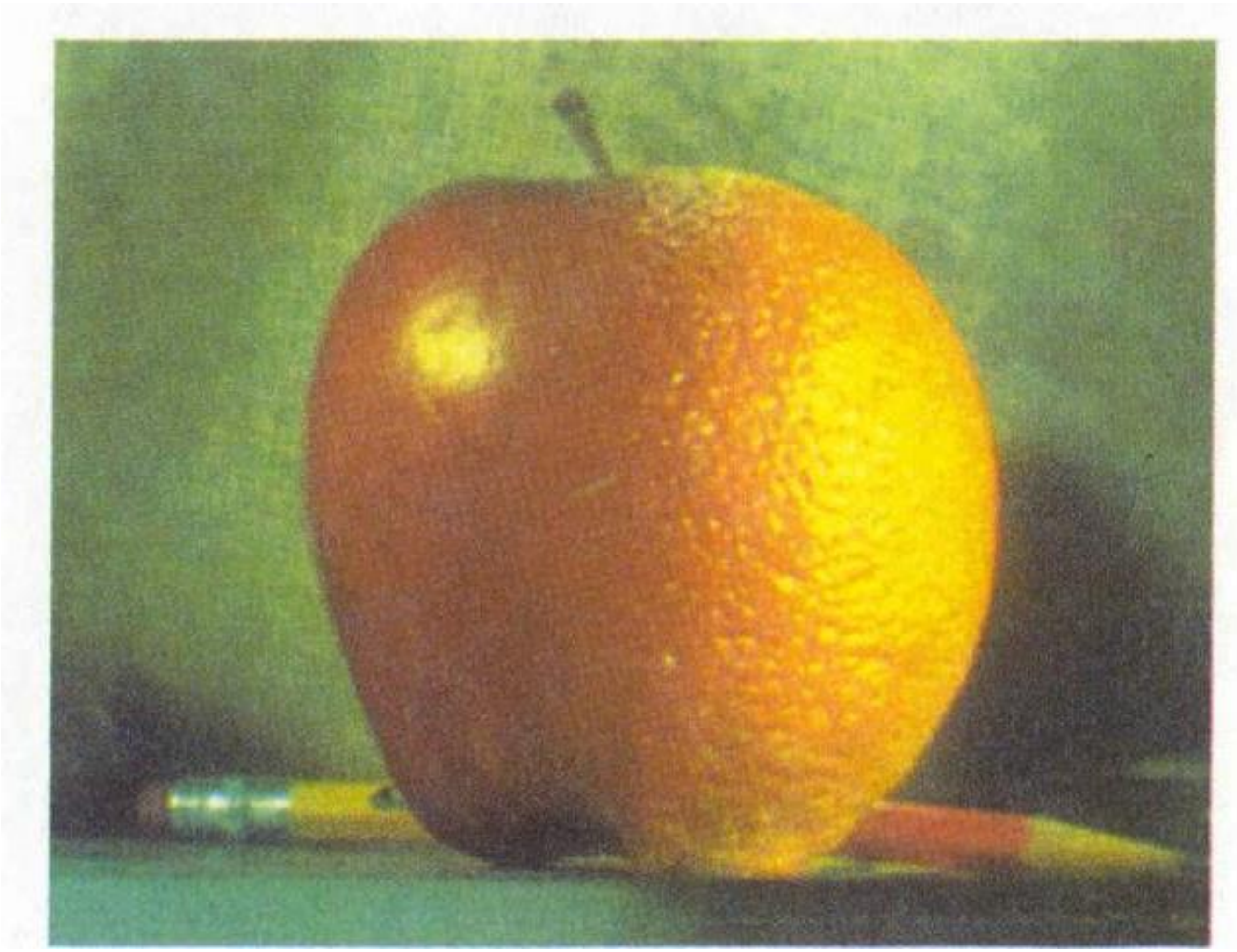
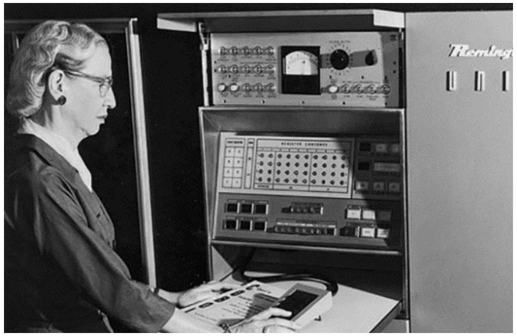
Pyramid Blending, Templates, NL Filters



CS180: Intro to Comp. Vision and Comp. Photo
Efros & Kanazawa, UC Berkeley, Fall 2025

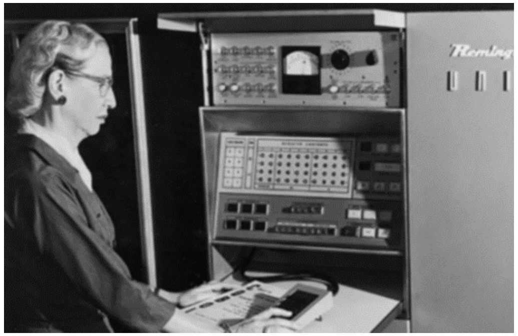
Low Pass vs. High Pass filtering

Image



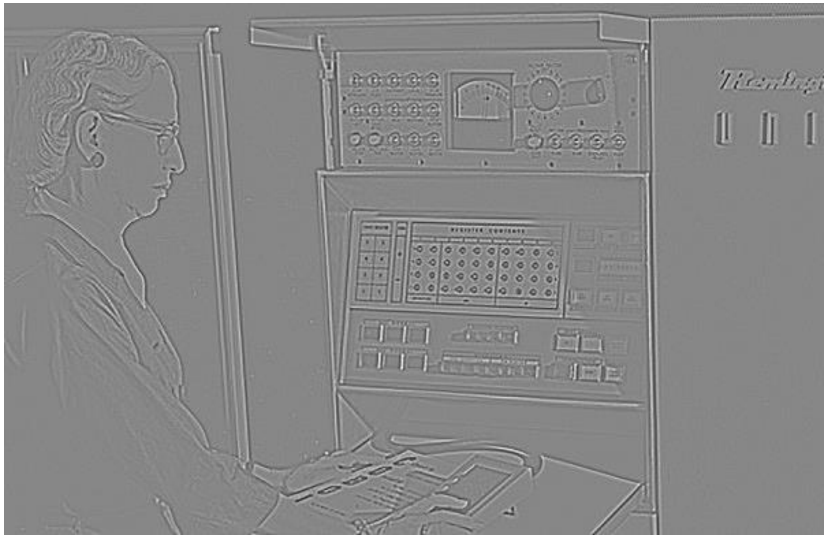
-

Smoothed



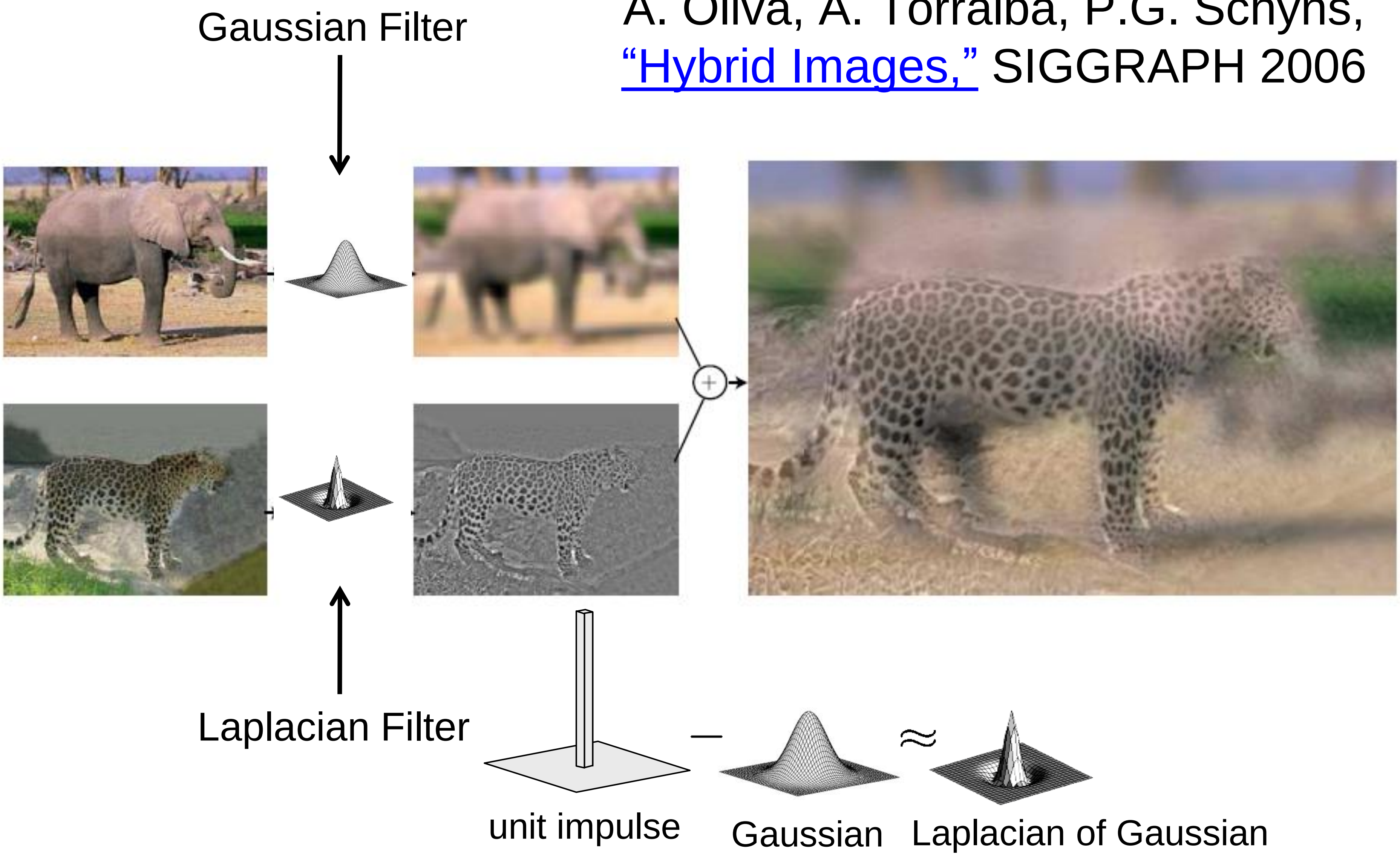
Details

=

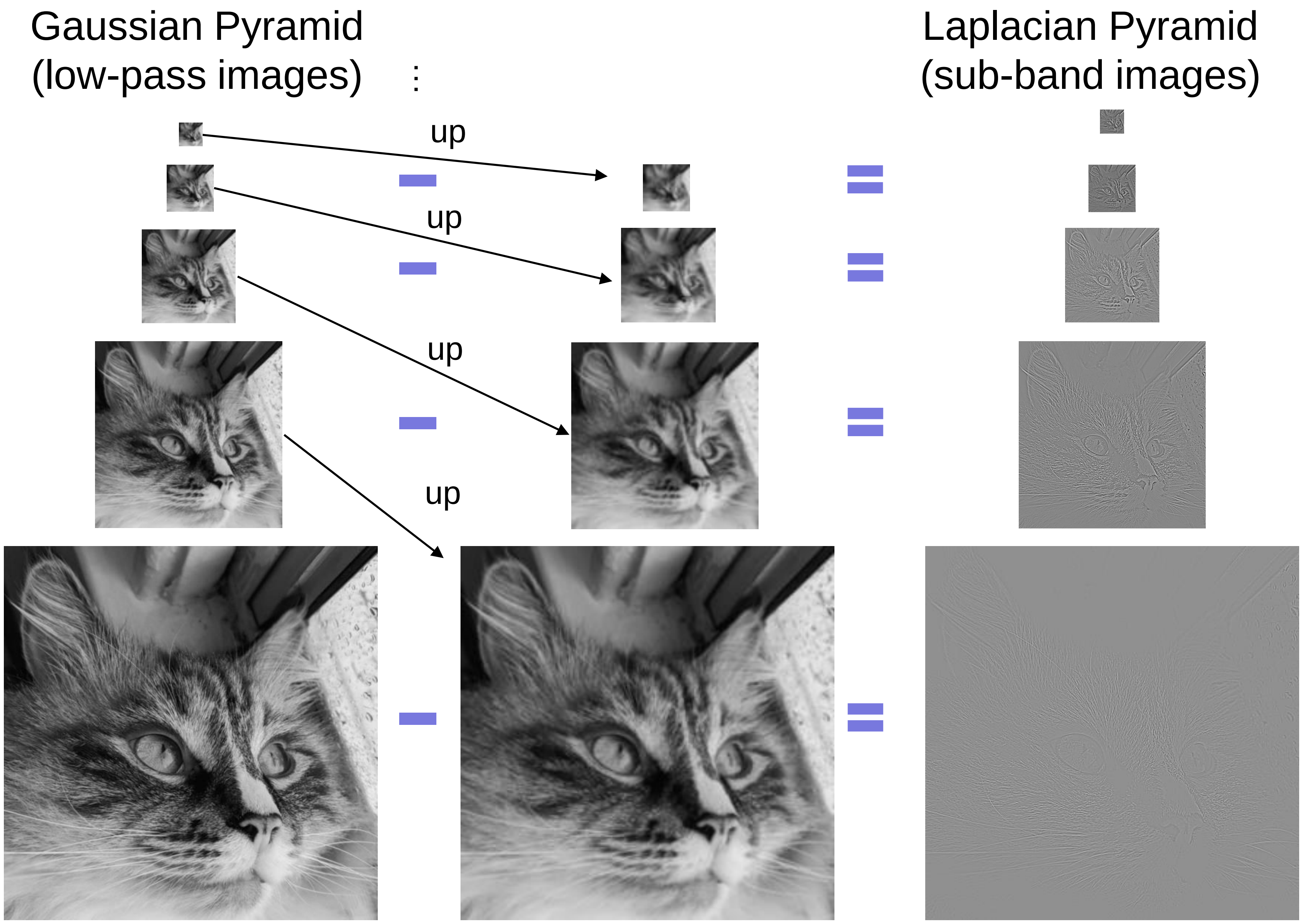


Application: Hybrid Images

A. Oliva, A. Torralba, P.G. Schyns, [“Hybrid Images,”](#) SIGGRAPH 2006

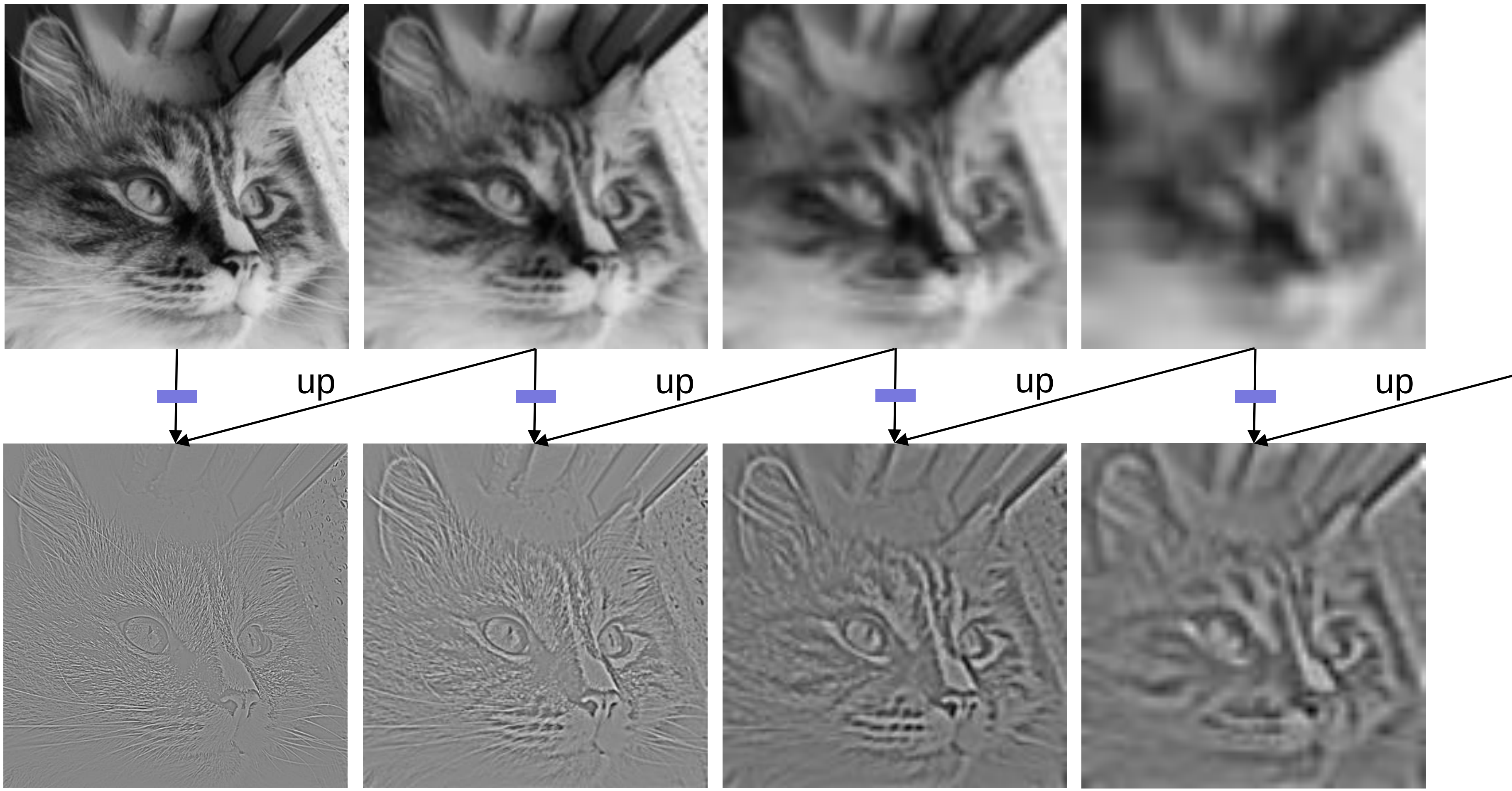


Band-pass filtering in spatial domain



As a stack

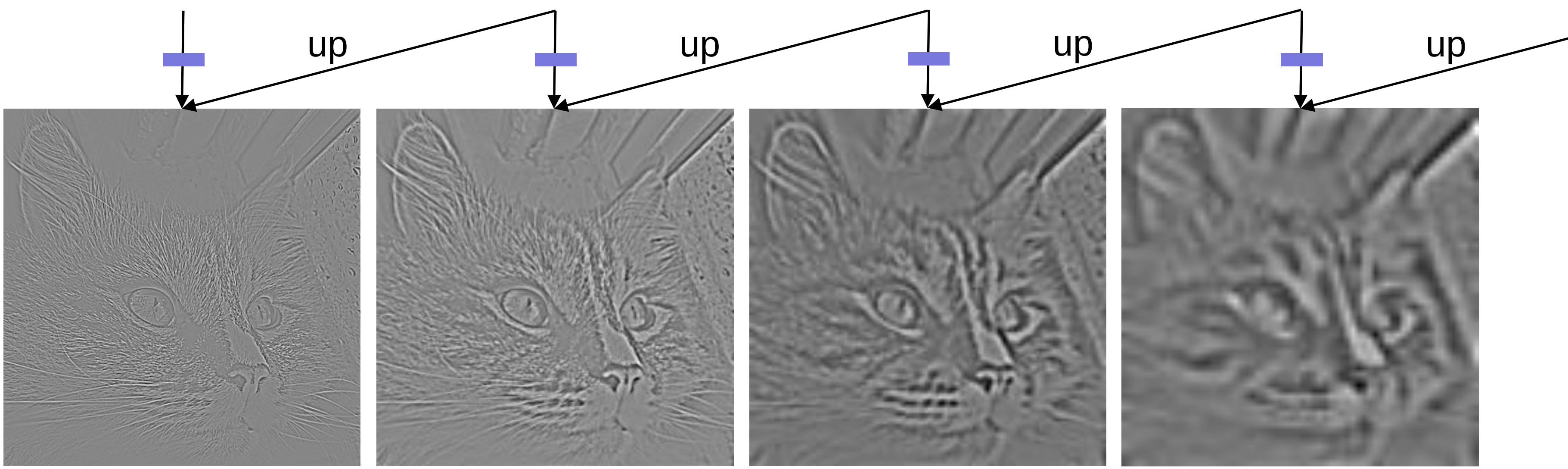
Gaussian Pyramid (low-pass images)



Laplacian Pyramid (sub-band images)

Created from Gaussian pyramid by subtraction

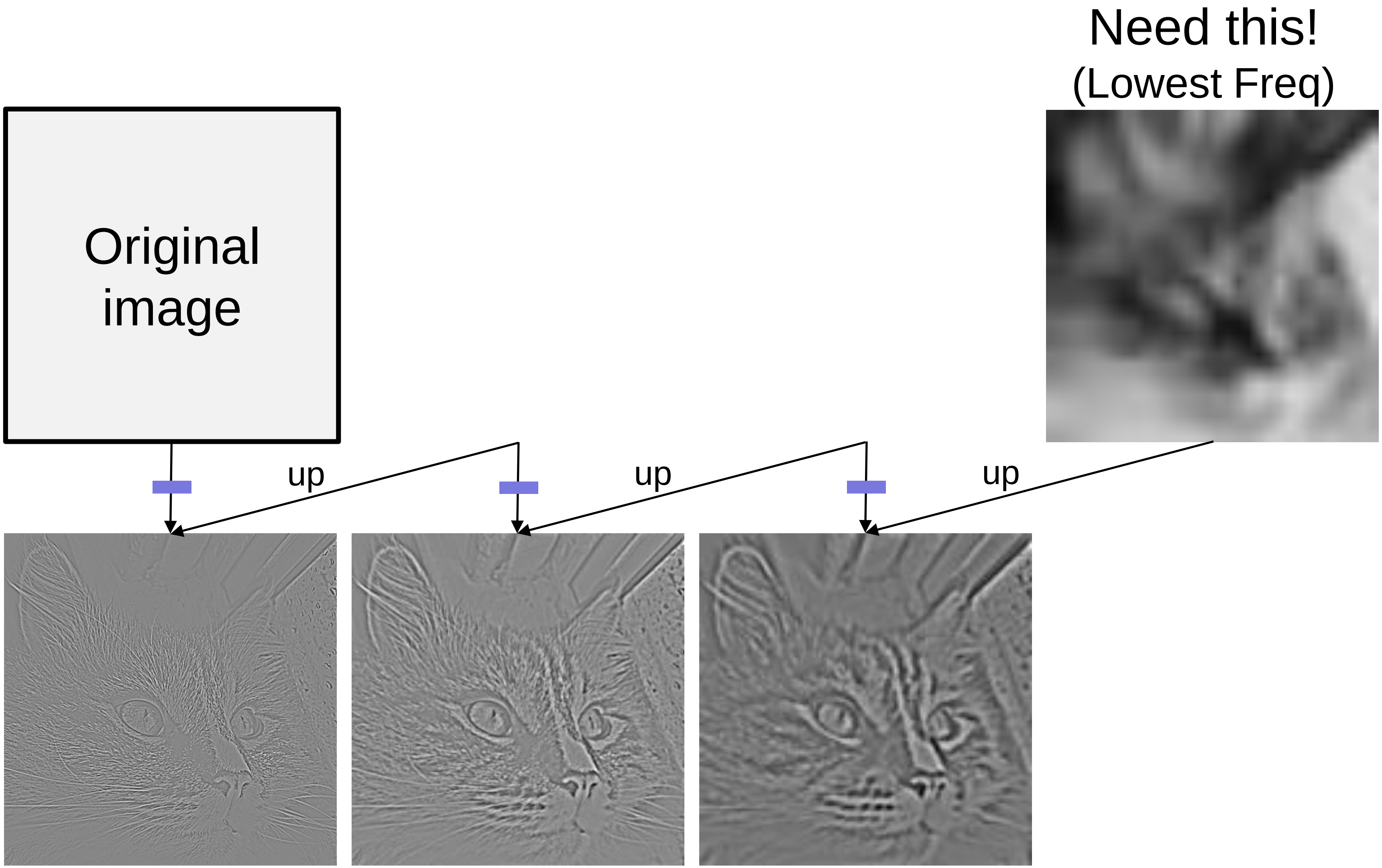
Collapsing Laplacian Pyramid



Laplacian Pyramid (sub-band images)

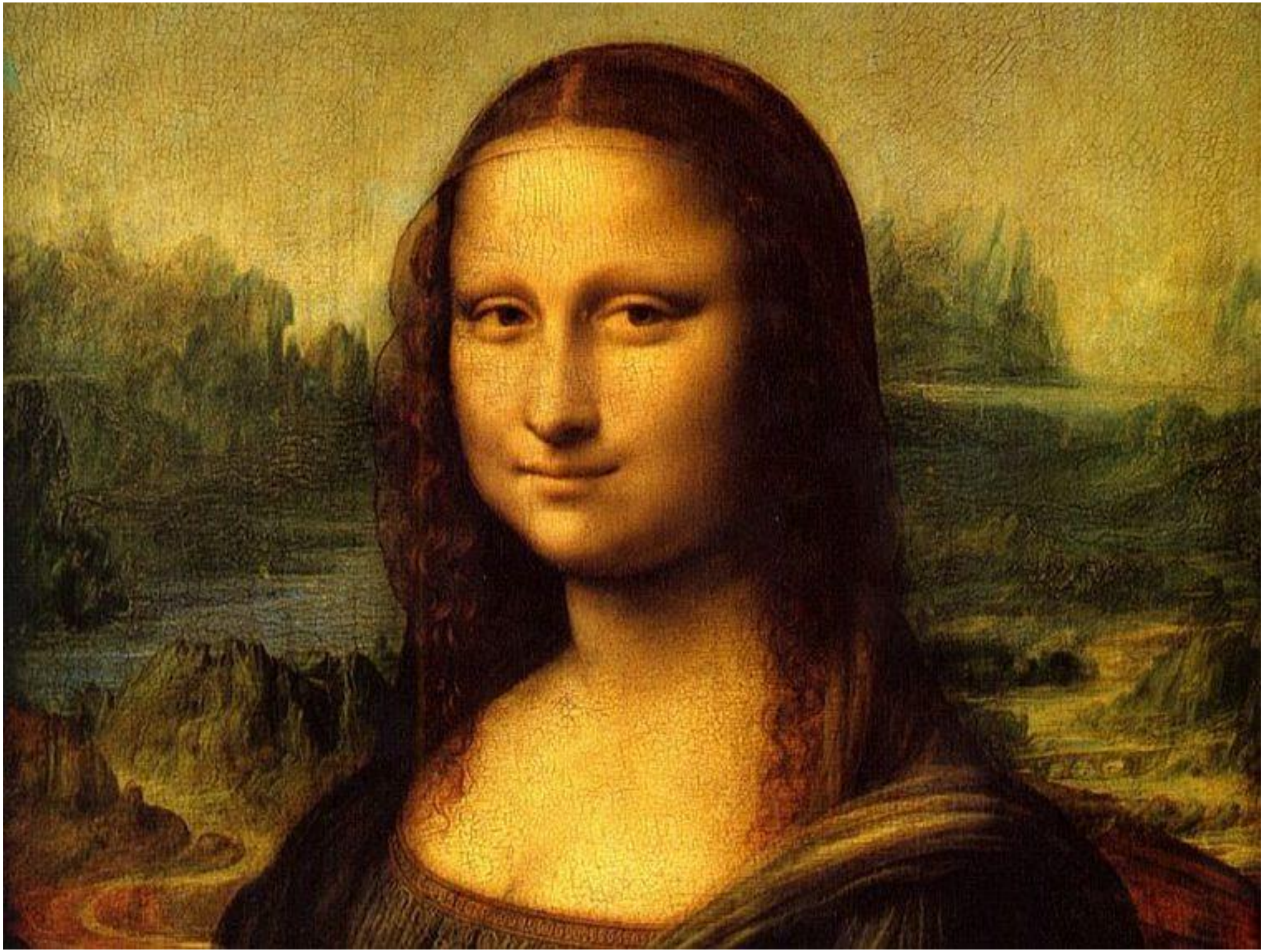
Created from Gaussian pyramid by subtraction

Collapsing Laplacian Pyramid

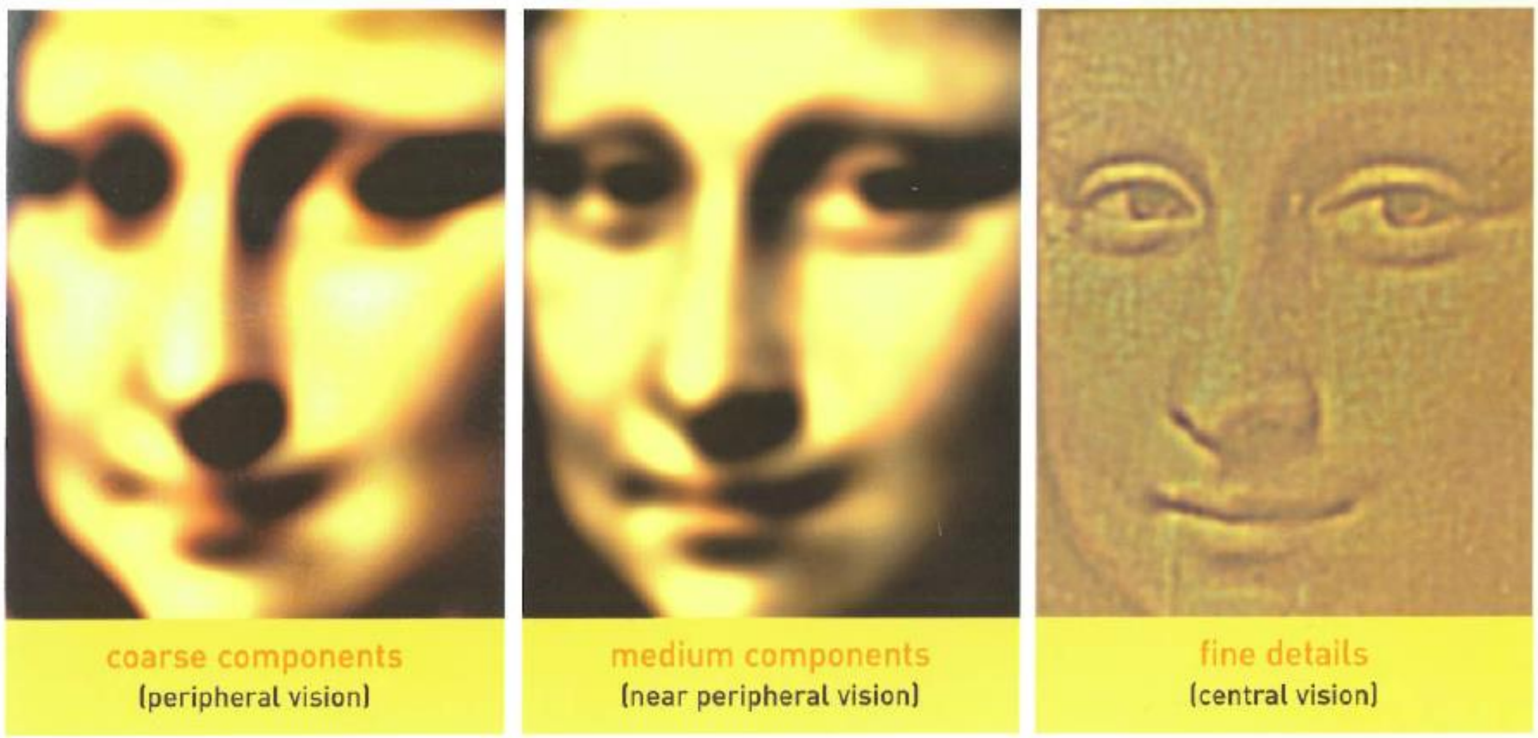


How can we reconstruct (collapse) this pyramid into the original image?

Da Vinci and The Laplacian Pyramid



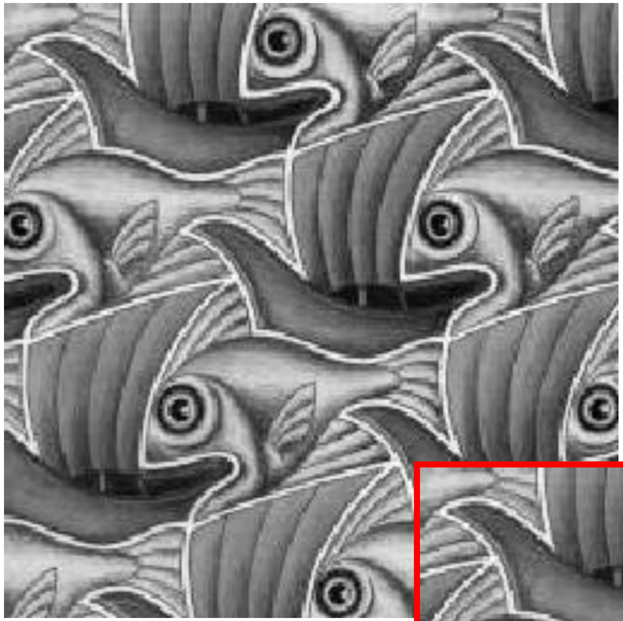
Da Vinci and The Laplacian Pyramid

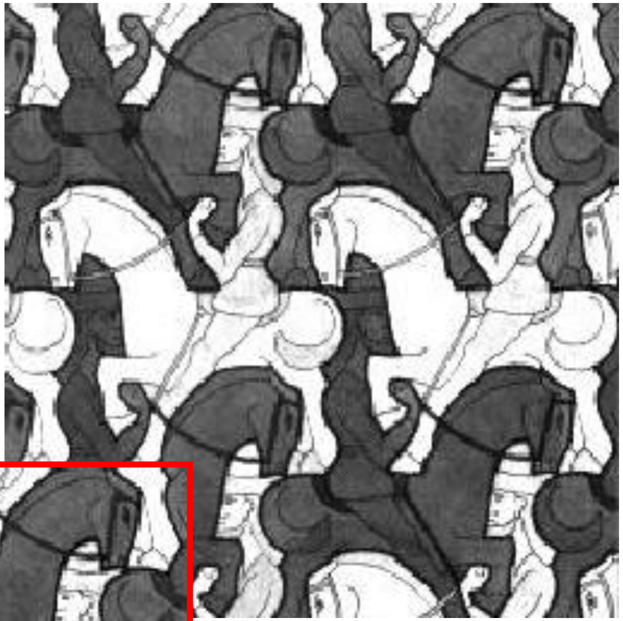


Leonardo playing with peripheral vision

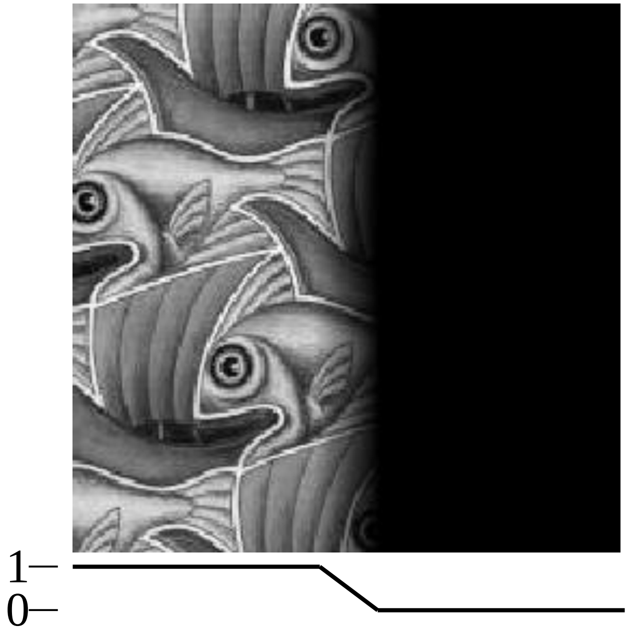
[Livingstone, Vision and Art: The Biology of Seeing]

Blending

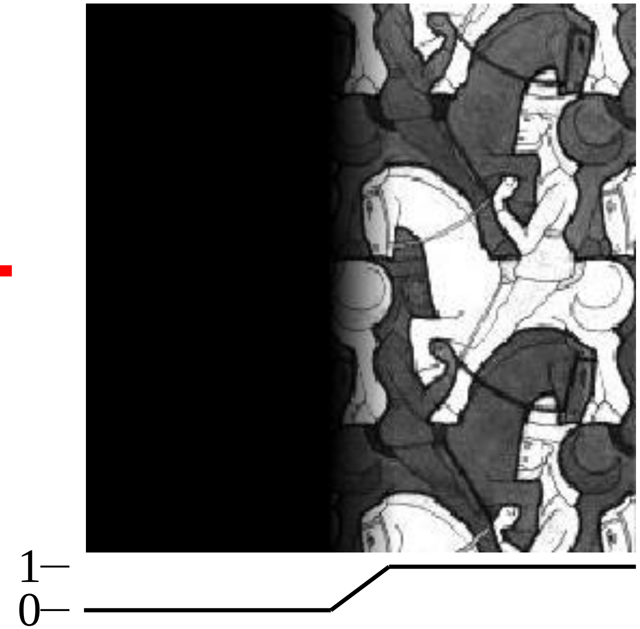




Alpha Blending / Feathering



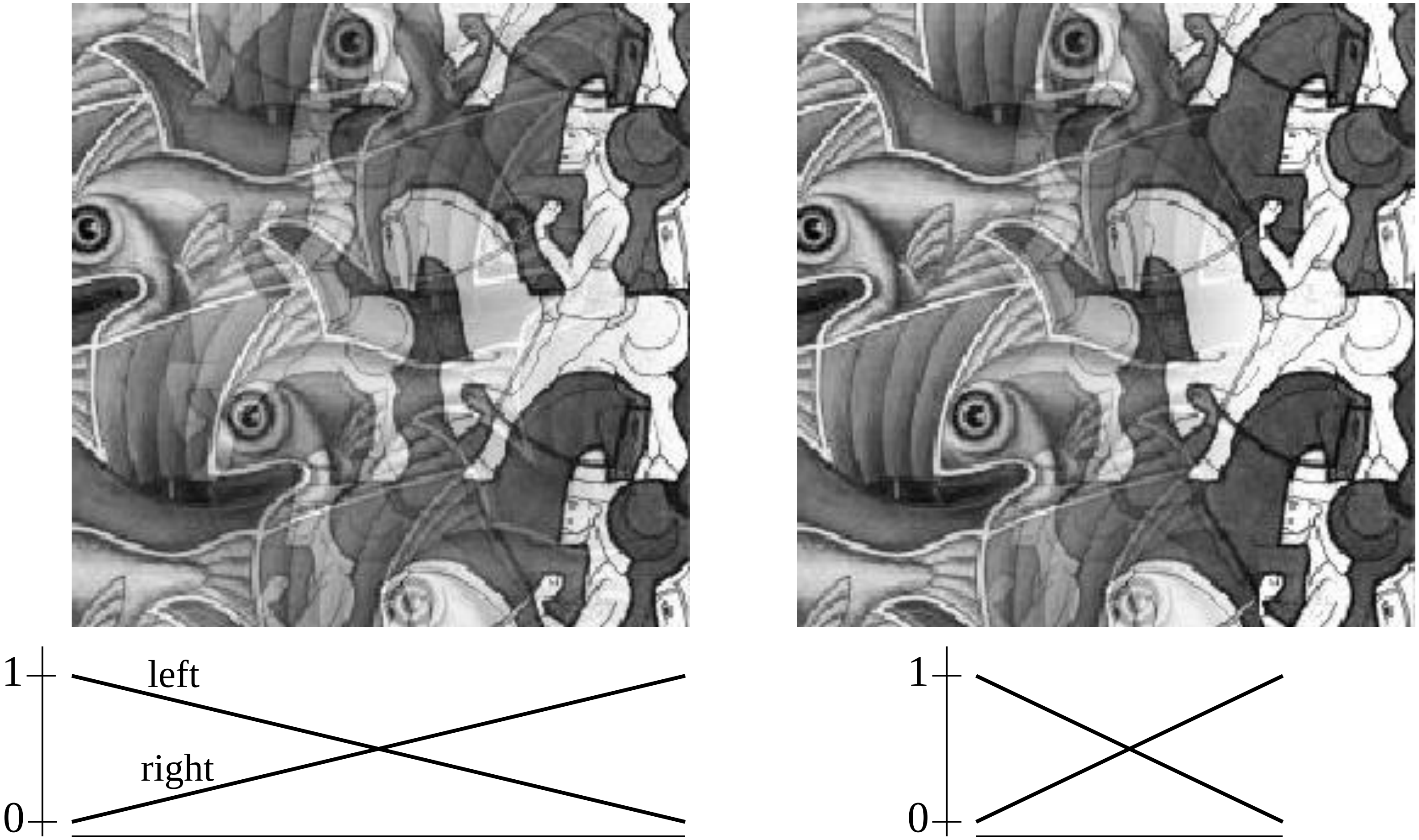
+



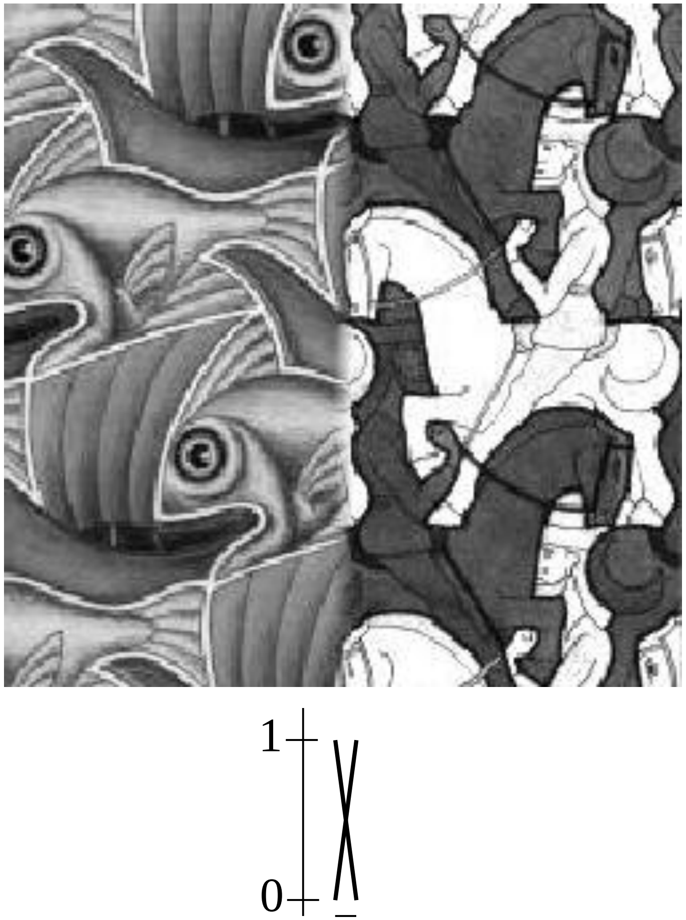
=

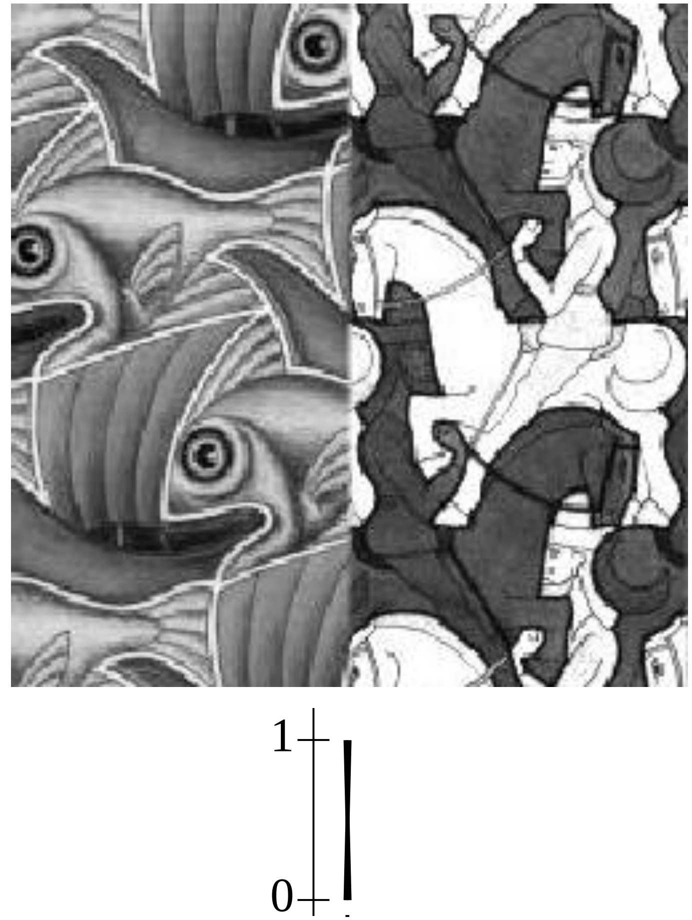
$$I_{blend} = \alpha I_{left} + (1-\alpha) I_{right}$$

Affect of Window Size

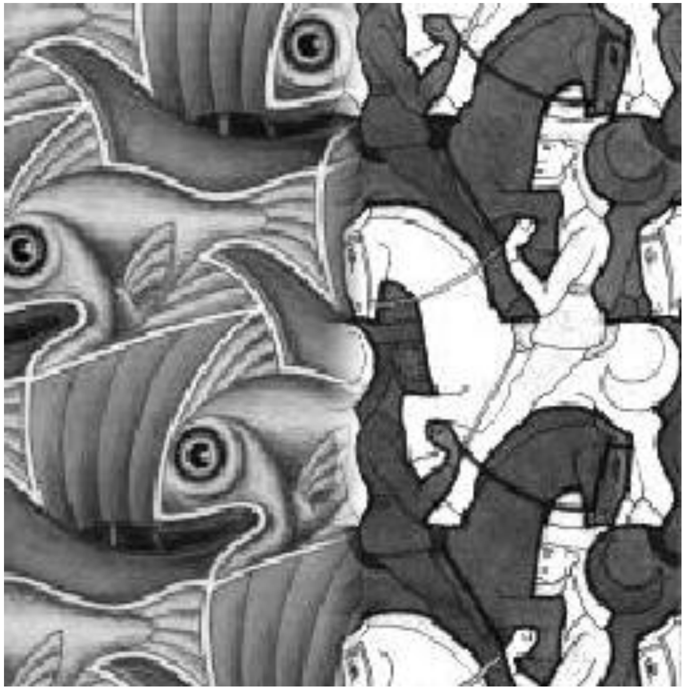


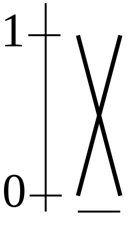
Affect of Window Size





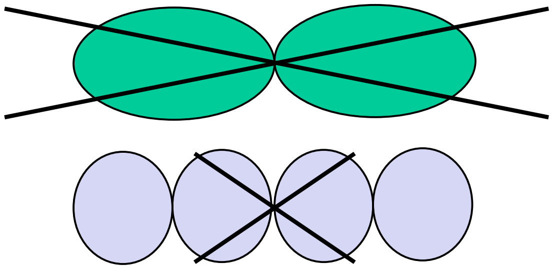
Good Window Size





“Optimal” Window: smooth but not ghosted

What is the Optimal Window?



To avoid seams

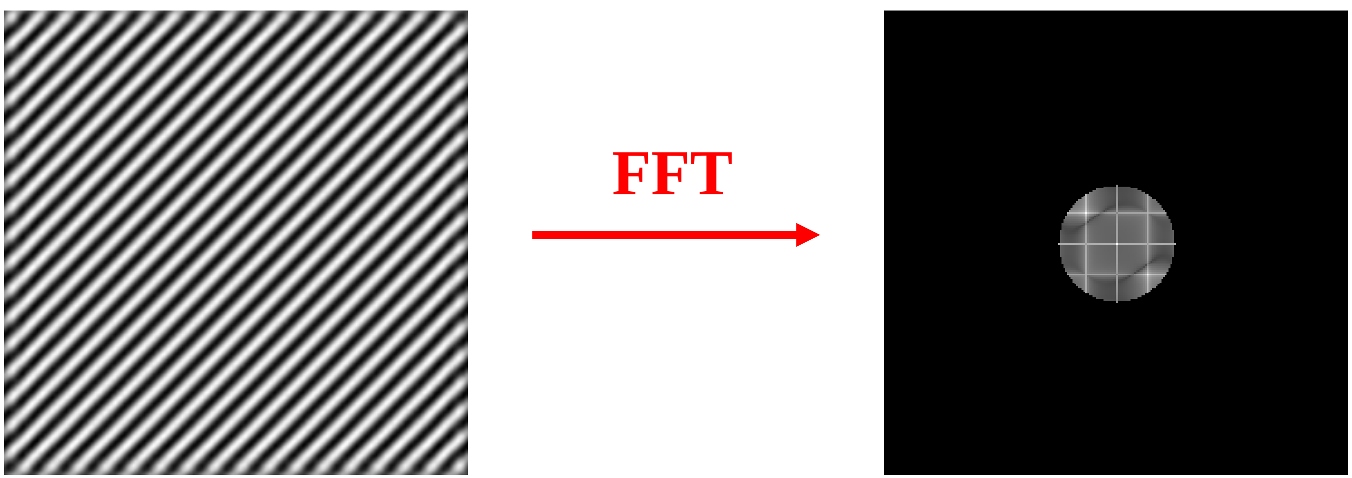
- window = size of largest prominent feature

To avoid ghosting

- window <= 2*size of smallest prominent feature

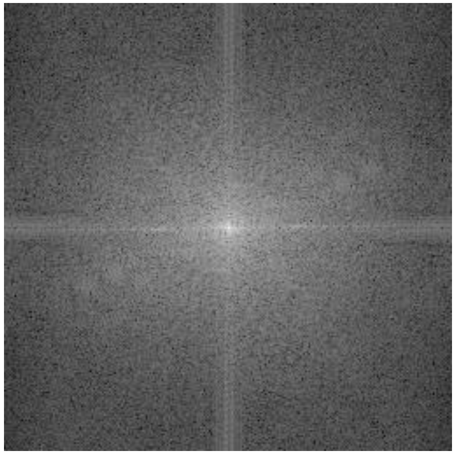
Natural to cast this in the *Fourier domain*

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



What if the Frequency Spread is Wide

FFT

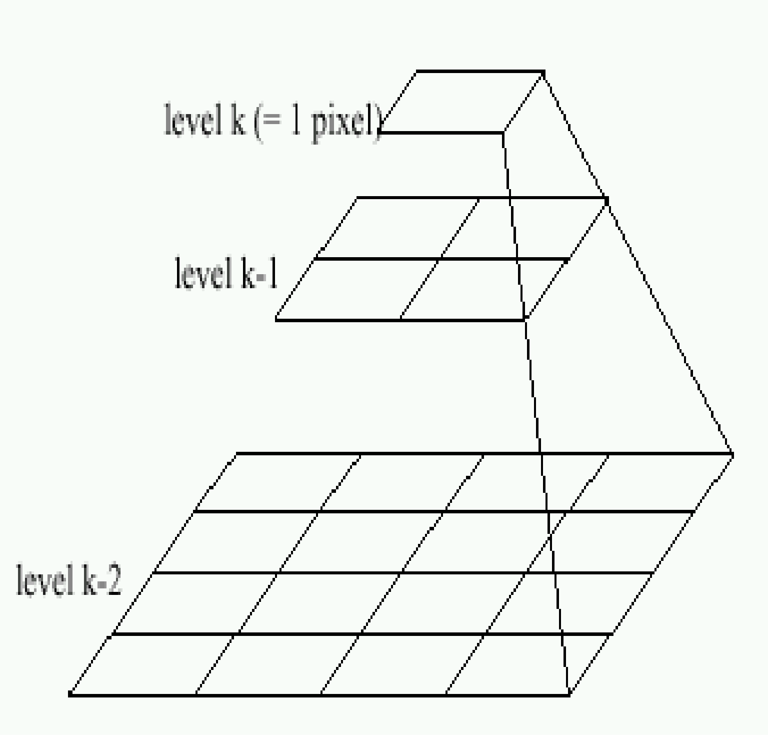


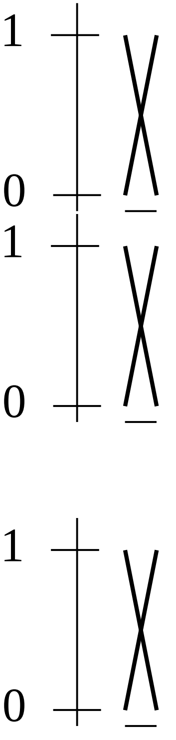
Use a band-pass (Laplacian) Pyramid!

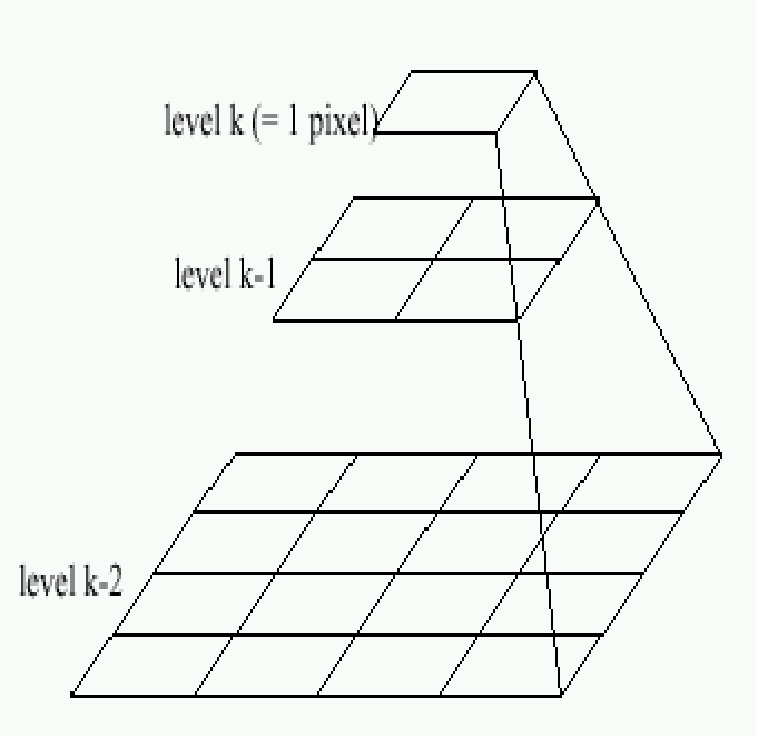
- Split image into set of band-pass images (one octave of frequencies each)
- Blend each level of the pyramid separately
- Collapse the pyramid!

Burt and Adelson (1983), A Multiresolution Spline With Application to Image Mosaics

Band-pass Pyramid Blending

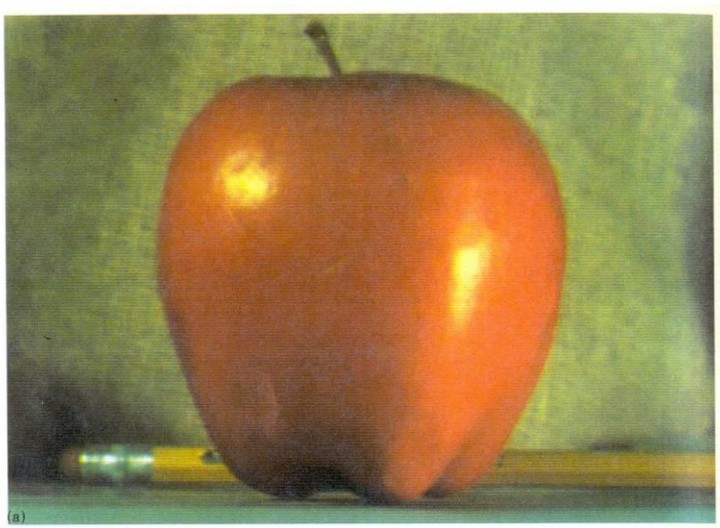




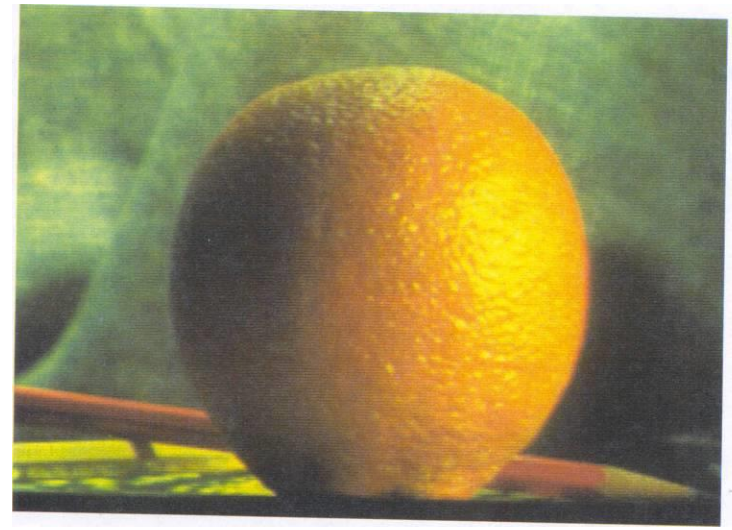


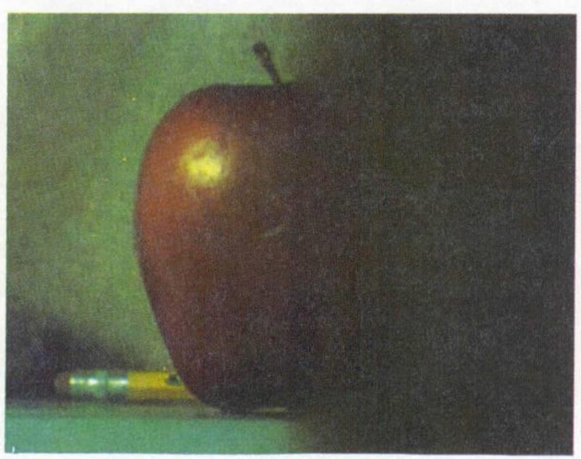
Left pyramid   blend   Right pyramid

Pyramid Blending (Burt and Adelson)

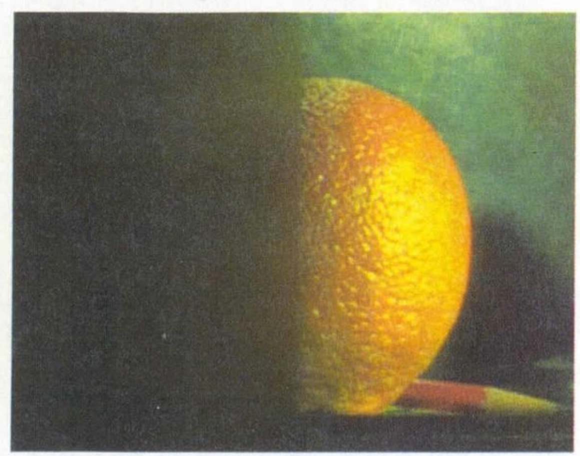


(a)

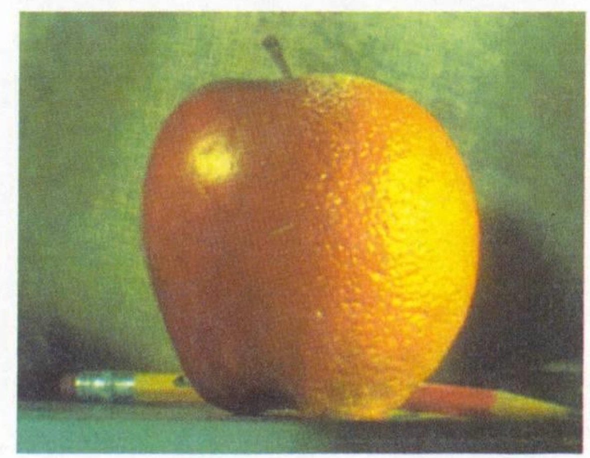




(d)



(h)



(l)

Burt and Adelson (1983), A Multiresolution Spline With Application to Image Mosaics

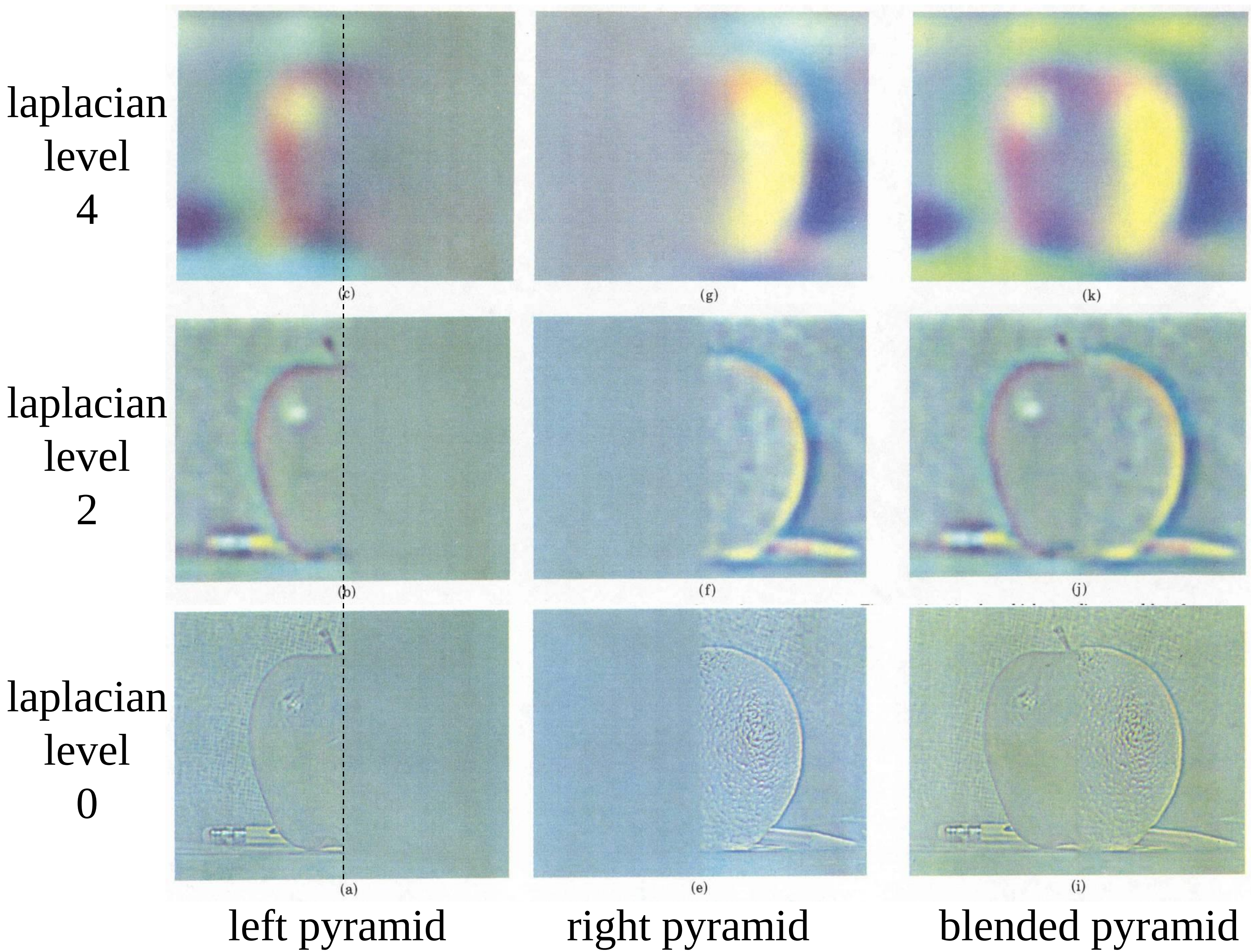
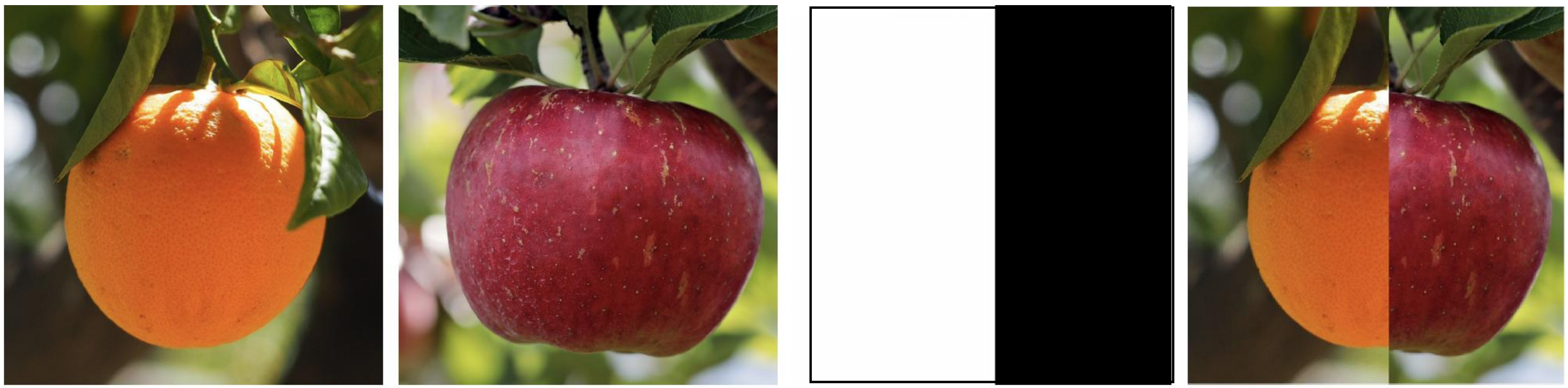

laplacian
level
4
laplacian
level
2
laplacian
level
0
(c)
(g)
(k)
(b)
(f)
(j)
(a)
(e)
(i)
left pyramid
right pyramid
blended pyramid

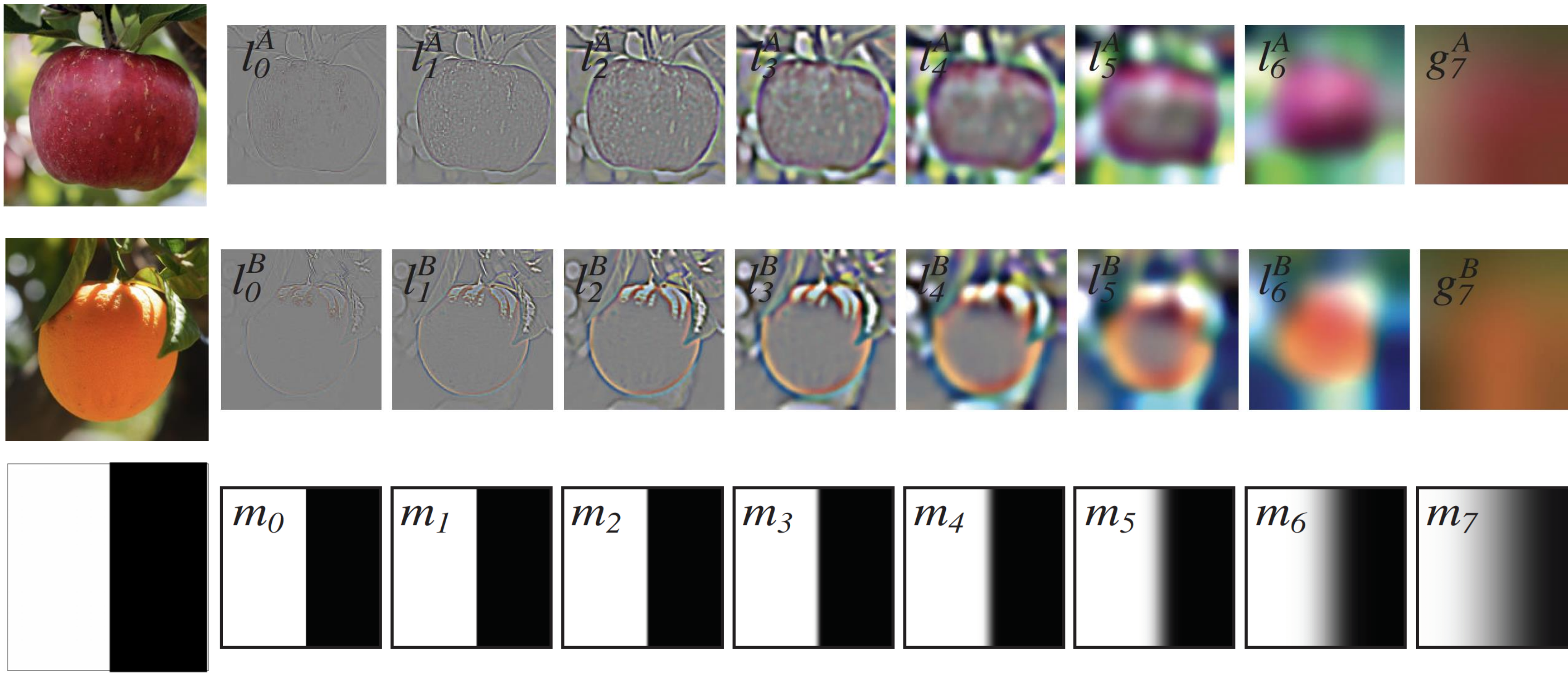
Image Blending with mask



I^A I^B m I

$$I = m * I^A + (1 - m) * I^B$$

Image Blending with mask



$$l_k = l_k^A * m_k + l_i^B * (1 - m_k)$$

Result

Blending Regions

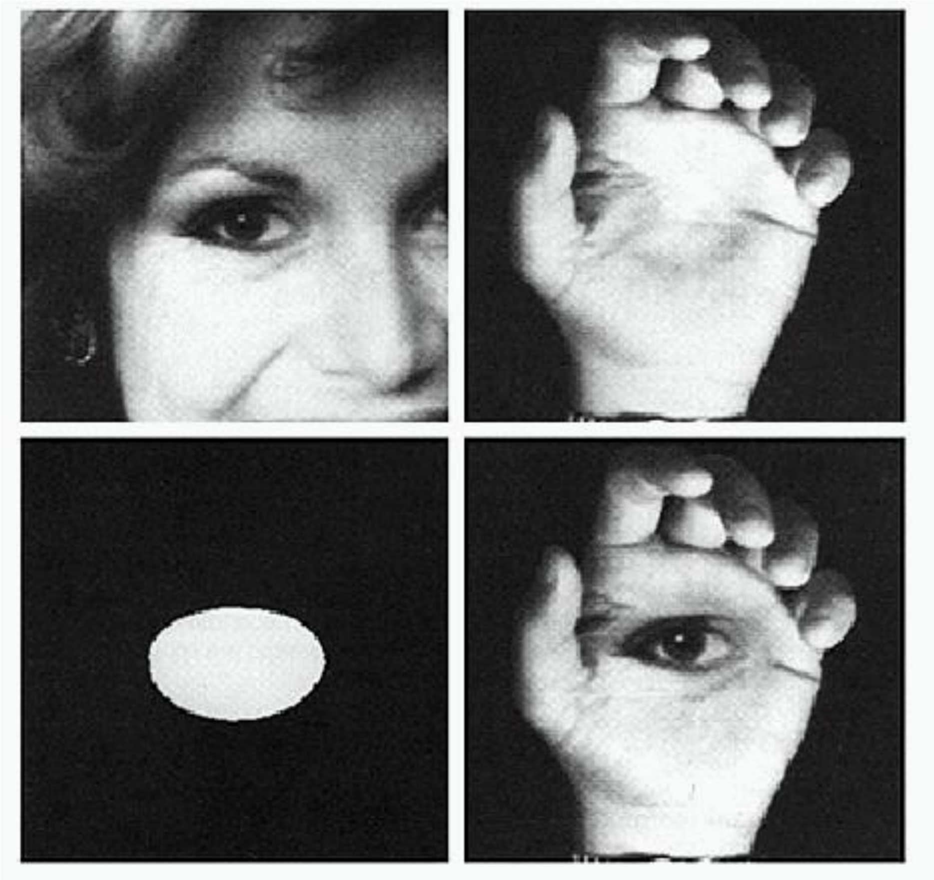


Image Blending with the Laplacian Pyramid

Build Laplacian pyramid for both images: LA, LB

Build Gaussian pyramid for mask: G

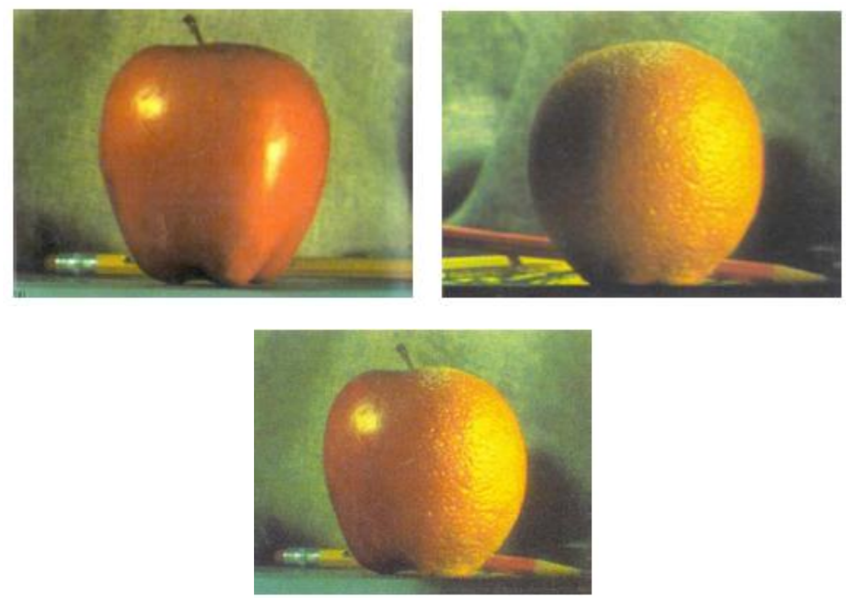
Build a combined Laplacian pyramid L

Collapse L to obtain the blended image

532 IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. COM-31, NO. 4, APRIL 1983

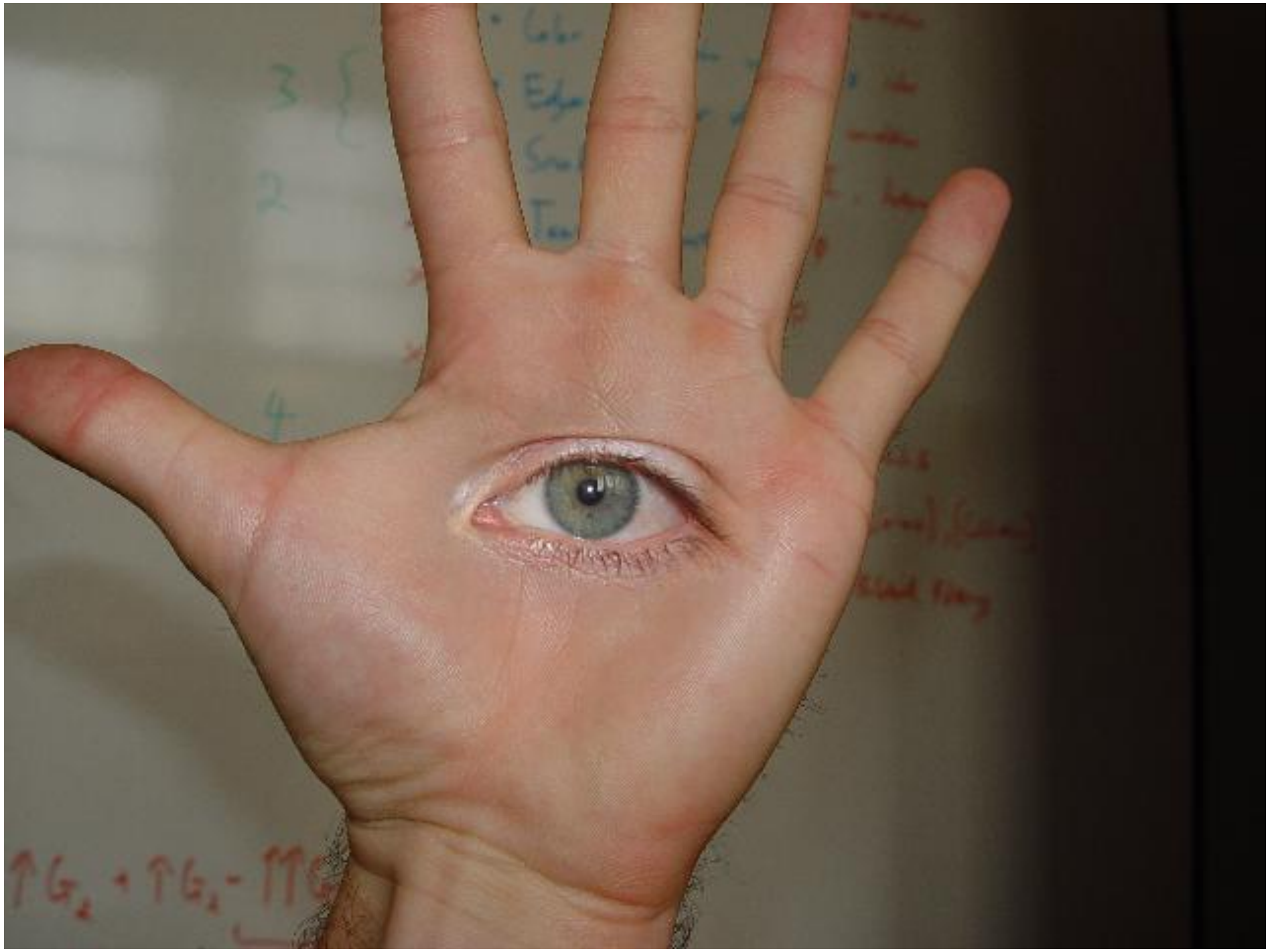
The Laplacian Pyramid as a Compact Image Code

PETER J. BURT, MEMBER, IEEE, AND EDWARD H. ADELSON



http://persci.mit.edu/pub_pdfs/pyramid83.pdf

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. – without downsampling
- Blends low freq. smoothly
- Blend high freq. with no smoothing: use binary alpha

2-band “Laplacian Stack” Blending

Low frequency (λ > 2 pixels)

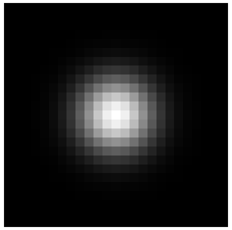
High frequency (λ < 2 pixels)

Linear Blending

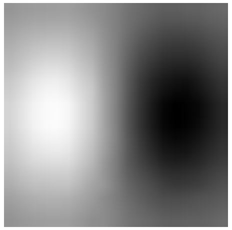
2-band Blending

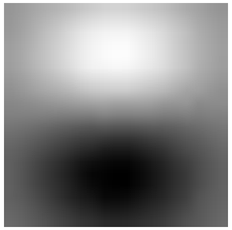
Review: Smoothing vs. derivative filters

Smoothing filters



- Gaussian: remove “high-frequency” components; “low-pass” filter
- Can the values of a smoothing filter be negative?
- What should the values sum to?
  - **One:** constant regions are not affected by the filter



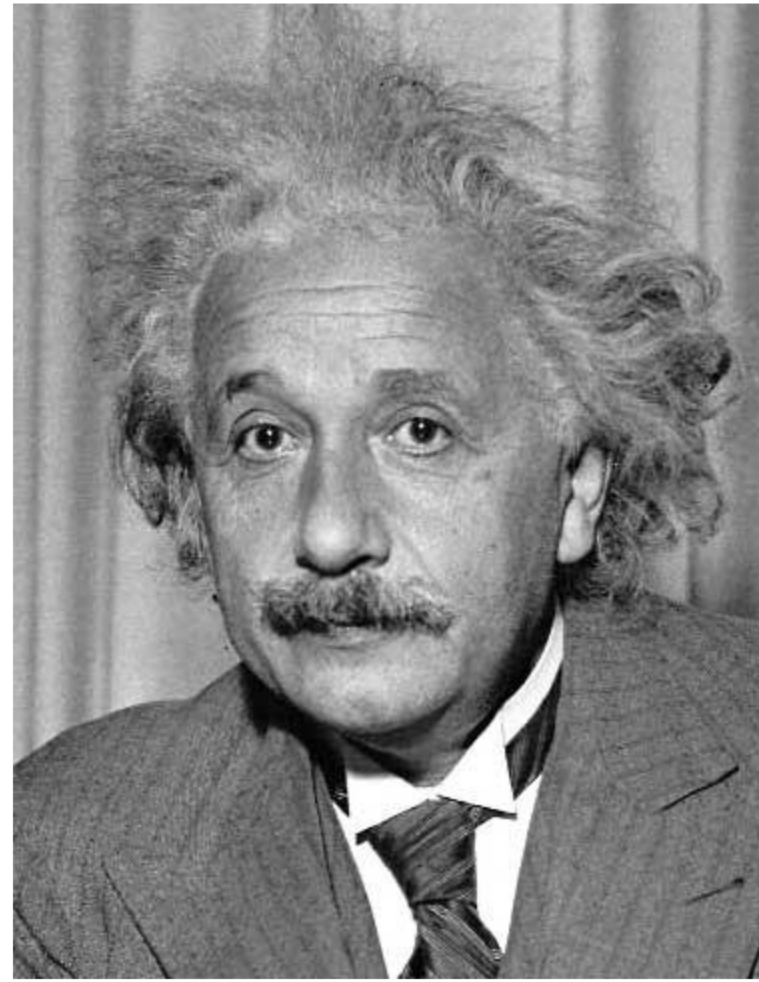


Derivative filters

- Derivatives of Gaussian
- Can the values of a derivative filter be negative?
- What should the values sum to?
  - **Zero:** no response in constant regions
- High absolute value at points of high contrast

Template matching

Goal: find  in image



Main challenge: What is a good similarity or distance measure between two patches?

- Correlation
- Zero-mean correlation
- L2 distance
- Normalized Cross Correlation

Side by Derek Hoiem

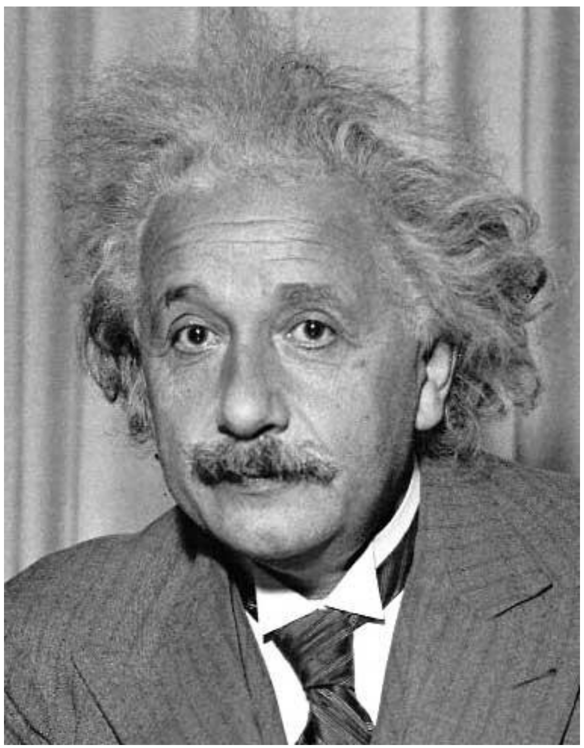
Matching with filters

Goal: find  in image

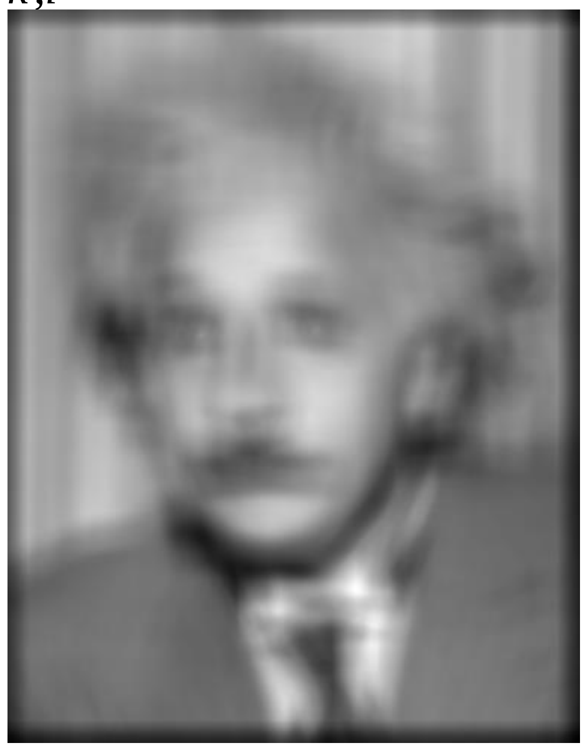
Method 0: filter the image with eye patch

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

f = image
g = filter



Input



Filtered Image

What went wrong?

Side by Derek Hoiem

Matching with filters

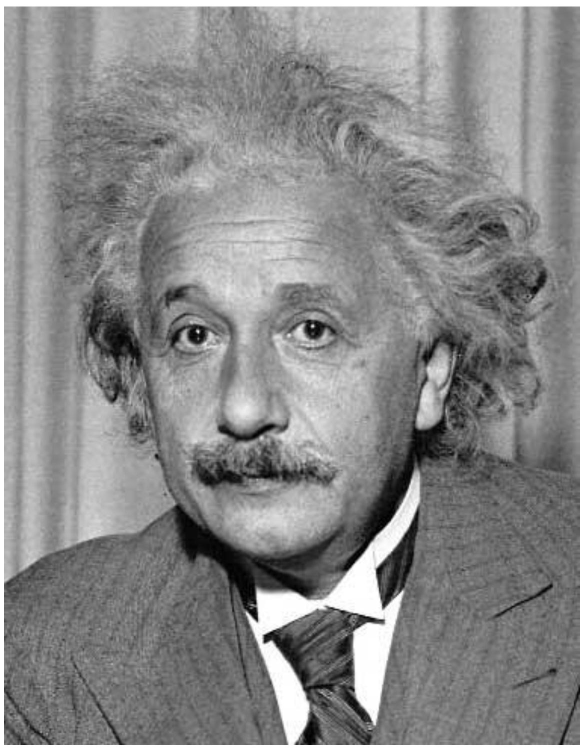
f = image
g = filter

Goal: find  in image

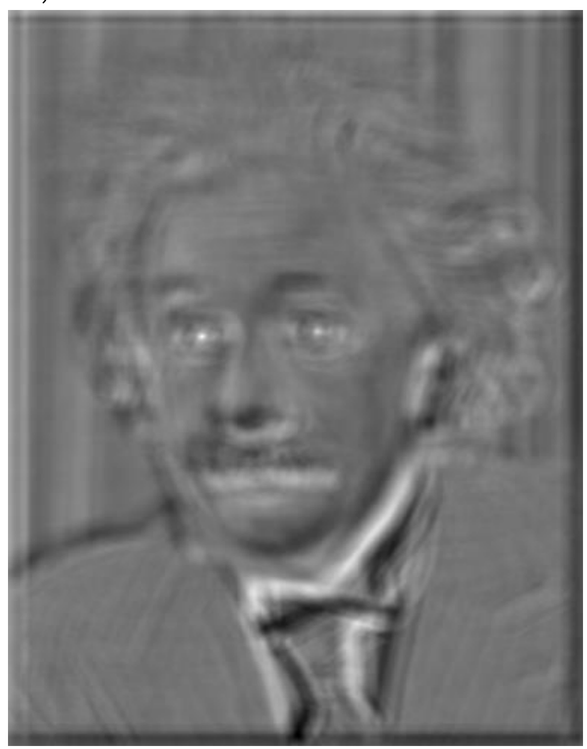
Method 1: filter the image with zero-mean eye

$$h[m,n] = \sum_{k,l} (g[k,l] - \bar{g})(f[m+k,n+l])$$

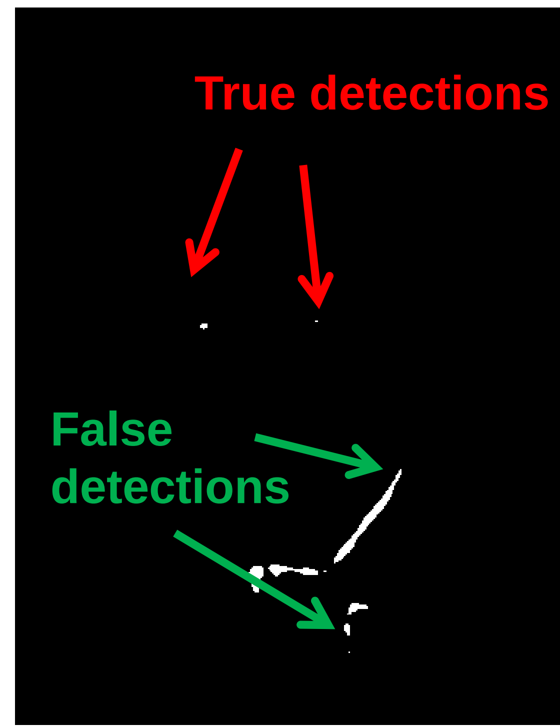
mean of g



Input



Filtered Image (scaled)



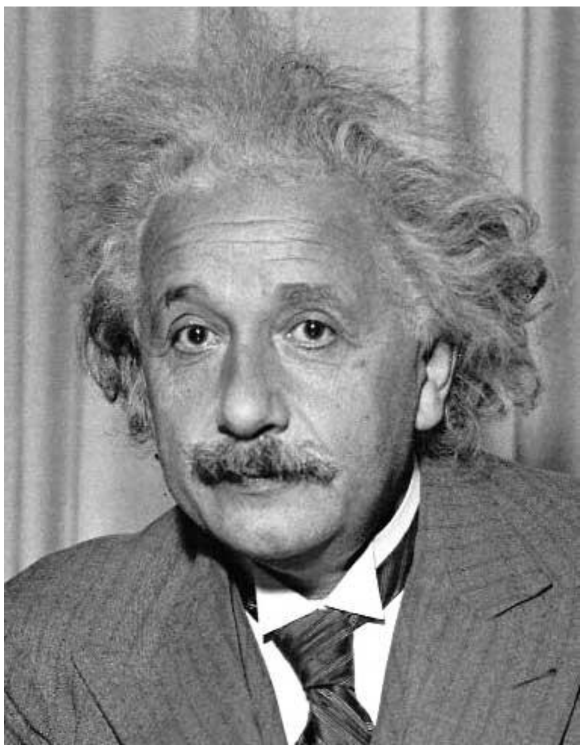
Thresholded Image

Matching with filters

Goal: find  in image

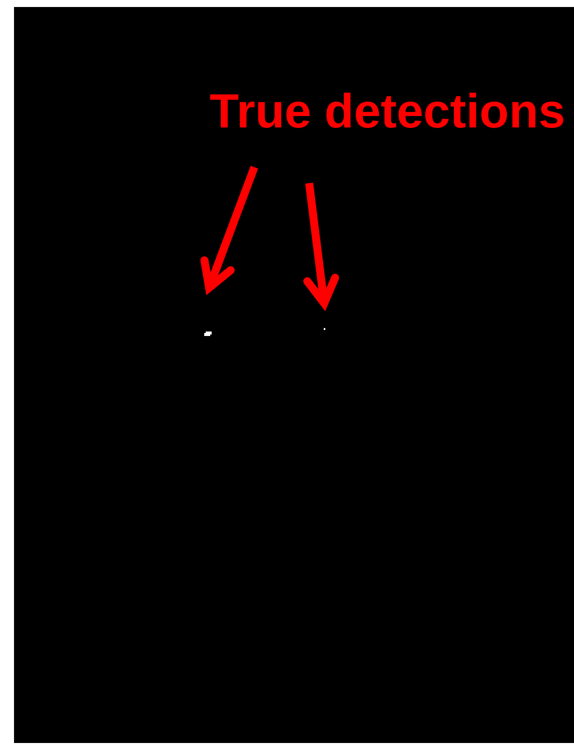
Method 2: L2 distance (sum of squared diffs)

$$h[m,n]=\sum_{k,l}(g[k,l]-f[m+k,n+l])^2$$



Input

1- sqrt(SSD)



Thresholded Image

Matching with filters

Can L2 be implemented with linear filters?

$$h[m,n] = \sum_{k,l} (g[k,l] - f[m+k, n+l])^2$$

Side by Derek Hoiem

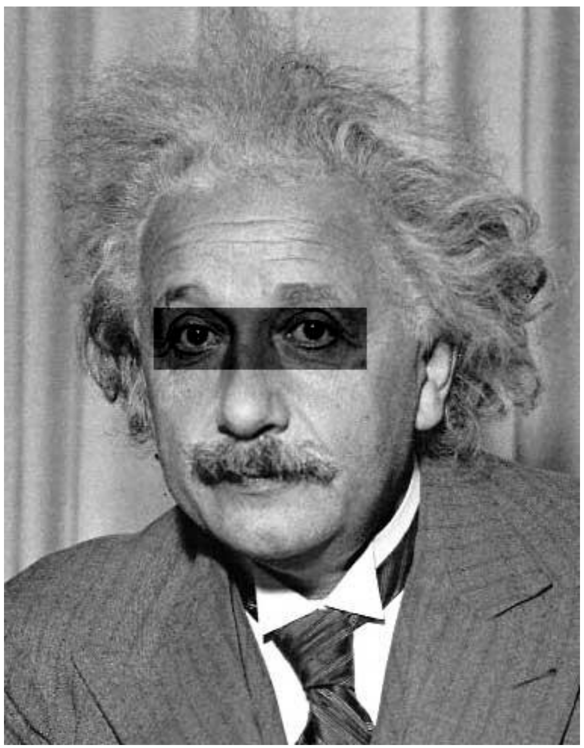
Matching with filters

Goal: find  in image

What's the potential downside of L2?

Method 2: L2 (SSD)

$$h[m,n]=\sum_{k,l}(g[k,l]-f[m+k,n+l])^2$$



Input

1- sqrt(SSD)

Side by Derek Hoiem

Matching with filters

Goal: find  in image

Method 3: Normalized cross-correlation

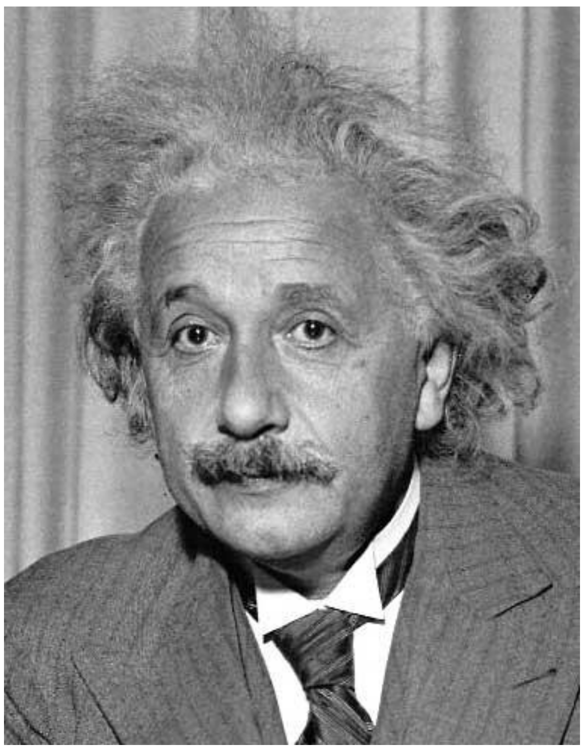
$$h[m,n] = \frac{\sum_{k,l} (g[k,l] - \overset{\substack{\text{mean template}\\ \downarrow}}{\bar{g}})(f[m+k,n+l] - \overset{\substack{\text{mean image patch}\\ \downarrow}}{\bar{f}_{m,n}})}{\left(\sum_{k,l} (g[k,l] - \bar{g})^2 \sum_{k,l} (f[m+k,n+l] - \bar{f}_{m,n})^2 \right)^{0.5}}$$

Side by Derek Hoiem

Matching with filters

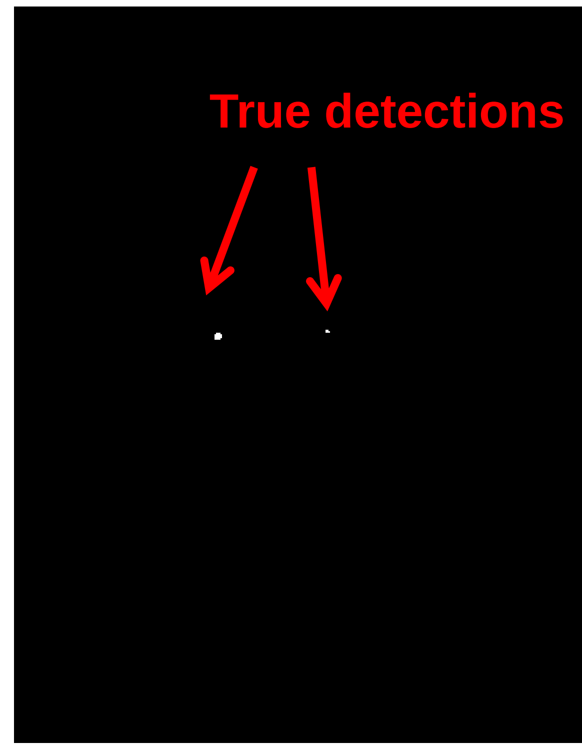
Goal: find  in image

Method 3: Normalized cross-correlation



Input

Normalized X-Correlation

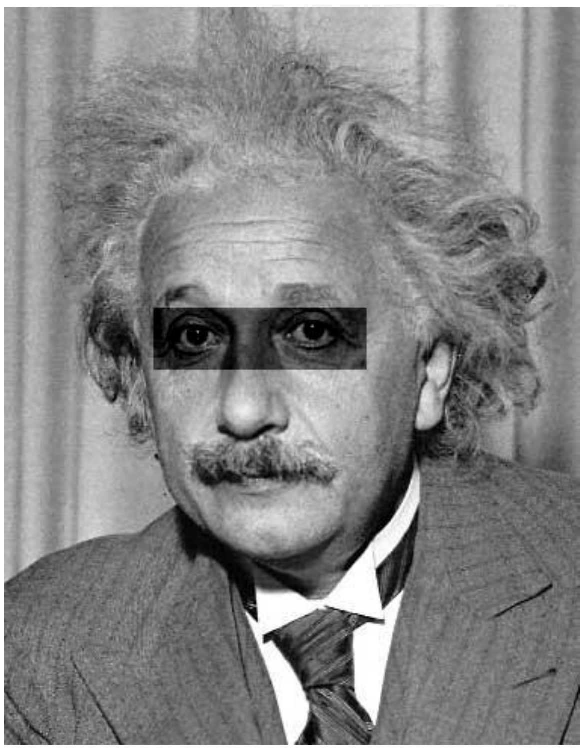


Thresholded Image

Matching with filters

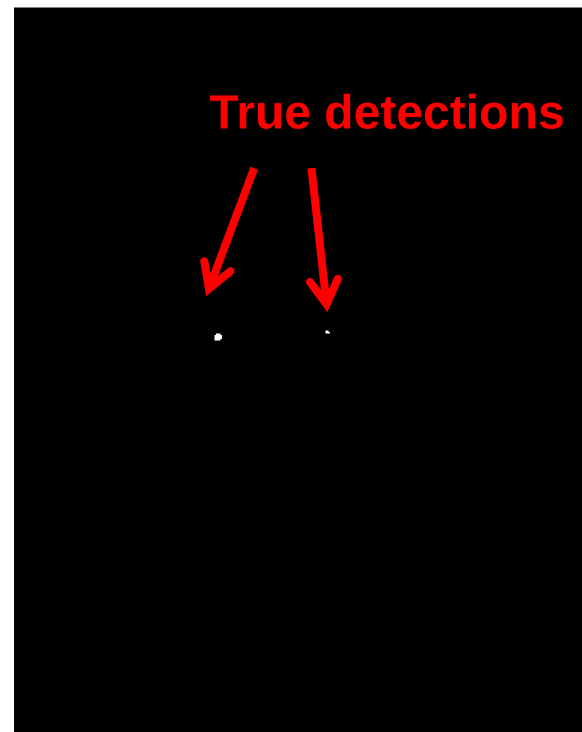
Goal: find  in image

Method 3: Normalized cross-correlation



Input

Normalized X-Correlation



Thresholded Image

Q: What is the best method to use?

A: Depends

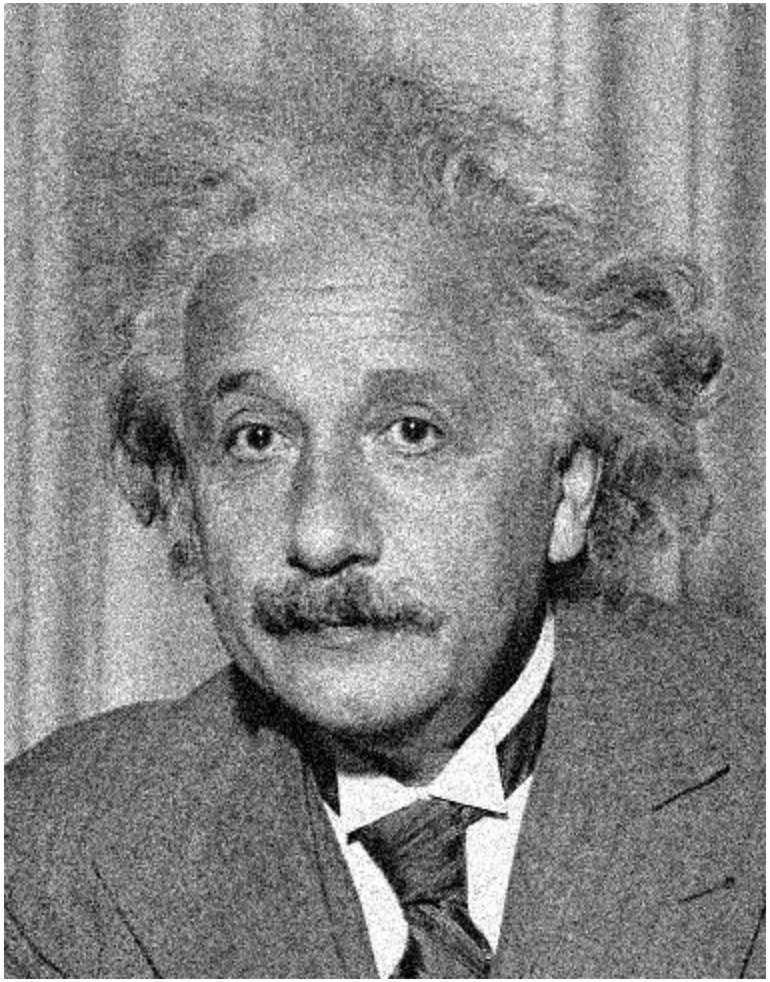
Zero-mean filter: fastest but not a great matcher

L2/SSD: next fastest, sensitive to overall intensity

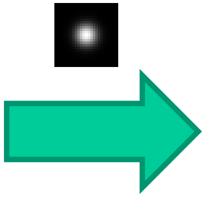
Normalized cross-correlation: slowest, invariant to local average intensity and contrast

Side by Derek Hoiem

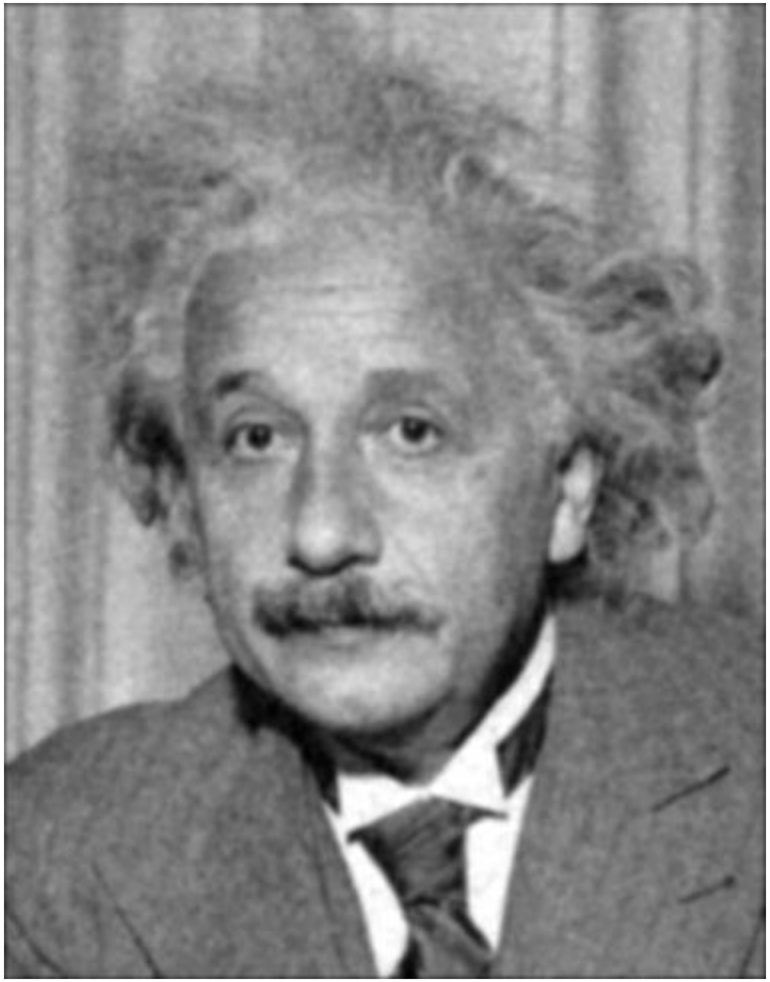
Denoising



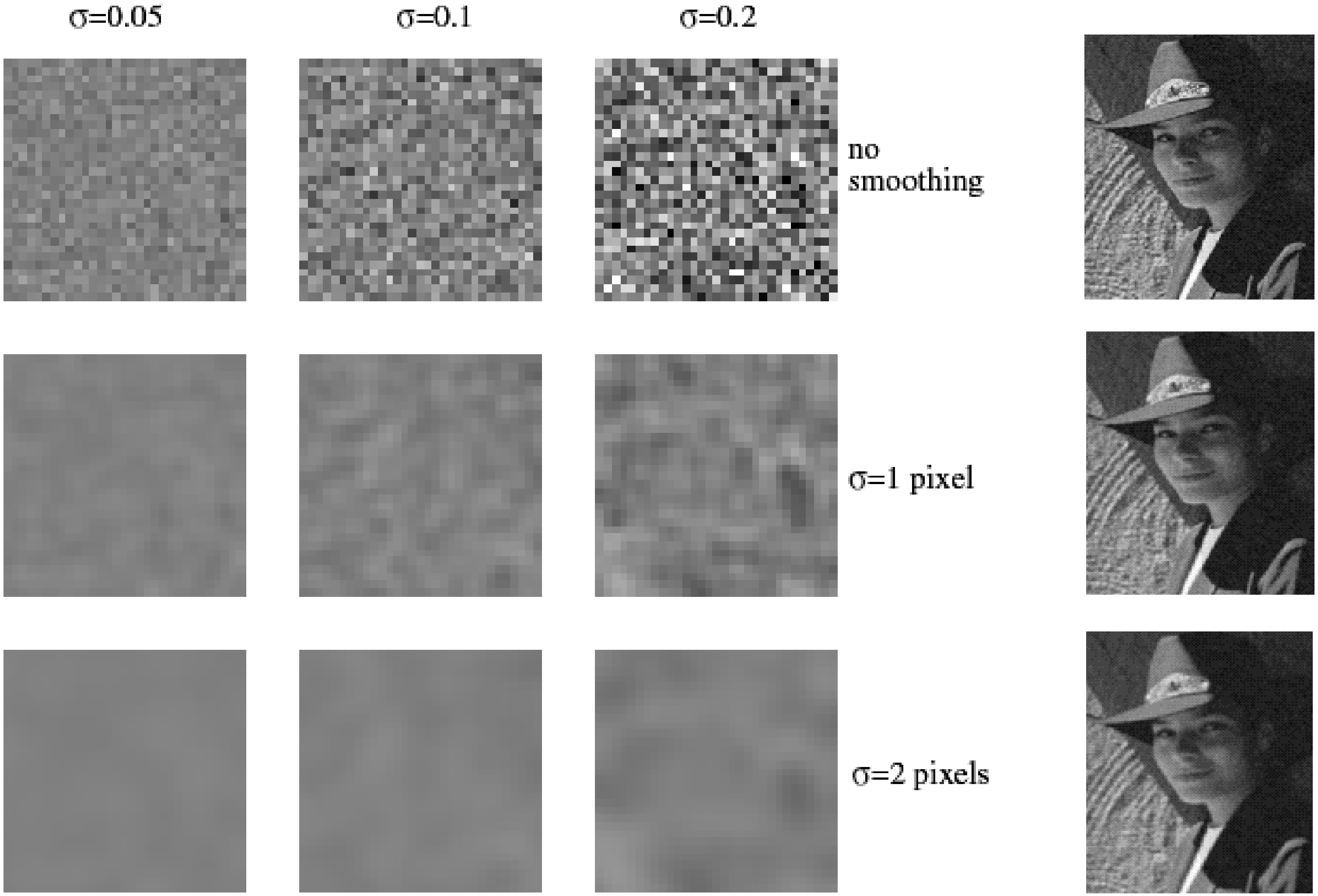
Additive Gaussian Noise



Gaussian Filter



Reducing Gaussian noise



Smoothing with larger standard deviations suppresses noise, but also blurs the image

Source: S. Lazebnik

Reducing salt-and-pepper noise by Gaussian smoothing

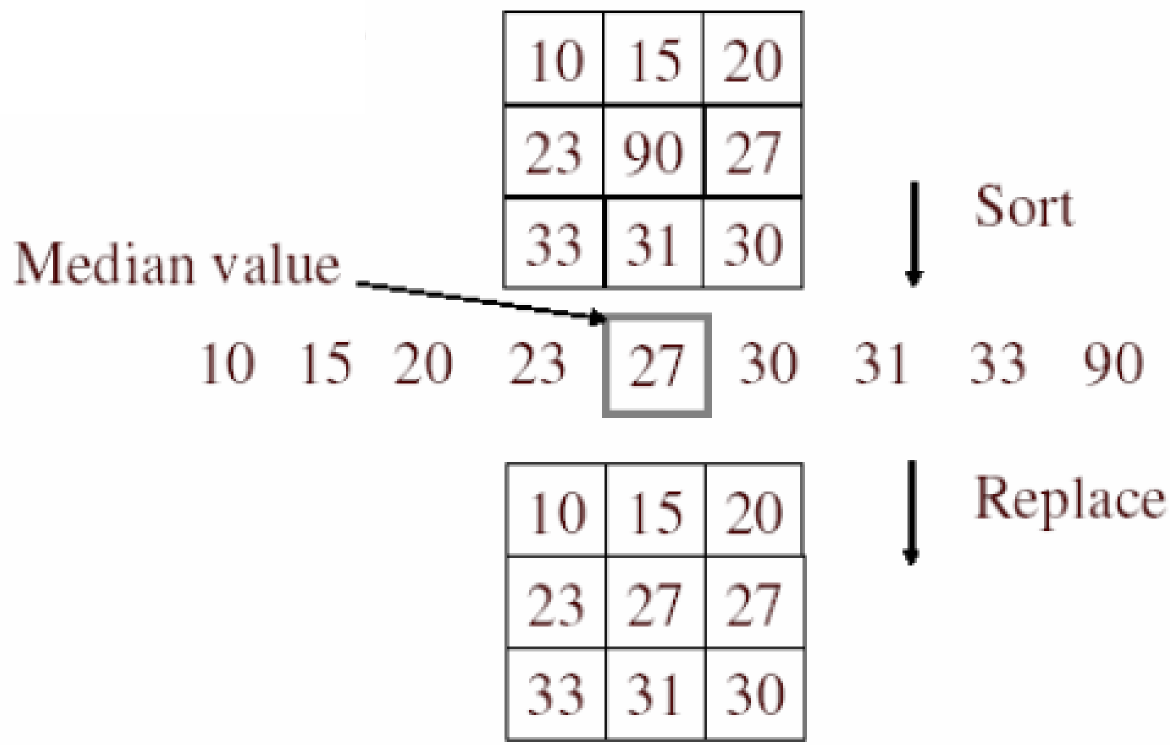
3x3

5x5

7x7

Alternative idea: Median filtering

A **median filter** operates over a window by selecting the median intensity in the window



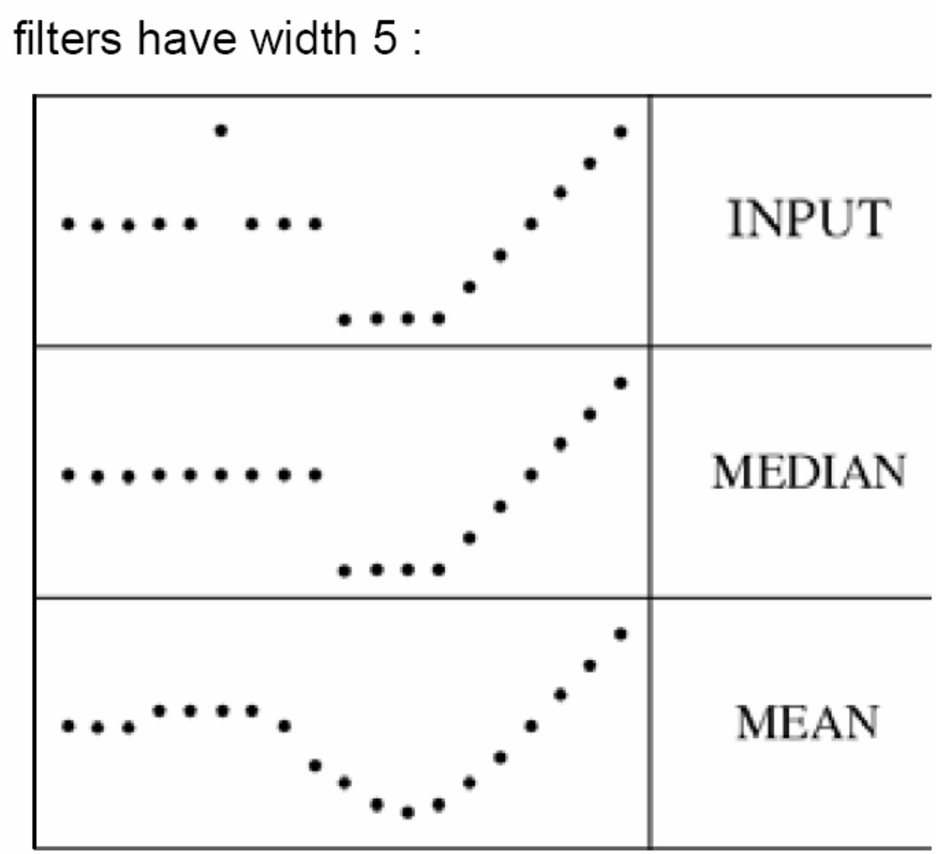
- Is median filtering linear?

Source: K. Grauman

Median filter

What advantage does median filtering have over Gaussian filtering?

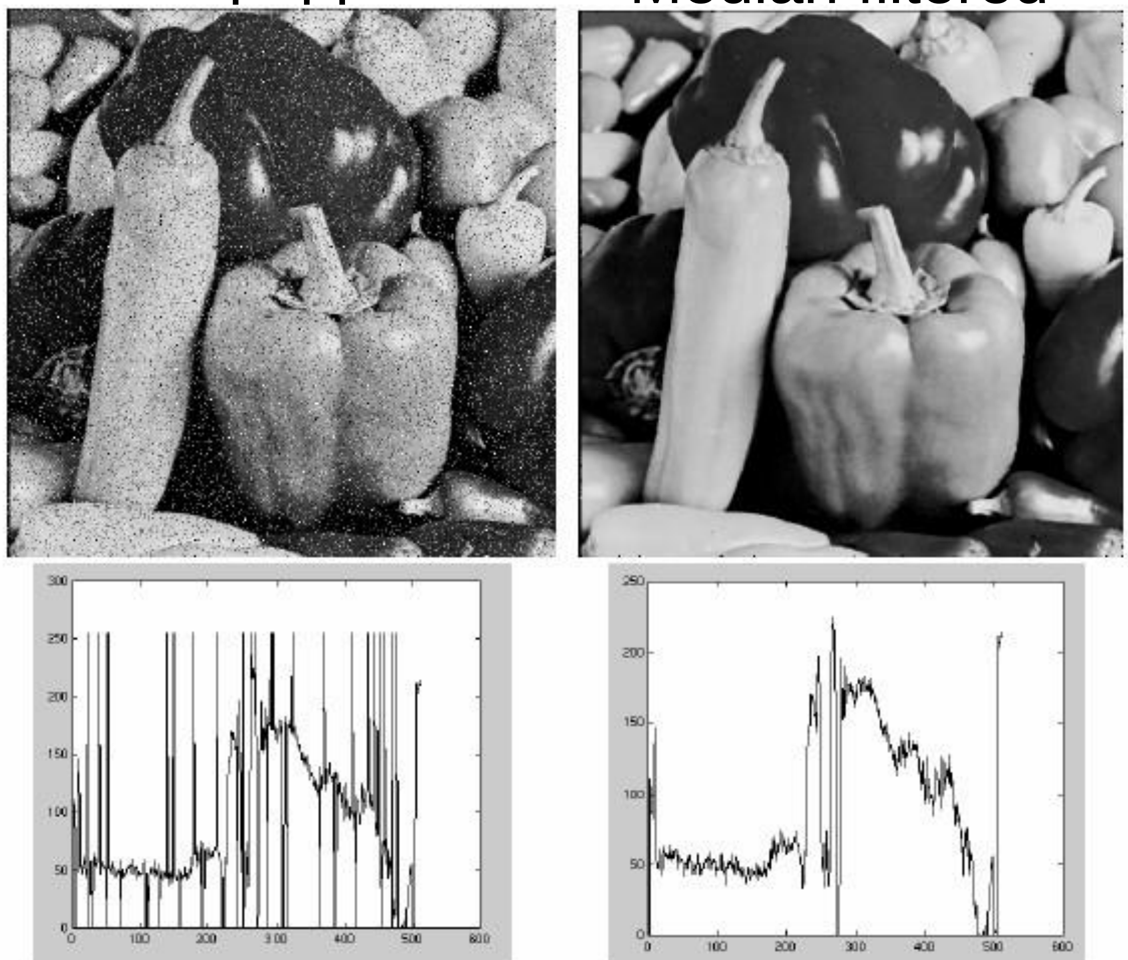
- Robustness to outliers



Source: K. Grauman

Median filter

Salt-and-pepper noise Median filtered



medfilt2(image, [h w])

Source: M. Hebert

Median vs. Gaussian filtering

3x3 5x5 7x7

Gaussian

Median

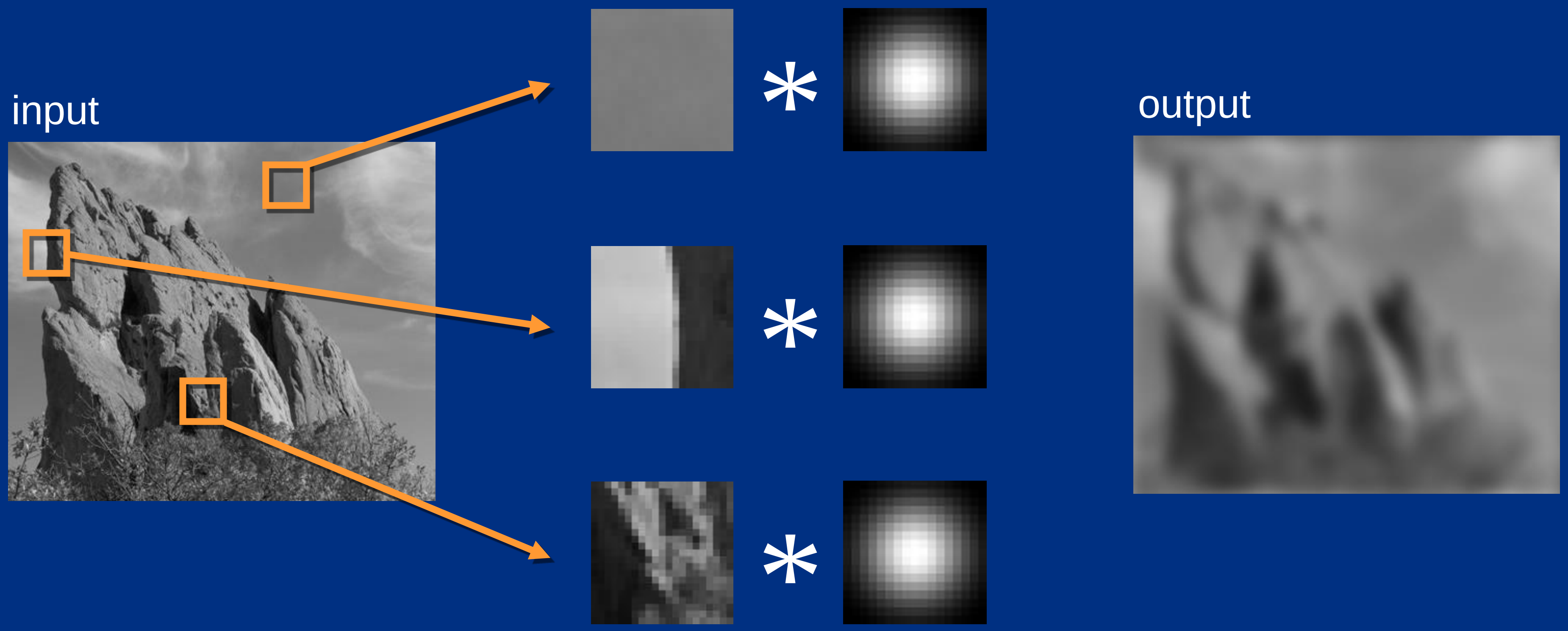
A Gentle Introduction to Bilateral Filtering and its Applications

SIGGRAPH2007

"Fixing the Gaussian Blur": the Bilateral Filter

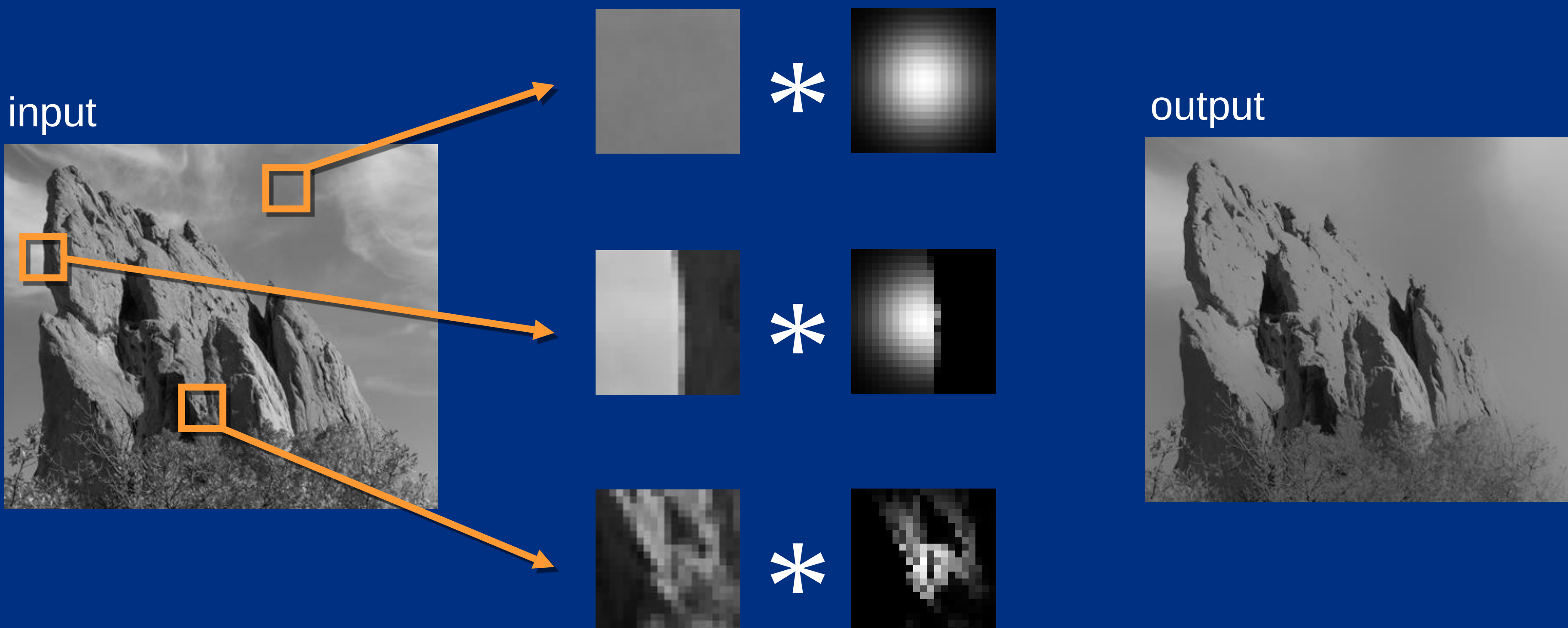
Sylvain Paris – MIT CSAIL

Blur Comes from Averaging across Edges



Same Gaussian kernel everywhere.

Bilateral Filter [Aurich 95, Smith 97, Tomasi 98]
No Averaging across Edges



The kernel shape depends on the image content.

Bilateral Filter Definition: an Additional Edge Term

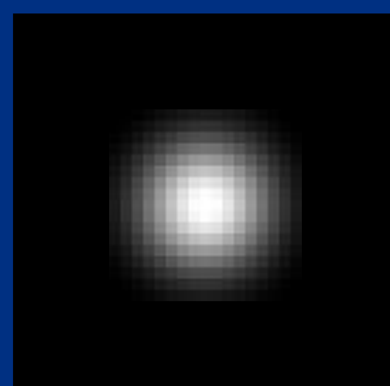
Same idea: **weighted average of pixels**.

new — not new — new

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G_{\sigma_{\mathrm{s}}}\left(\|\mathbf{p}-\mathbf{q}\|\right) G_{\sigma_{\mathrm{r}}}\left(|I_{\mathbf{p}}-I_{\mathbf{q}}|\right) I_{\mathbf{q}}$$

normalization factor

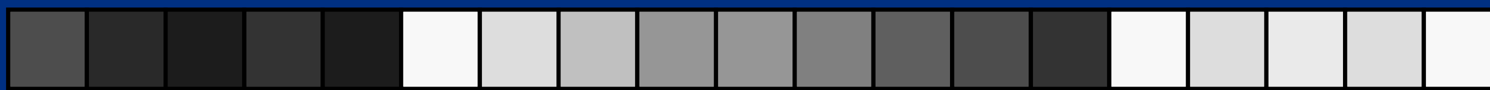
space weight



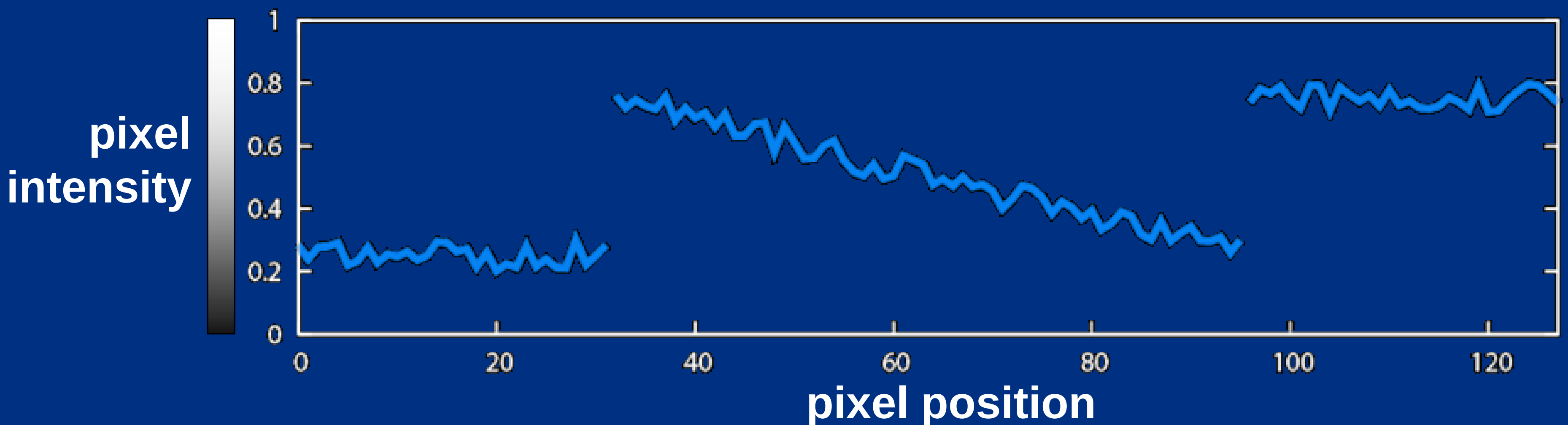
range weight

Illustration a 1D Image

- 1D image = line of pixels

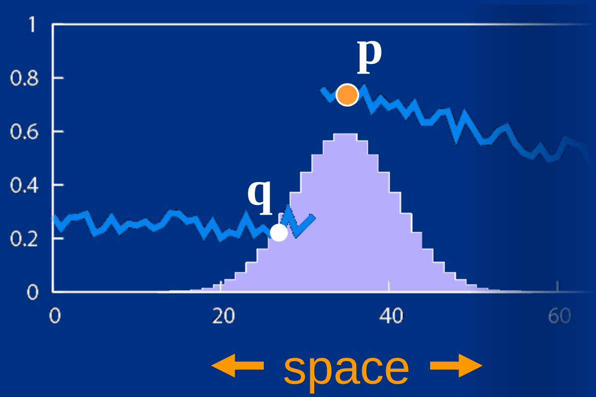


- Better visualized as a plot



Gaussian Blur and Bilateral Filter

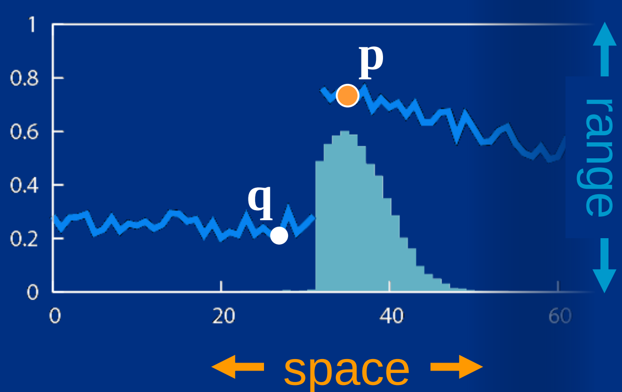
Gaussian blur



$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in S} \underbrace{G_{\sigma}(\| \mathbf{p} - \mathbf{q} \|)}_{\text{space}} I_{\mathbf{q}}$$

Bilateral filter

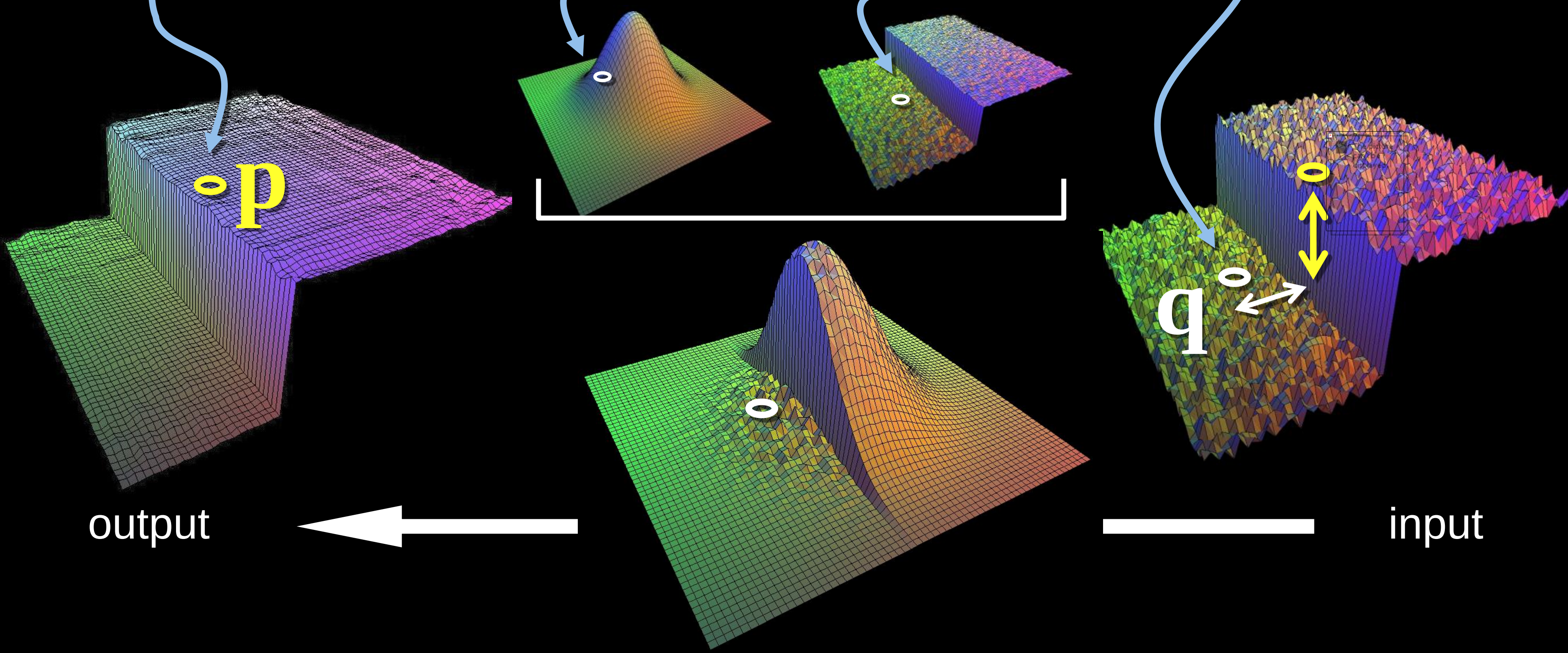
[Aurich 95, Smith 97, Tomasi 98]



$$BF[I]_{\mathbf{p}} = \underbrace{\frac{1}{W_{\mathbf{p}}}}_{\text{normalization}} \sum_{\mathbf{q} \in S} \underbrace{G_{\sigma_s}(\| \mathbf{p} - \mathbf{q} \|)}_{\text{space}} \underbrace{G_{\sigma_r}(| I_{\mathbf{p}} - I_{\mathbf{q}} |)}_{\text{range}} I_{\mathbf{q}}$$

Bilateral Filter on a Height Field

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\; G_{\sigma_r}(|I_{\mathbf{p}}-I_{\mathbf{q}}|)\; I_{\mathbf{q}}$$



reproduced from [Durand 02]

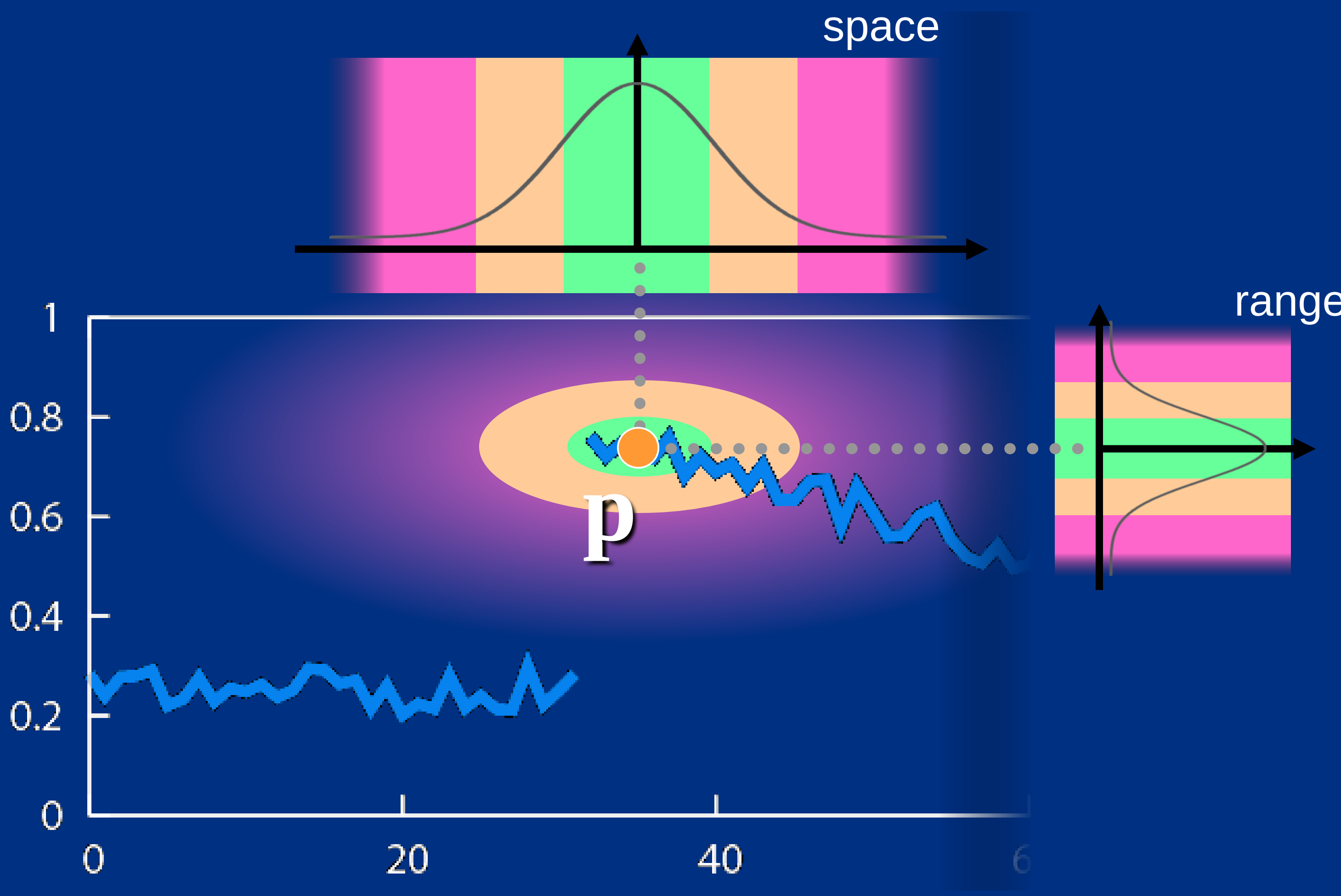
Space and Range Parameters

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_{\mathrm{s}}}(\| \mathbf{p} - \mathbf{q} \|) \, G_{\sigma_{\mathrm{r}}}(| I_{\mathbf{p}} - I_{\mathbf{q}} |) \, I_{\mathbf{q}}$$

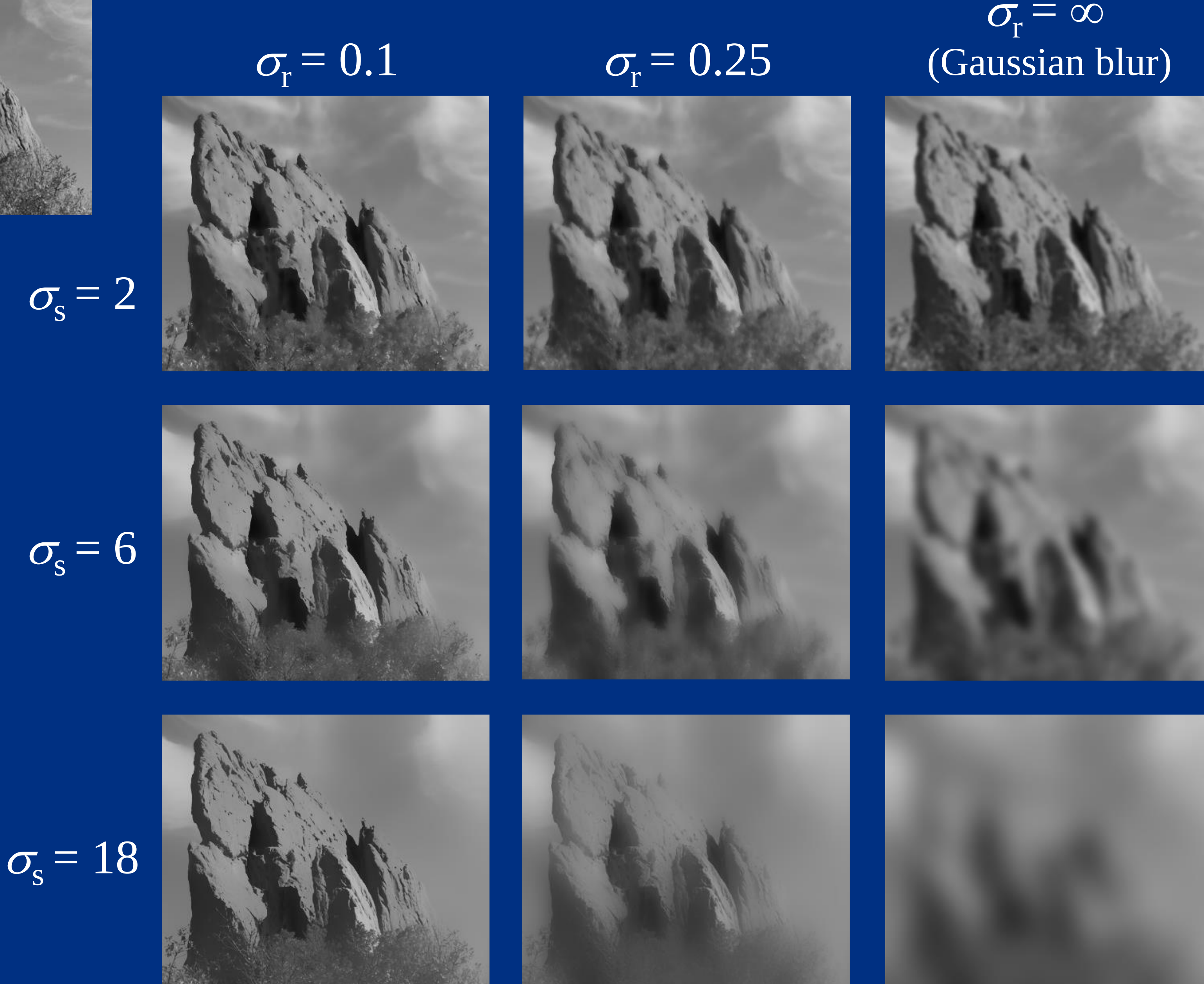
- space σ_{s} : spatial extent of the kernel, size of the considered neighborhood.
- range σ_{r} : “minimum” amplitude of an edge

Influence of Pixels

Only pixels close in space and in range are considered.



Exploring the Parameter Space



Varying the Range Parameter

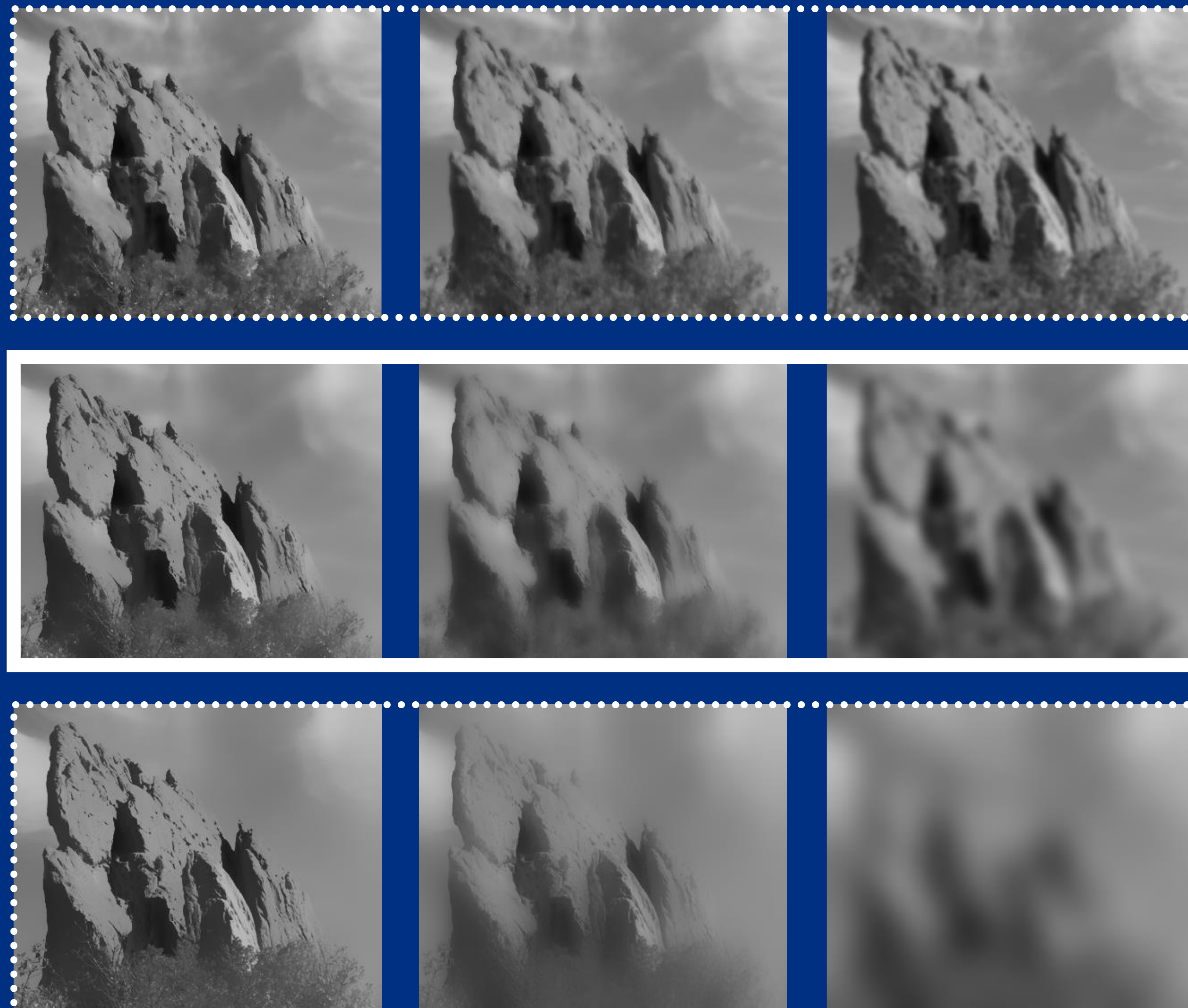
input

$\sigma_r = 0.1$ | $\sigma_r = 0.25$ | $\sigma_r = \infty$ (Gaussian blur)

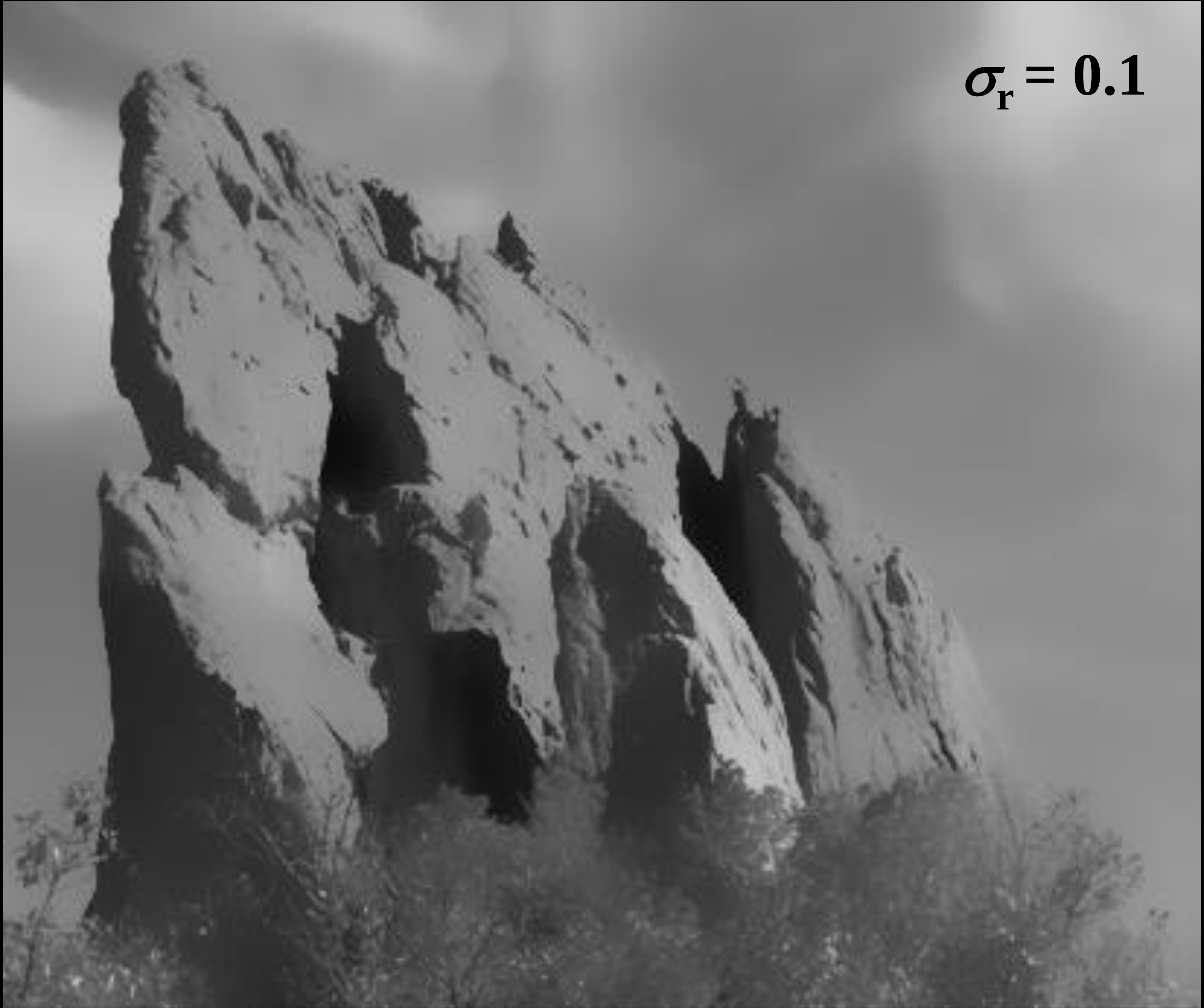
$\sigma_s = 2$

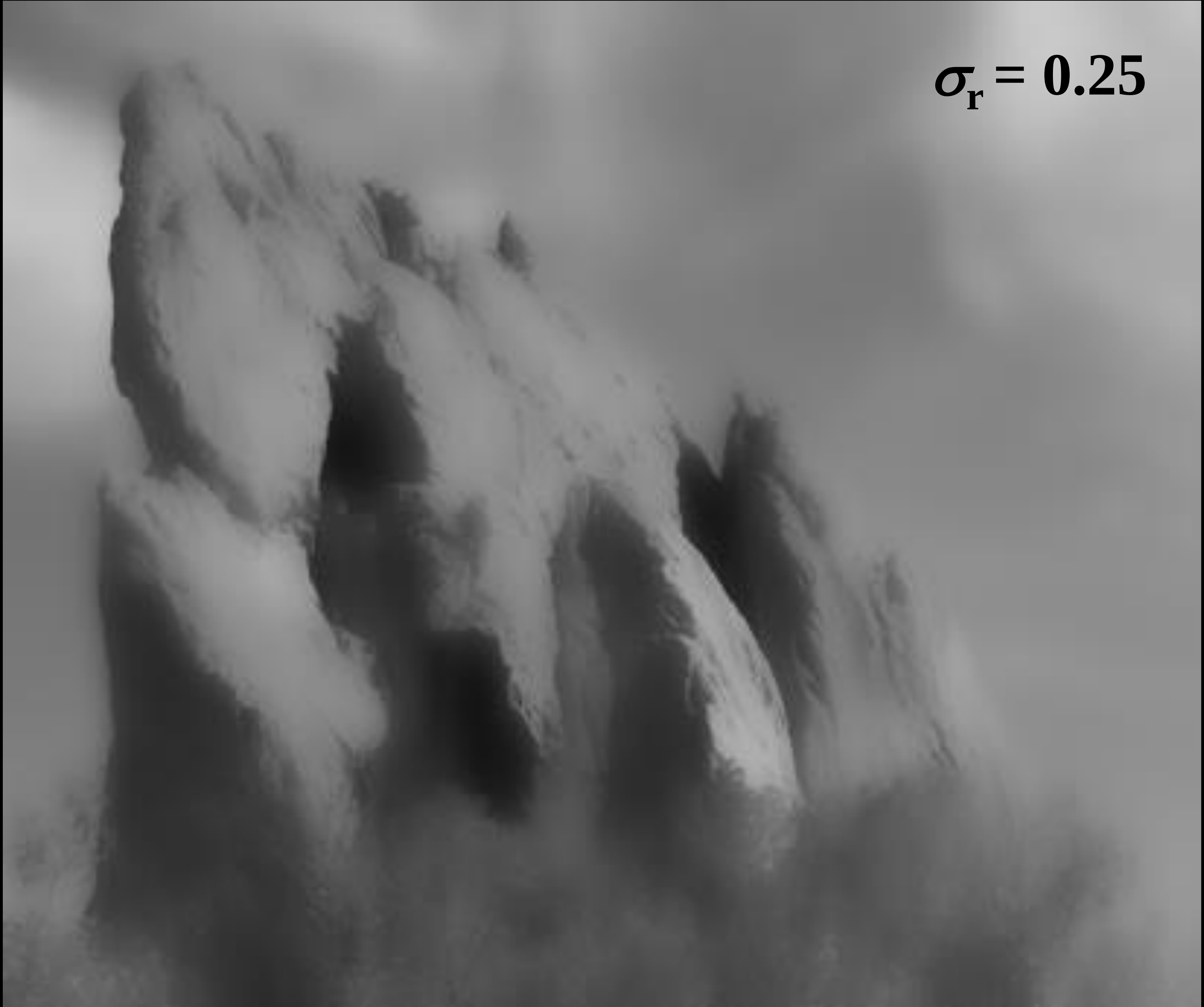
$\sigma_s = 6$

$\sigma_s = 18$




input


$\sigma_r = 0.1$


$\sigma_r = 0.25$


$\sigma_r = \infty$
(Gaussian blur)

Varying the Space Parameter

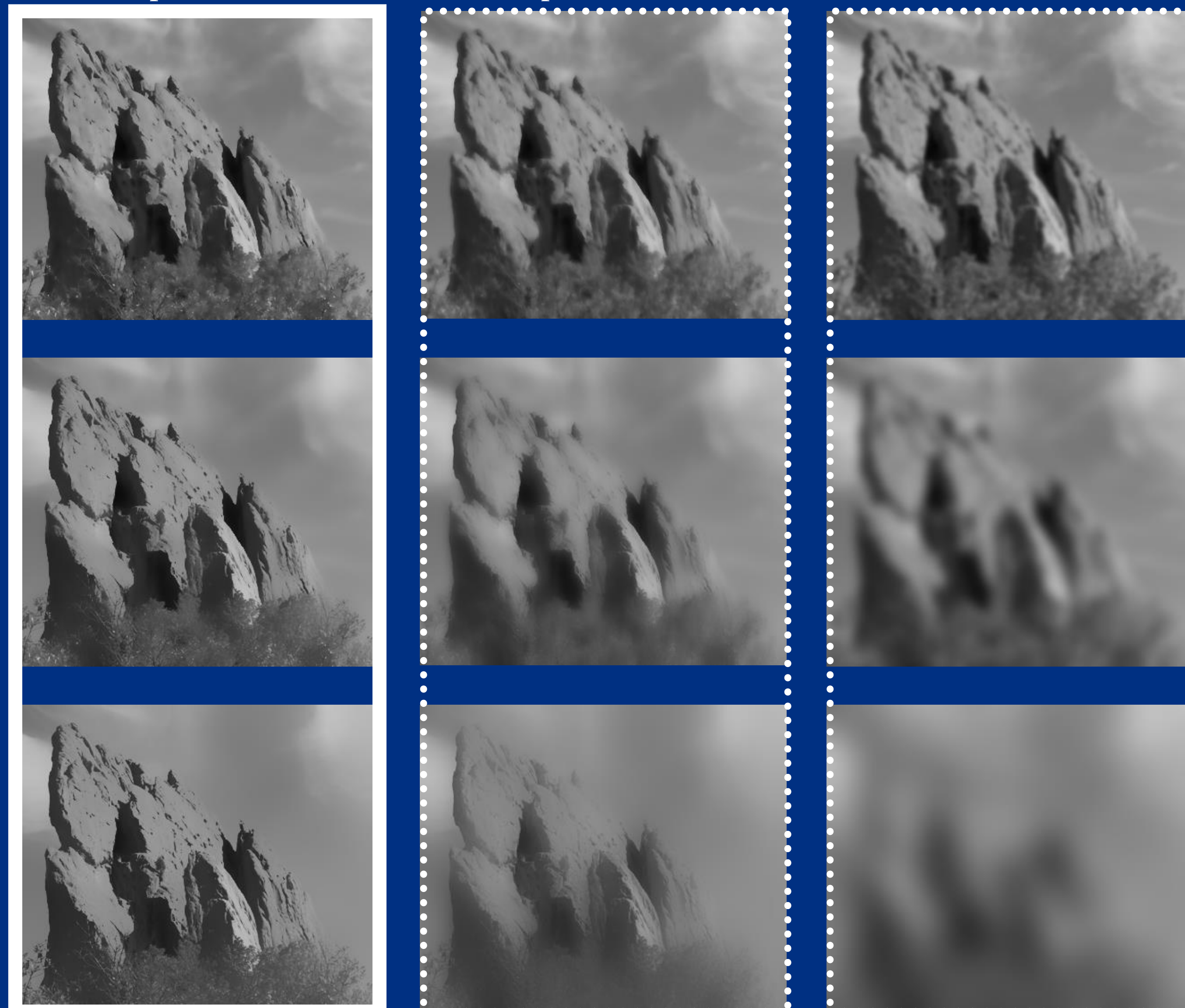
input

$\sigma_r = 0.1$ | $\sigma_r = 0.25$ | $\sigma_r = \infty$ (Gaussian blur)

$\sigma_s = 2$

$\sigma_s = 6$

$\sigma_s = 18$




input


$\sigma_s = 2$


$\sigma_s = 6$

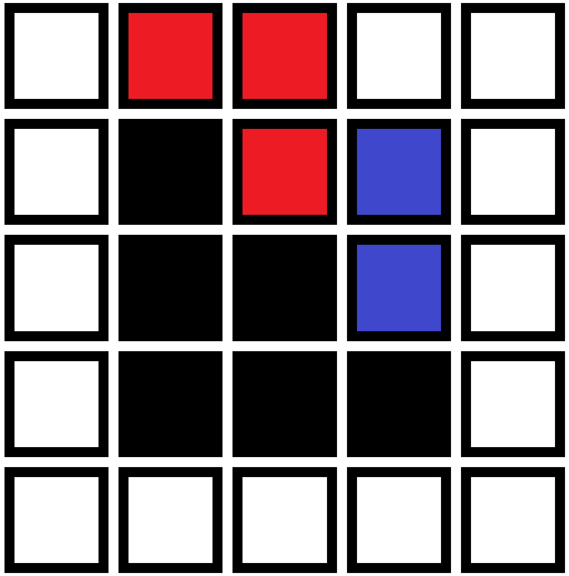

$\sigma_s = 18$

EXTRA SLIDES: Image Compression

89k

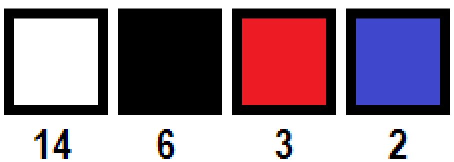
Lossless Compression (e.g. Huffman coding)

Input image:



Pixel code:

Pixel histogram:



Compressed image:

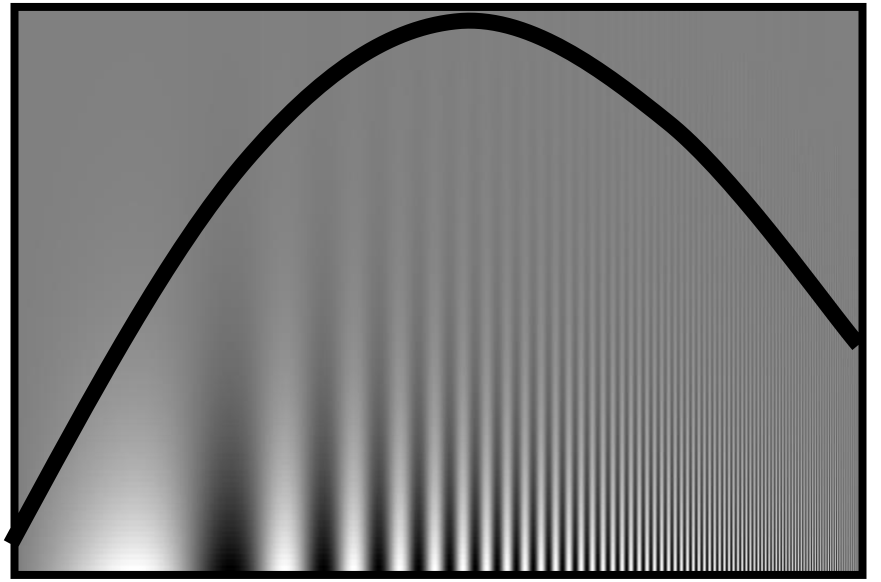
0 110 110 0 0

0 10 110 111 0

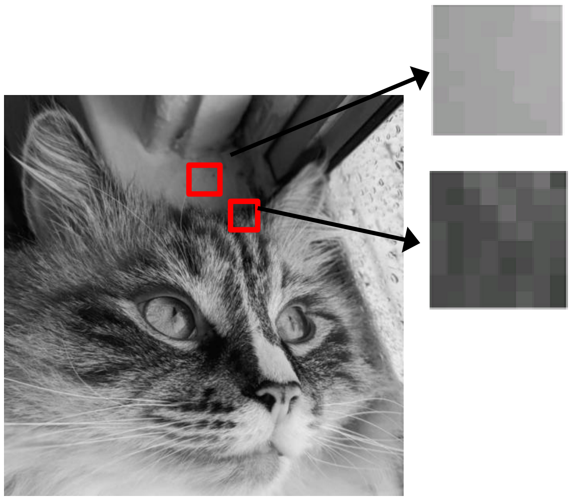
...

https://www.print-driver.com/stories/huffman-coding-jpeg

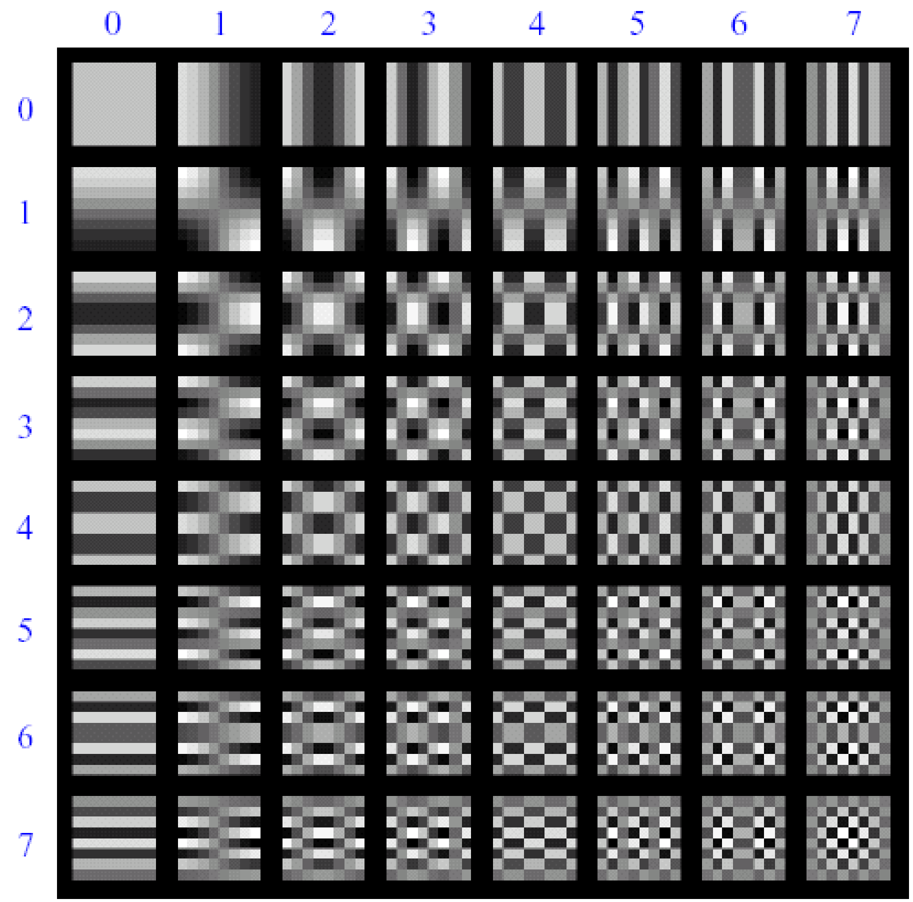
Lossless Compression not enough



Lossy Image Compression (JPEG)



cut up into 8x8 blocks

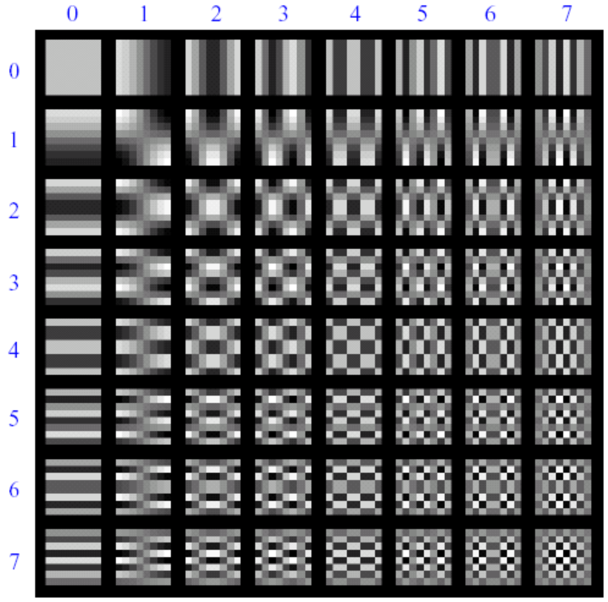


Block-based Discrete Cosine Transform (DCT)

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



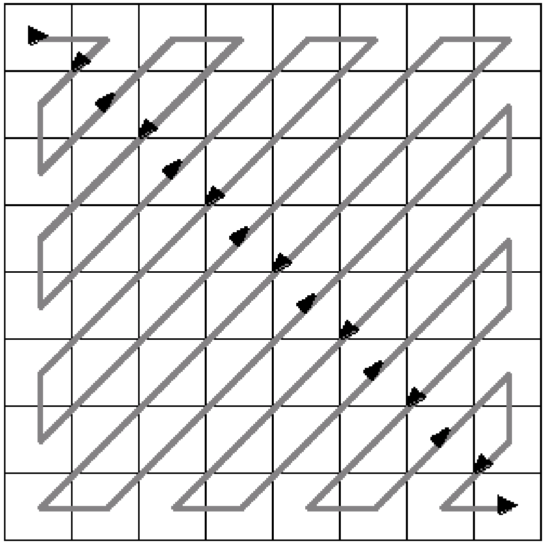


Image compression using DCT

Quantize

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

Encode

- Can decode with inverse dct

Filter responses

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

Quantization table

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

Quantized values

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

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)

Spatial dimension of color channels are reduced by 2 (lecture 2)!

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

JPEG compression comparison

89k

12k