

Announcements

- Kevin Matzen office hours
 - Tuesday 4-5pm, Thursday 2-3pm, Upson 317
- TA: Yin Lou
- Course lab: Upson 317
 - Card access will be setup soon
- Course webpage:
<http://www.cs.cornell.edu/courses/cs4670/2010fa/>

Projects

- Projects involving programming phones will be group projects
 - Groups will check out phones, specifics TBA

Questions?

Why is computer vision difficult?



Viewpoint variation



Illumination



Scale

Why is computer vision difficult?



Intra-class variation



Motion (Source: S. Lazebnik)

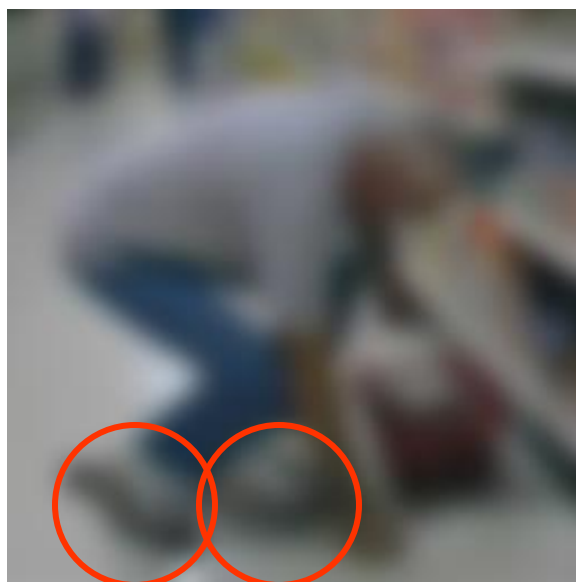
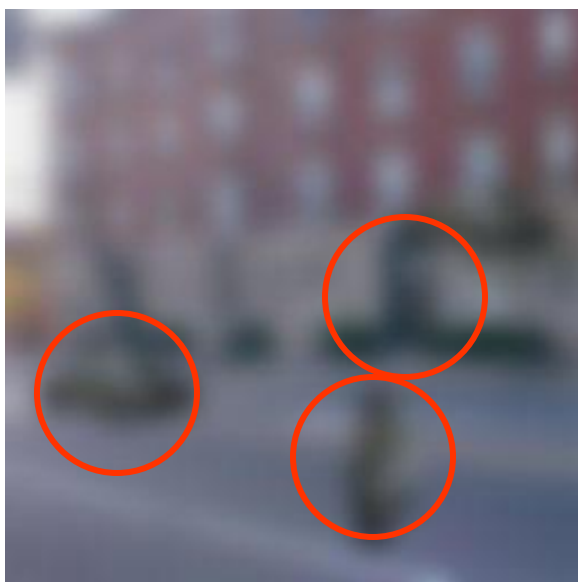
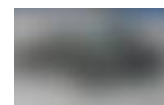
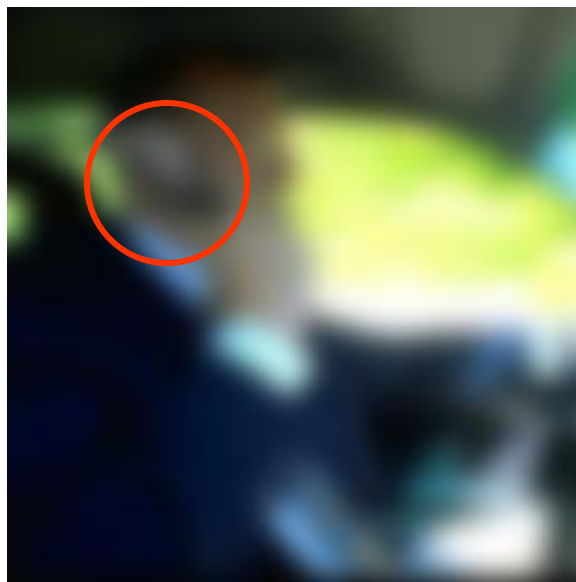
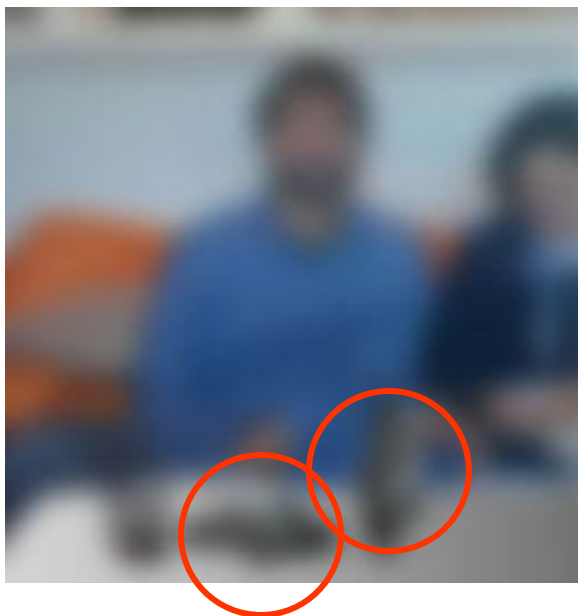


Background clutter



Occlusion

Challenges: local ambiguity



But there are lots of cues we can exploit...



Bottom line

- Perception is an inherently ambiguous problem
 - Many different 3D scenes could have given rise to a particular 2D picture

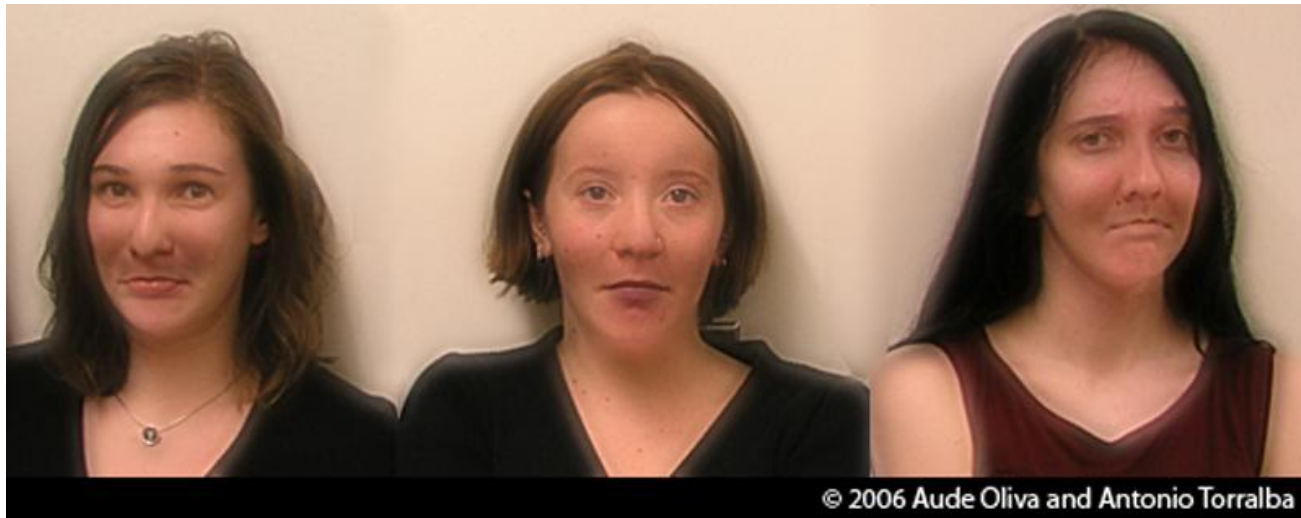


- We often need to use prior knowledge about the structure of the world

CS4670: Computer Vision

Noah Snavely

Lecture 1: Images and image filtering

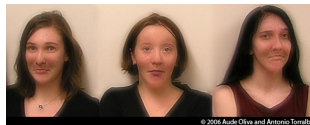


Hybrid Images, Oliva et al., <http://cvcl.mit.edu/hybridimage.htm>

CS4670: Computer Vision

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Lecture 1: Images and image filtering

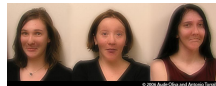


Hybrid Images, Oliva et al., <http://cvcl.mit.edu/hybridimage.htm>

CS4670: Computer Vision

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Lecture 1: Images and image filtering

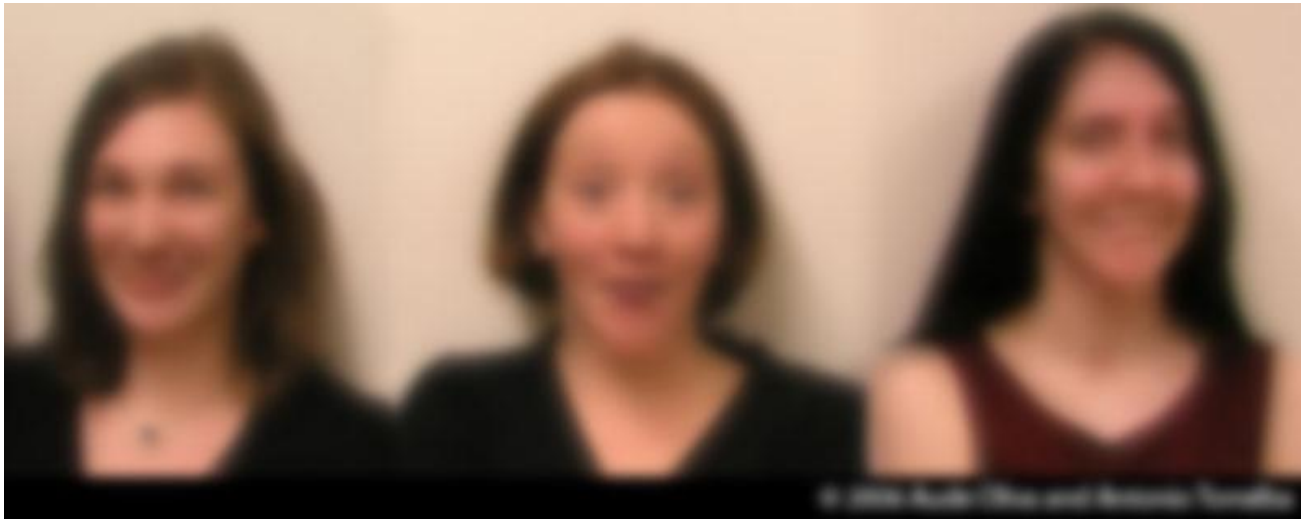


Hybrid Images, Oliva et al., <http://cvcl.mit.edu/hybridimage.htm>

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Lecture 1: Images and image filtering



Hybrid Images, Oliva et al., <http://cvcl.mit.edu/hybridimage.htm>

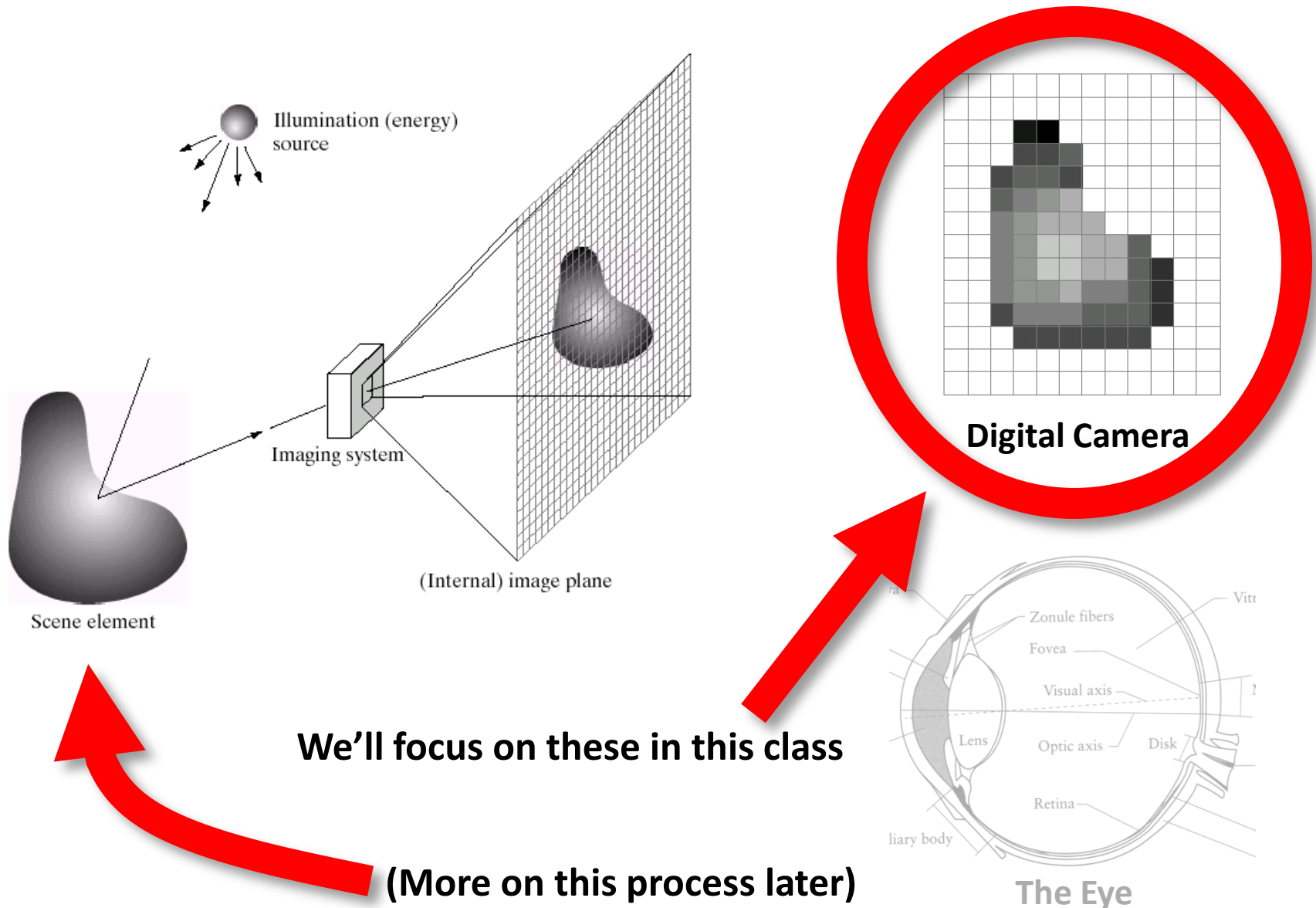
Reading

- Szeliski, Chapter 3.1-3.2

What is an image?

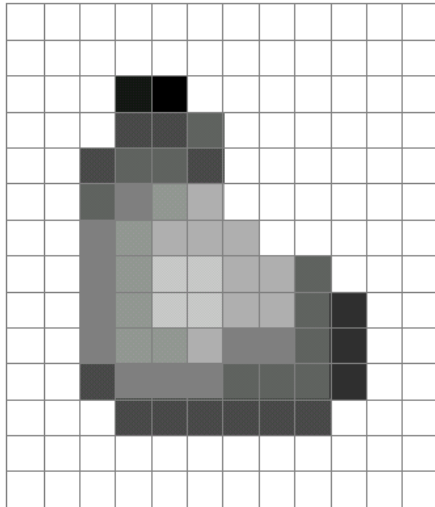


What is an image?



What is an image?

- A grid (matrix) of intensity values



=

| | | | | | | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 255 | 20 | 0 | 255 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 255 | 75 | 75 | 75 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 75 | 95 | 95 | 75 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 96 | 127 | 145 | 175 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 127 | 145 | 175 | 175 | 175 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 127 | 145 | 200 | 200 | 175 | 175 | 95 | 255 | 255 | 255 |
| 255 | 255 | 127 | 145 | 200 | 200 | 175 | 175 | 95 | 47 | 255 | 255 |
| 255 | 255 | 127 | 145 | 145 | 175 | 127 | 127 | 95 | 47 | 255 | 255 |
| 255 | 255 | 74 | 127 | 127 | 127 | 95 | 95 | 95 | 47 | 255 | 255 |
| 255 | 255 | 255 | 74 | 74 | 74 | 74 | 74 | 74 | 255 | 255 | 255 |
| 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 |
| 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 | 255 |

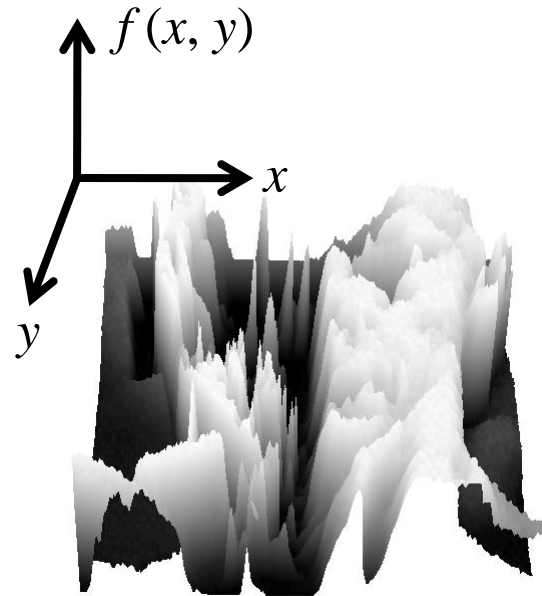
(common to use one byte per value: 0 = black, 255 = white)

What is an image?

- We can think of a (grayscale) image as a **function**, f , from \mathbb{R}^2 to \mathbb{R} :
 - $f(x, y)$ gives the **intensity** at position (x, y)



snoop



3D view

- A **digital** image is a discrete (**sampled, quantized**) version of this function

Image transformations

- As with any function, we can apply operators to an image



$$g(x,y) = f(x,y) + 20$$



$$g(x,y) = f(-x,y)$$

- We'll talk about a special kind of operator, *convolution* (linear filtering)

Question: Noise reduction

- Given a camera and a still scene, how can you reduce noise?



Take lots of images and average them!

What's the next best thing?

Image filtering

- Modify the pixels in an image based on some function of a local neighborhood of each pixel

| | | |
|----|---|---|
| 10 | 5 | 3 |
| 4 | 5 | 1 |
| 1 | 1 | 7 |

Local image data

Some function

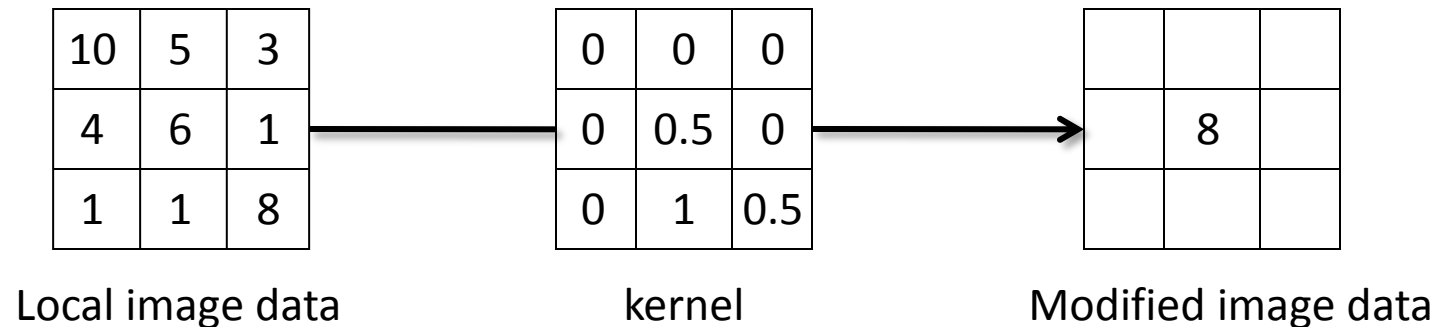


| | | |
|--|---|--|
| | | |
| | 7 | |
| | | |

Modified image data

Linear filtering

- One simple version: linear filtering (cross-correlation, convolution)
 - Replace each pixel by a linear combination of its neighbors
- The prescription for the linear combination is called the “kernel” (or “mask”, “filter”)



Cross-correlation

Let F be the image, H be the kernel (of size $2k+1 \times 2k+1$), and G be the output image

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

This is called a **cross-correlation** operation:

$$G = H \otimes F$$

Convolution

- Same as cross-correlation, except that the kernel is “flipped” (horizontally and vertically)

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

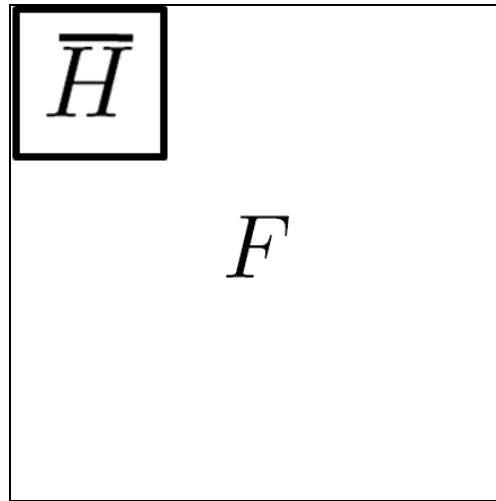
This is called a **convolution** operation:

$$G = H * F$$

- Convolution is **commutative** and **associative**

1D Demo

Convolution



Mean filtering

| | | |
|--|--|--|
| | | |
| | | |
| | | |

H



| | | | | | | | | | |
|---|---|----|----|----|----|----|----|---|---|
| 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 |

F

=

| | | | | | | | | | |
|--|----|----|----|----|----|----|----|----|--|
| | | | | | | | | | |
| | 0 | 10 | 20 | 30 | 30 | 30 | 20 | 10 | |
| | 0 | 20 | 40 | 60 | 60 | 60 | 40 | 20 | |
| | 0 | 30 | 60 | 90 | 90 | 90 | 60 | 30 | |
| | 0 | 30 | 50 | 80 | 80 | 90 | 60 | 30 | |
| | 0 | 30 | 50 | 80 | 80 | 90 | 60 | 30 | |
| | 0 | 20 | 30 | 50 | 50 | 60 | 40 | 20 | |
| | 10 | 20 | 30 | 30 | 30 | 30 | 20 | 10 | |
| | 10 | 10 | 10 | 0 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |

G

Linear filters: examples



Original



| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 0 | 0 | 0 |



Identical image

Linear filters: examples



Original



| | | |
|---|---|---|
| 0 | 0 | 0 |
| 1 | 0 | 0 |
| 0 | 0 | 0 |



Shifted left
By 1 pixel

Linear filters: examples

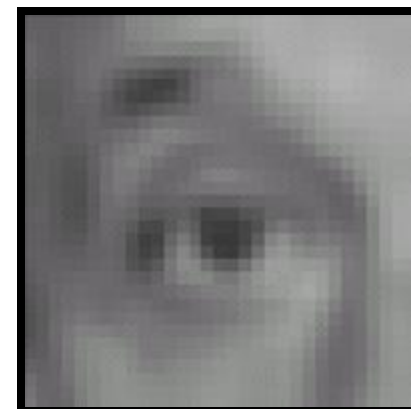


Original



$\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |



Blur (with a mean filter)

Linear filters: examples



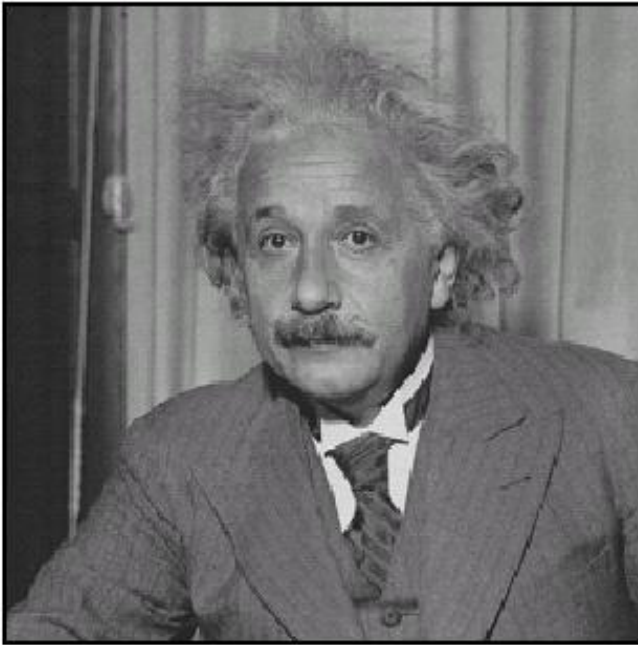
Original

$$* \left(\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 2 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} - \frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} \right) =$$

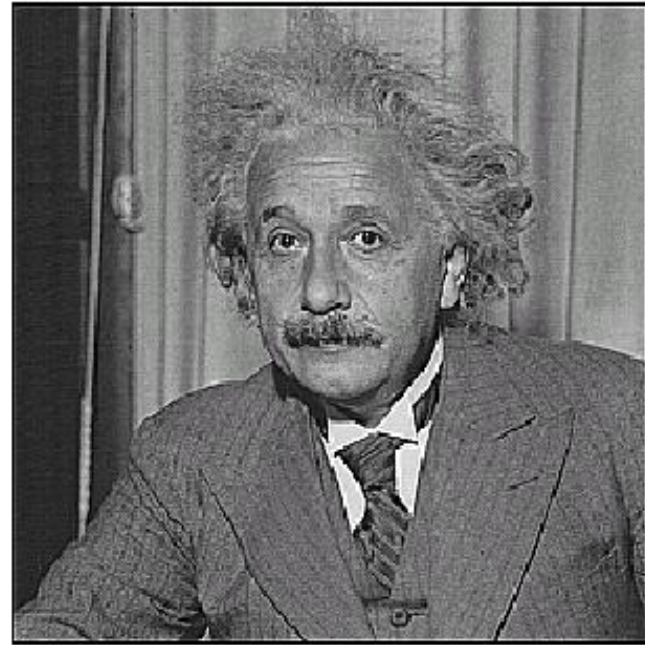


Sharpening filter
(accentuates edges)

Sharpening

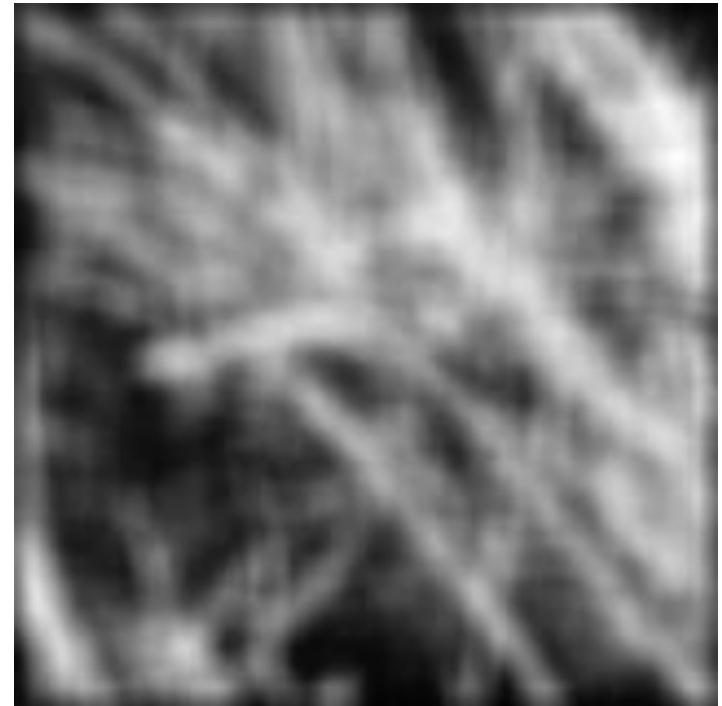
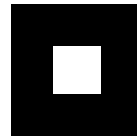


before

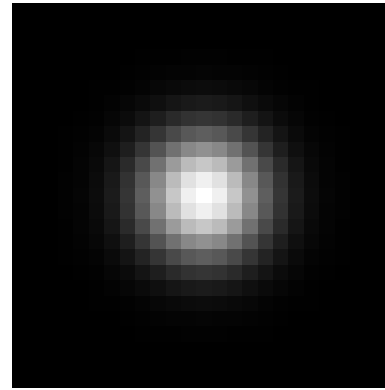
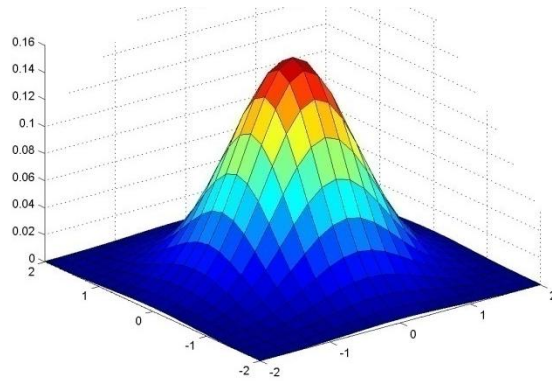


after

Smoothing with box filter revisited

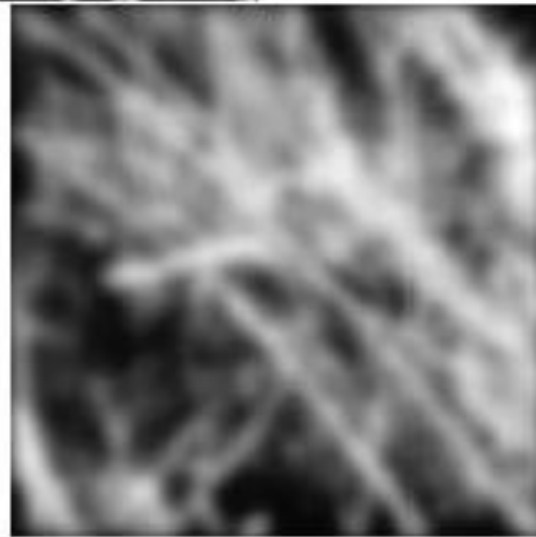
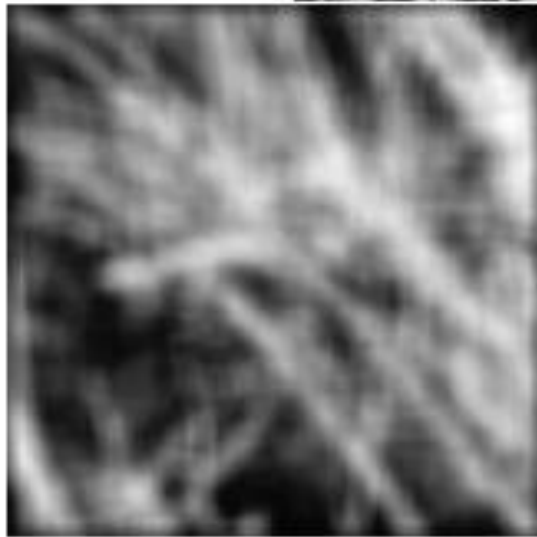


Gaussian Kernel



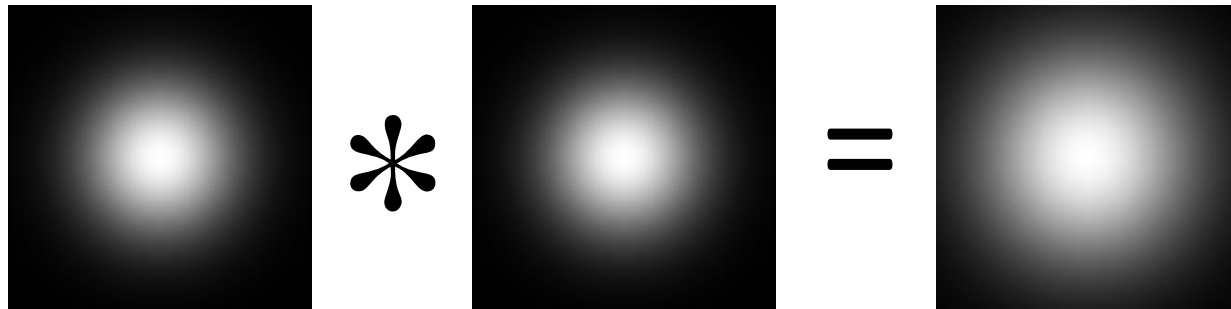
$$G_{\sigma} = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

Mean vs. Gaussian filtering



Gaussian filter

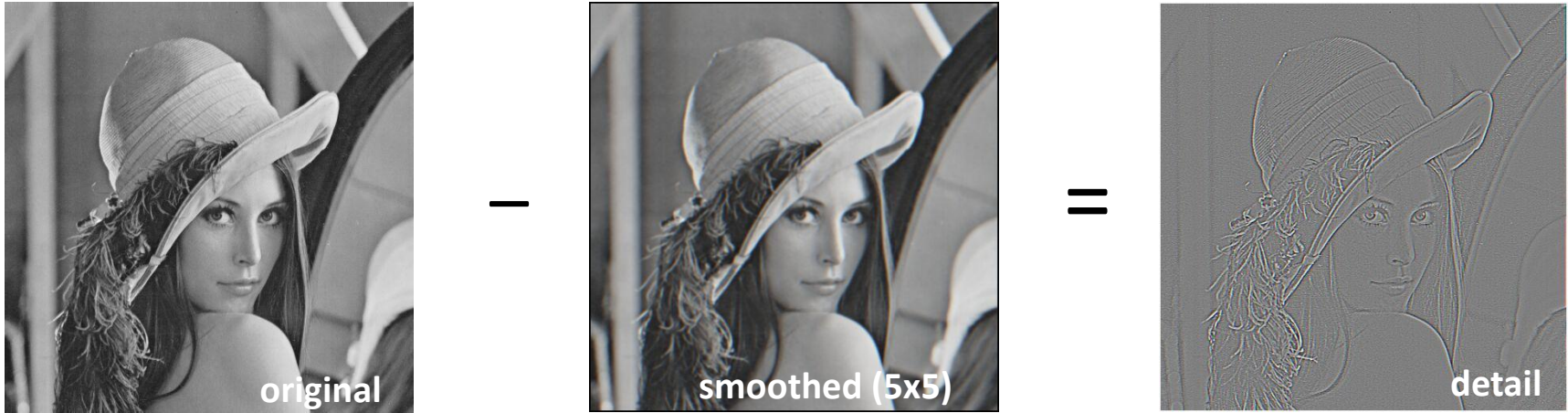
- Removes “high-frequency” components from the image (low-pass filter)
- Convolution with self is another Gaussian



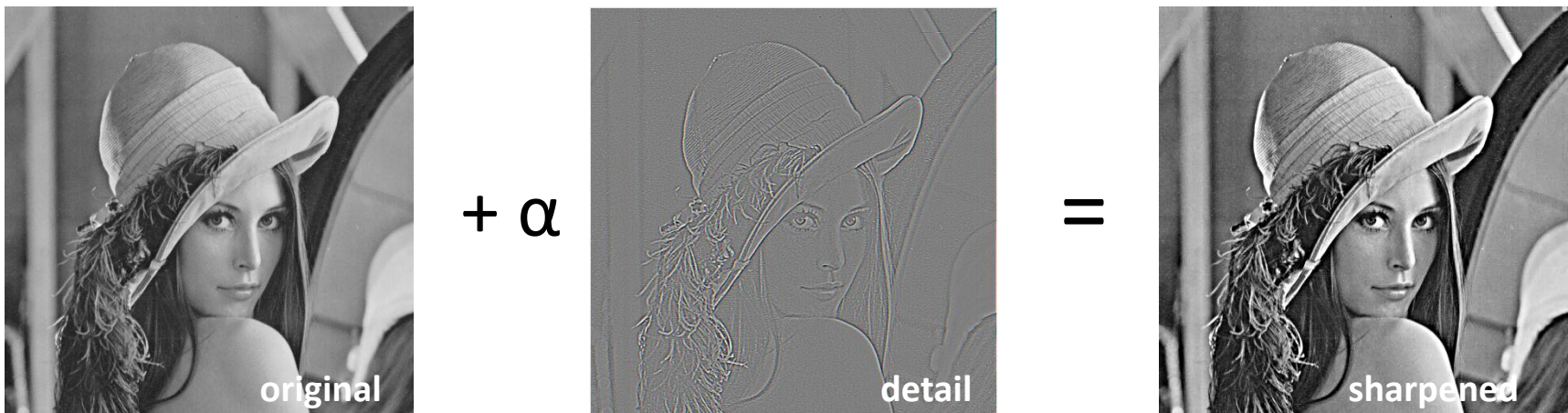
- Convoluting two times with Gaussian kernel of width σ = convoluting once with kernel of width $\sigma\sqrt{2}$

Sharpening revisited

- What does blurring take away?



Let's add it back:

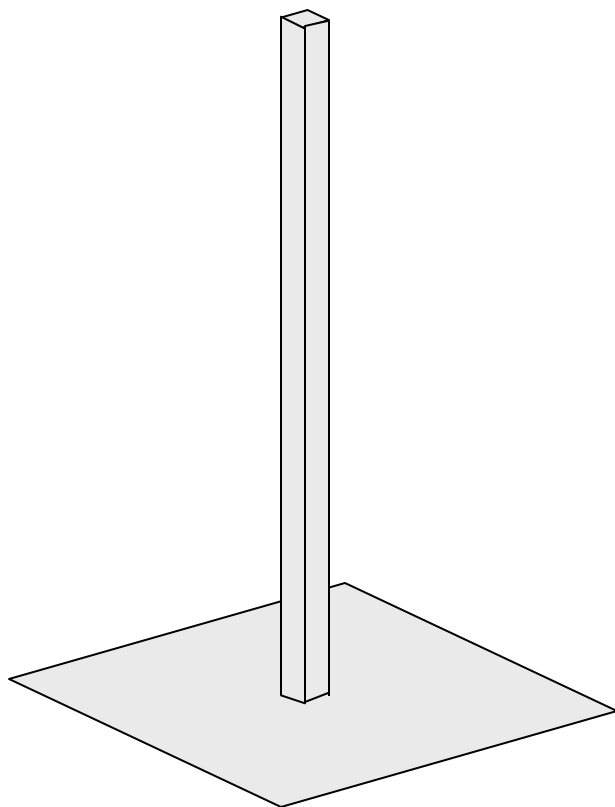


Sharpen filter

$$F + \alpha (F - \underbrace{F * H}_{\text{blurred image}})$$

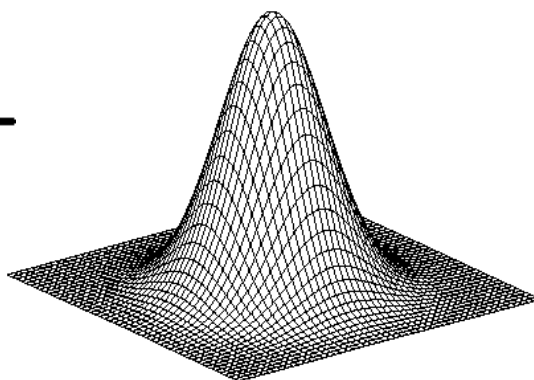
↑ image

↑
unit impulse
(identity)



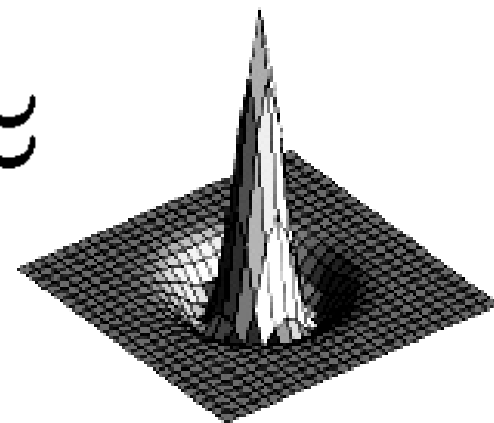
scaled impulse

−



Gaussian

≈



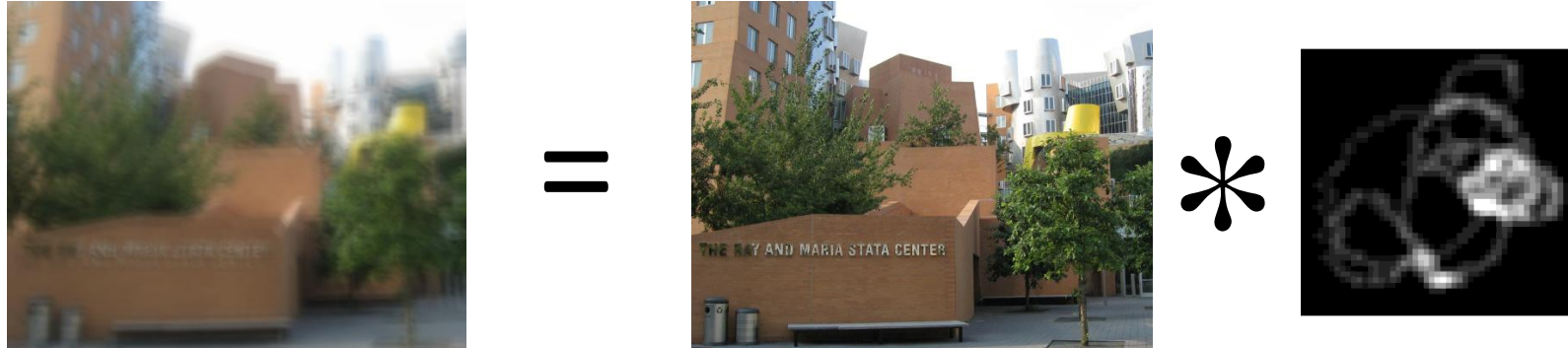
Laplacian of Gaussian

Sharpen filter



Convolution in the real world

Camera shake



Source: Fergus, *et al.* "Removing Camera Shake from a Single Photograph", SIGGRAPH 2006

Bokeh: Blur in out-of-focus regions of an image.



Source: <http://lullaby.homepage.dk/diy-camera/bokeh.html>

Questions?

- For next time:
 - Read Szeliski, Chapter 3.1-3.2