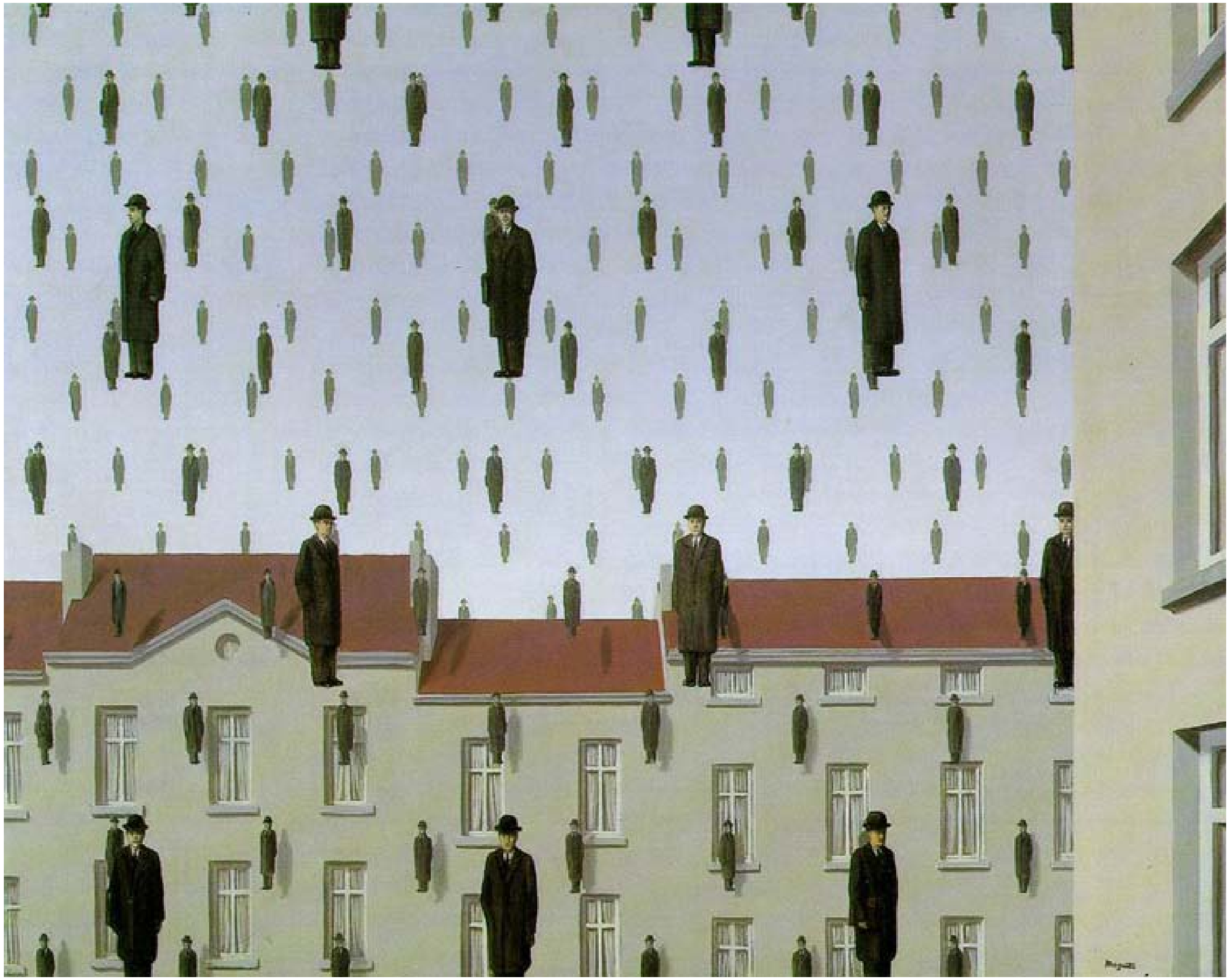
Templates, Image Pyramids, and Filter Banks



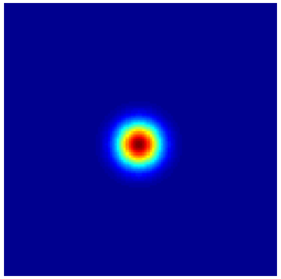
Computer Vision

Derek Hoiem, University of Illinois

Review

1. Match the spatial domain image to the Fourier magnitude image

1



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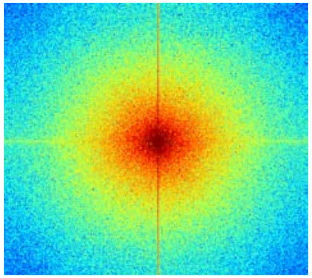

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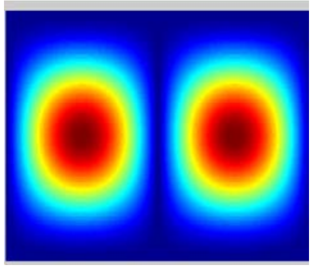
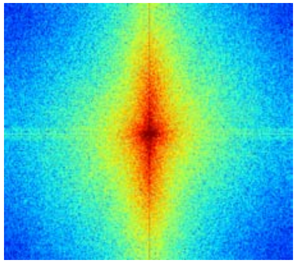
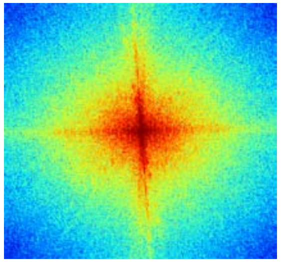


4



5

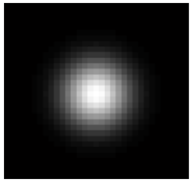


A

B

C

D



E

Reminder

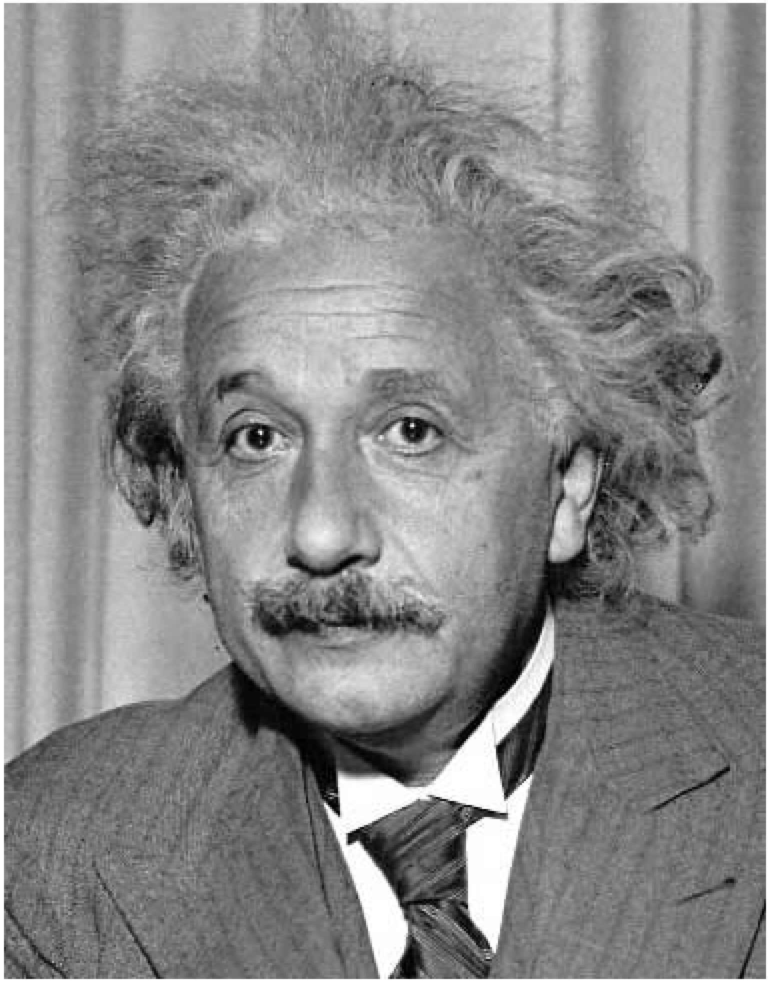
- HW 1 due in one week

Today’s class

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

Template matching

- Goal: find  in image



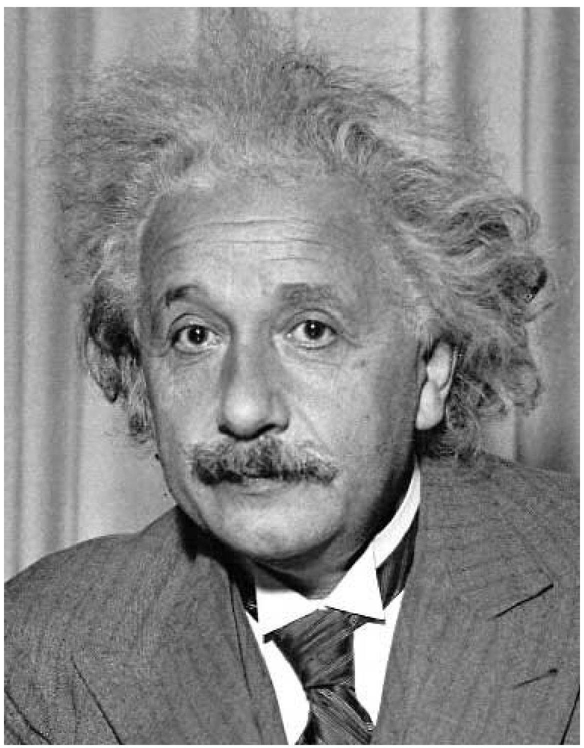
- Main challenge: What is a good similarity or distance measure between two patches?
  - Correlation
  - Zero-mean correlation
  - Sum Square Difference
  - Normalized Cross Correlation

Matching with filters

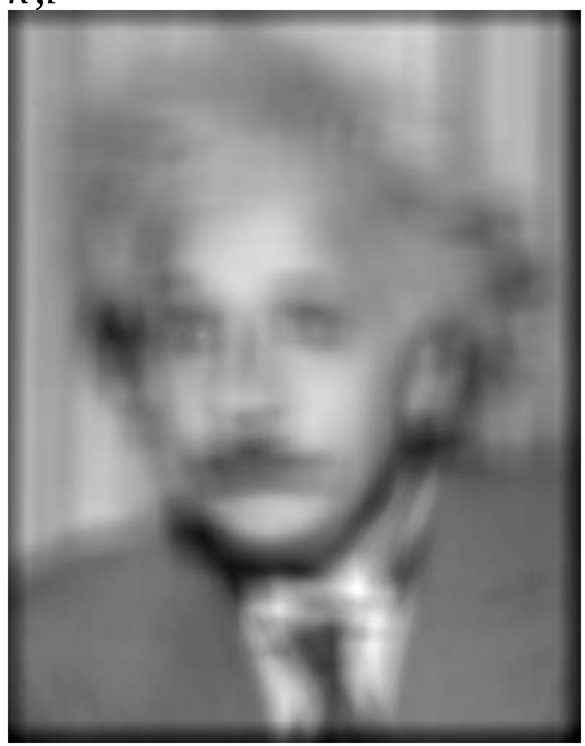
- Goal: find  in image
- Method 0: filter the image with eye patch

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

f = image
g = filter



Input



Filtered Image

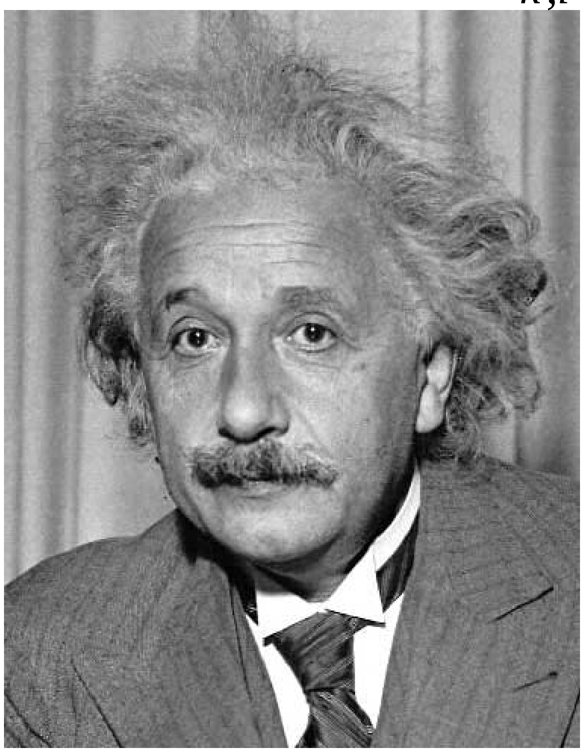
What went wrong?

Matching with filters

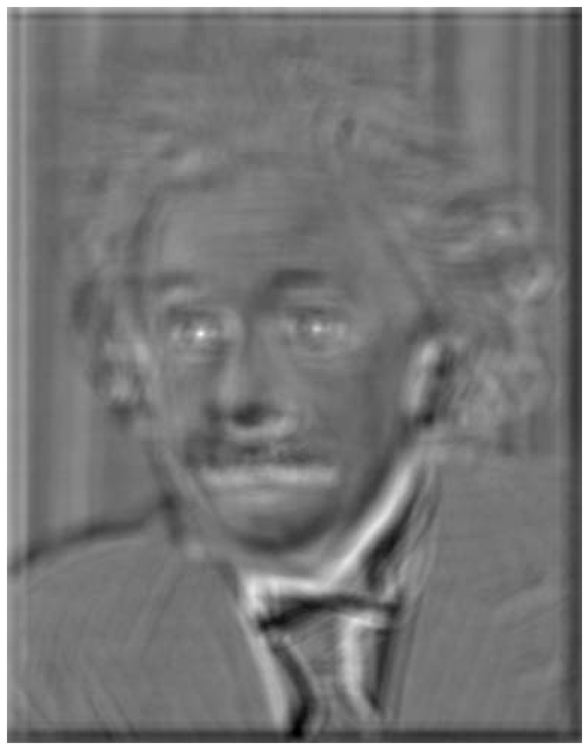
- Goal: find  in image
- Method 1: filter the image with zero-mean eye

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

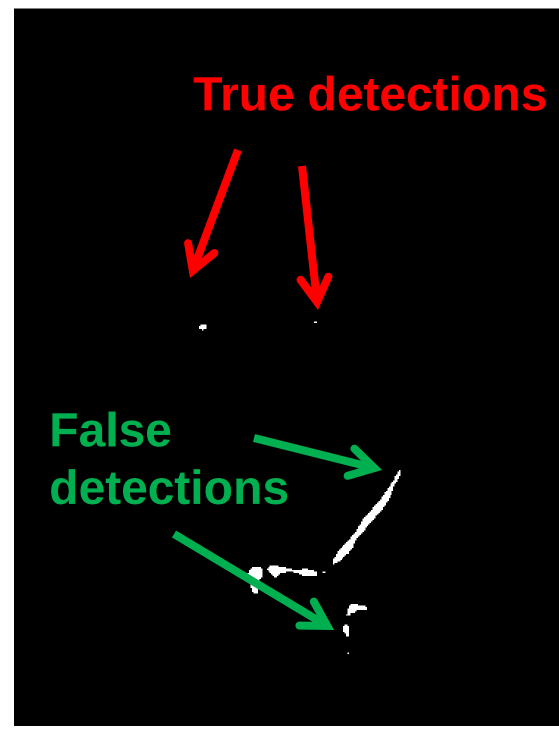
mean of f



Input



Filtered Image (scaled)

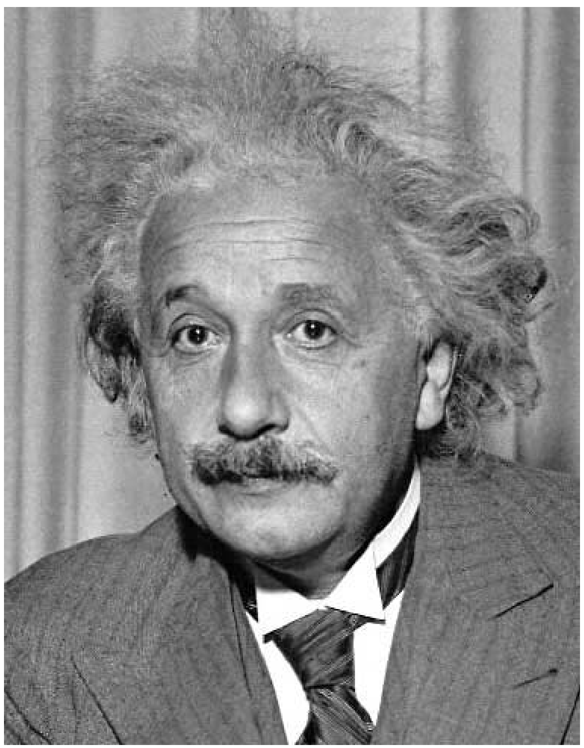


Thresholded Image

Matching with filters

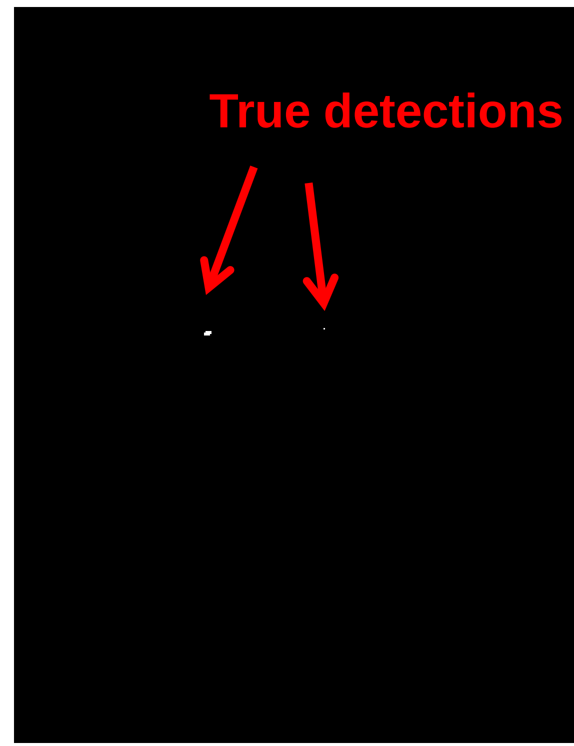
- Goal: find  in image
- Method 2: SSD

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



Input

1- sqrt(SSD)



Thresholded Image

Matching with filters

Can SSD be implemented with linear filters?

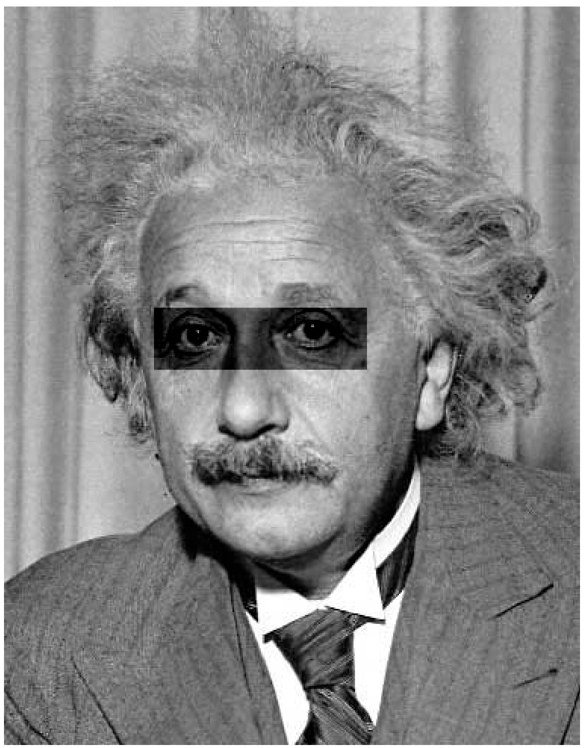
$$h[m,n] = \sum_{k,l} (g[k,l] - f[m+k,n+l])^2$$

Matching with filters

- Goal: find  in image
- Method 2: SSD

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

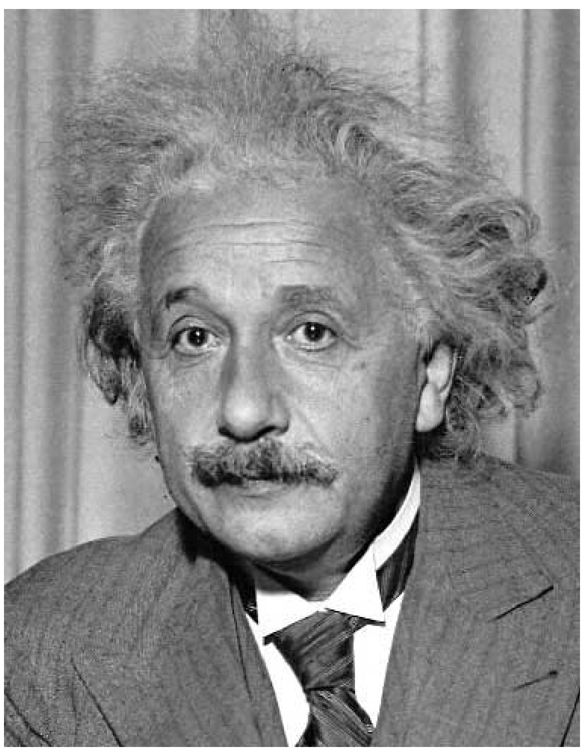
- Goal: find  in image
- Method 3: Normalized cross-correlation

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

Matlab: `normxcorr2(template, im)`

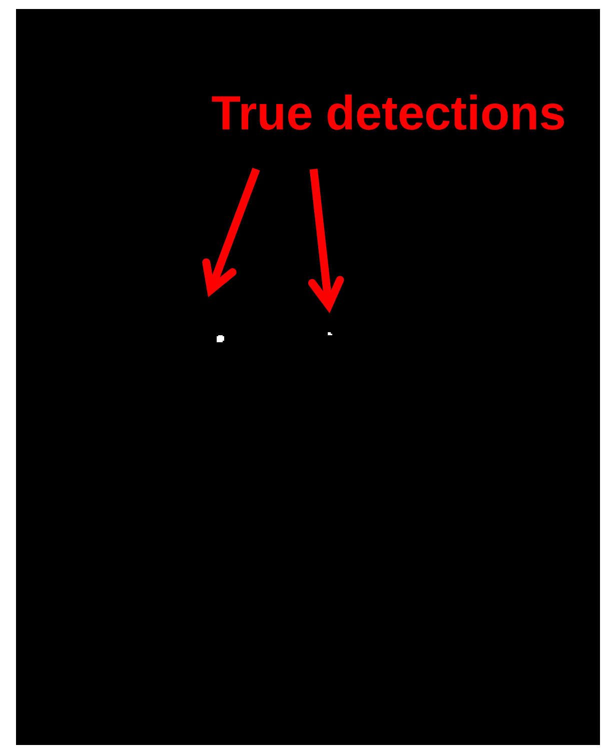
Matching with filters

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



Input

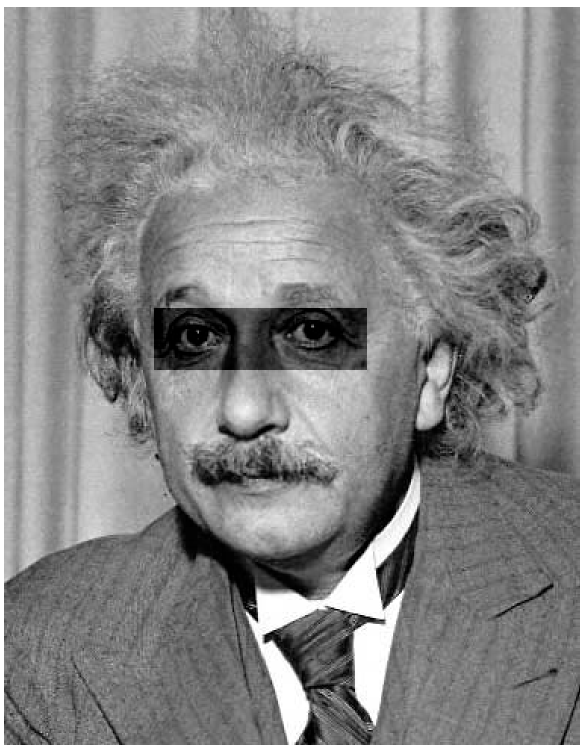
Normalized X-Correlation



Thresholded Image

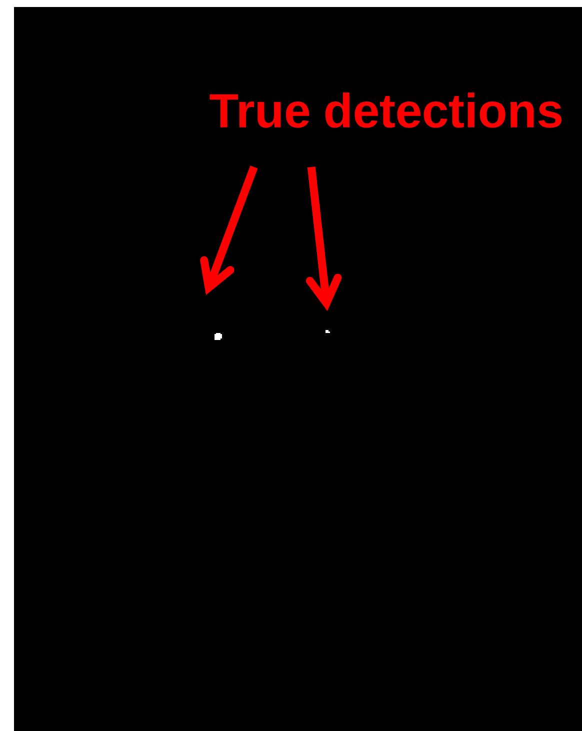
Matching with filters

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



Input

Normalized X-Correlation



Thresholded Image

Q: What is the best method to use?

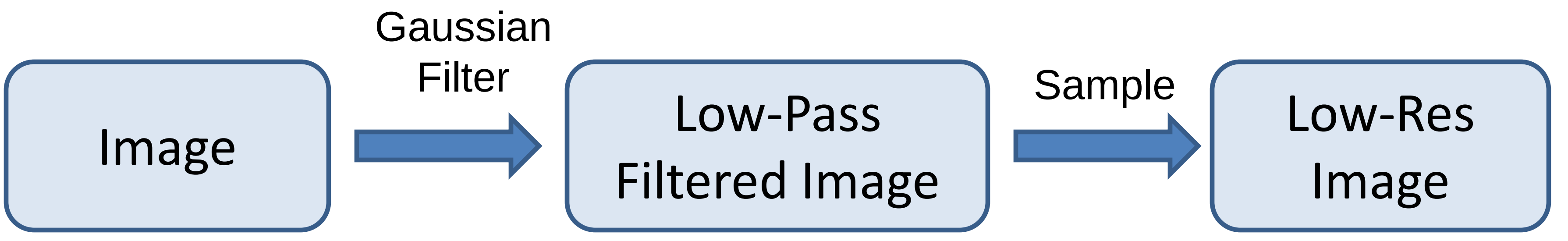
A: Depends

- 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

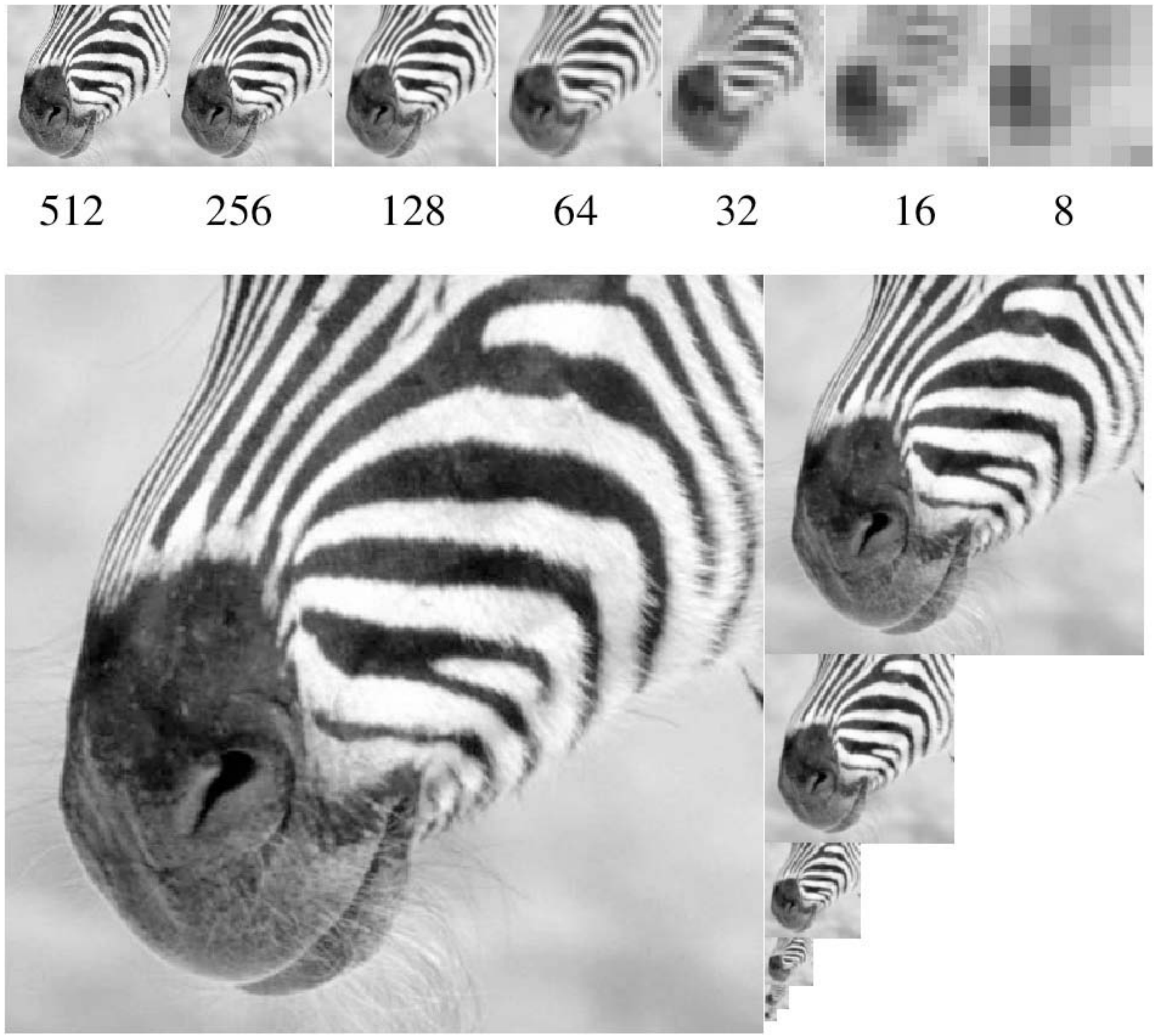
Q: What if we want to find larger or smaller eyes?

A: Image Pyramid

Review of Sampling



Gaussian pyramid



Source: Forsyth

Template Matching with Image Pyramids

Input: Image, Template

1. Match template at current scale

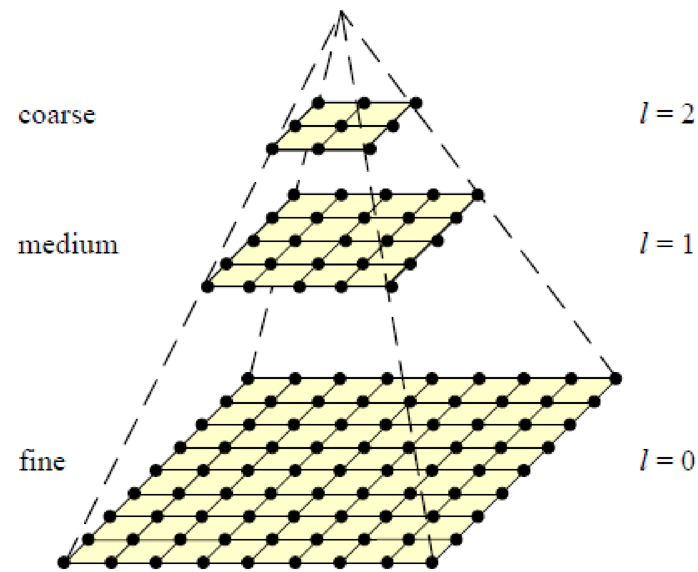
2. Downsample image

3. Repeat 1-2 until image is very small

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

Coarse-to-fine Image Registration

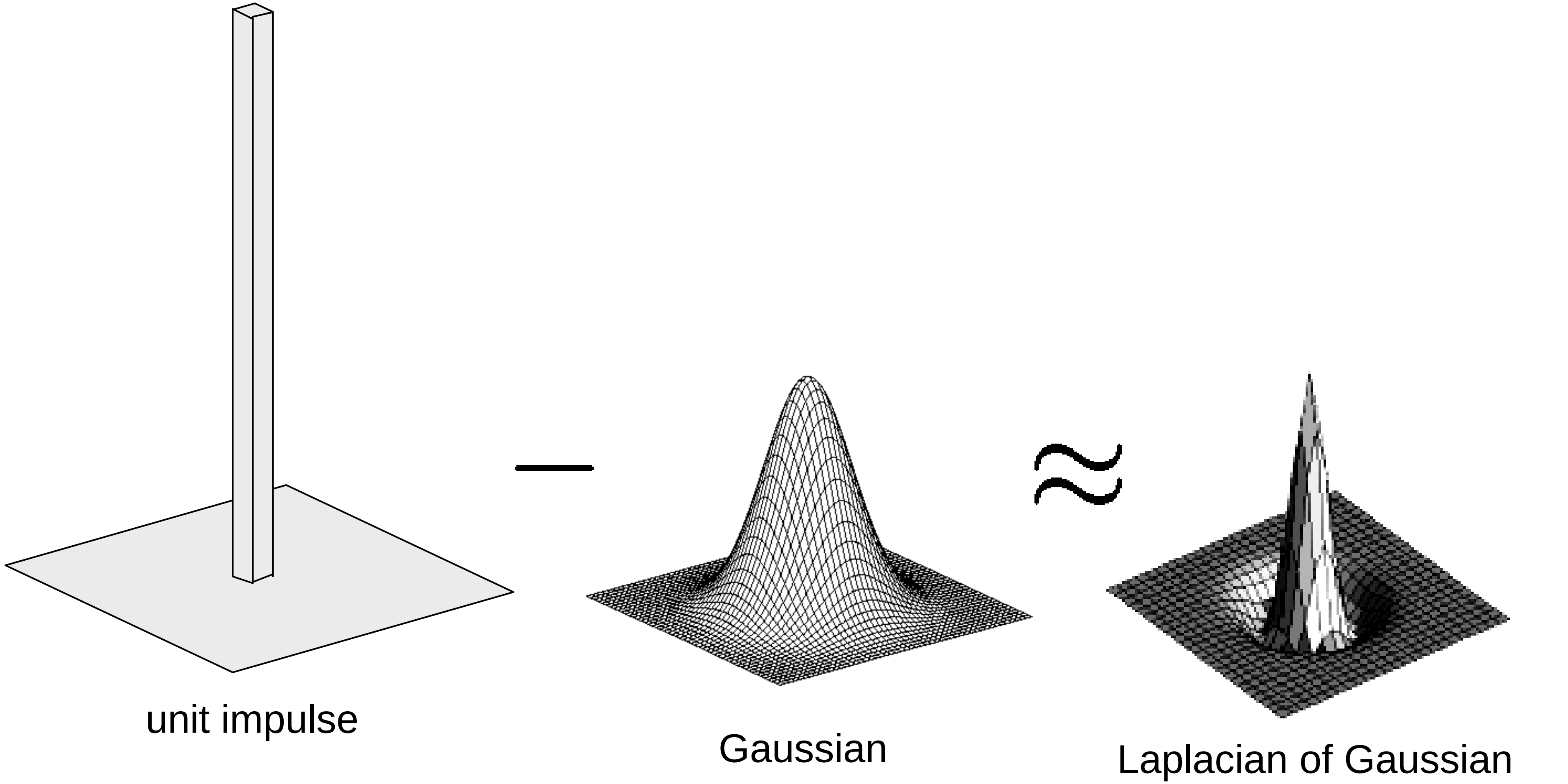
1. Compute Gaussian pyramid
2. Align with coarse pyramid
3. Successively align with finer pyramids
   – Search smaller range



Why is this faster?

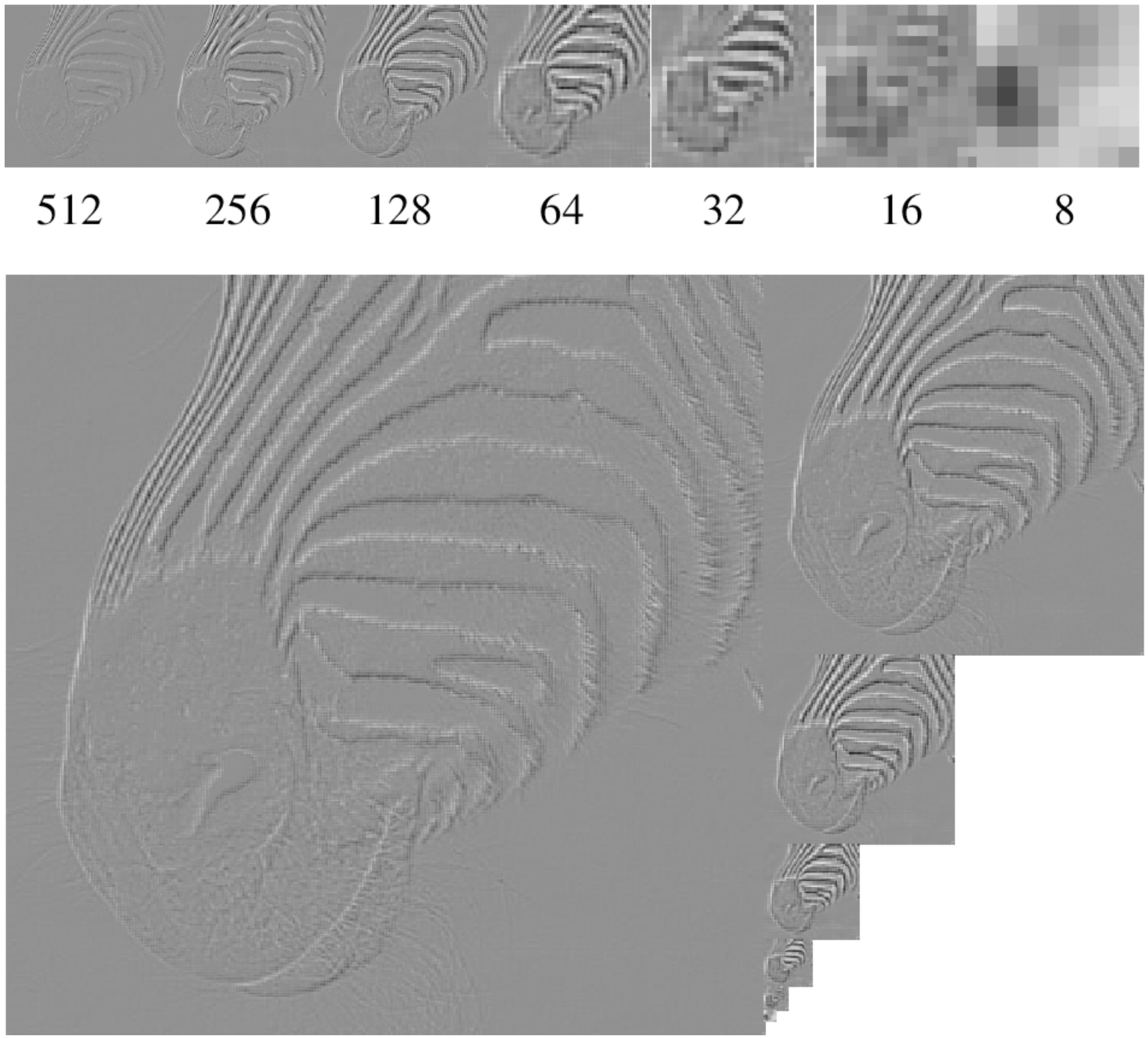
Are we guaranteed to get the same result?

Laplacian filter



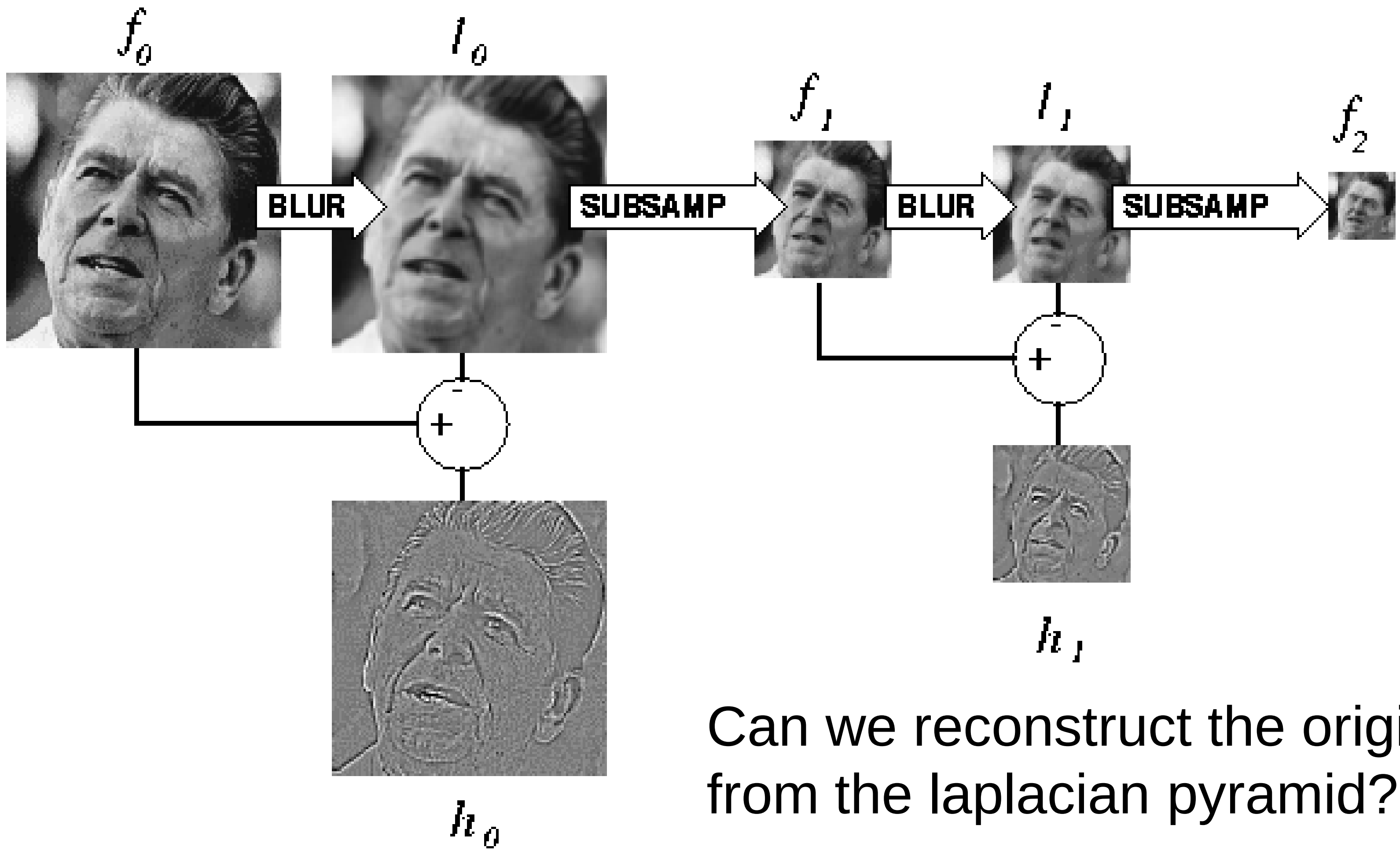
Source: Lazebnik

Laplacian pyramid



Source: Forsyth

Computing Gaussian/Laplacian Pyramid



Can we reconstruct the original from the laplacian pyramid?

http://sepwww.stanford.edu/~morgan/texturematch/paper_html/node3.html

Hybrid Image

Hybrid Image in Laplacian Pyramid

High frequency → Low frequency

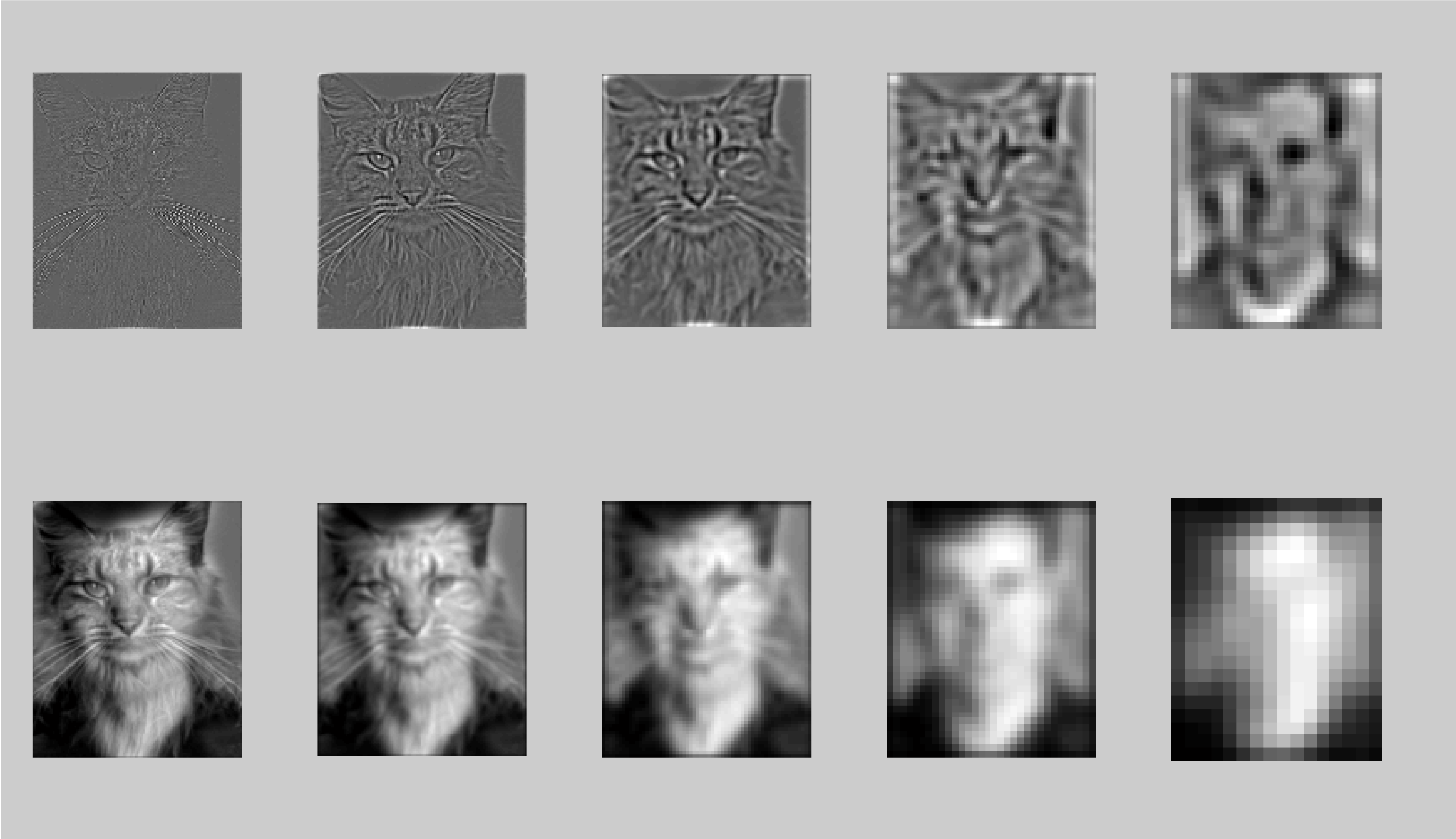


Image representation

- 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

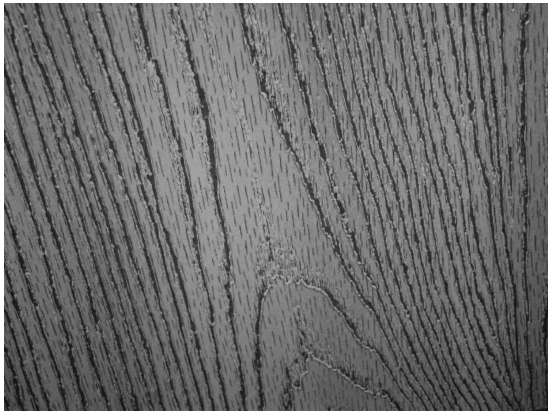
Major uses of image pyramids

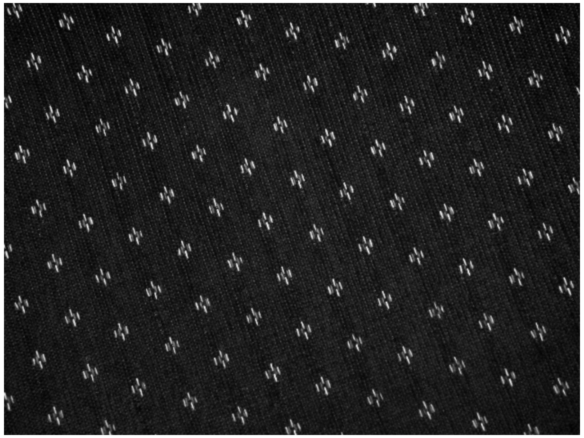
- Compression
- Object detection
  - Scale search
  - Features
- Detecting stable interest points
- Registration
  - Course-to-fine

Application: Representing Texture

Source: Forsyth

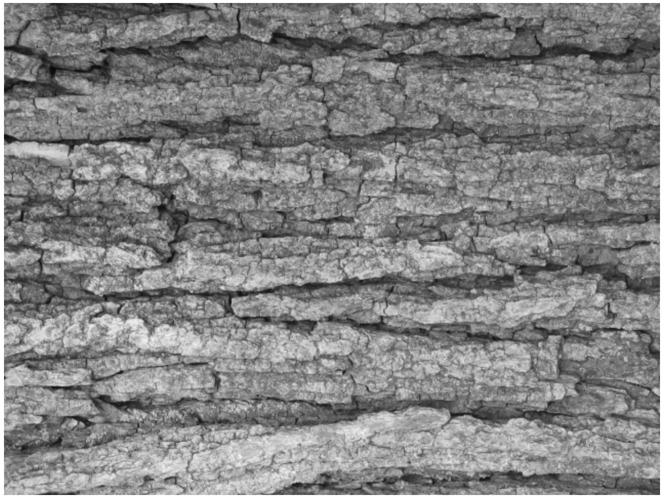
Texture and Material





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?

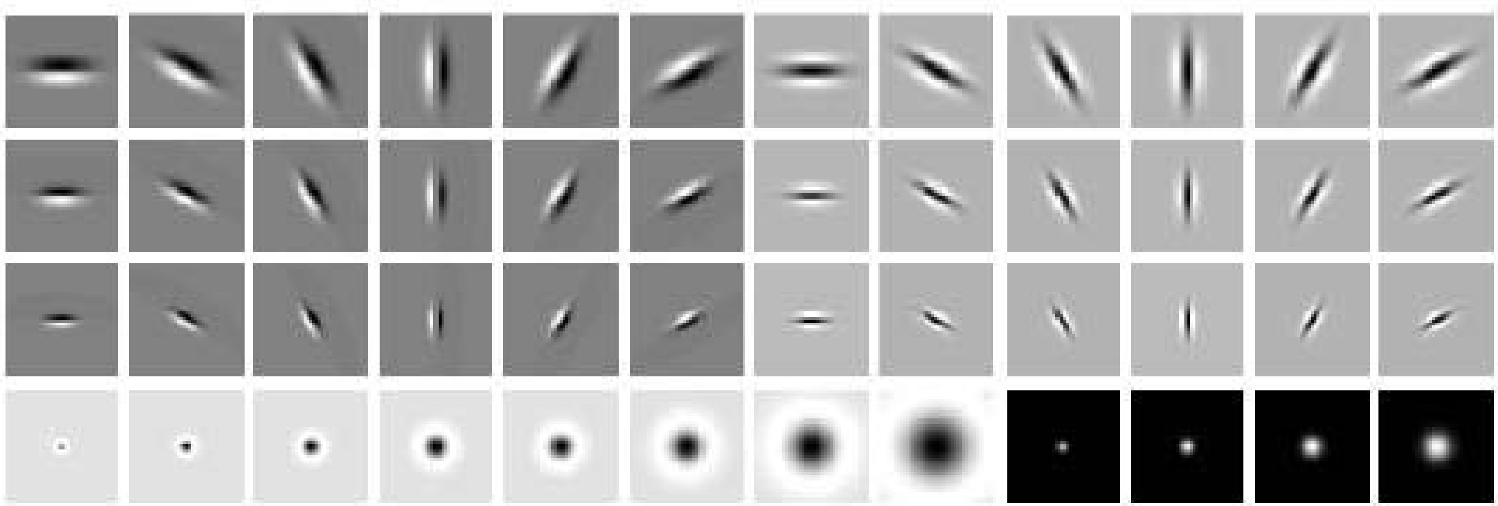
Regular or stochastic patterns caused by bumps, grooves, and/or markings

How can we represent texture?

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

Overcomplete representation: filter banks

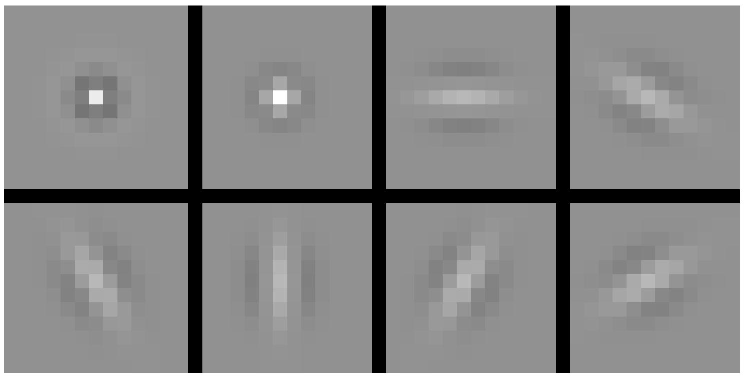
LM Filter Bank

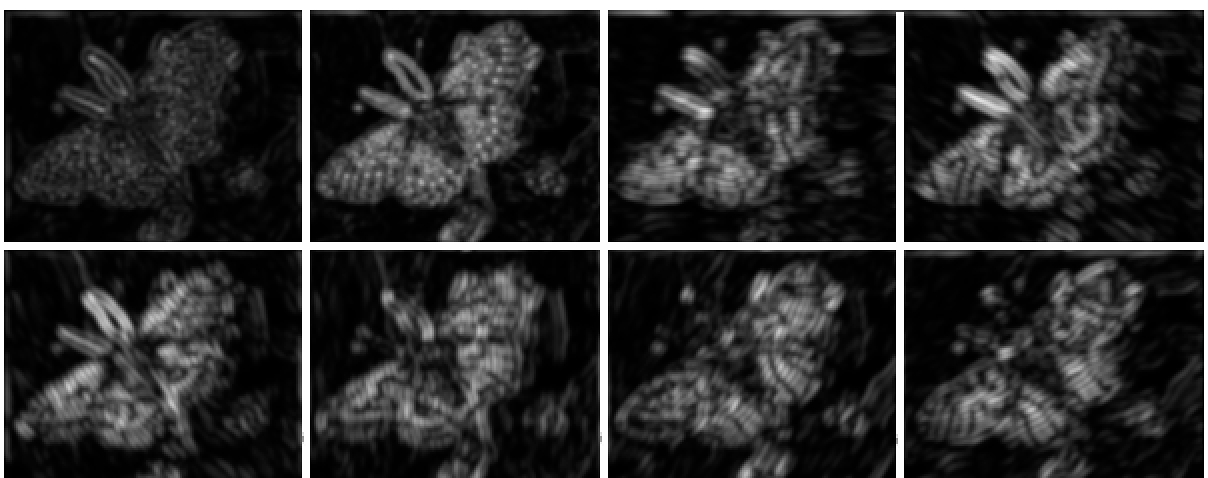


Code for filter banks: *www.robots.ox.ac.uk/~vgg/research/texclass/filters.html*

Filter banks

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



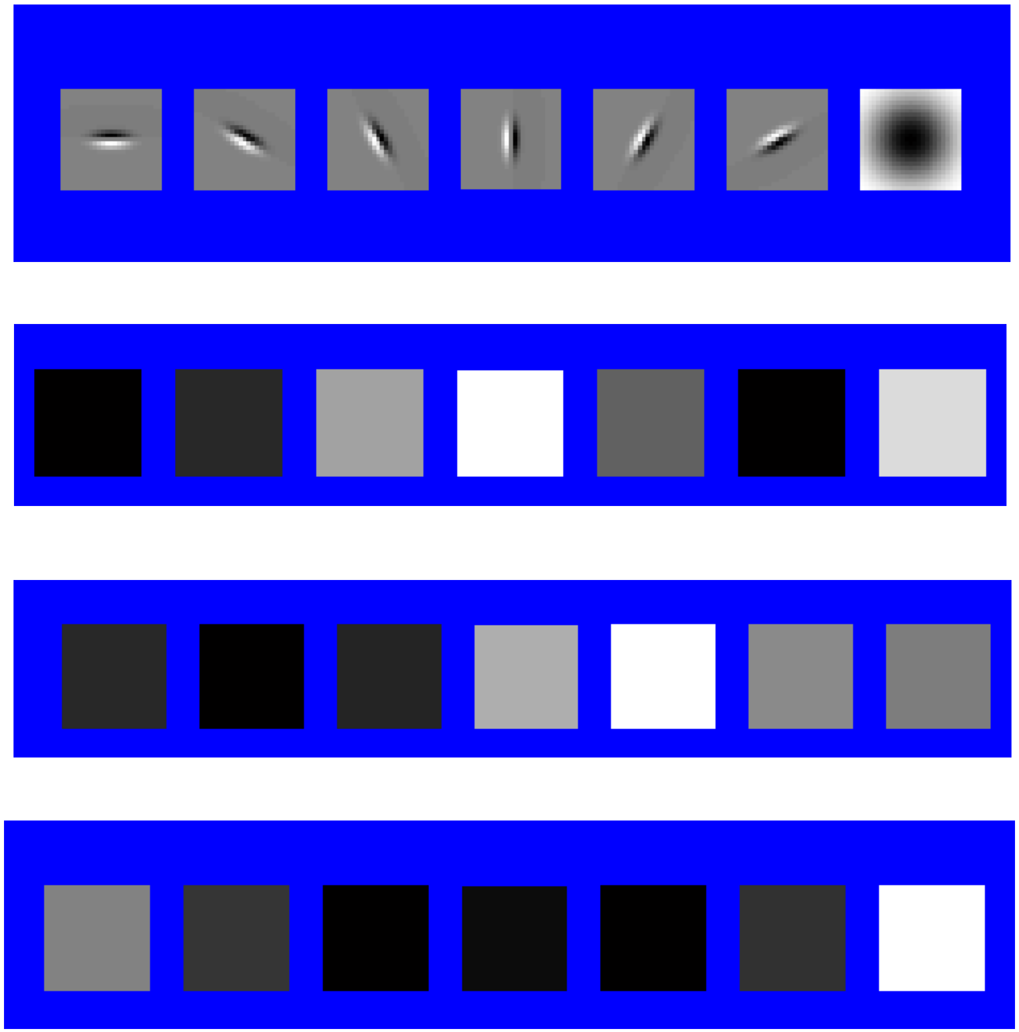


How can we represent texture?

- 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



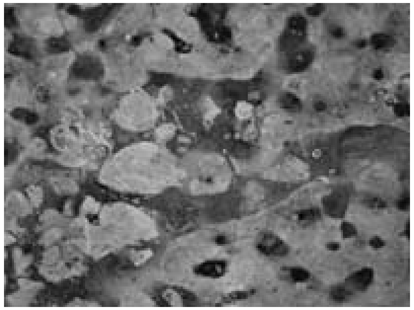
1

2

3

Mean abs responses

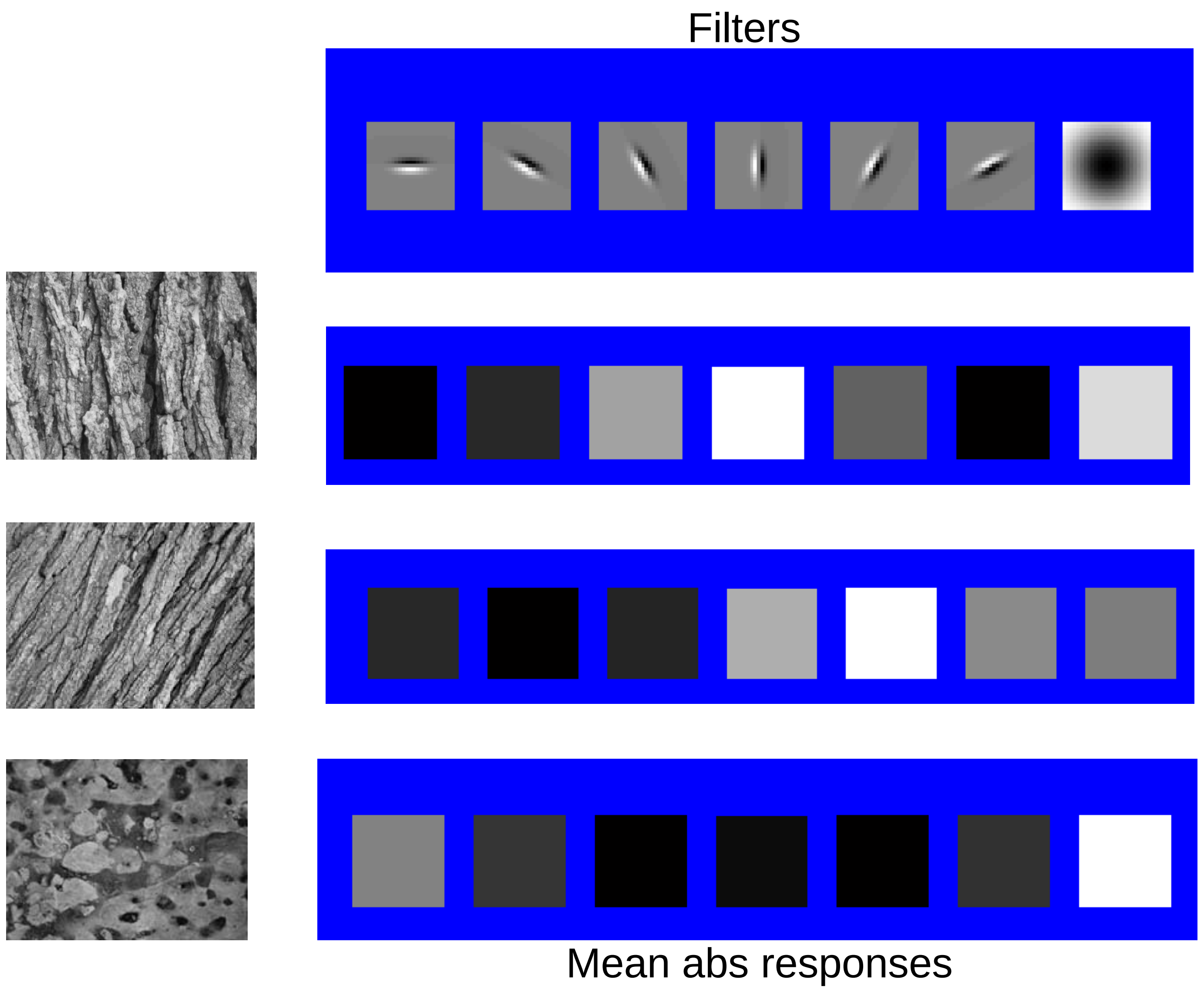
A



B

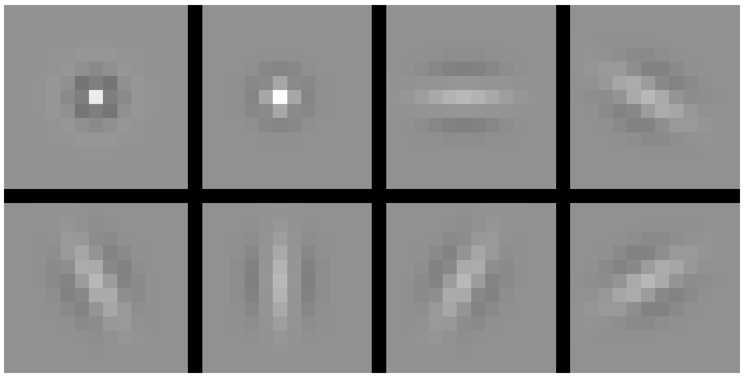
C

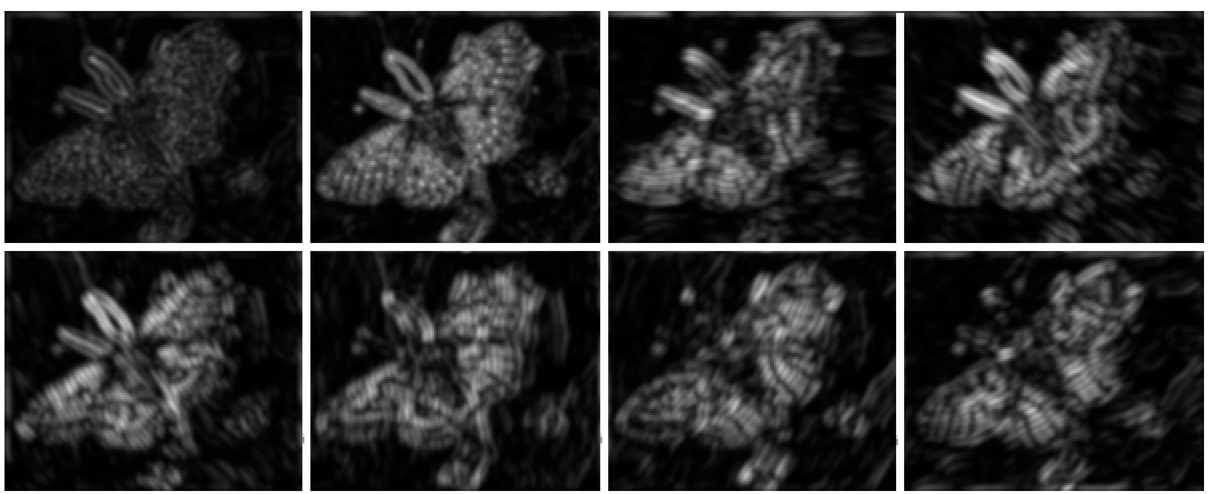
Representing texture by mean abs response



Representing texture

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

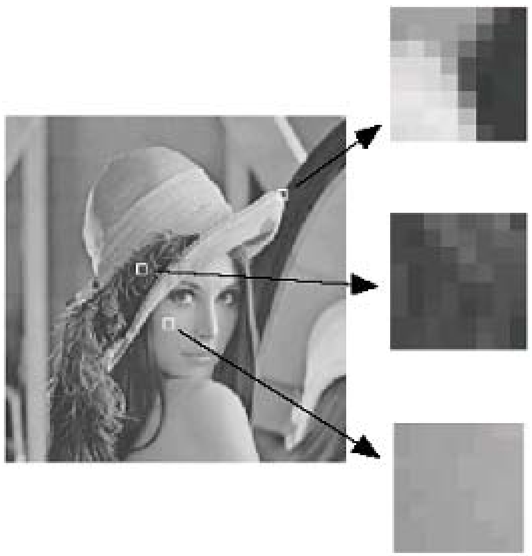


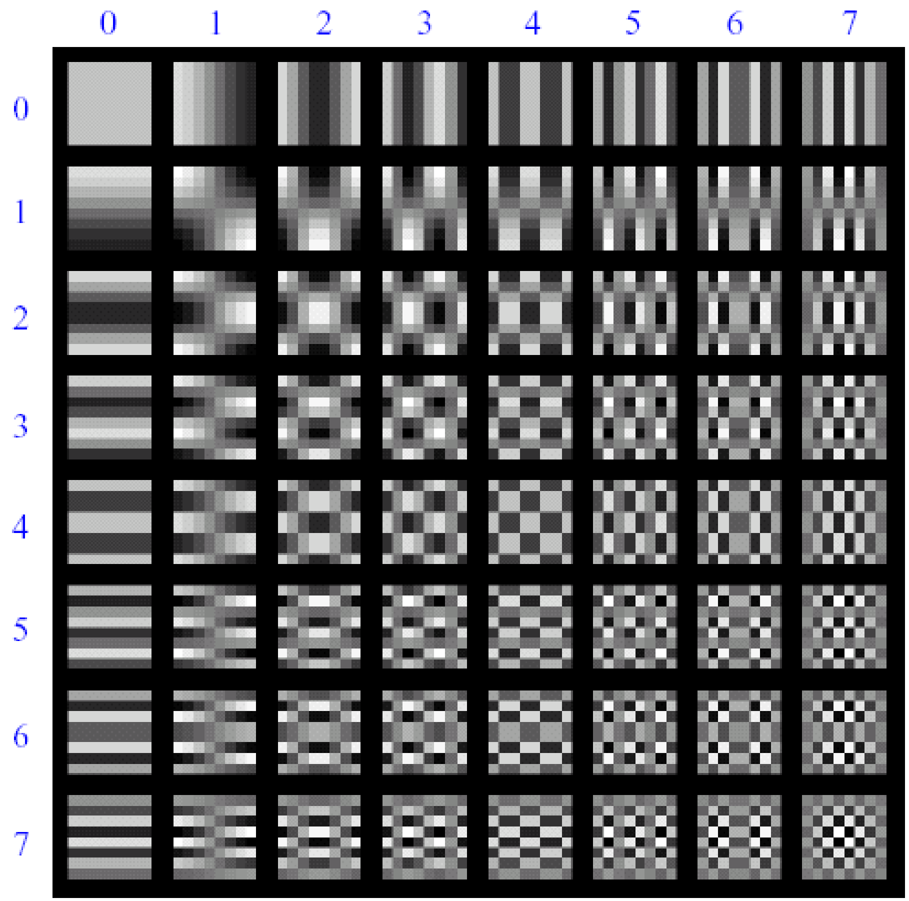


Compression

How is it that a 4MP image can be compressed to a few hundred KB without a noticeable change?

Lossy Image Compression (JPEG)

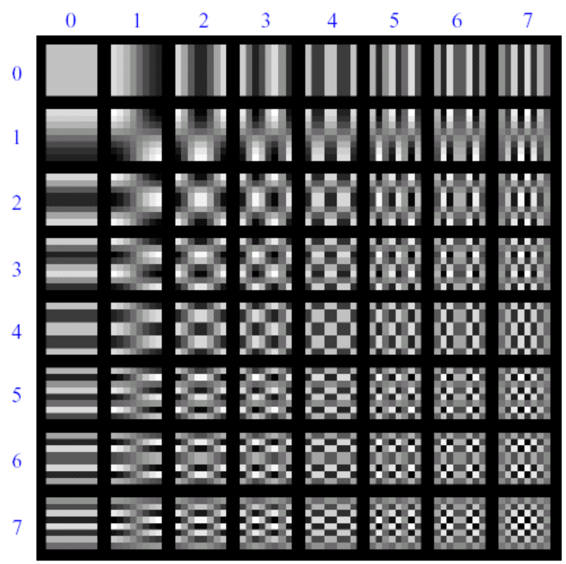




Block-based Discrete Cosine Transform (DCT)

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



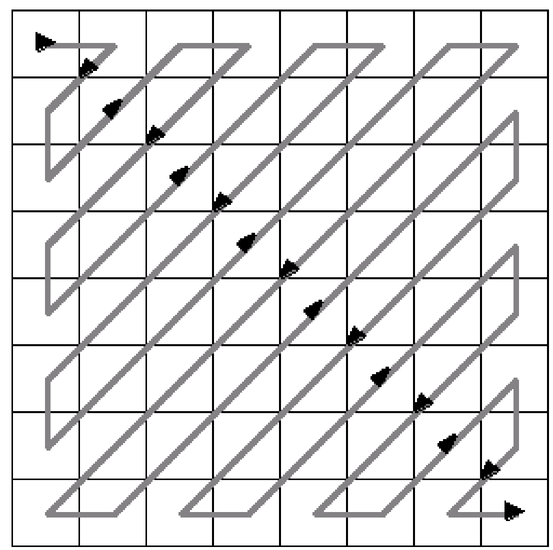


Image compression using DCT

- 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

$$\xrightarrow{u}$$

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

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

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

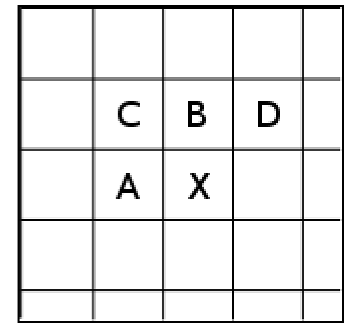
JPEG Compression Summary

1. Convert image to YCrCb
2. Subsample color by factor of 2
   – 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)

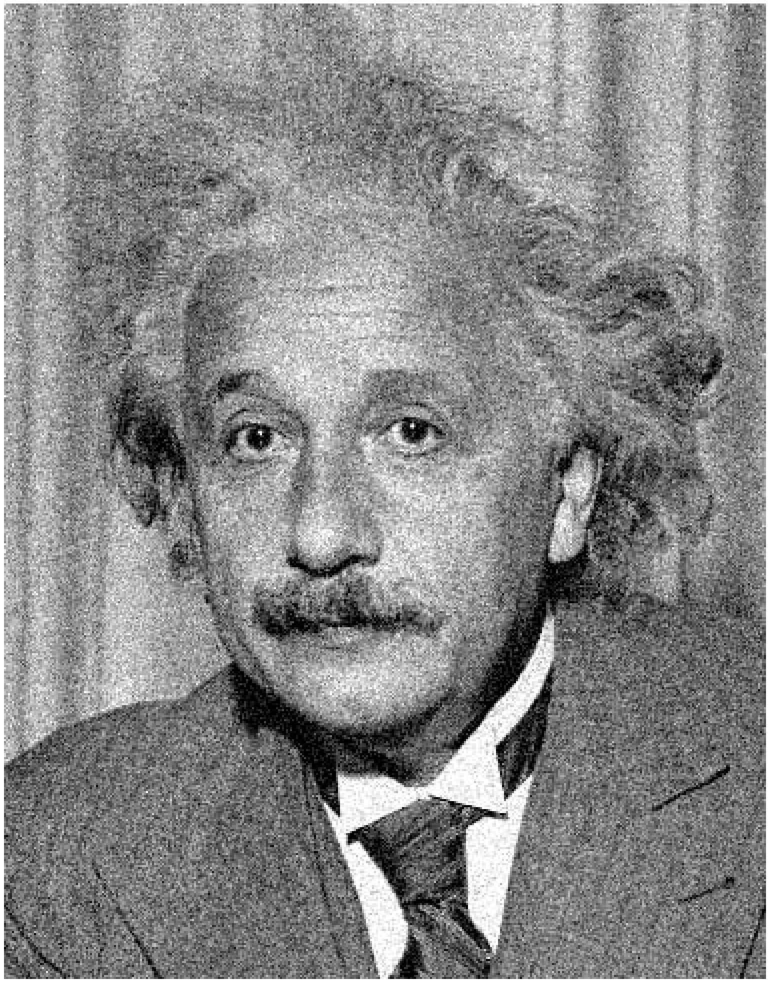
http://en.wikipedia.org/wiki/YCbCr
http://en.wikipedia.org/wiki/JPEG

Lossless compression (PNG)

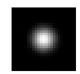
1. Predict that a pixel's value based on its upper-left neighborhood
2. Store difference of predicted and actual value
3. Pkzip it (DEFLATE algorithm)



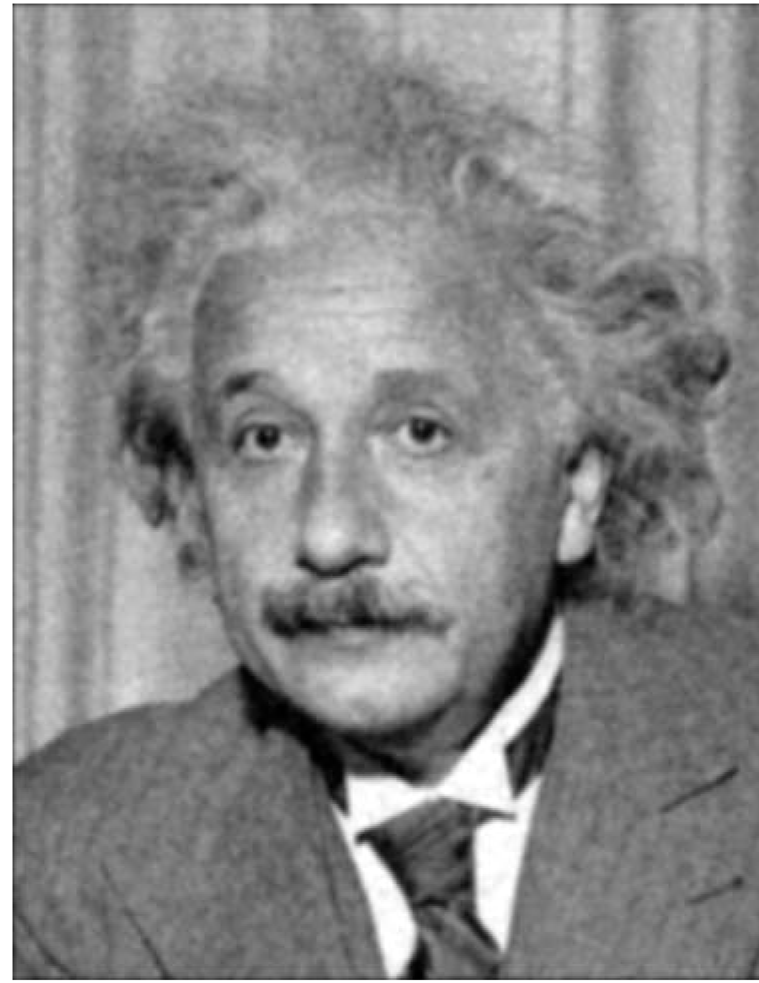
Denoising



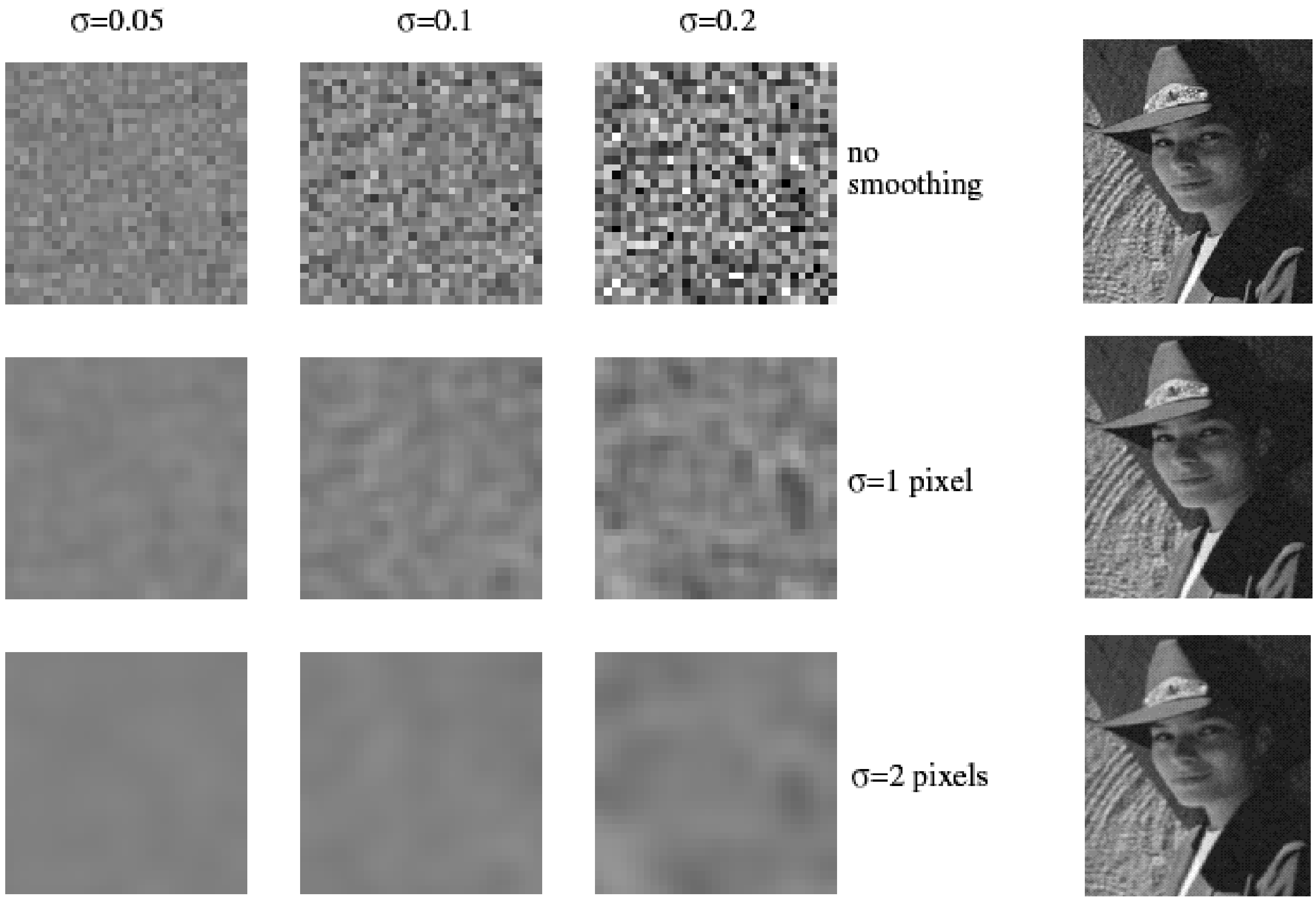
Additive Gaussian Noise



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

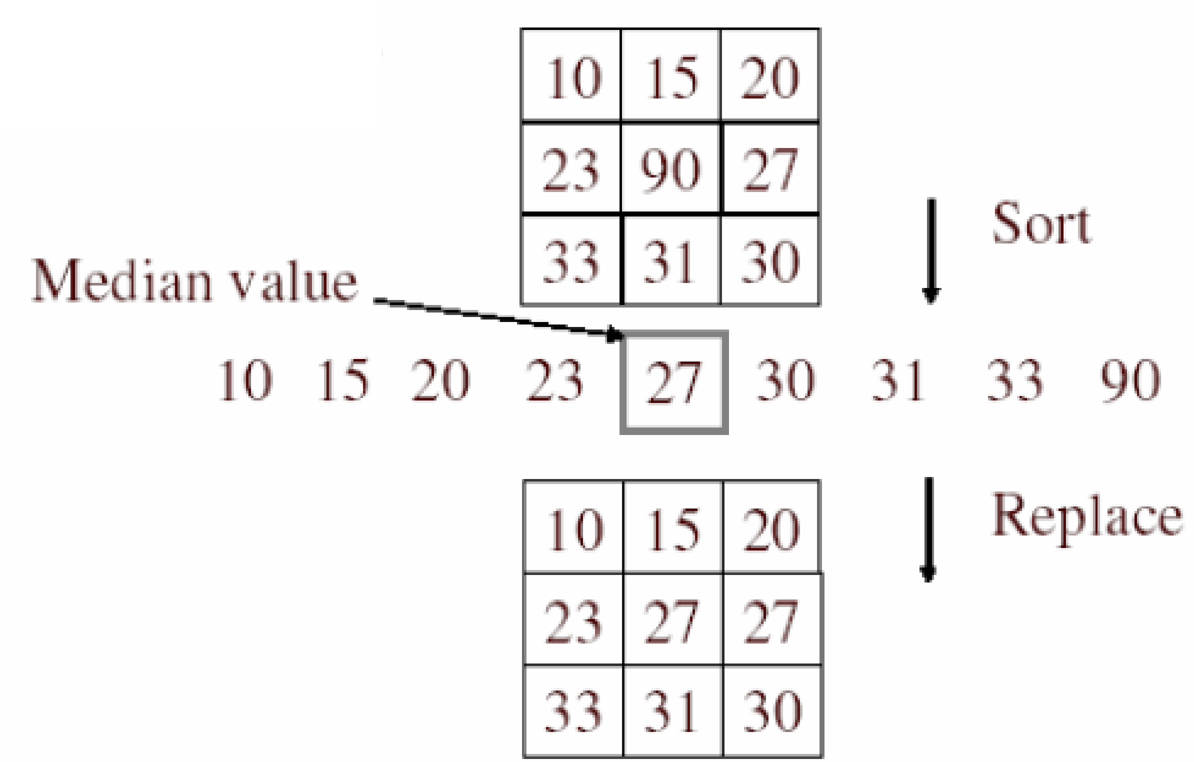
3x3

5x5

7x7

Alternative idea: Median filtering

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



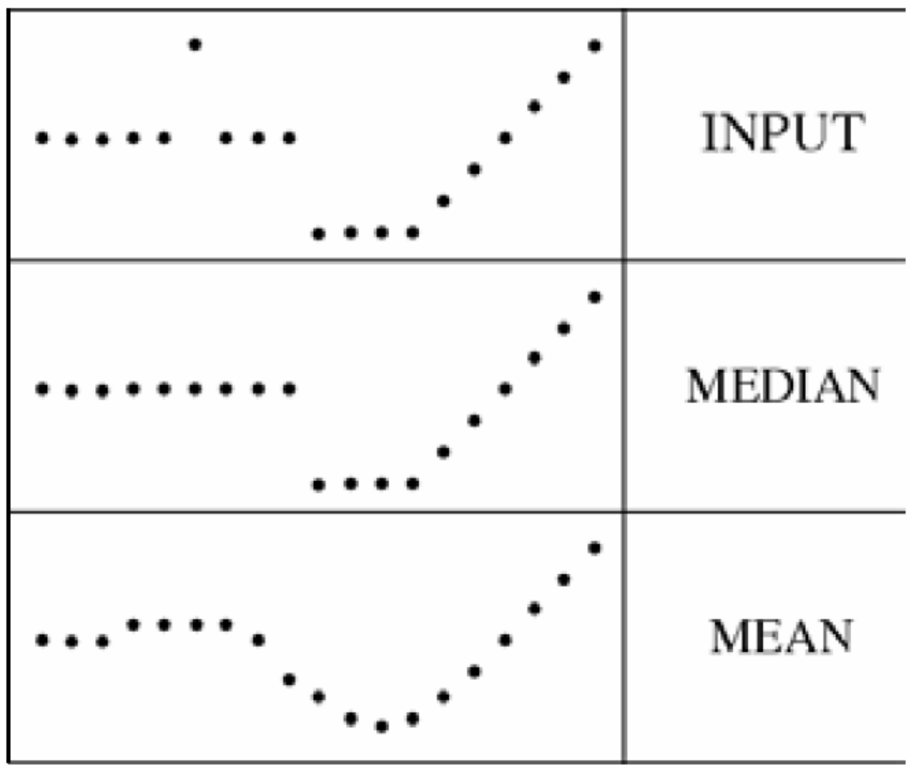
- Is median filtering linear?

Source: K. Grauman

Median filter

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

filters have width 5 :

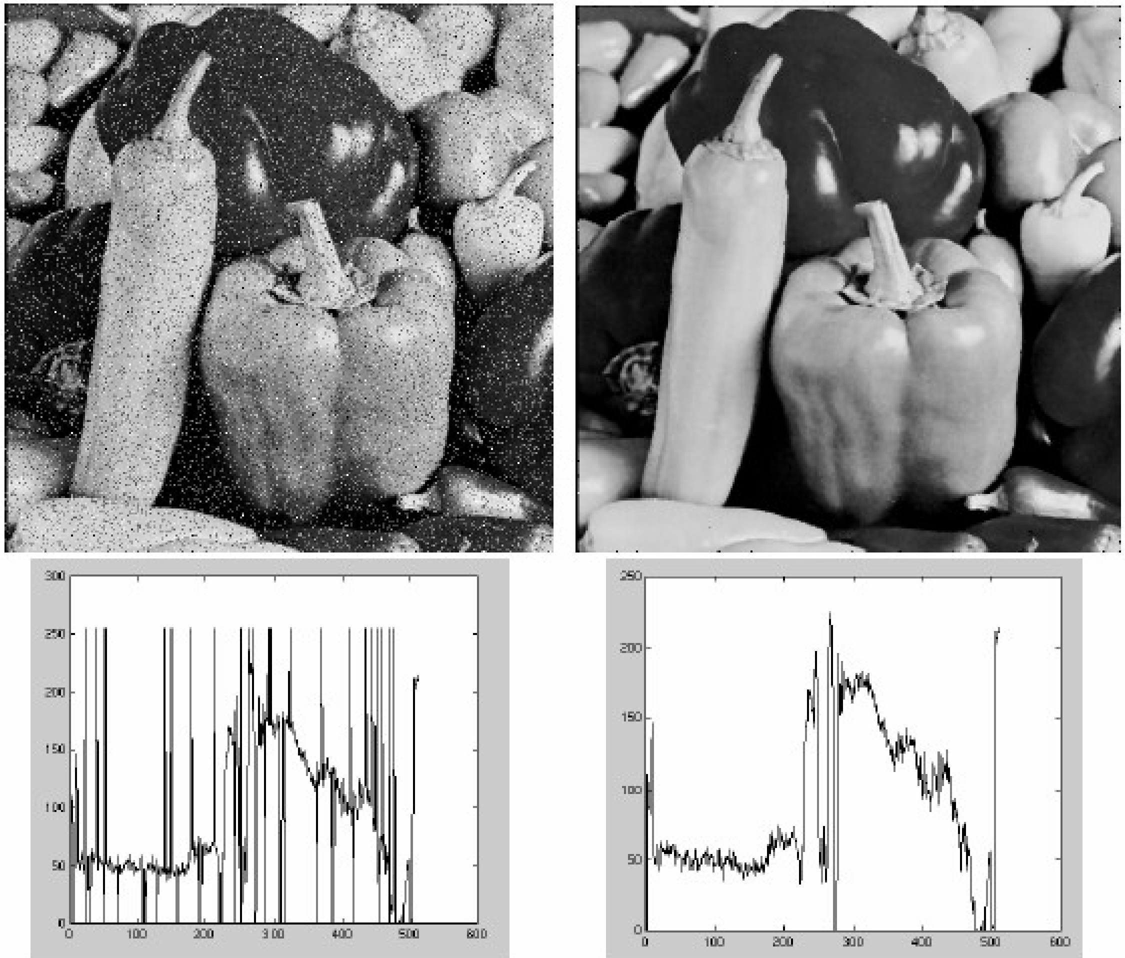


Source: K. Grauman

Median filter

Salt-and-pepper noise

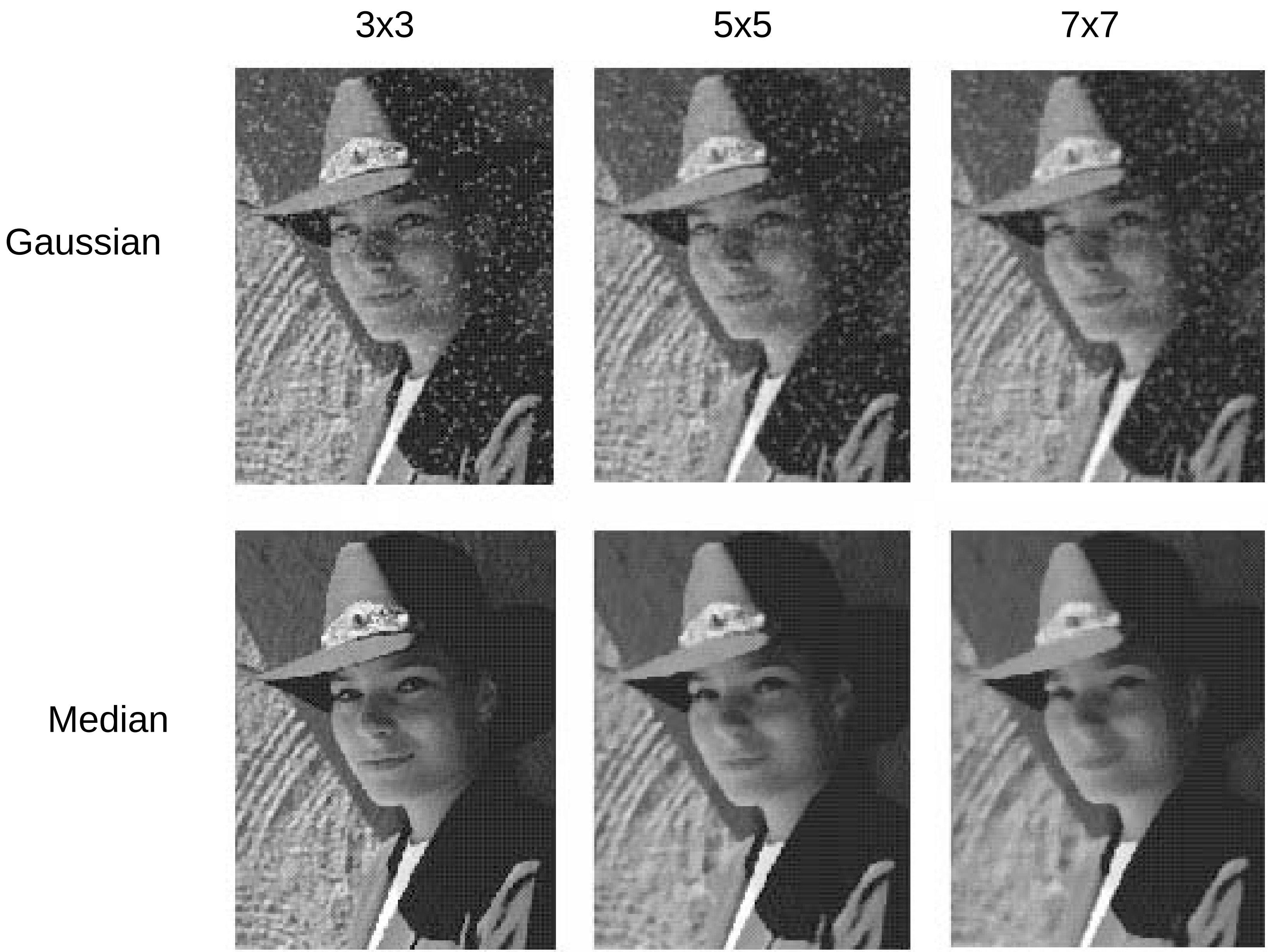
Median filtered



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

Source: M. Hebert

Median vs. Gaussian filtering



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

Review of last three days

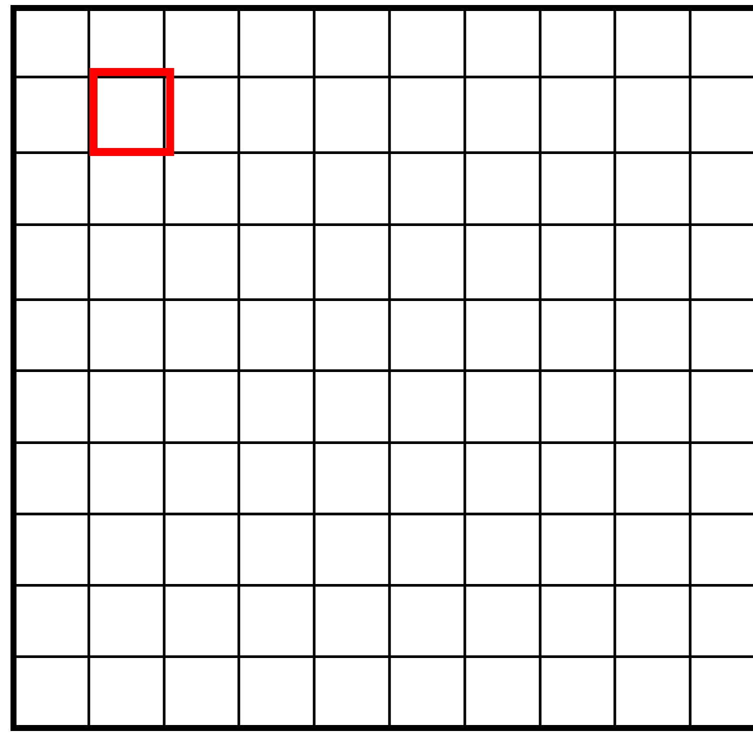
Review: Image filtering

$g[\cdot\,,\cdot\,]\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$

$f\,[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$



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

Credit: S. Seitz

Image filtering

$$g[\cdot,\cdot]\ \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10							

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

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

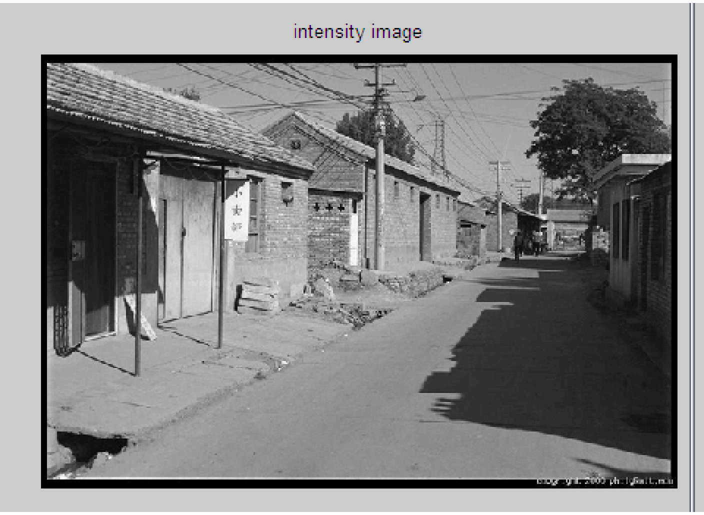
	0	10	20						

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

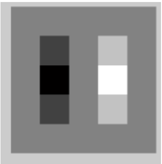
Credit: S. Seitz

Filtering in spatial domain

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



*



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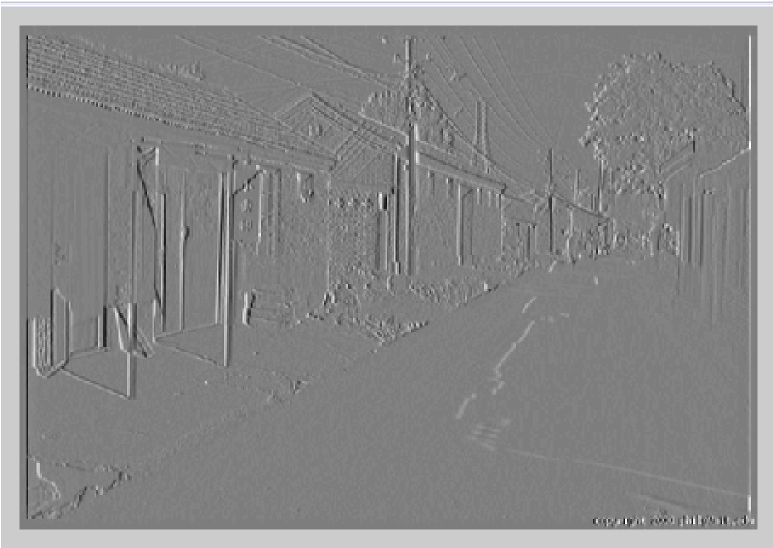
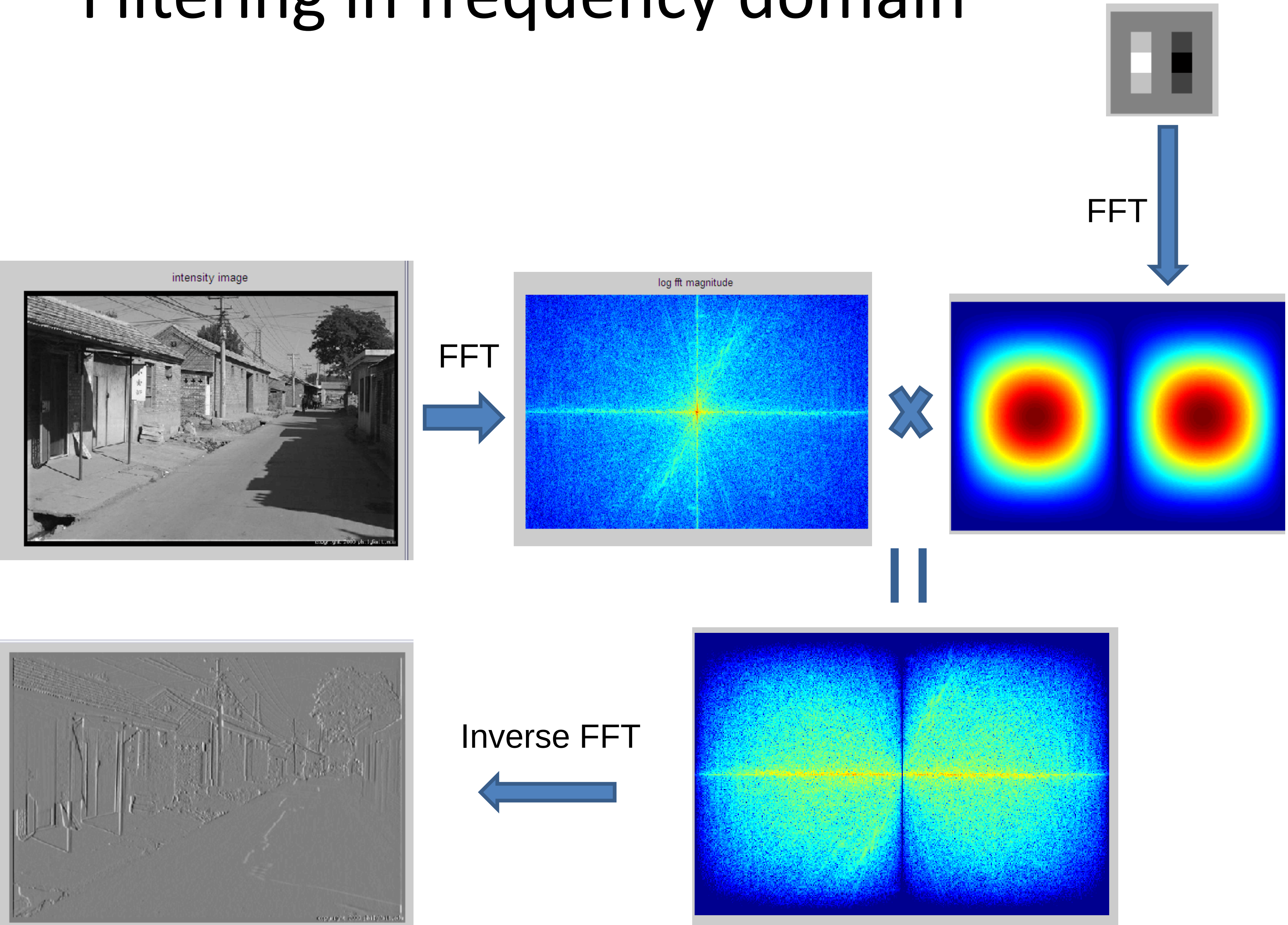


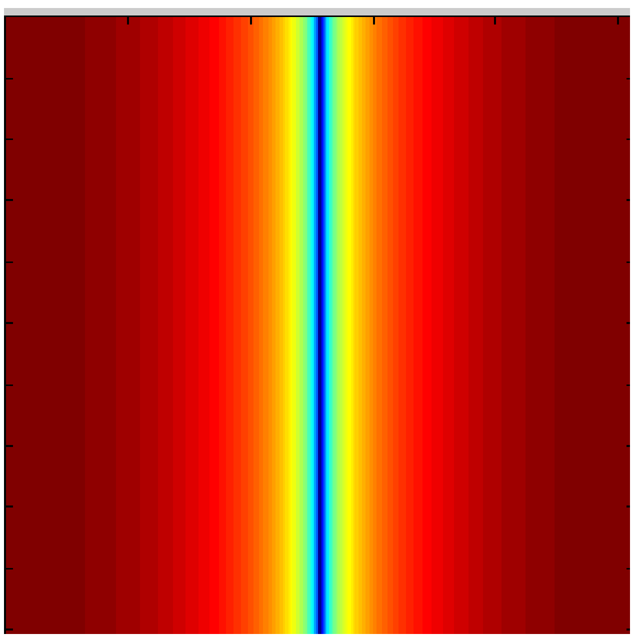
Filtering in frequency domain



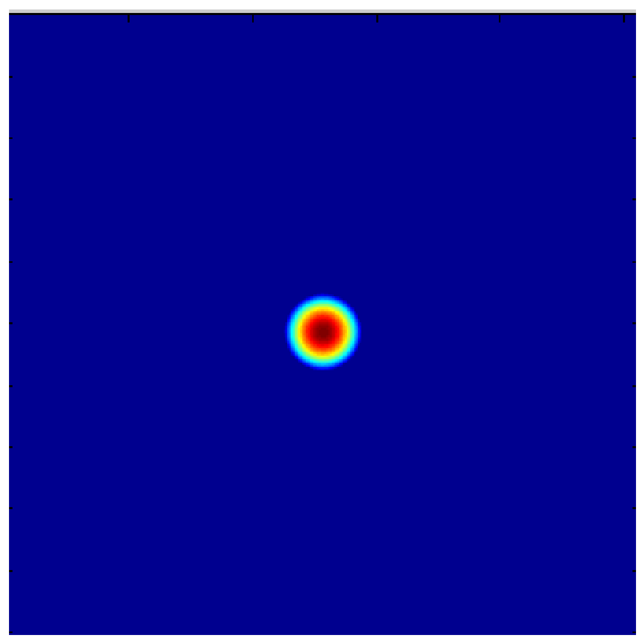
Review of Last 3 Days

- Linear filters for basic processing
  - Edge filter (high-pass)
  - Gaussian filter (low-pass)

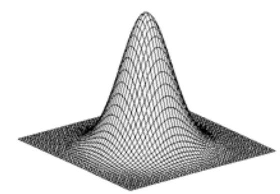
[-1 1]



FFT of Gradient Filter



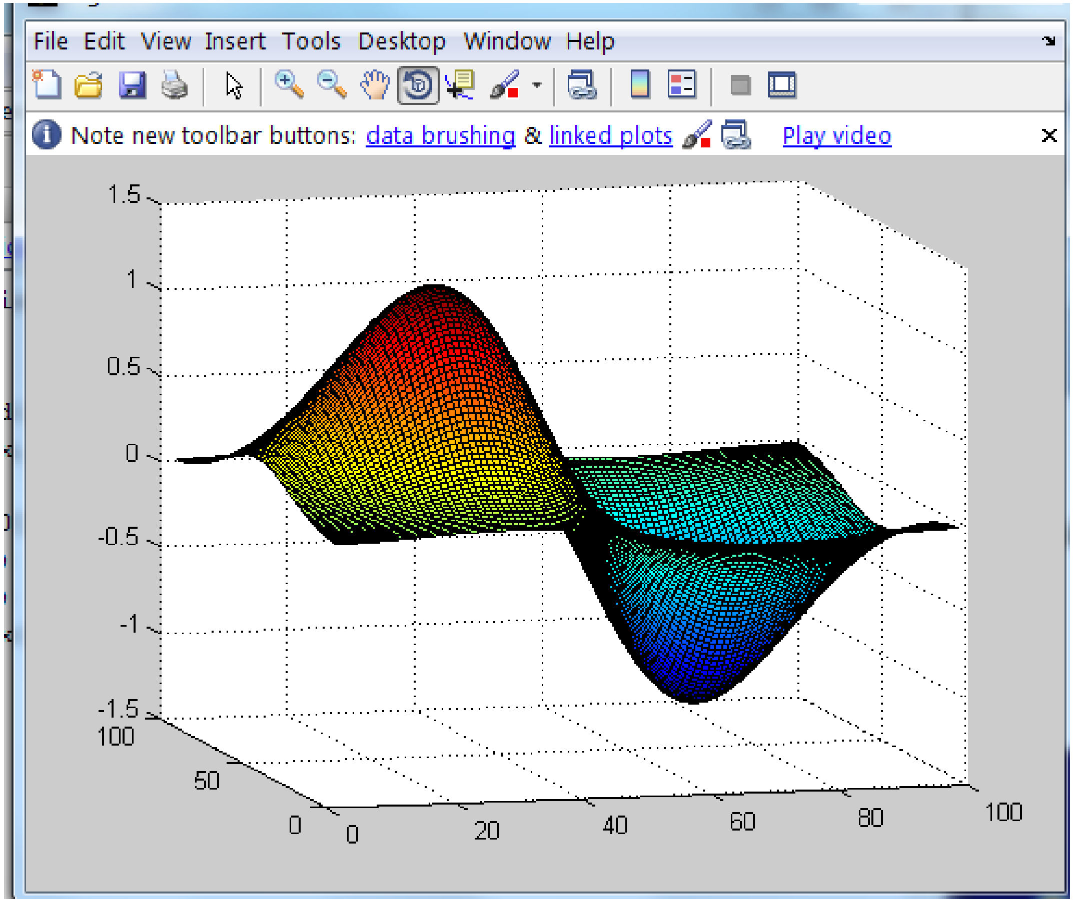
FFT of Gaussian



Gaussian

Review of Last 3 Days

- Derivative of Gaussian



Review of Last 3 Days

- 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

Review of Last 3 Days

- Applications of filters
  - Downsampling
    - Need to sufficiently low-pass before downsampling
  - Compression
    - In JPEG, coarsely quantize high frequencies

Next class: edge and line detection