High Level Computer Vision

Basic Image Processing - April 26, 2o17

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Today - Basics of Digital Image Processing

- Linear Filtering
  - Gaussian Filtering
- Multi Scale Image Representation
  - Gaussian Pyramid, Laplacian Pyramid
- Edge Detection
  - ‘Recognition using Line Drawings’
  - Image derivatives (1st and 2nd order)
- Hough Transform
  - Finding parametrized curves, generalized Hough transform
- Object Instance Identification using Color Histograms

- (Several slides are taken from Michael Black @ Brown)

Computer Vision and its Components

- computer vision: 'reverse' the imaging process
  - **2D (2-dimensional) digital image processing**
  - 'pattern recognition' / 3D image analysis
  - image understanding

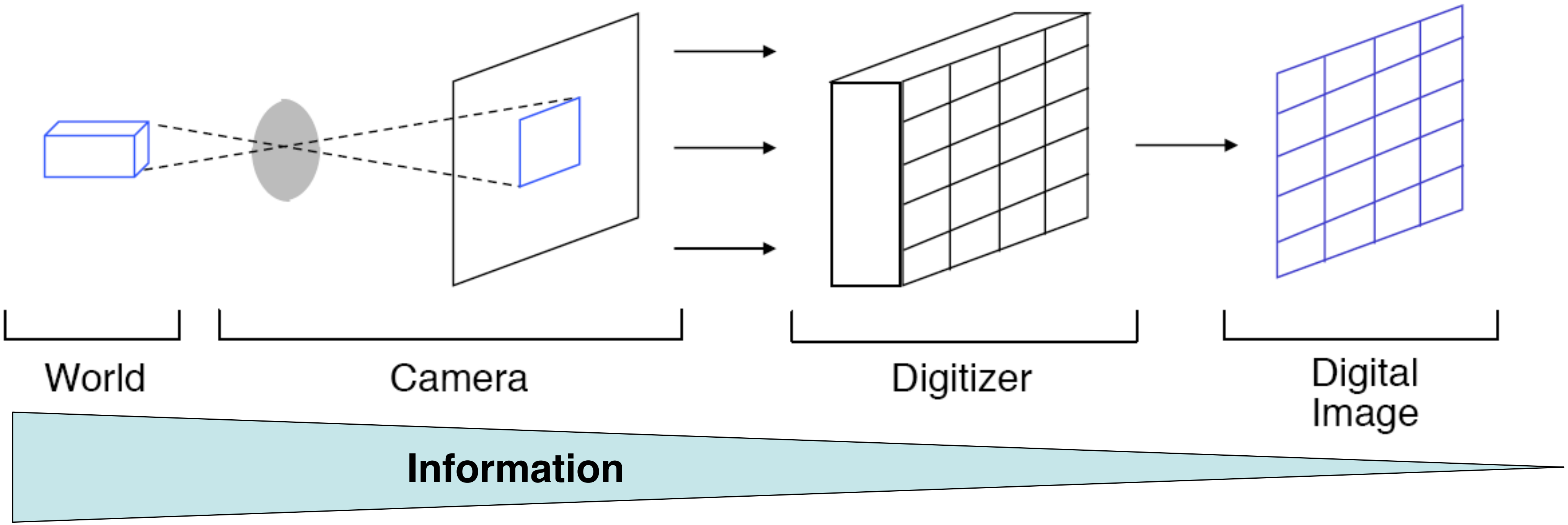


Image Filtering: 2D Signals and Convolution

- Image Filtering
  - to reduce noise,
  - to fill-in missing values/information
  - to extract image features (e.g.edges/corners), etc

- Simplest case:
  - linear filtering: replace each pixel by a linear combination of its neighbors

- 2D convolution (discrete):
  - discrete Image: I[m,n]
  - filter 'kernel': g[k,l]
  - 'filtered' image: f[m,n]

$$f[m,n] = I \otimes g = \sum_{k,l} I[m-k, n-l]g[k,l]$$

$$\underset{f[m,n]}{\begin{array}{|c|c|c|}\hline & & \\ \hline & 18 & \\ \hline & & \\ \hline\end{array}} = \underset{I[k,l]}{\begin{array}{|c|c|c|}\hline 8 & 5 & 2 \\ \hline 7 & 5 & 3 \\ \hline 9 & 4 & 1 \\ \hline\end{array}} \otimes \underset{g[k,l]}{\begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline\end{array}}$$

can be expressed as matrix multiplication!

Linear Systems

- Basic Properties:
  - homogeneity $T[a X] = a T[X]$
  - additivity $T[X_1 + X_2] = T[X_1] + T[X_2]$
  - superposition $T[aX_1 + bX_2] = a T[X_1] + b T[X_2]$
  - linear systems <=> superposition

- examples:
  - matrix operations (additions, multiplication)
  - convolutions

Filtering to Reduce Noise

- “Noise” is what we’re not interested in
  - low-level noise: light fluctuations, sensor noise, quantization effects, finite precision, …
  - complex noise (not today): shadows, extraneous objects.

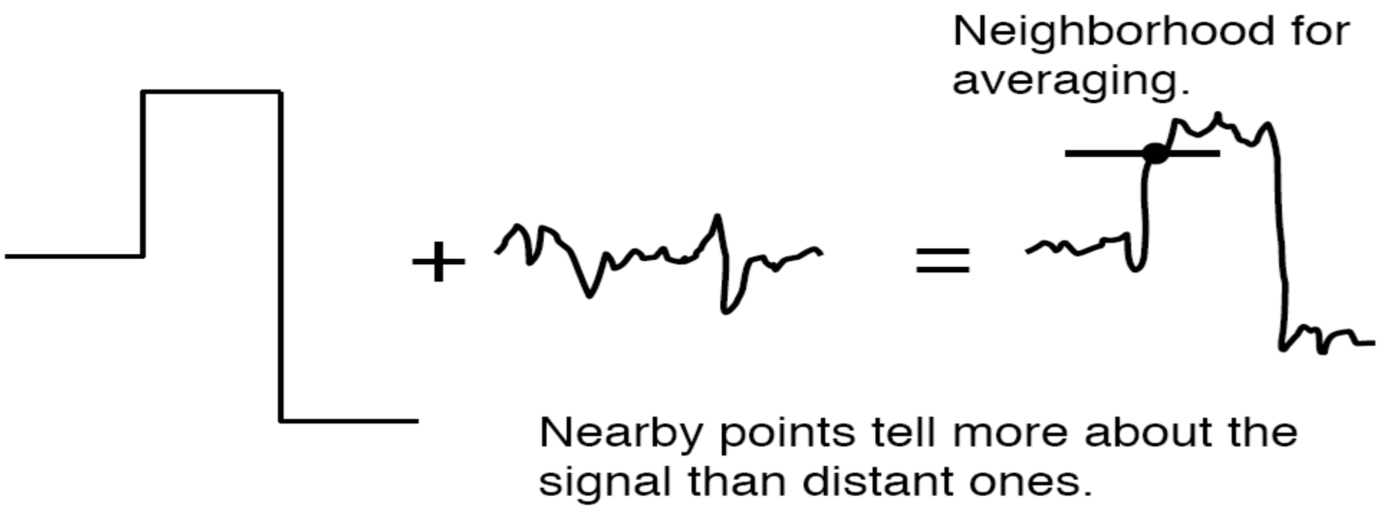
- Assumption:
  - the pixel’s neighborhood contains information about its intensity

$$\begin{array}{|c|c|c|}\hline 2 & 3 & 3 \\ \hline 3 & 20 & 2 \\ \hline 3 & 2 & 3 \\ \hline \end{array} \longrightarrow \begin{array}{|c|c|c|}\hline 2 & 3 & 3 \\ \hline 3 & 3 & 2 \\ \hline 3 & 2 & 3 \\ \hline \end{array}$$

Model: Additive Noise

- Image I = Signal S + Noise N:

$$S \quad + \quad N \quad = \quad I$$



Model: Additive Noise

- Image I = Signal S + Noise N
  - I.e. noise does not depend on the signal

- we consider:
  - I_i : intensity of i'th pixel
  - $I_i = s_i + n_i$ with $E(n_i) = 0$
    - s_i deterministic
    - n_i, n_j independent for $i \neq j$
    - n_i, n_j i.i.d. (independent, identically distributed)

- therefore:
  - intuition: averaging noise reduces its effect
  - better: smoothing as inference about the signal

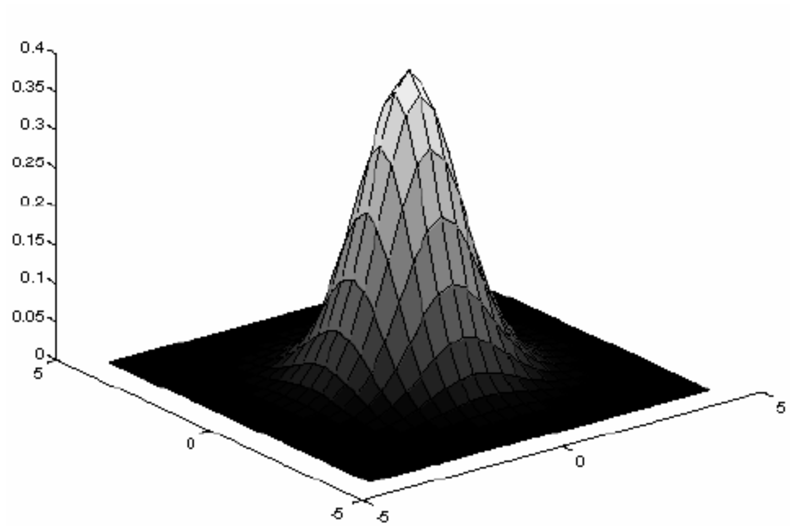
Average Filter

- Average Filter
  - replaces each pixel with an average of its neighborhood
  - Mask with positive entries that sum to 1
- if all weights are equal, it is called a BOX filter

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

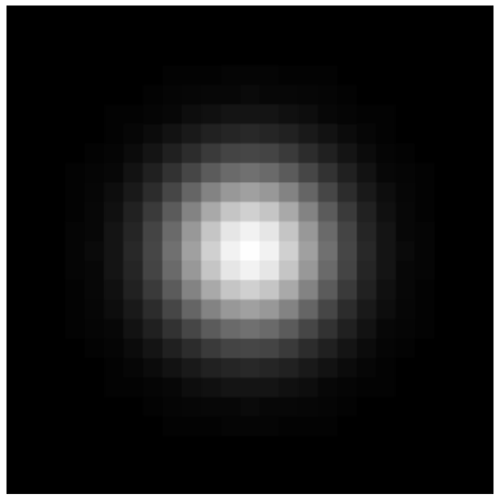
Gaussian Averaging (An Isotropic Gaussian)

- Rotationally symmetric
- Weights nearby pixels more than distant ones
  - this makes sense as ‘probabilistic’ inference



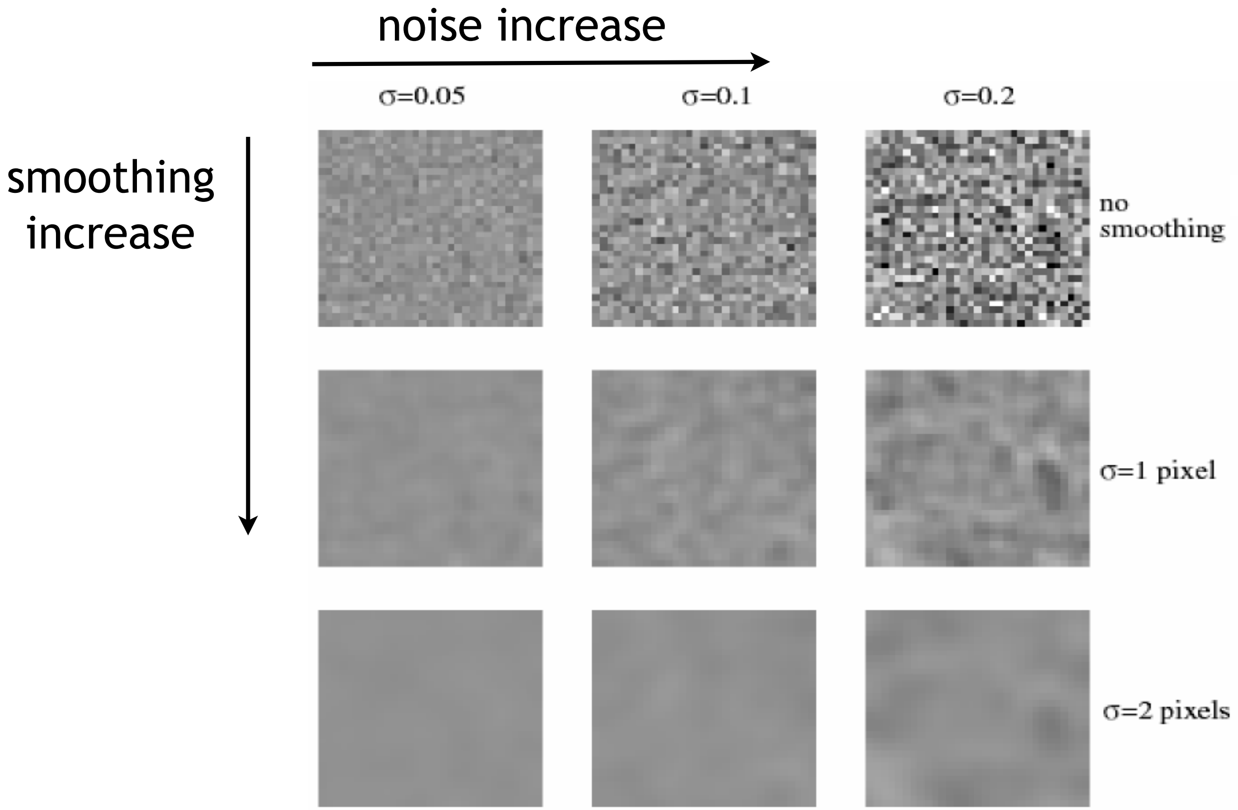
- the pictures show a smoothing kernel proportional to

$$g(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$



Smoothing with a Gaussian

- Effects of smoothing:
  - each column shows realizations of an image of Gaussian noise
  - each row shows smoothing with Gaussians of different width



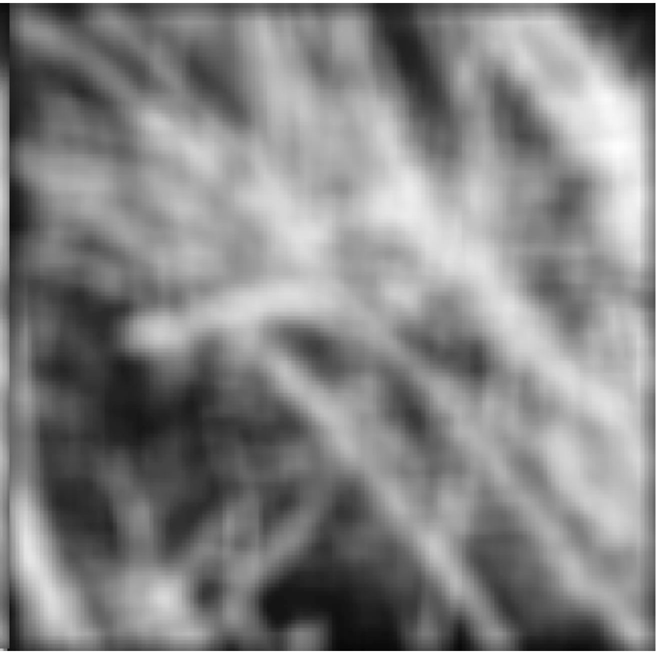
Smoothing with a Gaussian

- Example:

Original Image

Gaussian-filtered

Box-filtered



Efficient Implementation

- Both, the BOX filter and the Gaussian filter are separable:
  - first convolve each row with a 1D filter
  - then convolve each column with a 1D filter

$$(f_x \otimes f_y) \otimes I = f_x \otimes (f_y \otimes I)$$

  - remember:
    - convolution is linear - associative and commutative
- Example: separable BOX filter

$$\underbrace{\begin{array}{|c|c|c|}\hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \end{array}}_{f_x \otimes f_y} = \underbrace{\begin{array}{|c|c|c|}\hline \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \hline \end{array}}_{f_x} \otimes \underbrace{\begin{array}{|c|}\hline \frac{1}{3} \\ \hline \frac{1}{3} \\ \hline \frac{1}{3} \\ \hline \end{array}}_{f_y}$$

Example: Separable Gaussian

- Gaussian in x-direction

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$

- Gaussian in y-direction

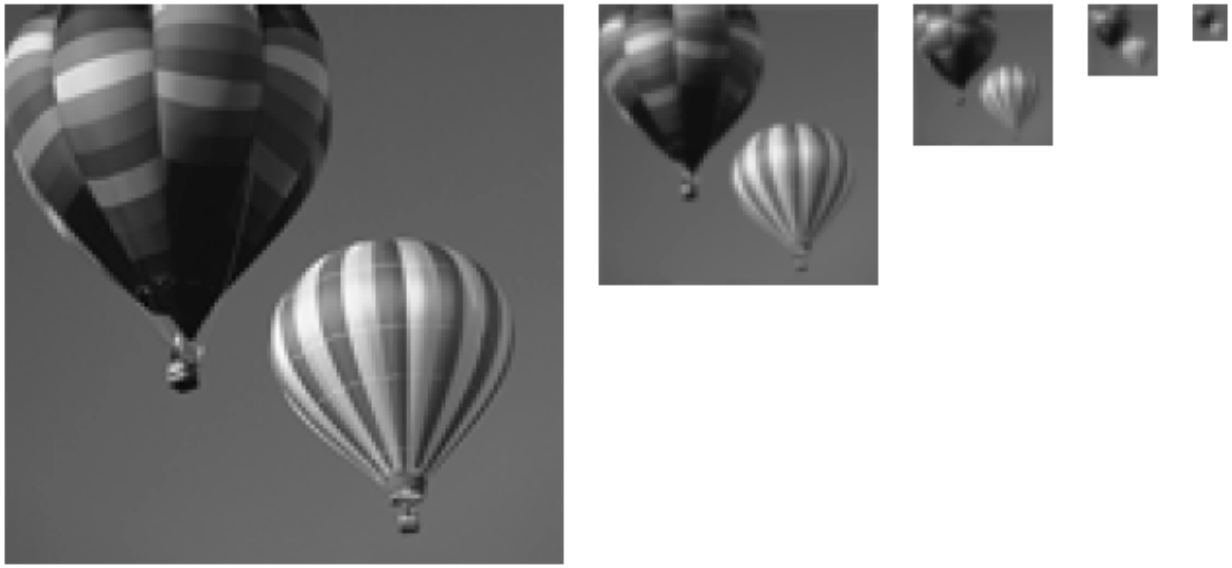
$$g(y) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{y^2}{2\sigma^2}\right)$$

- Gaussian in both directions

$$g(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

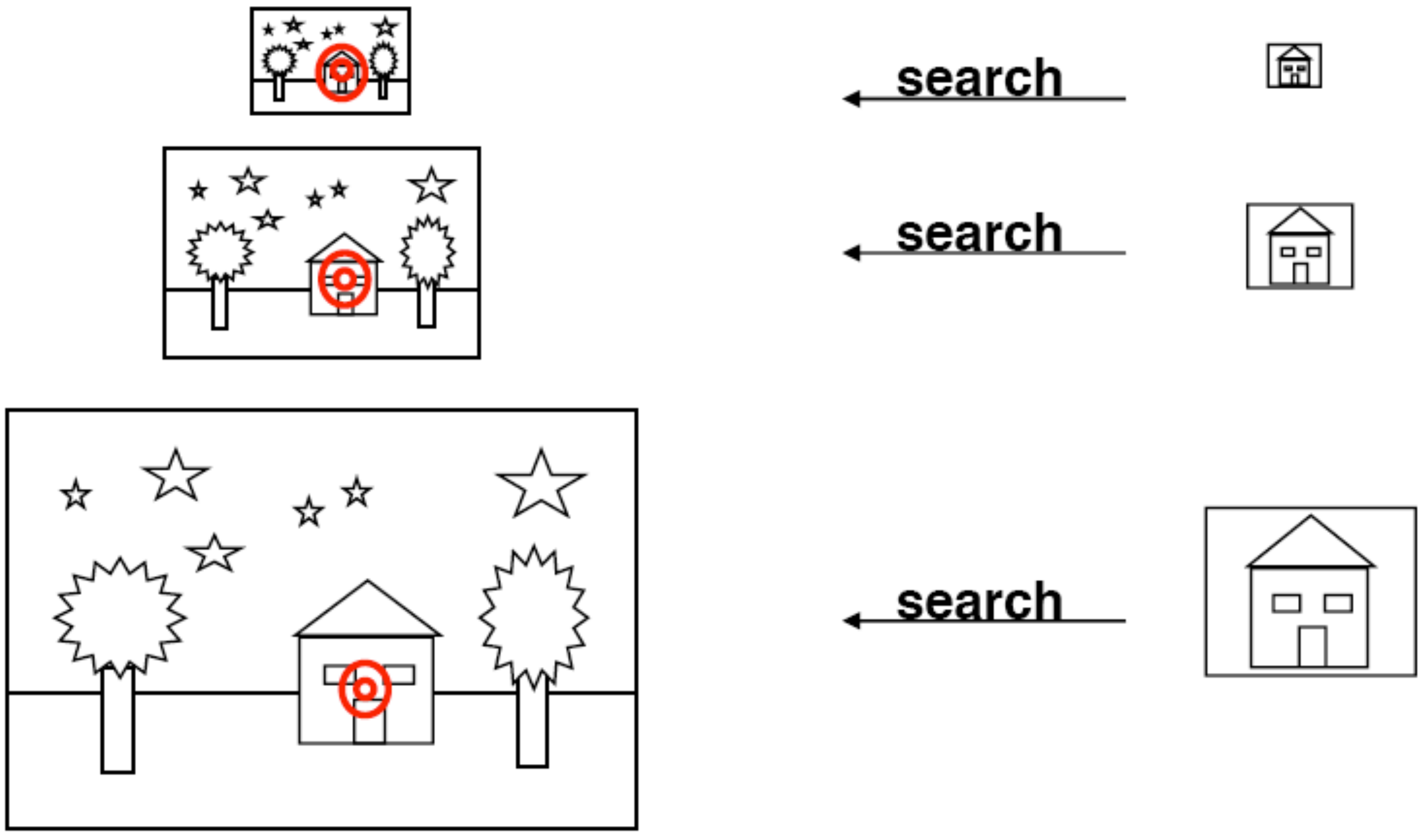
Multi-Scale Image Representation

- In this class:
  - Gaussian Pyramids
  - Laplacian Pyramids -> later
- Example of a Gaussian Pyramid



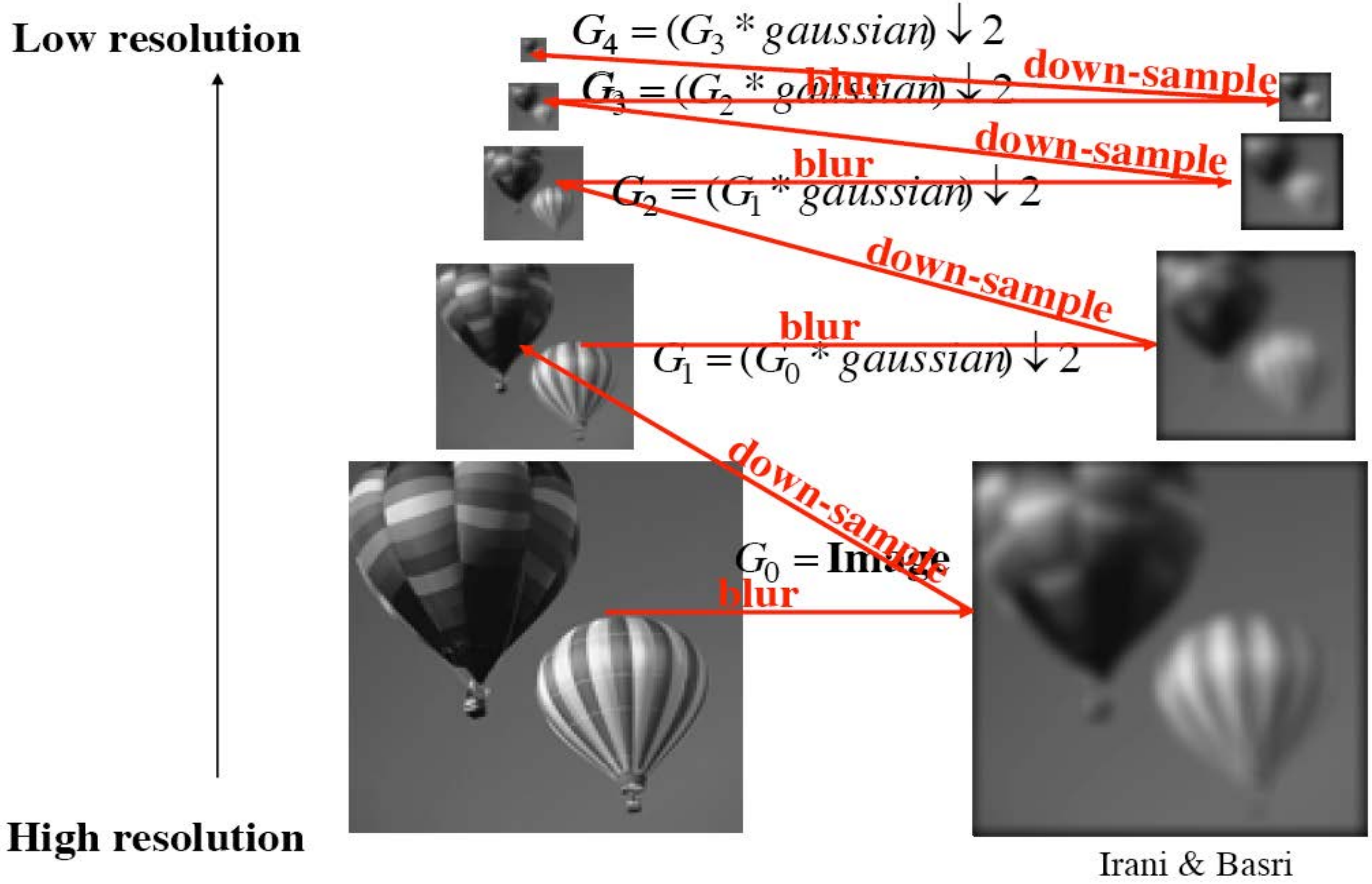
High resolution → Low resolution

Motivation: Search across Scales

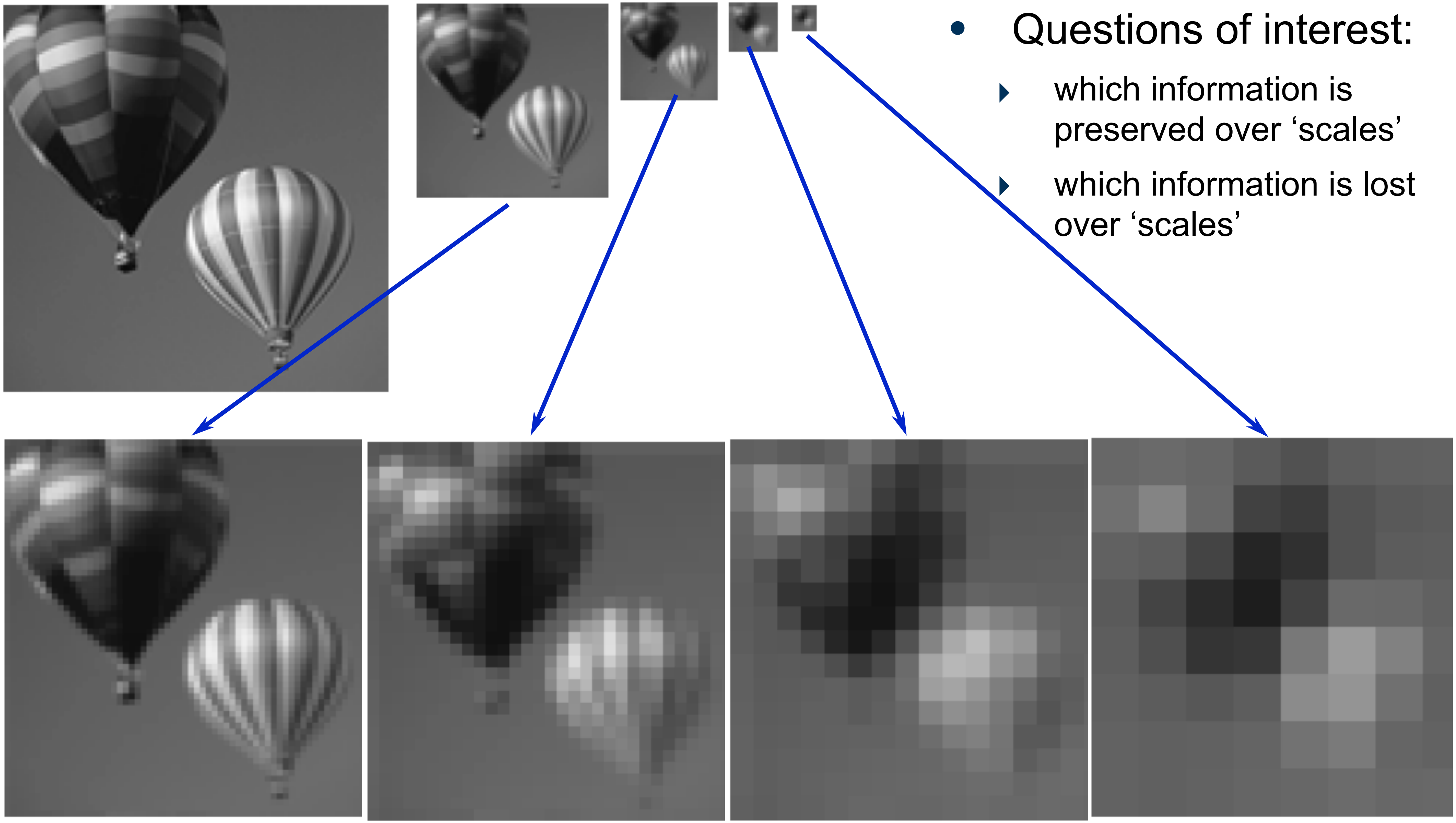


Irani & Basri

Computation of Gaussian Pyramid



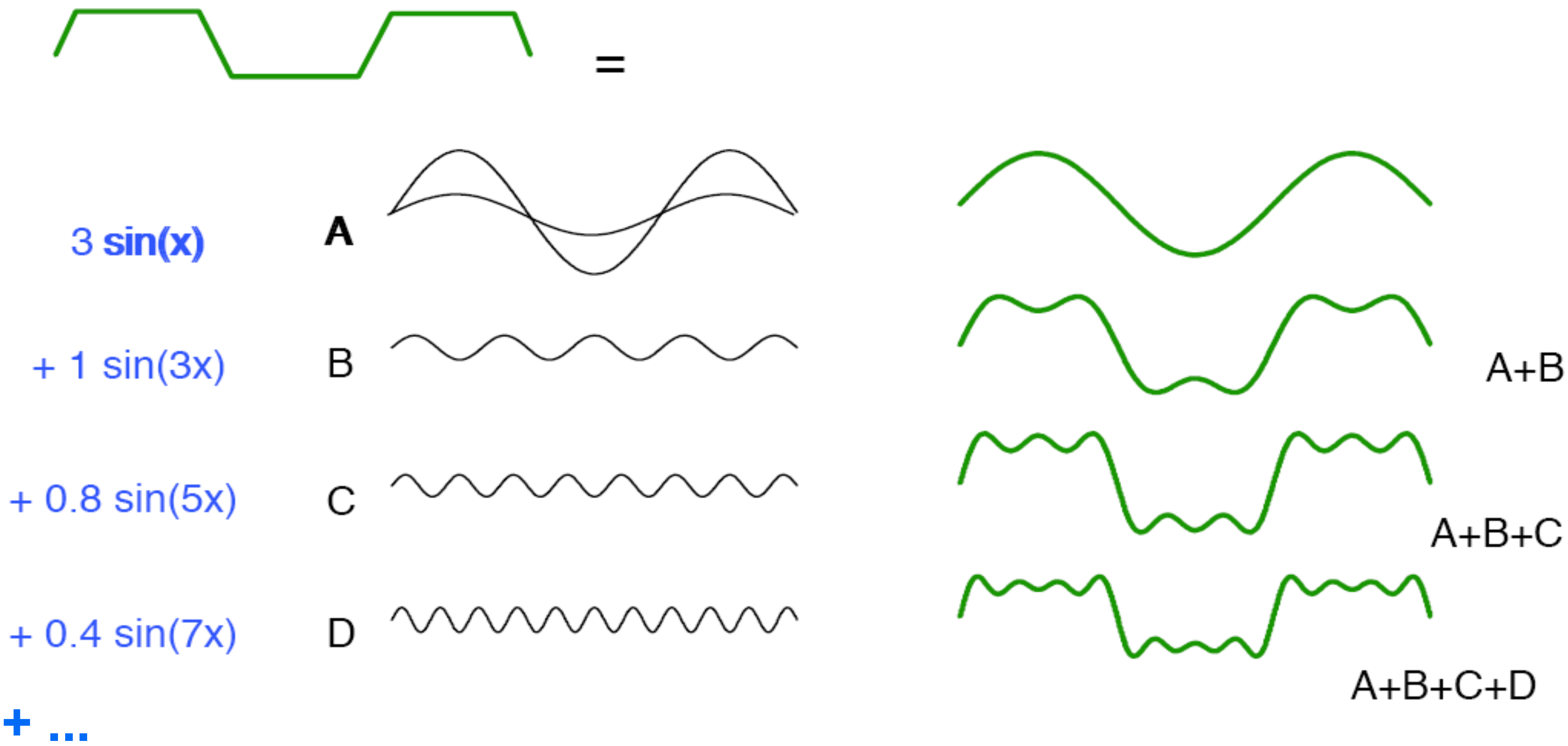
Gaussian Pyramid



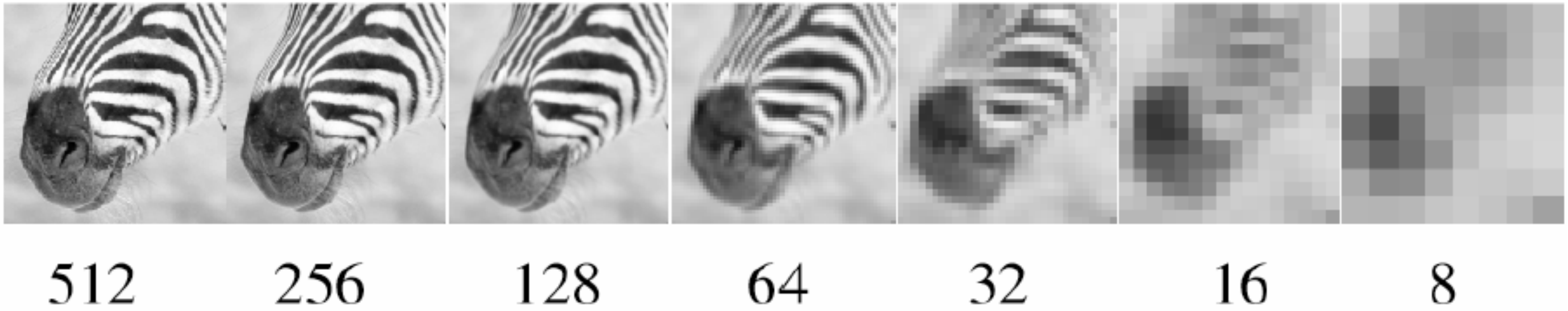
- Questions of interest:
  - which information is preserved over ‘scales’
  - which information is lost over ‘scales’

Fourier Transform in Pictures

- a *very* little about Fourier transform to talk about spatial frequencies…



Another Example



- a bar
  - in the big images is a hair (on the zebra's nose)
  - in smaller images, a stripe
  - in the smallest image, the animal's nose

Ponce & Forsyth

Ponce

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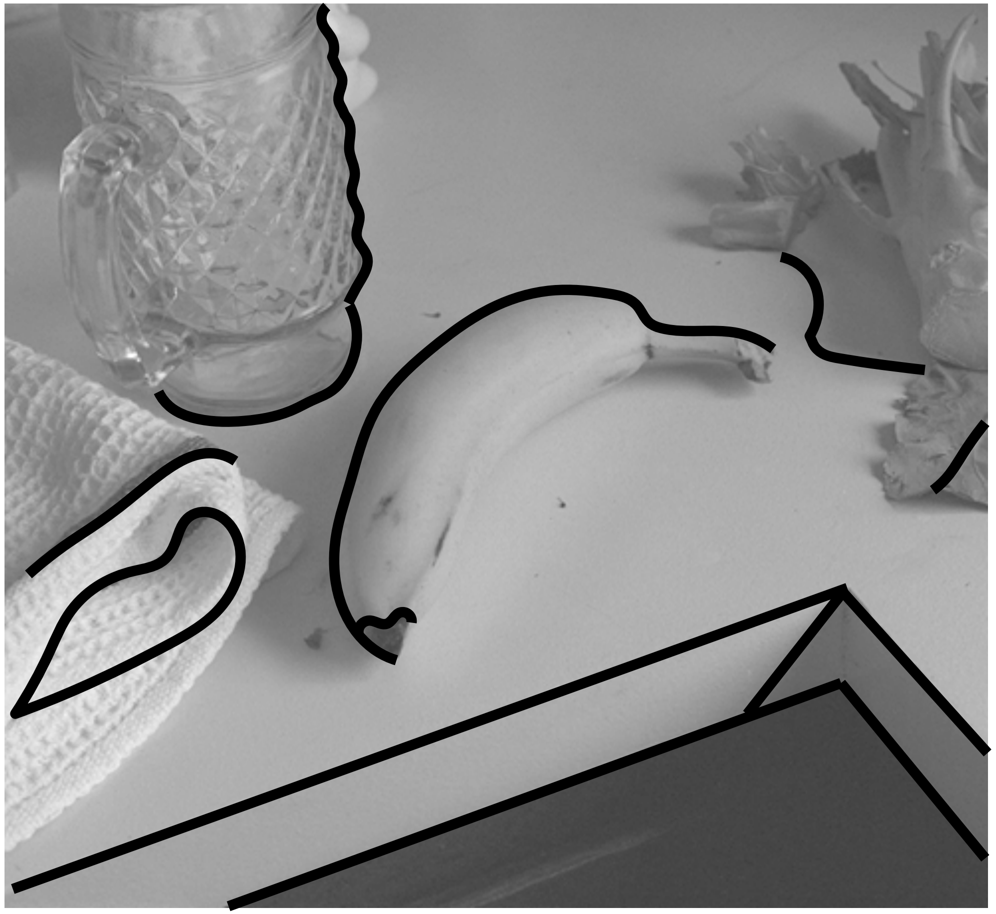
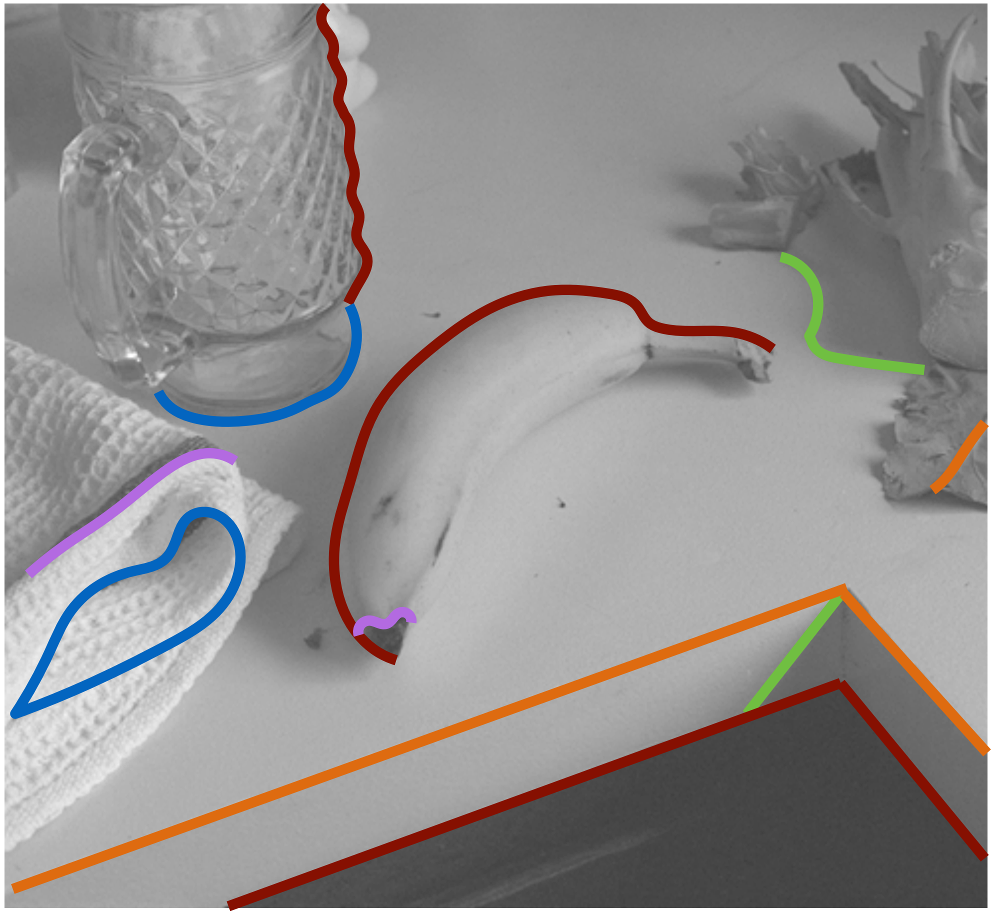
- (Several slides are taken from Michael Black @ Brown)

Image Edges: What are edges? Where do they come from?



- Edges are changes in pixel brightness

Image Edges:
What are edges? Where do they come from?

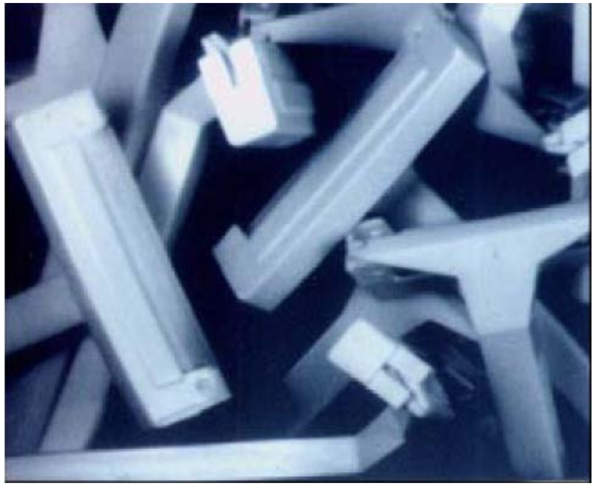


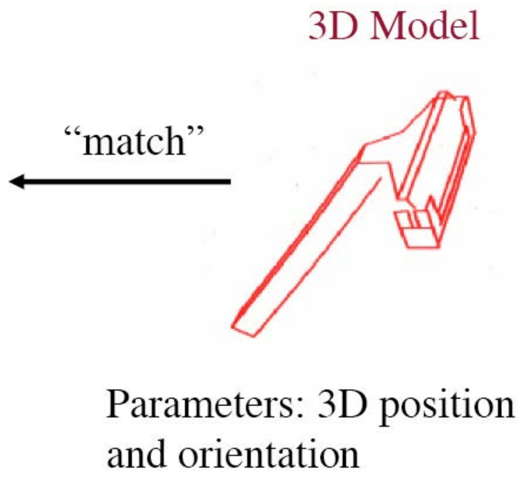
- Edges are changes in pixel brightness
  - **Foreground/Background Boundaries**
  - **Object-Object-Boundaries**
  - **Shadow Edges**
  - **Changes in Albedo or Texture**
  - **Changes in Surface Normals**

Line Drawings: Good Starting Point for Recognition?

Example of Recognition & Localization

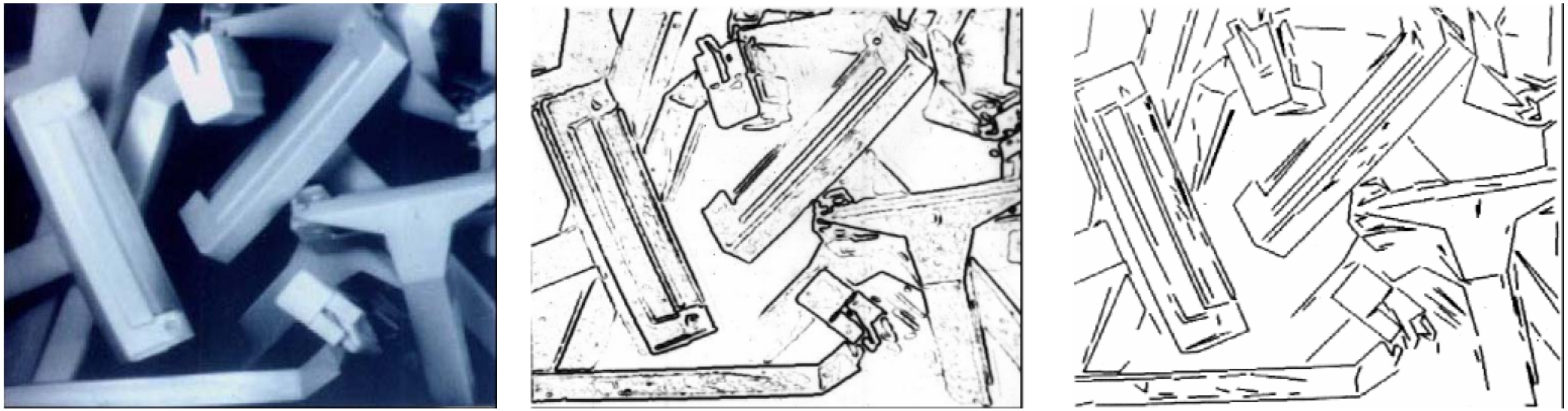
- David Lowe





Example of Recognition & Localization

- David Lowe
  - 1. ‘filter’ image to **find brightness changes**
  - 2. **‘fit’ lines** to the raw measurements

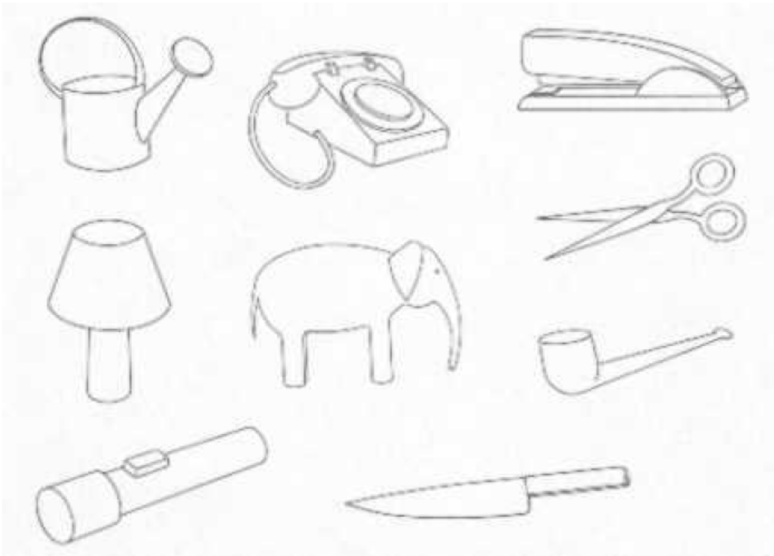


Example of Recognition & Localization

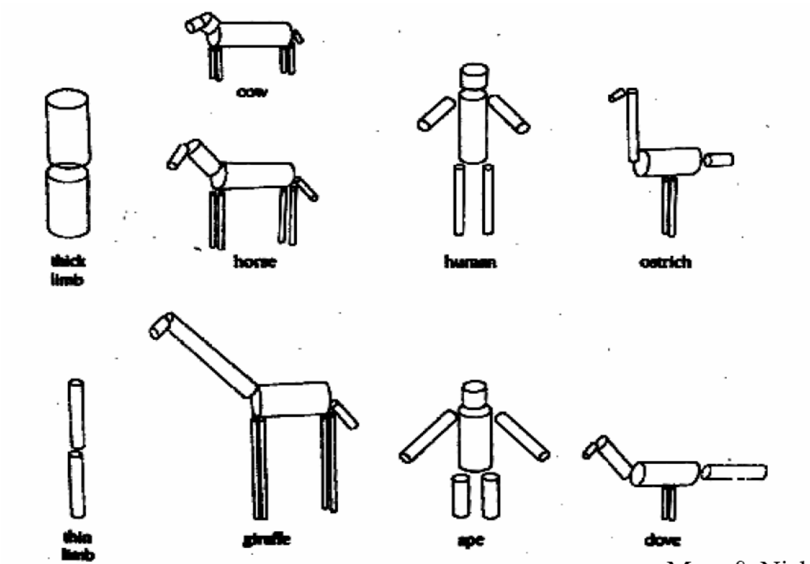
- David Lowe
  - 3. ‘project’ model into the image and **‘match’ to lines** (solving for 3D pose)

Class of Models

- Common Idea & Approach (in the 1980's)
  - matching of models (wire-frame/geons/generalized cylinders...) to edges and lines



Biederman's Geons

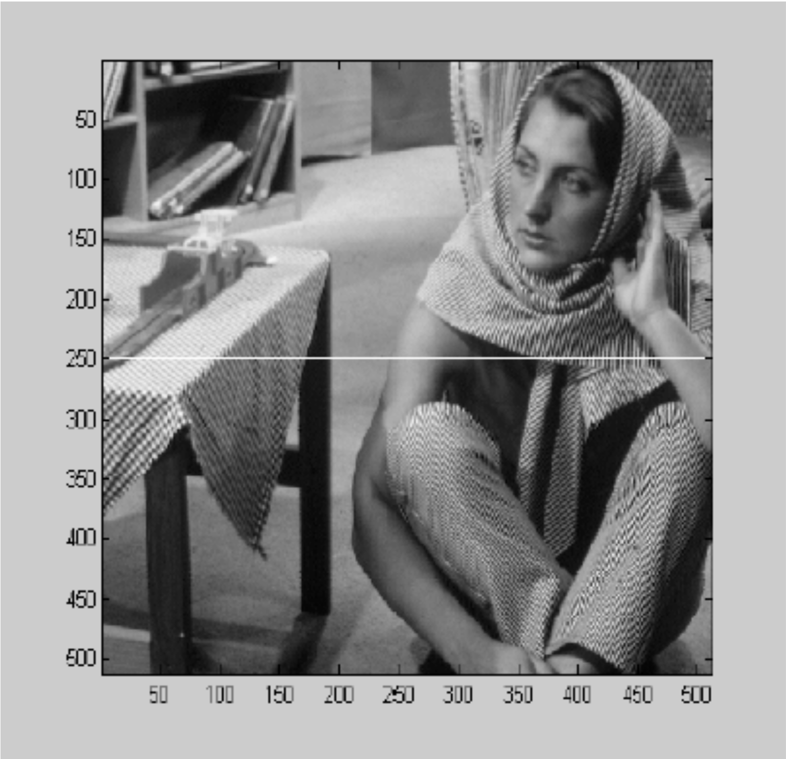


Marr & Nishihara

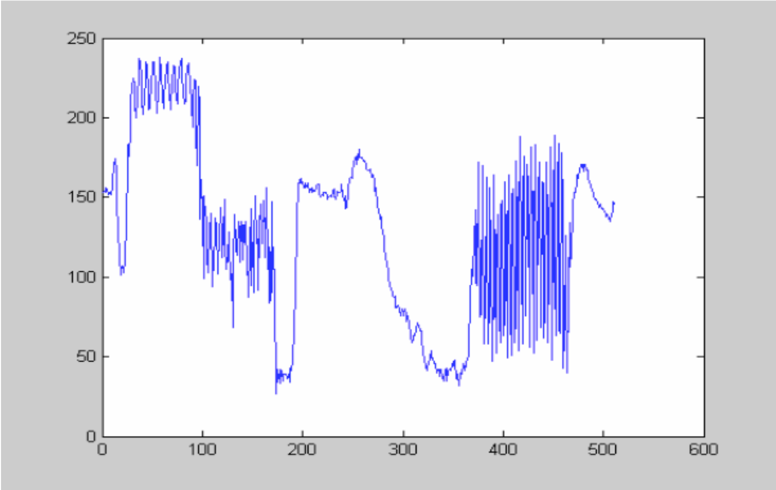
- so the 'only' remaining problem to solve is:
  - **reliably extract lines & edges** that can be matched to these models...

Actual 1D profile

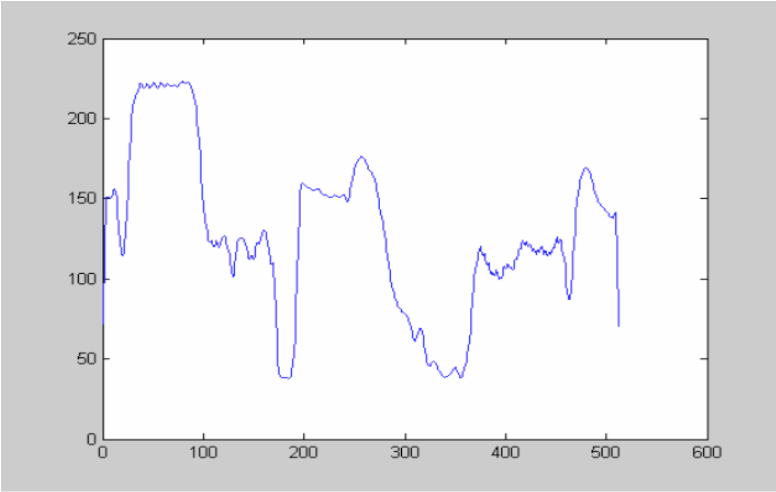
- Barbara Image:
  - entire image



- line 250:

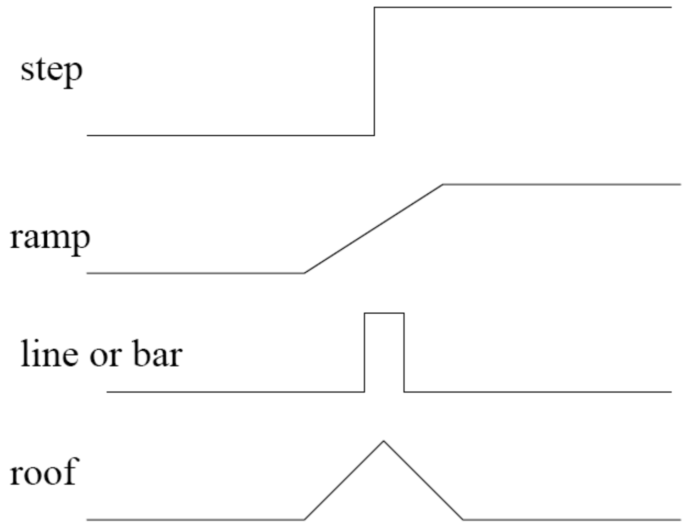


- line 250 smoothed with a Gaussian:

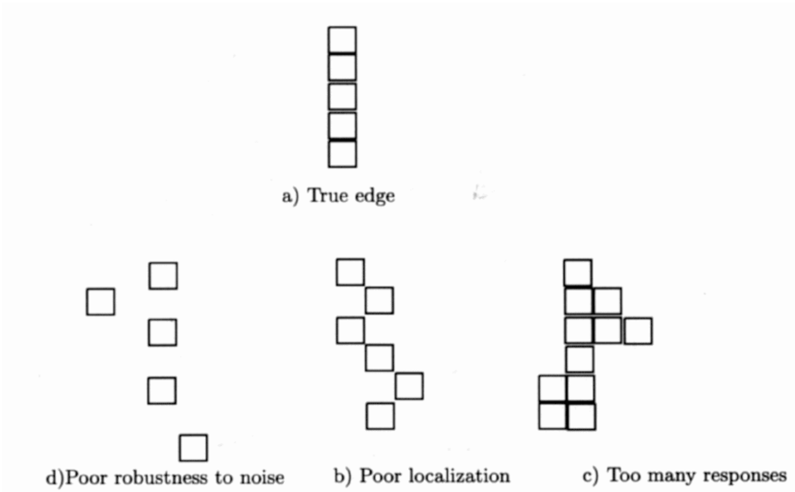


What are ‘edges’ (1D)

- Idealized Edge Types:



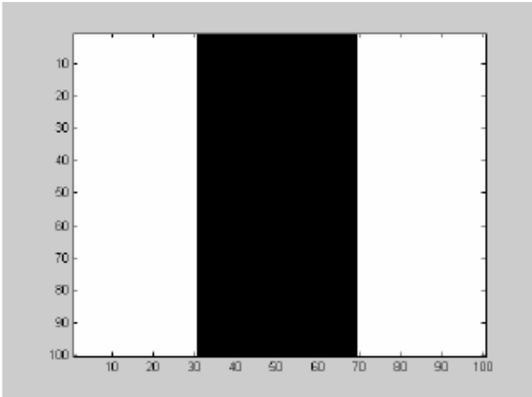
- Goals of Edge Detection:
  - **good detection**: filter responds to edge, not to noise
  - **good localization**: detected edge near true edge
  - **single response**: one per edge

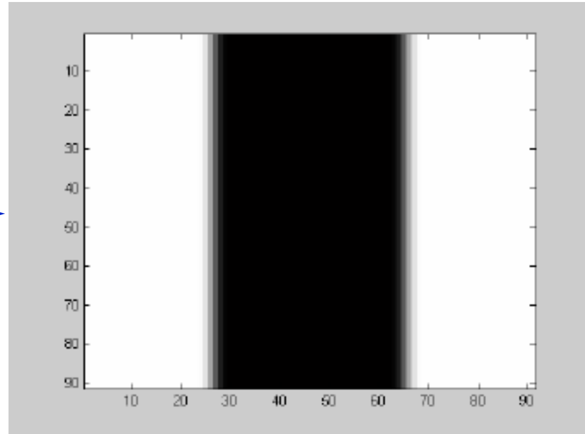


Edges

- Edges:
  - correspond to fast changes
  - where the magnitude of the derivative is large

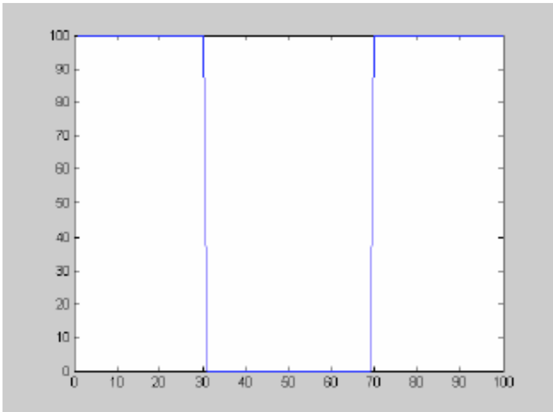
“image” of 2 step-edges

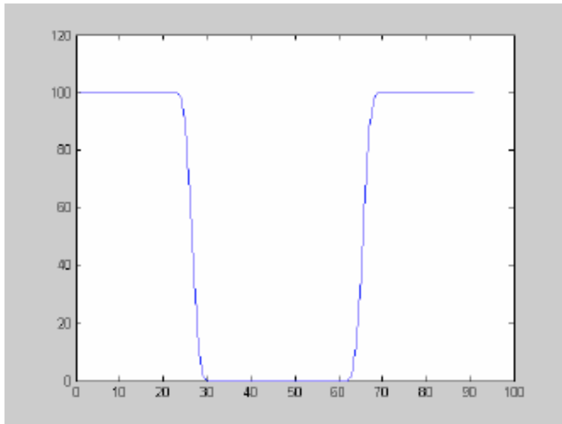




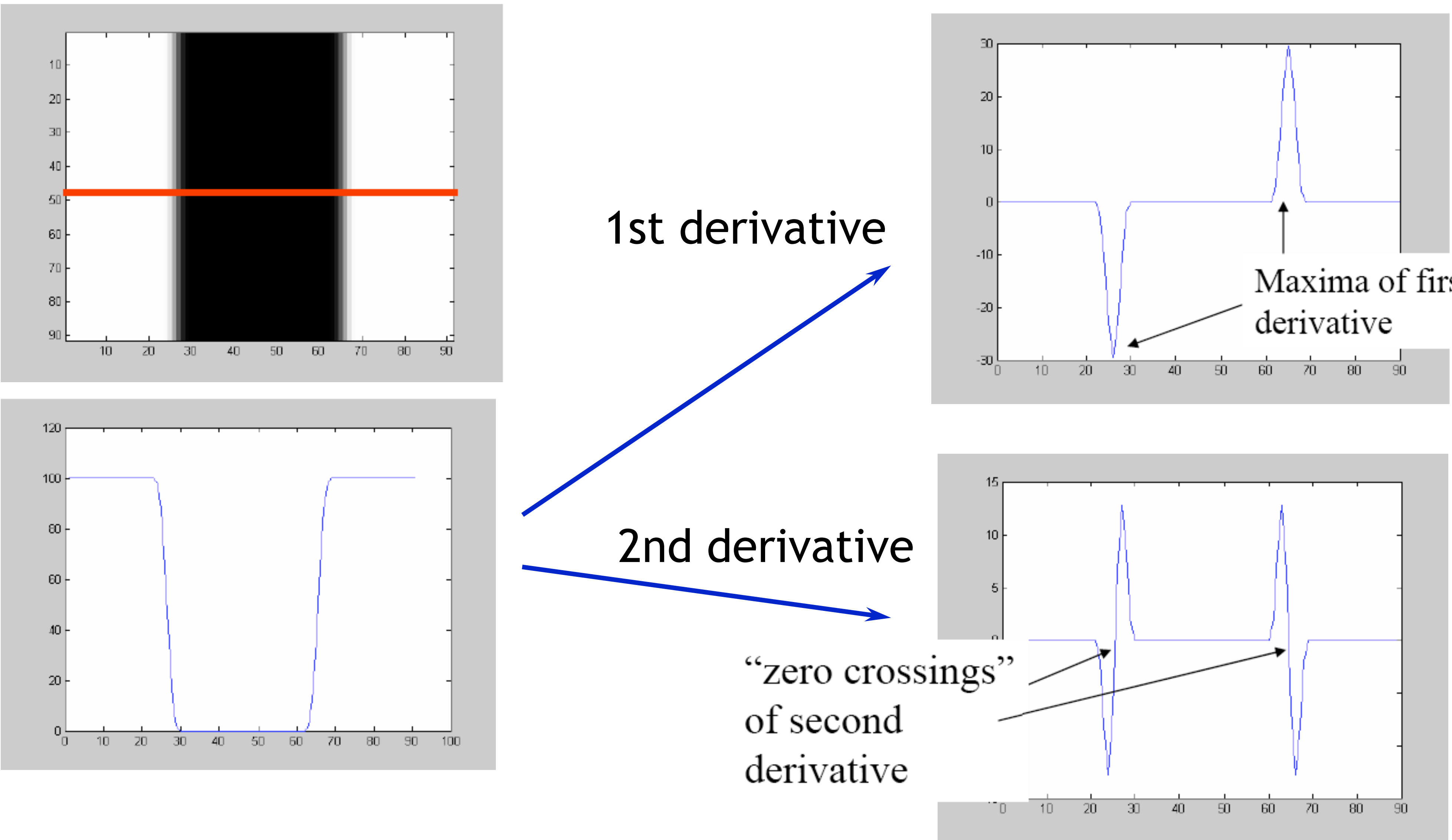
smoothing

single line of “image”





Edges & Derivatives…



Compute Derivatives

$$\frac{d}{dx} f(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h} \approx f(x+1) - f(x)$$

- we can implement this as a linear filter:
  - direct:

-1	1

  - or symmetric:

-1	0	1

Edge-Detection

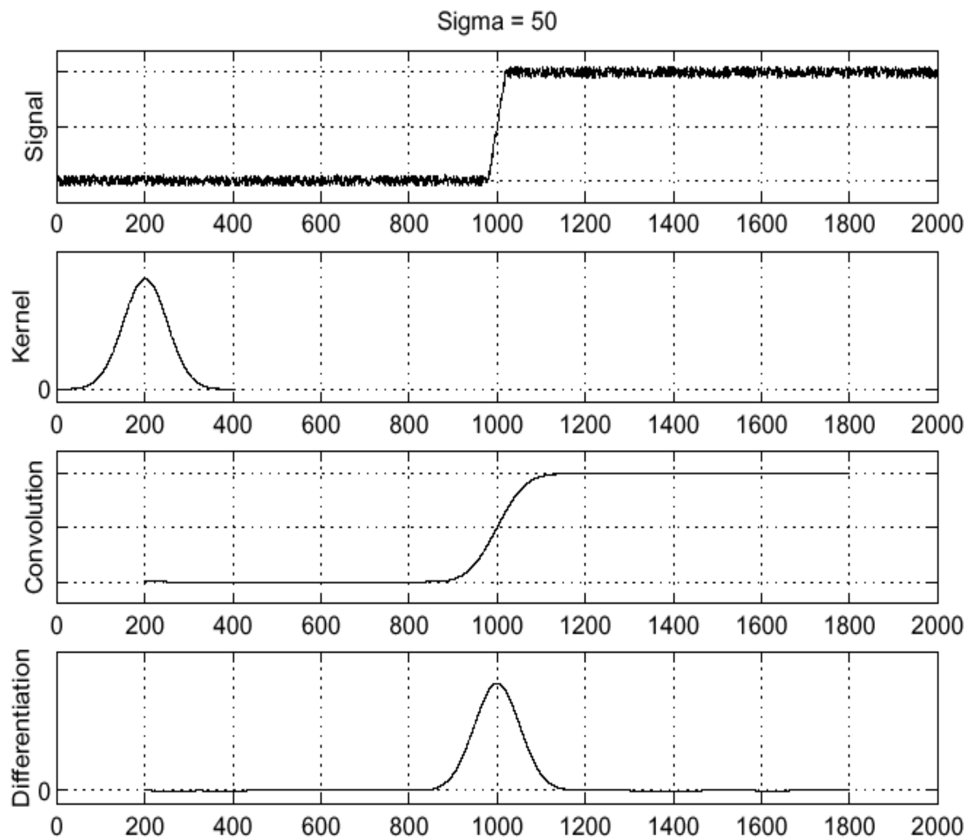
- based on 1st derivative:
  - smooth with Gaussian
  - calculate derivative
  - finds its maxima

$$f$$

$$g$$

$$g \otimes f$$

$$\frac{d}{dx}(g \otimes f)$$



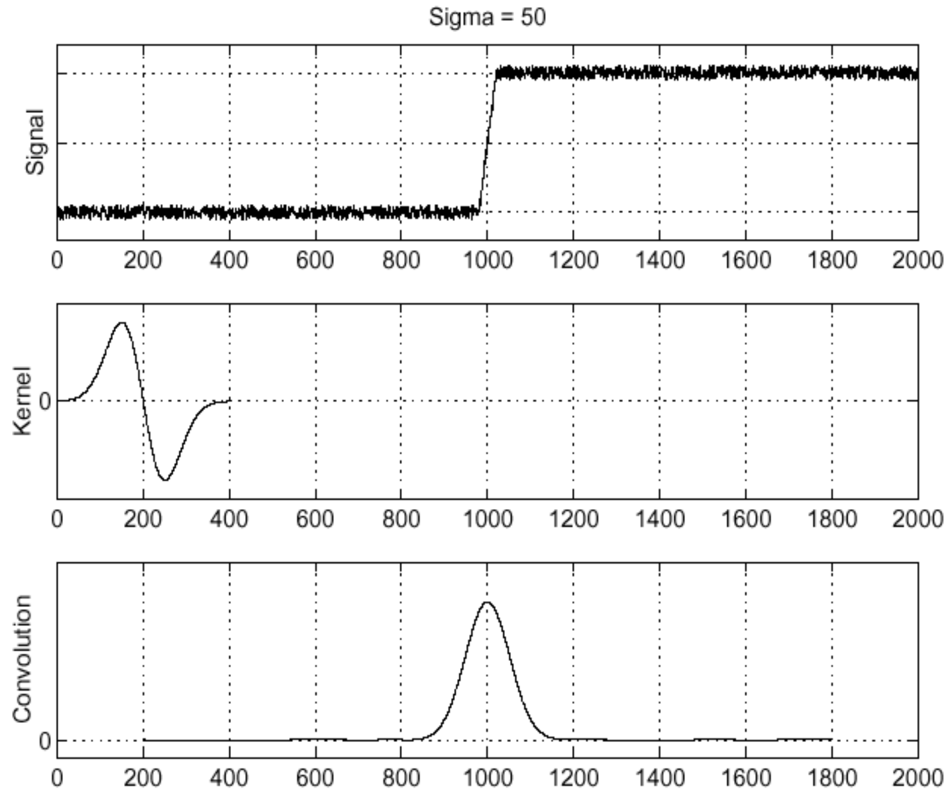
Edge-Detection

- Simplification: $$\frac{d}{dx}(g \otimes f) = \left(\frac{d}{dx}g\right) \otimes f$$
  - remember:
    derivative as well as convolution are linear operations
  - saves one operation

$$f$$

$$\frac{d}{dx}g$$

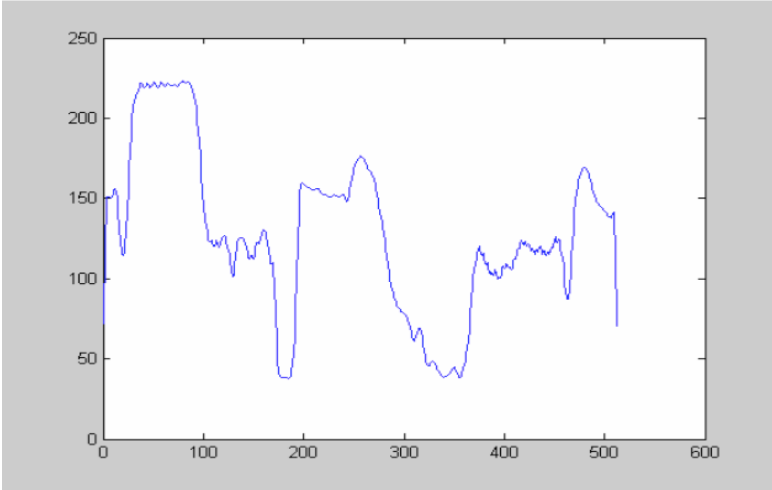
$$\left(\frac{d}{dx}g\right) \otimes f$$



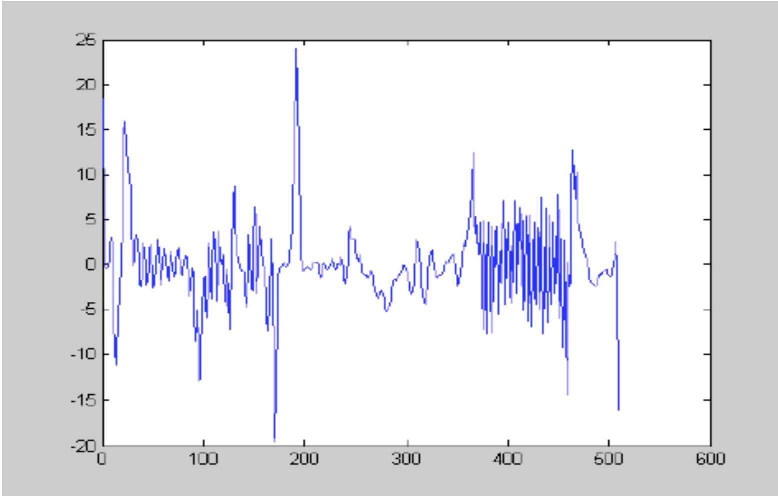
1D Barbara signal

- Barbara Image:
  - entire image

- line 250 (smoothed):



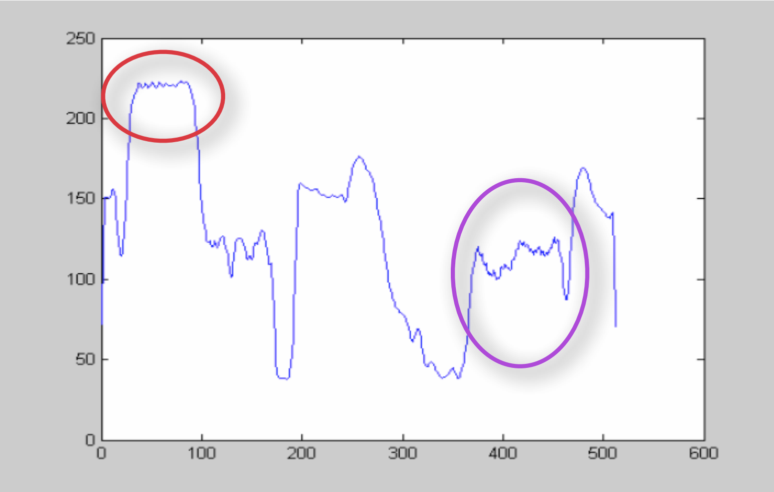
- 1st derivative



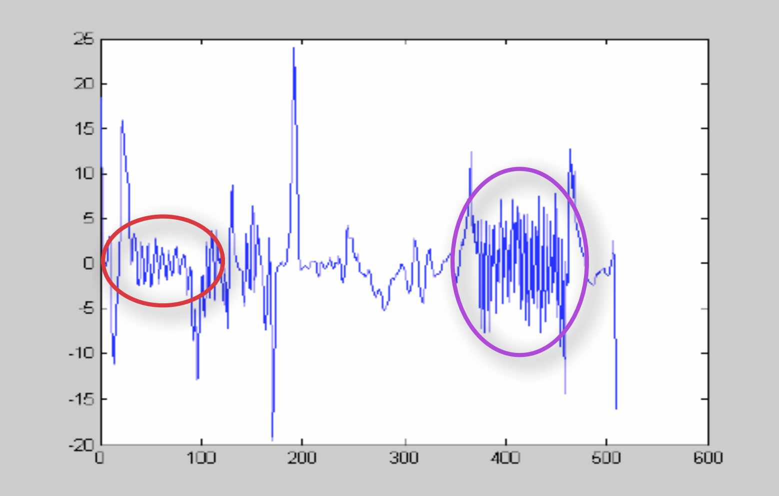
1D Barbara signal:
note the amplification of small variations

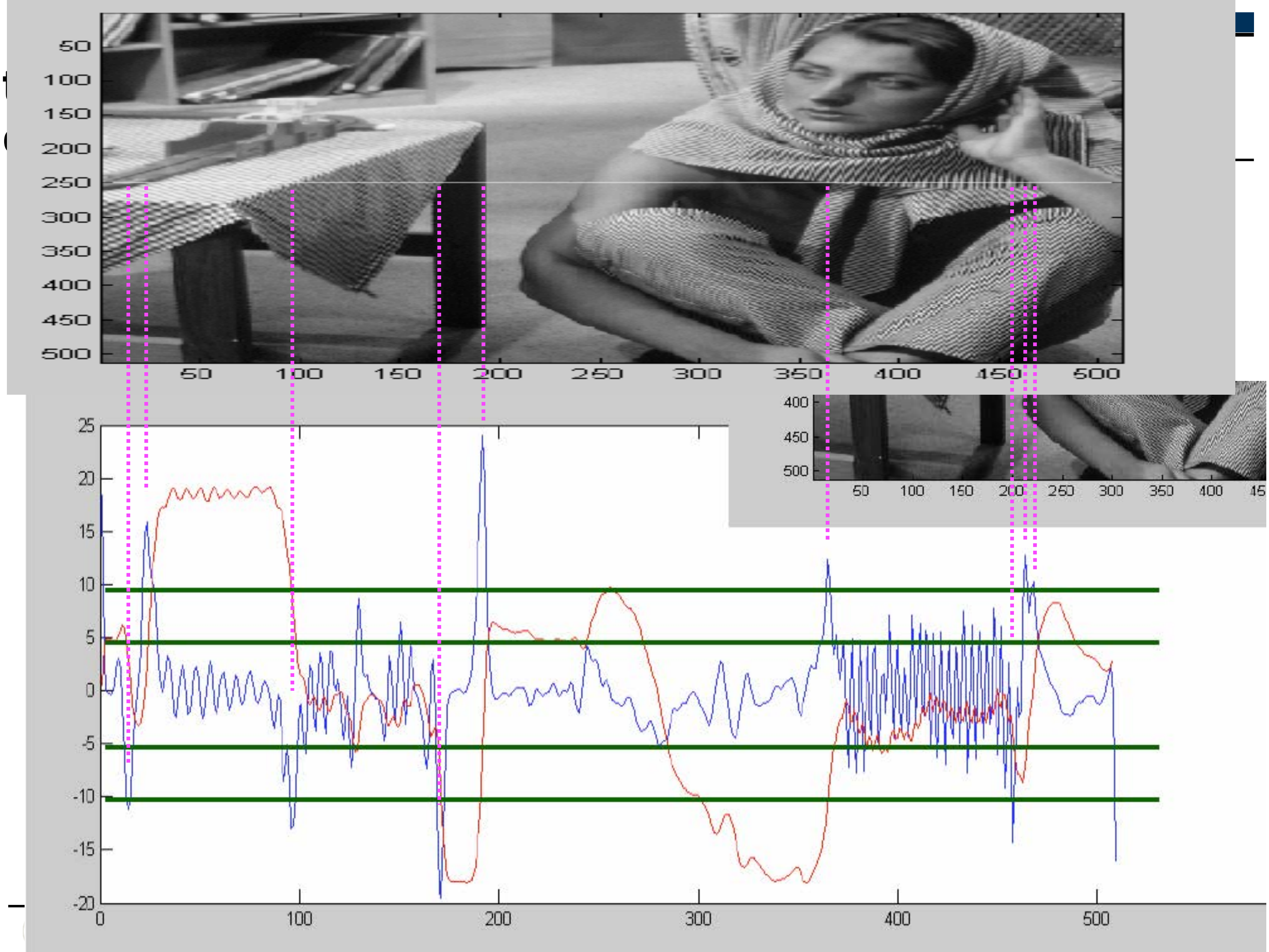
- Barbara Image:
  - entire image

- line 250 (smoothed):



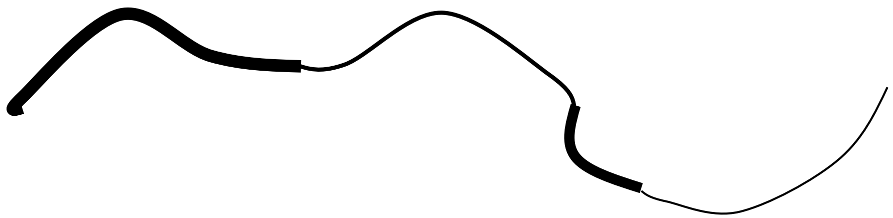
- 1st derivative




50 100 150 200 250 300 350 400 450 500
50 100 150 200 250 300 350 400 450 500
400 450 500
50 100 150 200 250 300 350 400 45
25 20 15 10 5 0 -5 -10 -15 -20
0 100 200 300 400 500

Implementing 1D edge detection

- algorithmically:
  - find peak in the 1st derivative
  - but
    - should be a local maxima
    - should be ‘sufficiently’ large
  - hysteresis: use 2 thresholds
    - high threshold to start edge curve (maximum value of gradient should be sufficiently large)
    - low threshold to continue them (in order to bridge “gaps” with lower magnitude)
    - (really only makes sense in 2D...)



Extension to 2D Edge Detection: Partial Derivatives

- partial derivatives
  - in x direction:
  - in y direction:

$$\frac{d}{dx} I(x, y) = I_x \approx I \otimes D_x$$

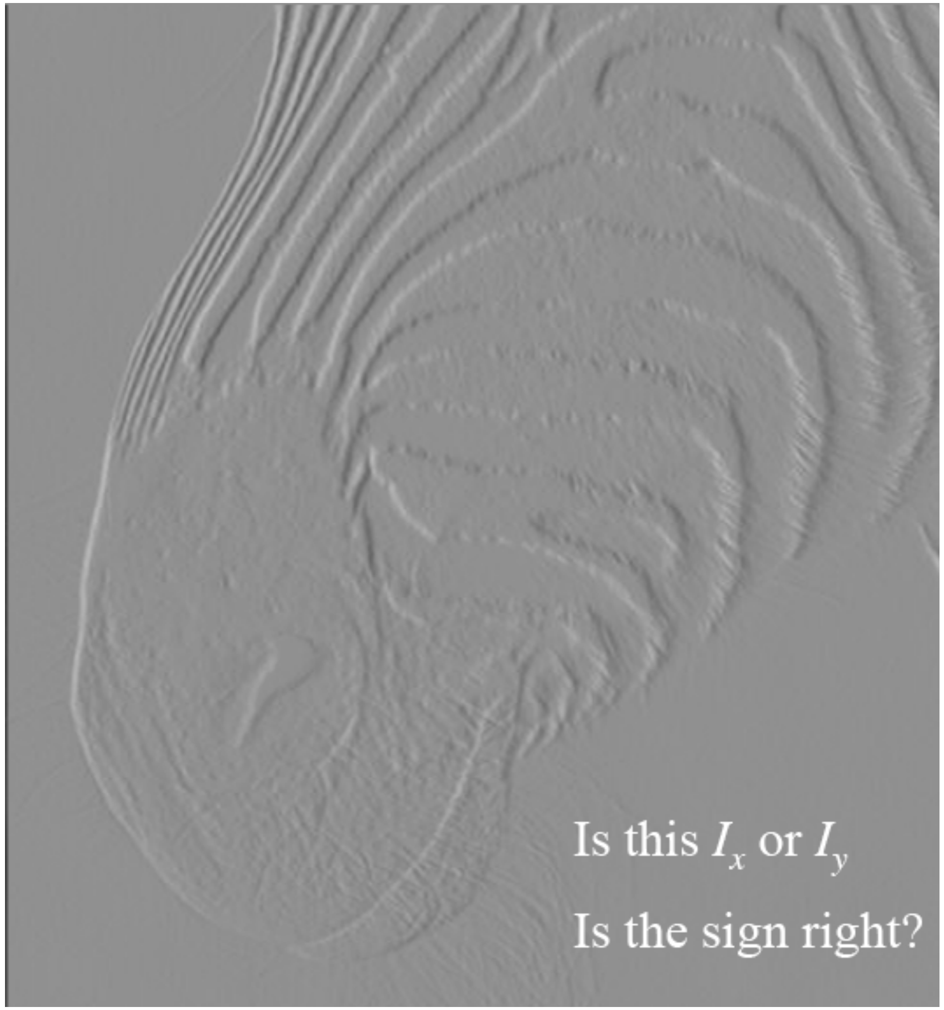
$$\frac{d}{dy} I(x, y) = I_y \approx I \otimes D_y$$

  - often approximated with simple filters (finite differences):

$$D_x = \frac{1}{3} \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array}$$

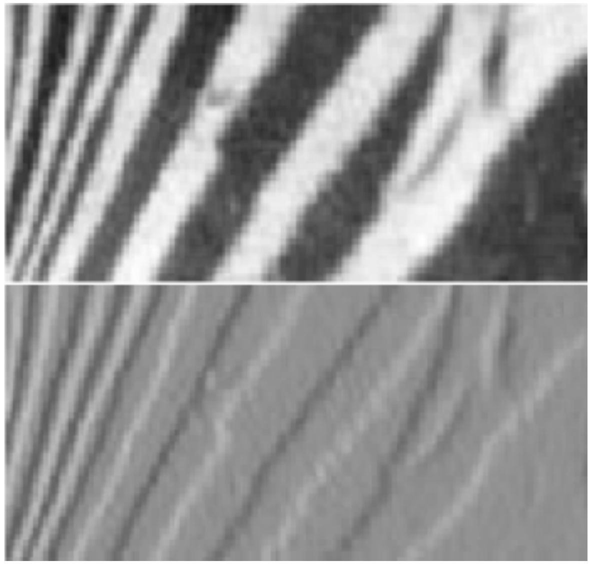
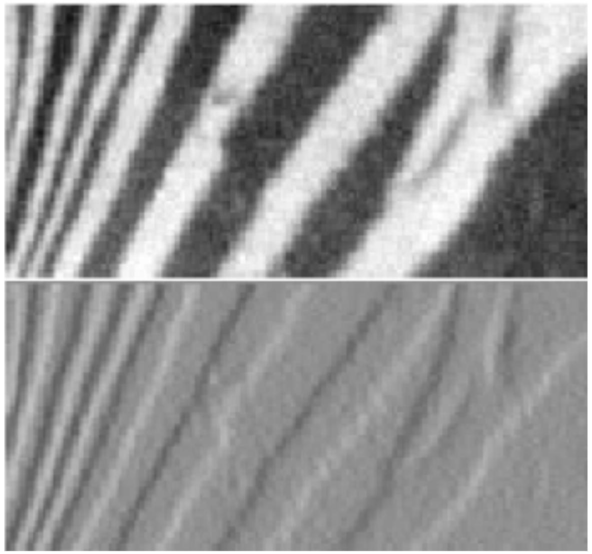
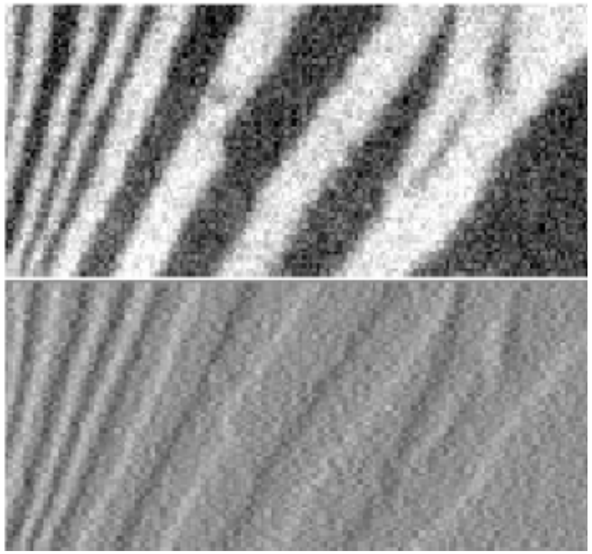
$$D_y = \frac{1}{3} \begin{array}{|c|c|c|} \hline -1 & -1 & -1 \\ \hline 0 & 0 & 0 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

Finite Differences



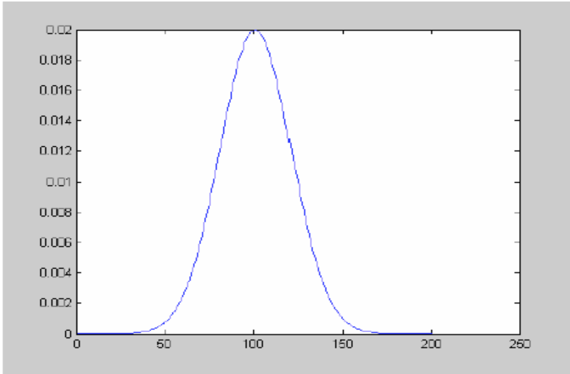
Finite Differences responding to noise

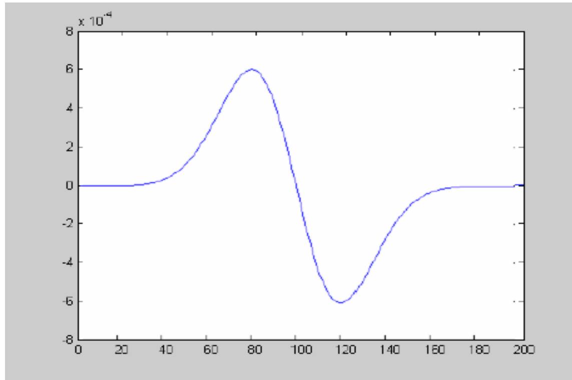
- increasing noise level (from left to right)
  - noise: zero mean additive Gaussian noise

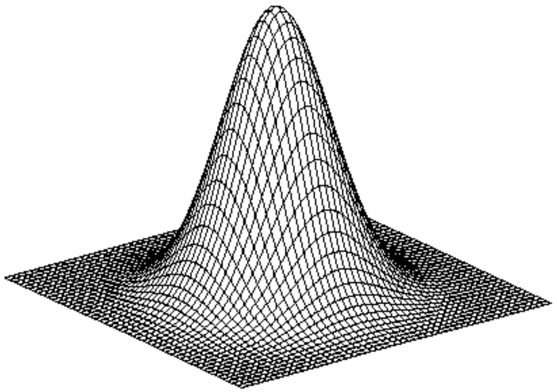
Again: Derivatives and Smoothing

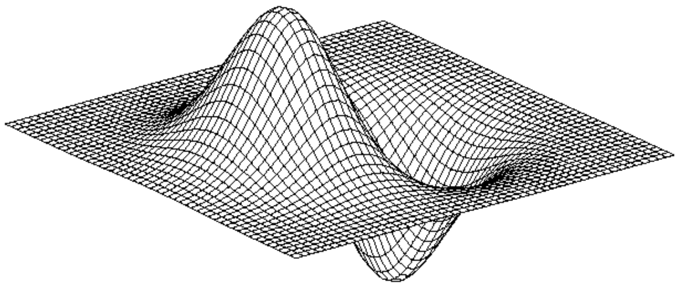
- derivative in x-direction: $D_x \otimes (G \otimes I) = (D_x \otimes G) \otimes I$
  - in 1D:



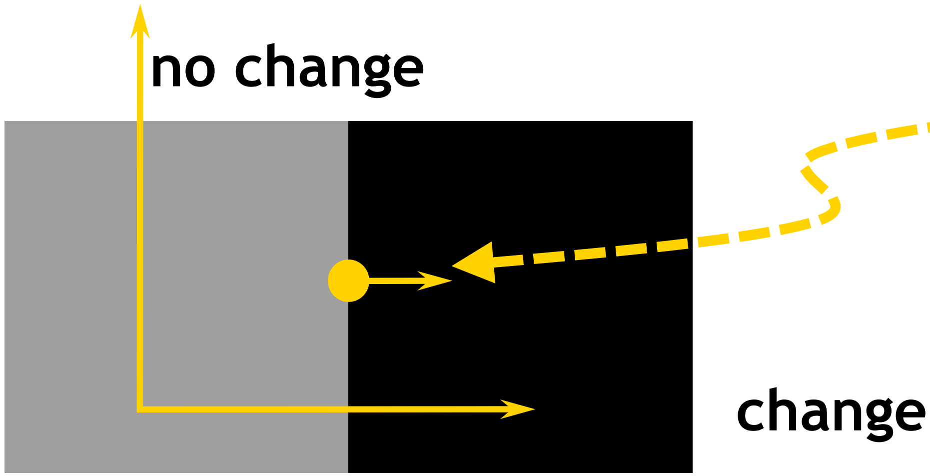


  - in 2D:

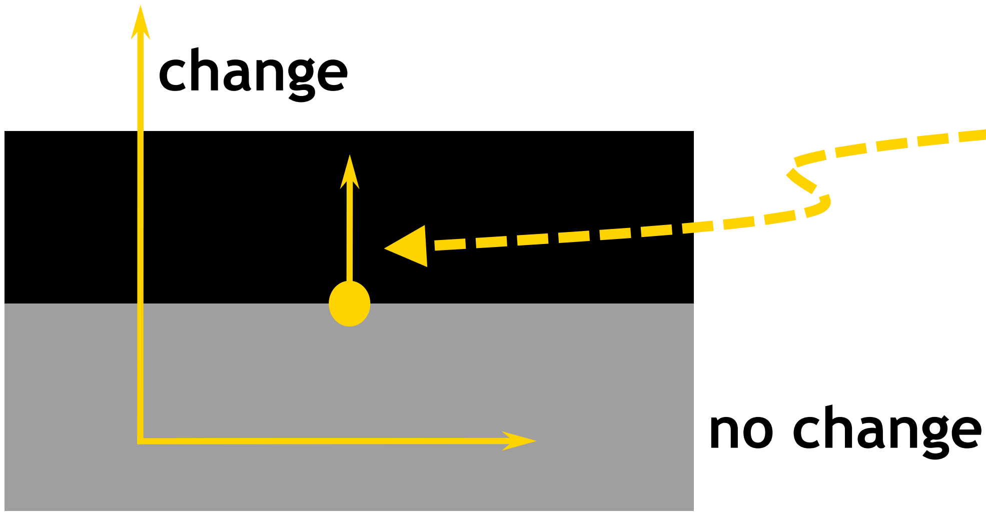




What is the gradient ?

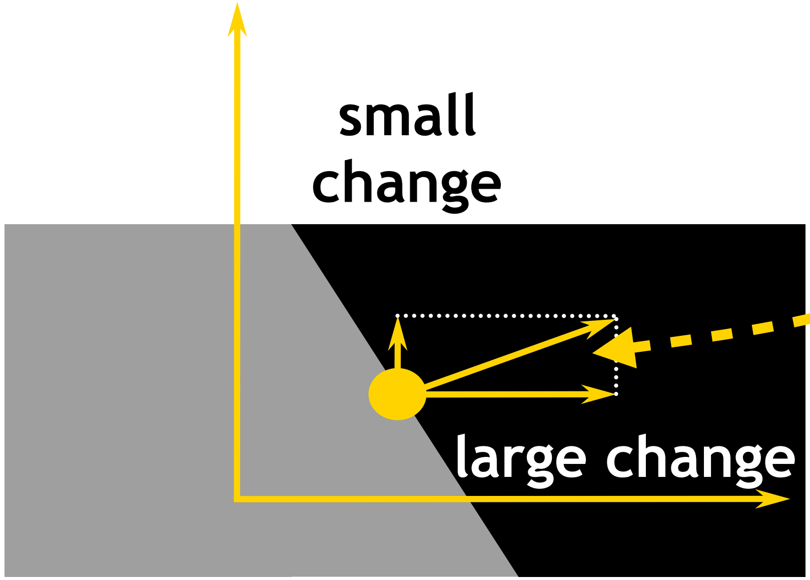


$$\left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right) = (k, 0)$$



$$\left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right) = (0, k)$$

What is the gradient ?



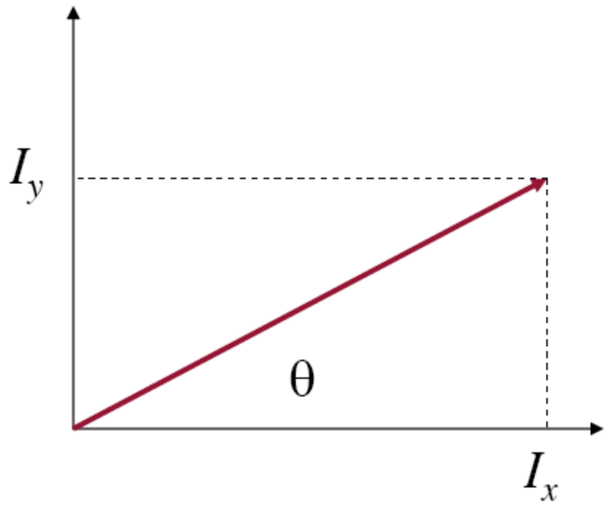
$$\left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right) = \left(k_x, k_y\right)$$

- gradient direction is perpendicular to edge
- gradient magnitude measures edge strength

2D Edge Detection

- calculate derivative
  - use the **magnitude** of the gradient
  - the gradient is:

$$\nabla I = \left(I_x, I_y \right) = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right)$$



  - the magnitude of the gradient is:

$$\left\| \nabla I \right\| = \sqrt{I_x^{\,2} + I_y^{\,2}}$$

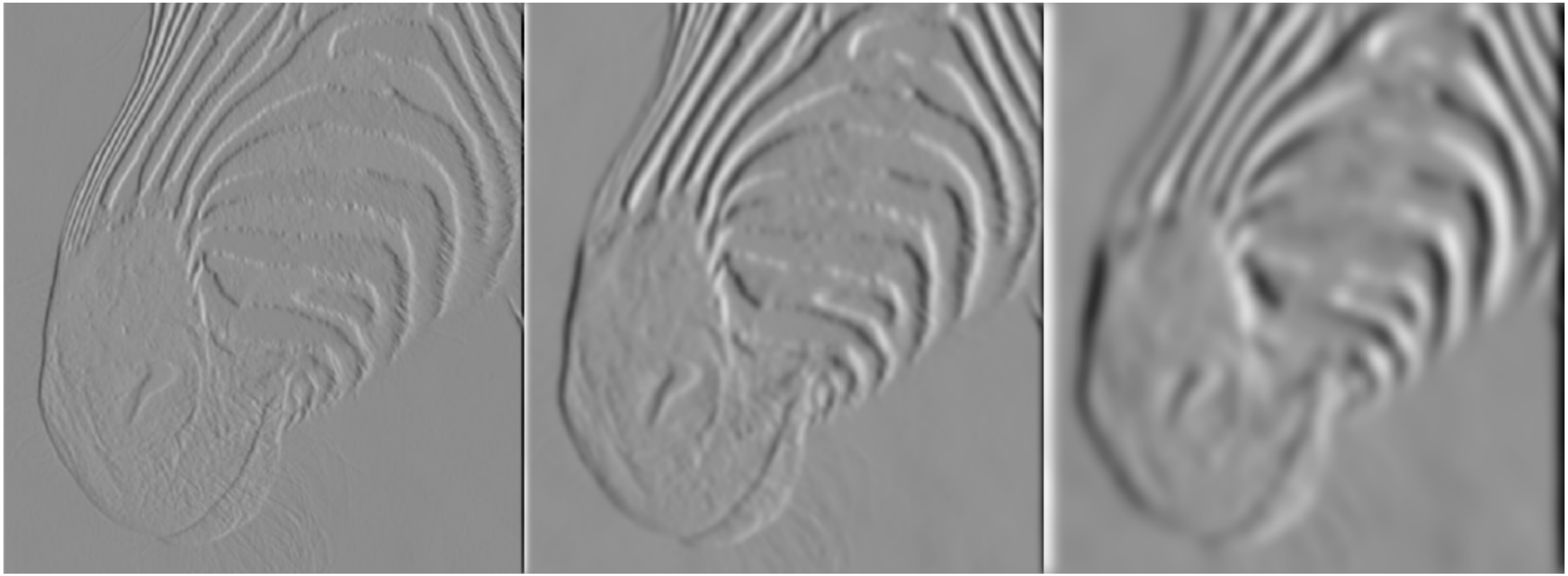
  - the direction of the gradient is:

$$\theta = \arctan\left(I_y, I_x \right)$$

2D Edge Detection

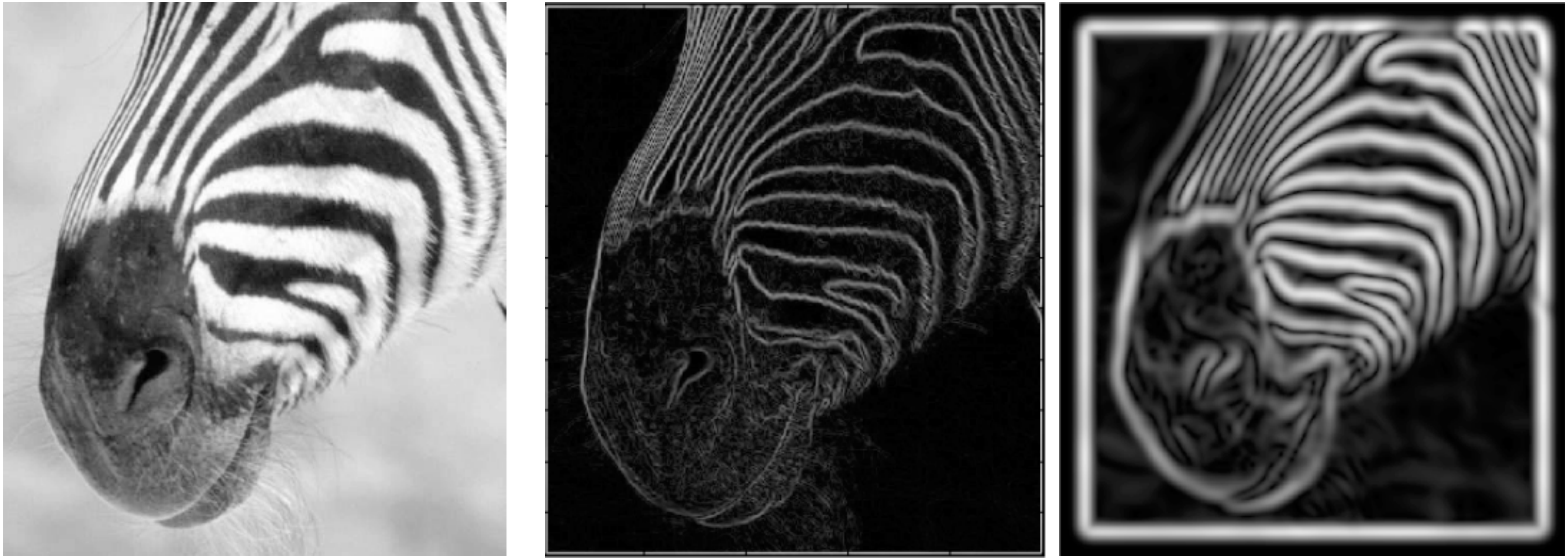
- the scale of the smoothing filter affects derivative estimates, and also the semantics of the edges recovered
  - note: strong edges persist across scales

1 pixel **3 pixels** **7 pixels**



2D Edge Detection

- there are 3 major issues:
  - the gradient magnitude at different scales is different; which should we choose?
  - the gradient magnitude is large along a thick trail; how do we identify the significant points?
  - how do we link the relevant points up into curves?



‘Optimal’ Edge Detection: Canny

- Assume:
  - linear filtering
  - additive i.i.d. Gaussian noise
- Edge Detection should have:
  - **good detection**: filter response to edge, not noise
  - **good localization**: detected edge near true edge
  - **single response**: one per edge
- then: optimal detector is approximately derivative of Gaussian
- detection/localization tradeoff:
  - more smoothing improves detection
  - and hurts localization

The Canny edge detector

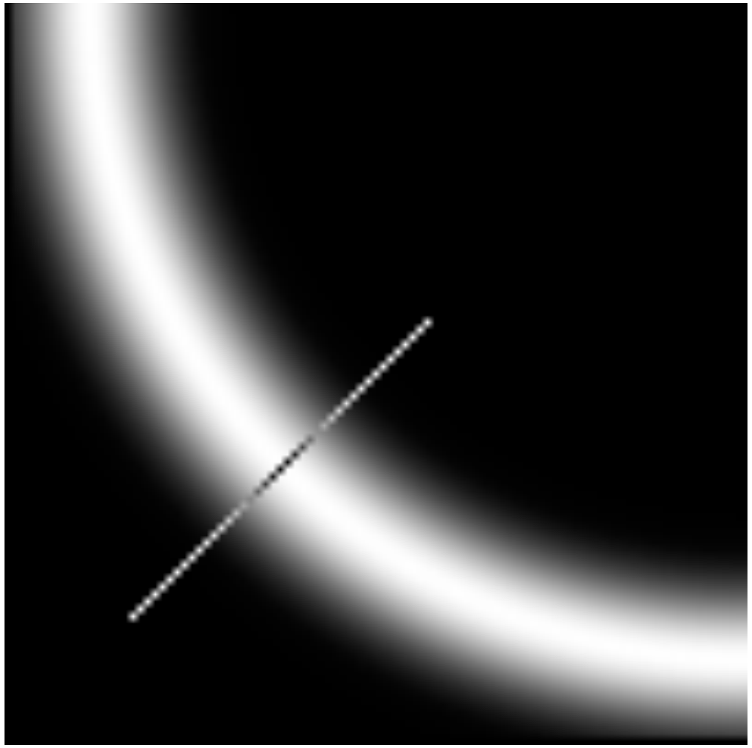
original image
(Lena)

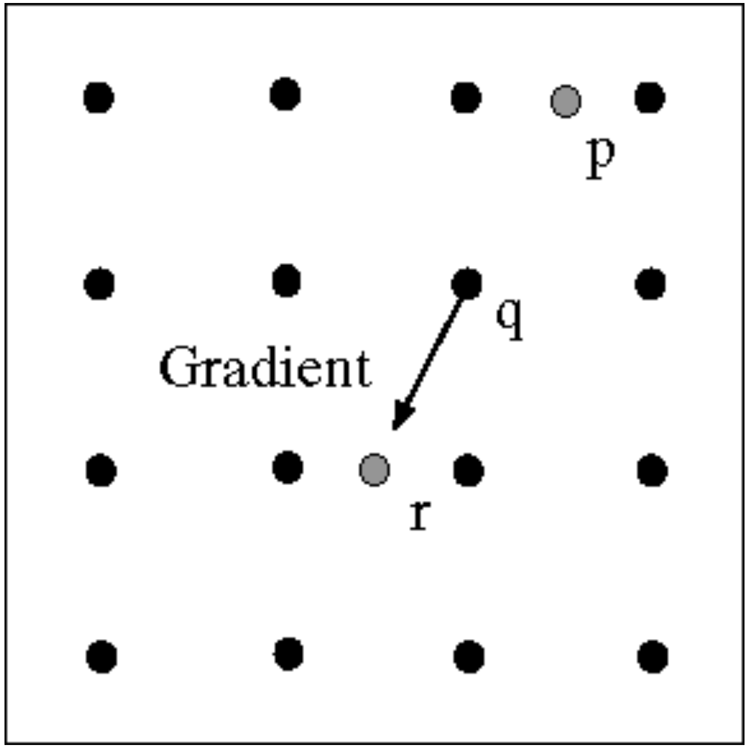
norm
(=magnitude) of
the gradient

thinning
(non-maximum
suppression

thresholding

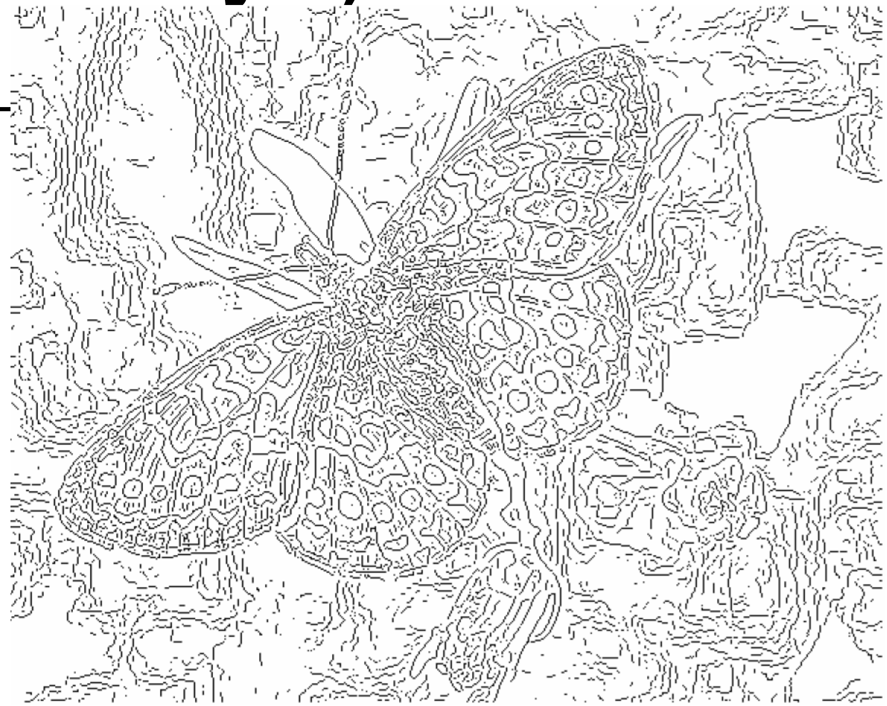
Non-maximum suppression





- Check if pixel is local maximum along gradient direction
  - choose the largest gradient magnitude along the gradient direction
  - requires checking interpolated pixels p and r

Butterfly Example (Ponce & Forsyth)

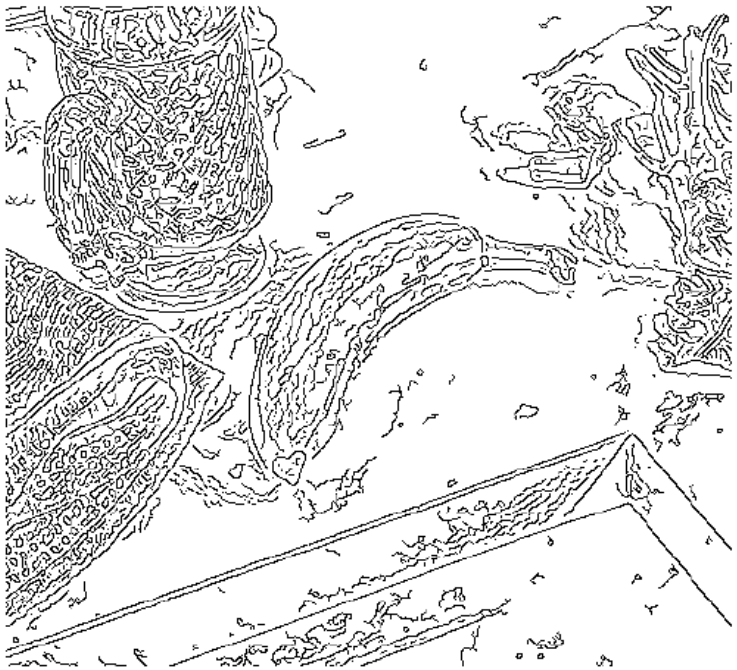


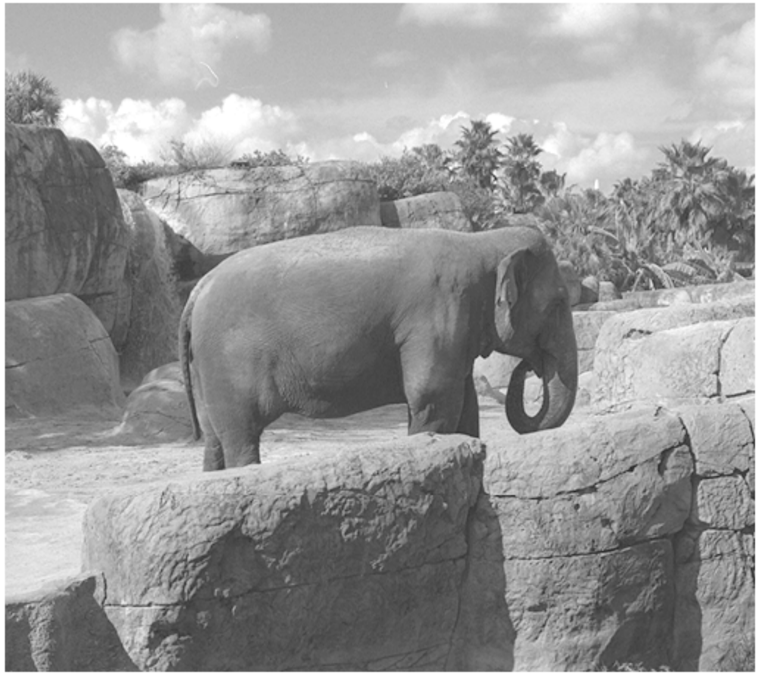
fine scale
high
threshold

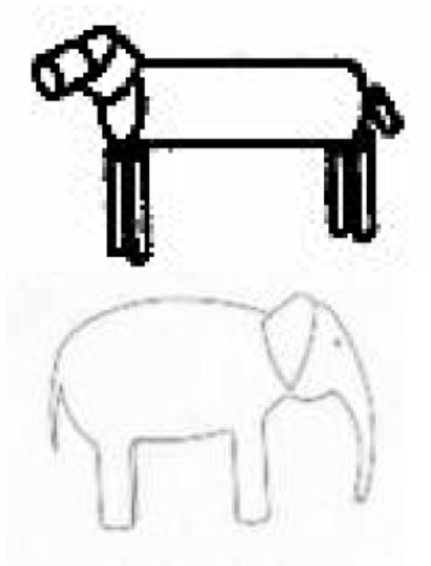
coarse
scale
low
threshold

coarse
scale,
high
threshold

line drawing vs. edge detection

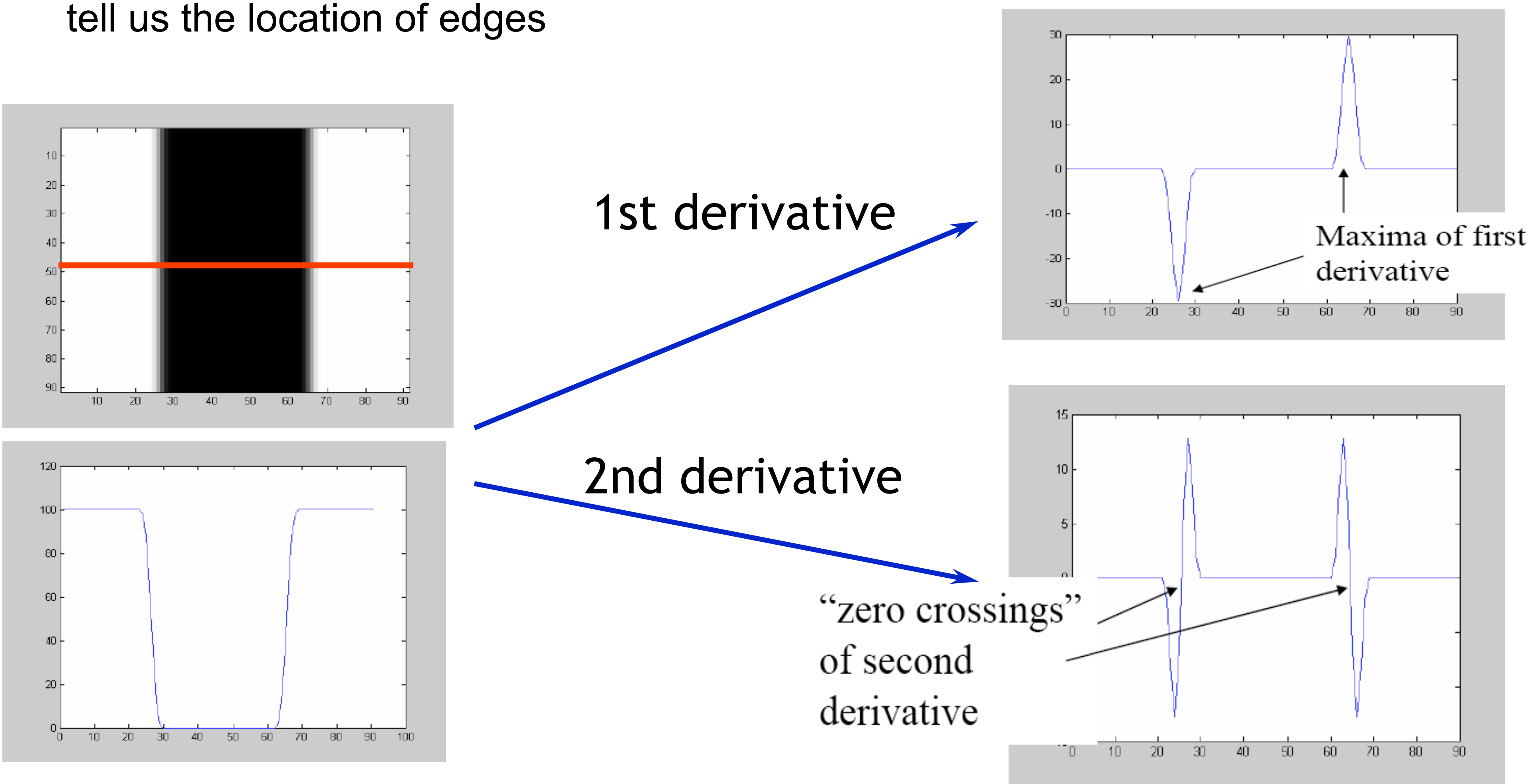



University of South Florida


Match "model" to measurements?

Edges & Derivatives…

- recall:
  - the zero-crossings of the second derivative tell us the location of edges



Compute 2nd order derivatives

- 1st derivative:

$$\frac{d}{dx}f(x) = \lim_{h\to 0}\frac{f(x+h)-f(x)}{h} \approx f(x+1)-f(x)$$

- 2nd derivative:

$$\frac{d^2}{dx^2}f(x) = \lim_{h\to 0}\frac{\frac{d}{dx}f(x+h)-\frac{d}{dx}f(x)}{h} \approx \frac{d}{dx}f(x+1)-\frac{d}{dx}f(x)$$

$$\approx f(x+2)-2f(x+1)+f(x)$$

- mask for
  - 1st derivative:

-1	1

2nd derivative:

1	-2	1

The Laplacian

- The Laplacian:

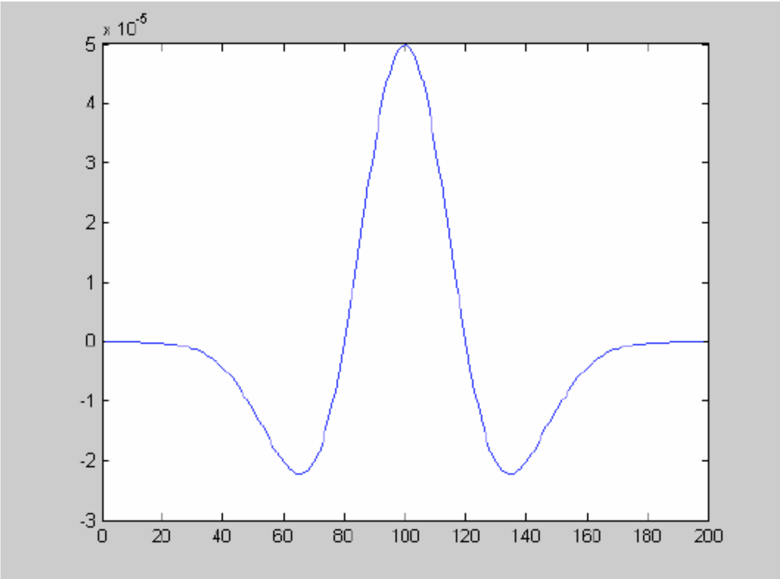
$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

  - just another linear filter:

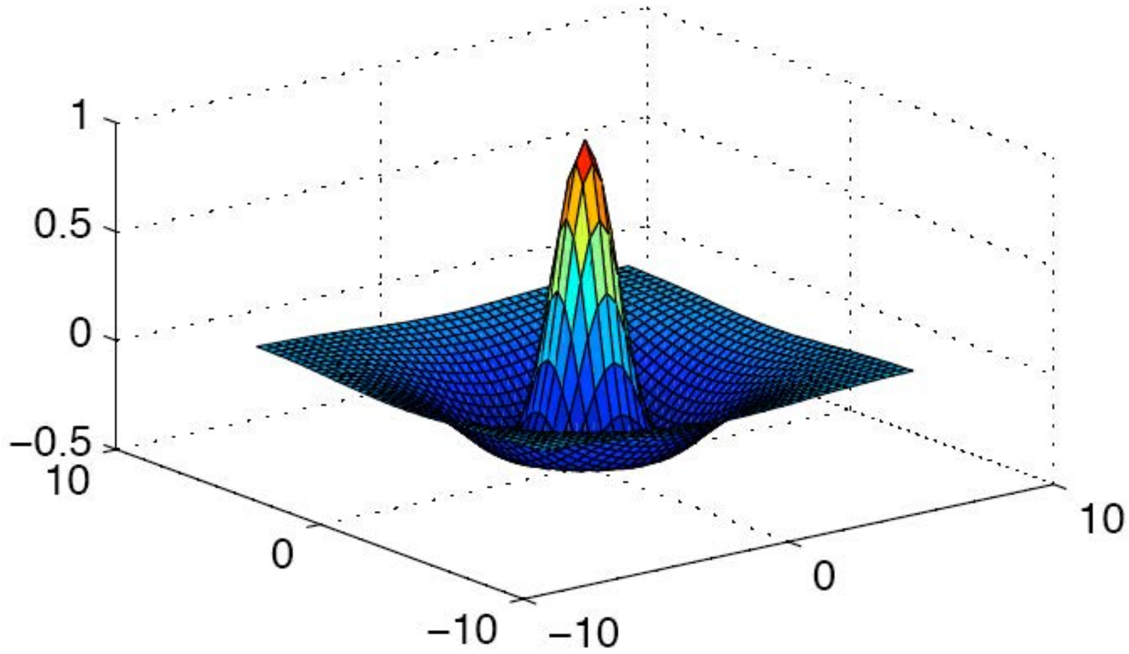
$$\nabla^2 \left(G \otimes f \right) = \nabla^2 G \otimes f$$

Second Derivative of Gaussian

- in 1D:



- in 2D ('mexican hat'):



1D edge detection

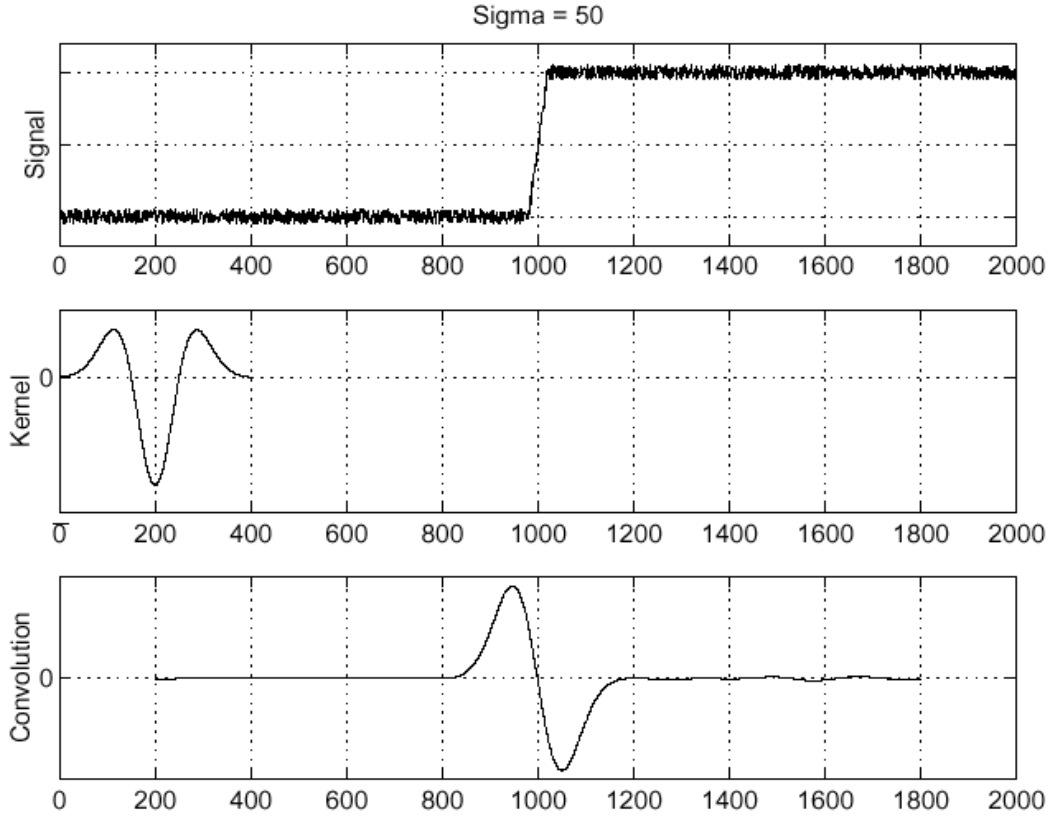
- using Laplacian

$$f$$

Laplacian of Gaussian operator

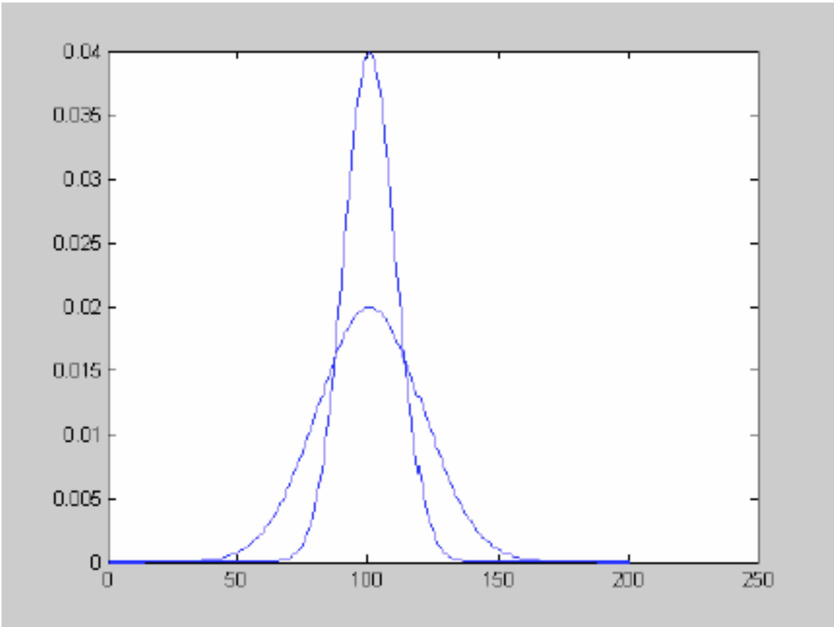
$$\frac{d^2}{dx^2} g$$

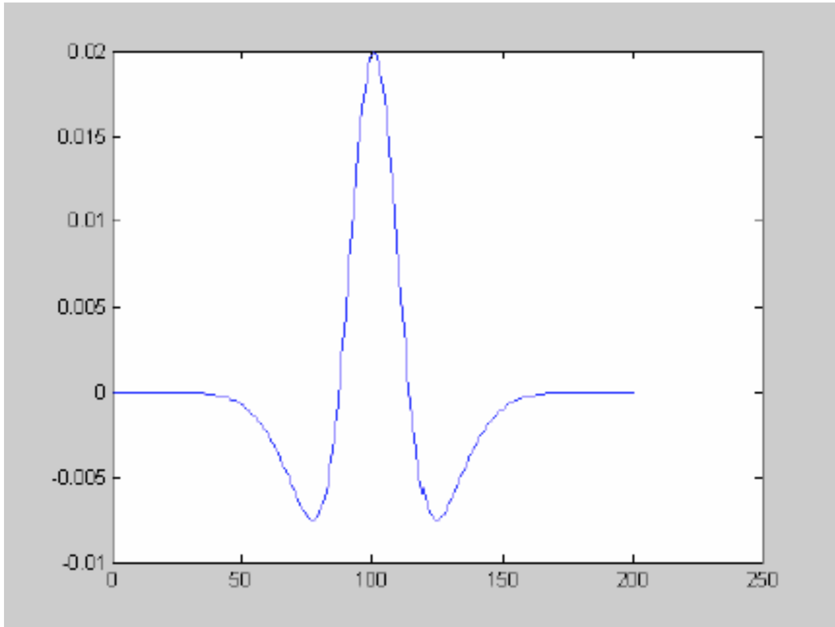
$$\left(\frac{d^2}{dx^2} g\right) \otimes f$$



Approximating the Laplacian

- Difference of Gaussians (DoG) at different scales:





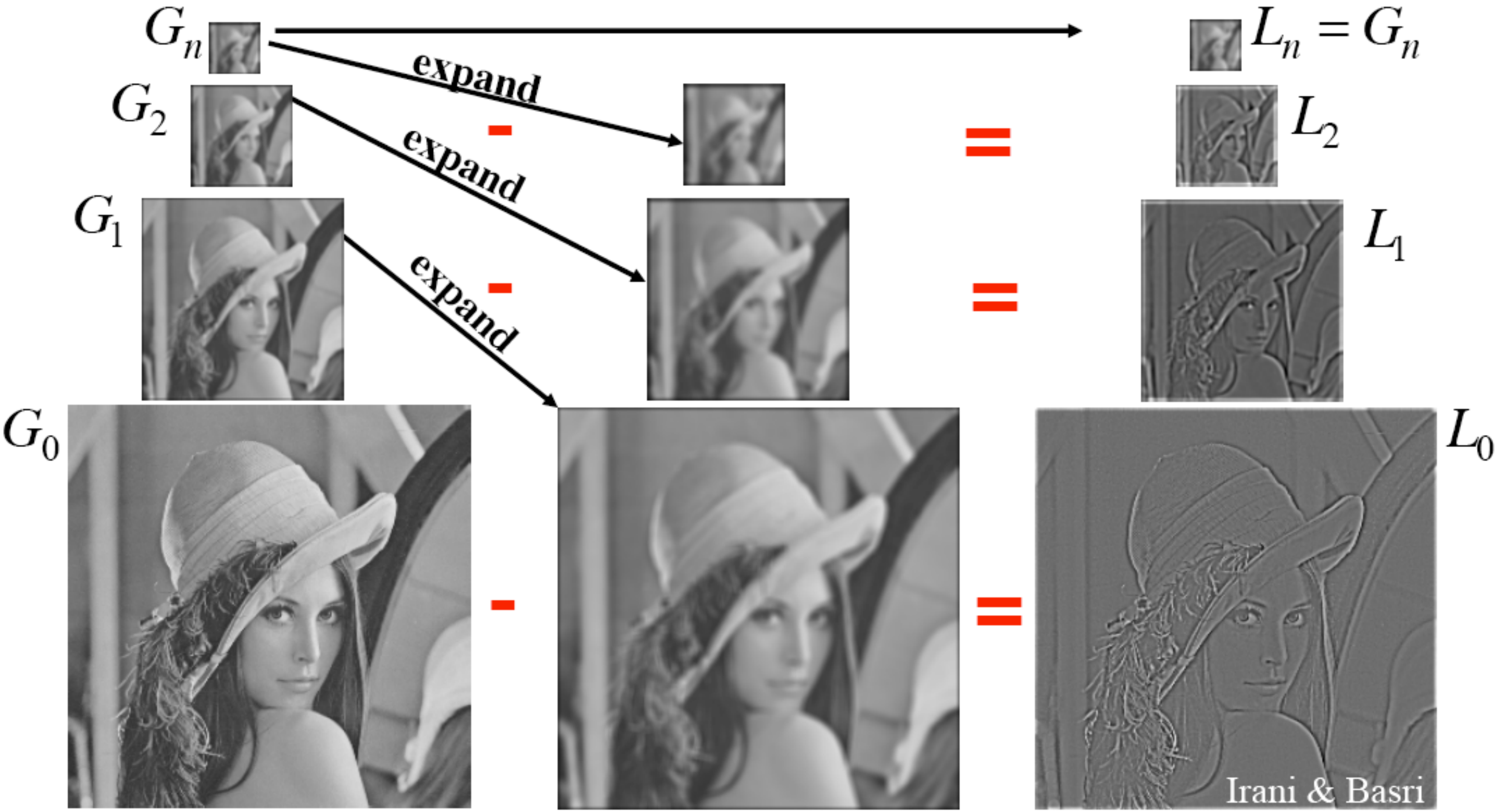
The Laplacian Pyramid

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

Gaussian Pyramid

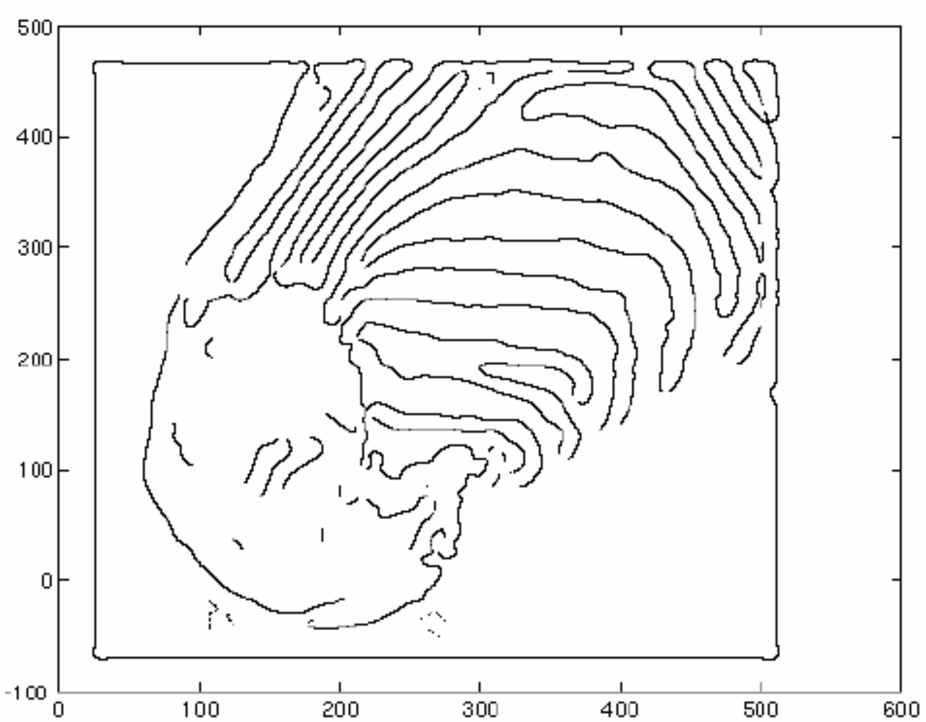
$$G_i = L_i + \text{expand}(G_{i+1})$$

Laplacian Pyramid

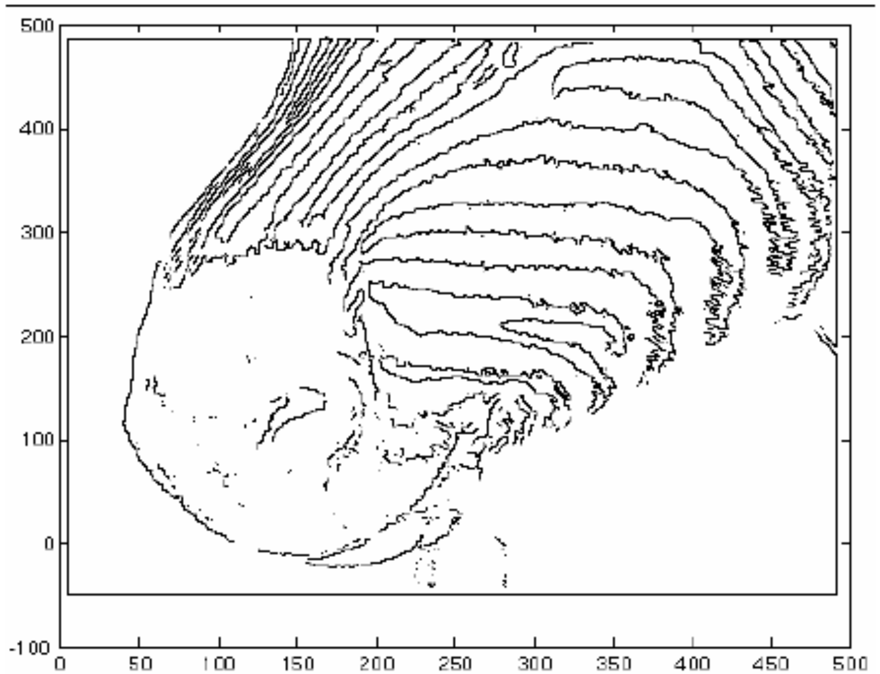


Edge Detection with Laplacian

- sigma = 4

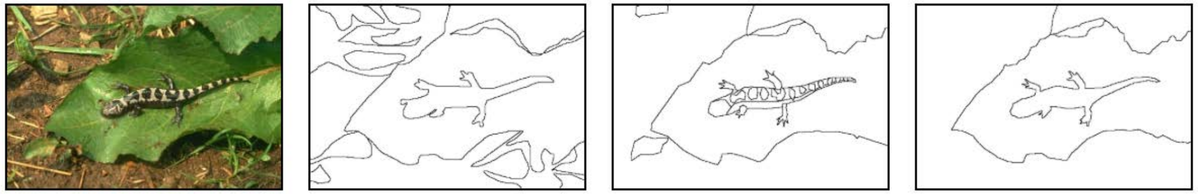


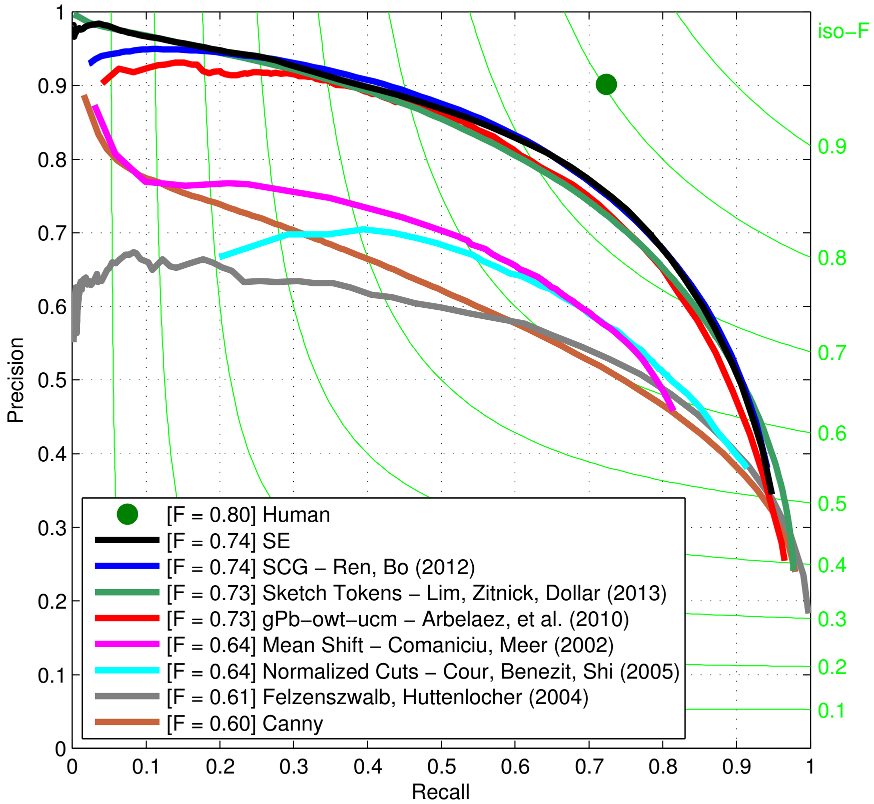
- sigma = 2



Edge Detection Today

- Still topic of active research after 40 years
- Today dominated by learning-based methods
- Quantitative Evaluation eg. on Berkeley Segmentation Data Set
  - 500 images
  - 5 Annotations per image





- References
  - P. Arbelaez, M. Maire, C. Fowlkes and J. Malik: Contour Detection and Hierarchical Image Segmentation; IEEE TPAMI, 2011
  - P.Dollar, C. Lawrence Zitnick: Fast Edge Detection using Structured Forests; International Conference on Computer Vision 2013; to appear in IEEE TPAMI 2015

Today - Basics of Digital Image Processing

- Linear Filtering
  - Gaussian Filtering
- Multi Scale Image Representation
  - Gaussian Pyramid, Laplacian Pyramid
- Edge Detection
  - ‘Recognition using Line Drawings’
  - Image derivatives (1st and 2nd order)
- Hough Transform
  - Finding parametrized curves, generalized Hough transform
- Object Instance Identification using Color Histograms

- (Several slides are taken from Michael Black @ Brown)

Discussion

- edge detection + contour extraction
  - edges are defined as discontinuities in the image
  - we can assemble them, to obtain corresponding object contours
  - but contours do not necessarily correspond to object boundaries

- problem:
  - there is basically no knowledge used how object contours look like
  - obviously humans use such knowledge to segment objects
  - in principle: if we knew which object is in the image it would be much simpler to segment the object

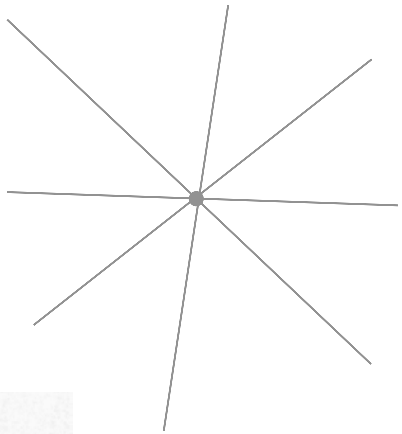
Hough Transformation

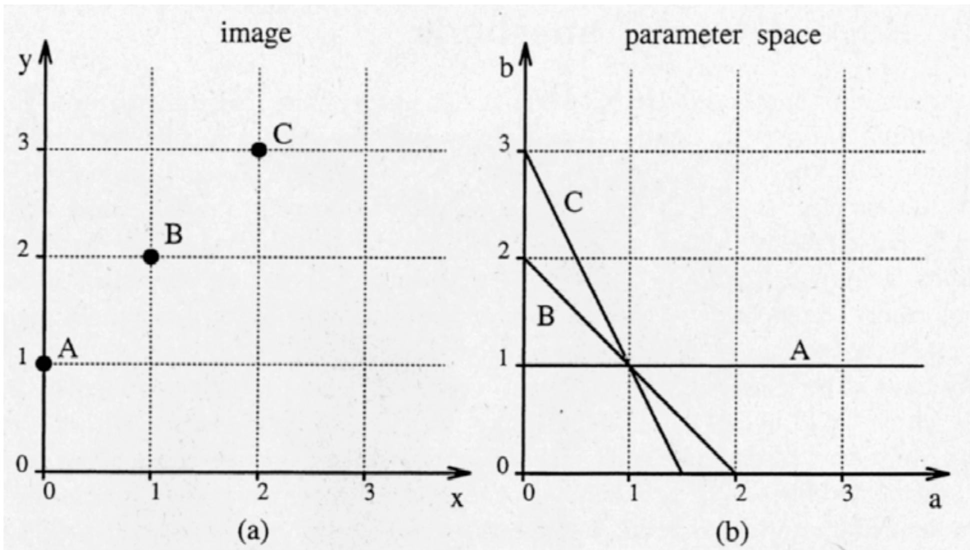
- detection of straight lines
  - use the ‘knowledge’ that many contours belong to straight lines

- representation of a line: y = a x + b
  - 2 parameters: a and b - determine all points of a line
  - this corresponds to a transformation: (a,b) -> (x,y)
    - y = a x + b
  - inverse interpretation: transformation of (x,y) -> (a,b)
    - b = (-x)a + y
  - usage: points for which the magnitude of the first derivate is large lie potentially on a line

Hough Transformation

- for a particular point (x,y) determine all lines which go through this point:
  - the parameters of all those lines are given by: b = (-x)a + y
  - I.e. those lines are given by a line in the parameter space (a,b)





Hough Transformation

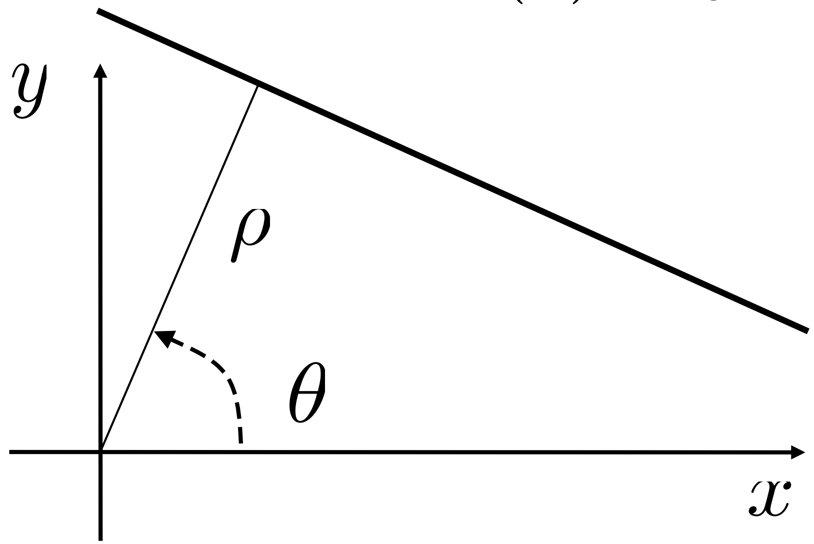
- implementation:
  - the parameter space (a,b) has to be discretized
  - for each candidate (x,y) for a line, store the line
    $b = (-a)\,x + y$
  - in principle each candidate (x,y) votes for the discretized parameters
  - the maxima in the parameter space (a,b) correspond to lines in the image

- problem of this particular parameterization
  - the parameter ‘a’ can become infinite (for vertical lines)
  - problematic for the discretization

Hough Transformation

- choose another parameterization:

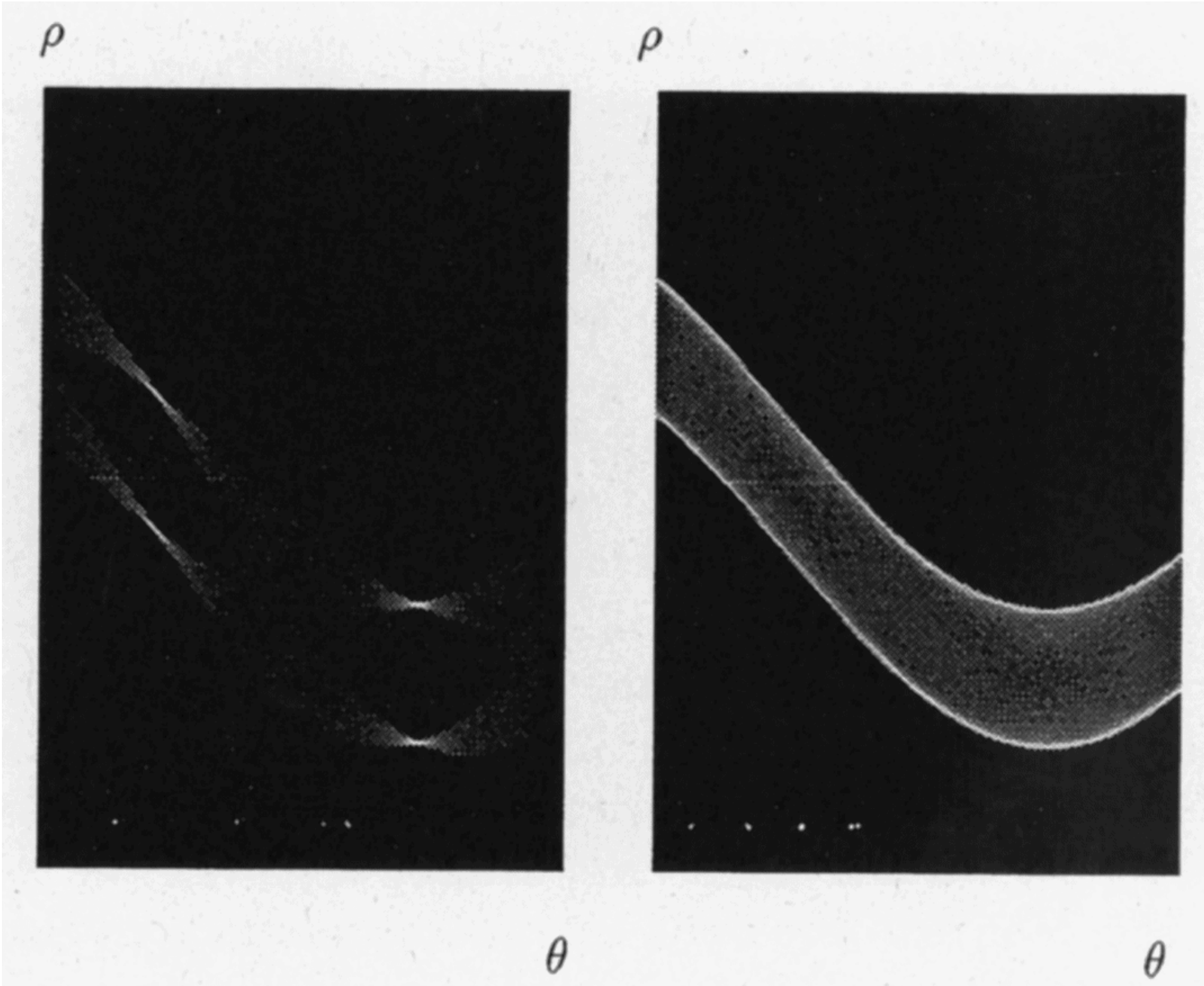
$$x\cos(\theta) + y\sin(\theta) = \rho$$



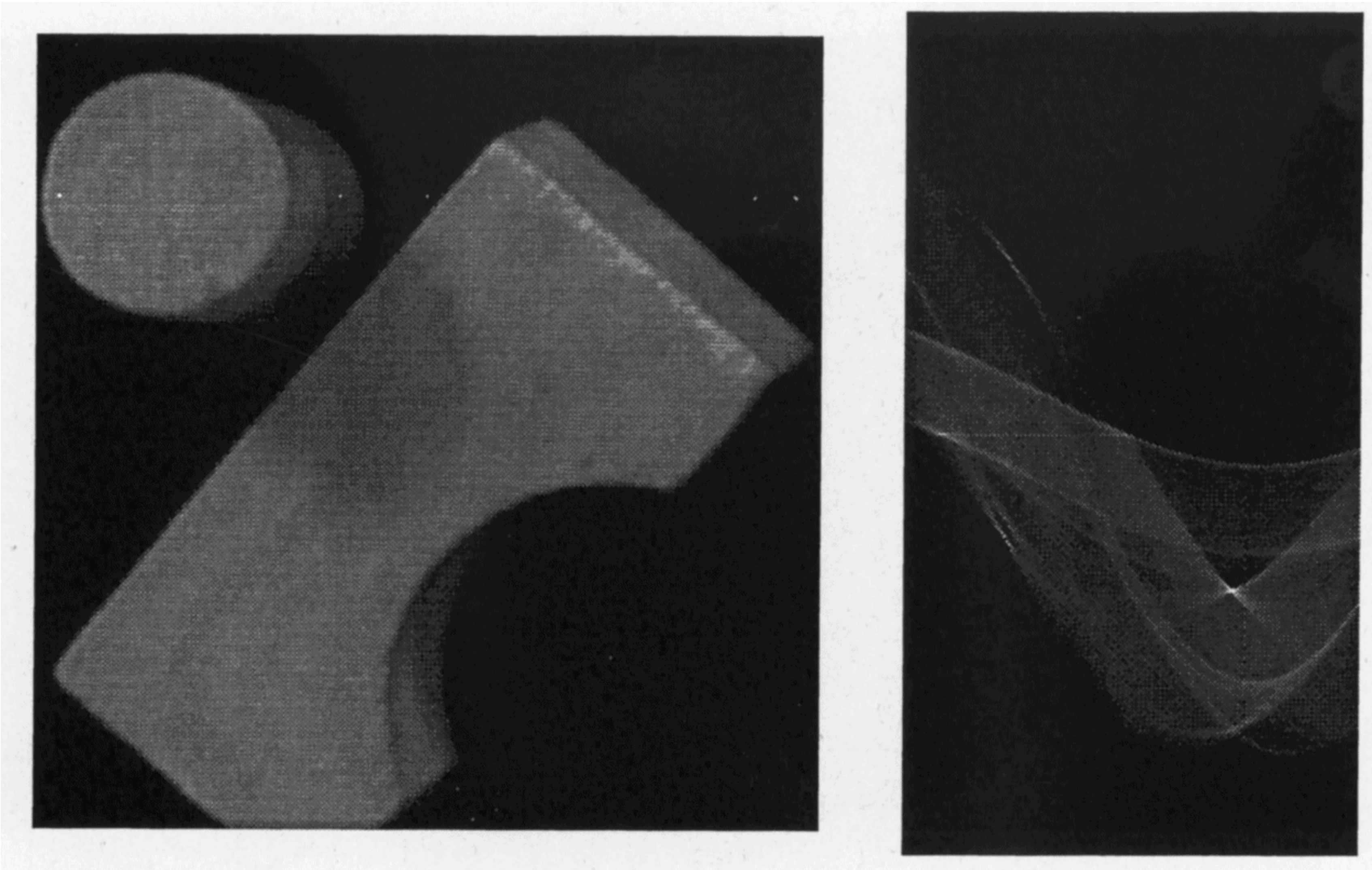
- for this parameterization the domain is limited:
  - ρ is limited by the size of the image
  - and $\theta \in [0, 2\pi]$

Examples

- Houghtransform for a square (left) and a circle (right)



Examples



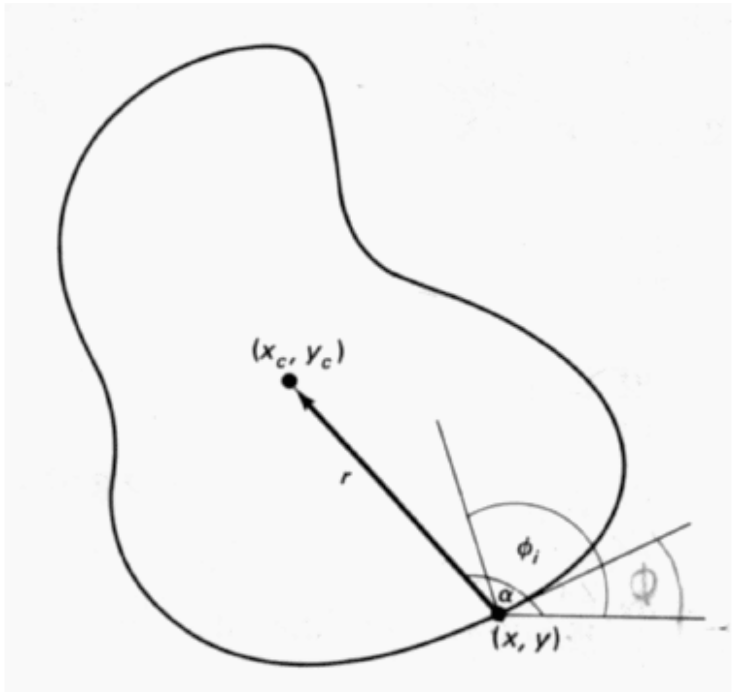
Hough Transform

- the same idea can be used for other parameterized contours
  - Example:
    - circle: $(x-a)^2 + (y-b)^2 = r^2$
    - 3 parameters: center point (a, b) and radius r

- Limitation:
  - the parameter space should not become too large
  - not all contours can be parameterized

Generalized Hough Transform

- Generalization for an arbitrary contour
  - choose reference point for the contour (e.g. centre)
  - for each point on the contour remember where it is located w.r.t. to the reference point
  - e.g. if the center is the reference point: remember radius r and angle relative to the tangent of the contour
  - recognition: whenever you find a contour point, calculate the tangent angle and ‘vote’ for all possible reference points



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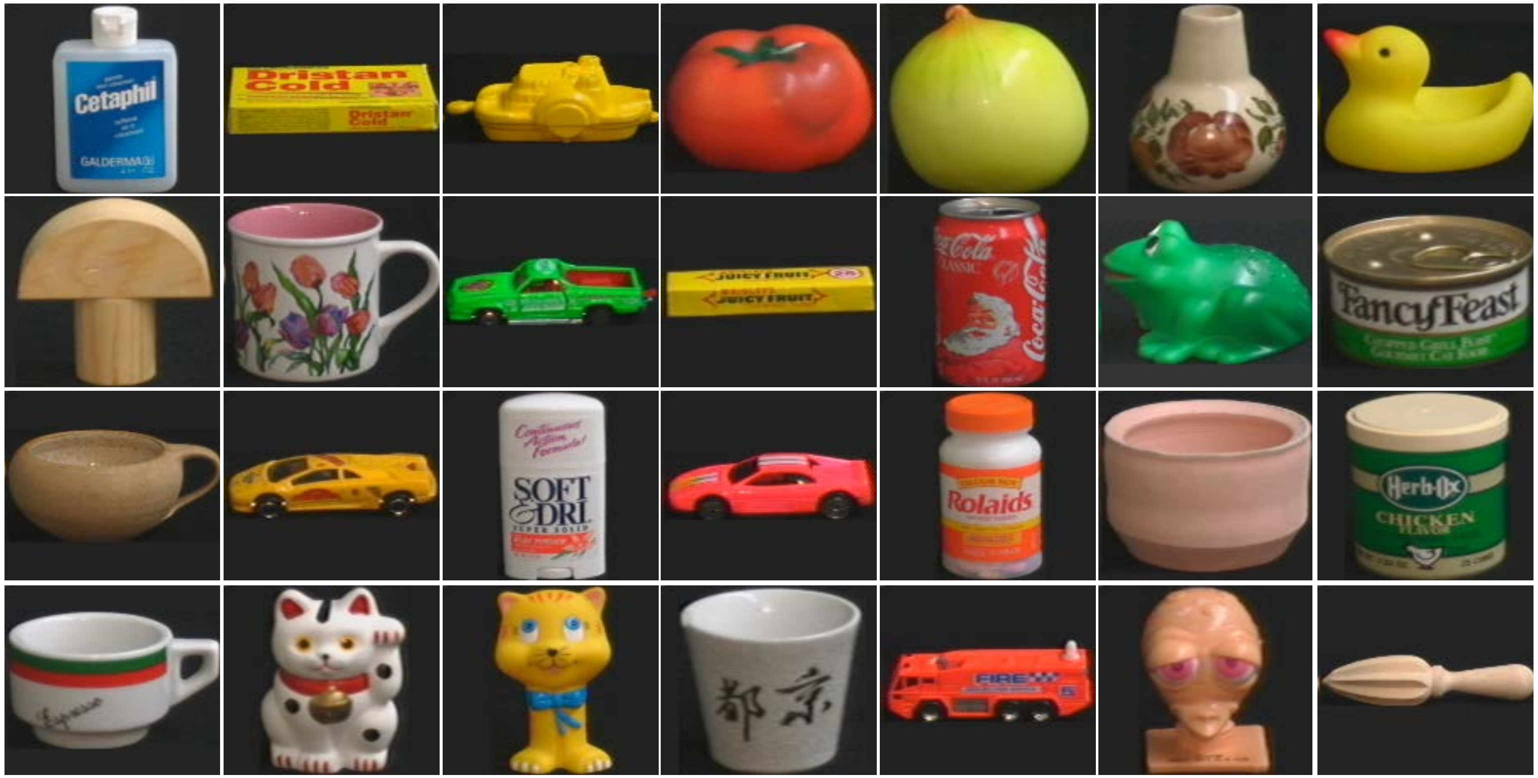
- (Several slides are taken from Michael Black @ Brown)

Object Recognition (reminder)

- Different Types of Recognition Problems:
  - Object **Identification**
    - recognize your apple, your cup, your dog
    - sometimes called: “instance recognition”
  - Object **Classification**
    - recognize any apple, any cup, any dog
    - also called: generic object recognition, object categorization, …
    - typical definition: ‘basic level category’

Object Identification

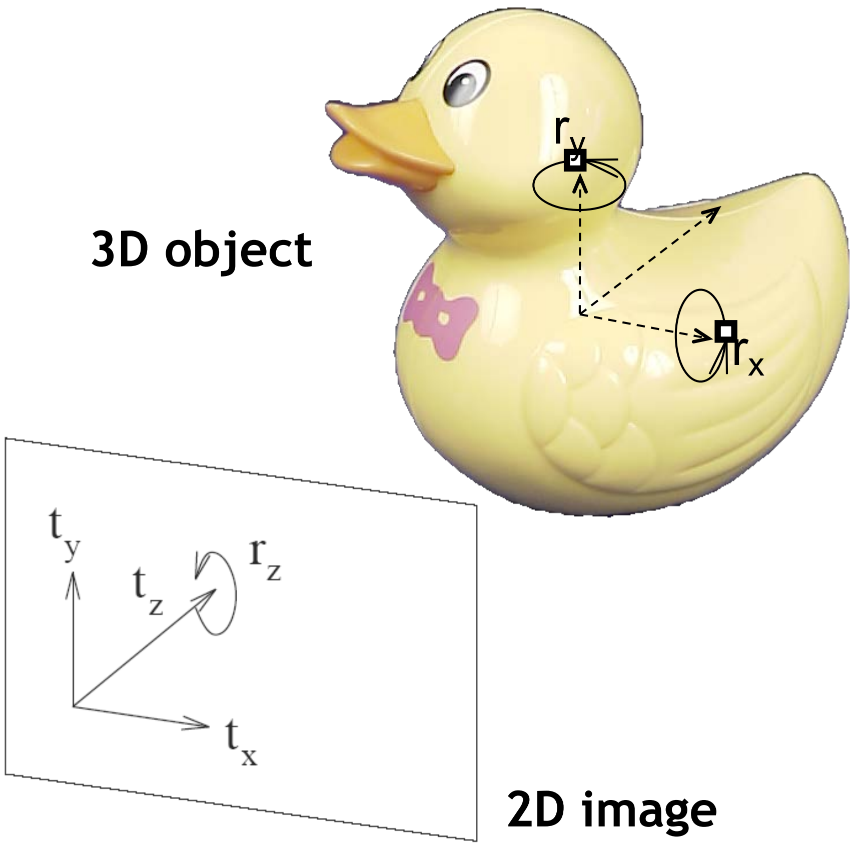
- Example Database for Object Identification:
  - COIL-100 - Columbia Object Image Library
  - contains 100 different objects, some form the same object class (e.g. cars,cups)



Challenges = Modes of Variation

- Viewpoint changes
  - Translation
  - Image-plane rotation
  - Scale changes
  - Out-of-plane rotation

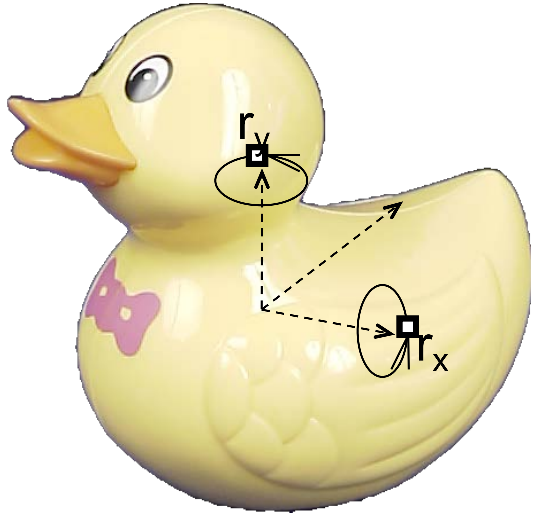
- Illumination
- Clutter
- Occlusion
- Noise



Appearance-Based Identification / Recognition

- Basic assumption
  - Objects can be represented by a collection of images (“appearances”).
  - For recognition, it is sufficient to just compare the 2D appearances.
  - No 3D model is needed.

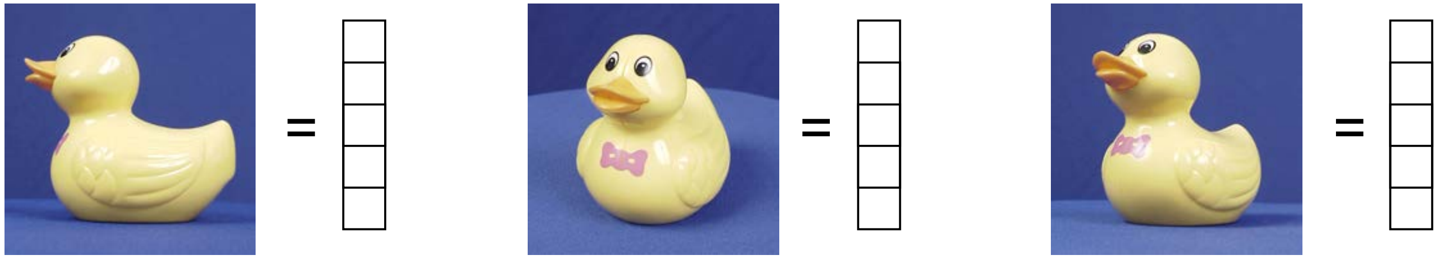
3D object



⇒ Fundamental paradigm shift in the 90’s

Global Representation

- Idea
  - Represent each view (of an object) by a global descriptor.



  - For recognizing objects, just match the (global) descriptors.
  - Modes of variation can be taken care of by:
    - built into the descriptor
      - e.g. a descriptor can be made invariant to image-plane rotations, translation
    - incorporate in the training data or the recognition process.
      - e.g. viewpoint changes, scale changes, out-of-plane rotation
    - robustness of descriptor or recognition process (descriptor matching)
      - e.g. illumination, noise, clutter, partial occlusion

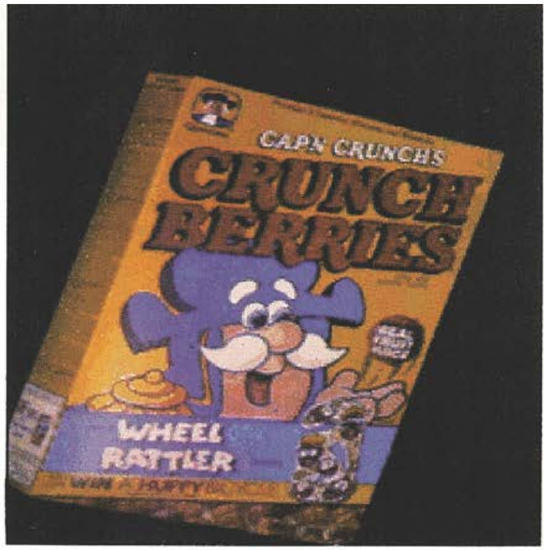
Case Study:
Use Color for Recognition

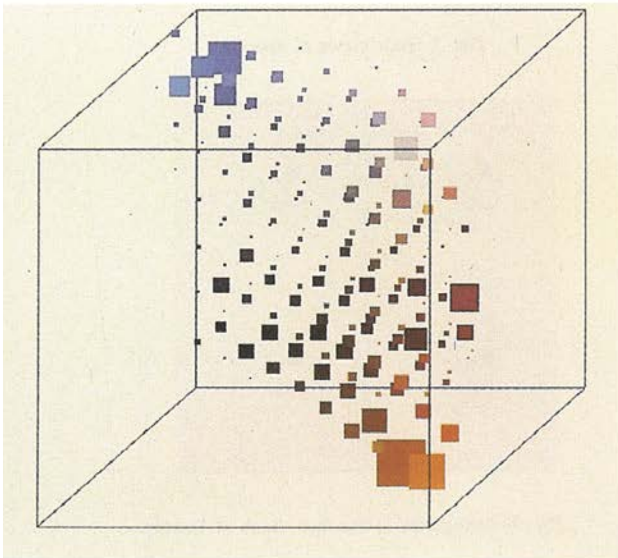
- Color:
  - Color stays constant under geometric transformations
  - Local feature
    - Color is defined for each pixel
    - Robust to partial occlusion

- Idea
  - Directly use object colors for identification / recognition
  - Better: use statistics of object colors

Color Histograms

- Color statistics
  - Given: tri-stimulus R,G,B for each pixel
  - Compute 3D histogram
    - H(R,G,B) = #(pixels with color (R,G,B))

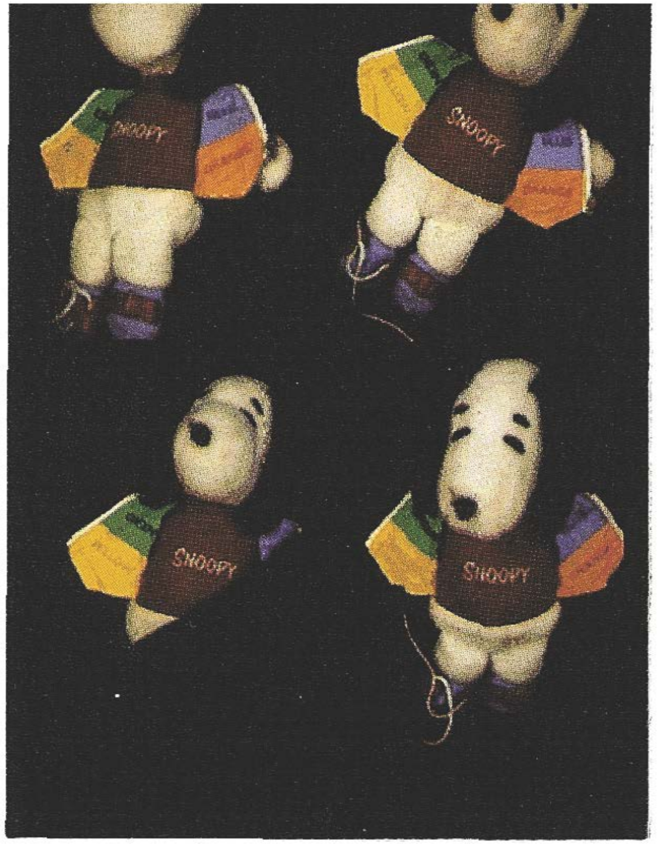


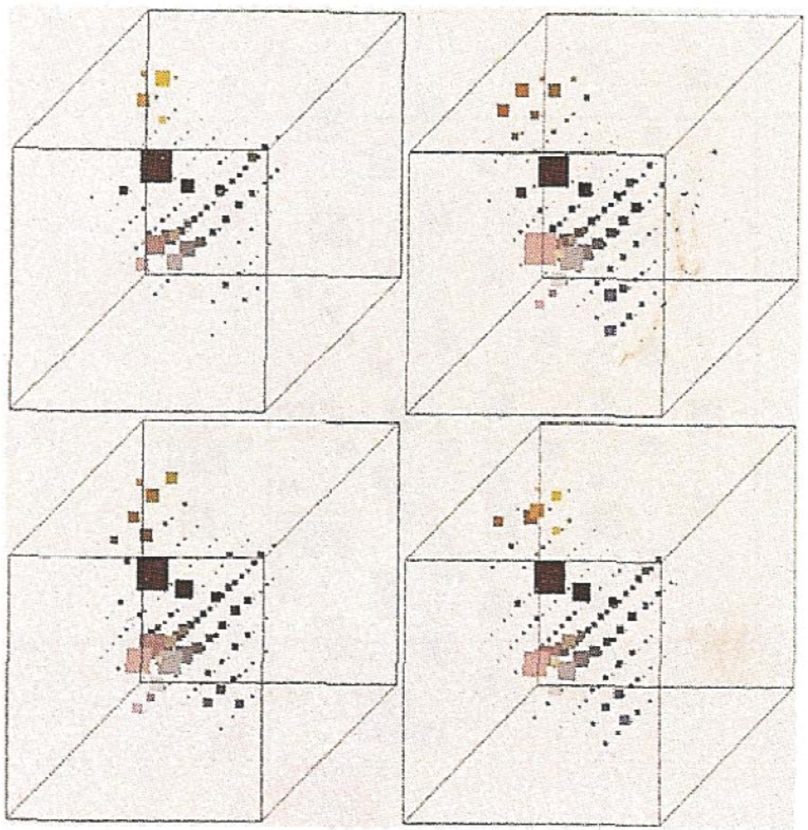


[Swain & Ballard, 1991]

Color Histograms

- Robust representation
  - presence of occlusion, rotation





[Swain & Ballard, 1991]

Color

- One component of the 3D color space is intensity
  - If a color vector is multiplied by a scalar, the intensity changes, but not the color itself.
  - This means colors can be normalized by the intensity.
    - Intensity is given by: I = R + G + B:
  - „Chromatic representation"

$$r = \frac{R}{R+G+B}$$

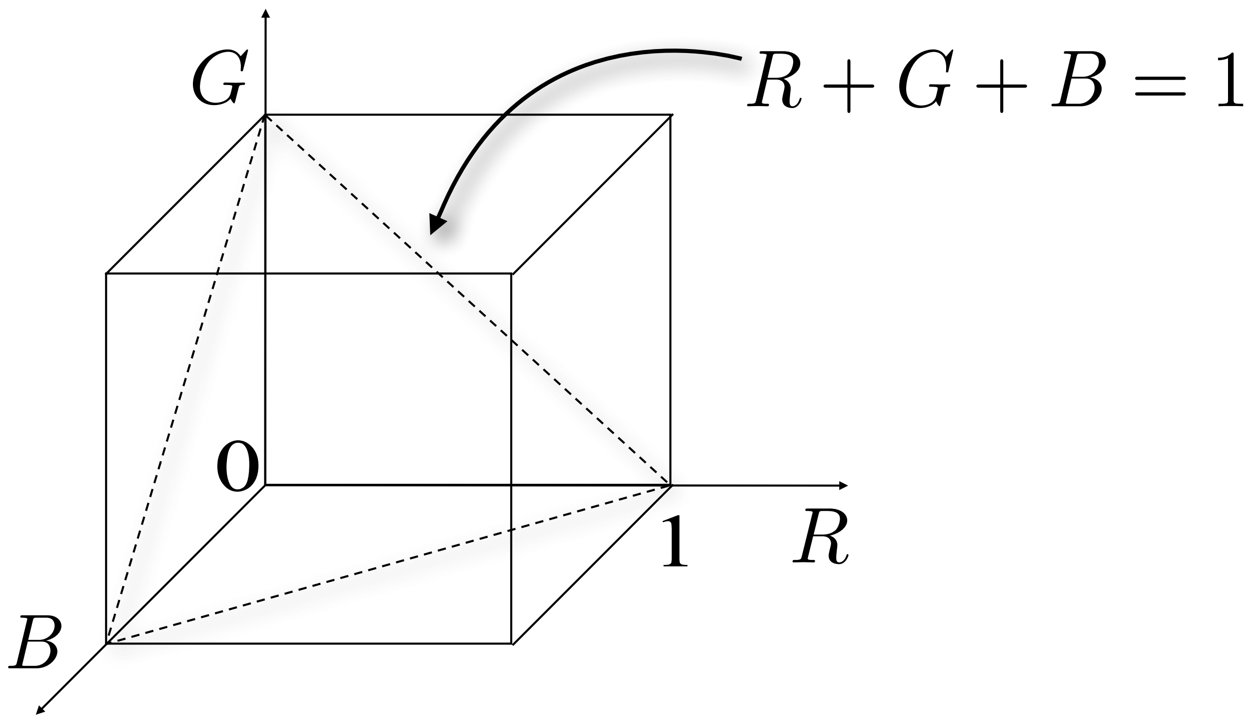
$$g = \frac{G}{R+G+B}$$

$$b = \frac{B}{R+G+B}$$

Color

- Observation:
  - Since r + g + b = 1, only 2 parameters are necessary
  - E.g. one can use r and g
  - and obtains b = 1 - r - g

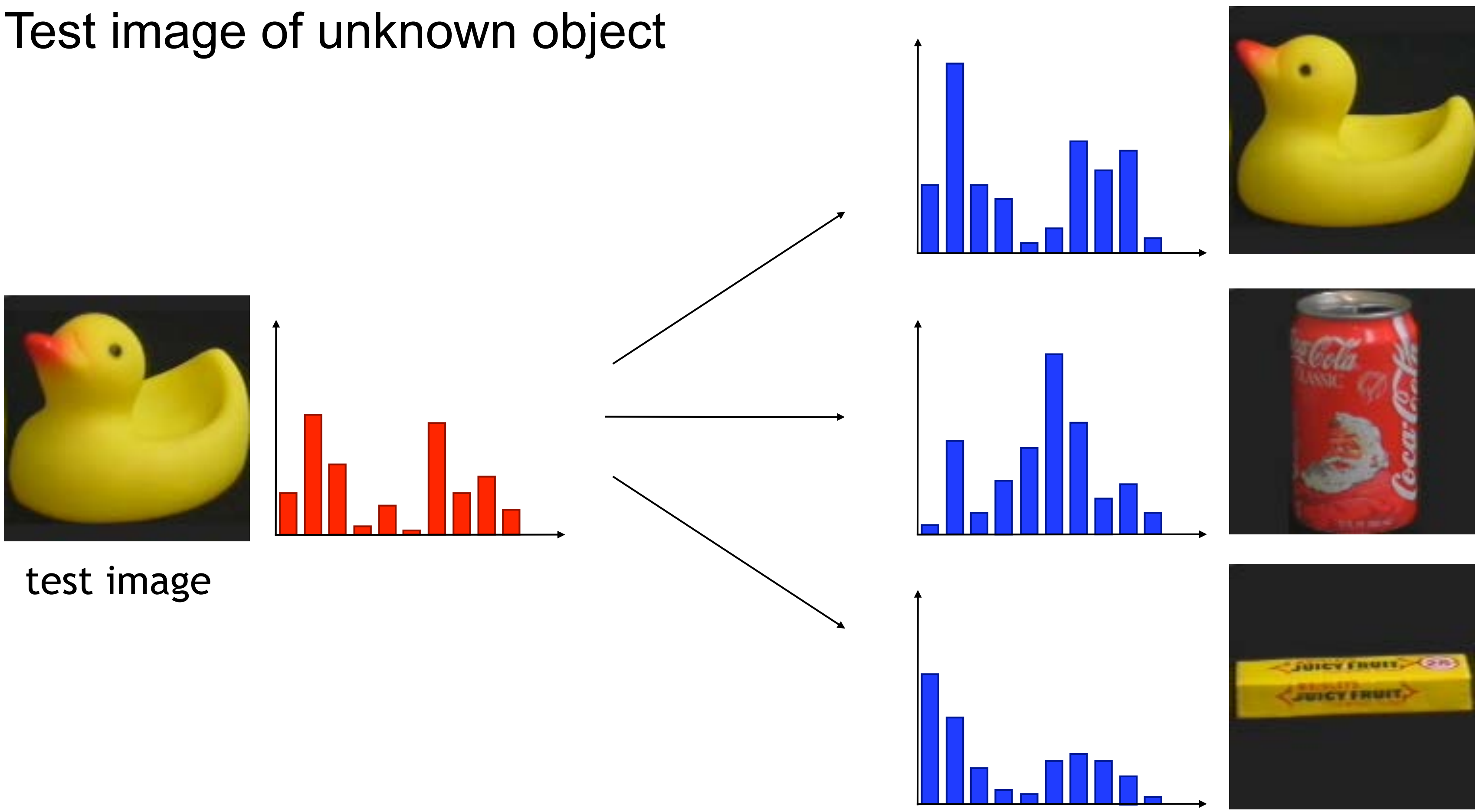
$$r + g + b = 1$$
$$\Rightarrow b = 1 - r - g$$



Recognition using Histograms

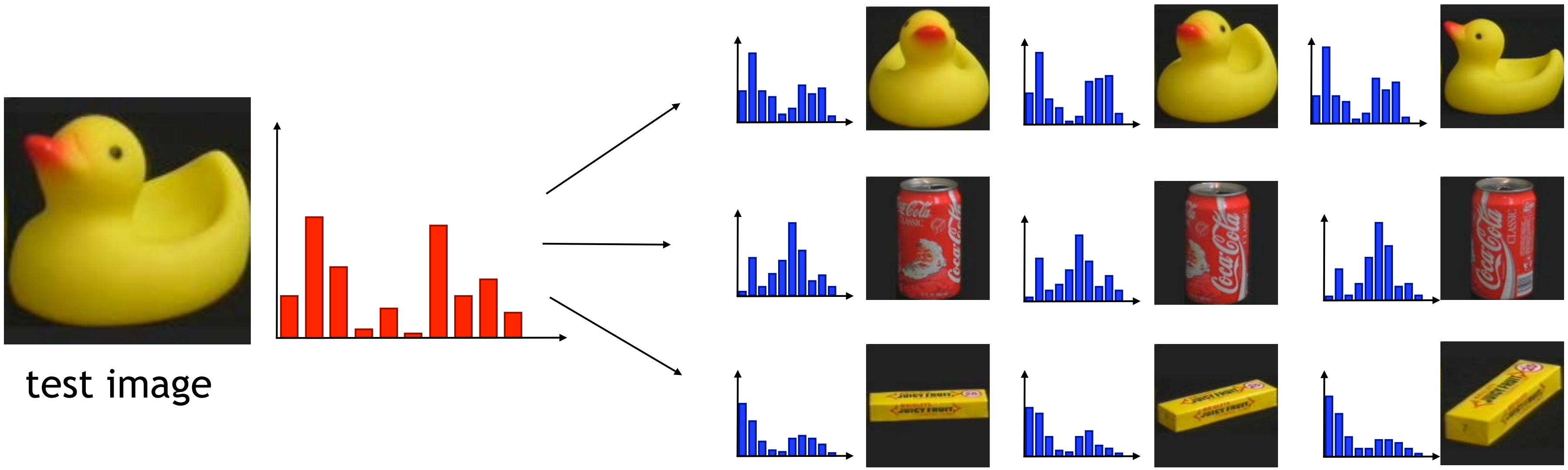
- Histogram comparison
  - Database of known objects
  - Test image of unknown object

known objects



Recognition using Histograms

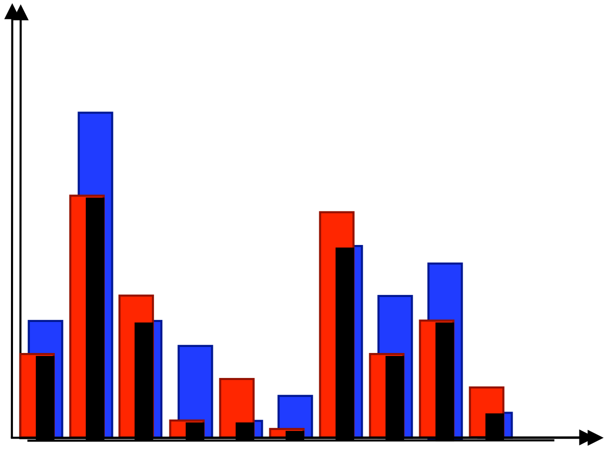
- Database with multiple training views per object



Histogram Comparison

- Comparison measures
  - Intersection

$$\cap(Q,V) = \sum_i \min(q_i, v_i)$$



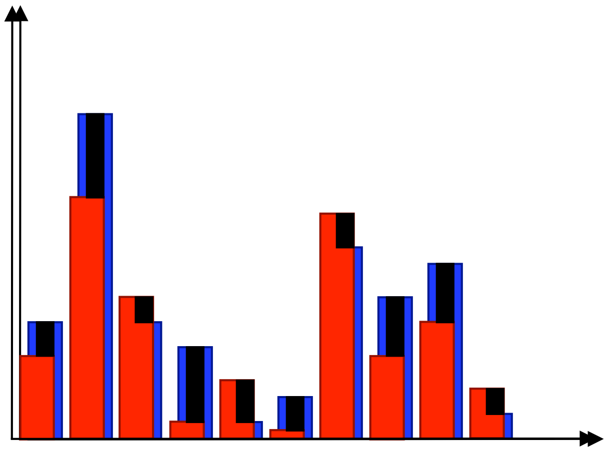
- Motivation
  - Measures the common part of both histograms
  - Range: [0,1]
  - For unnormalized histograms, use the following formula

$$\cap(Q,V) = \frac{1}{2}\left(\frac{\sum_i \min(q_i, v_i)}{\sum_i q_i} + \frac{\sum_i \min(q_i, v_i)}{\sum_i v_i}\right)$$

Histogram Comparison

- Comparison Measures
  - Euclidean Distance

$$d(Q,V) = \sum_i (q_i - v_i)^2$$

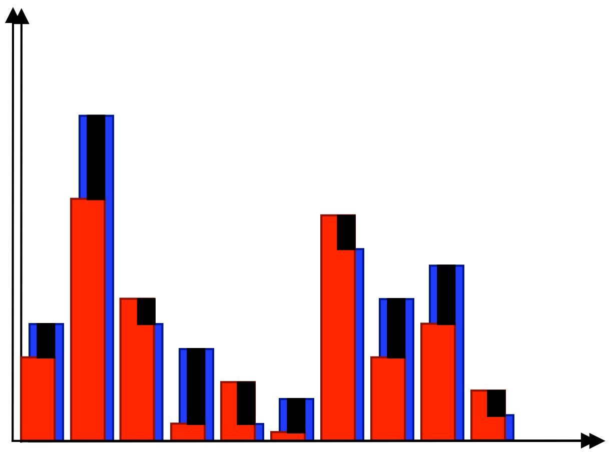


- Motivation
  - Focuses on the differences between the histograms
  - Range: $[0,\infty]$
  - All cells are weighted equally.
  - Not very discriminant

Histogram Comparison

- Comparison Measures
  - Chi-square

$$\chi^2(Q,V) = \sum_i \frac{(q_i - v_i)^2}{q_i + v_i}$$



- Motivation
  - Statistical background:
    - Test if two distributions are different
    - Possible to compute a significance score
  - Range: $[0,\infty]$
  - Cells are not weighted equally!
    - therefore more discriminant
    - may have problems with outliers (therefore assume that each cell contains at least a minimum of samples)

Histogram Comparison

- Which measure is best?
  - Depends on the application…
  - Both Intersection and χ^2 give good performance.
    - Intersection is a bit more robust.
    - χ^2 is a bit more discriminative.
    - Euclidean distance is not robust enough.
  - There exist many other measures
    - e.g. statistical tests: Kolmogorov-Smirnov
    - e.g. information theoretic: Kullback-Leiber divergence, Jeffrey divergence, ...

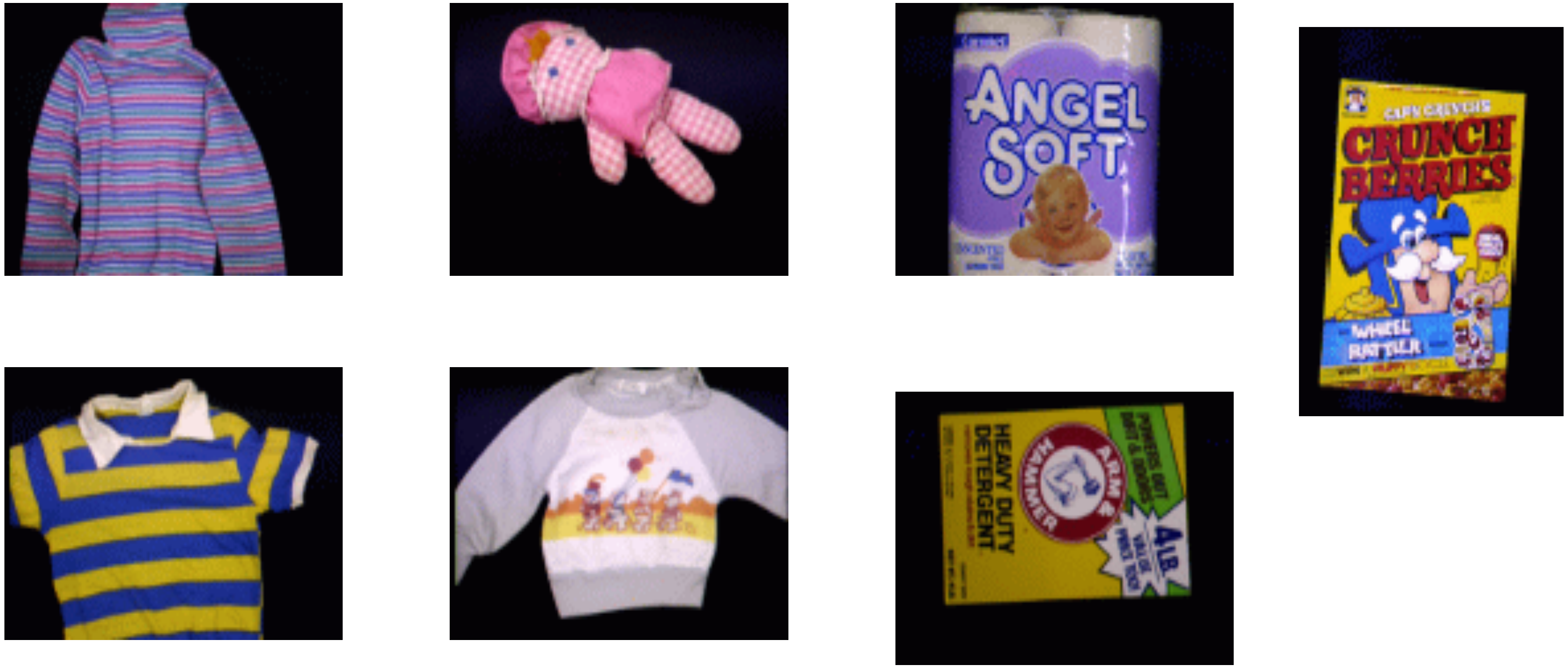
Recognition using Histograms

- Simple algorithm
  1. Build a set of histograms $H = \{M_1, M_2, M_3, \ldots\}$ for each known object
     - more exactly, for each view of each object
  2. Build a histogram T for the test image.
  3. Compare T to each $M_k \in H$
     - using a suitable comparison measure
  4. Select the object with the best matching score
     - or reject the test image if no object is similar enough.

"Nearest-Neighbor" strategy

Color Histograms

- Recognition (here object identification)
  - Works surprisingly well
  - In the first paper (1991), 66 objects could be recognized almost without errors



[Swain & Ballard, 1991]

Discussion: Color Histograms

- Advantages
  - Invariant to object translations
  - Invariant to image rotations
  - Slowly changing for out-of-plane rotations
  - No perfect segmentation necessary
  - Histograms change gradually when part of the object is occluded
  - Possible to recognize deformable objects
    - e.g. pullover

- Problems
  - The pixel colors change with the illumination („color constancy problem“)
    - Intensity
    - Spectral composition (illumination color)
  - Not all objects can be identified by their color distribution.