

$$U^{-1}\vec{F} = \vec{f}$$

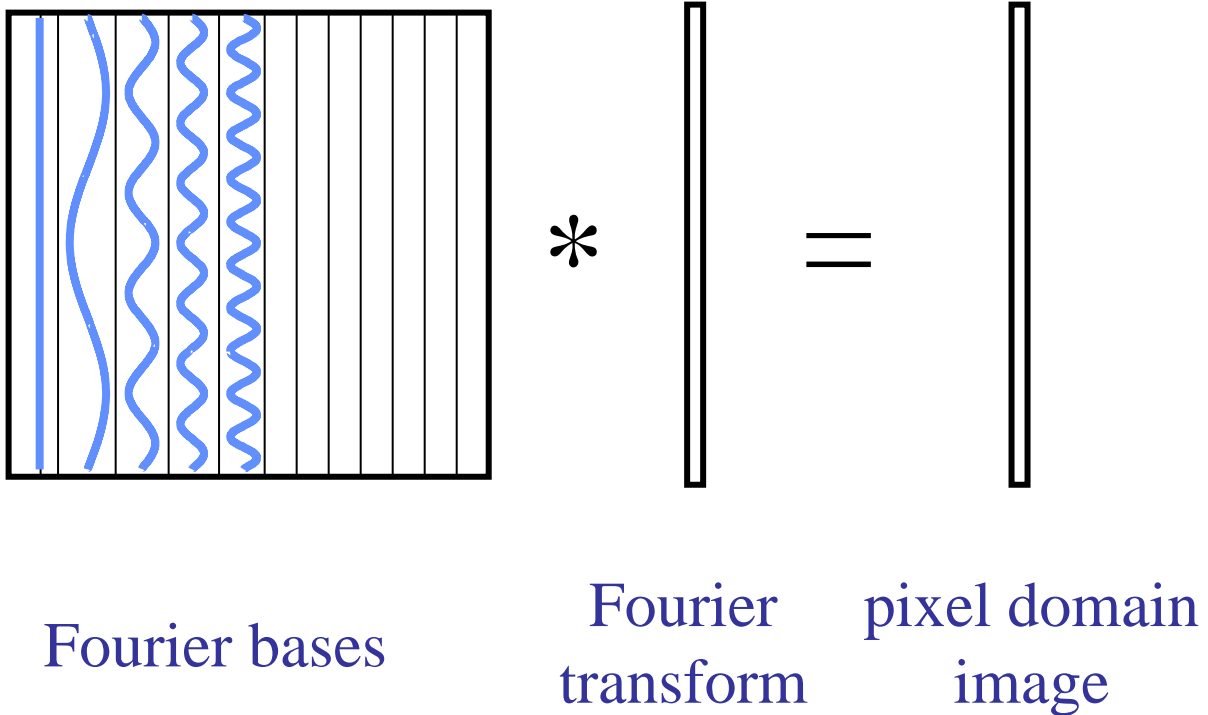
Basis vectors

transformed image

Vectorized image

Detailed description: The diagram shows the equation  $U^{-1}\vec{F} = \vec{f}$ . Three green arrows point from labels below to terms in the equation: one from 'Basis vectors' to  $U^{-1}$ , one from 'transformed image' to  $\vec{F}$ , and one from 'Vectorized image' to  $\vec{f}$ .

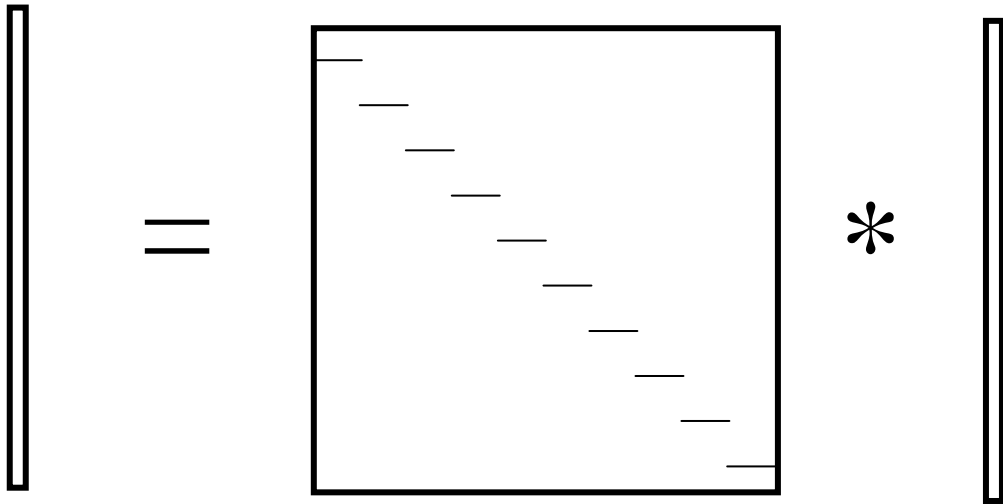
# Inverse Fourier Transform



Every image pixel is a linear combination of the Fourier basis weighted by the coefficient.

Note that if  $U$  is orthonormal basis then  $U^{-1} = U^t$

# Convolution



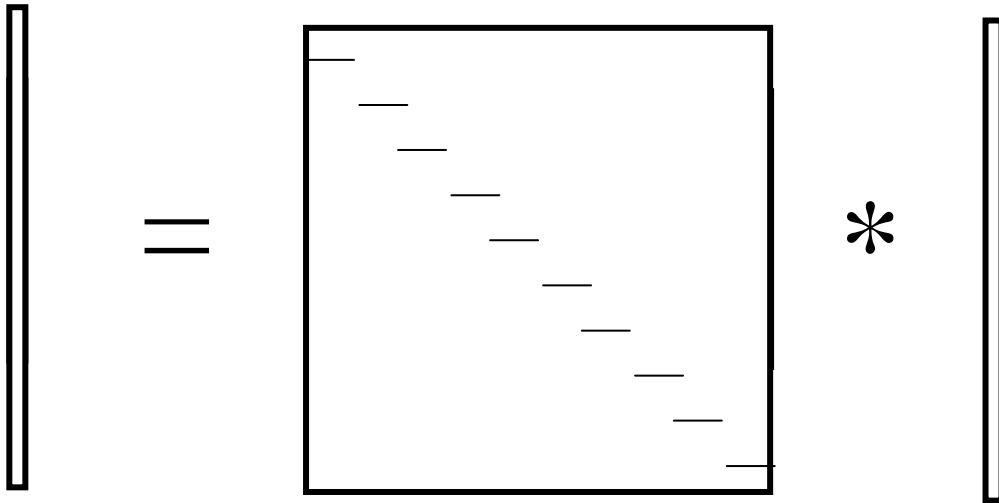
Convolution  
Result

Circular Matrix  
of  
Filter Kernels

pixel image



# Pyramid = Convolution + Sampling



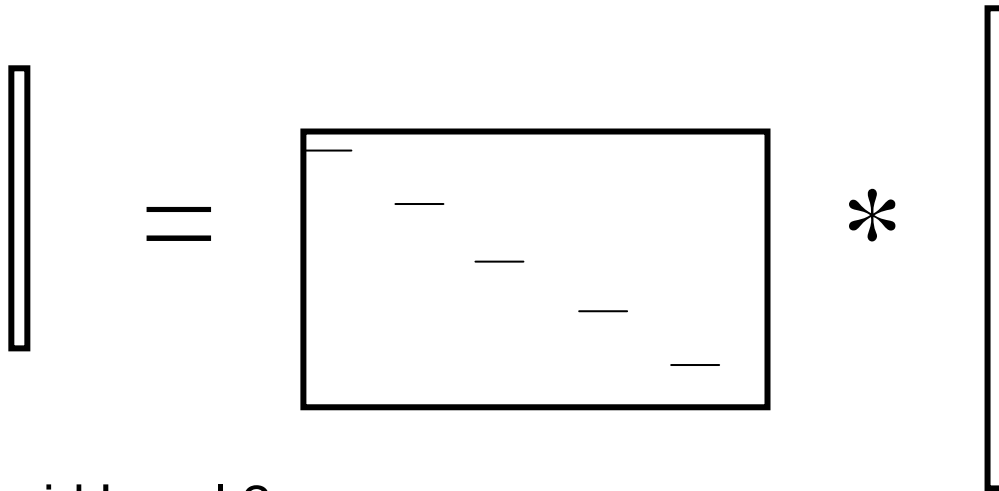
Convolution  
Result

Matrix of  
Filter Kernels

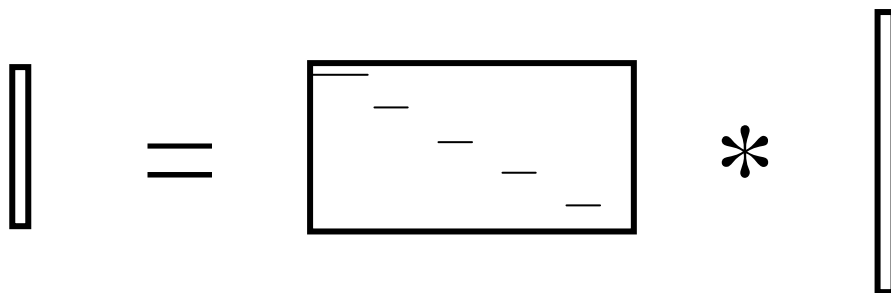
pixel image

# Pyramid = Convolution + Sampling

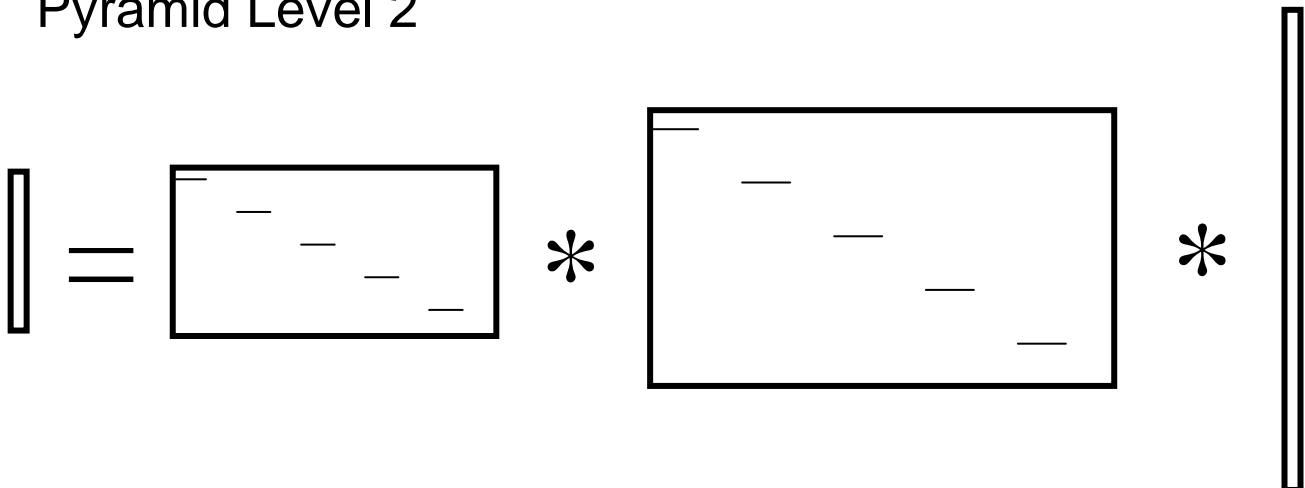
Pyramid Level 1



Pyramid Level 2

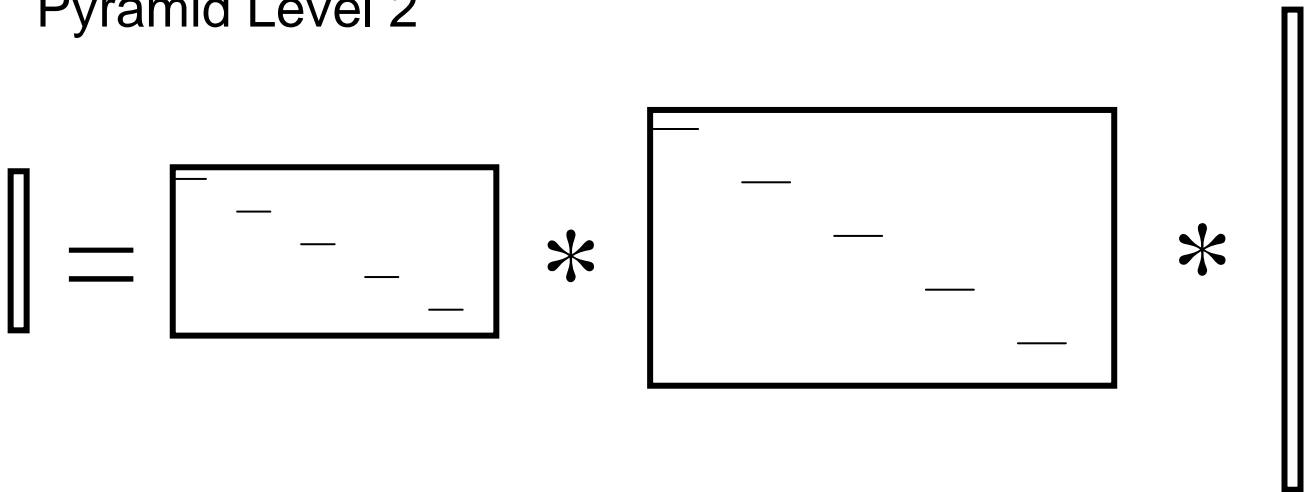


Pyramid Level 2

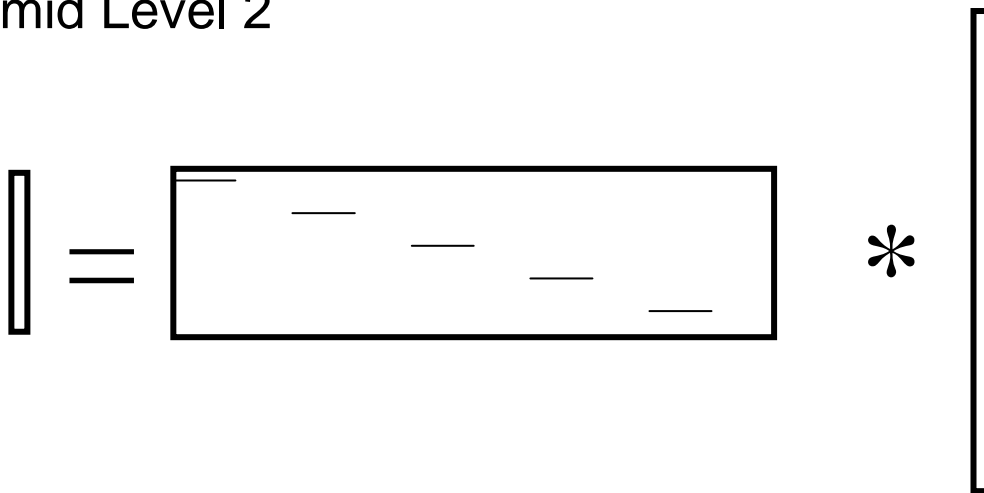


# Pyramid = Convolution + Sampling

Pyramid Level 2



Pyramid Level 2



# Pyramid as Matrix

## Computation - Example

U1 =

1	4	6	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	4	6	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	4	6	4	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	4	6	4	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	4	6	4	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	4	6	4	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	4	6	4	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	6	4	1	0

- Next pyramid level

U2 =

1	4	6	4	1	0	0	0
0	0	1	4	6	4	1	0
0	0	0	0	1	4	6	4
0	0	0	0	0	0	1	4

- The combined effect of the two pyramid levels

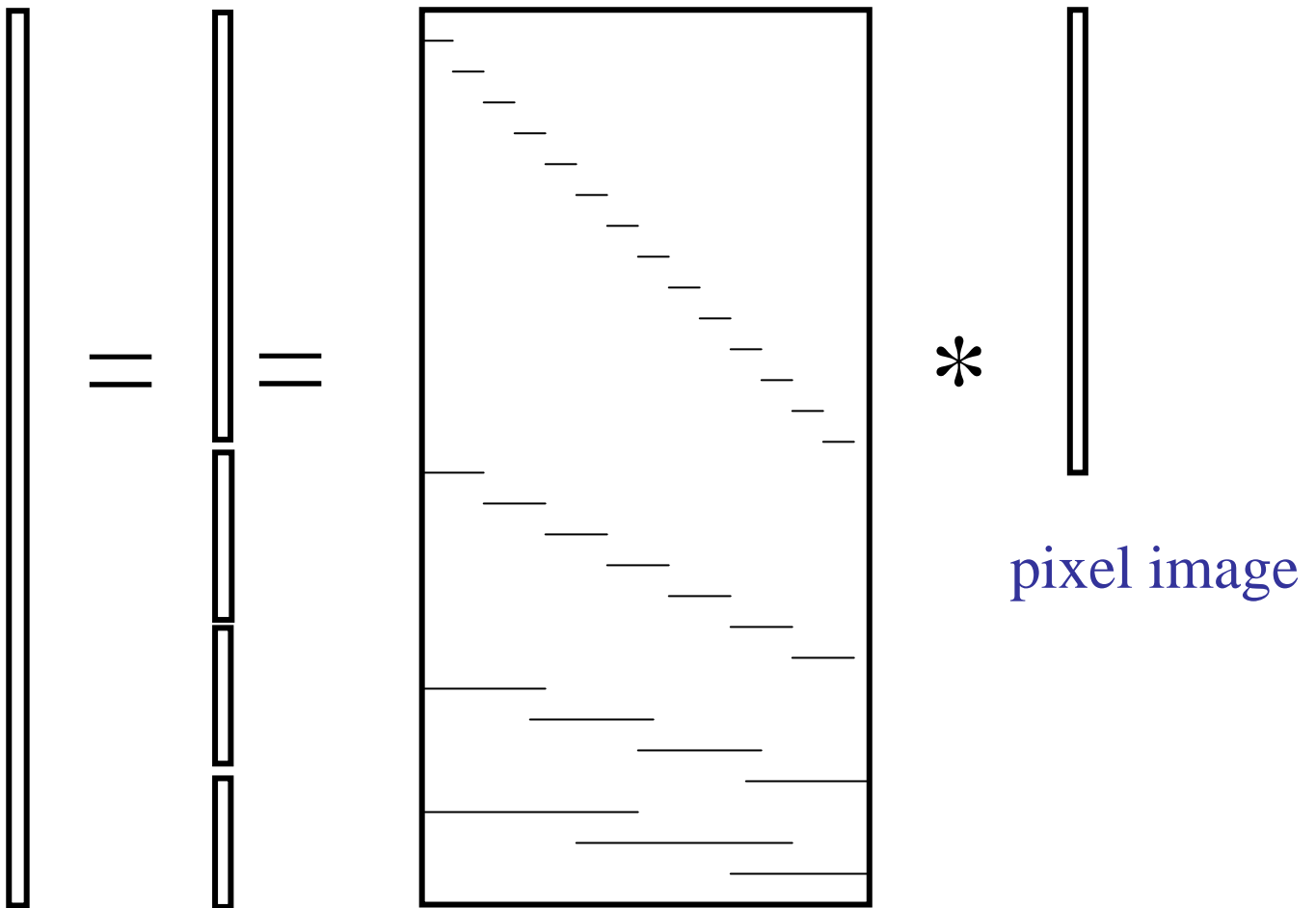
U2 \* U1 =

1	4	10	20	31	40	44	40	31	20	10	4	1	0	0	0	0	0	0	0
0	0	0	0	1	4	10	20	31	40	44	40	31	20	10	4	1	0	0	0
0	0	0	0	0	0	0	0	1	4	10	20	31	40	44	40	30	16	4	0
0	0	0	0	0	0	0	0	0	0	0	0	1	4	10	20	25	16	4	0

from: B.Freeman

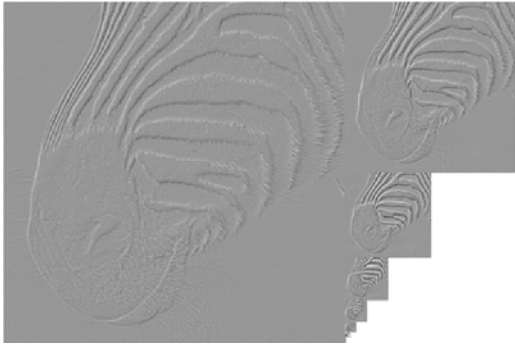


# Gaussian Pyramid

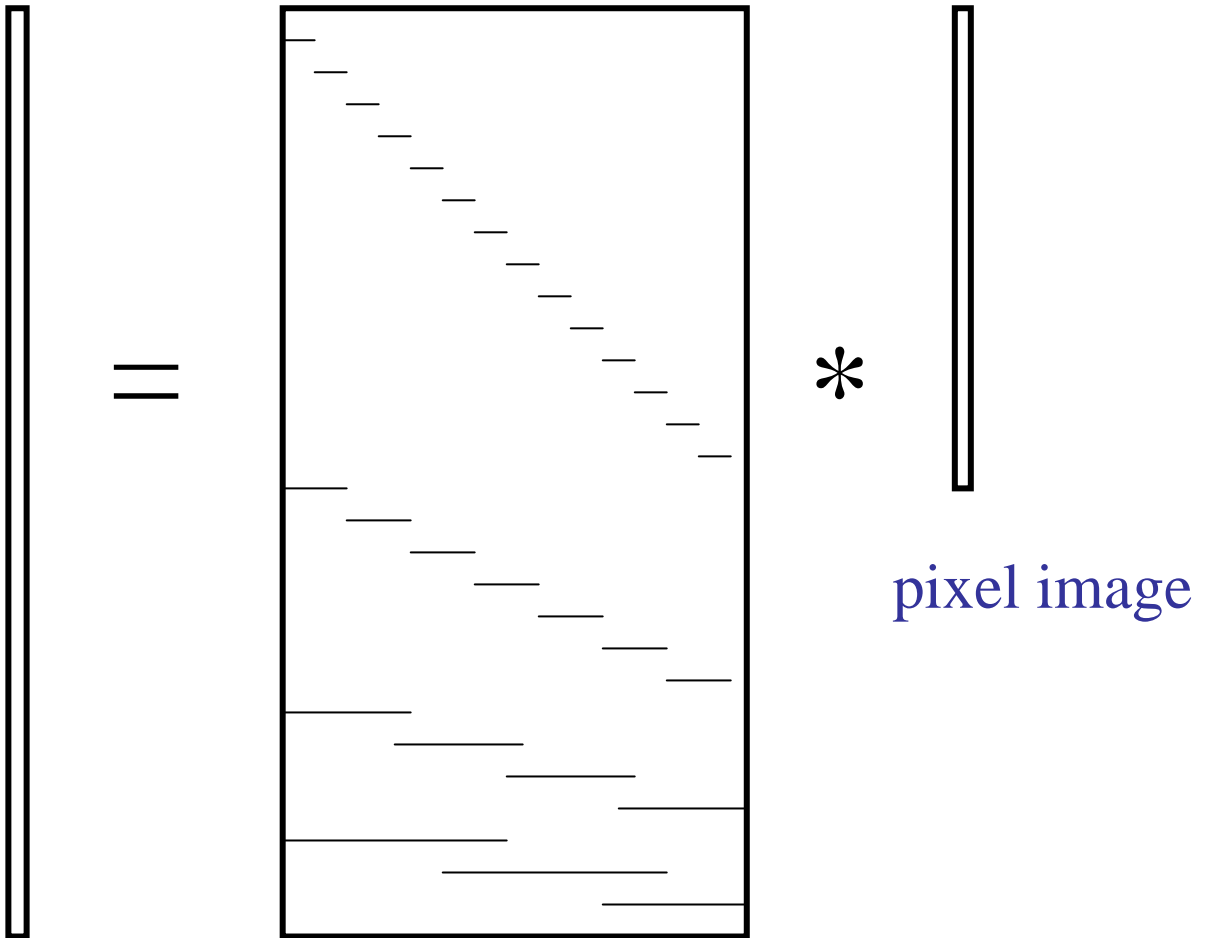
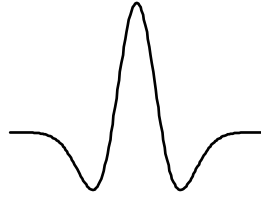


Gaussian pyramid

Overcomplete representation.  
Low-pass filters, sampled appropriately for their blur.



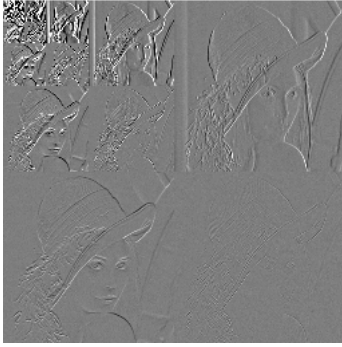
# Laplacian Pyramid



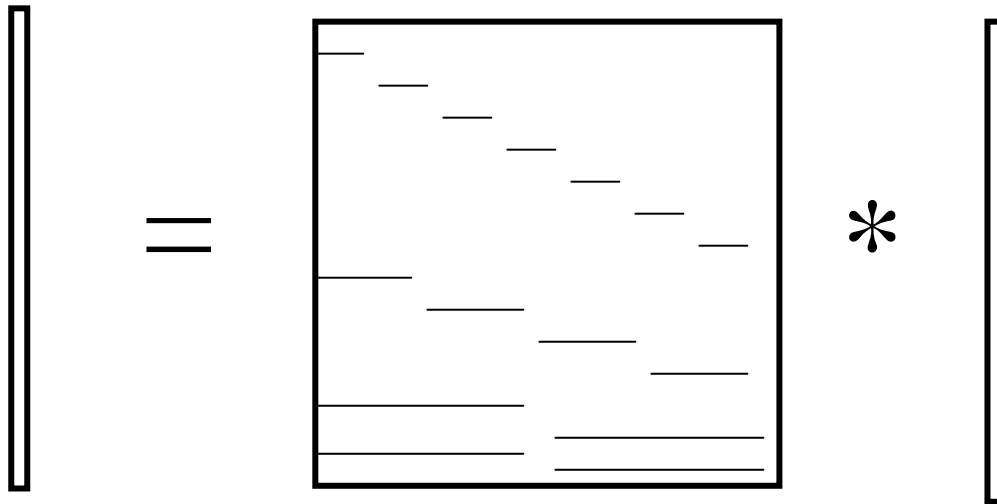
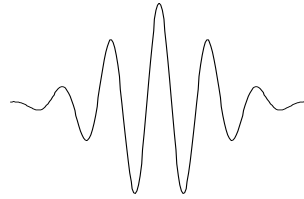
Laplacian pyramid

Overcomplete representation.  
Transformed pixels represent  
bandpassed image information.

From: B. Freeman



# Wavelet Transform



Wavelet pyramid

Ortho-normal transform (like Fourier transform), but with localized basis functions.

pixel image

The End