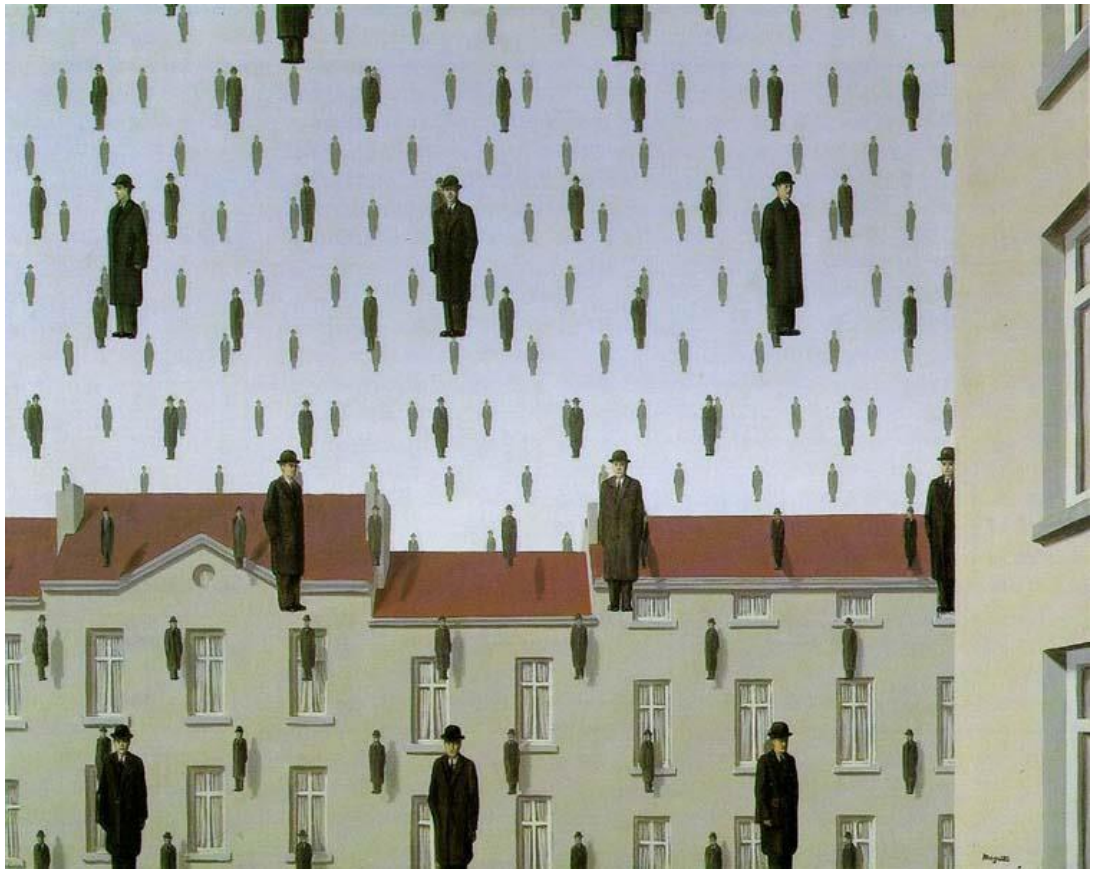
Image Pyramids and Applications



Computer Vision

Jia-Bin Huang, Virginia Tech

Golconda, René Magritte, 1953

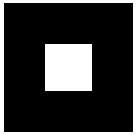
Administrative stuffs

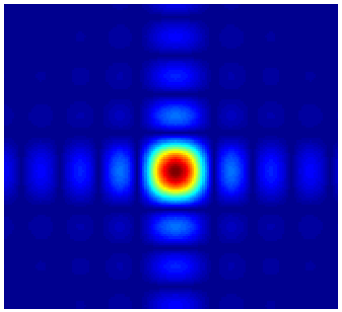
- HW 1 posted, due 11:59 PM Sept 19

- Anonymous feedback from students
  - Repeat students' questions and answers
  - Turn on some light in the classroom
  - Post frequently asked questions for HWs

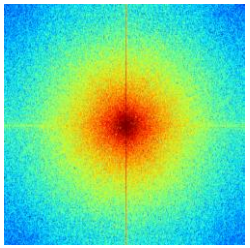
Previous class: Image Filtering

- Sometimes it makes sense to think of images and filtering in the frequency domain
  - Fourier analysis

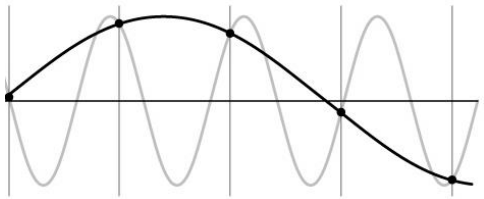




- Can be faster to filter using FFT for large images (N logN vs. N^2 for auto-correlation)

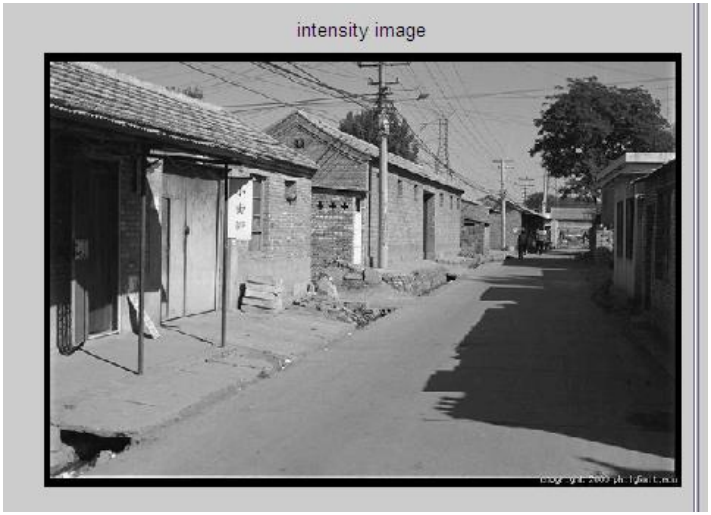


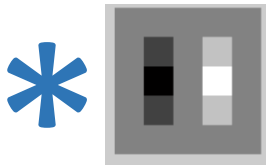
- Images are mostly smooth
  - Basis for compression

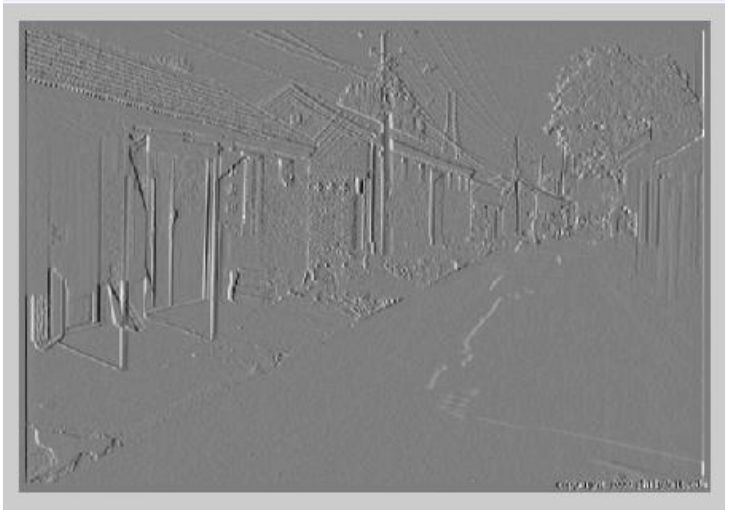


- Remember to low-pass before sampling

Spatial domain



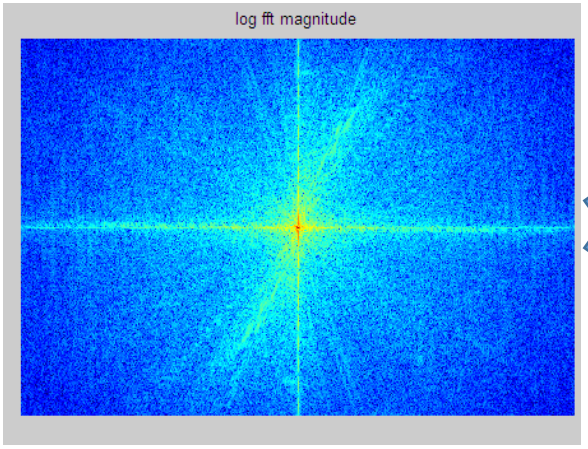


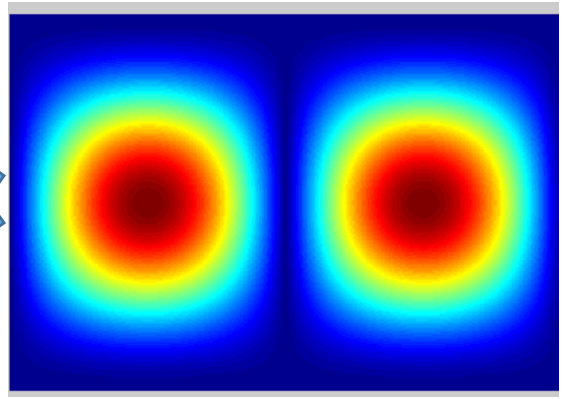


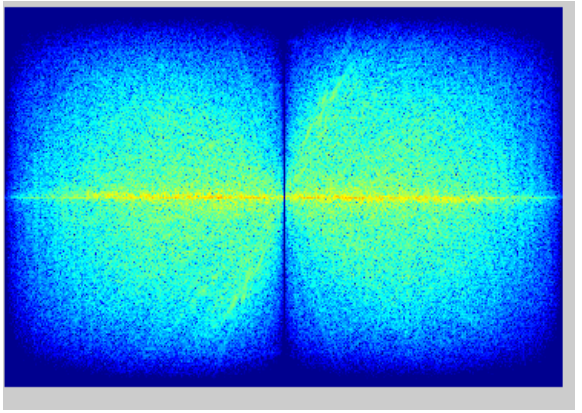
FFT

FFT

Inverse FFT







Frequency domain

Fourier Transform

Teases away fast vs. slow changes in the image.

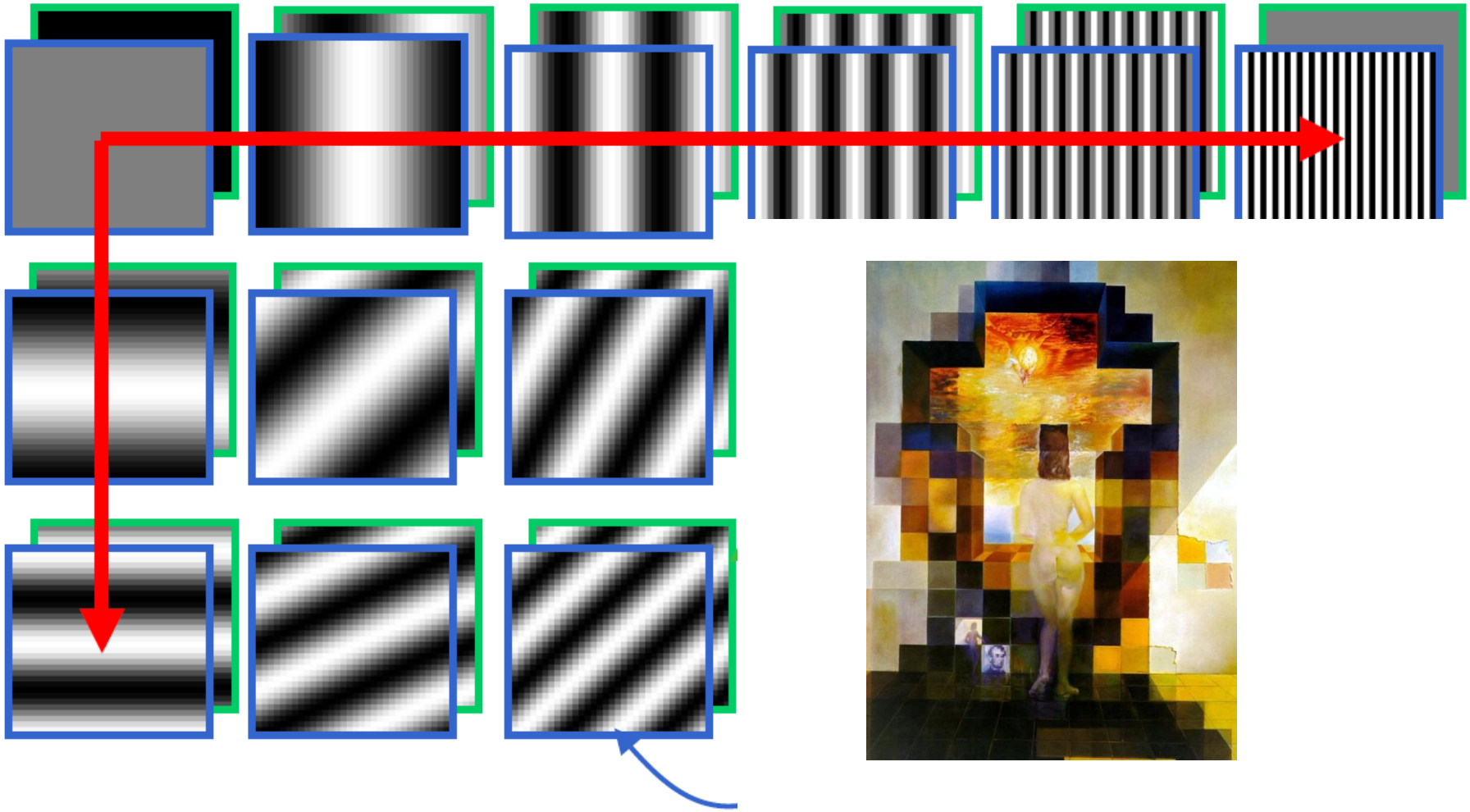
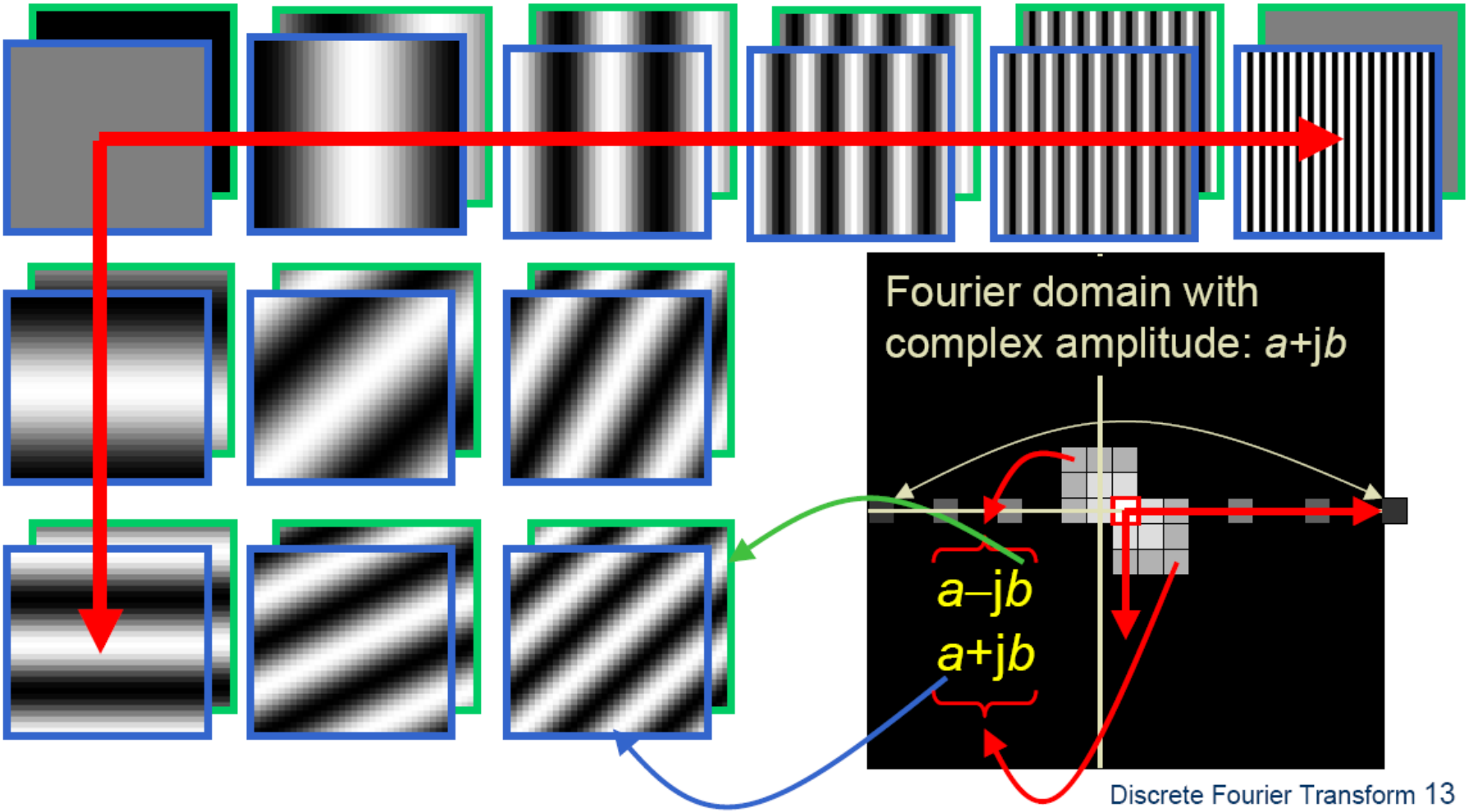


Image as a sum of basis images

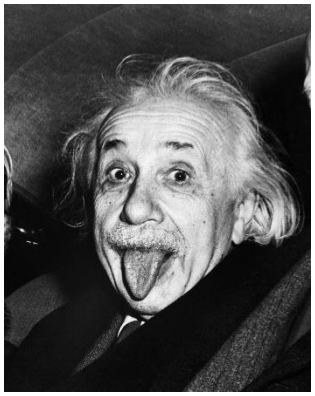
Slide credit: A Efros

Extension to 2D



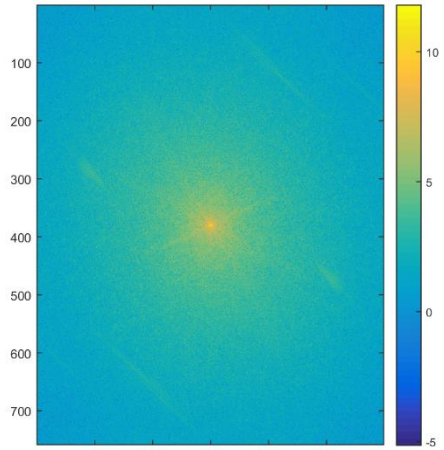
in Matlab, check out: imagesc(log(abs(fftshift(fft2(im)))));

Phase vs. Magnitude

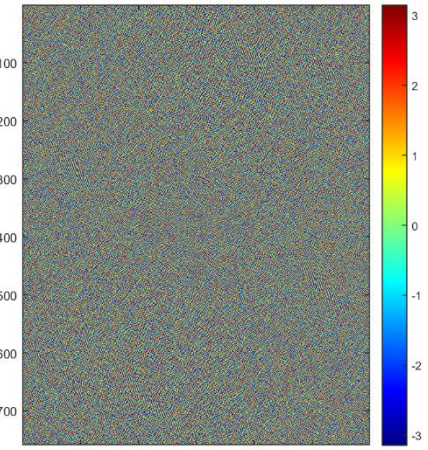


Intensity image

FFT



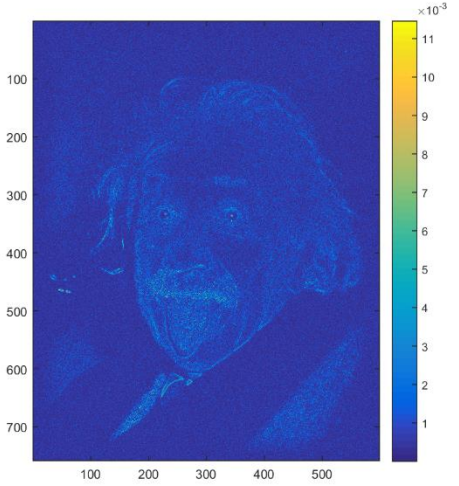
Magnitude



Phase

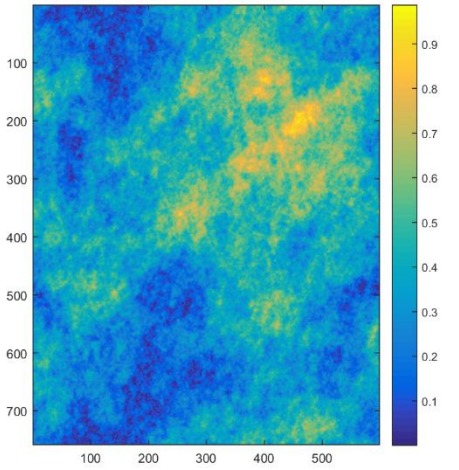
Use random magnitude

Inverse FFT



Use random phase

Inverse FFT



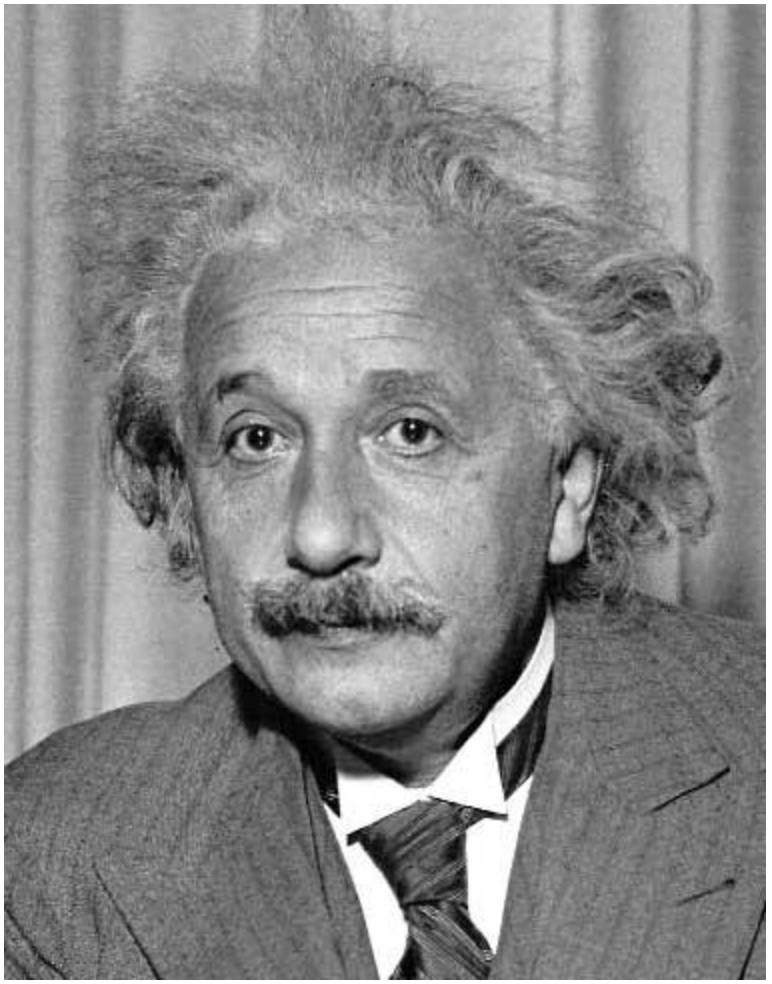
Today's class

- Template matching
- Image Pyramids
- Compression
- Introduction to HW1

Template matching

- Goal: find  in image

- Main challenge: What is a good similarity or distance measure between two patches? D(,)
  - Correlation
  - Zero-mean correlation
  - Sum Square Difference
  - Normalized Cross Correlation

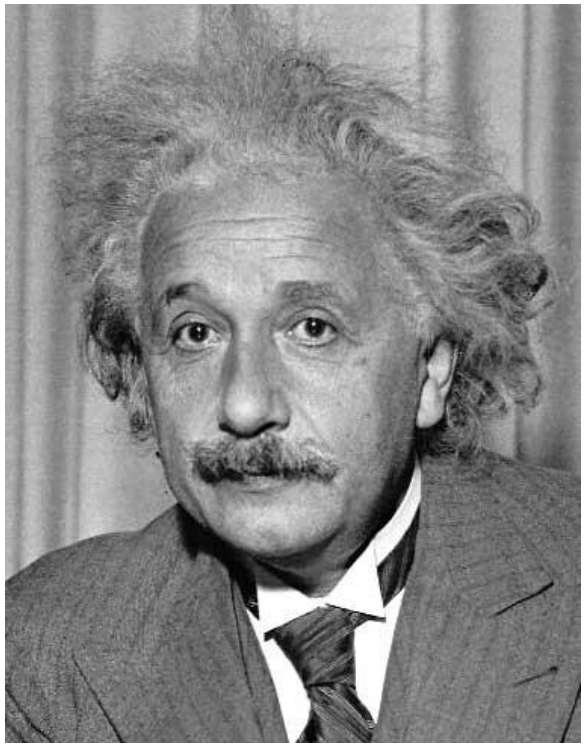


Matching with filters

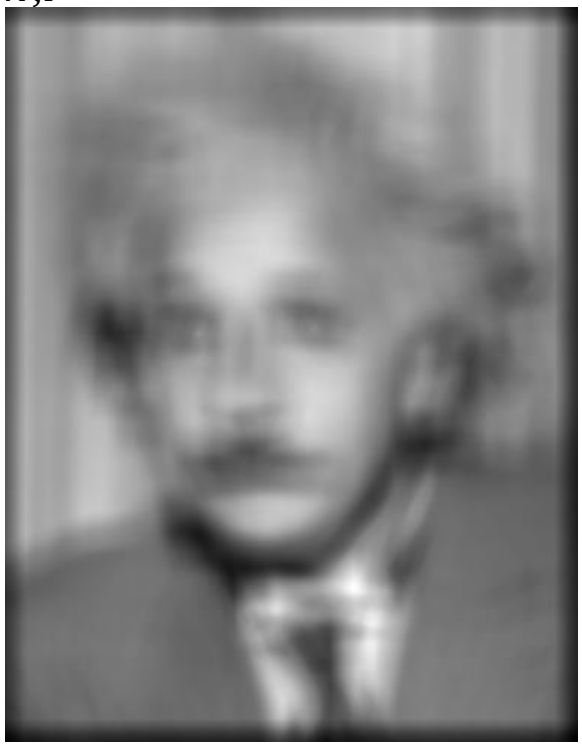
- Goal: find  in image
- Method 0: filter the image with eye patch

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

f = image
g = filter



Input



Filtered Image

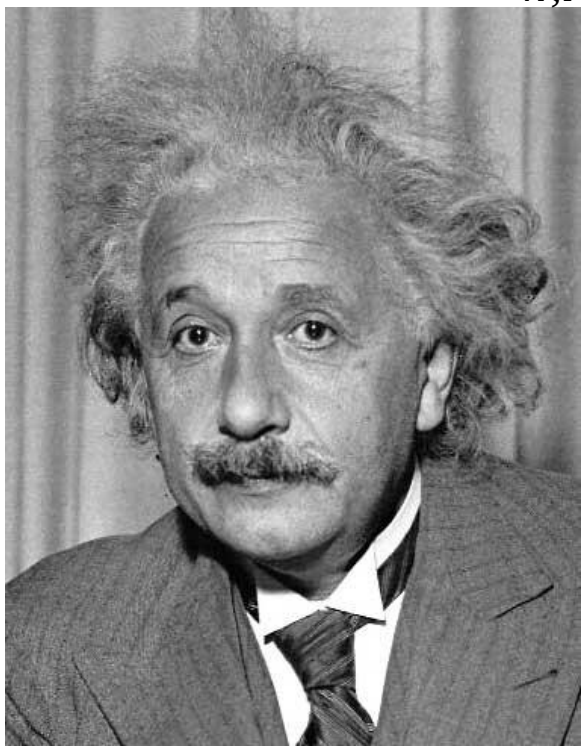
What went wrong?

Matching with filters

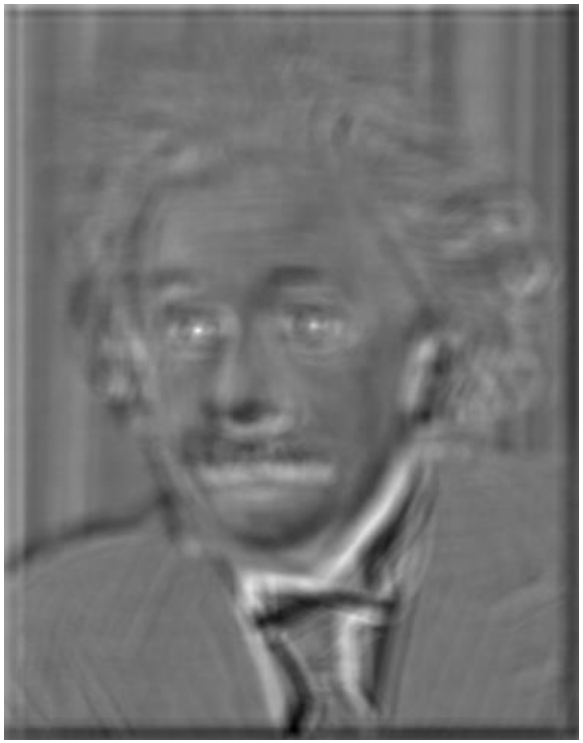
- Goal: find  in image
- Method 1: filter the image with zero-mean eye

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

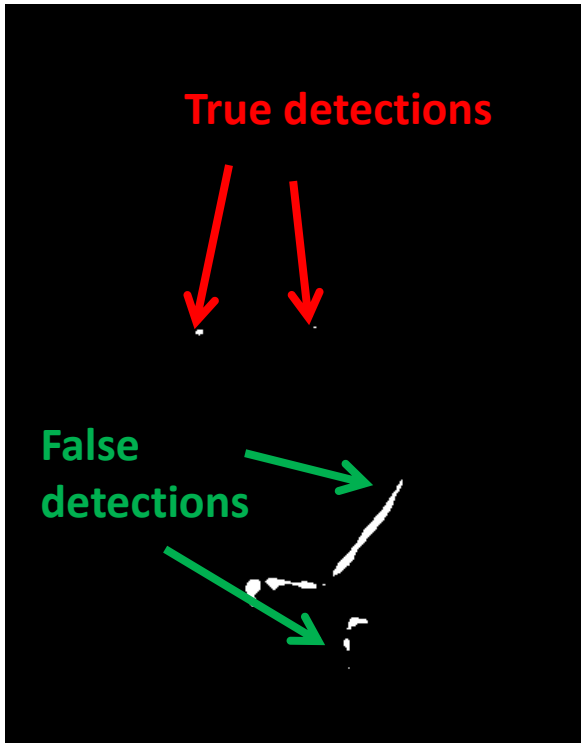
mean of template g



Input



Filtered Image (scaled)

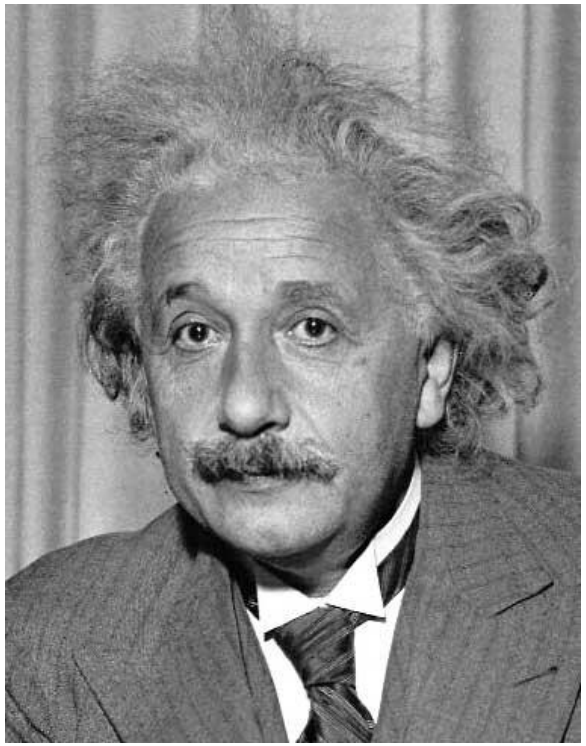


Thresholded Image

Matching with filters

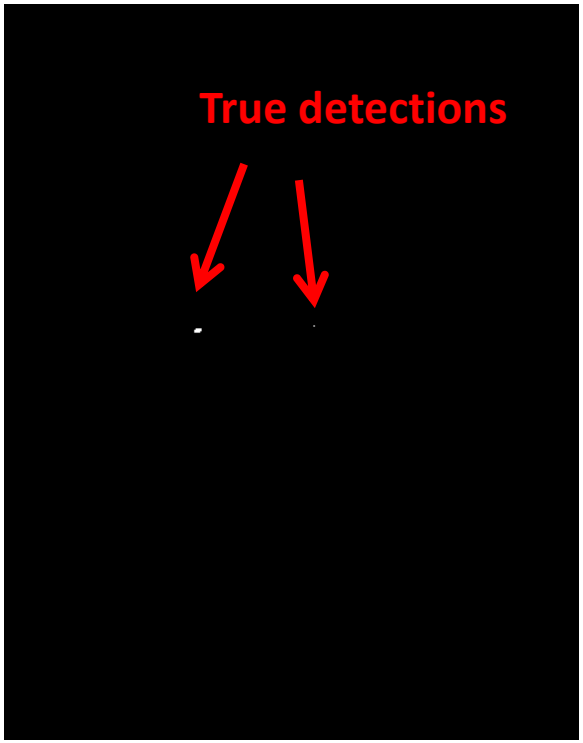
- Goal: find  in image
- Method 2: Sum of squared differences (SSD)

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



Input

1- sqrt(SSD)



Thresholded Image

Matching with filters

Can SSD be implemented with linear filters?

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

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

Constant

Filtering with g

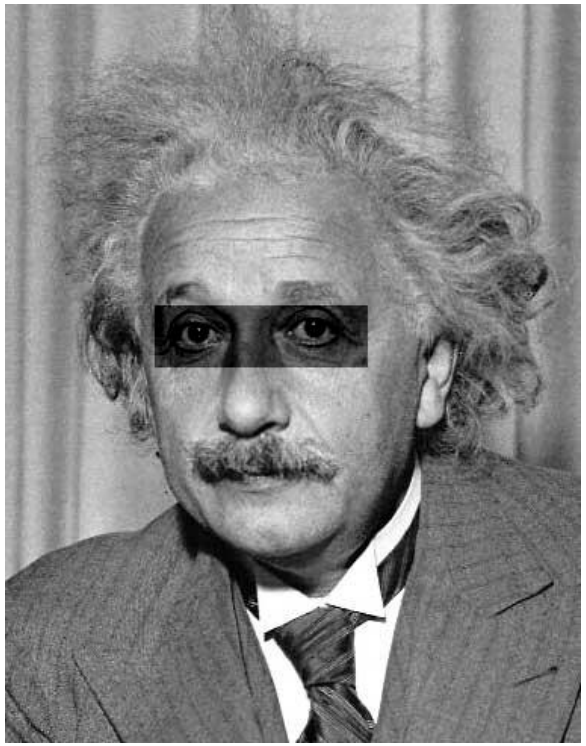
Filtering with box filter

Matching with filters

- Goal: find  in image
- Method 2: SSD

What's the potential downside of SSD?

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



Input

1- sqrt(SSD)

Matching with filters

- Goal: find  in image
- Method 3: Normalized cross-correlation

mean template

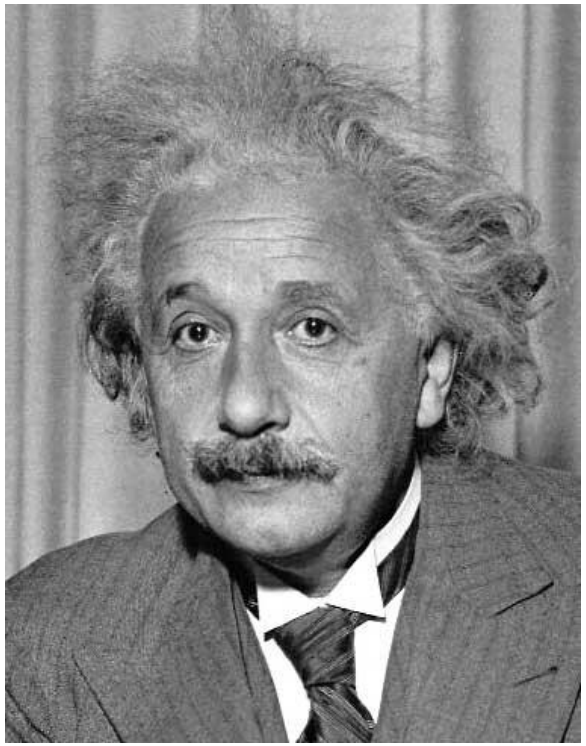
mean image patch

$$h[m,n] = \frac{\sum_{k,l}(g[k,l]-\bar{g})(f[m+k,n+l]-\bar{f}_{m,n})}{\left(\sum_{k,l}(g[k,l]-\bar{g})^2 \sum_{k,l}(f[m+k,n+l]-\bar{f}_{m,n})^2\right)^{0.5}}$$

Matlab: `normxcorr2(template, im)`

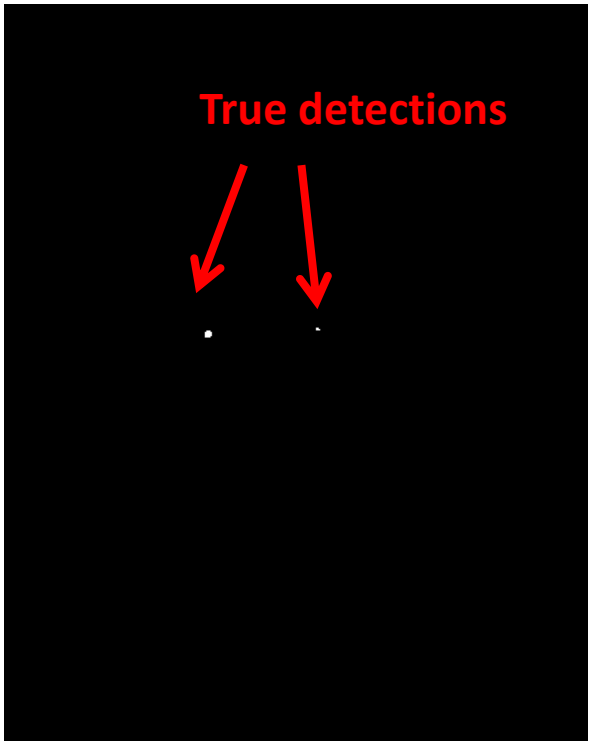
Matching with filters

- Goal: find  in image
- Method 3: Normalized cross-correlation



Input

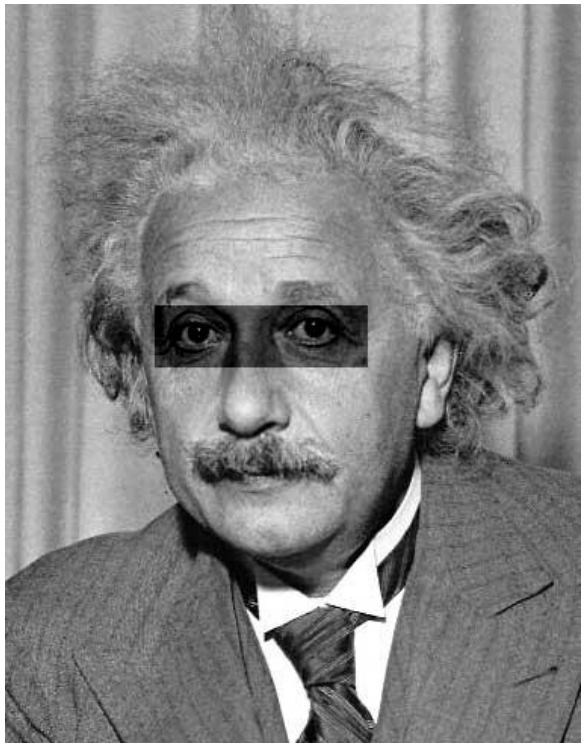
Normalized X-Correlation



Thresholded Image

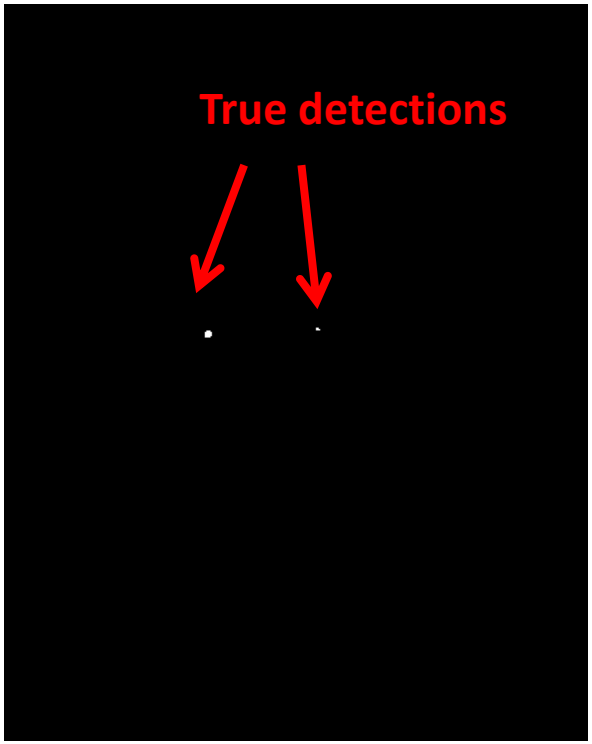
Matching with filters

- Goal: find  in image
- Method 3: Normalized cross-correlation



Input

Normalized X-Correlation



Thresholded Image

Q: What is the best method to use?

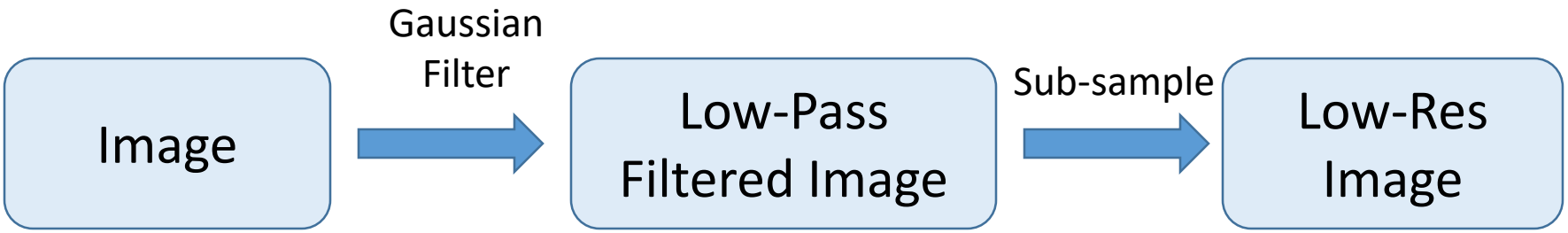
A: Depends

- Zero-mean filter: fastest but not a great matcher
- SSD: next fastest, sensitive to overall intensity
- Normalized cross-correlation: slowest, invariant to local average intensity and contrast

Q: What if we want to find larger or smaller eyes?

A: Image Pyramid

Review of Sampling



Gaussian pyramid

512 256 128 64 32 16 8

Source: Forsyth

Template Matching with Image Pyramids

Input: Image, Template

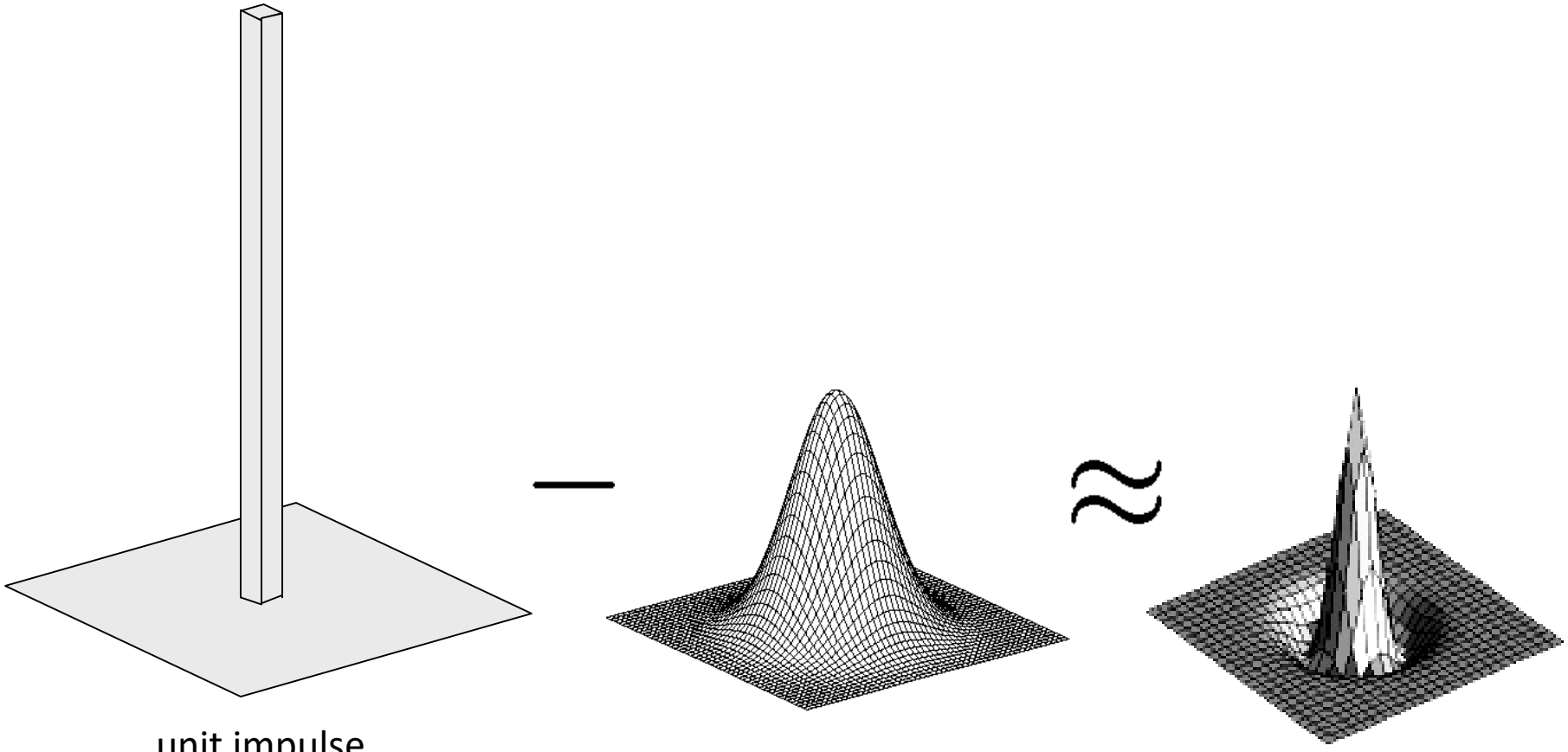
1. Match template at current scale

2. Downsample image
   - In practice, scale step of 1.1 to 1.2

3. Repeat 1-2 until image is very small

4. Take responses above some threshold, perhaps with non-maxima suppression

Laplacian filter



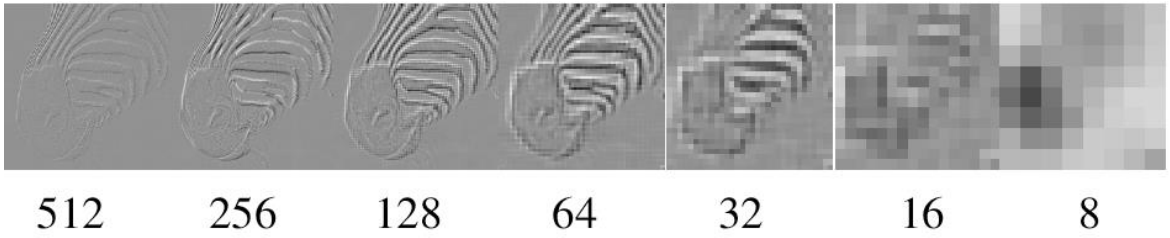
unit impulse

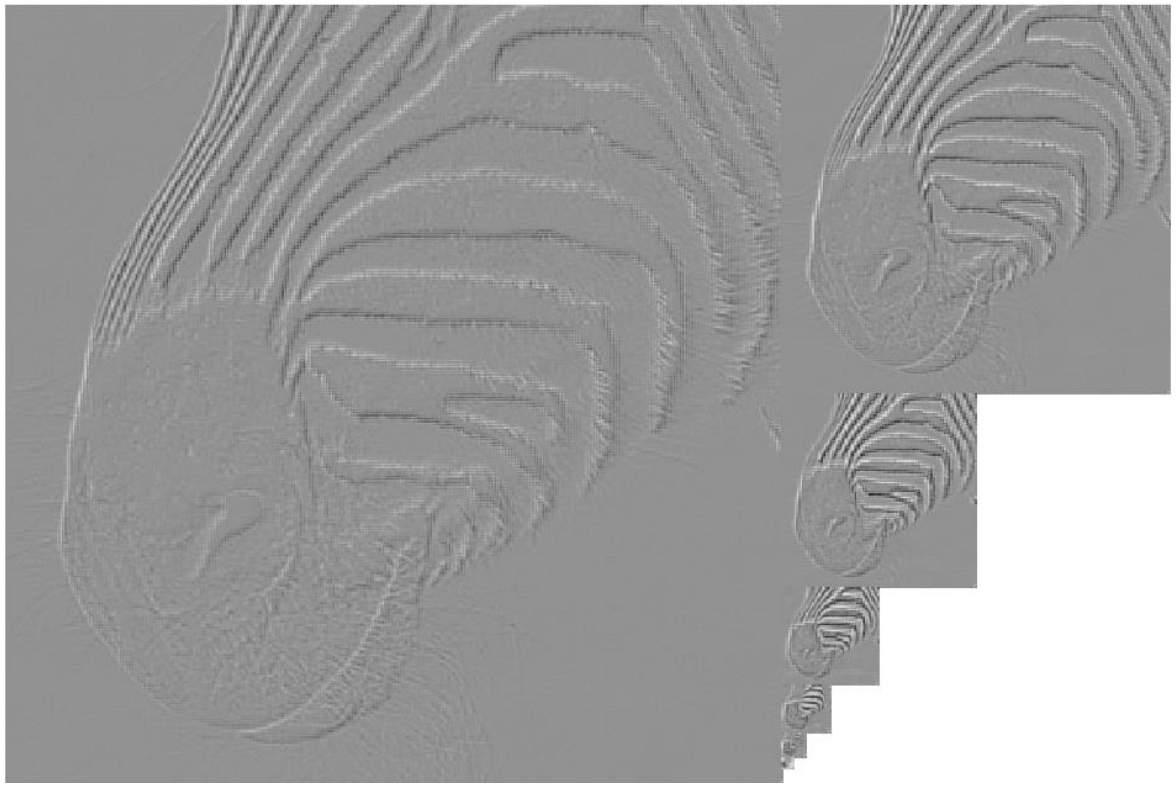
Gaussian

Laplacian of Gaussian

Source: Lazebnik

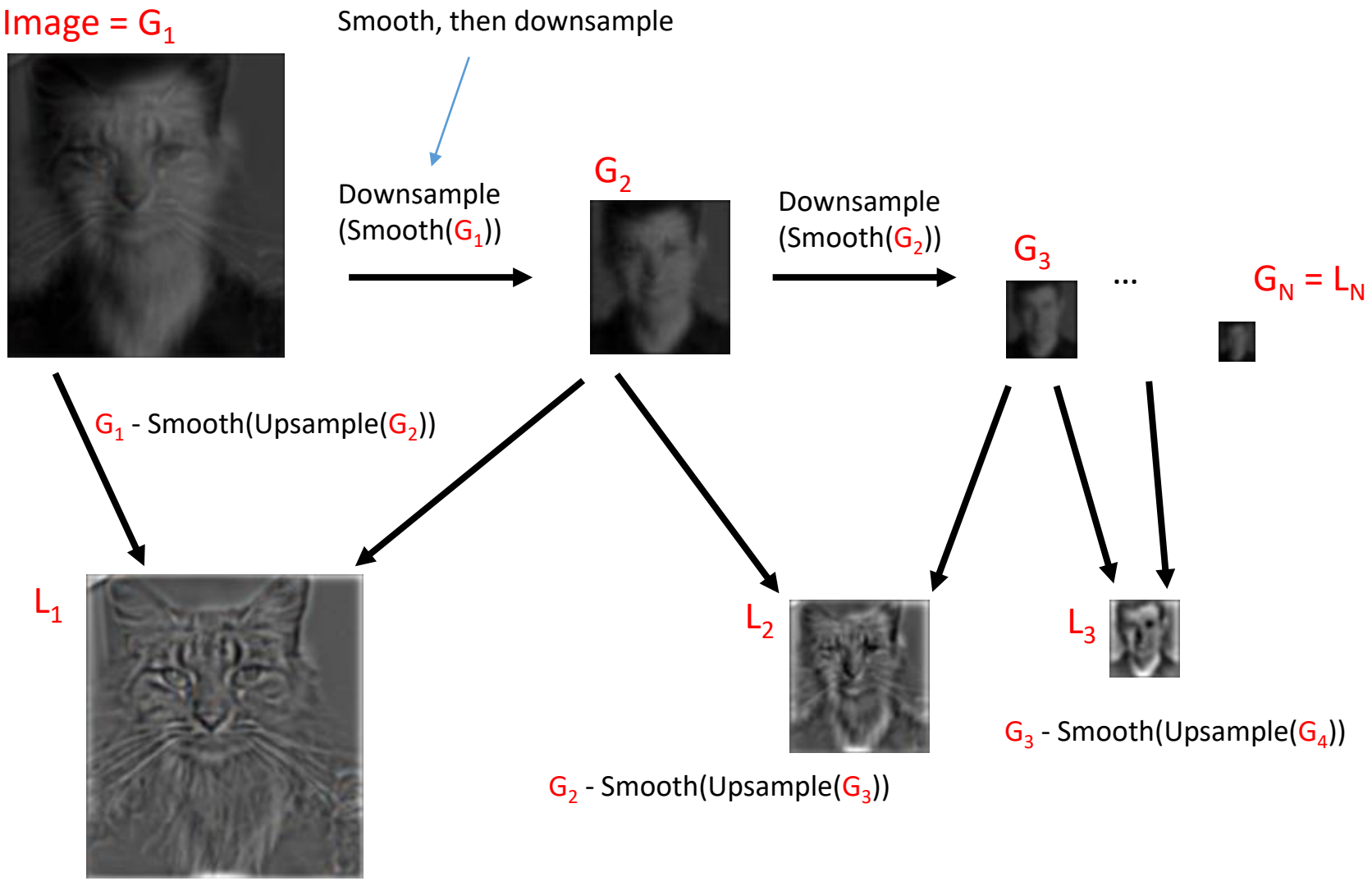
Laplacian pyramid





Source: Forsyth

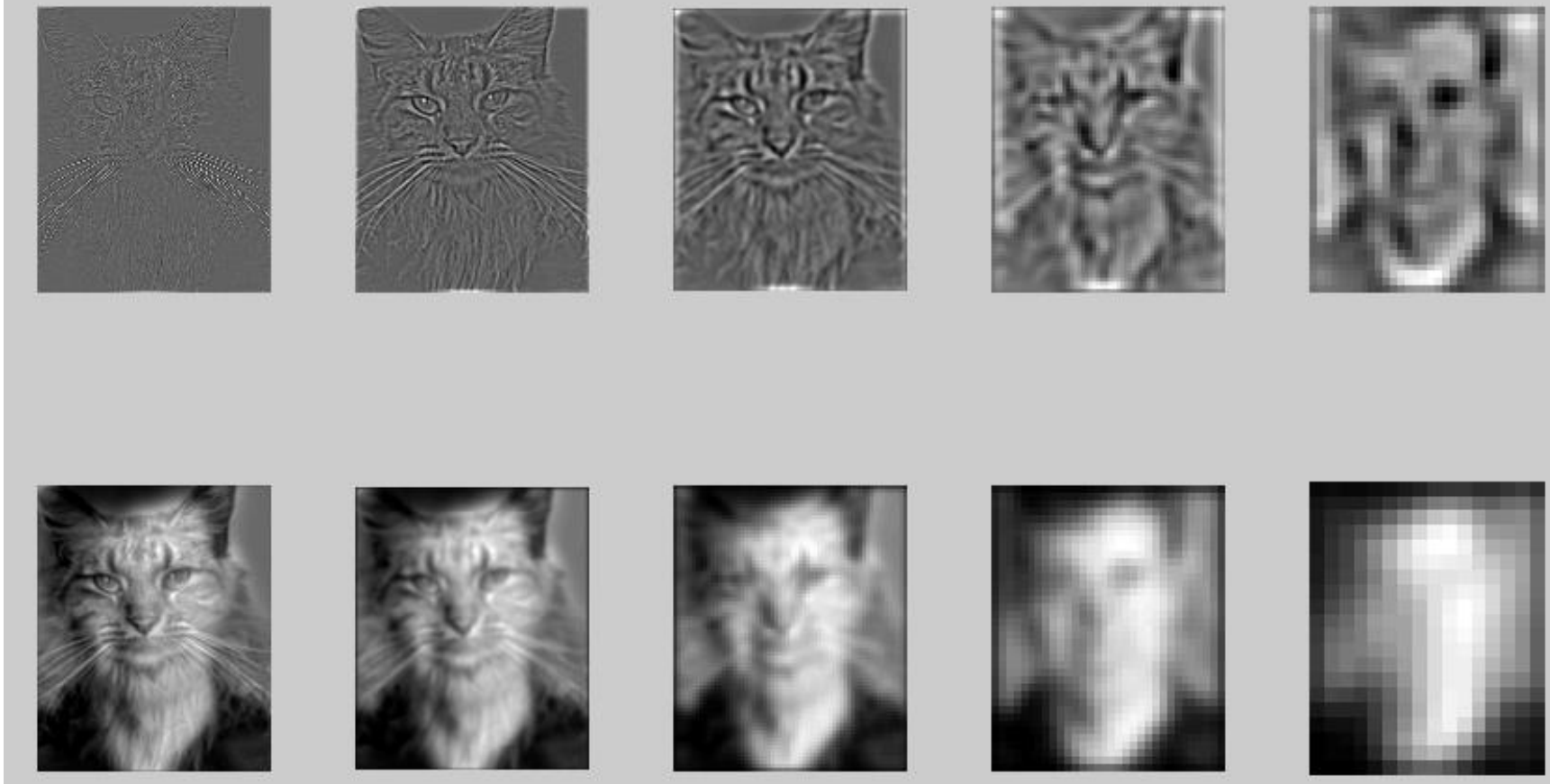
Creating the Gaussian/Laplacian Pyramid



- Use same filter for smoothing in each step (e.g., Gaussian with $\sigma = 2$)
- Downsample/upsample with "nearest" interpolation

Hybrid Image in Laplacian Pyramid

High frequency → Low frequency



Reconstructing image from Laplacian pyramid

Image = L_1 + Smooth(Upsample(G_2))

$G_2 = L_2$ + Smooth(Upsample(G_3))

$G_3 = L_3$ + Smooth(Upsample(L_4))

L_4

L_1

L_2

L_3

- Use same filter for smoothing as in desconstruction
- Upsample with “nearest” interpolation
- Reconstruction will be lossless

Major uses of image pyramids

- Object detection
  - Scale search
  - Features
- Detecting stable interest points
- Course-to-fine registration
- Compression


LEGEND
IN THE MAKING


LEGEND
IN THE MAKING

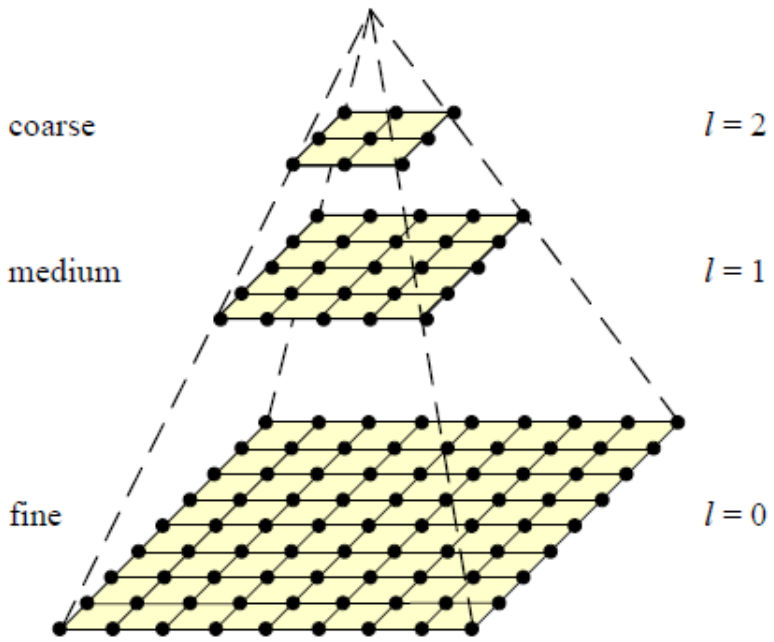

LEGEND
IN THE MAKING

Coarse-to-fine Image Registration

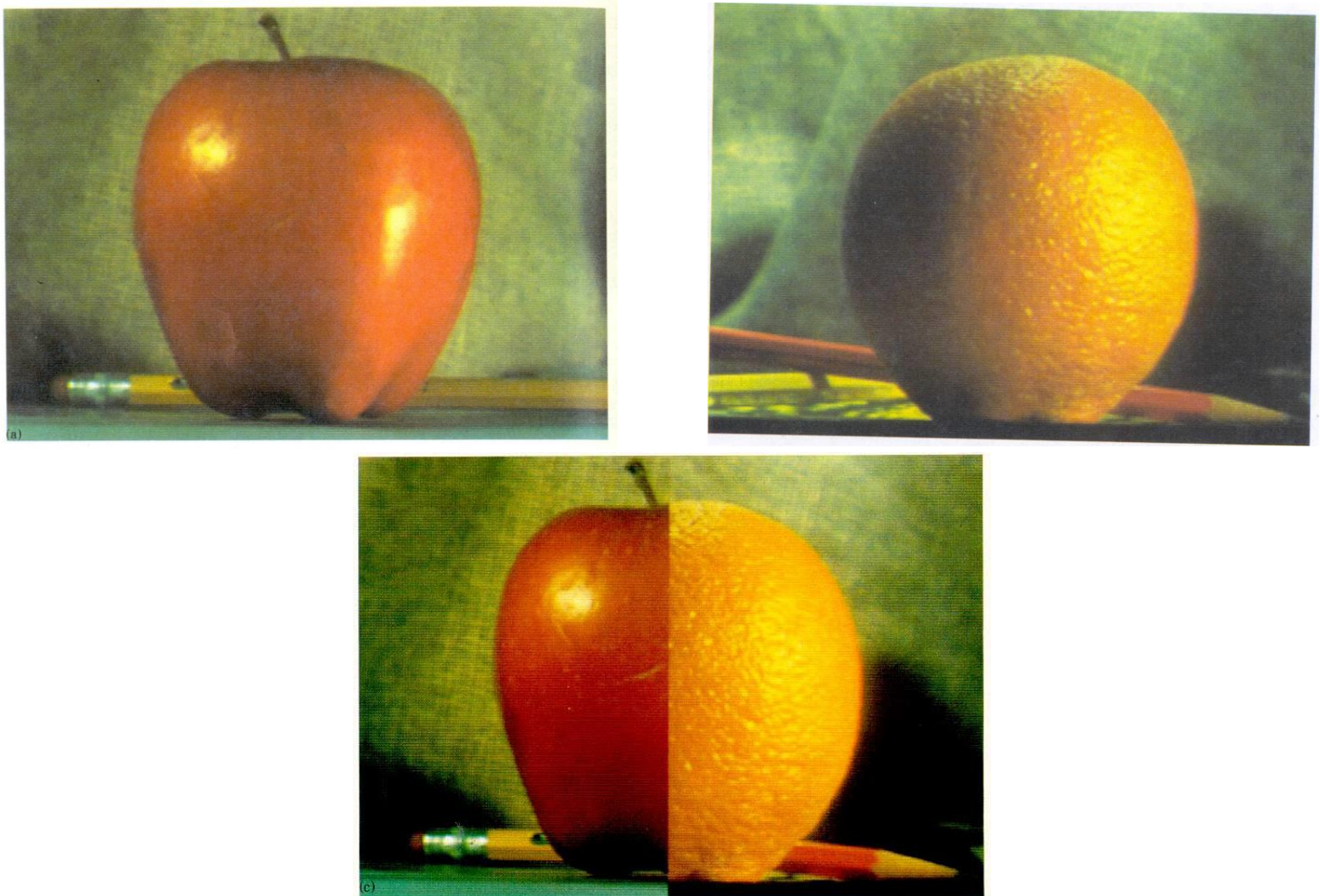
1. Compute Gaussian pyramid
2. Align with coarse pyramid
3. Successively align with finer pyramids
   - Search smaller range

Why is this faster?

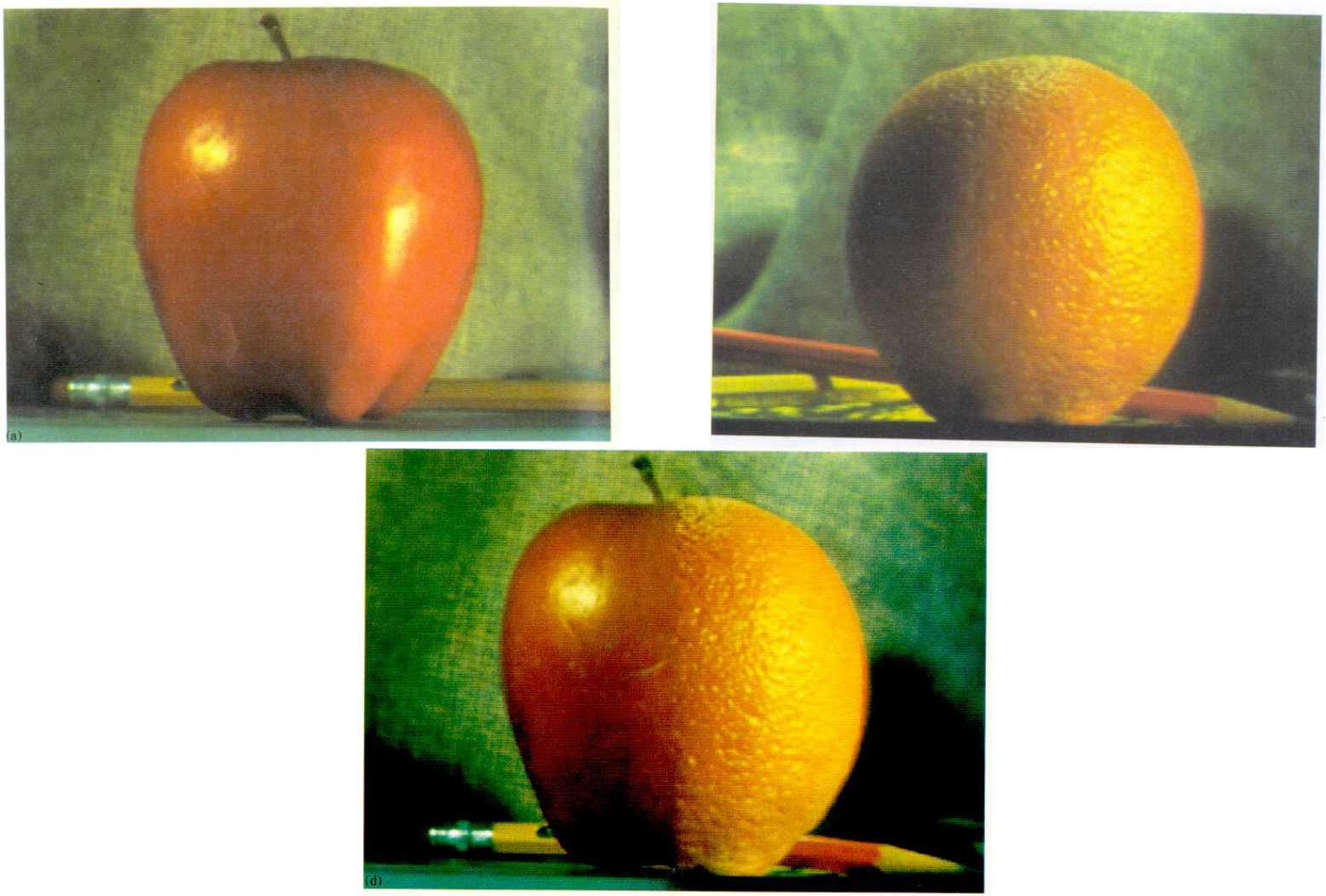
Are we guaranteed to get the same result?



Applications: Pyramid Blending

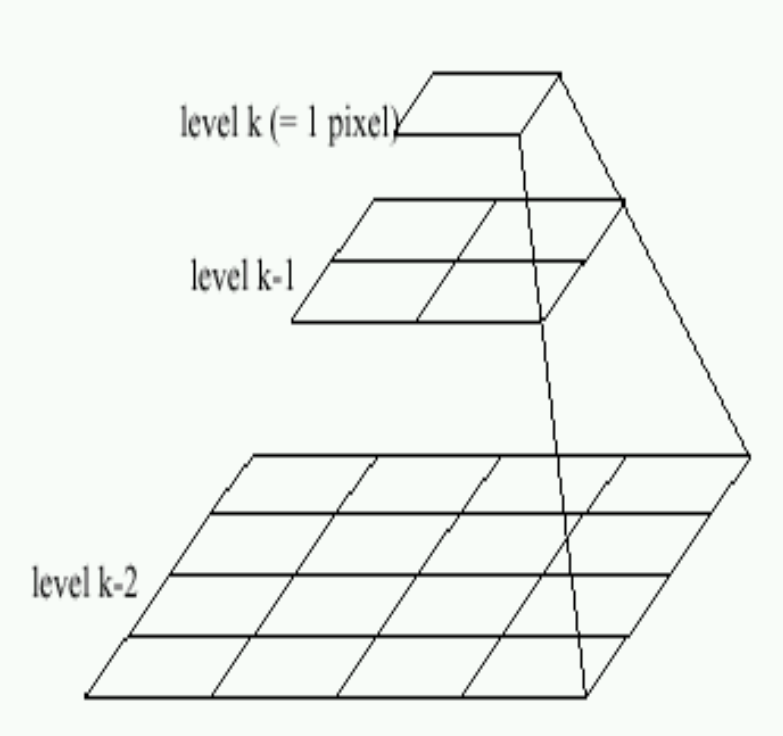


Applications: Pyramid Blending

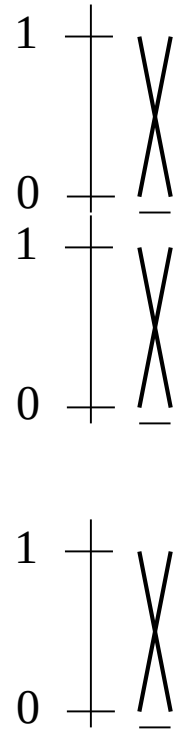


Pyramid Blending

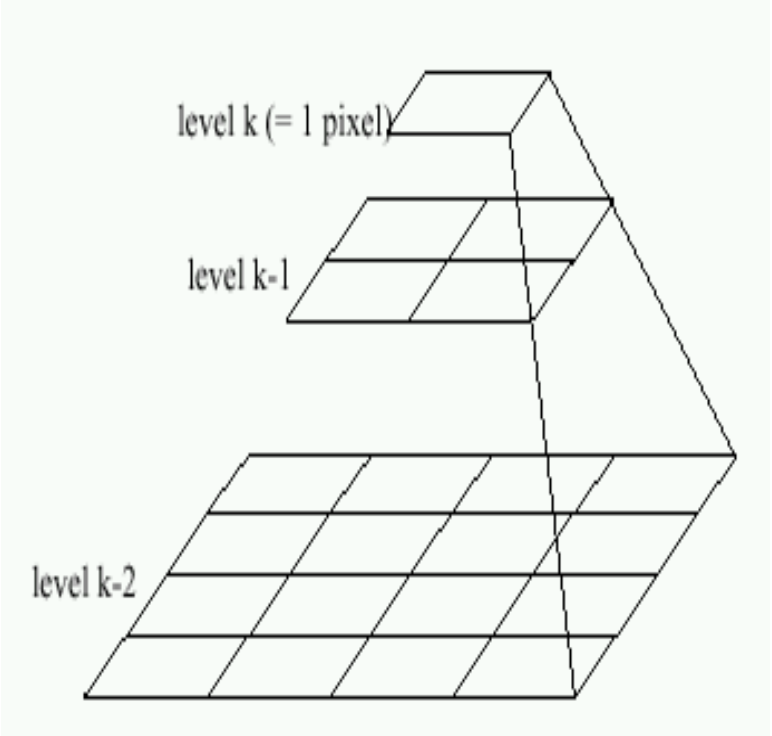
- At low frequencies, blend slowly
- At high frequencies, blend quickly



Left pyramid



blend



Right pyramid

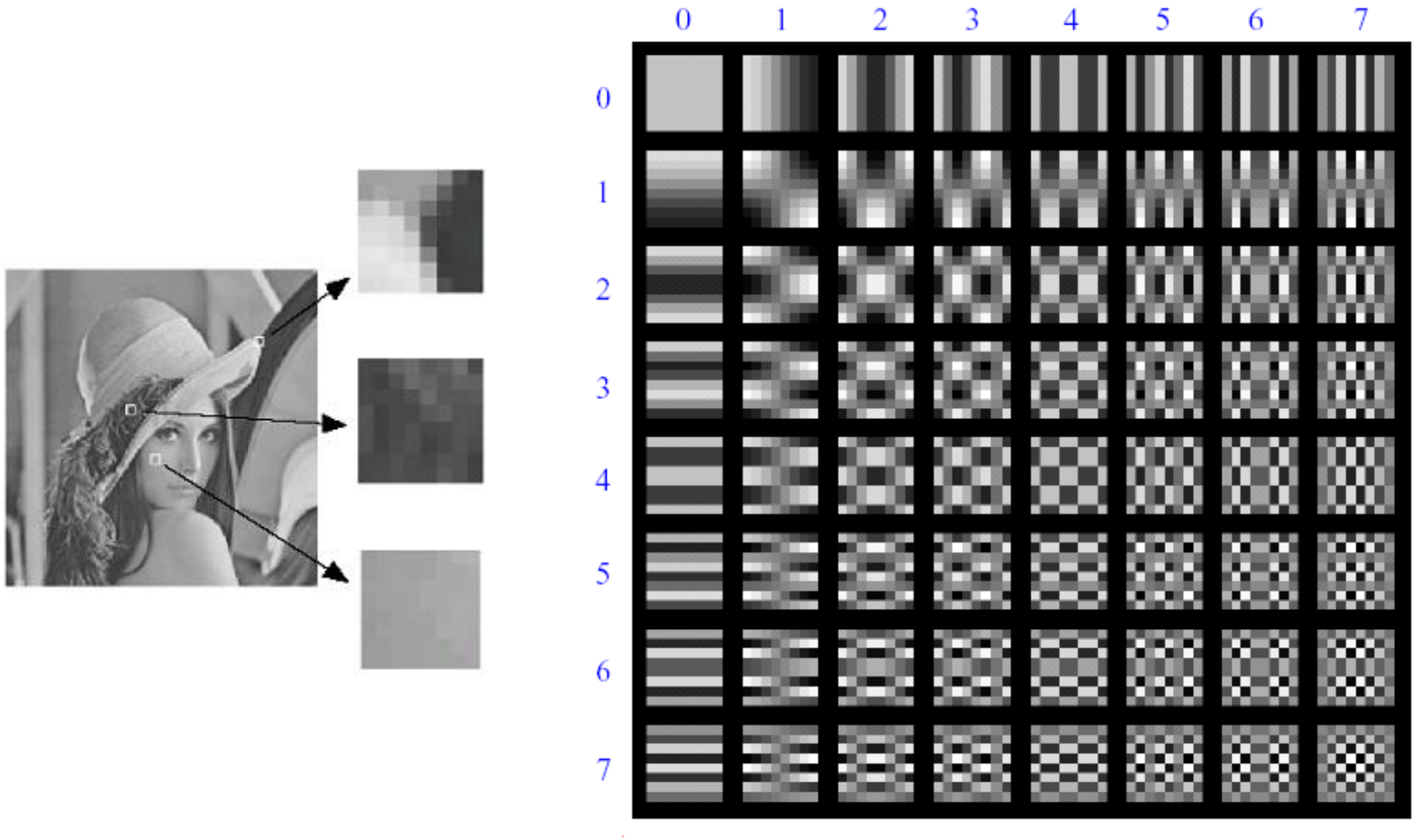
Image representation

- Pixels:
  - great for spatial resolution, poor access to frequency
- Fourier transform:
  - great for frequency, not for spatial info
- Pyramids/filter banks:
  - balance between spatial and frequency information

Compression

How is it that a 4MP image (12000KB) can be compressed to 400KB without a noticeable change?

Lossy Image Compression (JPEG)

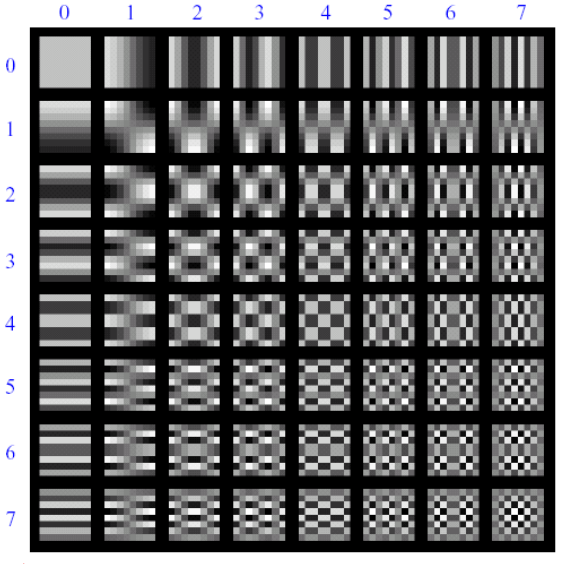


Block-based Discrete Cosine Transform (DCT)

Slides: Efros

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



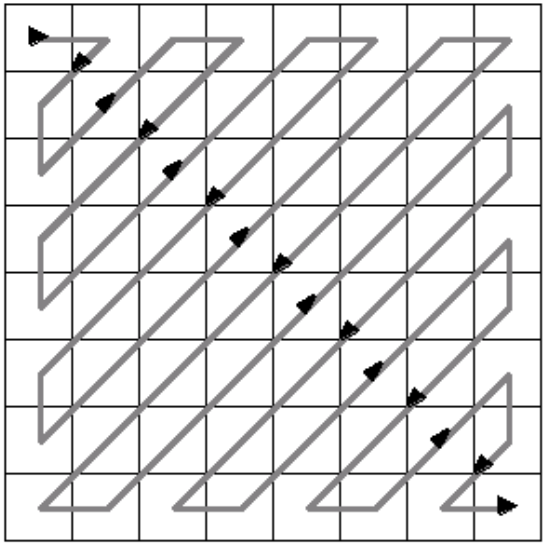


Image compression using DCT

- 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

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

($u \rightarrow$, $v \downarrow$)

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

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

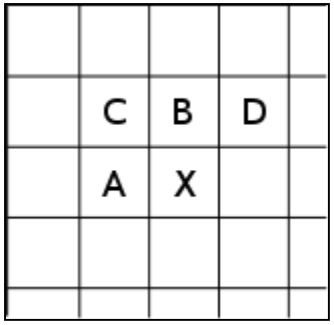
JPEG Compression Summary

1. Convert image to YCrCb
2. Subsample color by factor of 2
   - People have bad resolution for color
3. Split into blocks (8x8, typically), subtract 128
4. 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

Lossless compression (PNG)

1. Predict that a pixel's value based on its upper-left neighborhood
2. Store difference of predicted and actual value
3. Pkzip it (DEFLATE algorithm)



Three views of image filtering

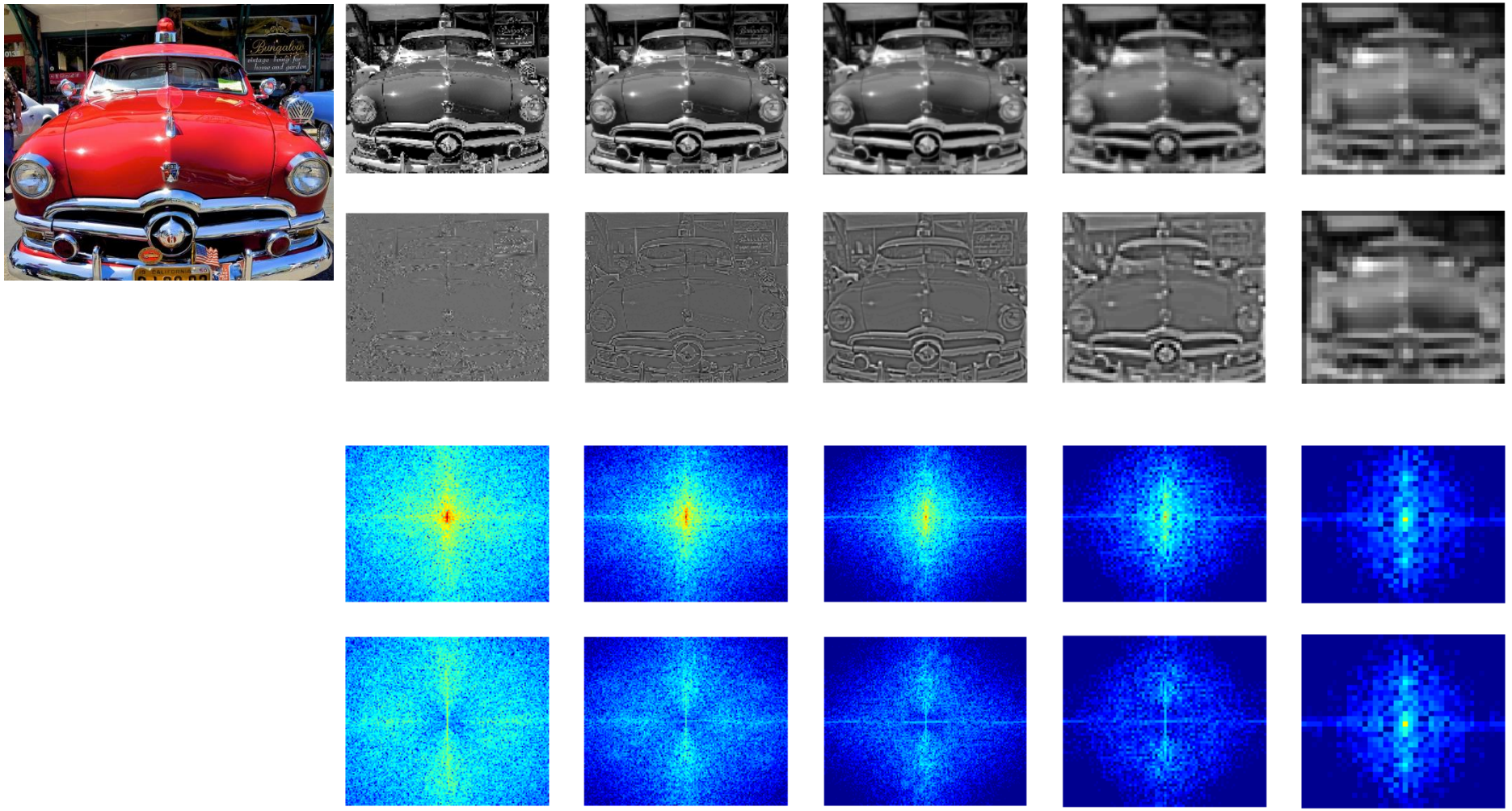
- Image filters in spatial domain
  - Filter is a mathematical operation on values of each patch
  - Smoothing, sharpening, measuring texture
- Image filters in the frequency domain
  - Filtering is a way to modify the frequencies of images
  - Denoising, sampling, image compression
- Templates and Image Pyramids
  - Filtering is a way to match a template to the image
  - Detection, coarse-to-fine registration

HW 1 – Hybrid Image

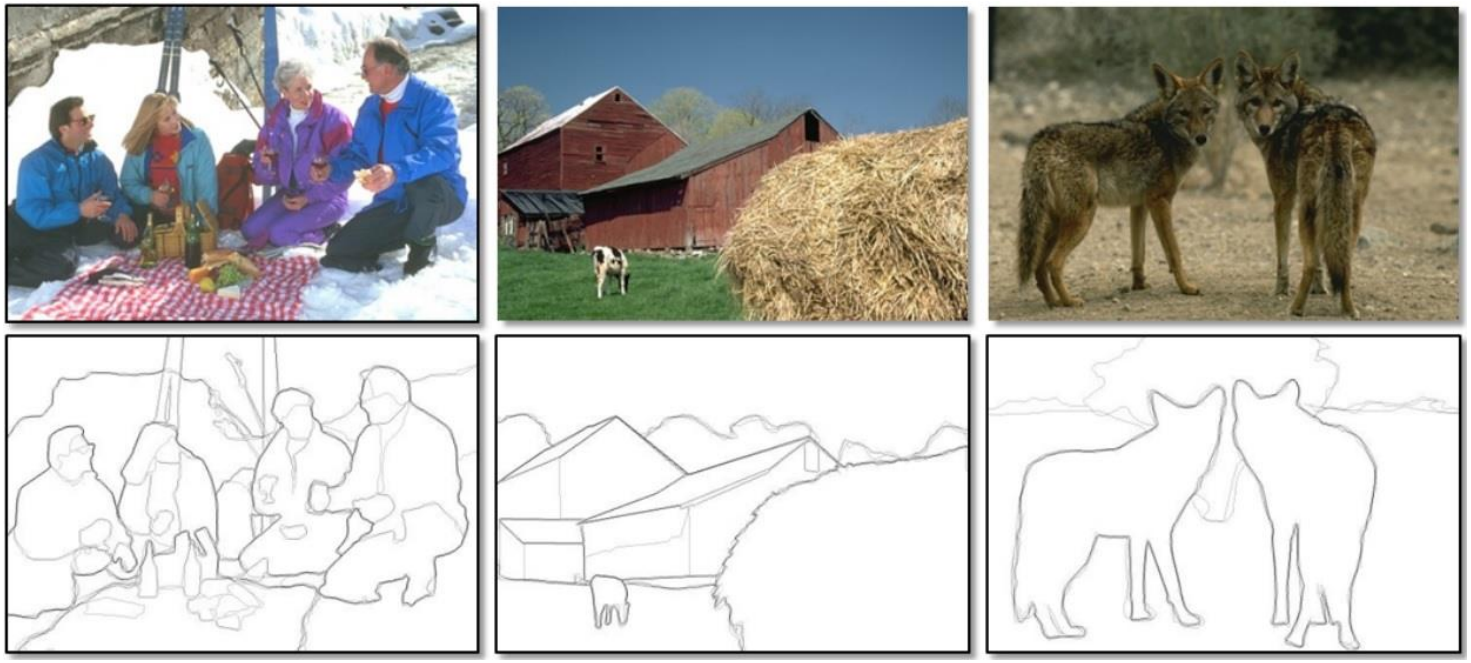
- Hybrid image =

Low-Freq(Image A) + Hi-Freq(Image B)

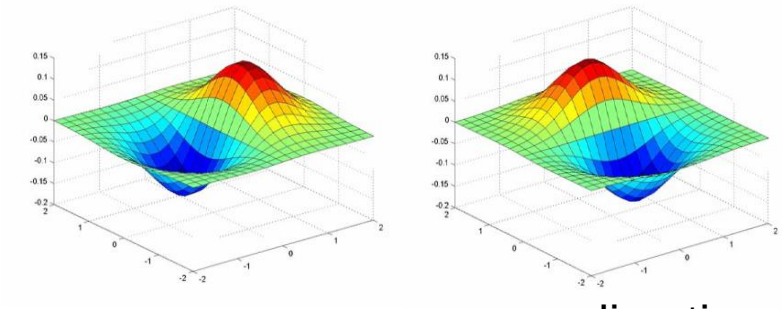
HW 1 – Image Pyramid



HW 1 – Edge Detection



Derivative of Gaussian filters

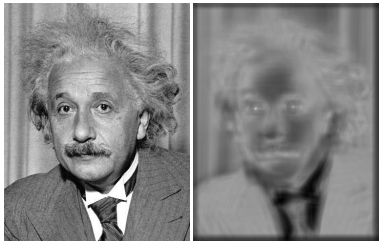


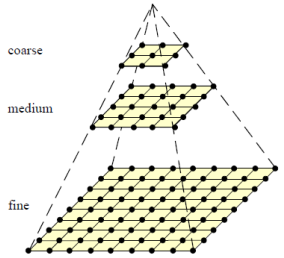
x-direction

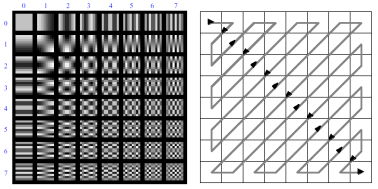
y-direction

Things to remember

- Template matching (SSD or Normxcorr2)
  - SSD can be done with linear filters, is sensitive to overall intensity
- Gaussian pyramid
  - Coarse-to-fine search, multi-scale detection
- Laplacian pyramid
  - More compact image representation
  - Can be used for compositing in graphics
- Compression
  - In JPEG, coarsely quantize high frequencies







Thank you

- See you this Thursday
- Next class:
  - Edge detection