Computer Vision – Lecture 4

Gradients & Edges

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Bastian Leibe
RWTH Aachen
http://www.vision.rwth-aachen.de

leibe@vision.rwth-aachen.de

Announcements

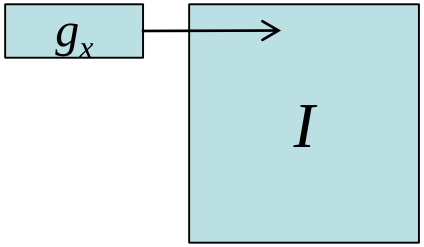
- Exercise sheet 2 is available
  - Thresholding, Morphology
  - Gaussian smoothing
  - Image gradients
  - Edge Detection

  ⇒ *Deadline: Sunday night, 13.11. (in two weeks).*
- Reminder
  - You're encouraged to form teams of up to 3 people!
  - Hints:
    - Turn in everything as a single zip archive.
    - Use the provided Matlab framework.
    - For each exercise, you need to implement the corresponding `apply` function. If the screen output matches the expected output (shown in class), you will know that your solution is correct.
    - Matlab helps you to find errors (red lines under your code)!

Course Outline

- Image Processing Basics
  - Image Formation
  - Binary Image Processing
  - Linear Filters
  - Edge & Structure Extraction
- Segmentation
- Local Features & Matching
- Object Recognition and Categorization
- 3D Reconstruction
- Motion and Tracking

Topics of This Lecture

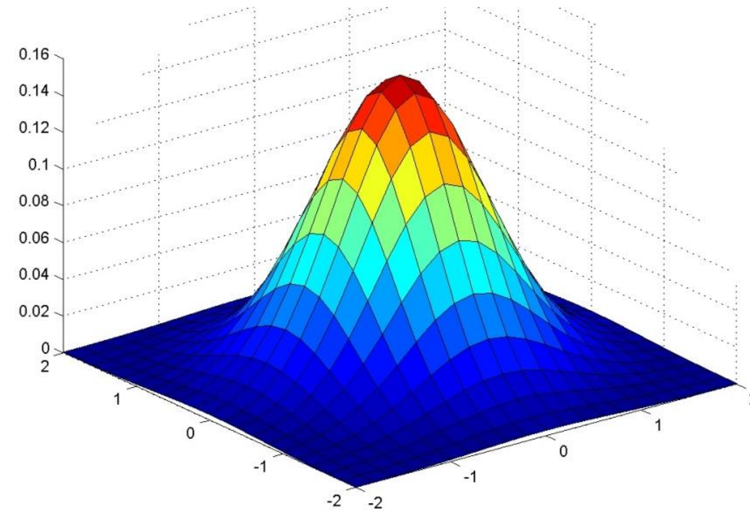


- Recap: Linear Filters
- Multi-Scale representations
  - How to properly rescale an image?
- Filters as templates
  - Correlation as template matching
- Image gradients
  - Derivatives of Gaussian
- Edge detection
  - Canny edge detector

Recap: Gaussian Smoothing

- Gaussian kernel

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



- Rotationally symmetric
- Weights nearby pixels more than distant ones
  - This makes sense as ‘probabilistic’ inference about the signal

- A Gaussian gives a good model of a fuzzy blob

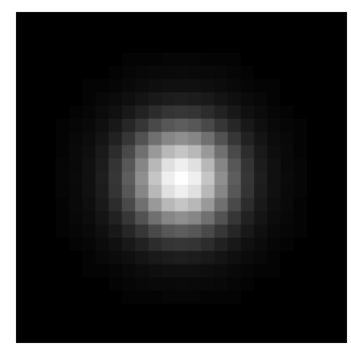
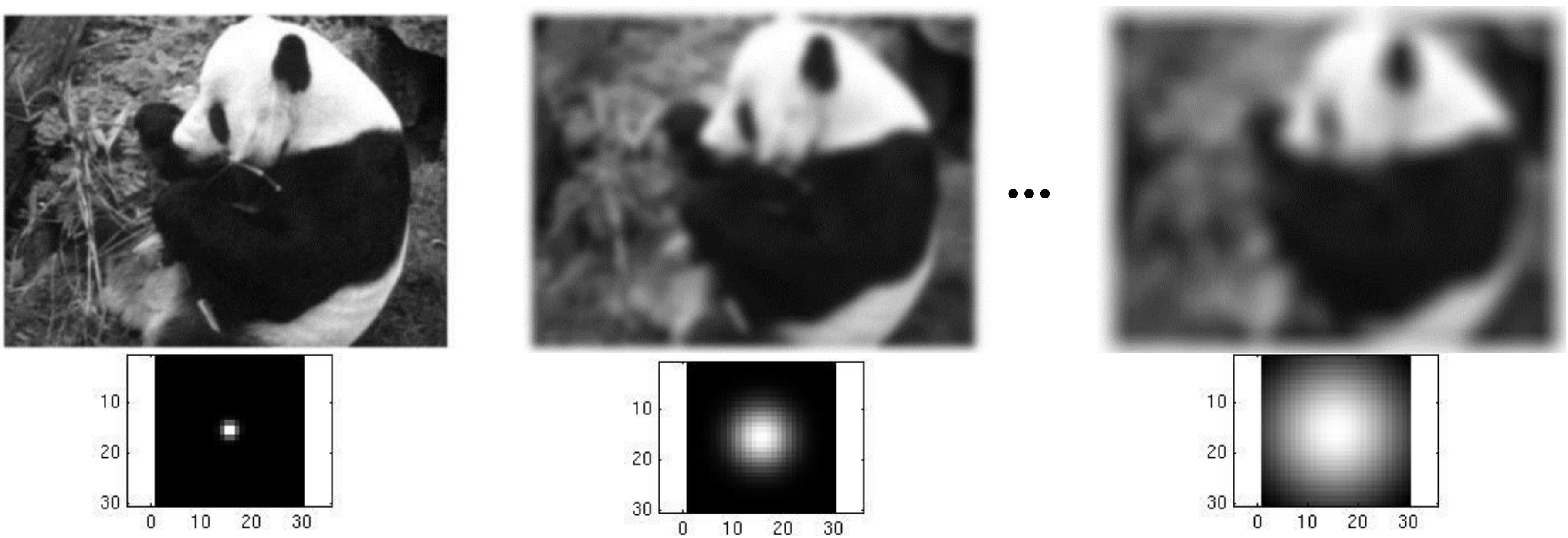


Image Source: Forsyth & Ponce

Recap: Smoothing with a Gaussian

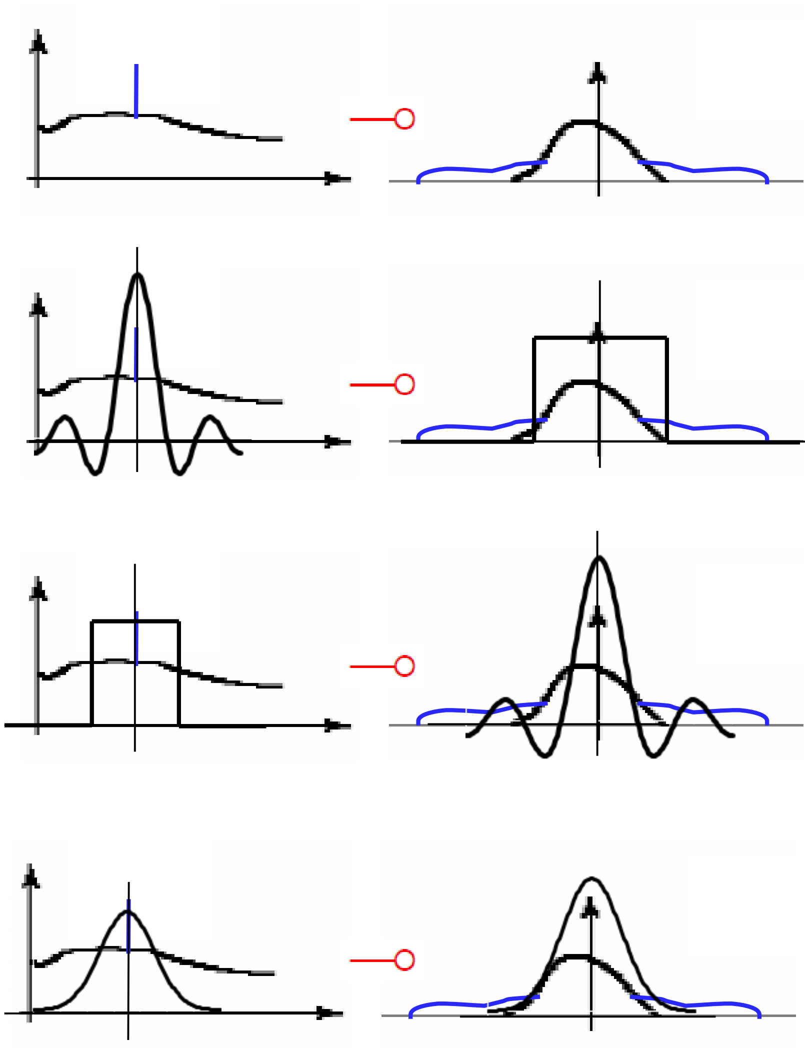
- Parameter σ is the "scale" / "width" / "spread" of the Gaussian kernel and controls the amount of smoothing.



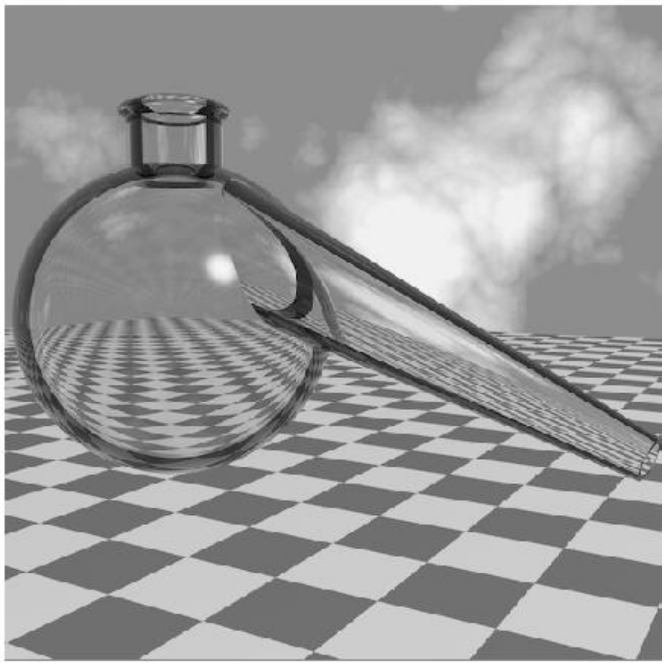

```
for sigma=1:3:10
   h = fspecial('gaussian', fsize, sigma);
   out = imfilter(im, h);
   imshow(out);
   pause;
end
```

Recap: Effect of Filtering

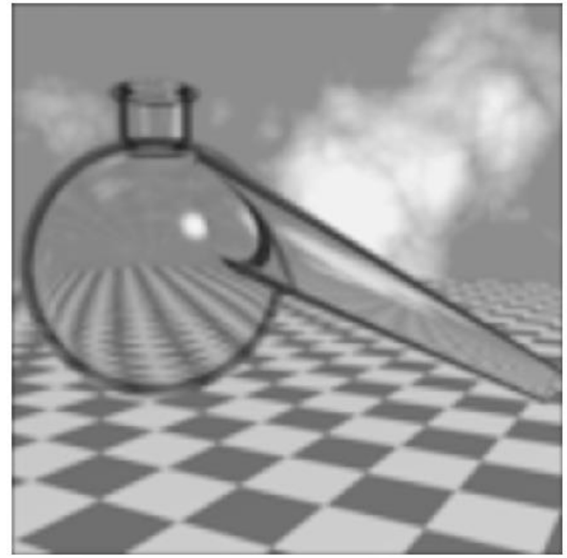
- Noise introduces high frequencies. To remove them, we want to apply a "low-pass" filter.
- The ideal filter shape in the frequency domain would be a box. But this transfers to a spatial sinc, which has infinite spatial support.
- A compact spatial box filter transfers to a frequency sinc, which creates artifacts.
- A Gaussian has compact support in both domains. This makes it a convenient choice for a low-pass filter.



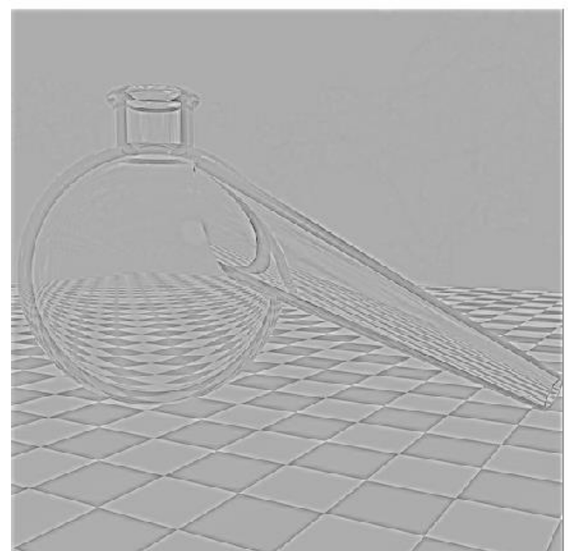
Recap: Low-Pass vs. High-Pass



Original image



Low-pass filtered



High-pass filtered

Image Source: S. Chenney

Topics of This Lecture

- Recap: Linear Filters
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Motivation: Fast Search Across Scales

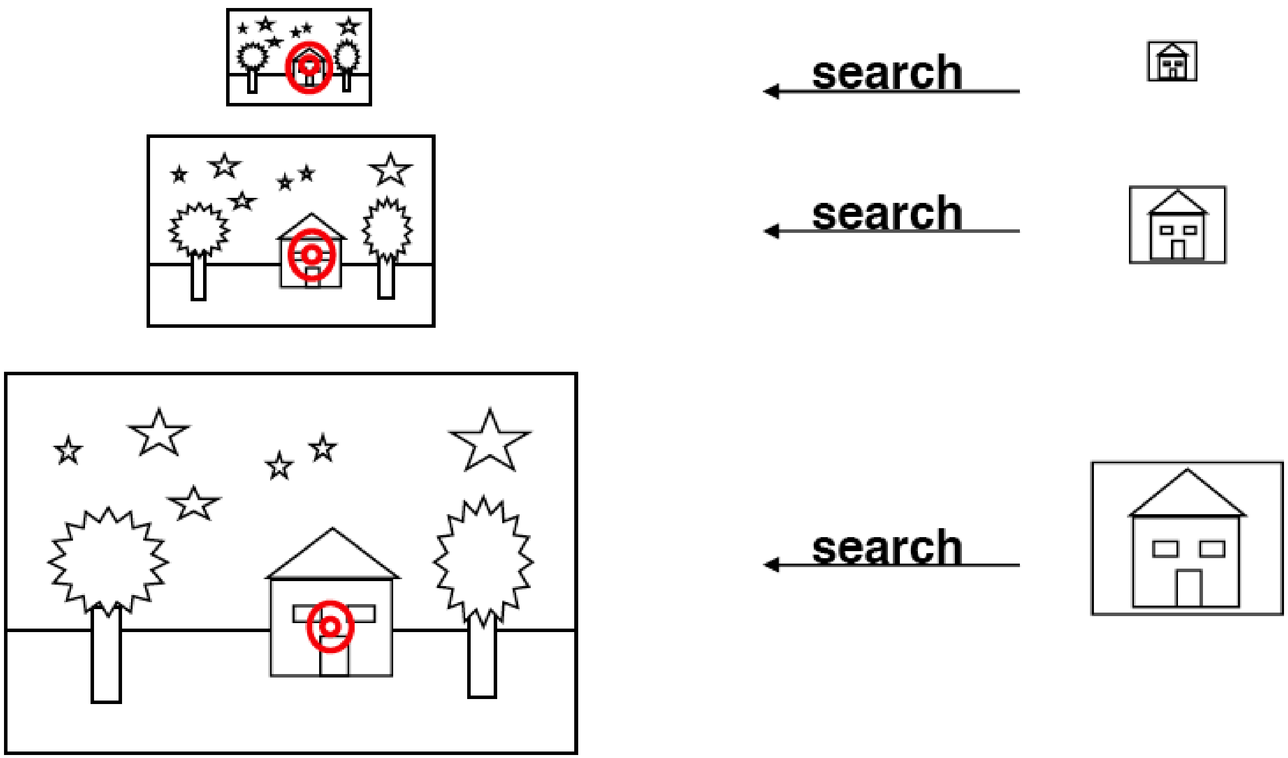


Image Source: Irani & Basri

Recap: Sampling and Aliasing

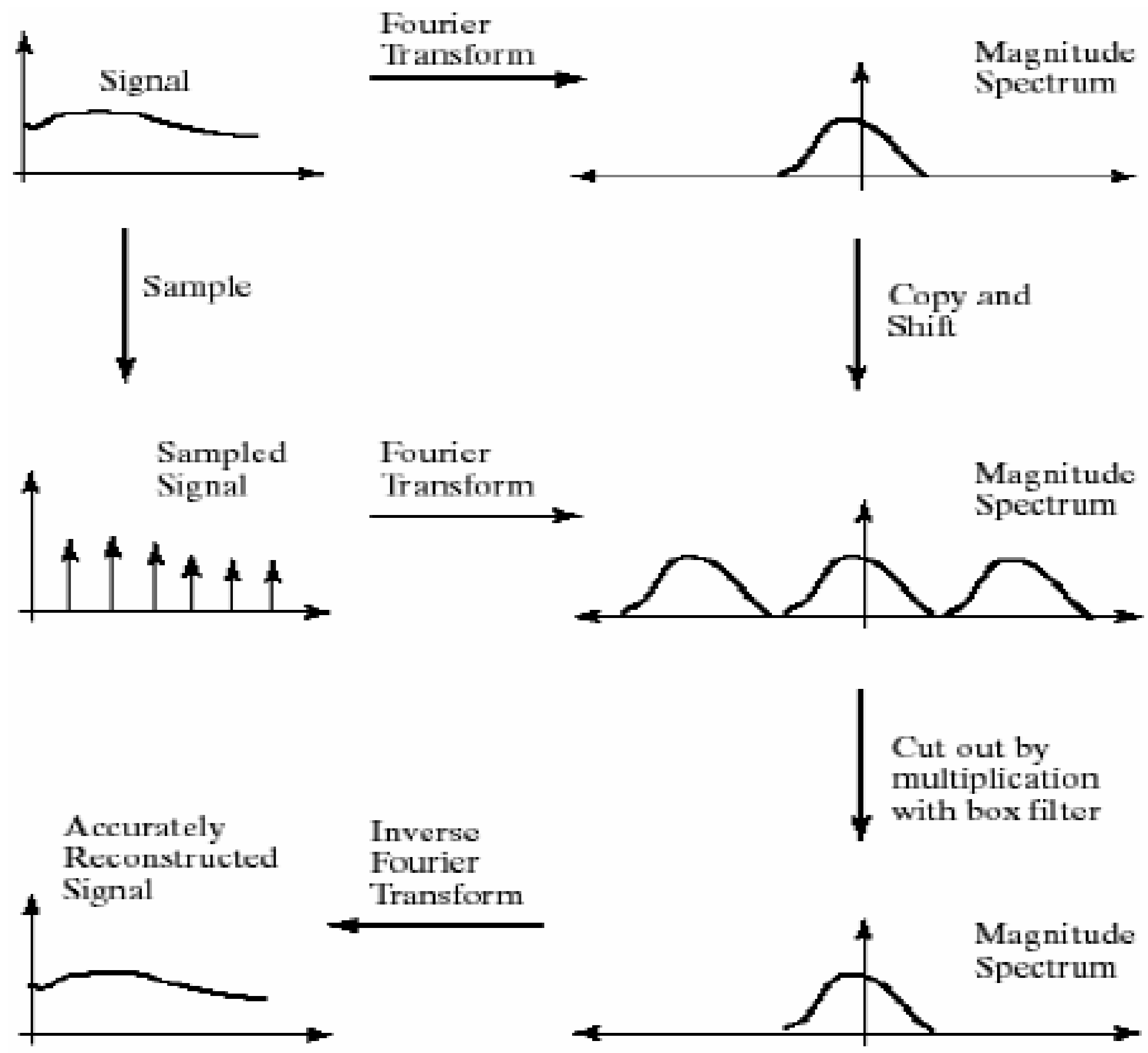


Image Source: Forsyth & Ponce

Recap: Sampling and Aliasing

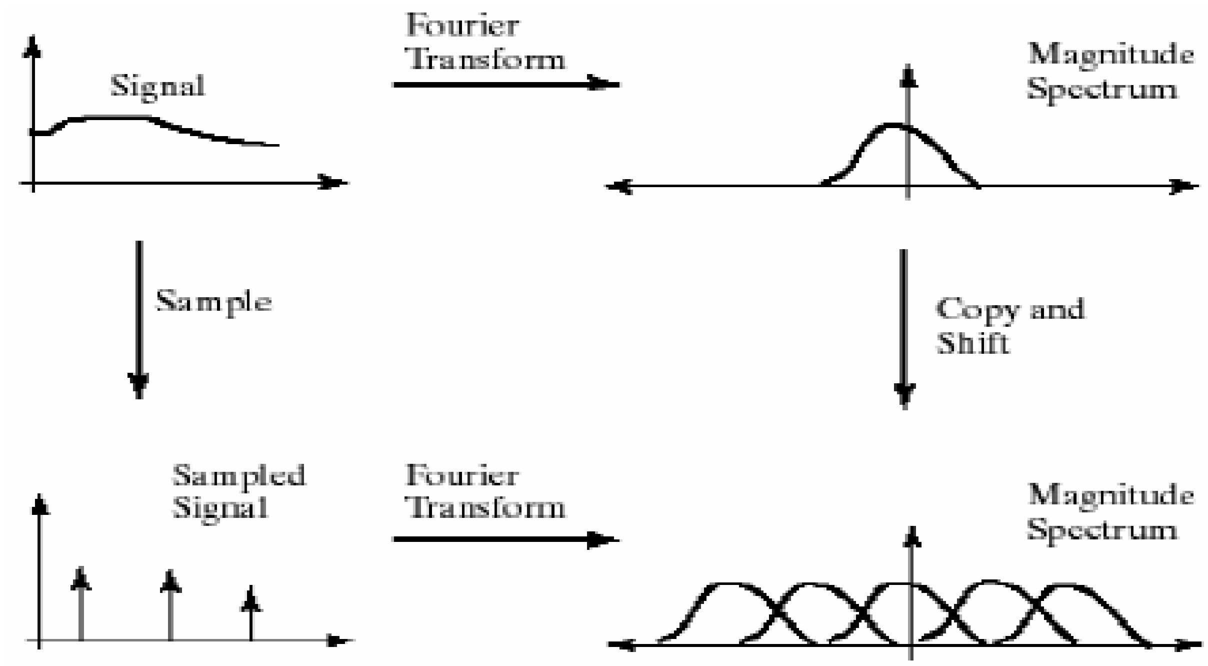


Image Source: Forsyth & Ponce

Recap: Sampling and Aliasing

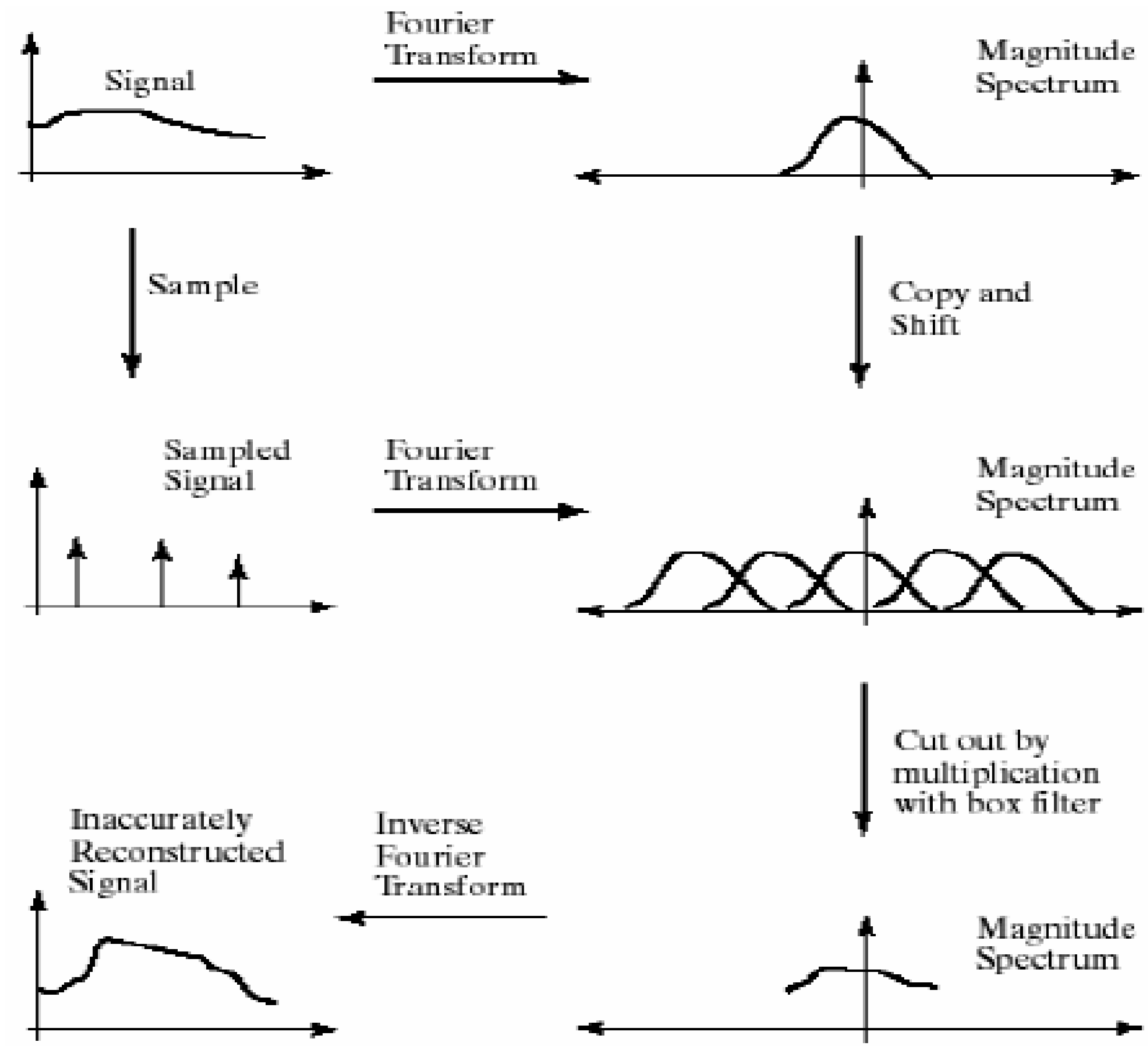
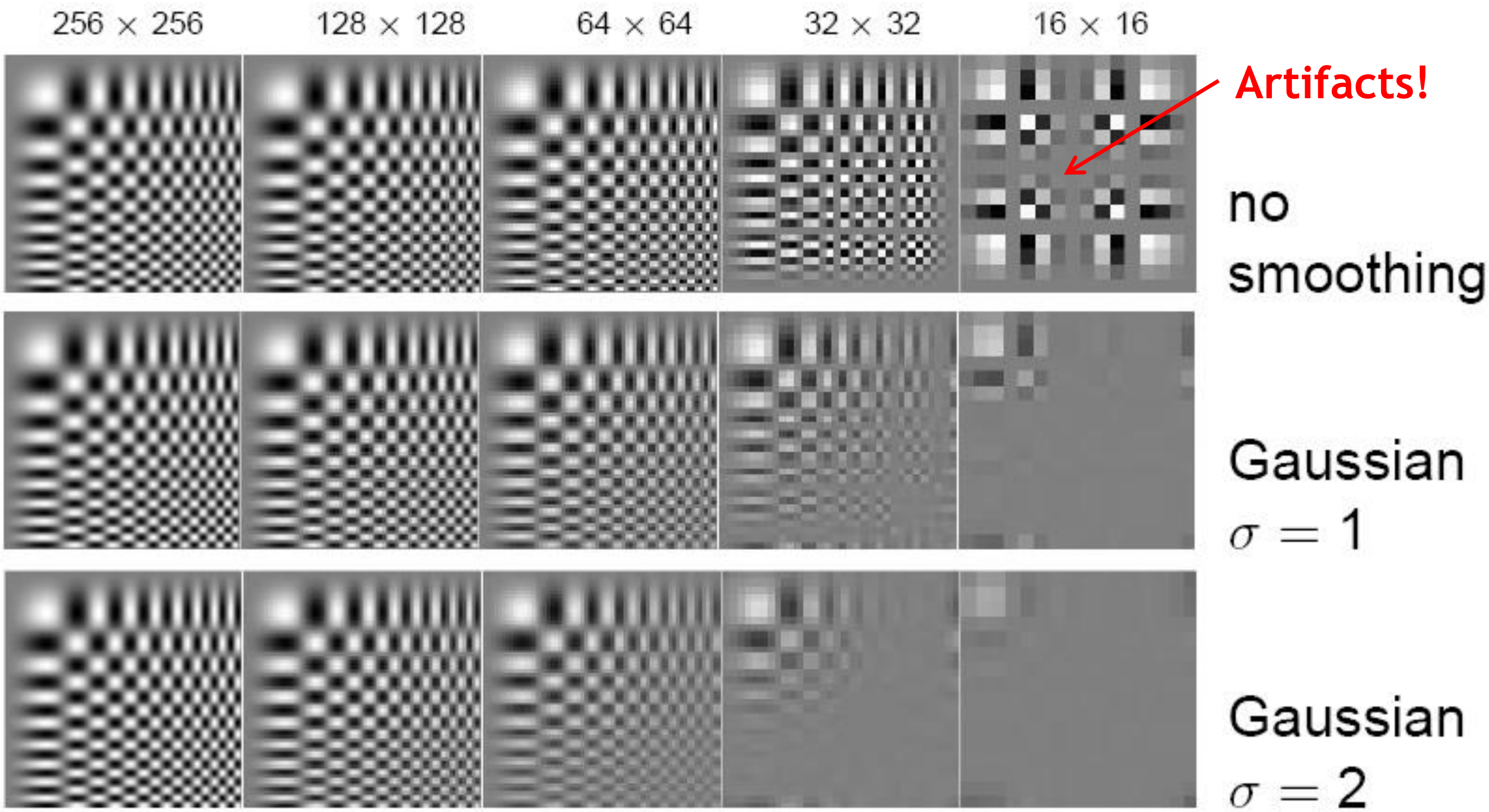


Image Source: Forsyth & Ponce

Recap: Resampling with Prior Smoothing

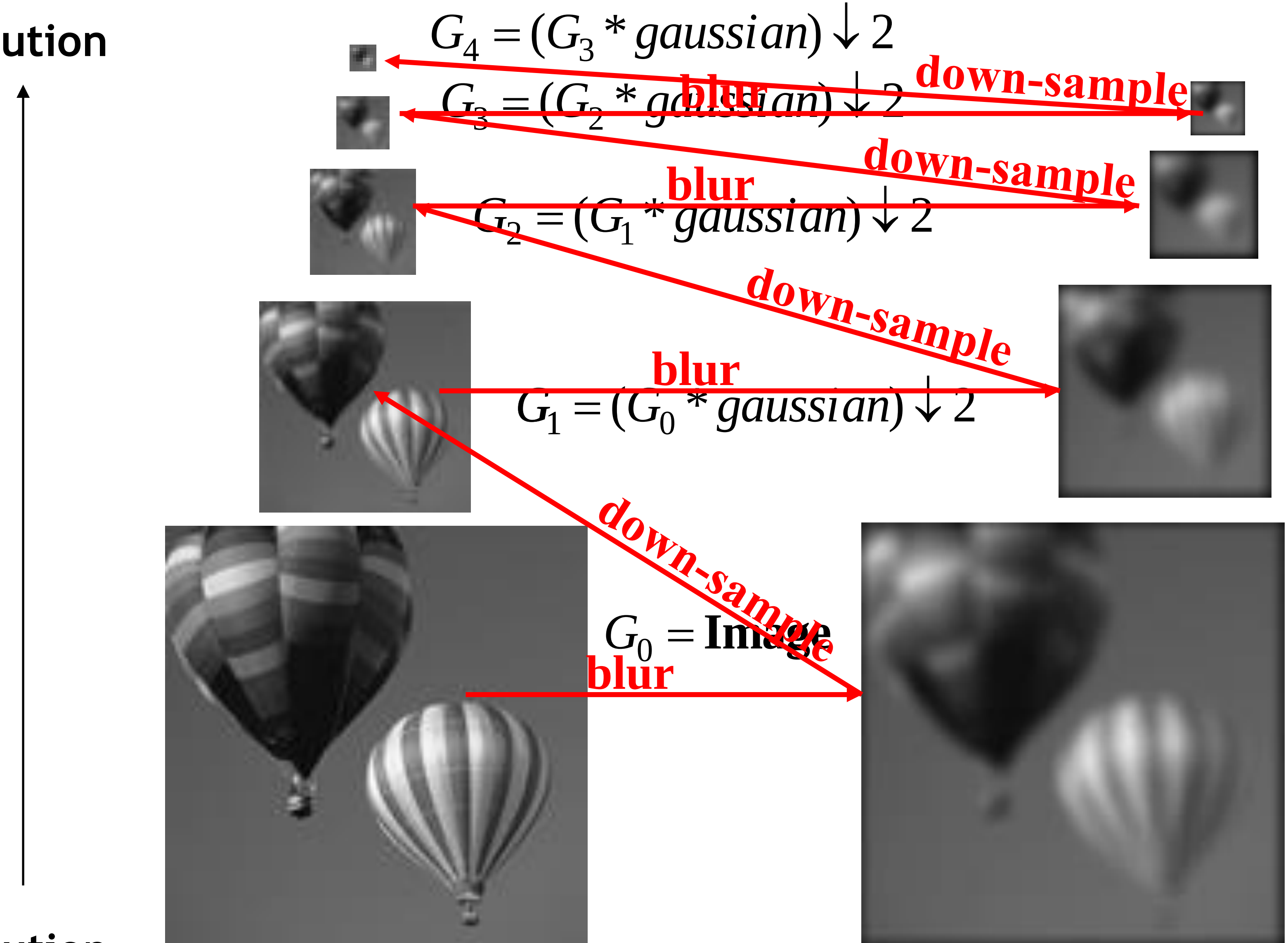


- **Note: We cannot recover the high frequencies, but we can avoid artifacts by smoothing before resampling.**

Image Source: Forsyth & Ponce

The Gaussian Pyramid

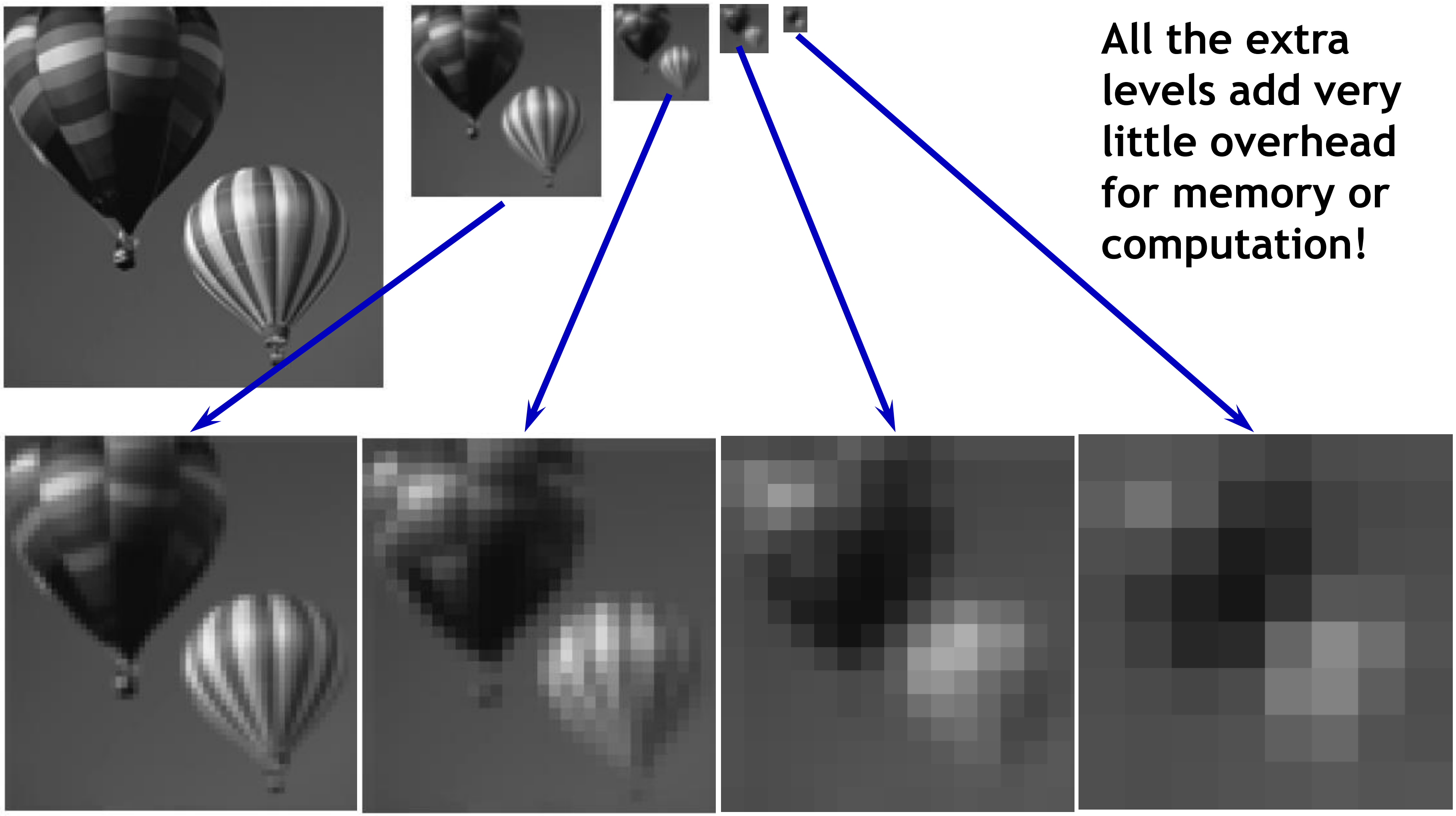
Low resolution



High resolution

Source: Irani & Basri

Gaussian Pyramid – Stored Information



All the extra levels add very little overhead for memory or computation!

Source: Irani & Basri

Summary: Gaussian Pyramid

- Construction: create each level from previous one
  - Smooth and sample
- Smooth with Gaussians, in part because
  - a Gaussian*Gaussian = another Gaussian
  - $G(\sigma_1) * G(\sigma_2) = G(\text{sqrt}(\sigma_1^{\,2} + \sigma_2^{\,2}))$
- Gaussians are low-pass filters, so the representation is redundant once smoothing has been performed.

  $\Rightarrow$ There is no need to store smoothed images at the full original resolution.

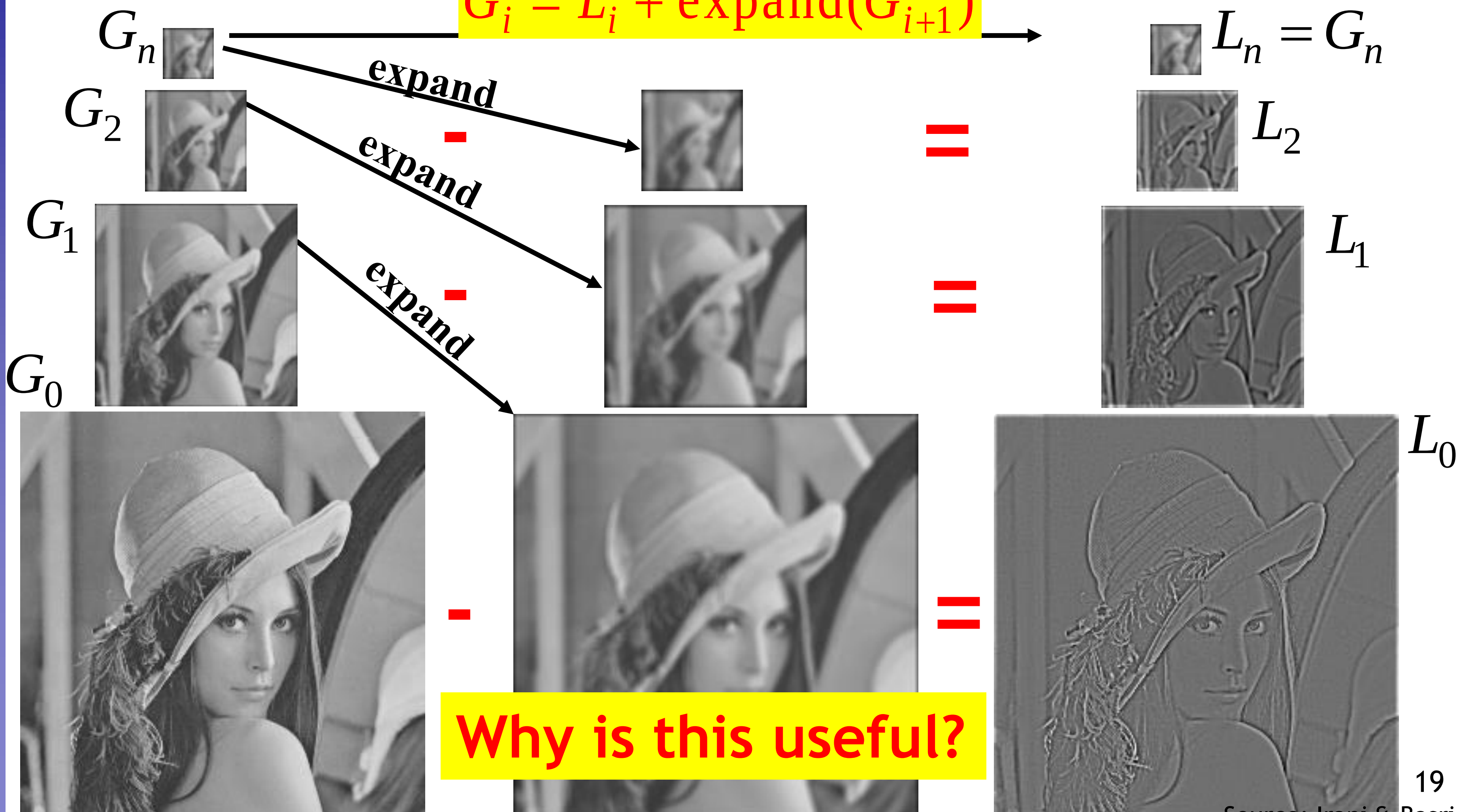
The Laplacian Pyramid

$$L_i = G_i - \text{expand}(G_{i+1})$$

$$G_i = L_i + \text{expand}(G_{i+1})$$

Gaussian Pyramid

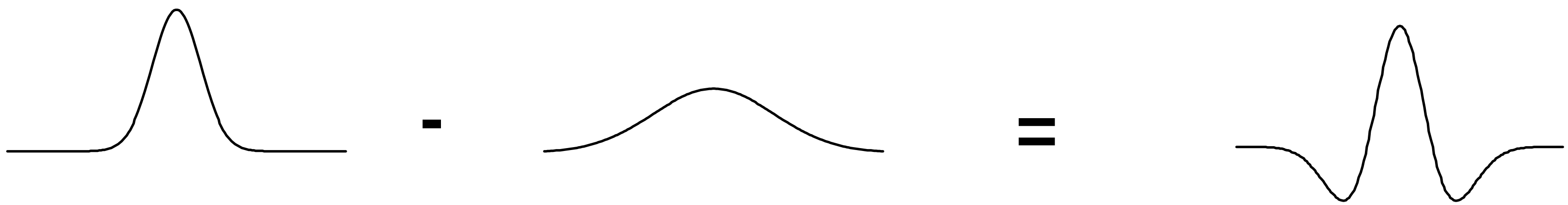
Laplacian Pyramid

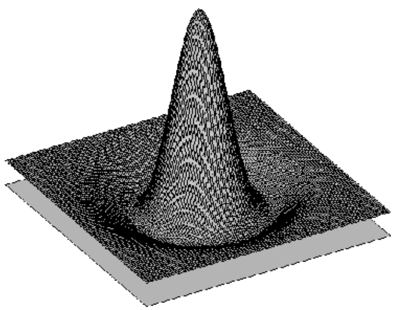


Why is this useful?

Source: Irani & Basri

Laplacian ~ Difference of Gaussian





DoG = Difference of Gaussians

Cheap approximation - no derivatives needed.

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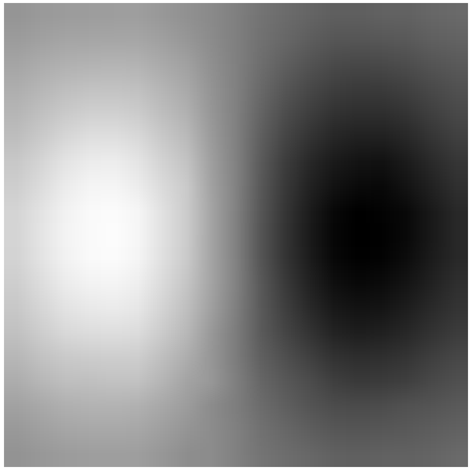
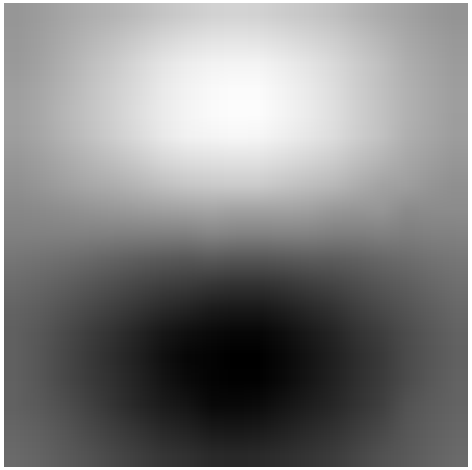
Note: Filters are Templates

- Applying a filter at some point can be seen as taking a dot-product between the image and some vector.
- Filtering the image is a set of dot products.

- Insight
  - Filters look like the effects they are intended to find.
  - Filters find effects they look like.





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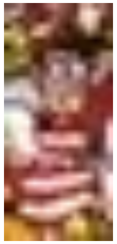
Where's Waldo?

Scene



Template

Slide credit: Kristen Grauman

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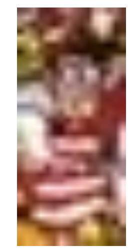
Where's Waldo?

Detected template

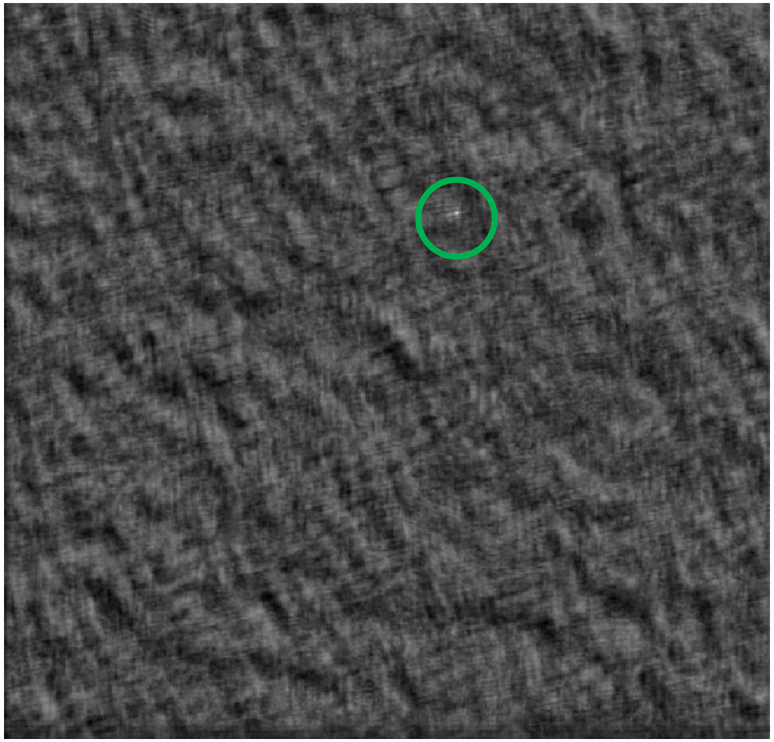


Template

Slide credit: Kristen Grauman

Where's Waldo?

Detected template



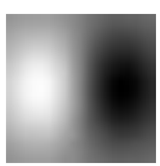
Correlation map

Correlation as Template Matching

- **Think of filters as a dot product of the filter vector with the image region**
  - **Now measure the angle between the vectors**

$$a \cdot b = |a||b| \cos\theta \qquad \cos\theta = \frac{a \cdot b}{|a||b|}$$

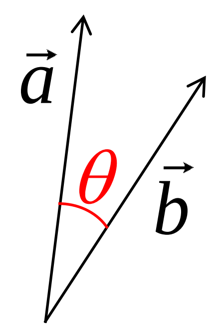
  - **Angle (similarity) between vectors can be measured by normalizing the length of each vector to 1 and taking the dot product.**



Template

·

Image region



Vector interpretation

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- Recap: Linear Filters
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- **Image gradients**
  - **Derivatives of Gaussian**
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  - Canny edge detector

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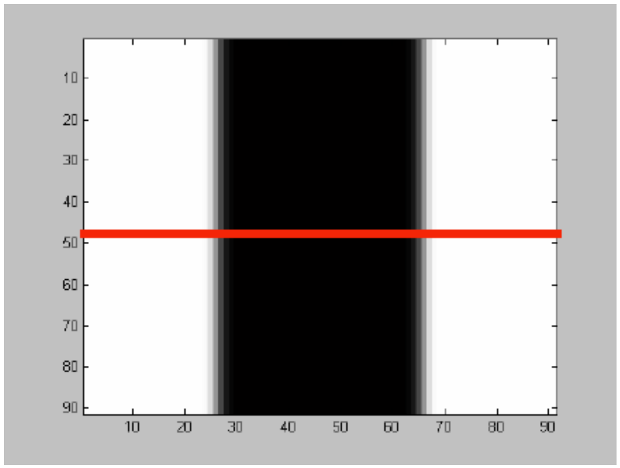
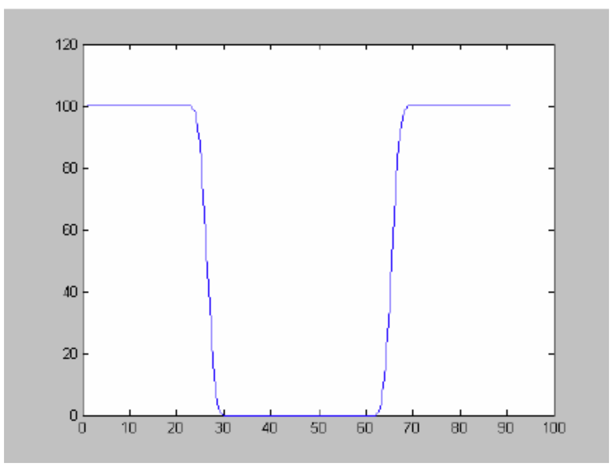
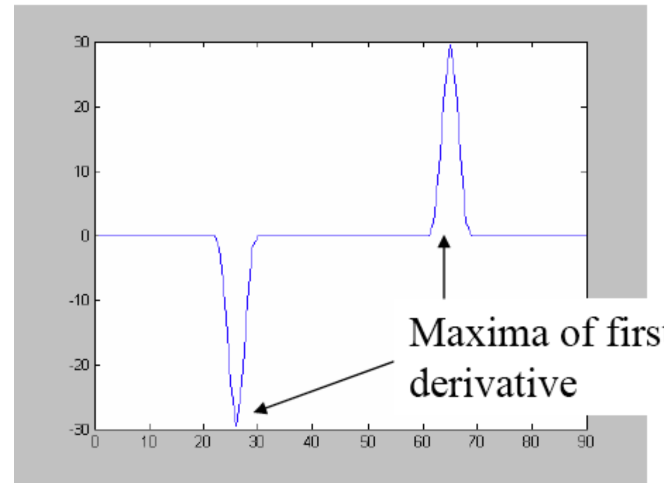
Derivatives and Edges…

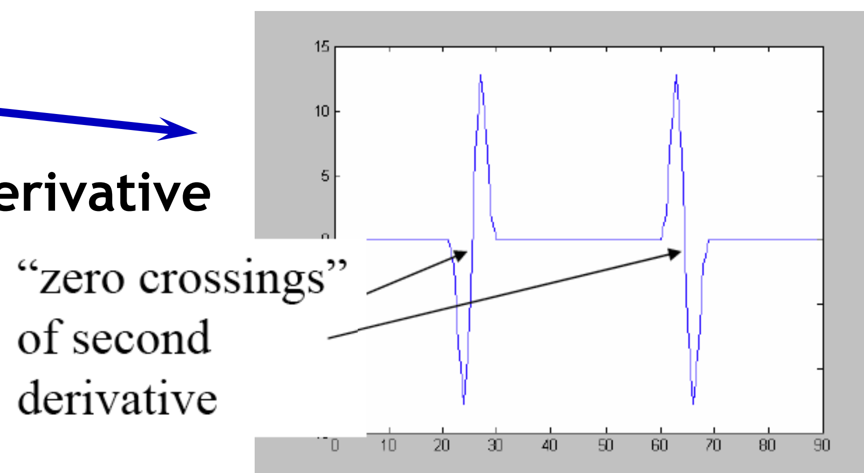




1st derivative



2nd derivative



Differentiation and Convolution

- For the 2D function $f(x,y)$, the partial derivative is:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon, y) - f(x,y)}{\varepsilon}$$

- For discrete data, we can approximate this using finite differences:

$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1, y) - f(x,y)}{1}$$

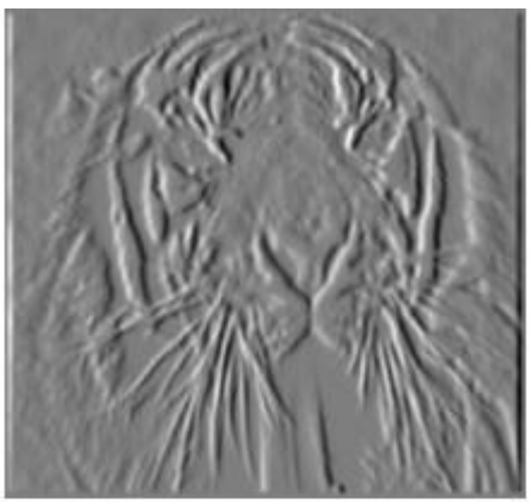
- To implement the above as convolution, what would be the associated filter?

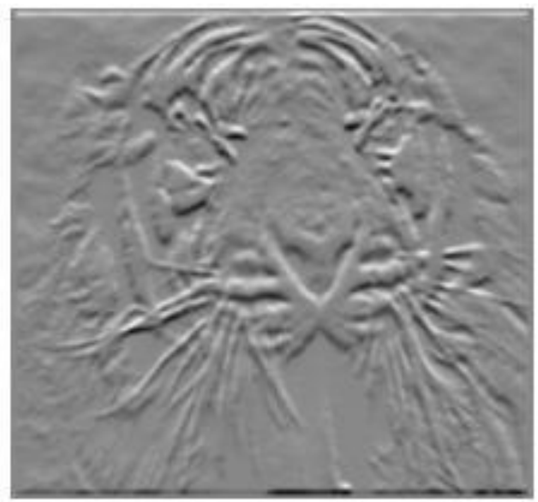
1	-1

Partial Derivatives of an Image

$$\frac{\partial f(x,y)}{\partial x}$$

-1	1





$$\frac{\partial f(x,y)}{\partial y}$$

-1
1

? or

1
-1

Which shows changes with respect to x?

Assorted Finite Difference Filters

Prewitt: $M_x =$

-1	0	1
-1	0	1
-1	0	1

; $M_y =$

1	1	1
0	0	0
-1	-1	-1

Sobel: $M_x =$

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

; $M_y =$

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

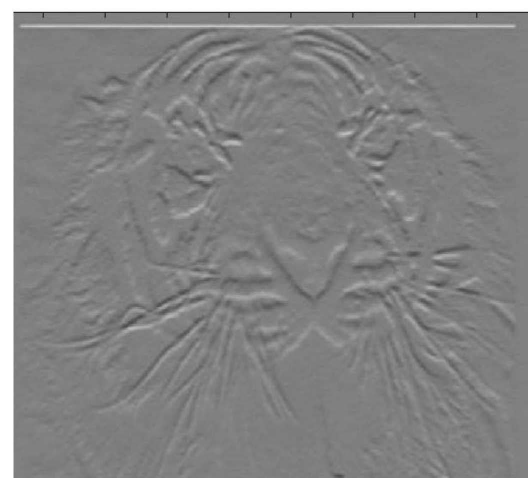
Roberts: $M_x =$

0	1
-1	0

; $M_y =$

1	0
0	-1

```
>> My = fspecial('sobel');
>> outim = imfilter(double(im), My);
>> imagesc(outim);
>> colormap gray;
```



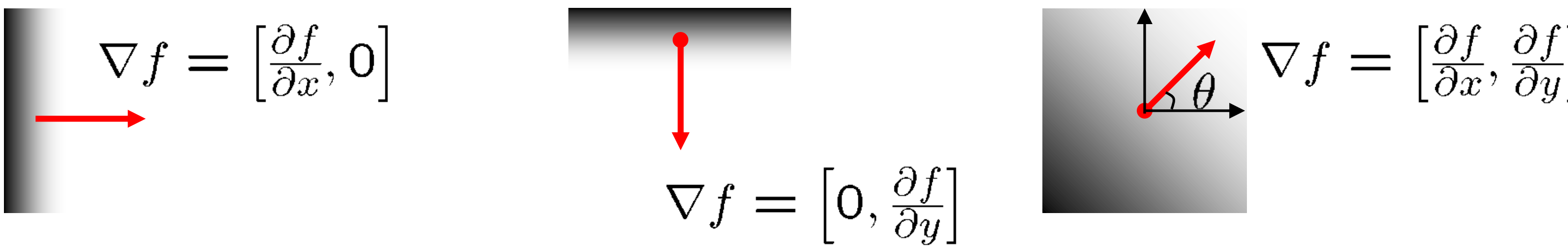
Slide credit: Kristen Grauman

Image Gradient

- **The gradient of an image:**

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

- **The gradient points in the direction of most rapid intensity change**



- **The gradient direction (orientation of edge normal) is given by:**

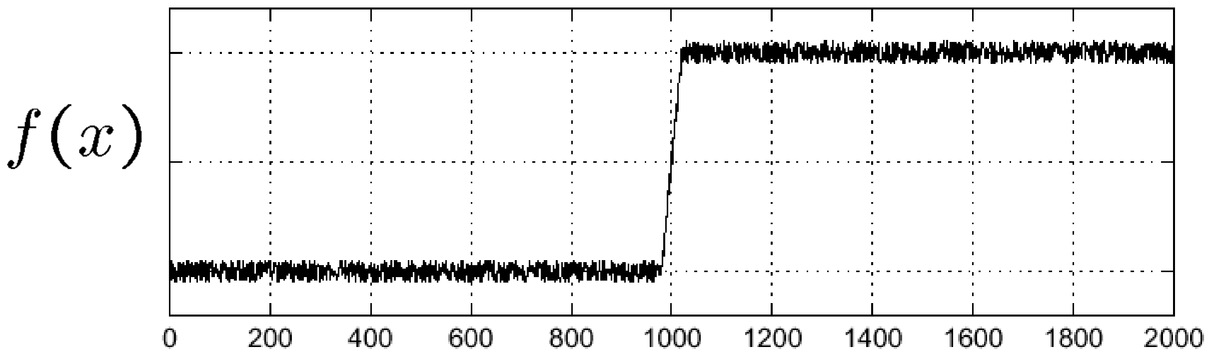
$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

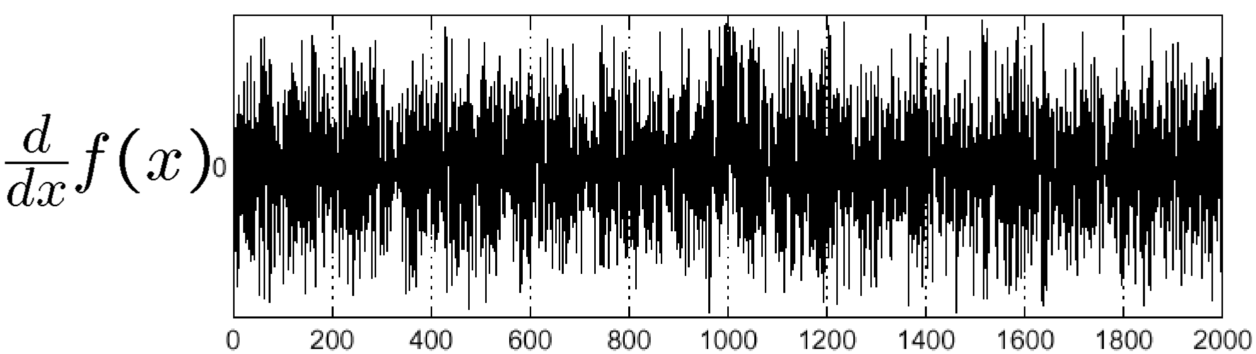
- **The edge strength is given by the gradient magnitude**

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Effect of Noise

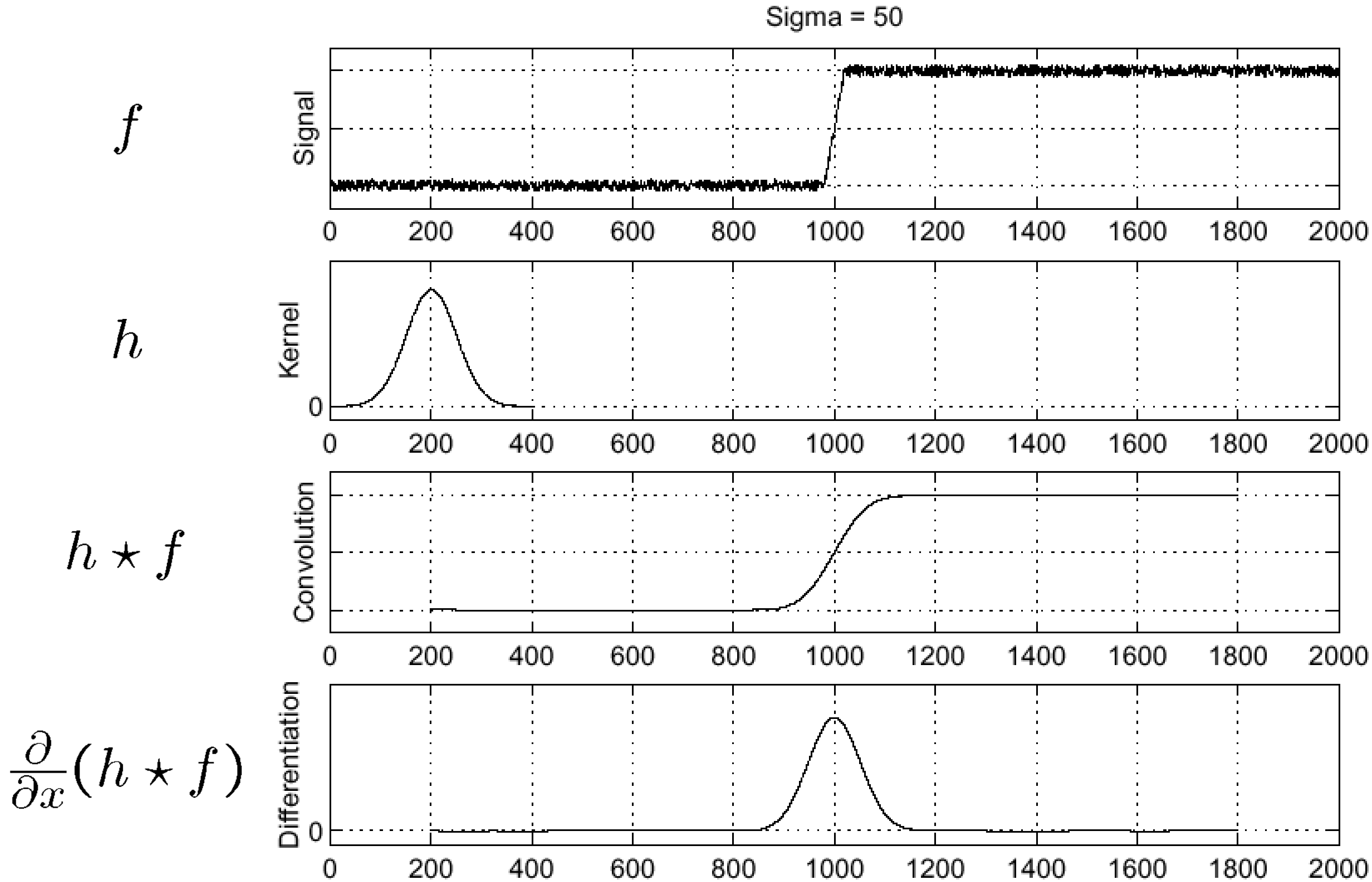
- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal





Where is the edge?

Solution: Smooth First



Where is the edge? **Look for peaks in** $\frac{\partial}{\partial x}(h \star f)$

Slide credit: Steve Seitz

Derivative Theorem of Convolution

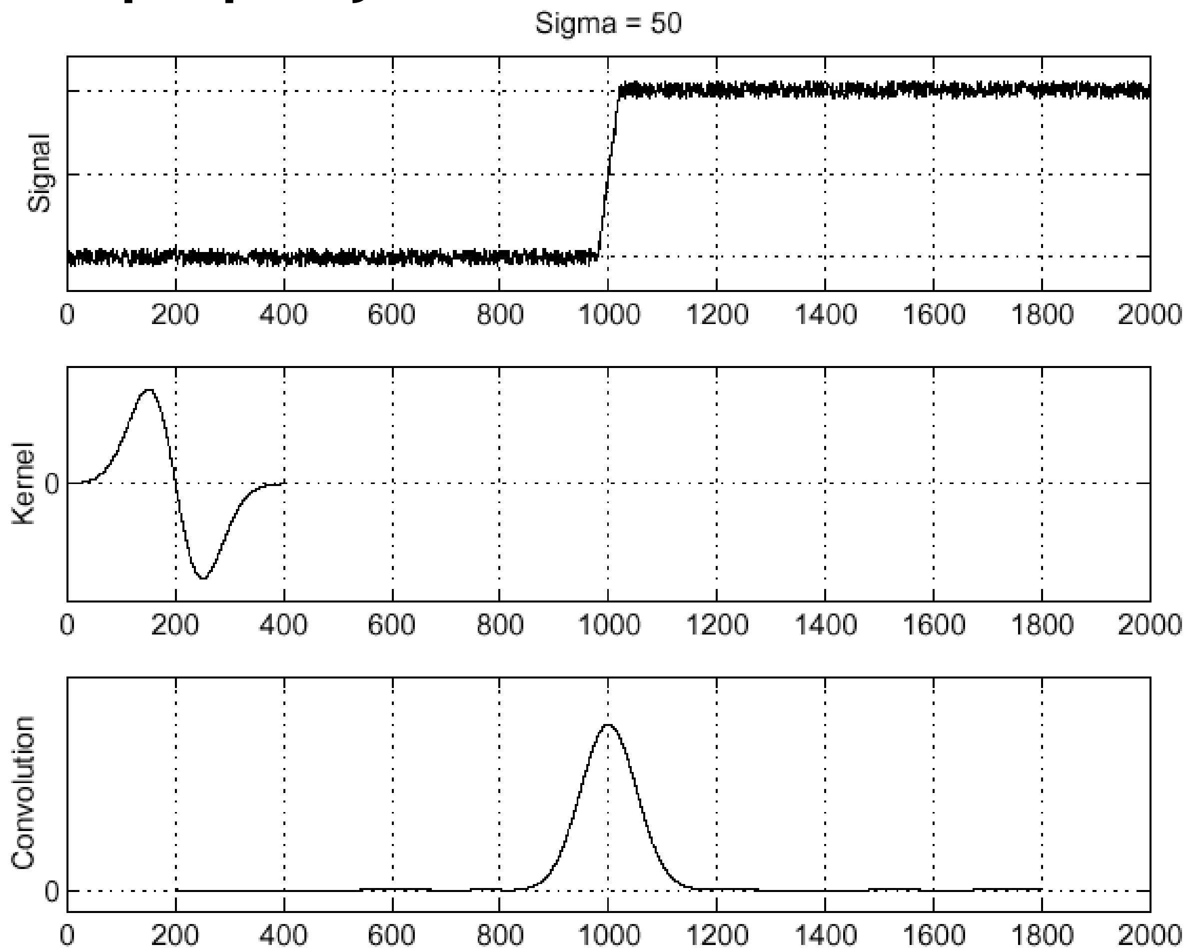
$$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$$

- **Differentiation property of convolution.**

f

$\frac{\partial}{\partial x}h$

$(\frac{\partial}{\partial x}h) \star f$



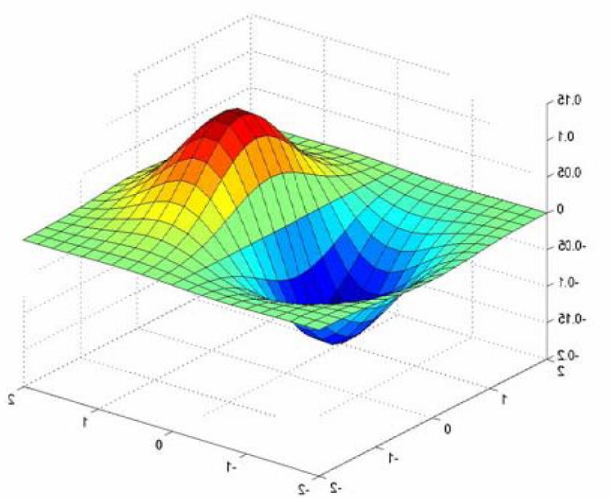
Derivative of Gaussian Filter

$$g * (h * I) = (g * h) * I$$

$$\begin{bmatrix} 1 & -1 \end{bmatrix} * \begin{bmatrix} 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0219 & 0.0983 & 0.1621 & 0.0983 & 0.0219 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \end{bmatrix}$$

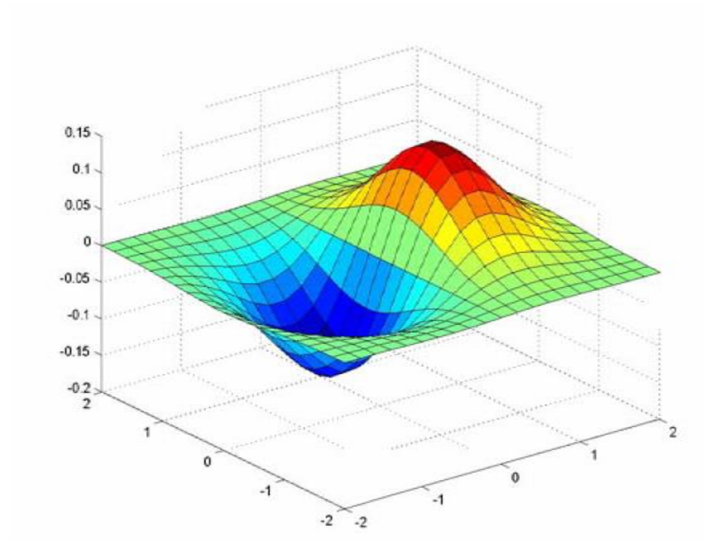
0.0030	0.0133	0.0219	0.0133	0.0030
0.0133	0.0596	0.0983	0.0596	0.0133
0.0219	0.0983	0.1621	0.0983	0.0219
0.0133	0.0596	0.0983	0.0596	0.0133
0.0030	0.0133	0.0219	0.0133	0.0030

Why is this preferable?

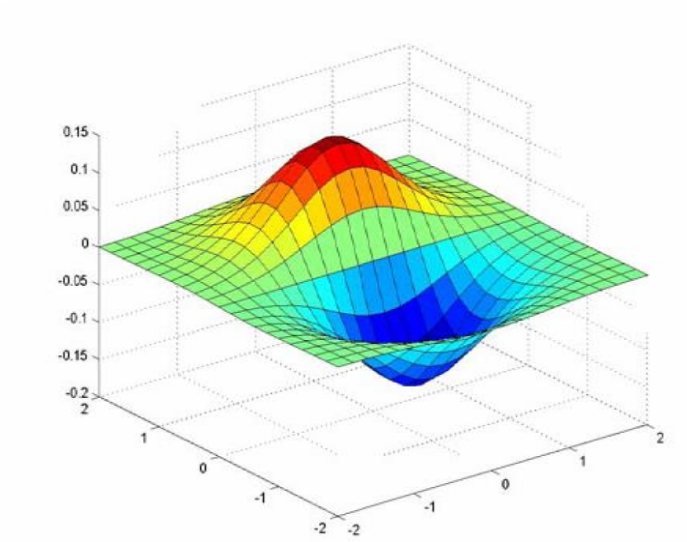


Slide adapted from Kristen Grauman

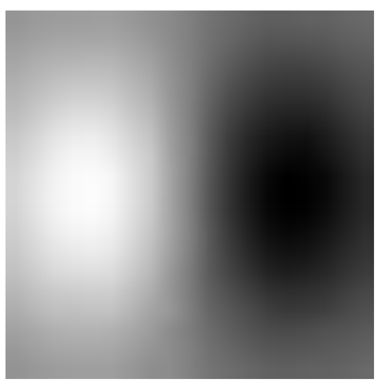
Derivative of Gaussian Filters

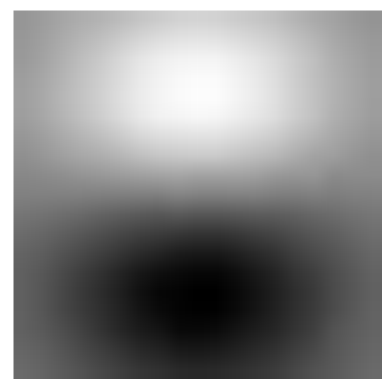


x-direction



y-direction





Source: Svetlana Lazebnik

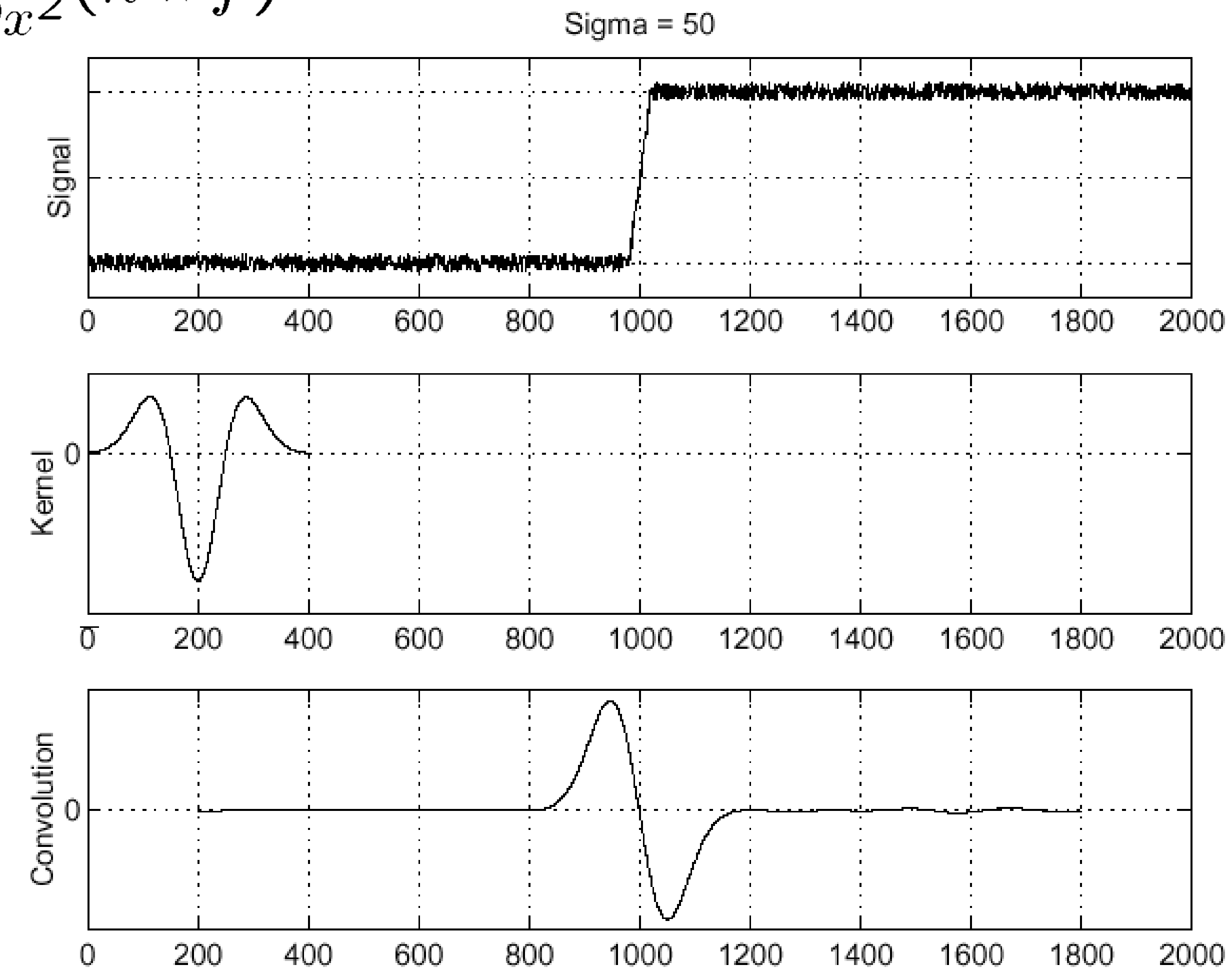
Laplacian of Gaussian (LoG)

- **Consider** $\frac{\partial^2}{\partial x^2}(h \star f)$

f

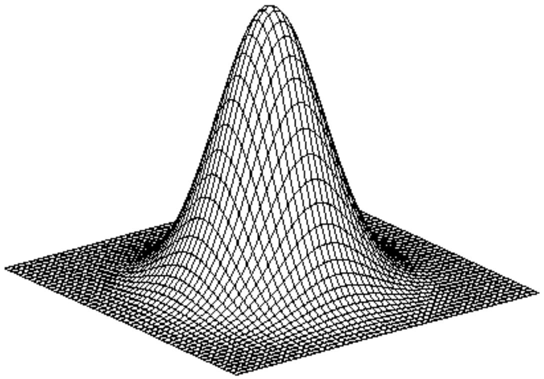
$\frac{\partial^2}{\partial x^2}h$

$(\frac{\partial^2}{\partial x^2}h) \star f$



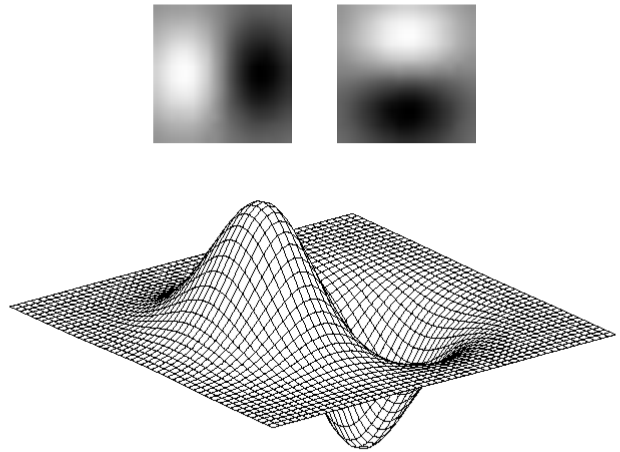
Where is the edge? **Zero-crossings of bottom graph**

Summary: 2D Edge Detection Filters



Gaussian

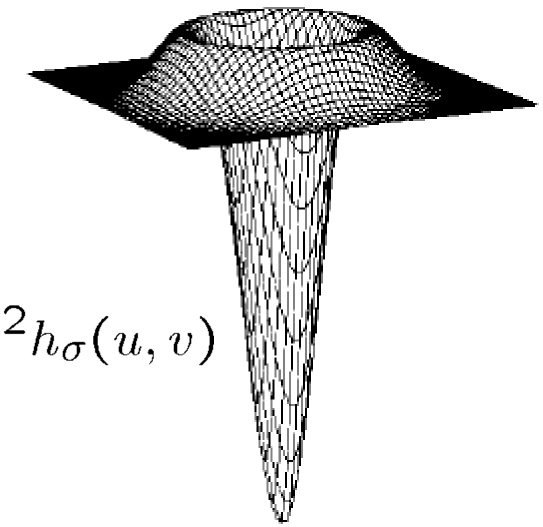
$$h_\sigma(u,v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



Derivative of Gaussian

$$\frac{\partial}{\partial x} h_\sigma(u,v)$$

Laplacian of Gaussian



$$\nabla^2 h_\sigma(u,v)$$

- ∇^2 **is the Laplacian operator:**

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

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- **Edge detection**
  - **Canny edge detector**

Edge Detection

- Goal: map image from 2D array of pixels to a set of curves or line segments or contours.
- Why?

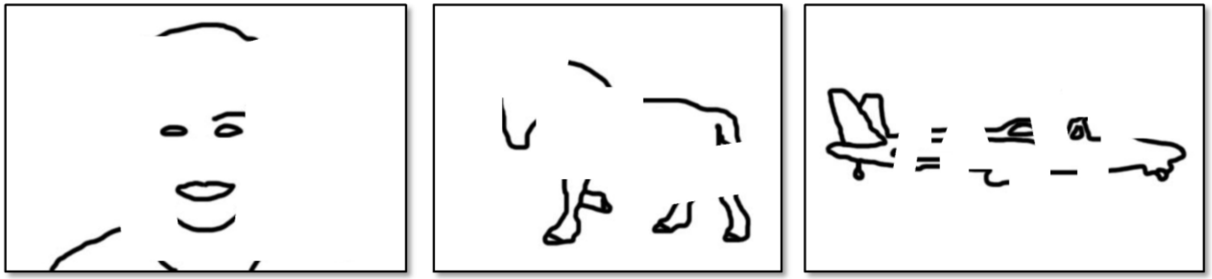
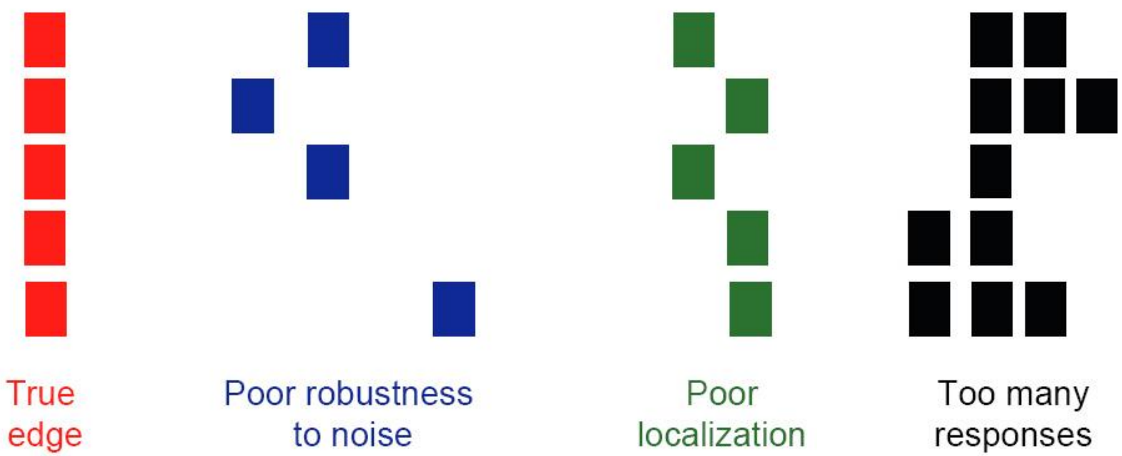


Figure from J. Shotton et al., PAMI 2007

- Main idea: look for strong gradients, post-process

Designing an Edge Detector

- Criteria for an "optimal" edge detector:
  - **Good detection**: the optimal detector should minimize the probability of false positives (detecting spurious edges caused by noise), as well as that of false negatives (missing real edges).
  - **Good localization**: the edges detected should be as close as possible to the true edges.
  - **Single response**: the detector should return one point only for each true edge point; that is, minimize the number of local maxima around the true edge.



Source: Li Fei-Fei

Gradients → Edges

Primary edge detection steps

1. Smoothing: suppress noise
2. Edge enhancement: filter for contrast
3. Edge localization
   - Determine which local maxima from filter output are actually edges vs. noise
   - Thresholding, thinning

- Two issues
  - At what scale do we want to extract structures?
  - How sensitive should the edge extractor be?

Scale: Effect of σ on Derivatives

σ = 1 pixel

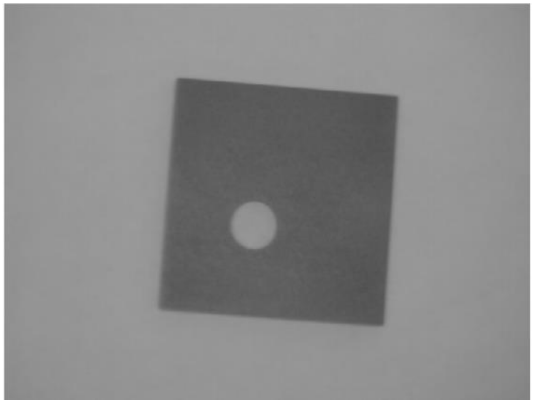
σ = 3 pixels

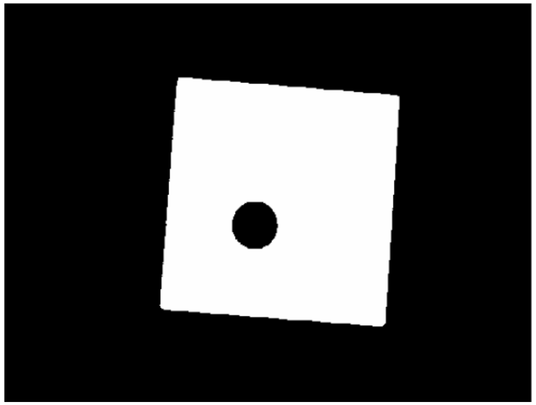
- The apparent structures differ depending on Gaussian's scale parameter.

⇒ Larger values: larger-scale edges detected
⇒ Smaller values: finer features detected

Sensitivity: Recall Thresholding

- Choose a threshold t
- Set any pixels less than t to zero (off).
- Set any pixels greater than or equal t to one (on).



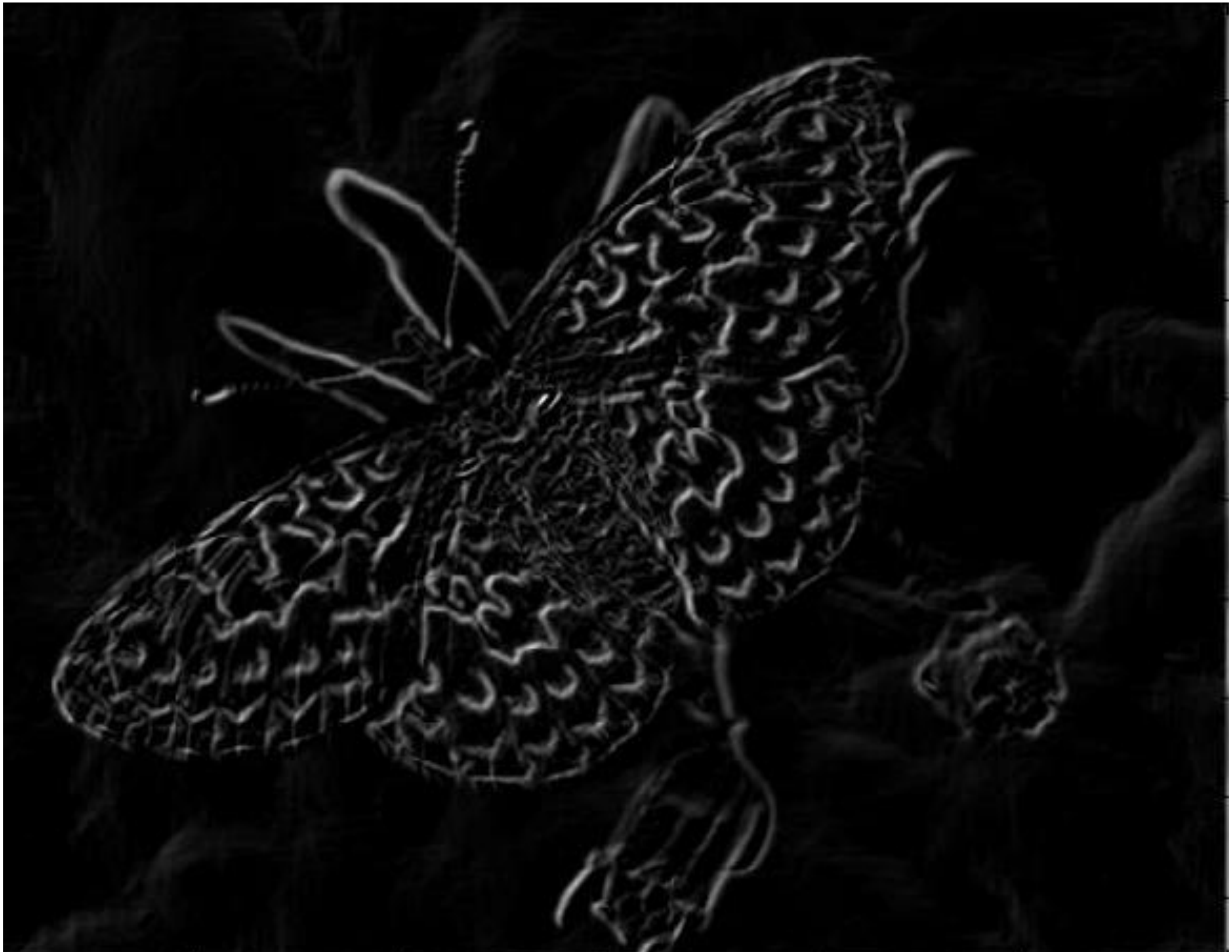


$$F_T[i,j] = \begin{cases} 1, & \text{if } F[i,j] \geq t \\ 0, & \text{otherwise} \end{cases}$$

Original Image

Slide credit: Kristen Grauman

Gradient Magnitude Image



Slide credit: Kristen Grauman

Thresholding with a Lower Threshold

Slide credit: Kristen Grauman

Thresholding with a Higher Threshold

Slide credit: Kristen Grauman

Canny Edge Detector

- Probably the most widely used edge detector in computer vision
- Theoretical model: step-edges corrupted by additive Gaussian noise
- Canny has shown that the first derivative of the Gaussian closely approximates the operator that optimizes the product of *signal-to-noise ratio* and localization.

J. Canny, A Computational Approach To Edge Detection, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 8:679-714, 1986.

Source: Li Fei-Fei

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The Canny Edge Detector

Original image (Lenna)

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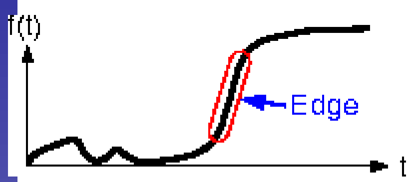
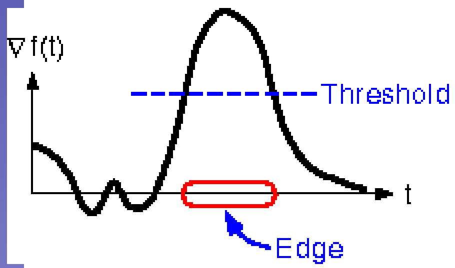
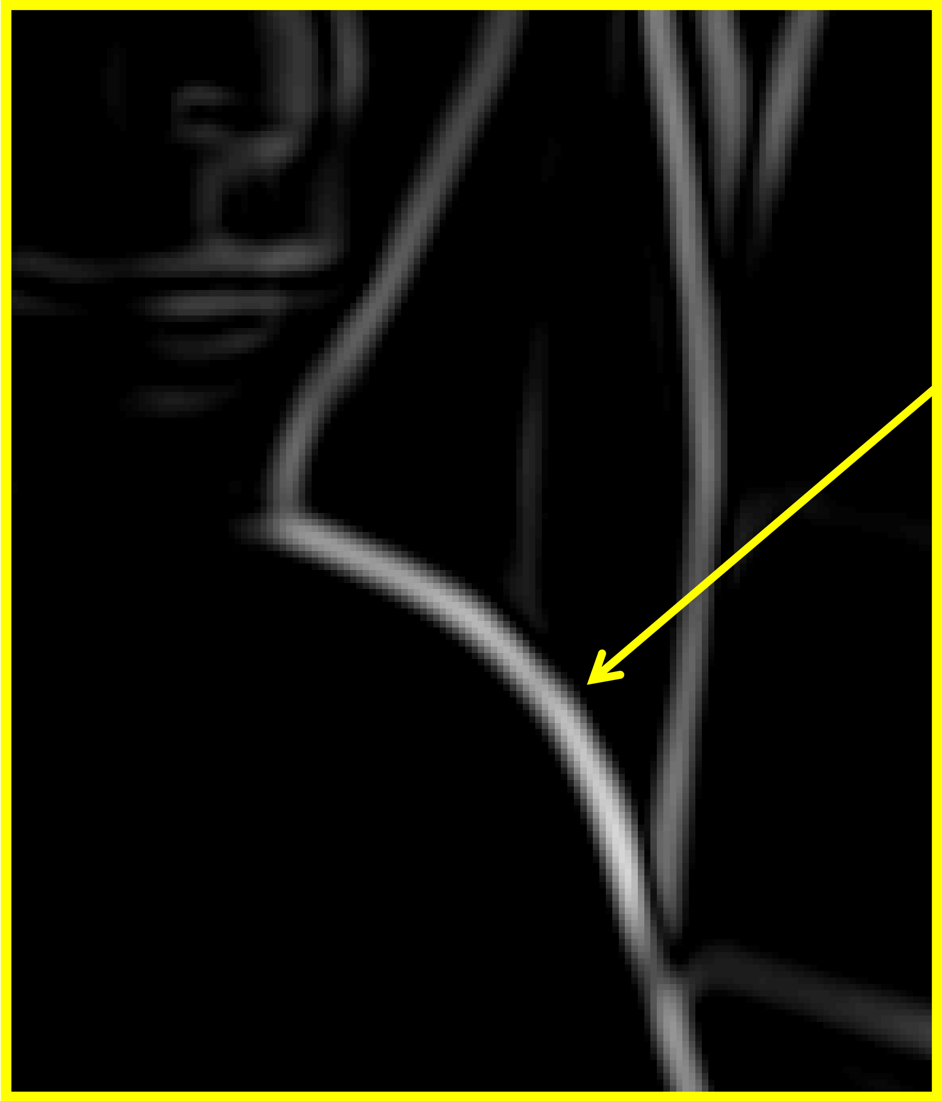
The Canny Edge Detector

Gradient magnitude

The Canny Edge Detector







How to turn these thick regions of the gradient into curves?

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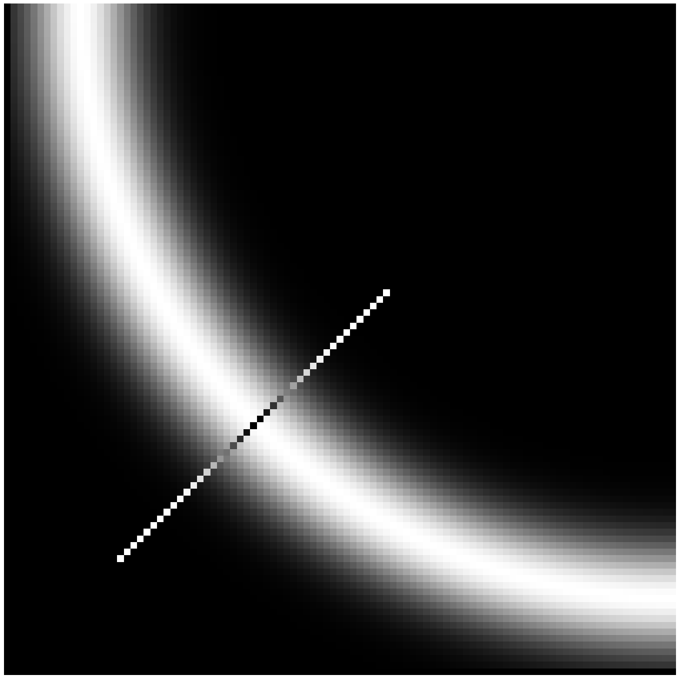
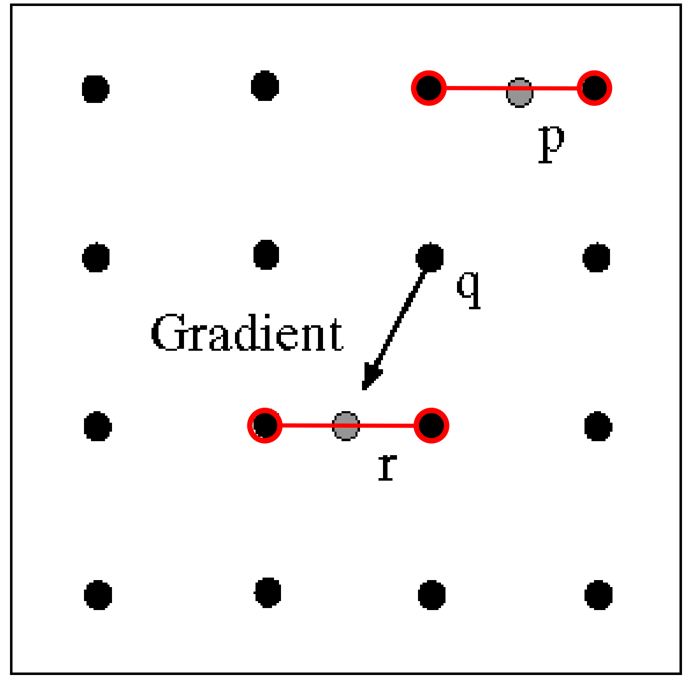
Non-Maximum Suppression





- **Check if pixel is local maximum along gradient direction, select single max across width of the edge**
  - **Requires checking interpolated pixels p and r**
  - **⇒ Linear interpolation based on gradient direction**

Source: Forsyth & Ponce

The Canny Edge Detector

Problem: pixels along this edge didn't survive the thresholding.

Thinning
(non-maximum suppression)

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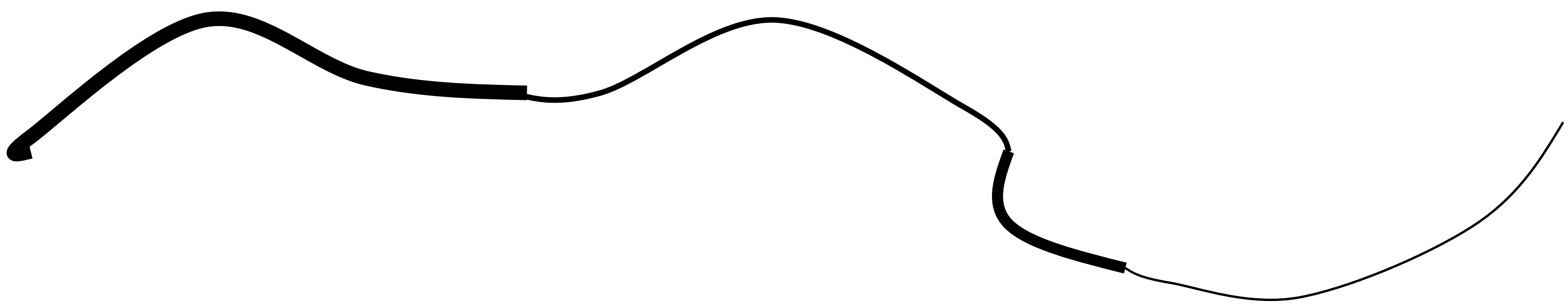
Solution: Hysteresis Thresholding

- Hysteresis: A lag or momentum factor
- Idea: Maintain two thresholds k_{high} and k_{low}
  - Use k_{high} to find strong edges to start edge chain
  - Use k_{low} to find weak edges which continue edge chain
- Typical ratio of thresholds is roughly

$$k_{high} \,/\, k_{low} = 2$$



Source: D. Lowe, S. Seitz

Hysteresis Thresholding

Original image

High threshold
(strong edges)

Low threshold
(weak edges)

courtesy of G. Loy

Hysteresis threshold

Source: L. Fei-Fei

Summary: Canny Edge Detector

1. Filter image with derivative of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel wide "ridges" down to single pixel width
4. Linking and thresholding (hysteresis):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

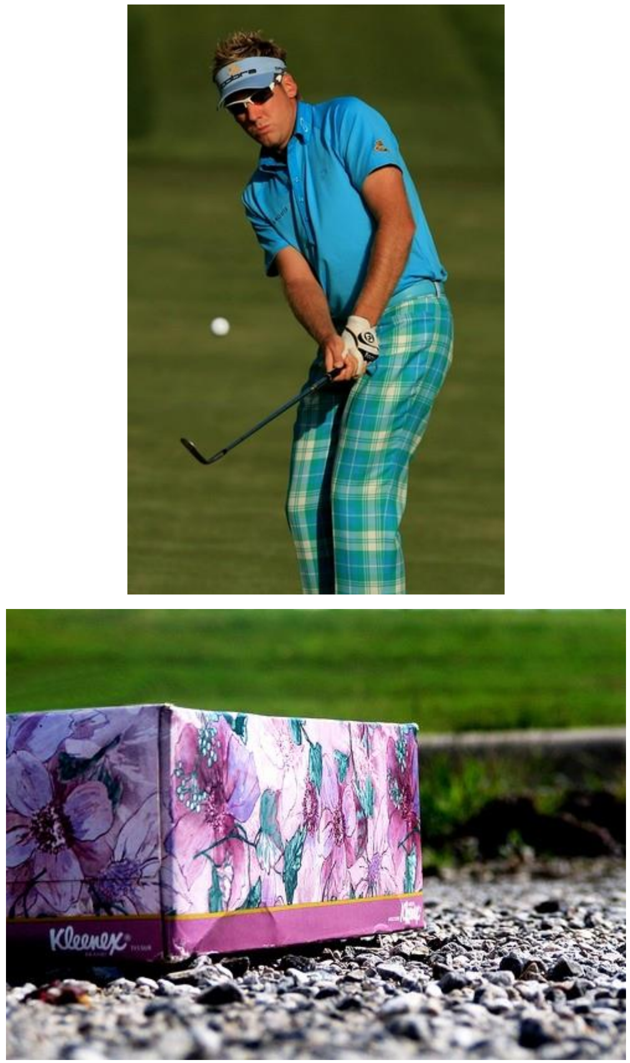
- MATLAB:

```
>> edge(image, 'canny');
>> help edge
```


Source: D. Lowe, L. Fei-Fei

Object Boundaries vs. Edges

Background



Texture

Shadows

Slide credit: Kristen Grauman

Edge Detection is Just the Beginning…

Image | Human segmentation | Gradient magnitude

- **Berkeley segmentation database:**
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

Source: L. Lazebnik

References and Further Reading

- Background information on linear filters and their connection with the Fourier transform can be found in Chapter 7 of F&P. Additional information on edge detection is available in Chapter 8.
  - D. Forsyth, J. Ponce, *Computer Vision – A Modern Approach*. Prentice Hall, 2003