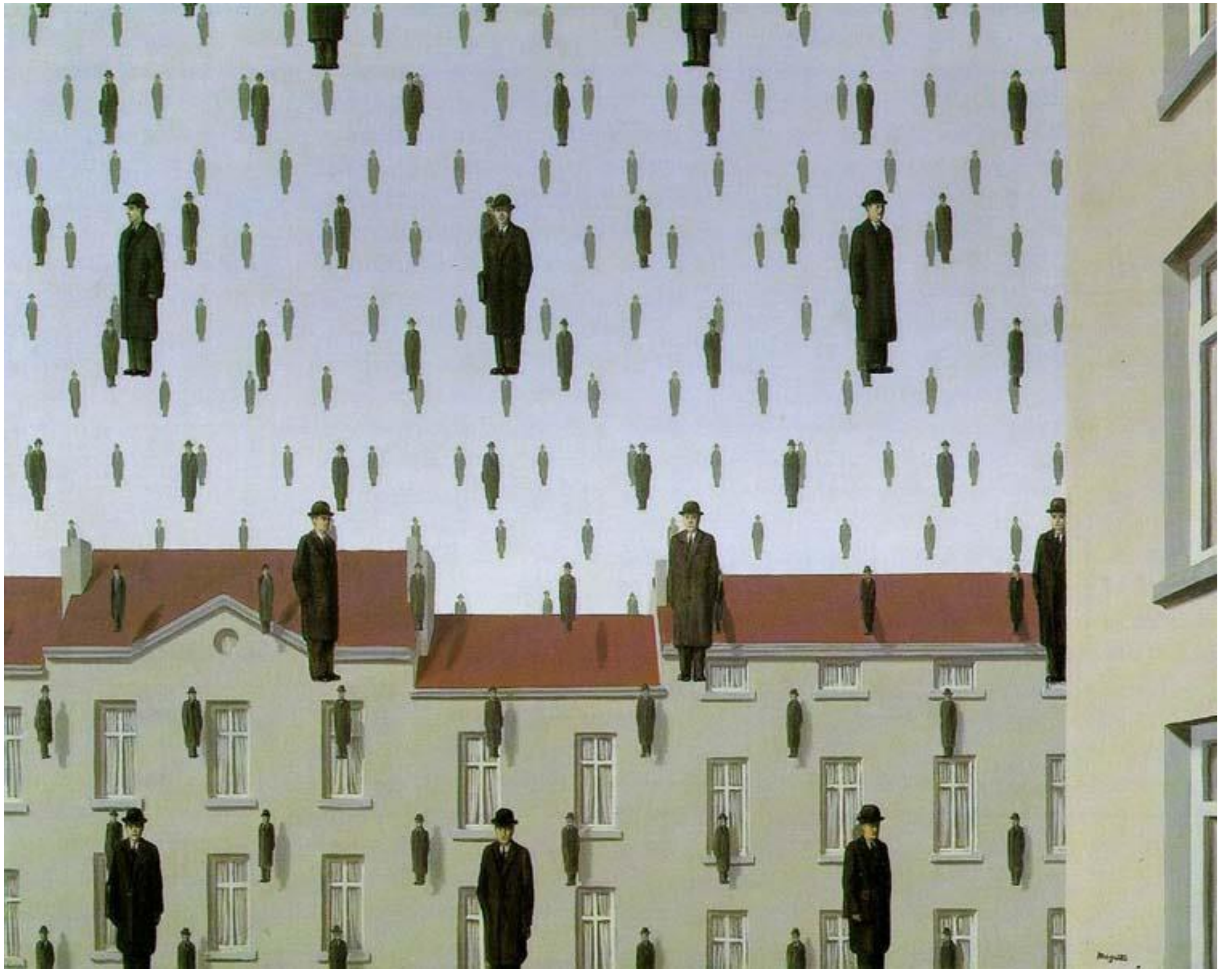
01/31/17

Templates, Image Pyramids, and Filter Banks

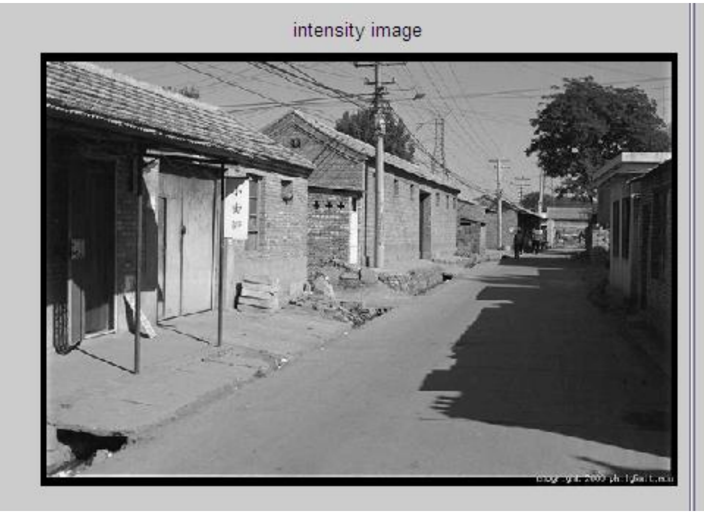


Computer Vision

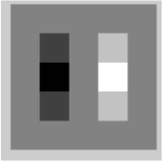
Derek Hoiem, University of Illinois

Review: filtering in spatial domain

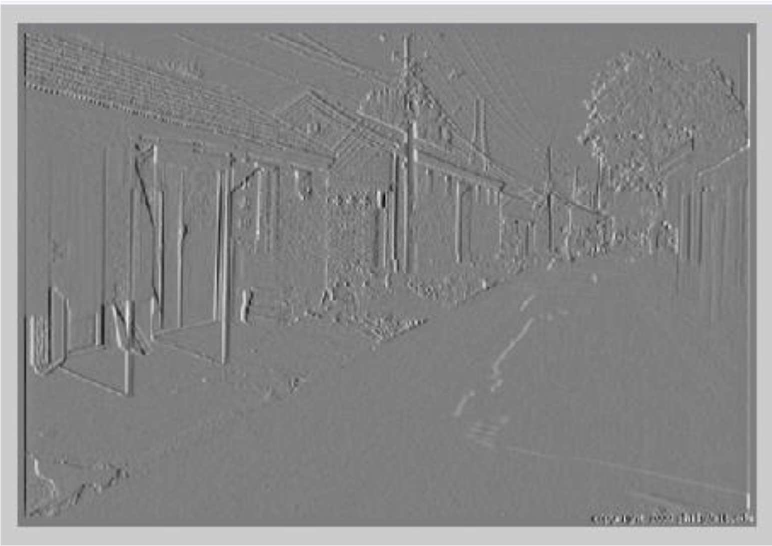
1	0	-1
2	0	-2
1	0	-1



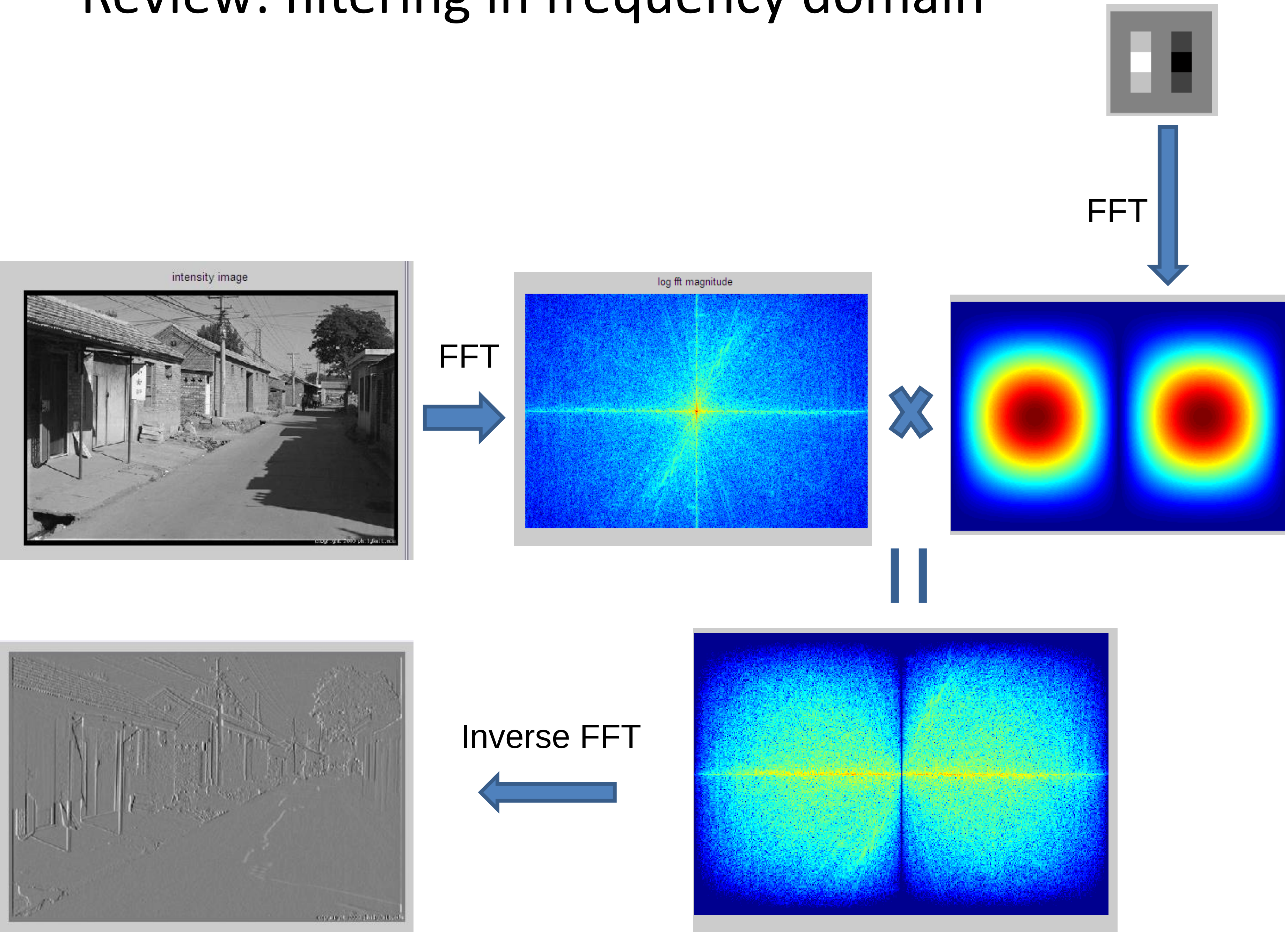
*



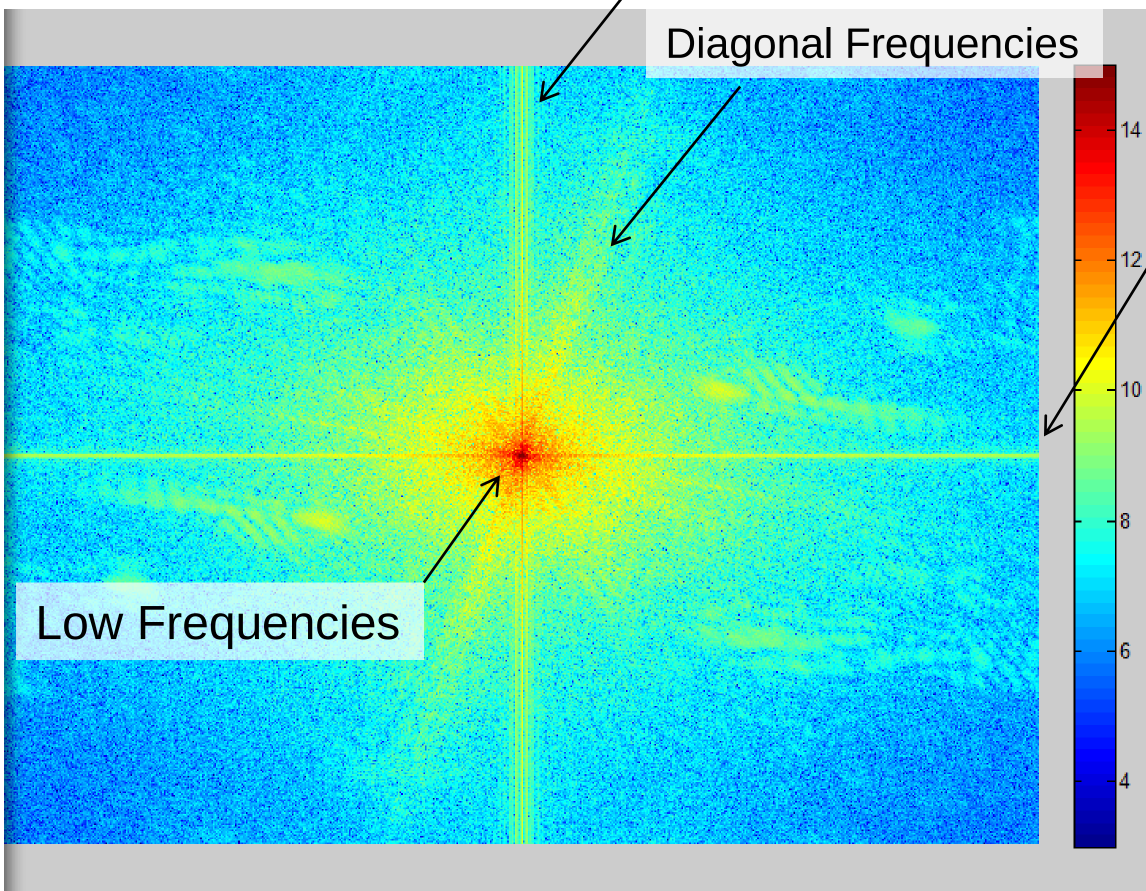
=



Review: filtering in frequency domain



Review



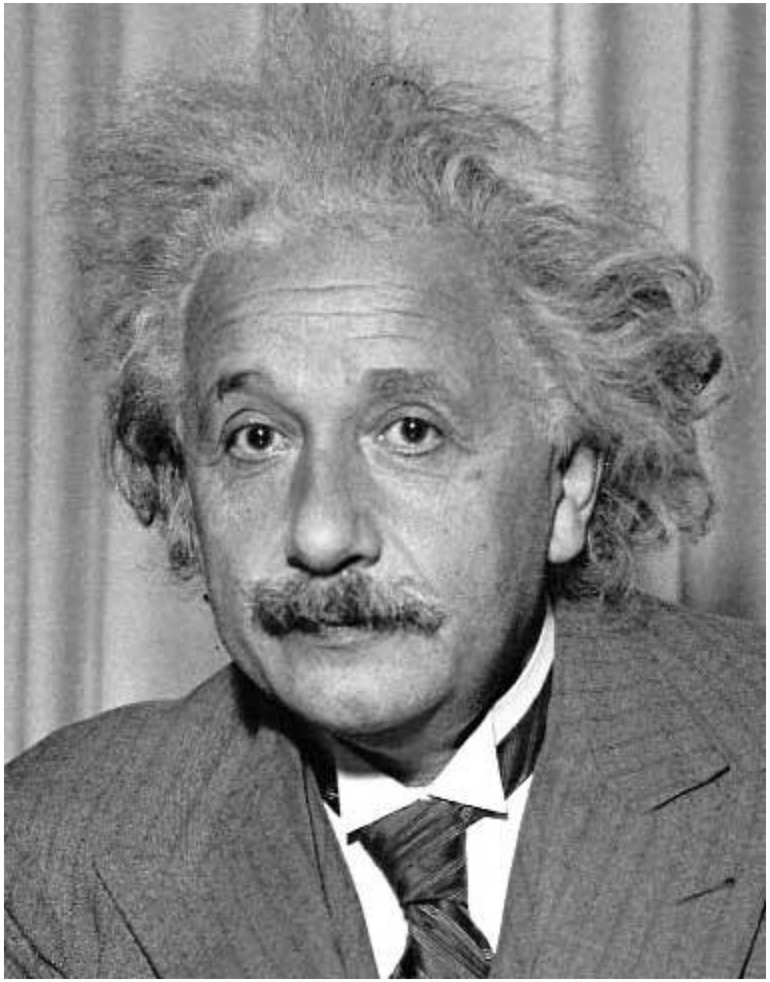
Strong Vertical Frequency
(Sharp Horizontal Edge)
Diagonal Frequencies
Strong Horz. Frequency
(Sharp Vert. Edge)
Low Frequencies
Log Magnitude
14
12
10
8
6
4

Today’s class

- Template matching
- Image Pyramids
- Filter banks and texture
- Denoising, Compression

Template matching

- Goal: find  in image



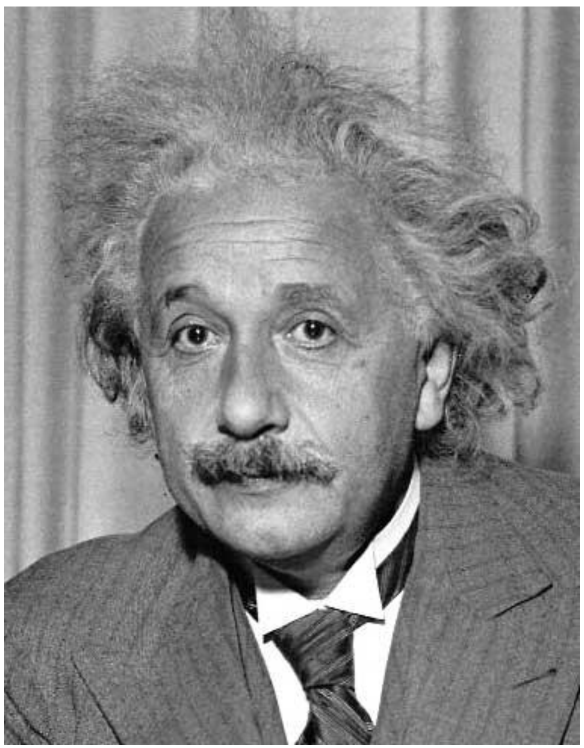
- Main challenge: What is a good similarity or distance measure between two patches?
  - Correlation
  - Zero-mean correlation
  - Sum Square Difference
  - Normalized Cross Correlation

Matching with filters

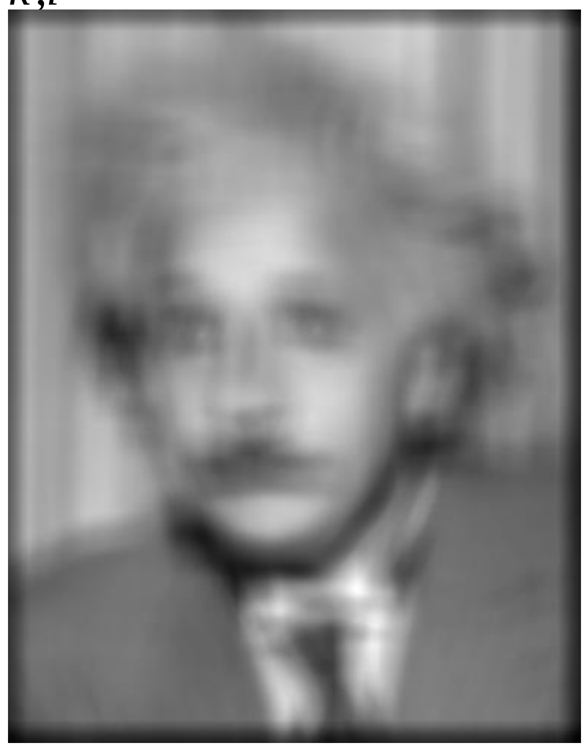
- Goal: find  in image
- Method 0: filter the image with eye patch

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

f = image
g = filter



Input



Filtered Image

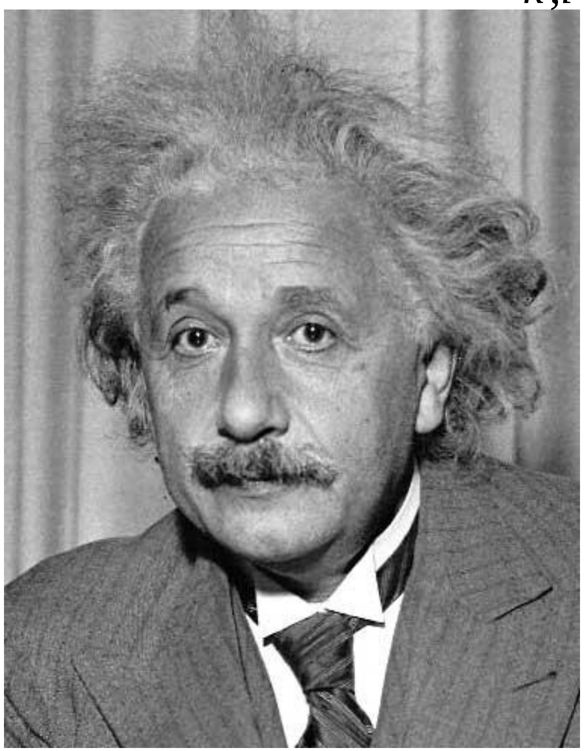
What went wrong?

Matching with filters

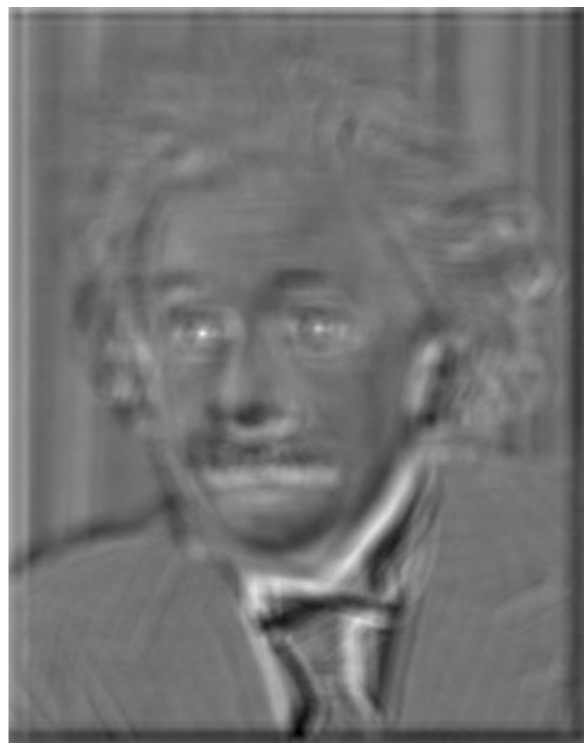
- Goal: find  in image
- Method 1: filter the image with zero-mean eye

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

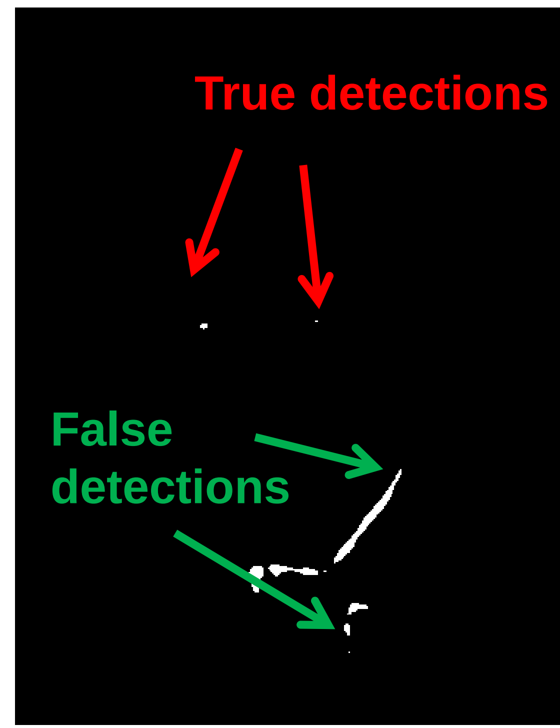
mean of template g



Input



Filtered Image (scaled)

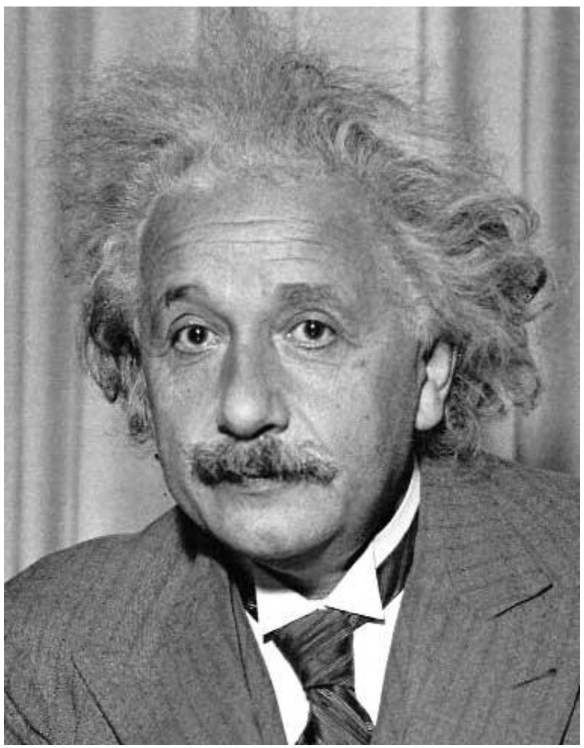


Thresholded Image

Matching with filters

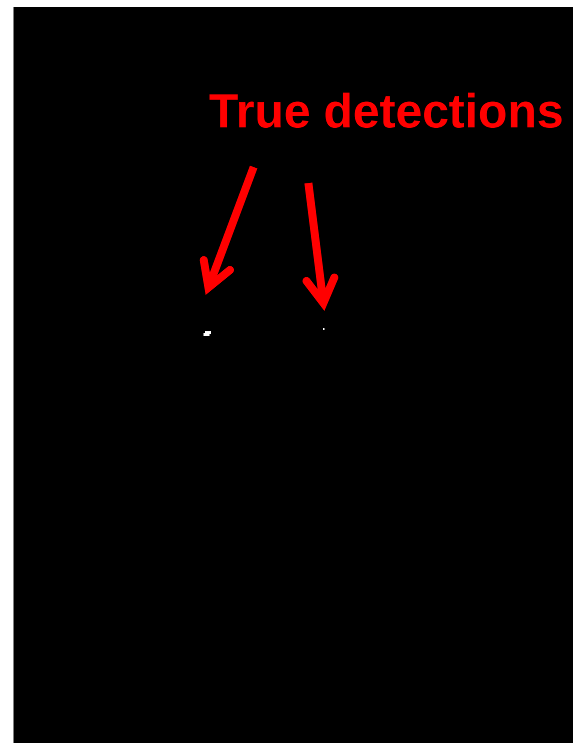
- Goal: find  in image
- Method 2: SSD

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



Input

1- sqrt(SSD)



Thresholded Image

Matching with filters

Can SSD be implemented with linear filters?

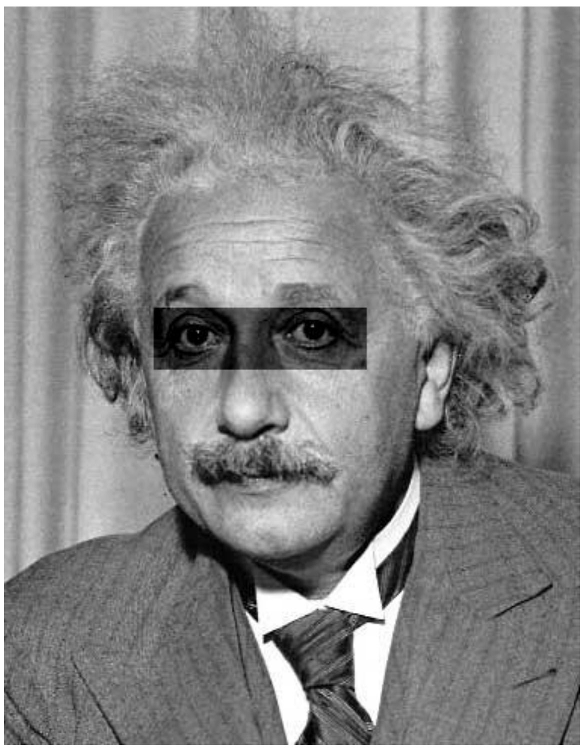
$$h[m,n] = \sum_{k,l} (g[k,l] - f[m+k,n+l])^2$$

Matching with filters

- Goal: find  in image
- Method 2: SSD

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

What's the potential downside of SSD?



Input

1- sqrt(SSD)

Matching with filters

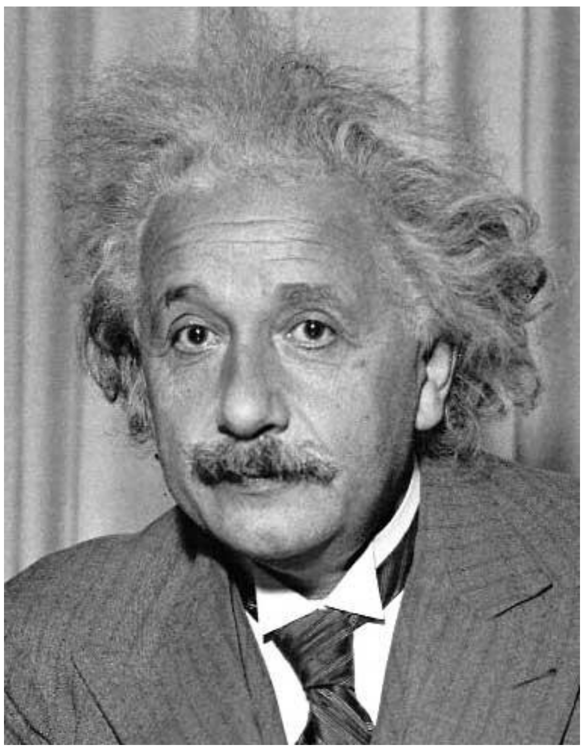
- Goal: find  in image
- Method 3: Normalized cross-correlation

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

Matlab: `normxcorr2(template, im)`

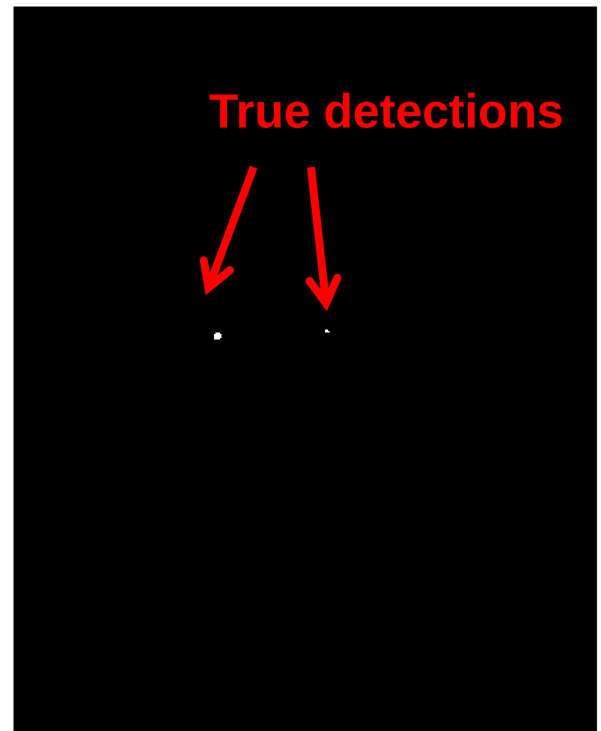
Matching with filters

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



Input

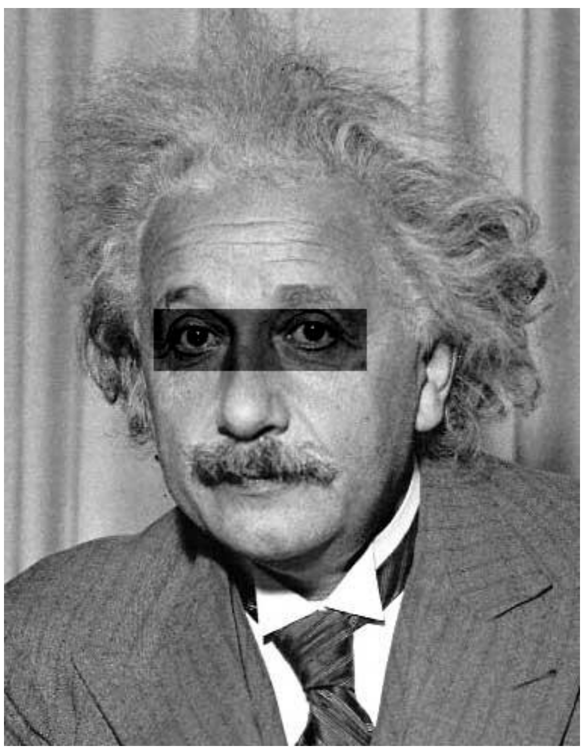
Normalized X-Correlation



Thresholded Image

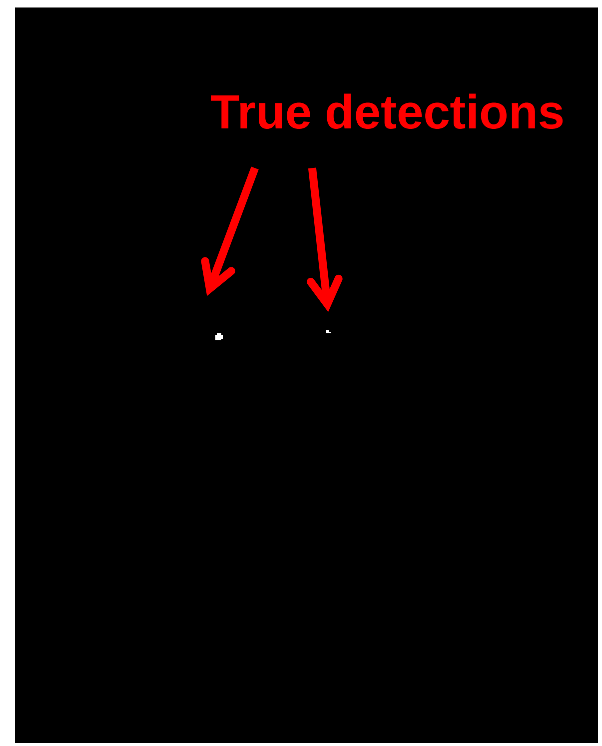
Matching with filters

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



Input

Normalized X-Correlation



Thresholded Image

Q: What is the best method to use?

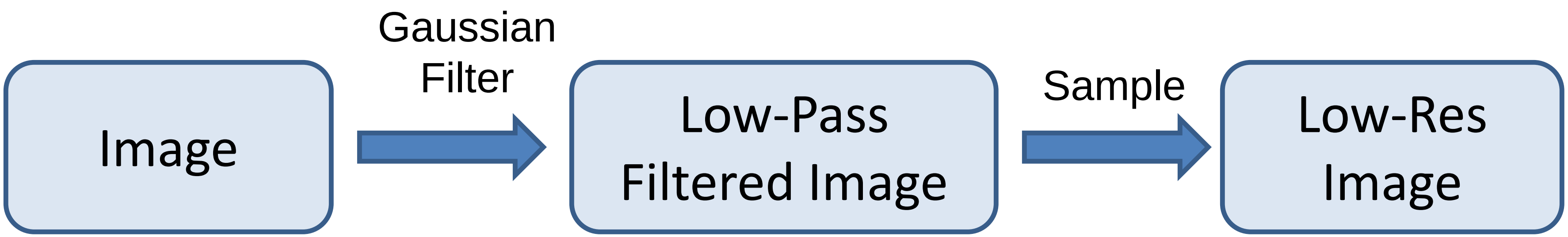
A: Depends

- 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

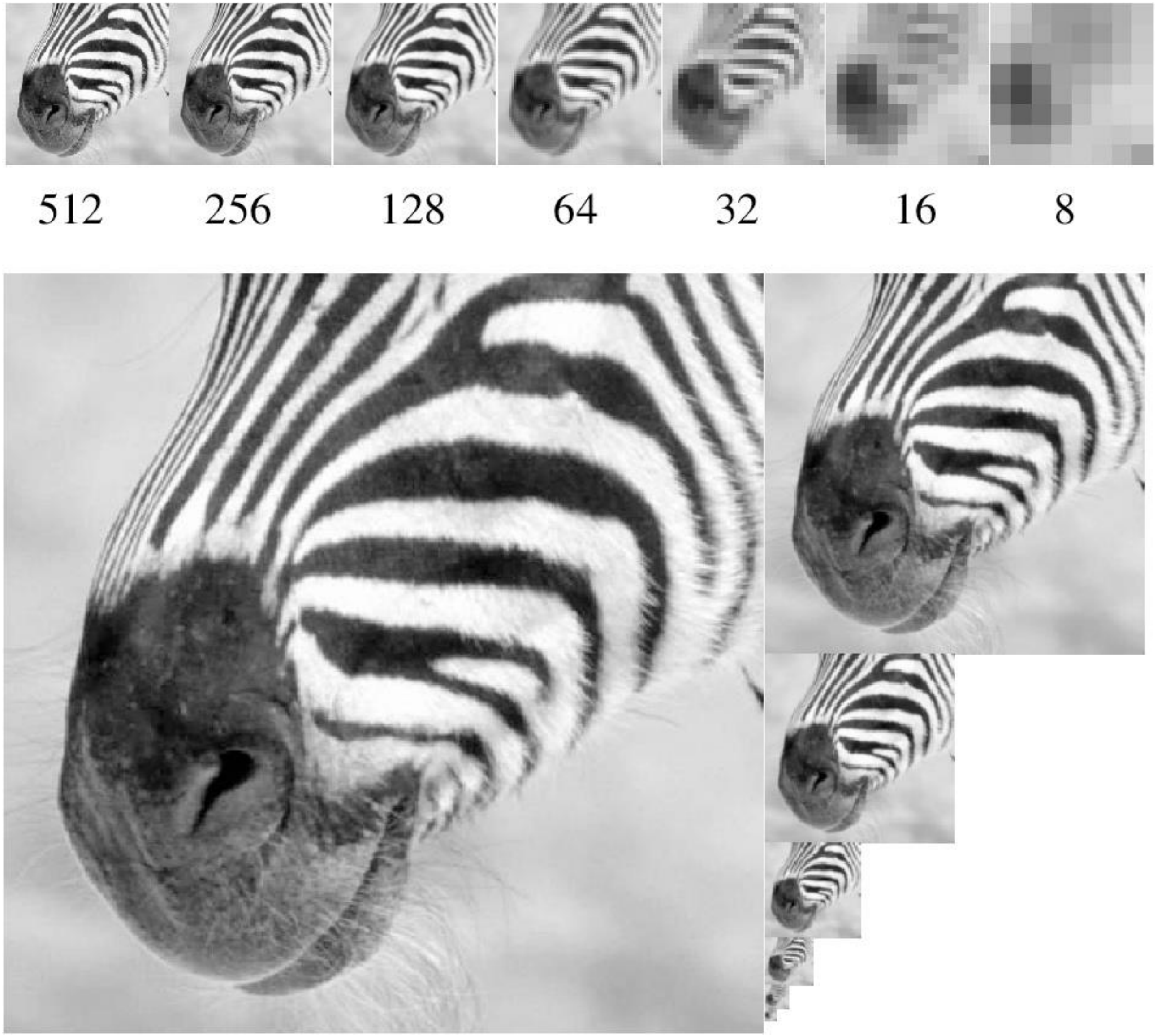
Q: What if we want to find larger or smaller eyes?

A: Image Pyramid

Review of Sampling



Gaussian pyramid



Source: Forsyth

Template Matching with Image Pyramids

Input: Image, Template

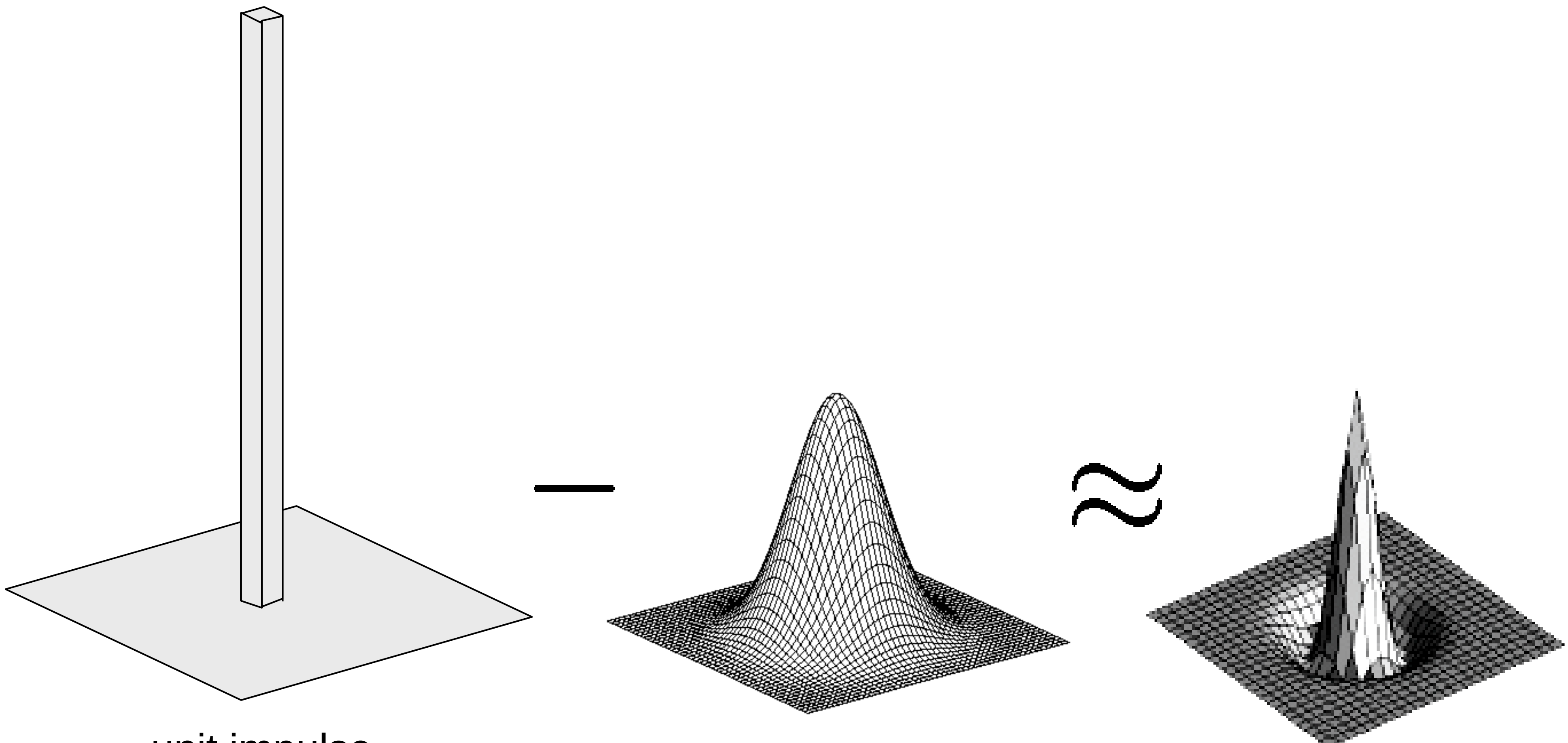
1. Match template at current scale

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

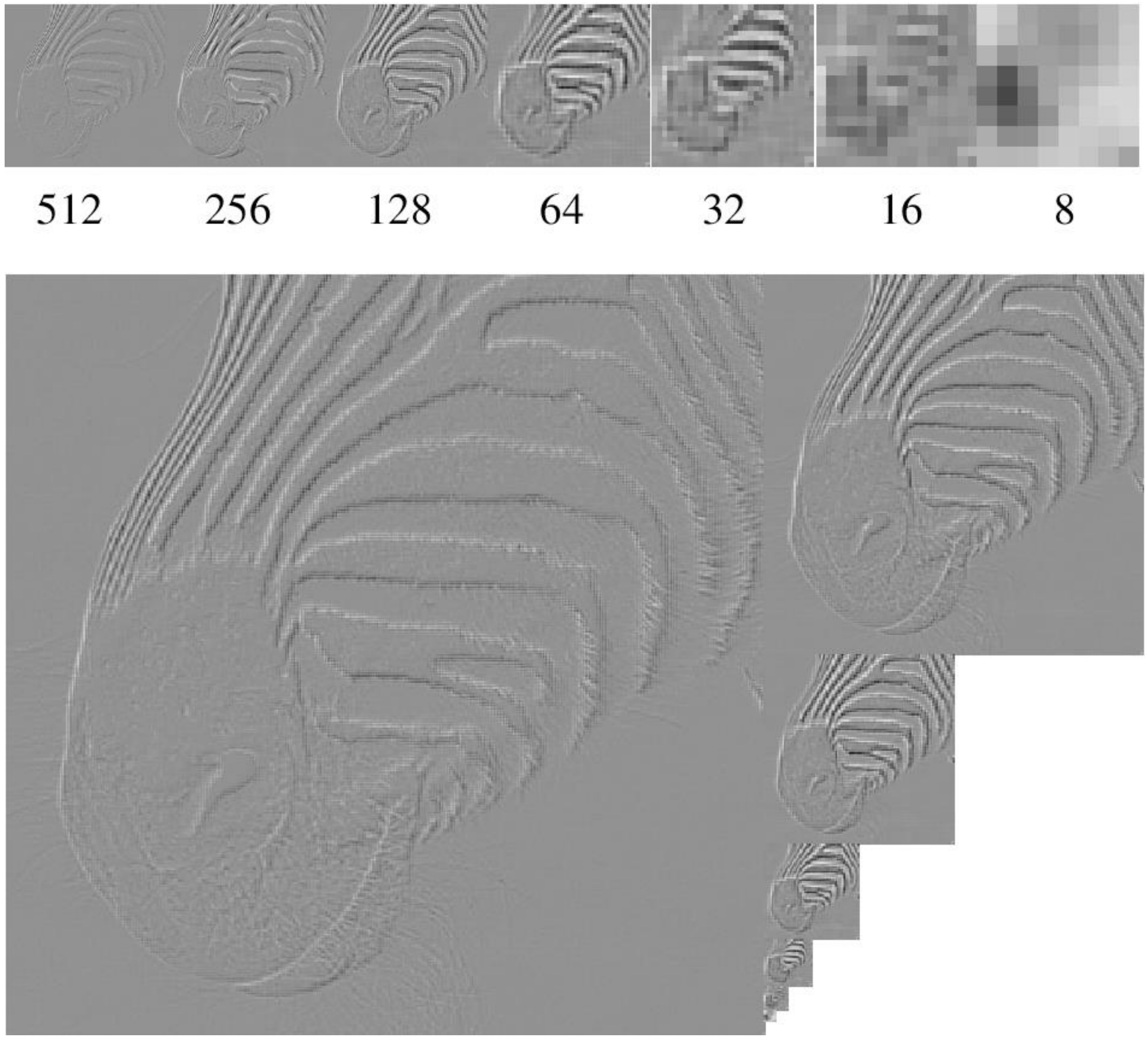
Laplacian filter



unit impulse — Gaussian ≈ Laplacian of Gaussian

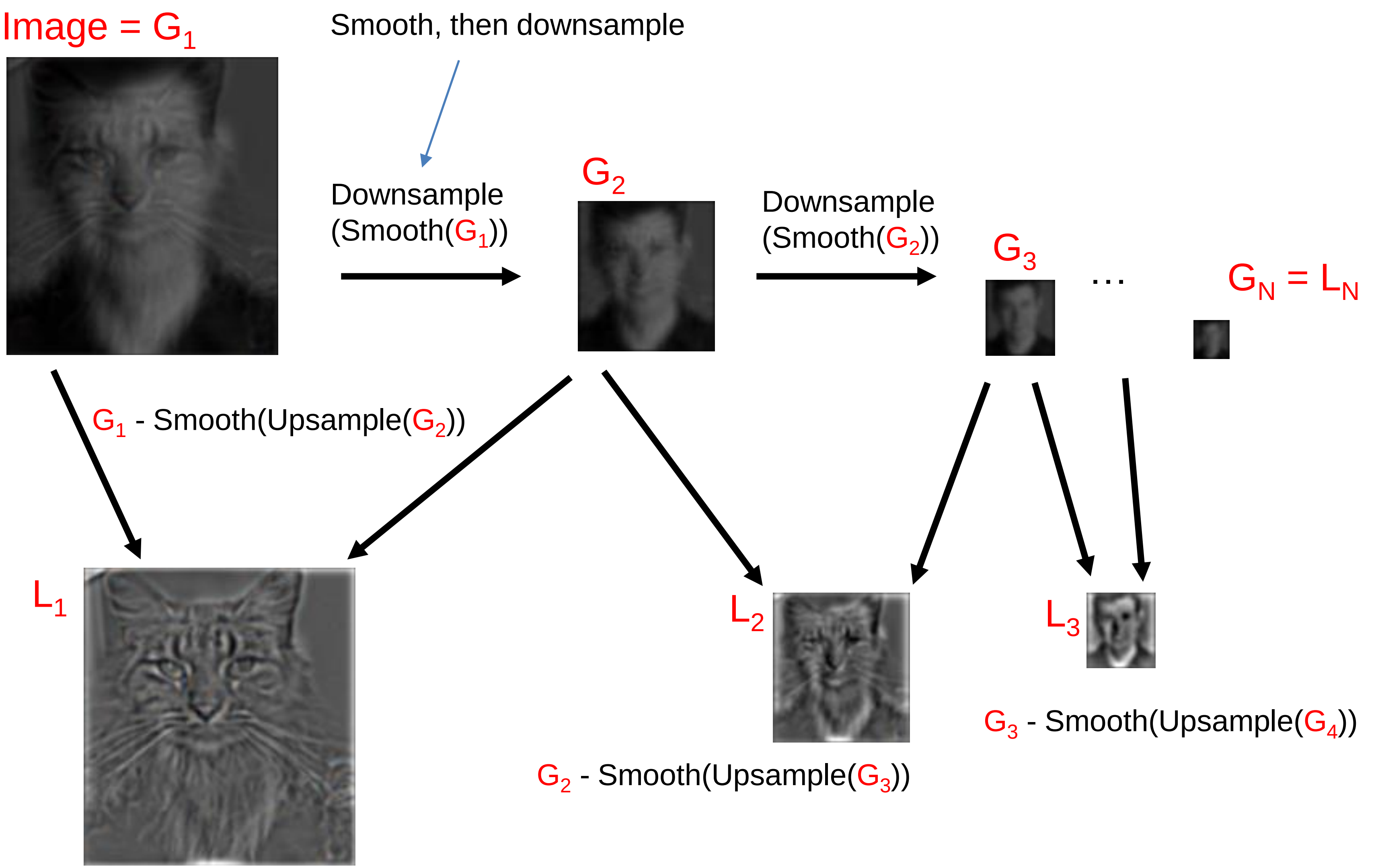
Source: Lazebnik

Laplacian pyramid



Source: Forsyth

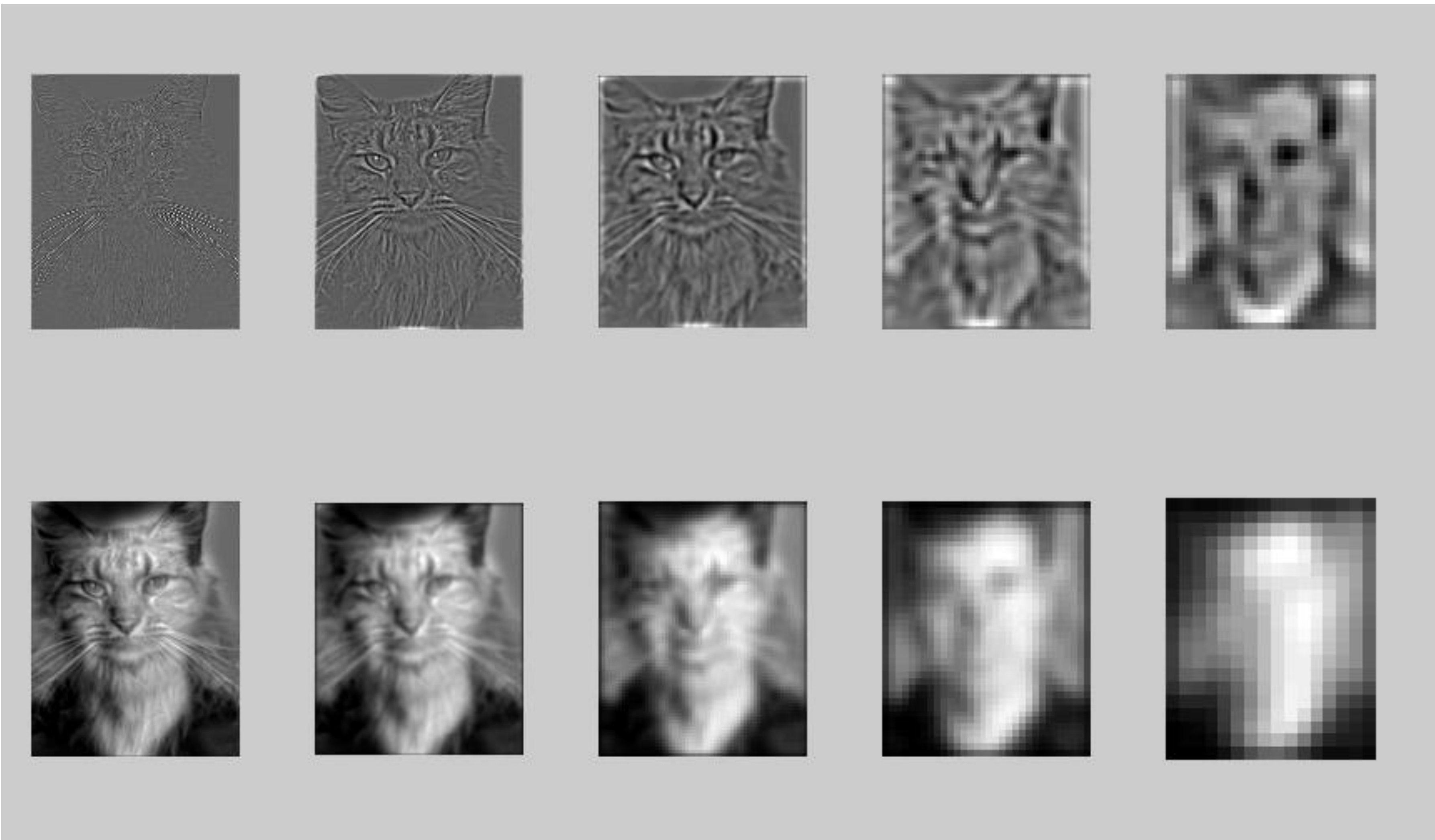
Creating the Gaussian/Laplacian Pyramid



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

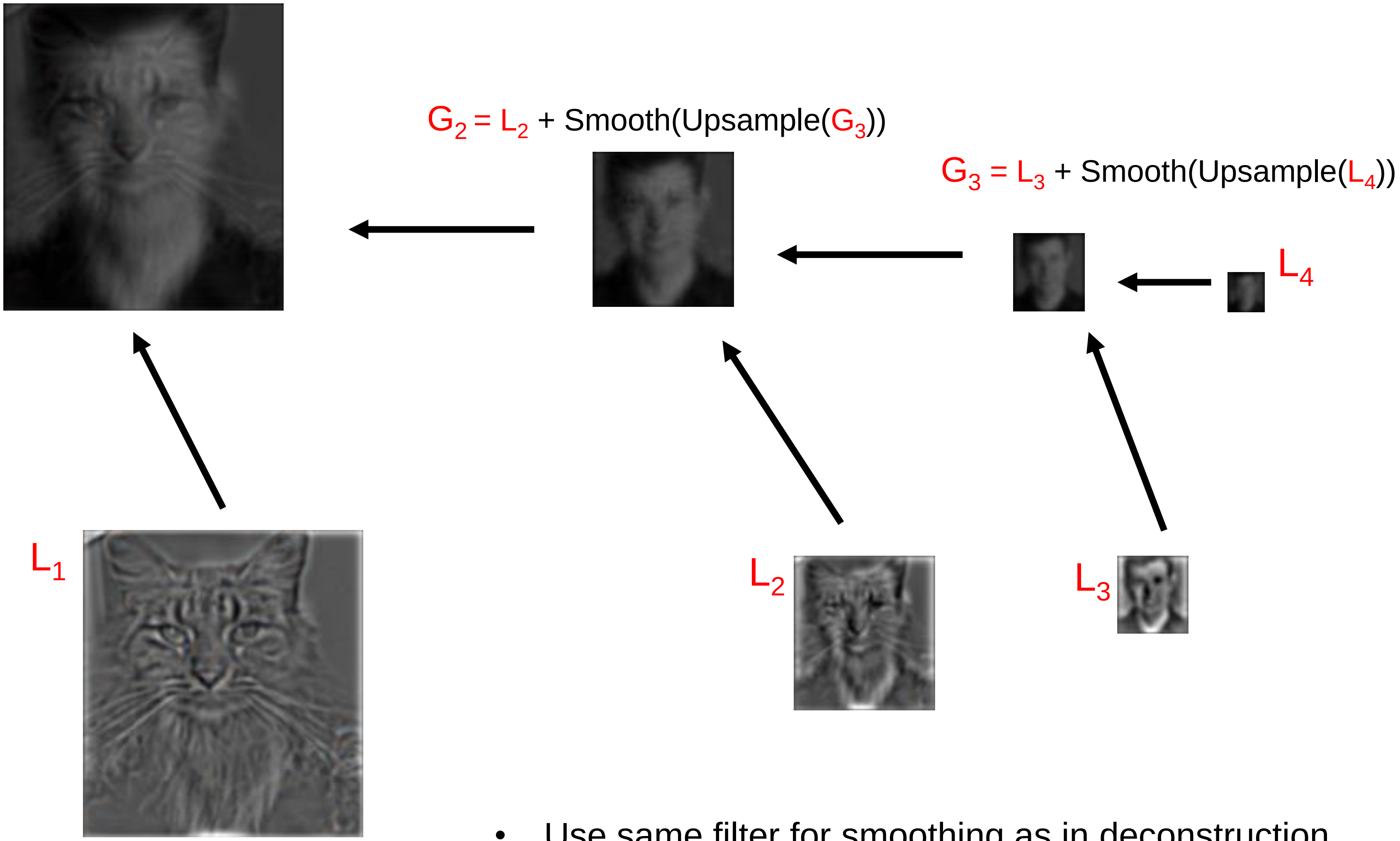
Hybrid Image in Laplacian Pyramid

High frequency → Low frequency



Reconstructing image from Laplacian pyramid

Image = L_1 + Smooth(Upsample(G_2))



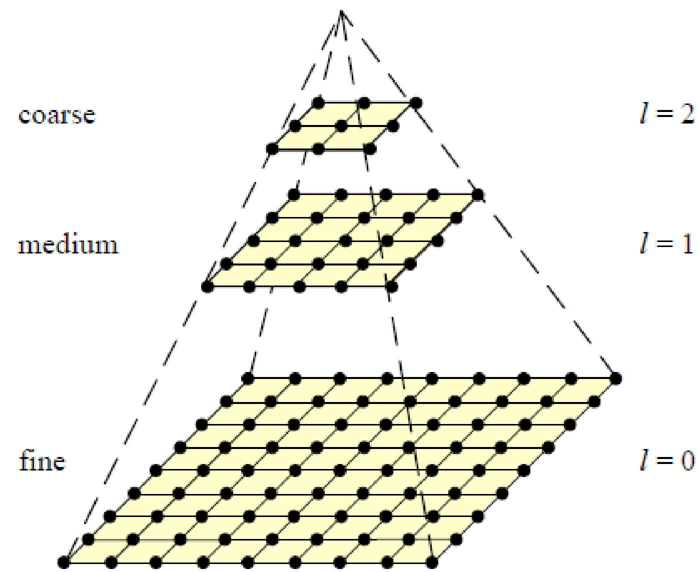
- Use same filter for smoothing as in deconstruction
- Upsample with “nearest” interpolation
- Reconstruction will be nearly lossless

Major uses of image pyramids

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

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?

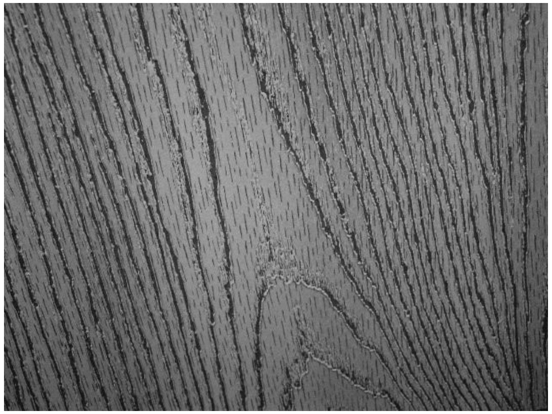
Image representation

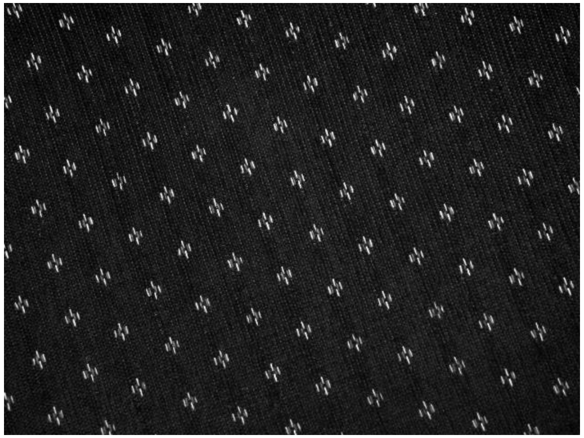
- Pixels: great for spatial resolution, poor access to frequency
- Fourier transform: great for frequency, not for spatial info
- Pyramids/filter banks: balance between spatial and frequency information

Application: Representing Texture

Source: Forsyth

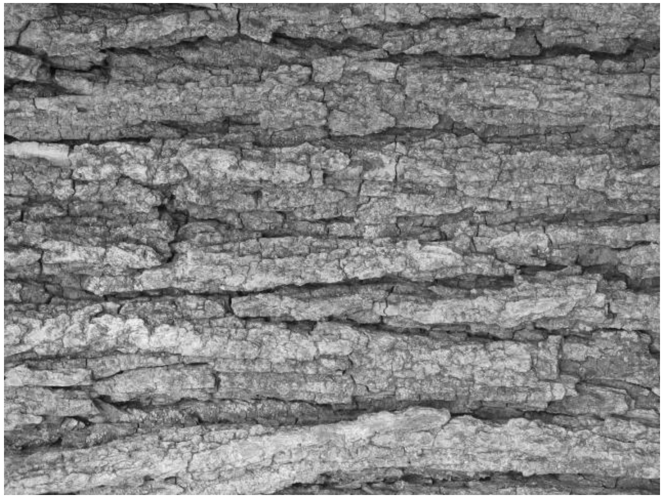
Texture and Material





http://www-cvr.ai.uiuc.edu/ponce_grp/data/texture_database/samples/

Texture and Orientation



http://www-cvr.ai.uiuc.edu/ponce_grp/data/texture_database/samples/

Texture and Scale

http://www-cvr.ai.uiuc.edu/ponce_grp/data/texture_database/samples/

What is texture?

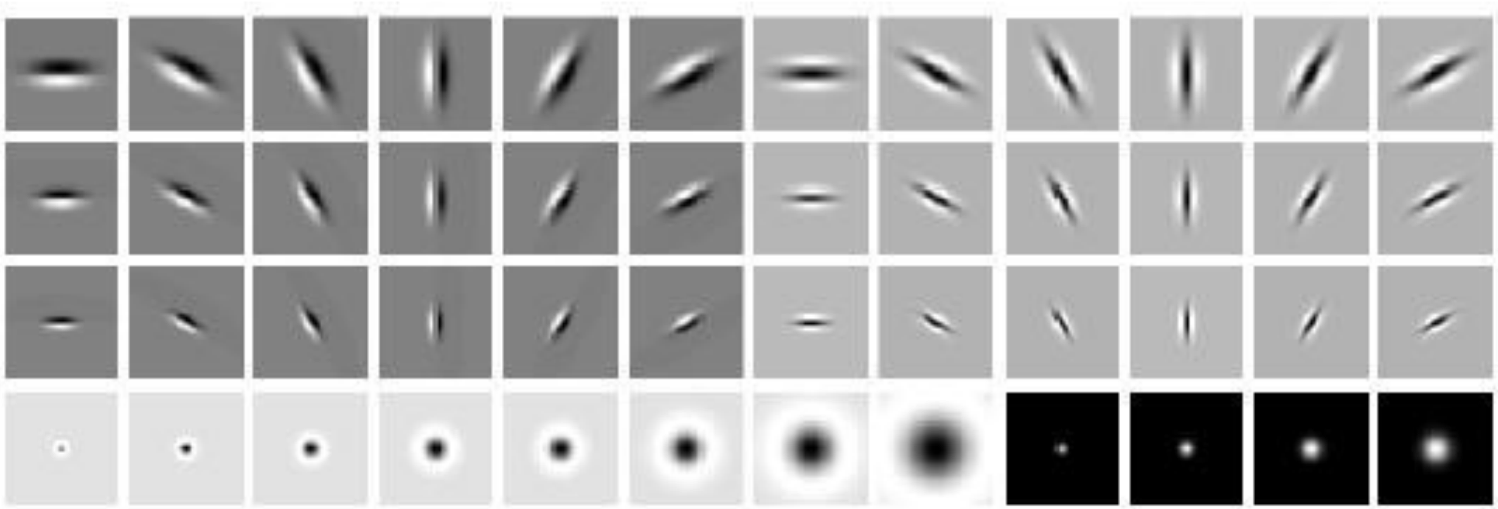
Regular or stochastic patterns caused by bumps, grooves, and/or markings

How can we represent texture?

- Compute responses of blobs and edges at various orientations and scales

Overcomplete representation: filter banks

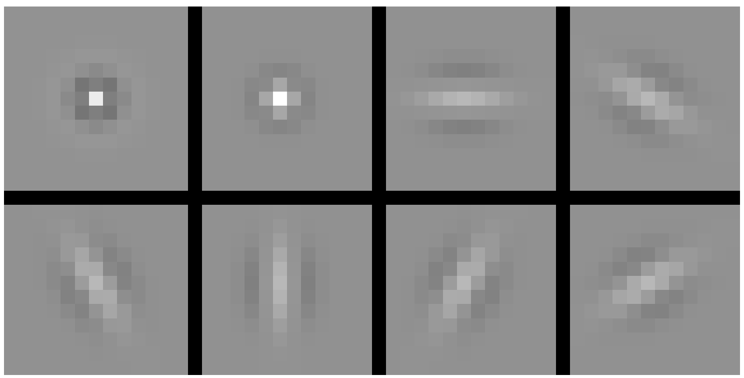
LM Filter Bank

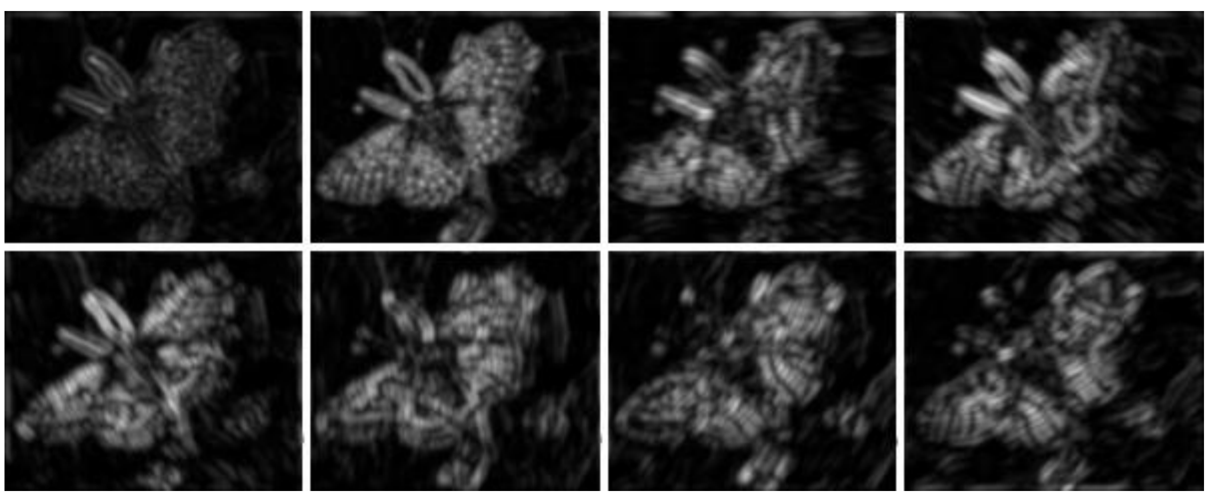


Code for filter banks: *www.robots.ox.ac.uk/~vgg/research/texclass/filters.html*

Filter banks

- Process image with each filter and keep responses (or squared/abs responses)





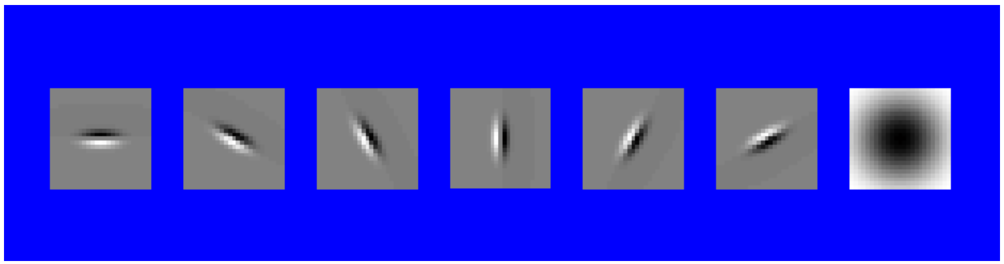
How can we represent texture?

- Measure responses of blobs and edges at various orientations and scales

- Idea 1: Record simple statistics (e.g., mean, std.) of absolute filter responses

Can you match the texture to the response?

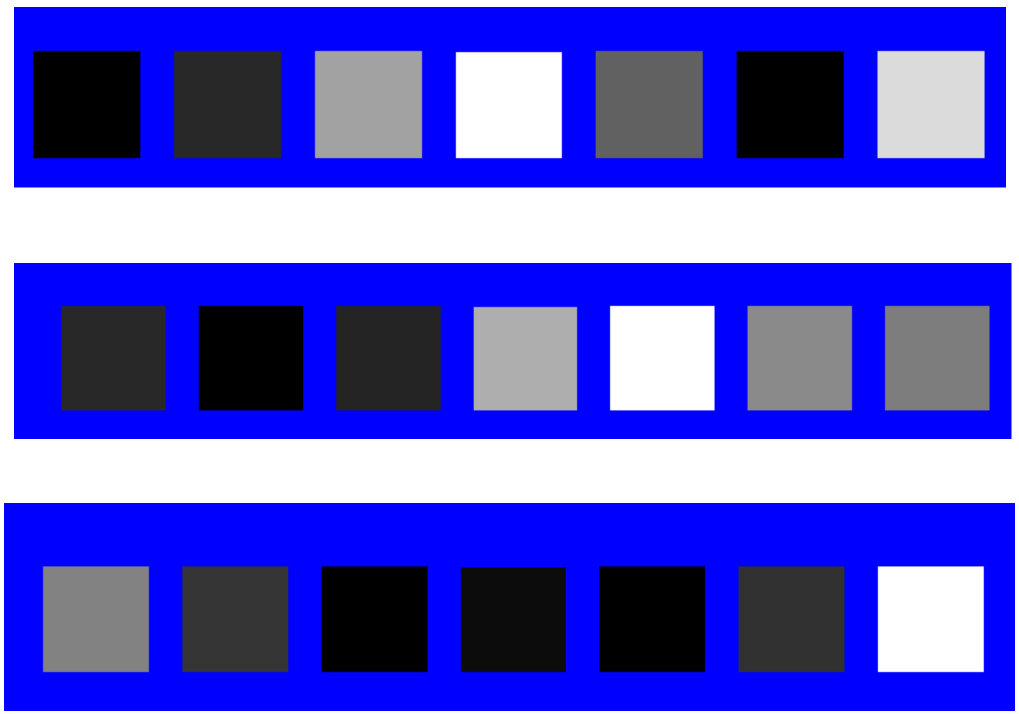
Filters



1

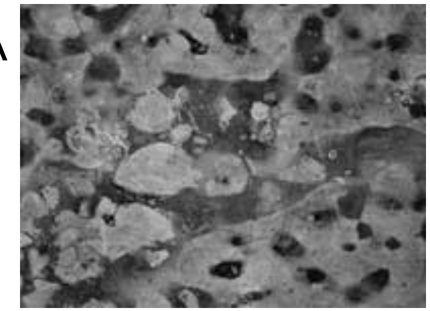
2

3



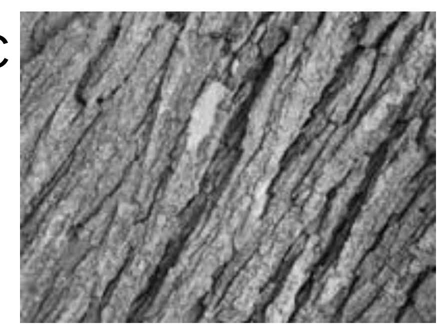
Mean abs responses

A

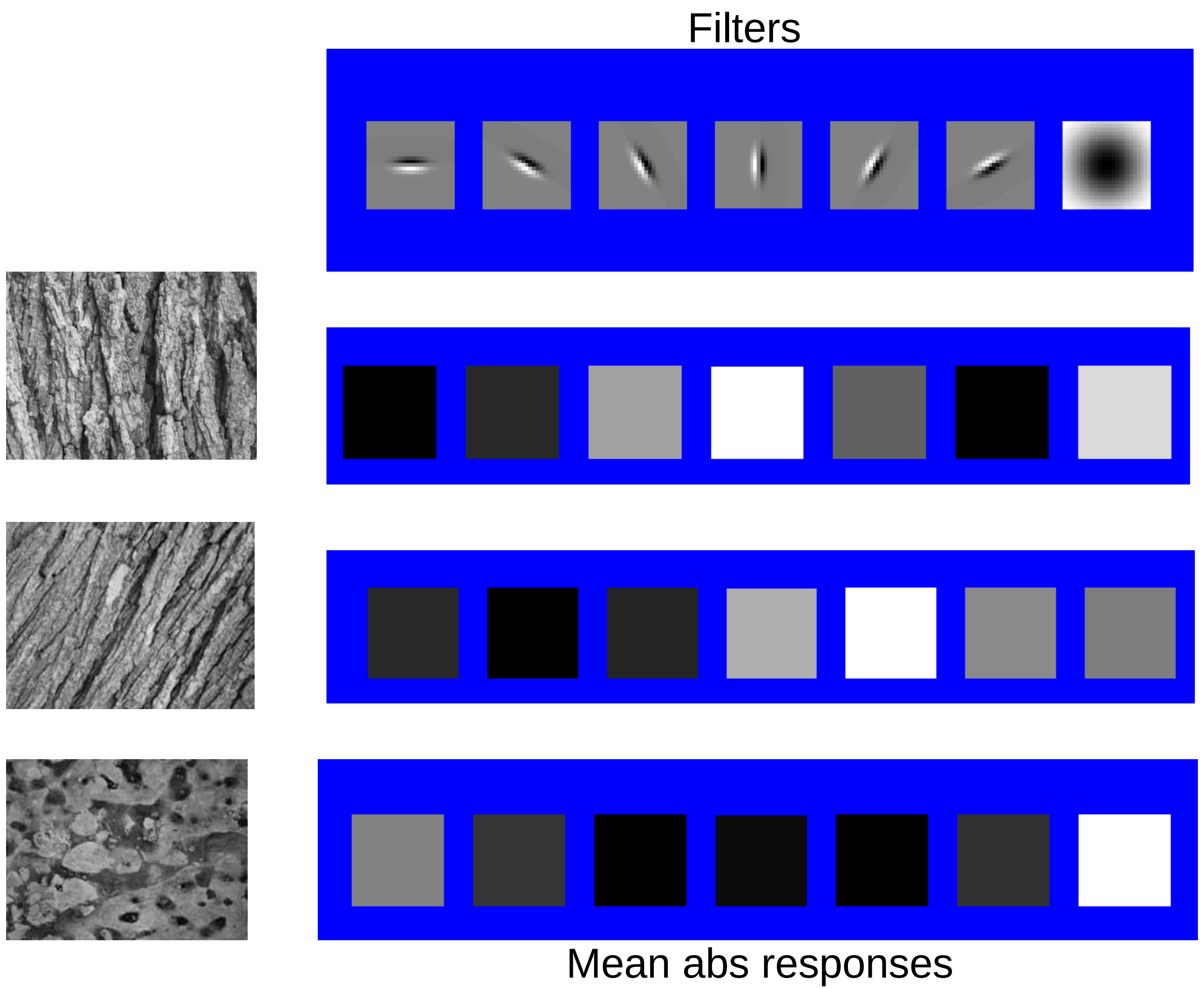


B

C

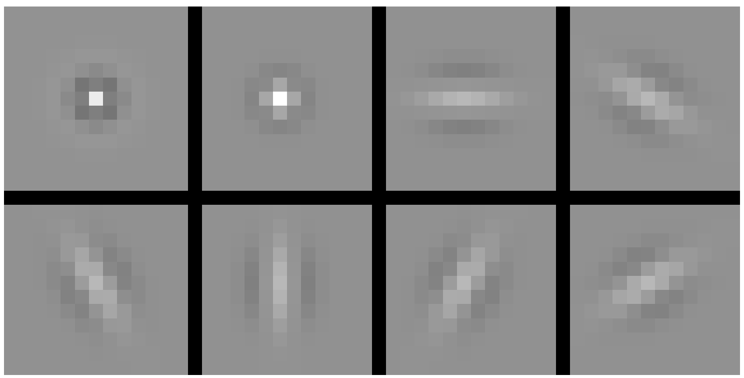


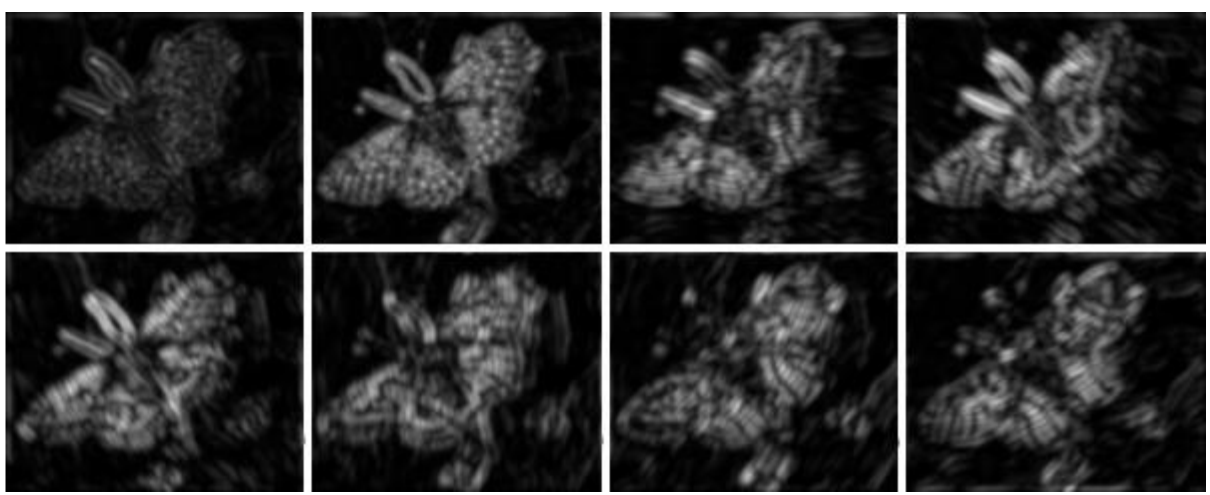
Representing texture by mean abs response



Representing texture

- Idea 2: take vectors of filter responses at each pixel and cluster them, then take histograms (more on this in coming weeks)

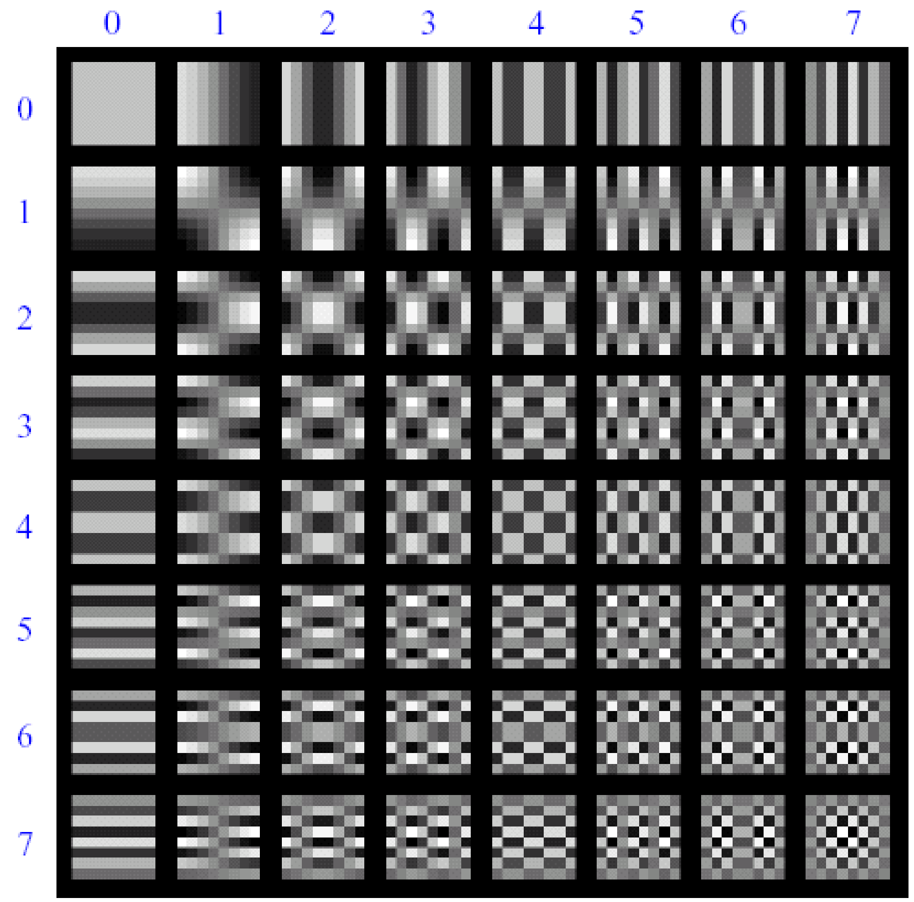




Compression

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

Lossy Image Compression (JPEG)

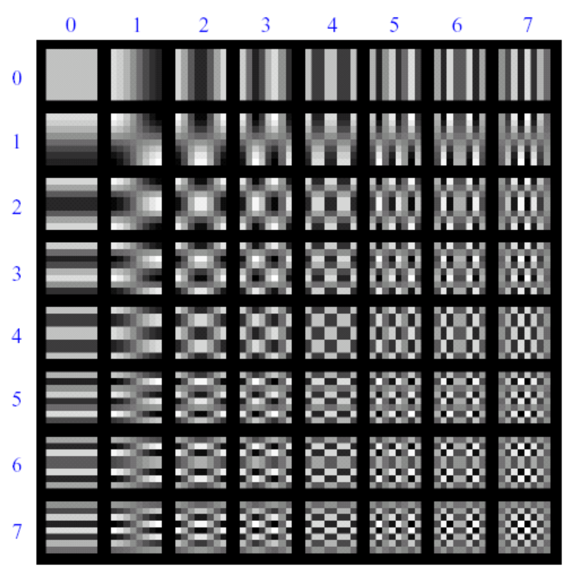


Block-based Discrete Cosine Transform (DCT)

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



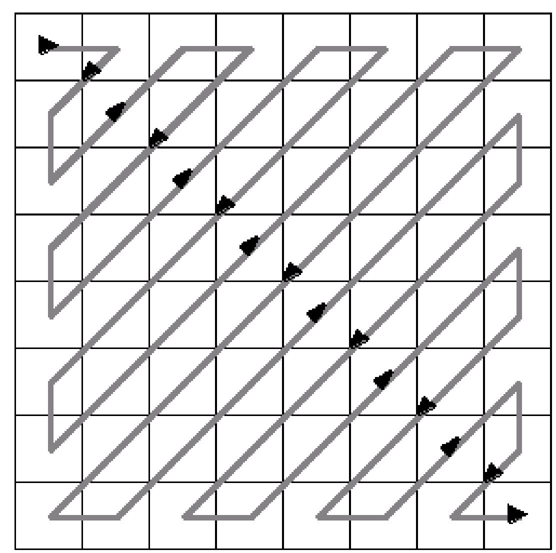


Image compression using DCT

- 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

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

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

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

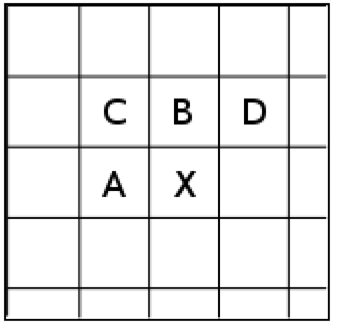
JPEG Compression Summary

1. Convert image to YCrCb
2. Subsample color by factor of 2
   – Color is interpolated anyway, and 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)

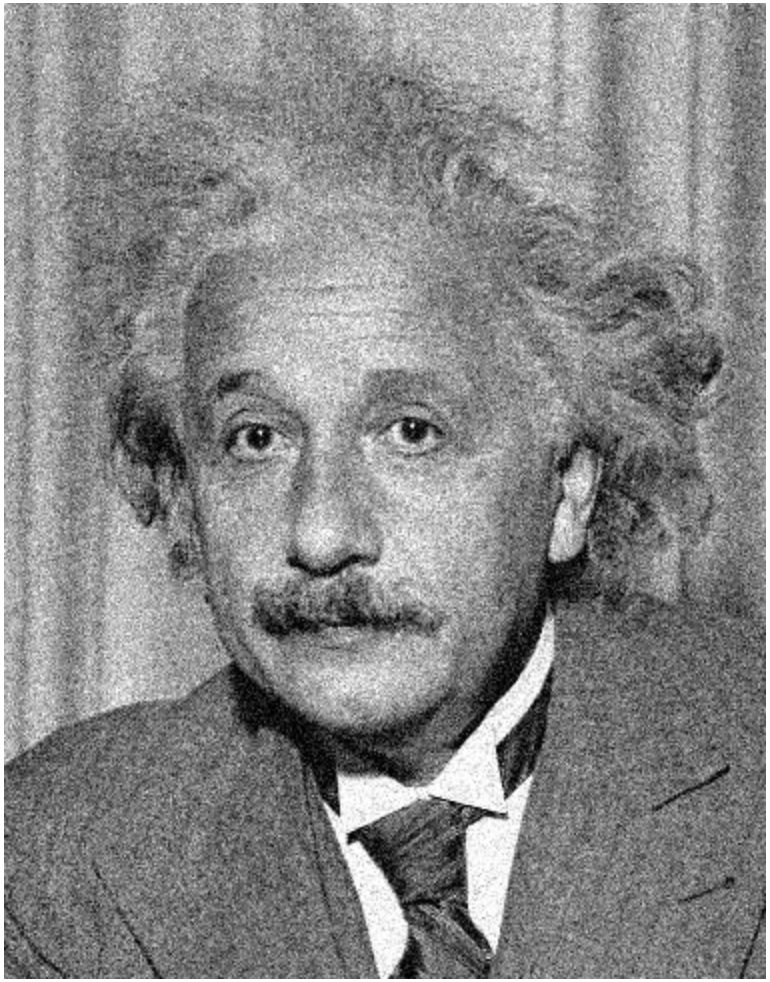
http://en.wikipedia.org/wiki/YCbCr
http://en.wikipedia.org/wiki/JPEG

Lossless compression (PNG)

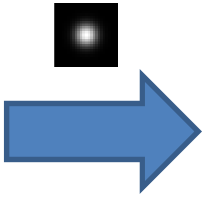
1. Predict that a pixel's value based on its upper-left neighborhood
2. Store difference of predicted and actual value
3. Pkzip it (DEFLATE algorithm)



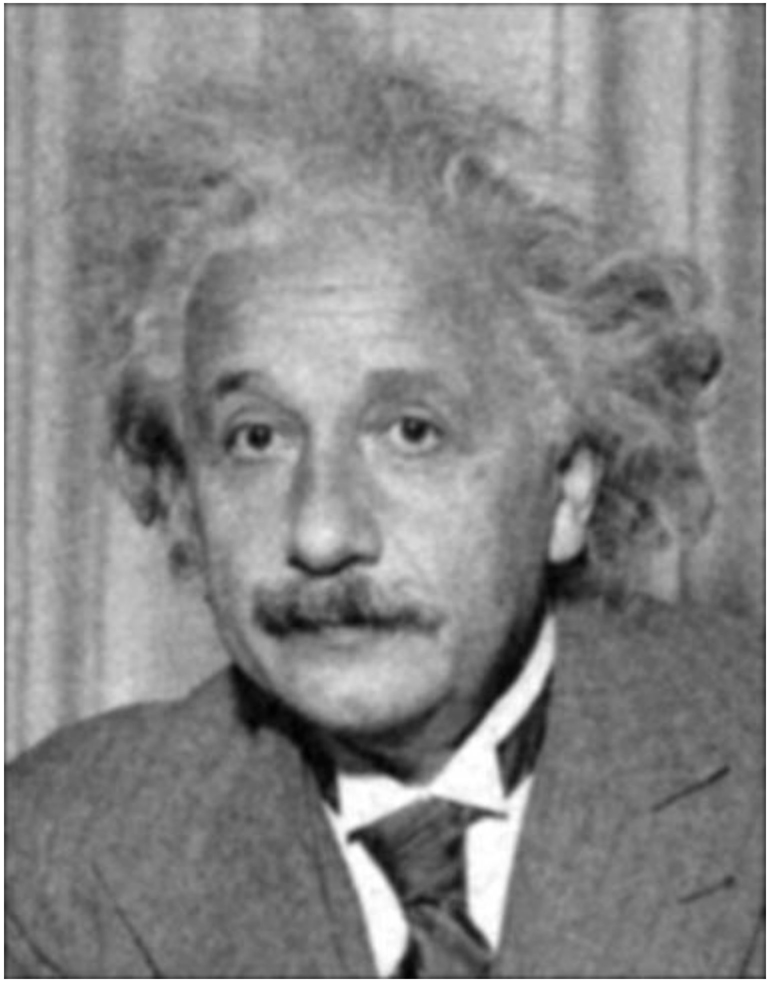
Denoising



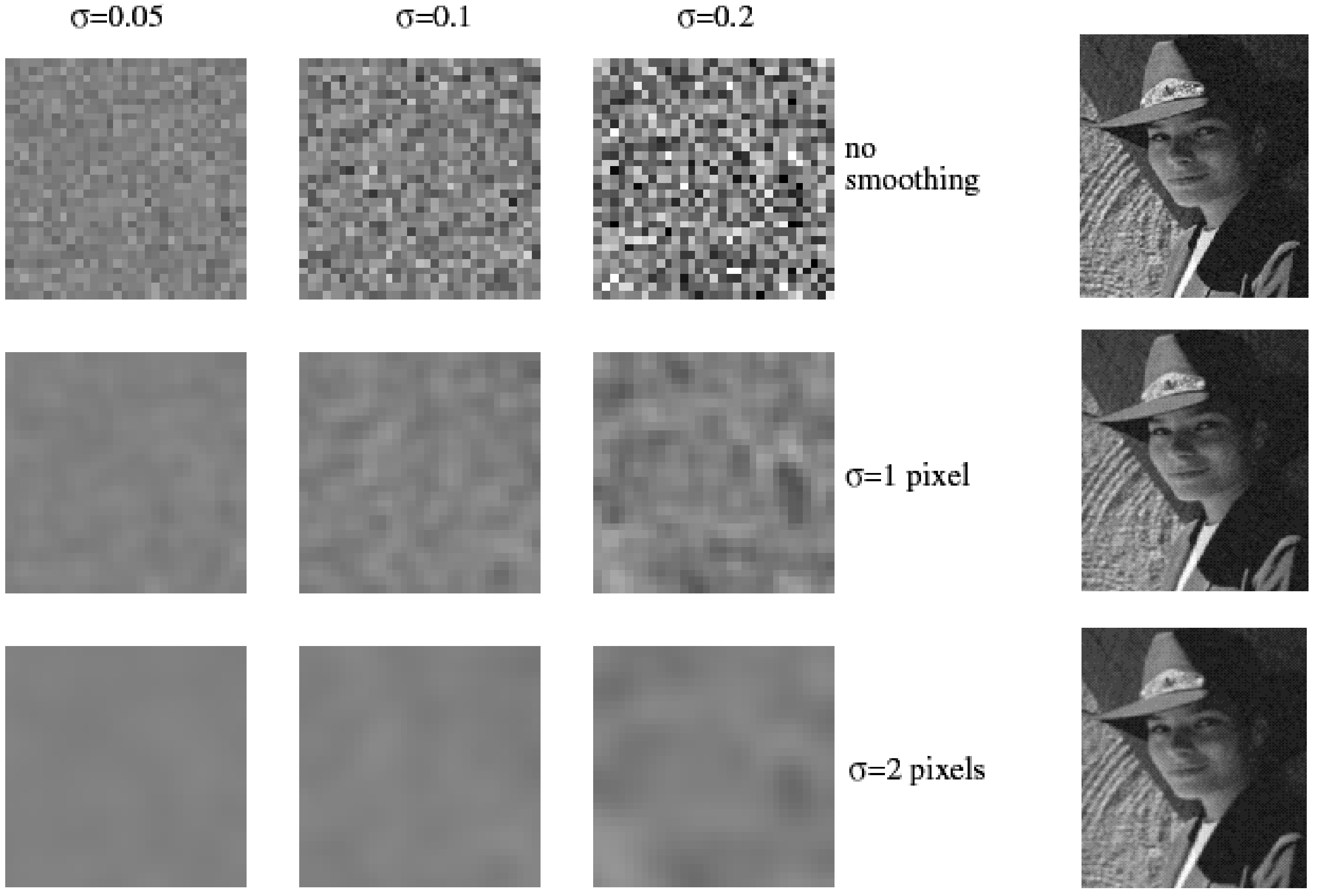
Additive Gaussian Noise



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

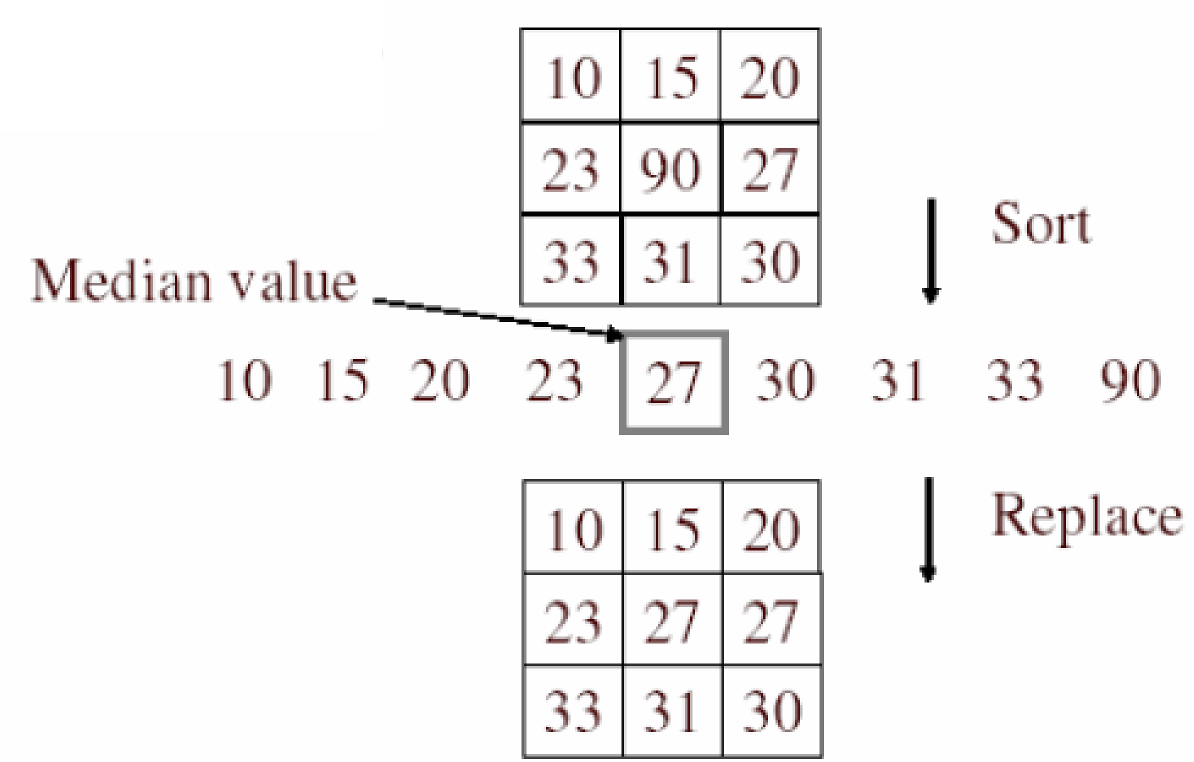
3x3

5x5

7x7

Alternative idea: Median filtering

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



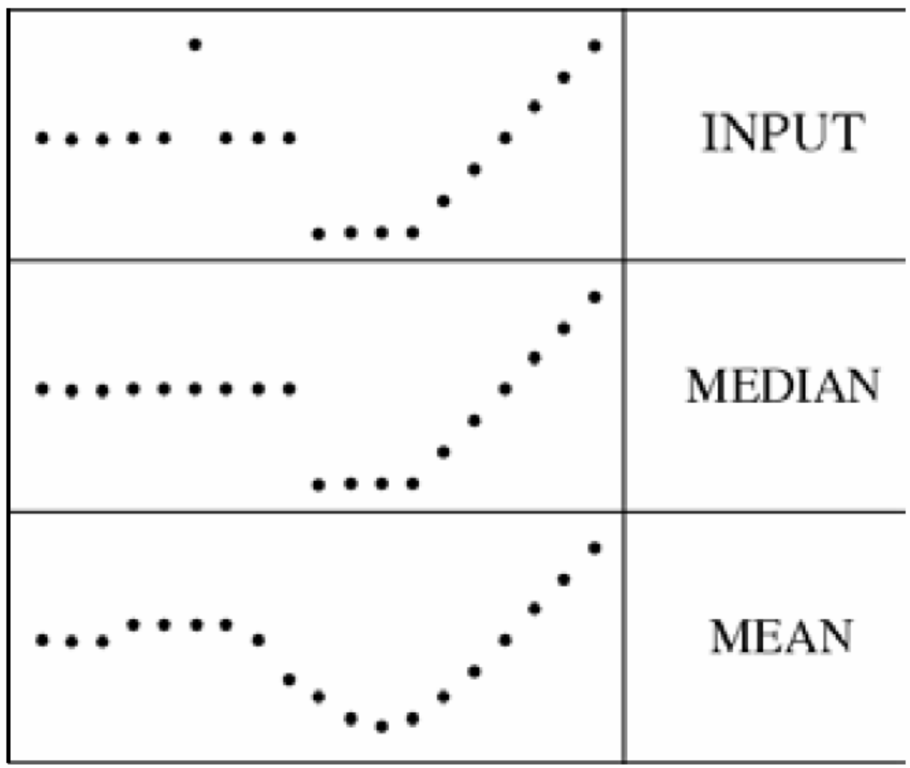
- Is median filtering linear?

Source: K. Grauman

Median filter

- What advantage does median filtering have over Gaussian filtering?
  - Robustness to outliers

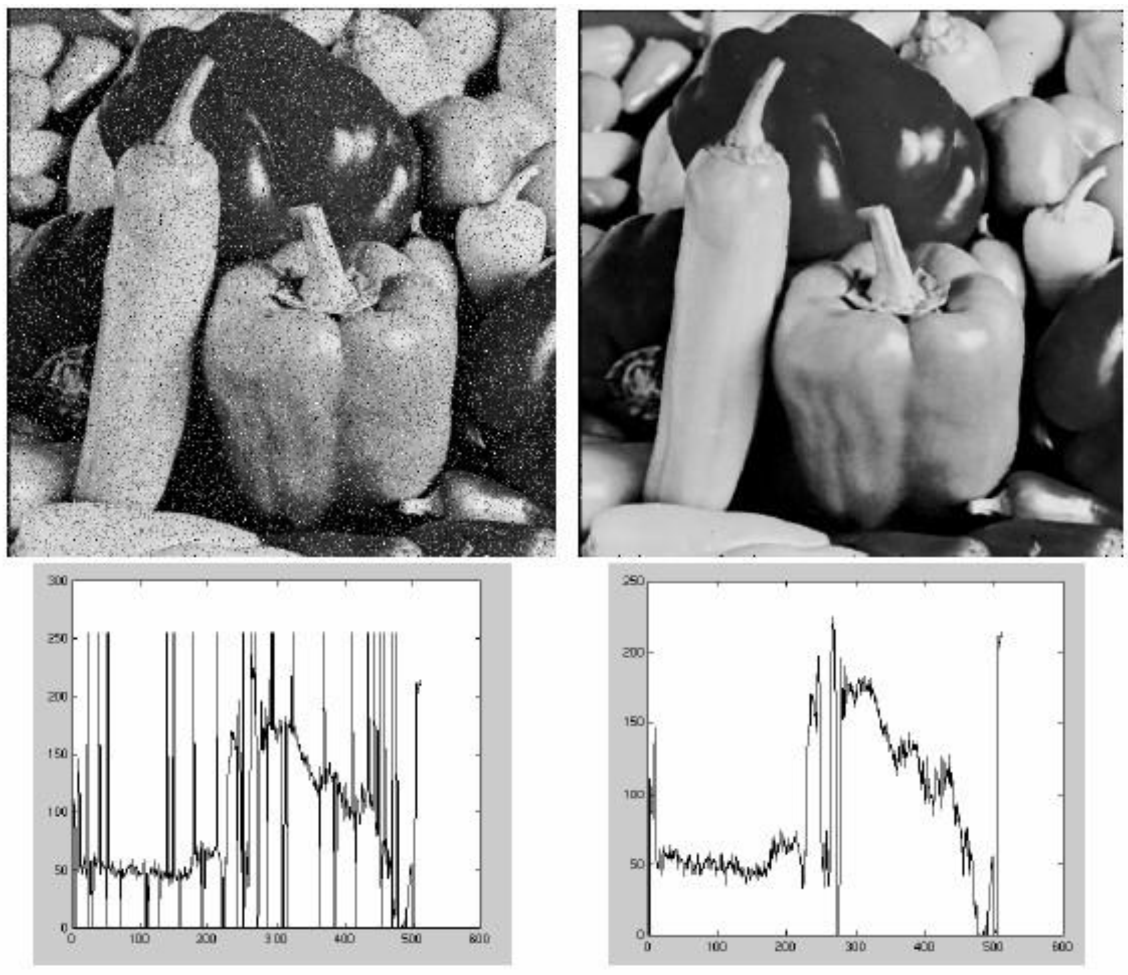
filters have width 5 :



Source: K. Grauman

Median filter

Salt-and-pepper noise Median filtered



- MATLAB: medfilt2(image, [h w])

Source: M. Hebert

Median vs. Gaussian filtering

3x3 5x5 7x7

Gaussian

Median

Other non-linear filters

- Weighted median (pixels further from center count less)
- Clipped mean (average, ignoring few brightest and darkest pixels)
- Bilateral filtering (weight by spatial distance *and* intensity difference)

Bilateral filtering

Image: http://vision.ai.uiuc.edu/?p=1455

Bilateral filters

- Edge preserving: weights similar pixels more

(a) (b) (c)

spatial similarity (e.g., intensity)

$$I^{\mathrm{b}}_{\mathbf{p}} = \frac{1}{W^{\mathrm{b}}_{\mathbf{p}}} \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_{\mathrm{s}}}(\|\mathbf{p} - \mathbf{q}\|)\, G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)\, I_{\mathbf{q}}$$

$$\text{with} \quad W^{\mathrm{b}}_{\mathbf{p}} = \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_{\mathrm{s}}}(\|\mathbf{p} - \mathbf{q}\|)\, G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)$$

Carlo Tomasi, Roberto Manduchi, Bilateral Filtering for Gray and Color Images, ICCV, 1998.

Summary

- Applications of filters
  - 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
  - Filter banks for representing texture
  - Denoising

Next class: edge detection