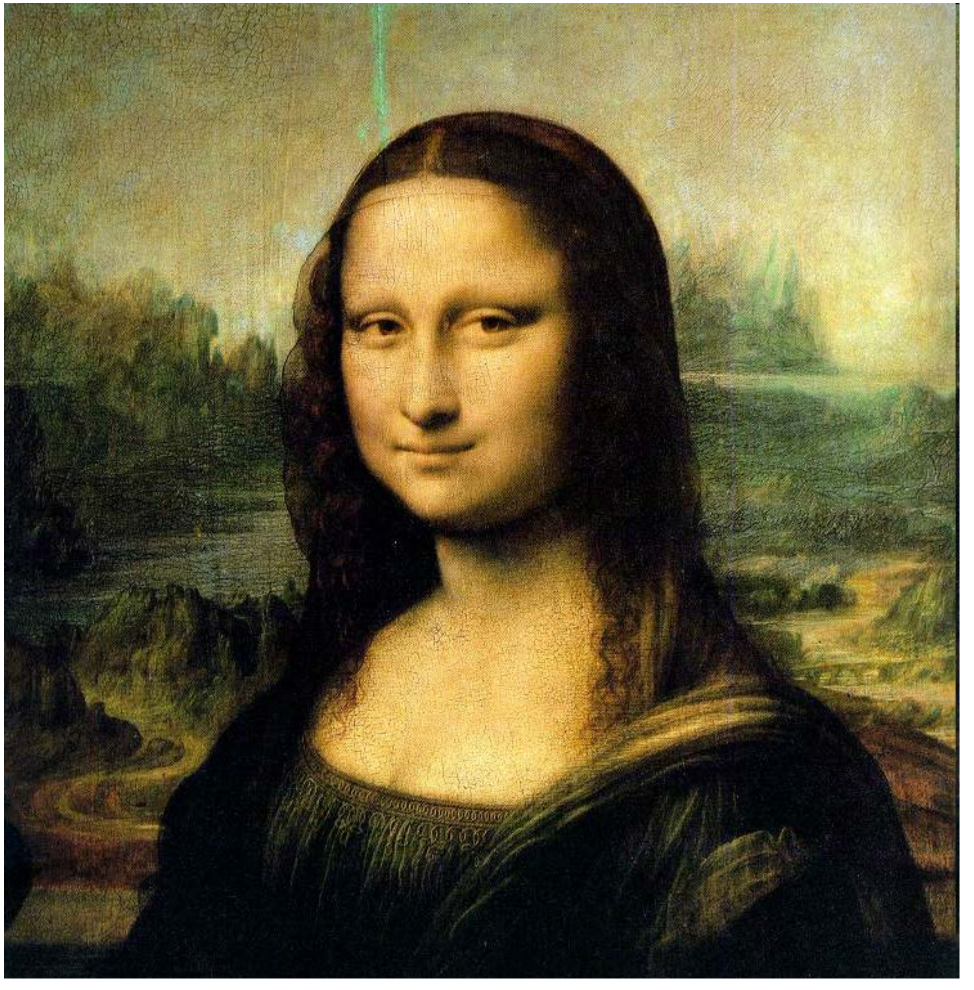
Laplacian Pyramids

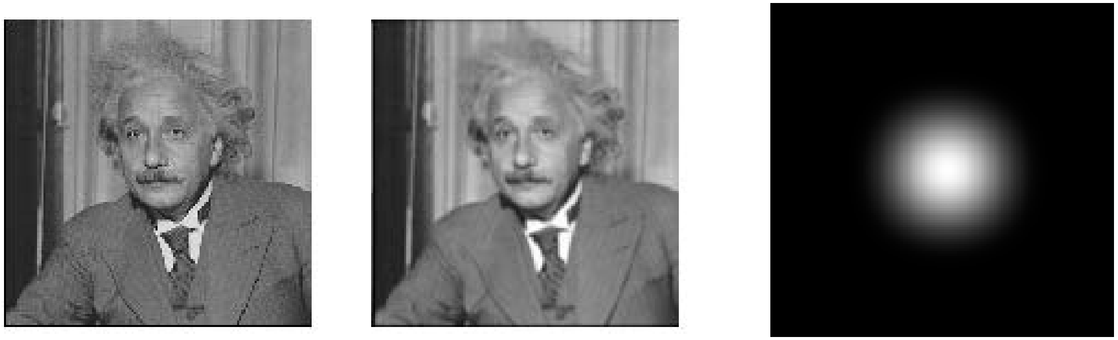


CS194: Image Manipulation & Computational Photography
Alexei Efros, UC Berkeley, Fall 2017

Many slides borrowed from Steve Seitz

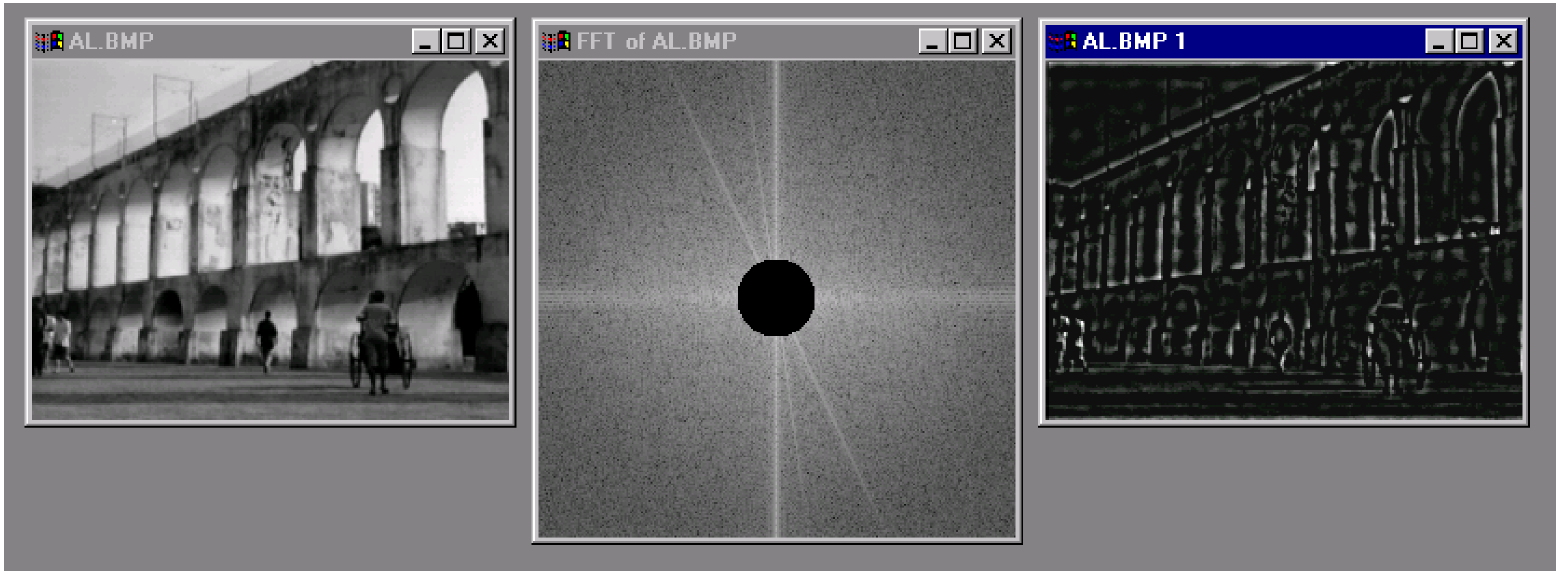
Low-pass, Band-pass, High-pass filters

low-pass:



High-pass / band-pass:

Edges in images



What does blurring take away?

original

What does blurring take away?

smoothed (5x5 Gaussian)

High-Pass filter

smoothed – original

Image “Sharpening”

What does blurring take away?

–

=

Let’s add it back:

+ α

=

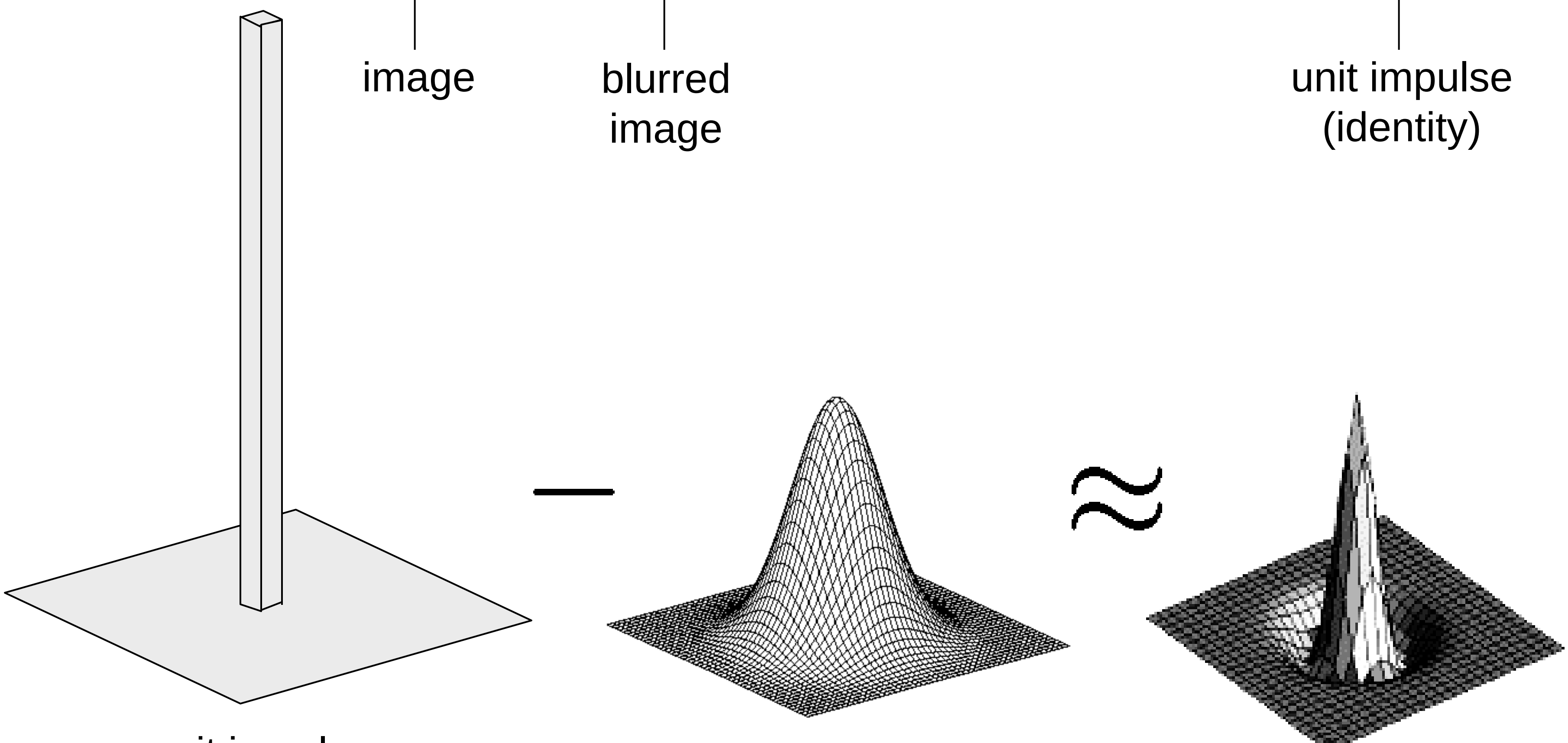
Unsharp mask filter

$$f + \alpha(f - f * g) = (1+\alpha)f - \alpha f * g = f * ((1+\alpha)e - \alpha g)$$

image

blurred image

unit impulse (identity)



unit impulse

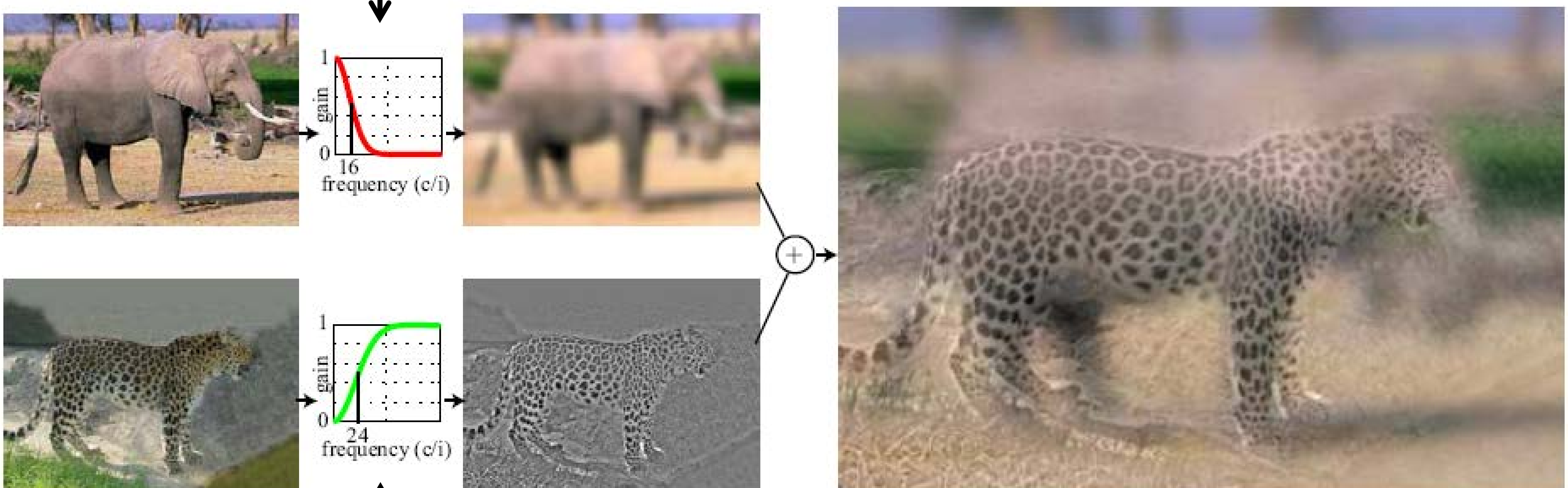
Gaussian

Laplacian of Gaussian

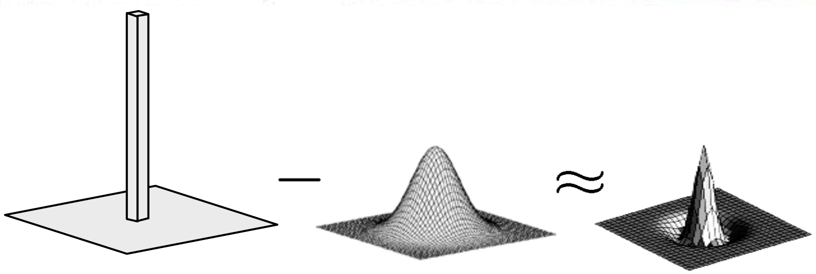
Hybrid Images

A. Oliva, A. Torralba, P.G. Schyns, “Hybrid Images,” SIGGRAPH 2006

Gaussian Filter!



Laplacian Filter!

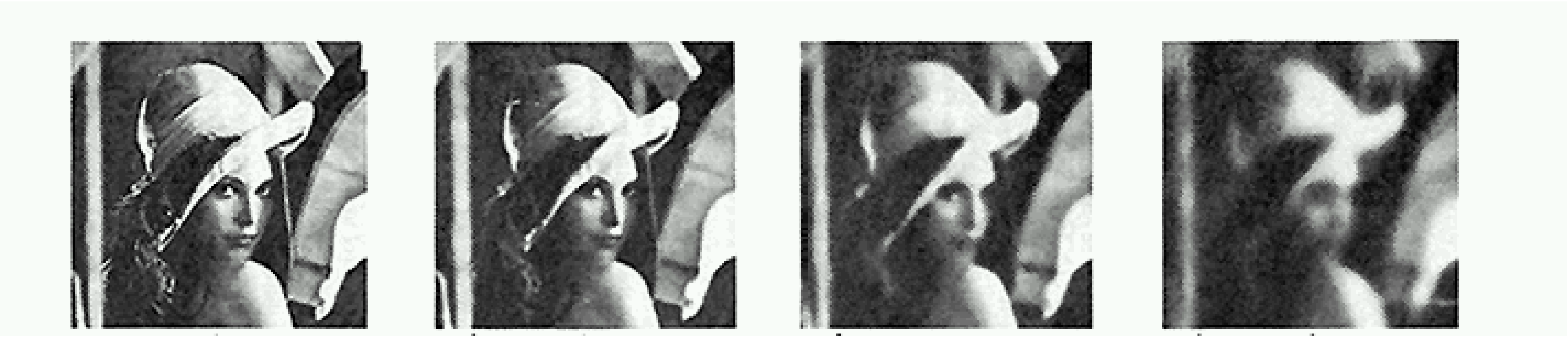


unit impulse — Gaussian ≈ Laplacian of Gaussian

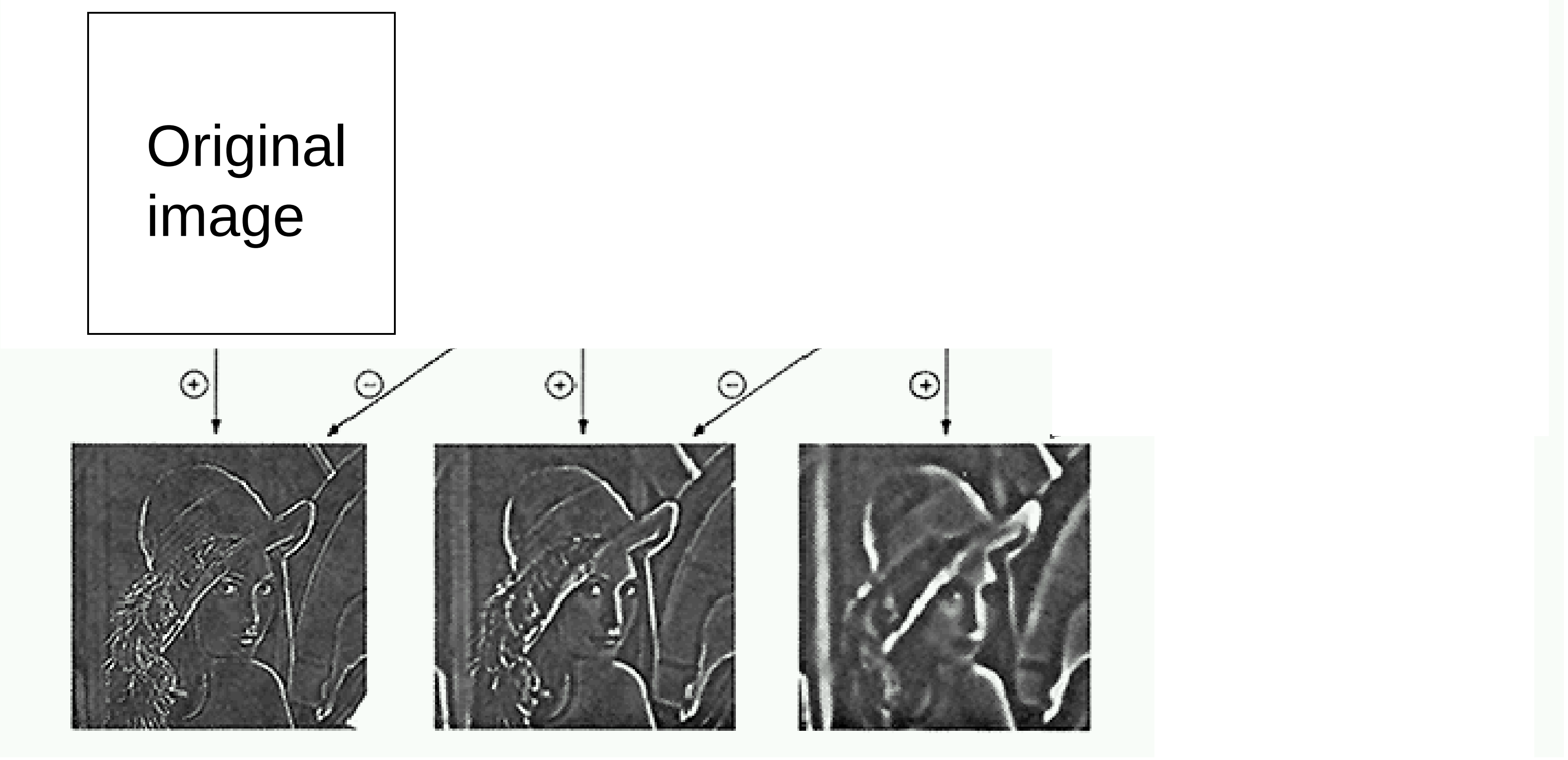
Salvador Dali
"Gala Contemplating the Mediterranean Sea, which at 30 meters becomes the portrait of Abraham Lincoln", 1976

Band-pass filtering

Gaussian Pyramid (low-pass images)

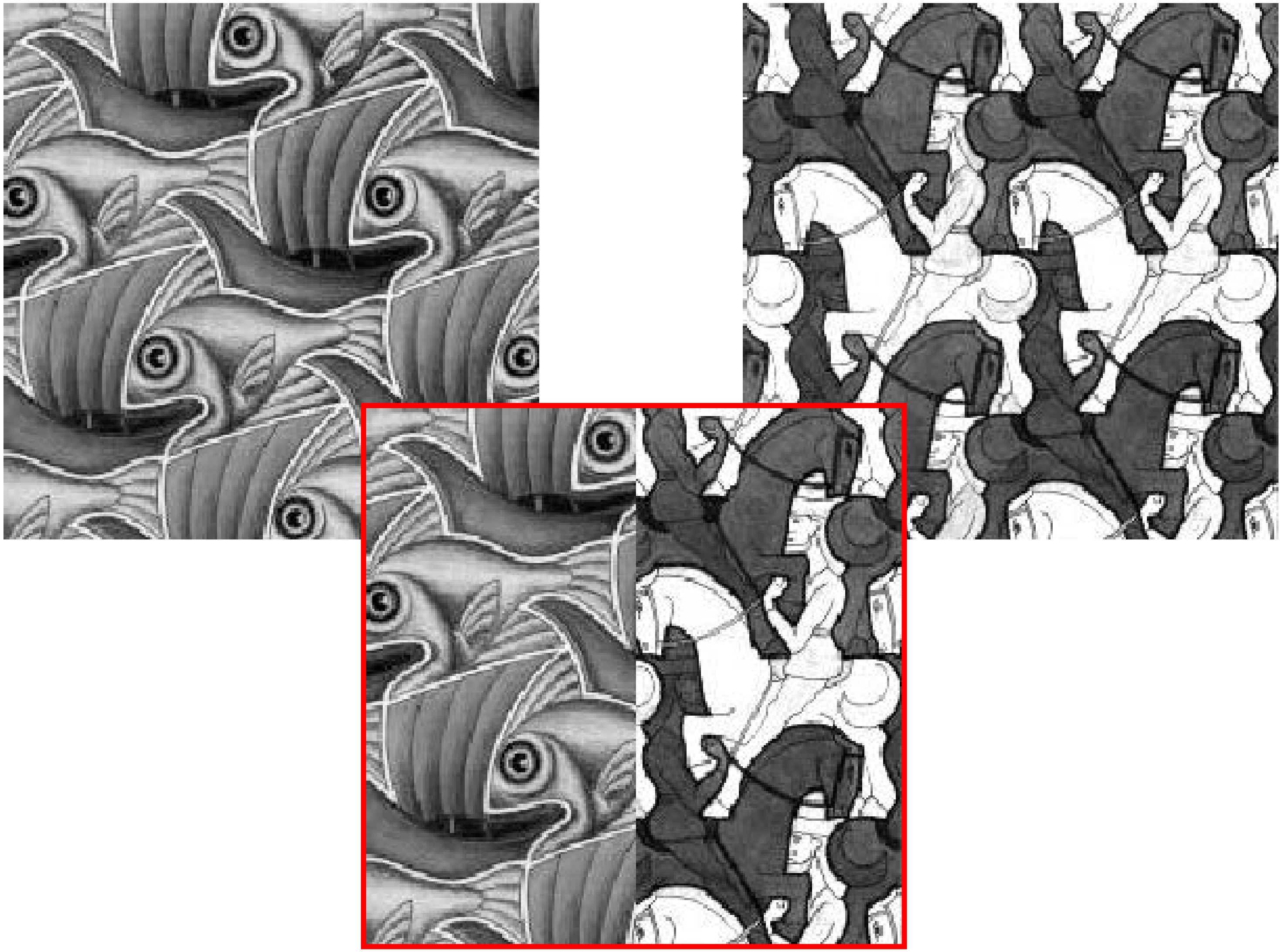


Laplacian Pyramid

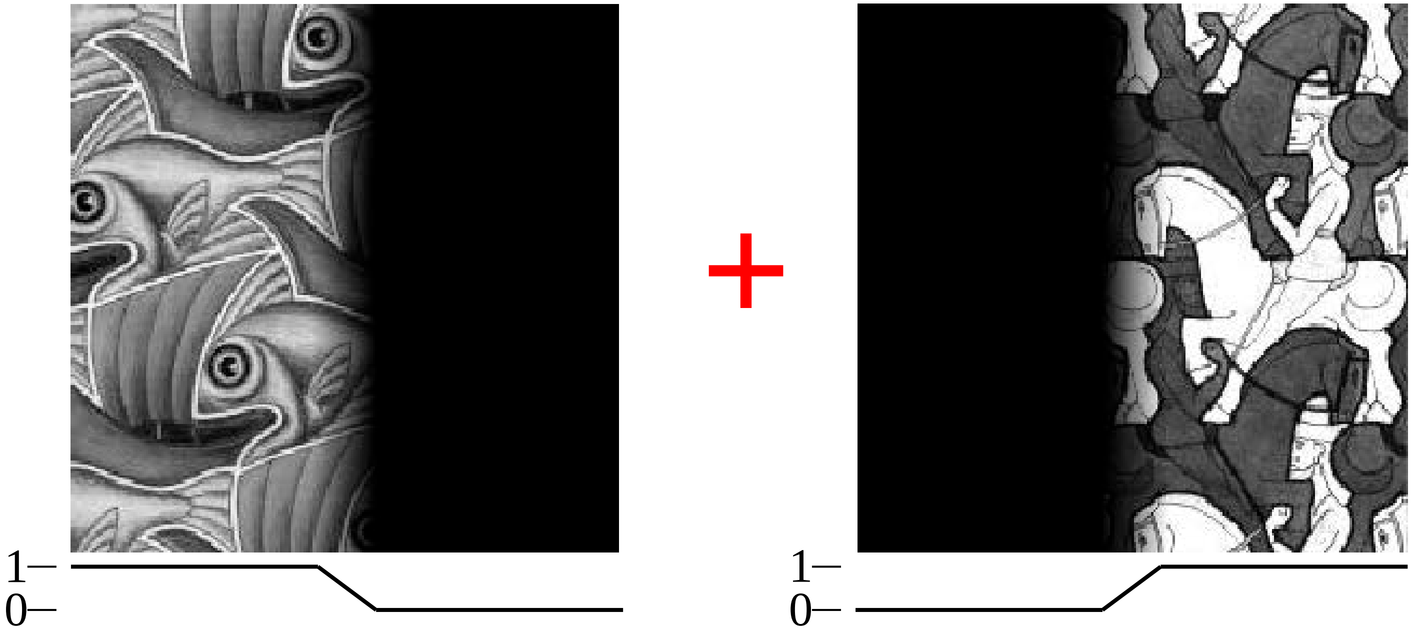


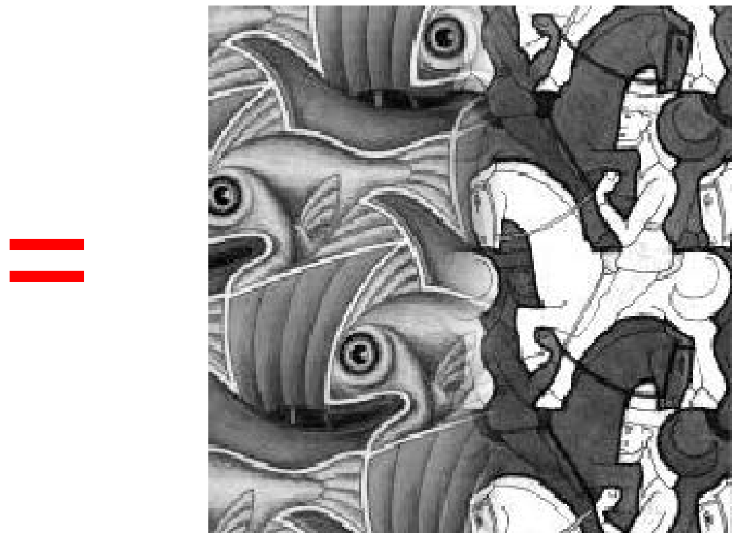
How can we reconstruct (collapse) this pyramid into the original image?

Blending



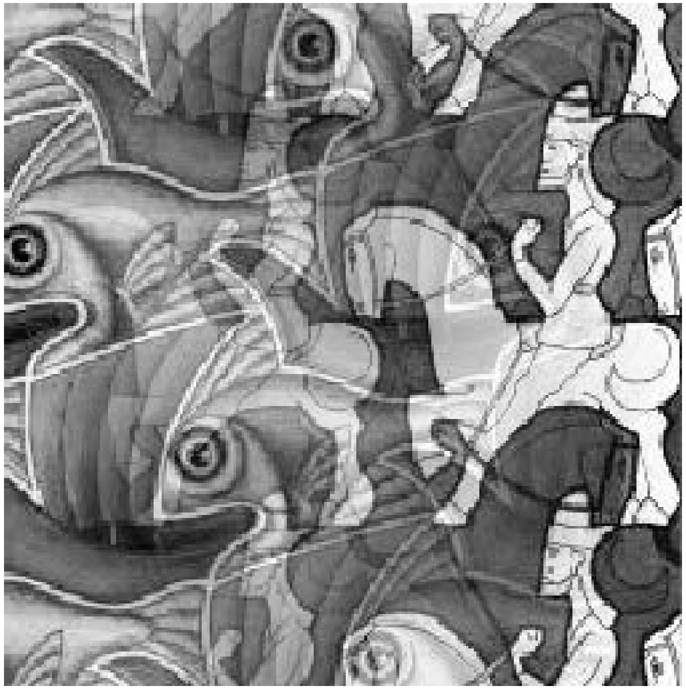
Alpha Blending / Feathering

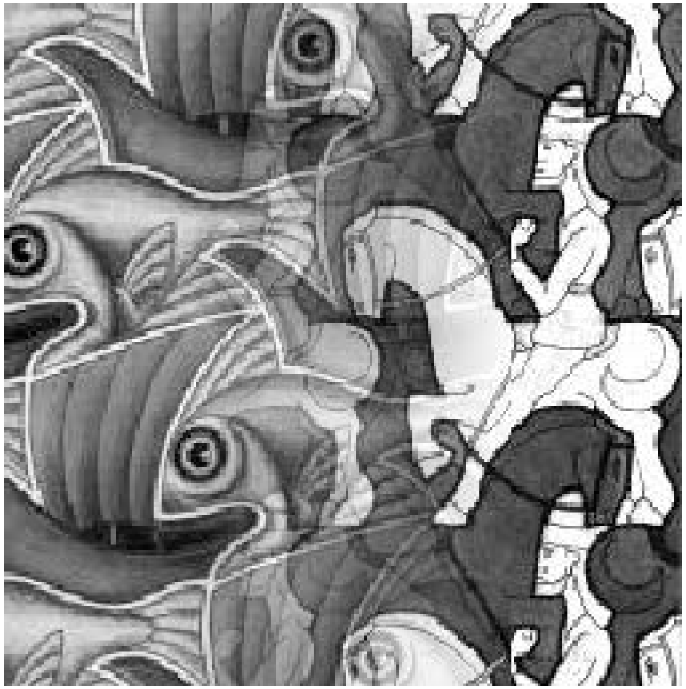


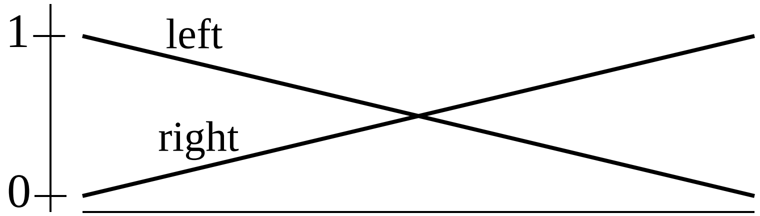


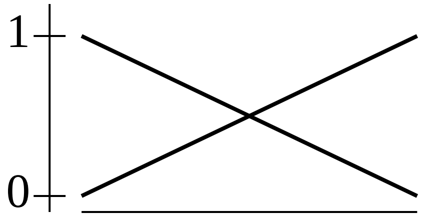
$$I_{blend} = \alpha I_{left} + (1-\alpha) I_{right}$$

Affect of Window Size

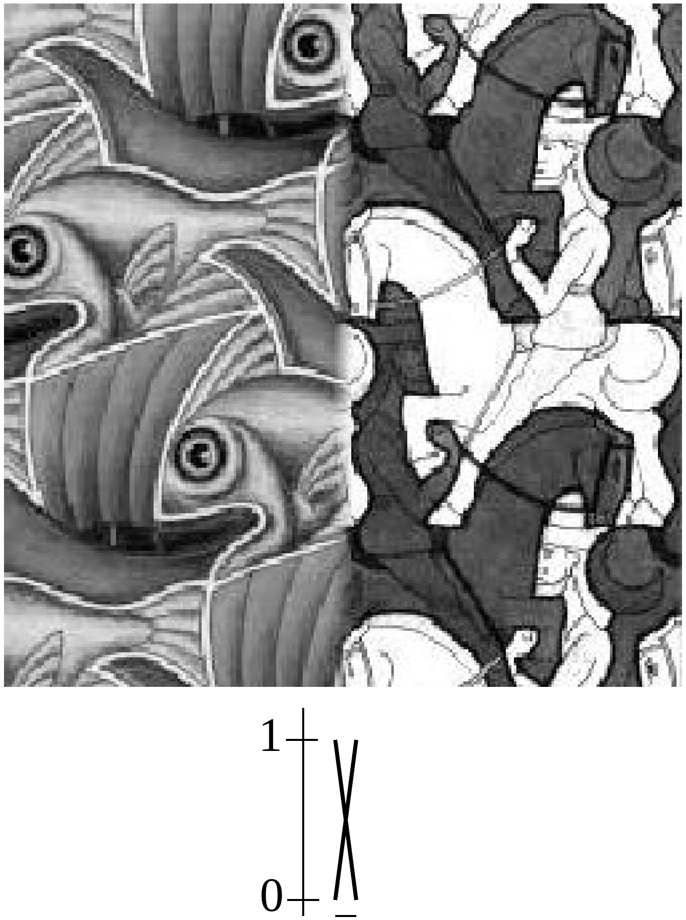


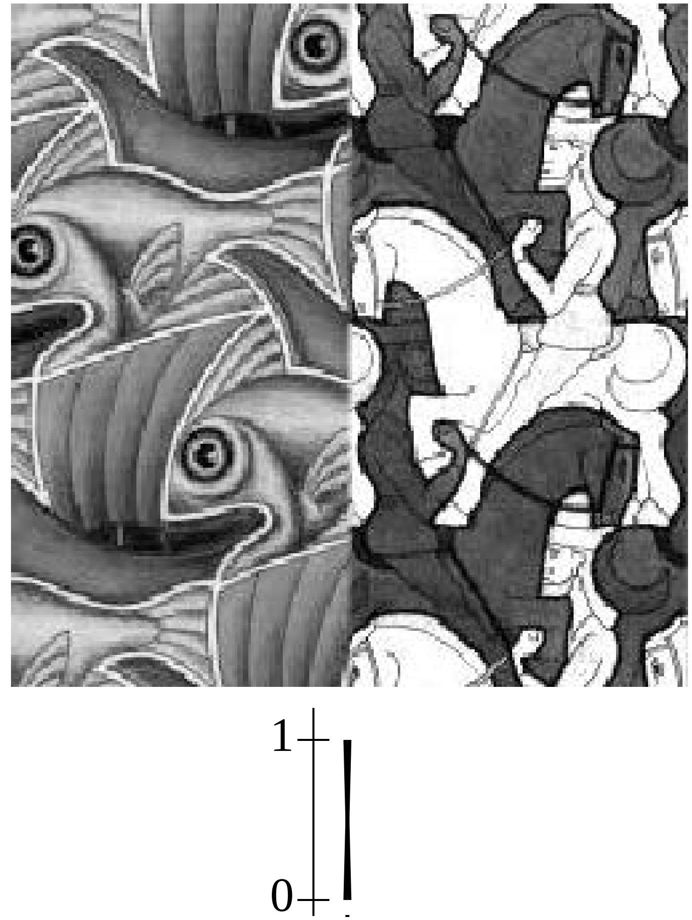




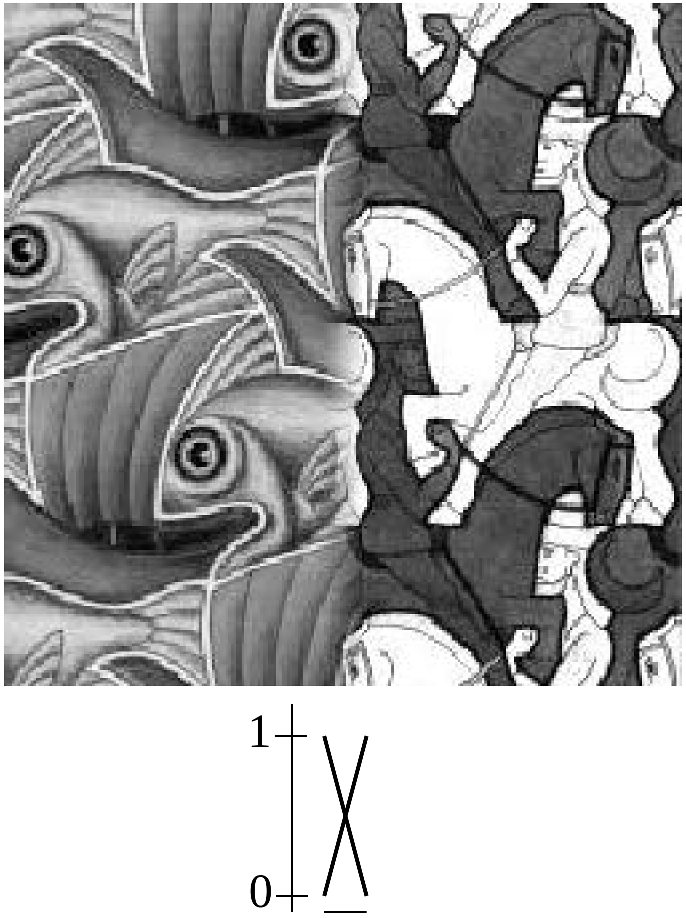


Affect of Window Size





Good Window Size



“Optimal” Window: smooth but not ghosted

What is the Optimal Window?

To avoid seams

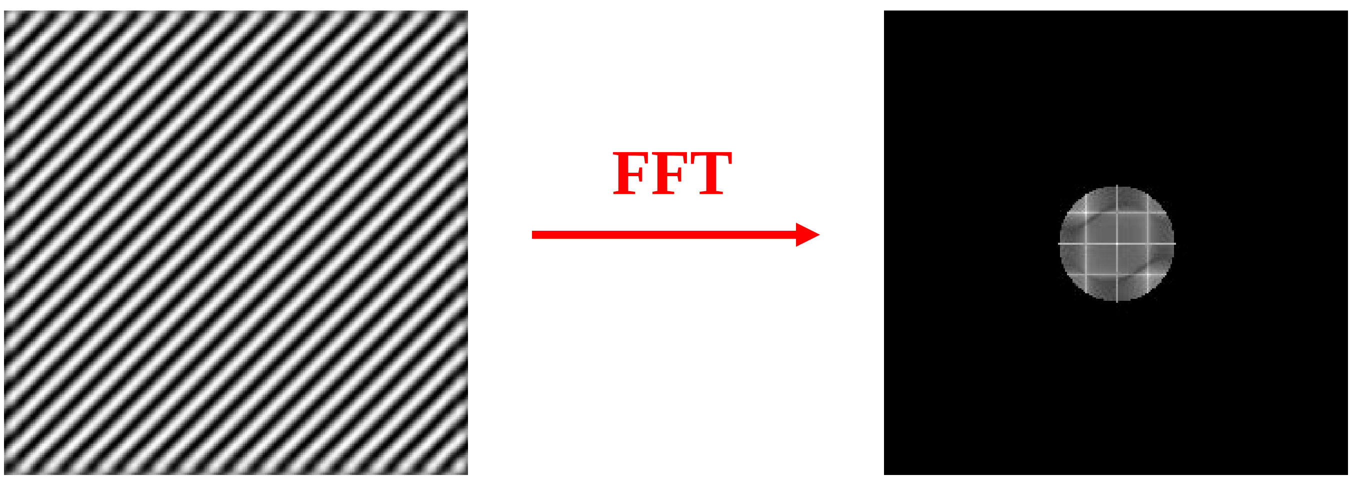
- window = size of largest prominent feature

To avoid ghosting

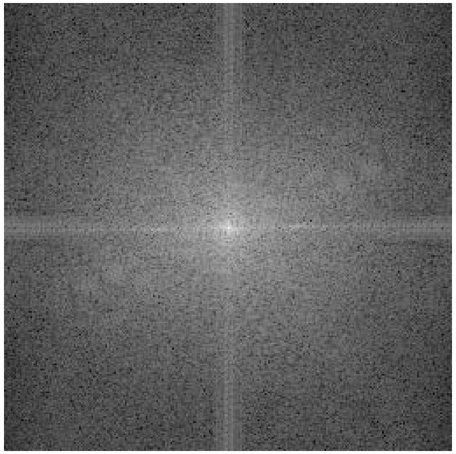
- window <= 2*size of smallest prominent feature

Natural to cast this in the *Fourier domain*

- largest frequency <= 2*size of smallest frequency
- image frequency content should occupy one “octave” (power of two)



What if the Frequency Spread is Wide



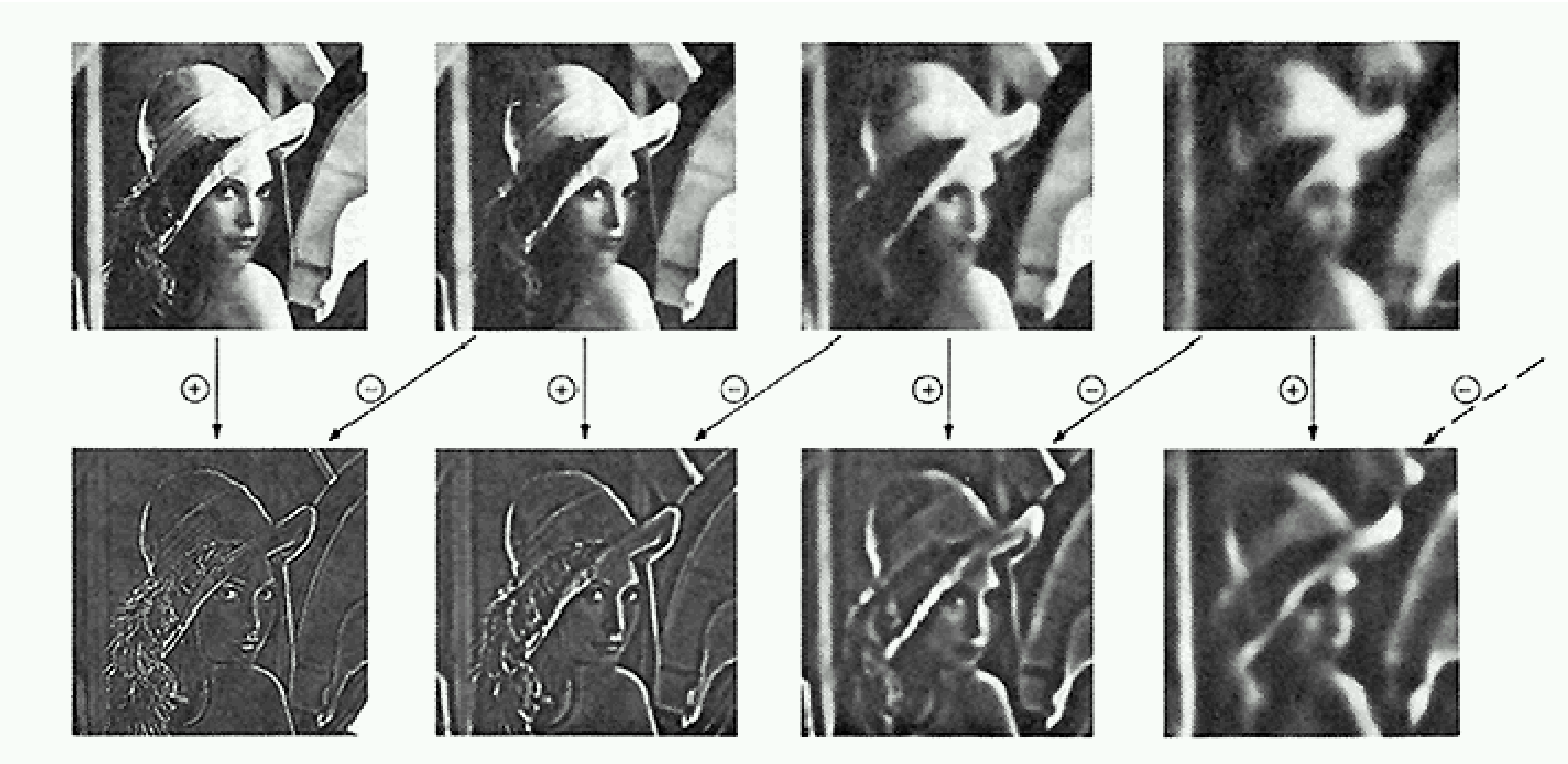
Idea (Burt and Adelson)

- Compute $F_{left} = FFT(I_{left})$, $F_{right} = FFT(I_{right})$
- Decompose Fourier image into octaves (bands)
  - $F_{left} = F_{left}^1 + F_{left}^2 + \ldots$
- Feather corresponding octaves F_{left}^i with F_{right}^i
  - Can compute inverse FFT and feather in spatial domain
- Sum feathered octave images in frequency domain

Better implemented in *spatial domain*

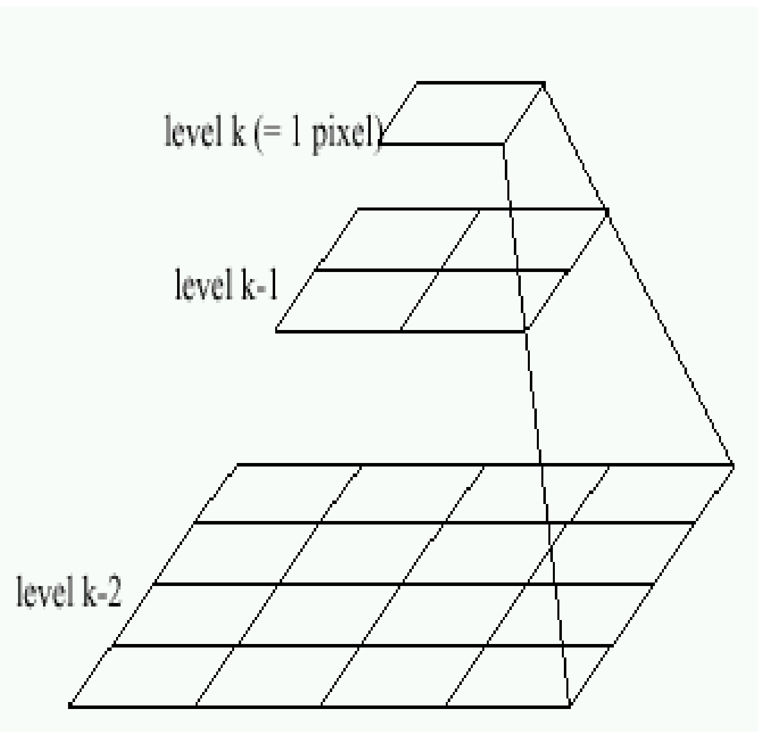
Octaves in the Spatial Domain

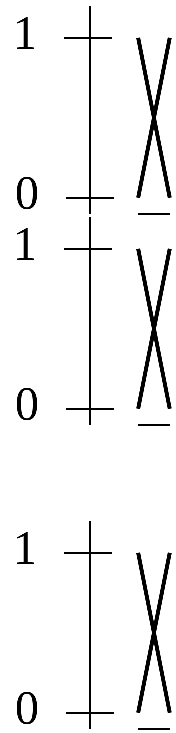
Lowpass Images

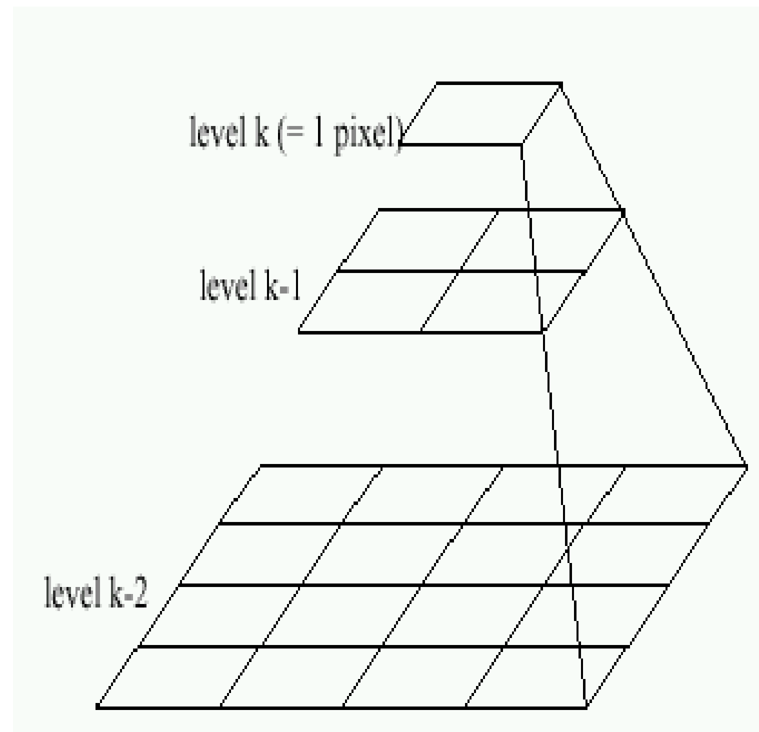


Bandpass Images

Pyramid Blending





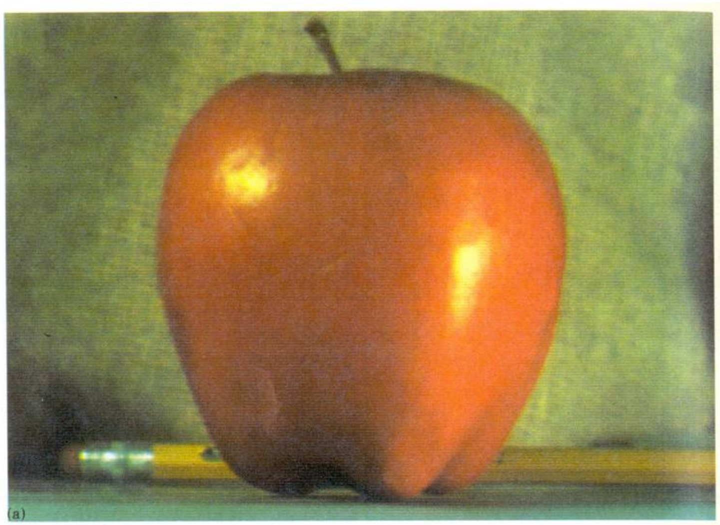


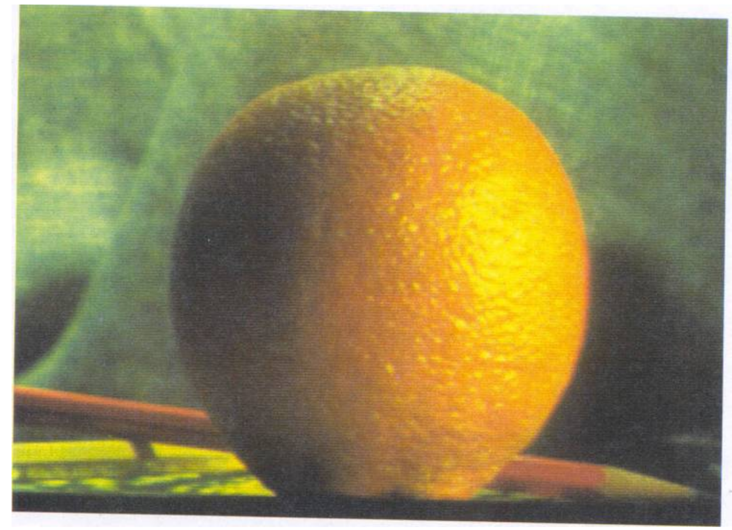
Left pyramid

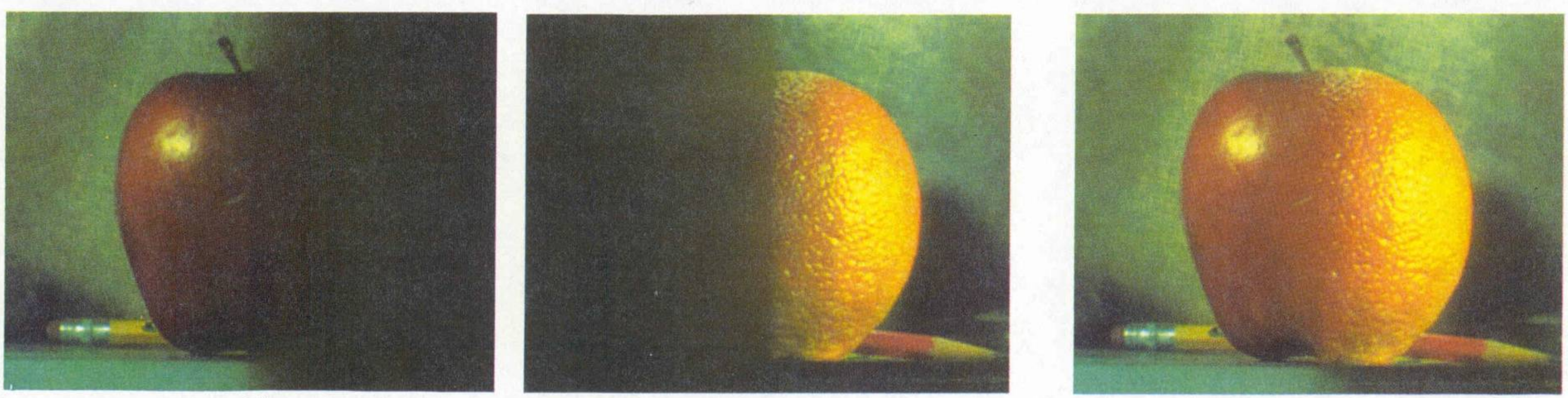
blend

Right pyramid

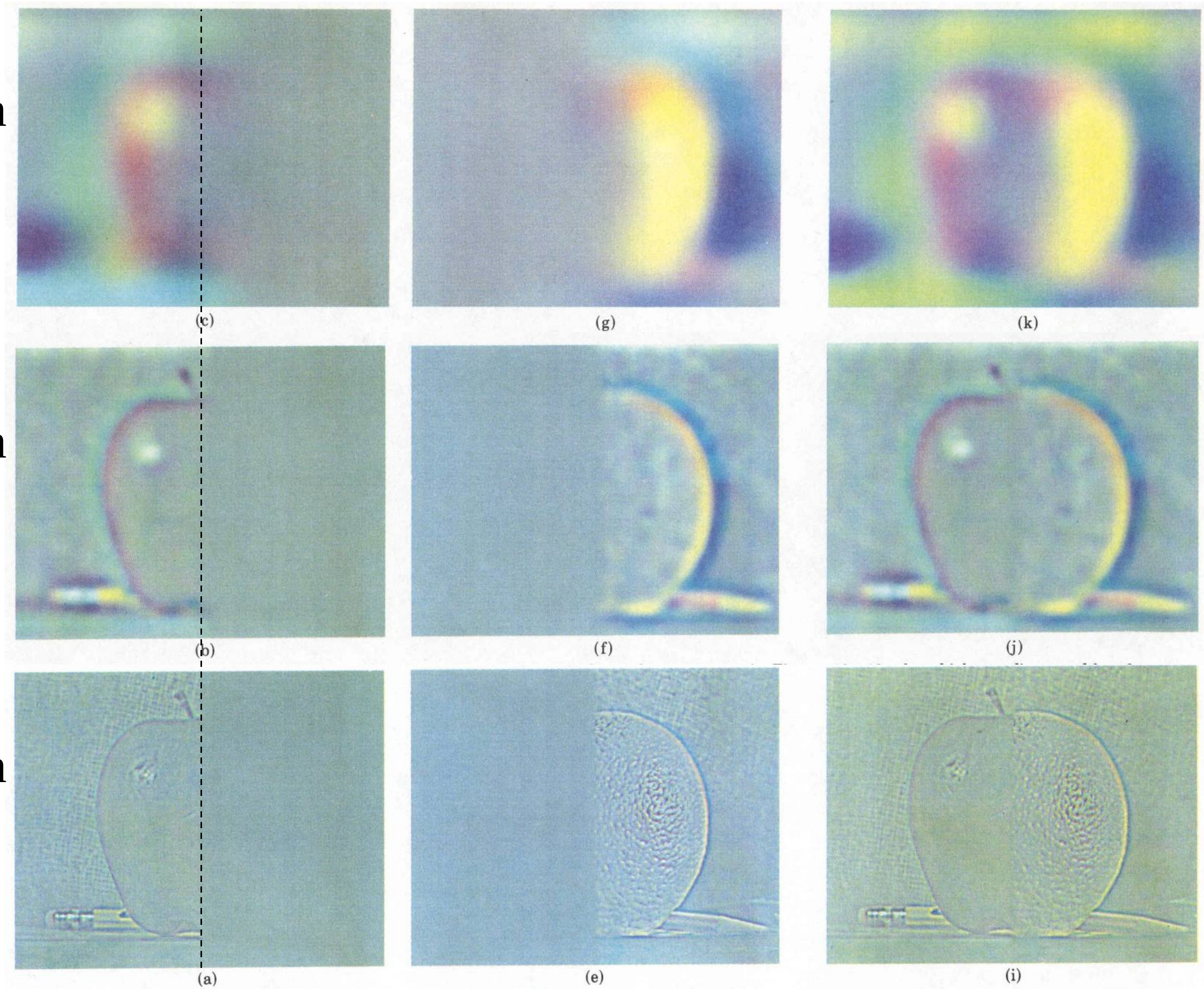
Pyramid Blending







(d) (h) (l)



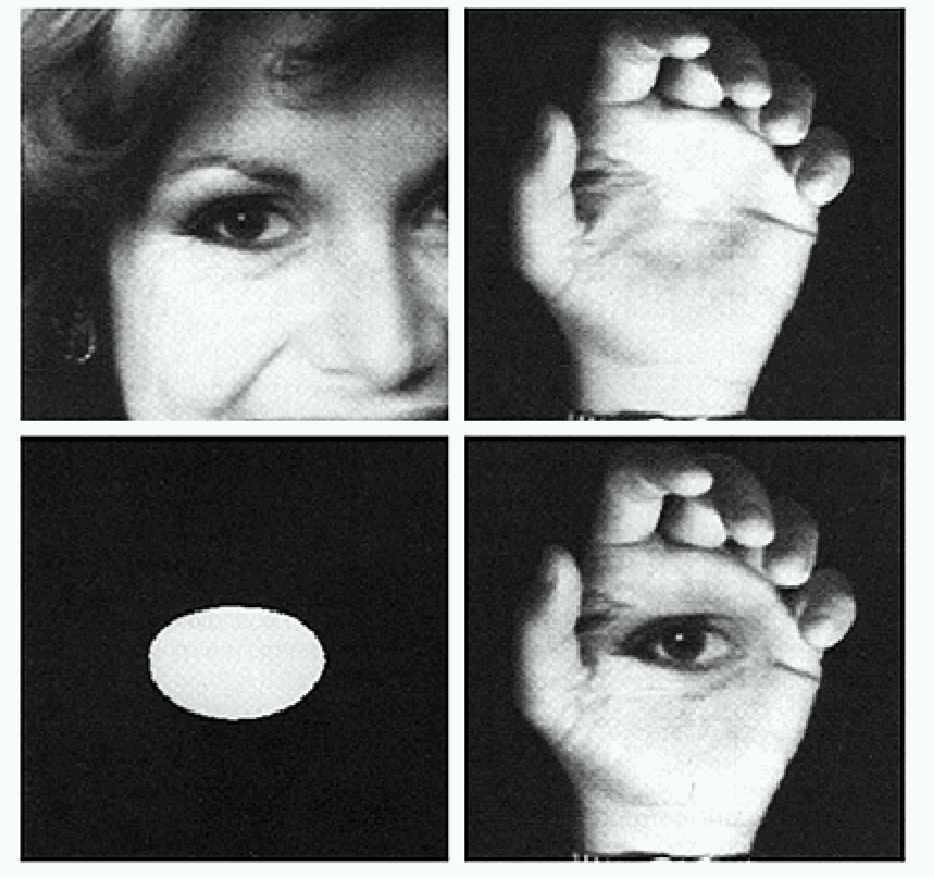
laplacian level 4

laplacian level 2

laplacian level 0

left pyramid | right pyramid | blended pyramid

Blending Regions

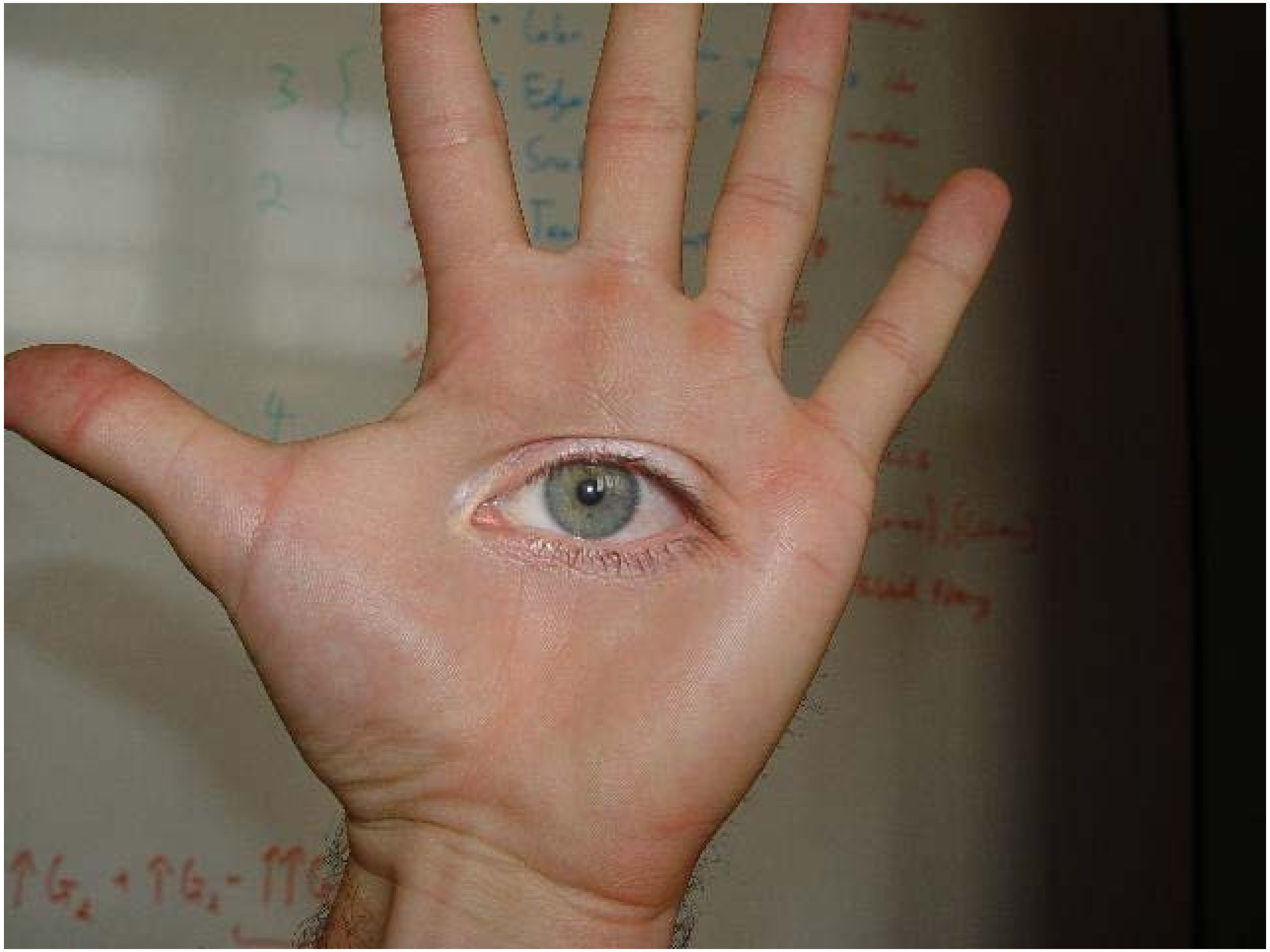


Laplacian Pyramid/Stack Blending

General Approach:

1. Build Laplacian pyramid/stack *LX* and *LY* from images *X* and *Y*
2. Build a Gaussian pyramid/stack *Ga* from the binary alpha mask *a*
3. Form a combined pyramid/stack *LBlend* from *LX* and *LY* using the corresponding levels of *GA* as weights:
   - *LBlend(i,j) = Ga(I,j,)*LX(I,j) + (1-Ga(I,j))*LY(I,j)*
4. Collapse the *LBlend* pyramid/stack to get the final blended image

Horror Photo



© david dmartin (Boston College)

Results from this class (fall 2005)

Simplification: Two-band Blending

Brown & Lowe, 2003

- Only use two bands: high freq. and low freq.
- Blends low freq. smoothly
- Blend high freq. with no smoothing: use binary alpha

2-band "Laplacian Stack" Blending

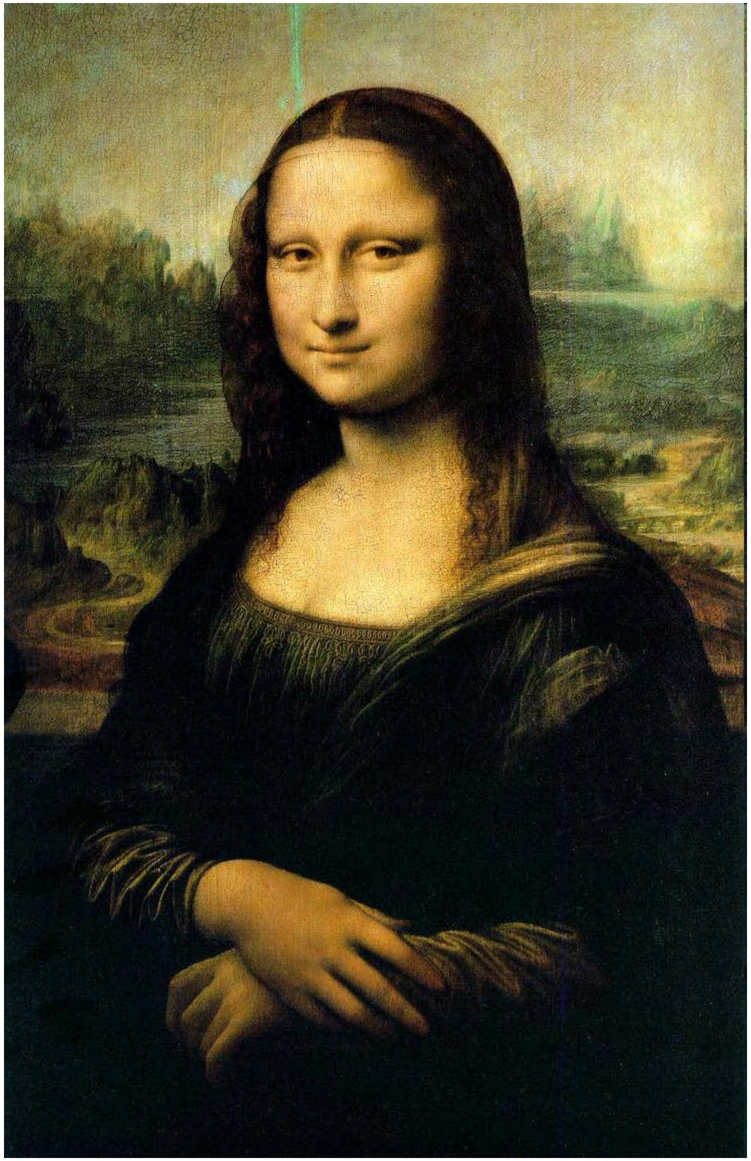
Low frequency (λ > 2 pixels)

High frequency (λ < 2 pixels)

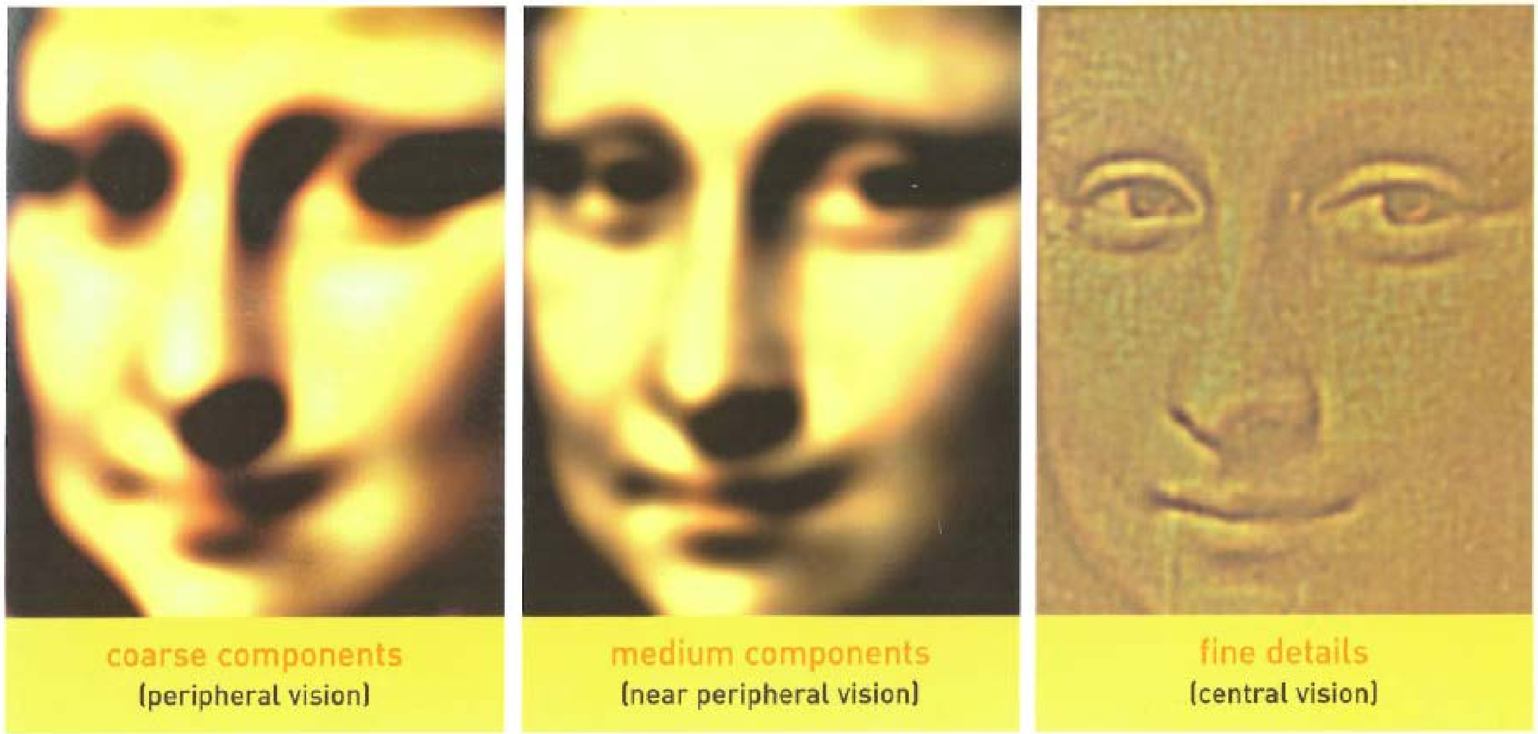
Linear Blending

2-band Blending

Da Vinci and Peripheral Vision



https://en.wikipedia.org/wiki/Speculations_about_Mona_Lisa#Smile



Leonardo playing with peripheral vision

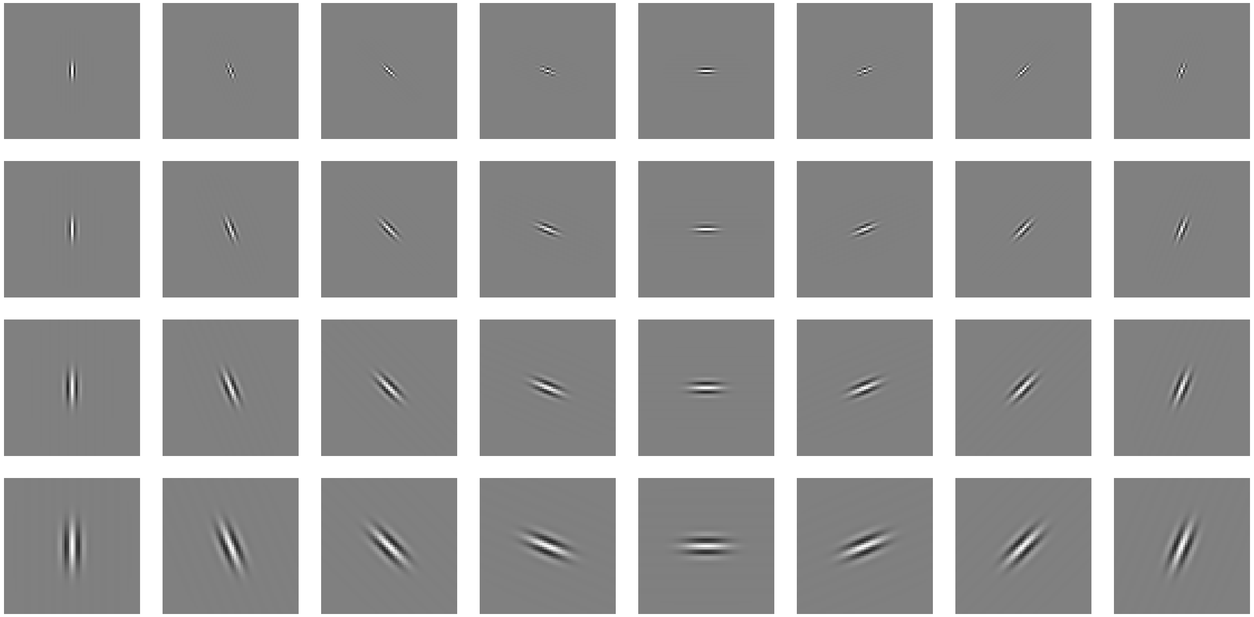
Livingstone, Vision and Art: The Biology of Seeing

Clues from Human Perception

Early processing in humans filters for various orientations and scales of frequency

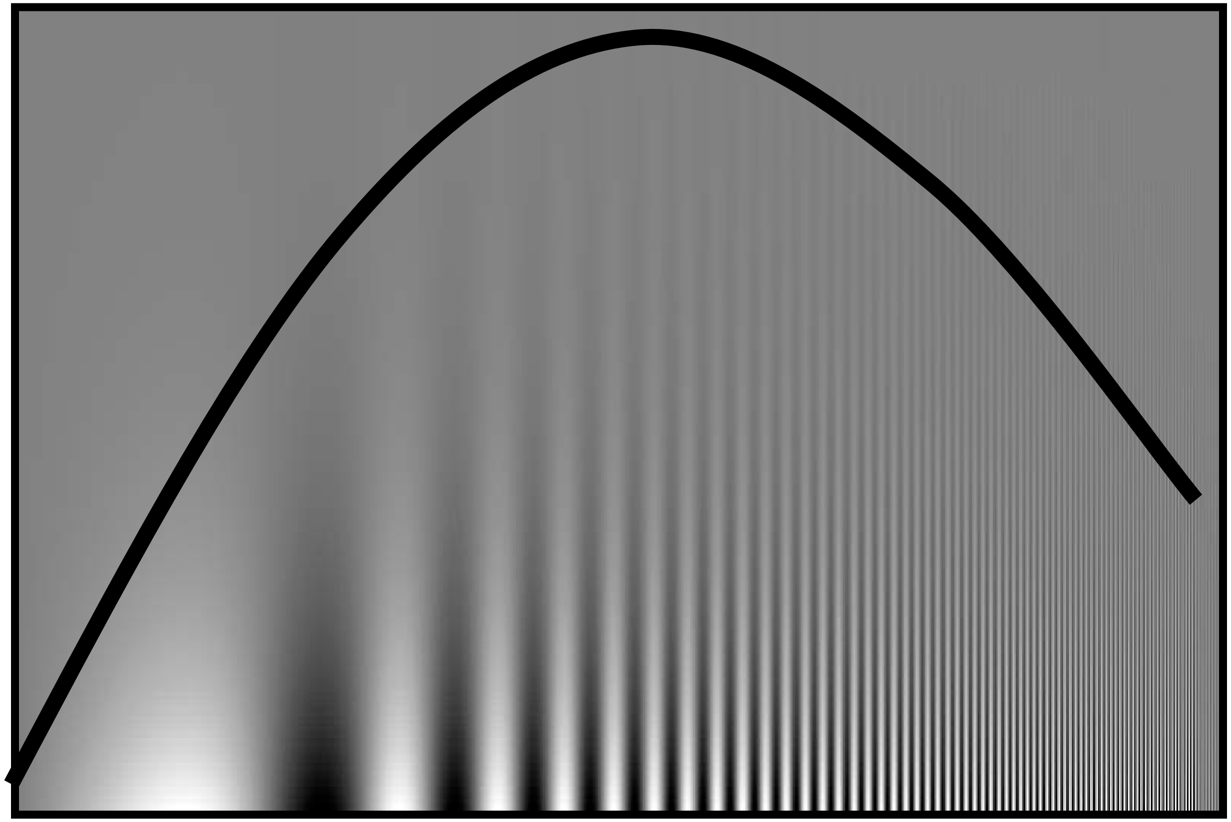
Perceptual cues in the mid frequencies dominate perception

When we see an image from far away, we are effectively subsampling it



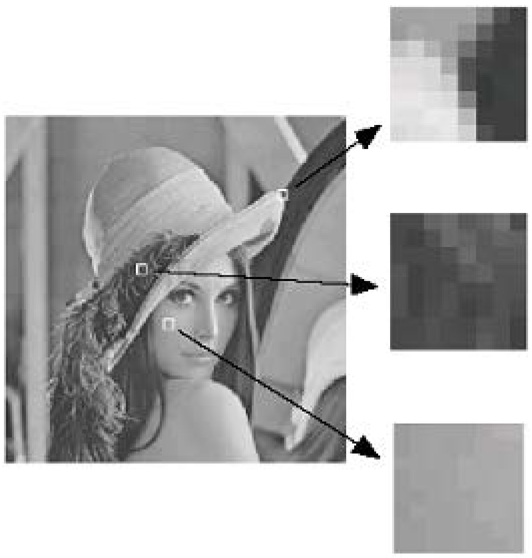
Early Visual Processing: Multi-scale edge and blob filters

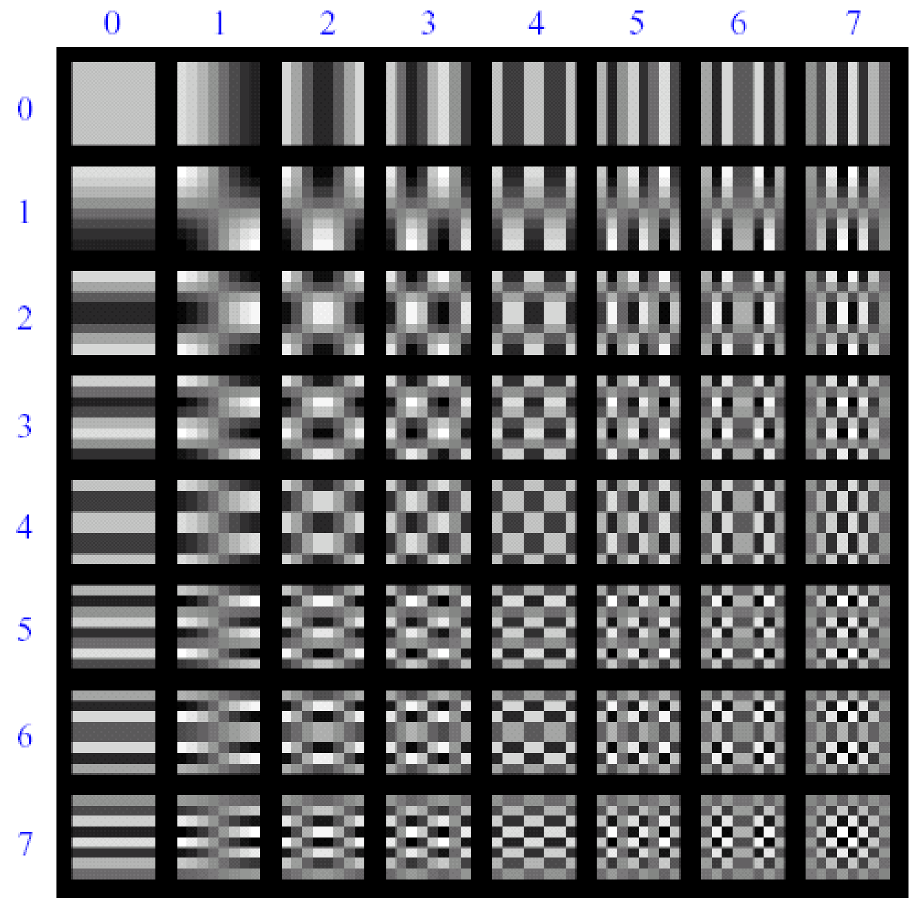
Frequency Domain and Perception



Campbell-Robson contrast sensitivity curve

Lossy Image Compression (JPEG)





Block-based Discrete Cosine Transform (DCT)

Using DCT in JPEG

The first coefficient $B(0,0)$ is the DC component, the average intensity

The top-left coeffs represent low frequencies, the bottom right – high frequencies

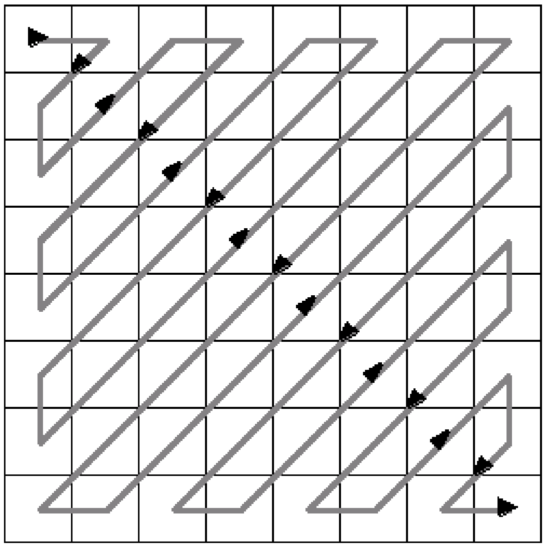


Image compression using DCT

Quantize

- More coarsely for high frequencies (which also tend to have smaller values)
- Many quantized high frequency values will be zero

Encode

- Can decode with inverse dct

Filter responses

$$G = \begin{bmatrix} -415.38 & -30.19 & -61.20 & 27.24 & 56.13 & -20.10 & -2.39 & 0.46 \\ 4.47 & -21.86 & -60.76 & 10.25 & 13.15 & -7.09 & -8.54 & 4.88 \\ -46.83 & 7.37 & 77.13 & -24.56 & -28.91 & 9.93 & 5.42 & -5.65 \\ -48.53 & 12.07 & 34.10 & -14.76 & -10.24 & 6.30 & 1.83 & 1.95 \\ 12.12 & -6.55 & -13.20 & -3.95 & -1.88 & 1.75 & -2.79 & 3.14 \\ -7.73 & 2.91 & 2.38 & -5.94 & -2.38 & 0.94 & 4.30 & 1.85 \\ -1.03 & 0.18 & 0.42 & -2.42 & -0.88 & -3.02 & 4.12 & -0.66 \\ -0.17 & 0.14 & -1.07 & -4.19 & -1.17 & -0.10 & 0.50 & 1.68 \end{bmatrix}$$

$u \longrightarrow$; $v \downarrow$

Quantized values

$$B = \begin{bmatrix} -26 & -3 & -6 & 2 & 2 & -1 & 0 & 0 \\ 0 & -2 & -4 & 1 & 1 & 0 & 0 & 0 \\ -3 & 1 & 5 & -1 & -1 & 0 & 0 & 0 \\ -3 & 1 & 2 & -1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Quantization table

$$Q = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

JPEG Compression Summary

Subsample color by factor of 2

- People have bad resolution for color

Split into blocks (8x8, typically), subtract 128

For each block

a. Compute DCT coefficients
b. Coarsely quantize
   - Many high frequency components will become zero
c. Encode (e.g., with Huffman coding)

http://en.wikipedia.org/wiki/YCbCr
http://en.wikipedia.org/wiki/JPEG

Block size in JPEG

Block size

- small block
  - faster
  - correlation exists between neighboring pixels
- large block
  - better compression in smooth regions
- It’s 8x8 in standard JPEG

JPEG compression comparison

89k

12k