

Edge Detection

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SHADOW



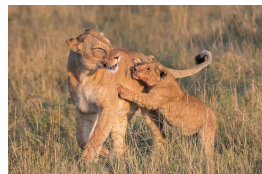
Previous lectures

- We are now touched on
 - Image formation
 - Image processing
- Now we are moving on to
 - Feature detection and matching

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The big picture ...



Feature
Detection



Feature
Description



Matching
Indexing
Detection

...

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Edge detection

- **Goal:** Identify visual changes (discontinuities) in an image
- **Ideal output:** Artist's line drawing (but artist is also using object-level knowledge)



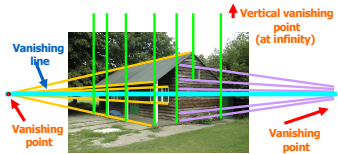
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Why do we care about edges?



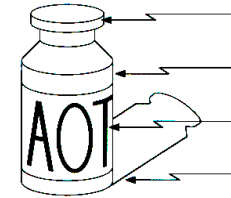
- Extract information
 - Recognize objects
 - Intuitively, most semantic and shape information from the image can be encoded in the edges
 - More compact than pixels
- Help recover geometry and viewpoint



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Origin of edges



- Surface normal discontinuity
- Depth discontinuity
- Surface color discontinuity
- Illumination discontinuity
- Edges are caused by a variety of factors

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Closeup of edges



There are a lot of edges with various causes

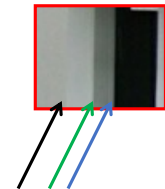
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Closeup of edges



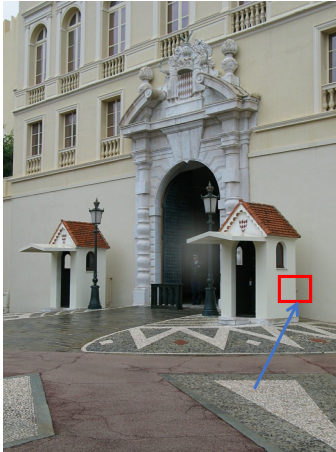
There are a lot of edges with various causes



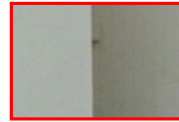
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Closeup of edges



There are a lot of edges with various causes



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Closeup of edges



There are a lot of edges with various causes

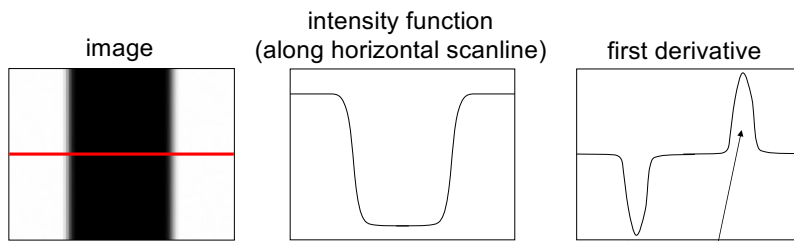


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Characterizing edges

- An edge is a place of rapid change in the image intensity function

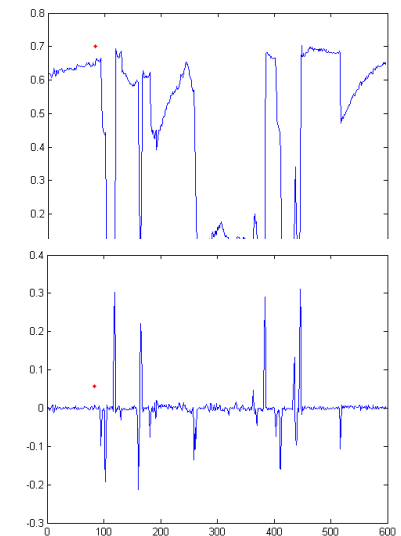
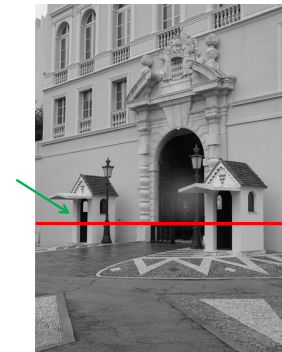


edges correspond to extrema of derivative

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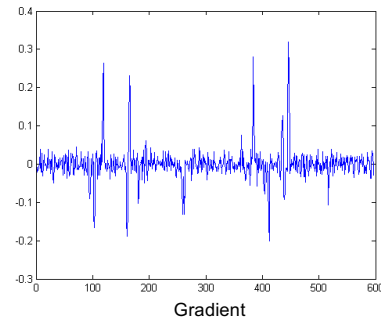
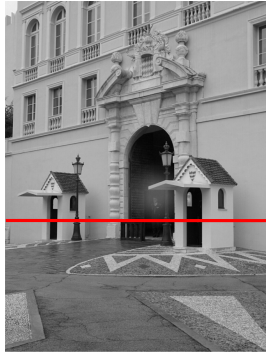
Intensity profile



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But with a little Gaussian noise

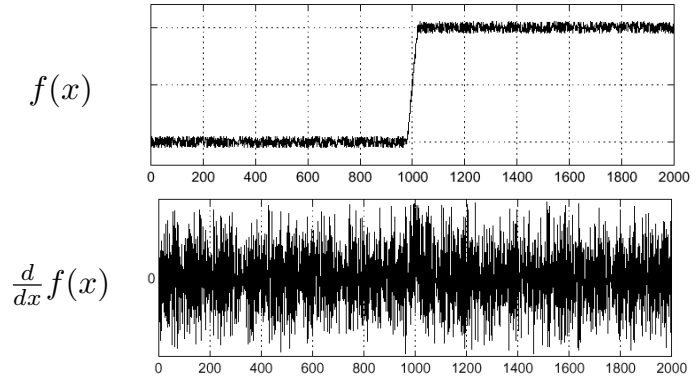


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Effects of noise

- Consider a single row or column of the image



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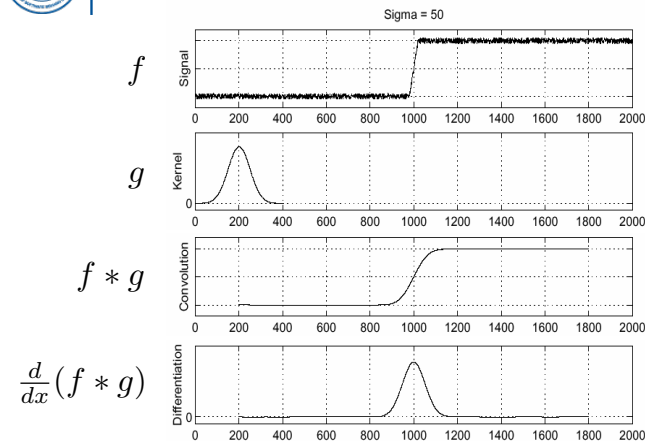
Effects of noise

- Difference filters respond strongly to noise
 - Image noise results in pixels that look very different from their neighbors
 - Generally, the larger the noise the stronger the response
- What can we do about it?

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Solution: smooth first



To find edges,
look for peaks
in $\frac{d}{dx}(f * g)$

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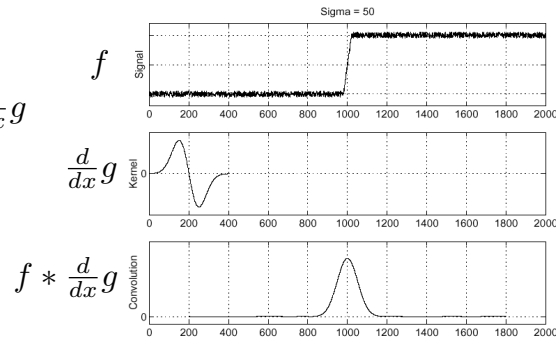


Derivative theorem of convolution

- Convolution is differentiable:

$$\frac{d}{dx}(f * g) = f * \frac{d}{dx}g$$

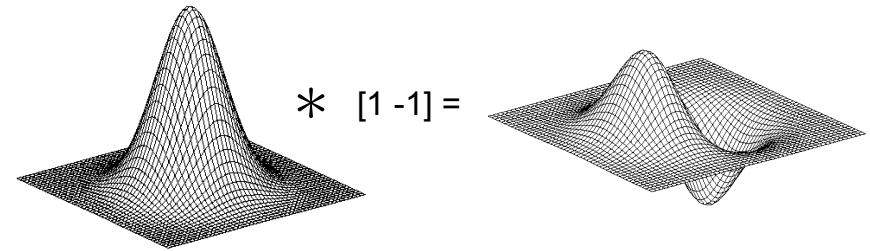
- This saves us one operation



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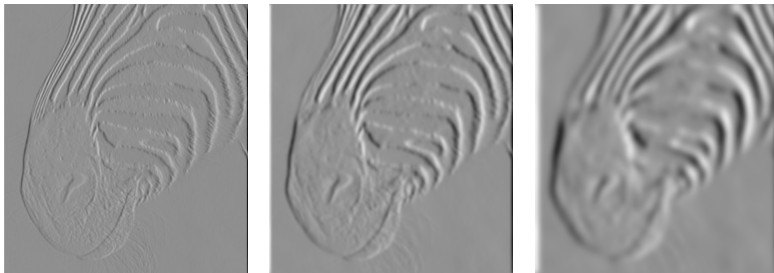
Derivative of 2D Gaussian filter



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Trade-off between smoothing and localization



1 pixel

3 pixels

7 pixels

- Smoothed derivative removes noise, but blurs edge. Also finds edges at different “scales”

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More problems...

- The gradient magnitude is large along a thick “trail” or “ridge”, so how do we identify the actual edge points?
- How do we link the edge points to form curves?



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Designing an edge detector

- **Criteria for a good edge detector:**
 - **Good detection:** the optimal detector should find all real edges, ignoring noise or other artifacts
 - **Good localization**
 - The edges detected must be as close as possible to the true edges
 - The detector must return one point only for each true edge point
- **Cues of edge detection**
 - Differences in color, intensity, or texture across the boundary
 - Continuity and closure
 - High-level knowledge

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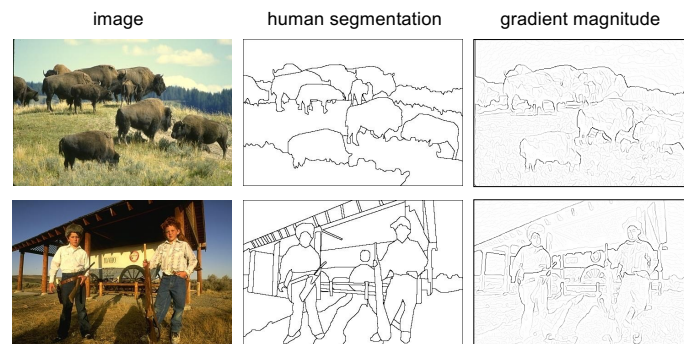
What are real edges?



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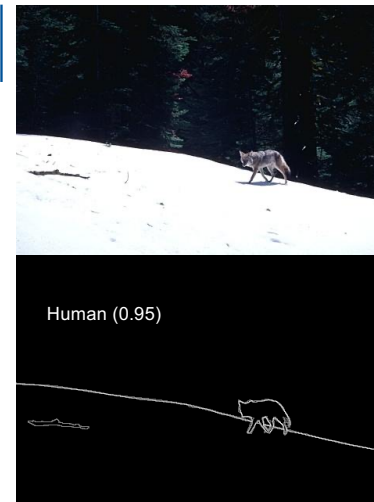


Where do humans see boundaries?

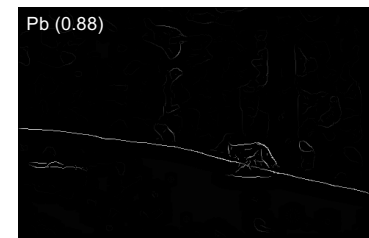


- **Berkeley segmentation database:**
<http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/>

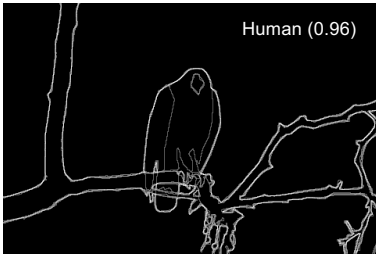
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- Score = confidence of edge
- For humans, this is averaged across multiple participants



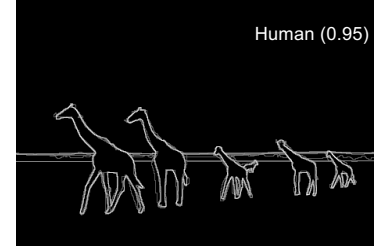
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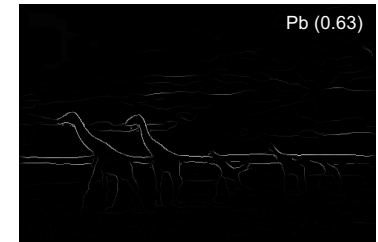
- Score = confidence of edge
- For humans, this is averaged across multiple participants



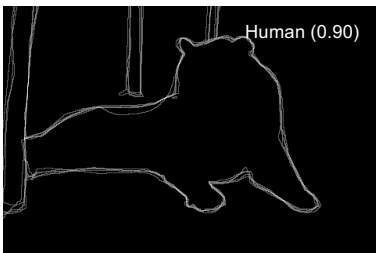
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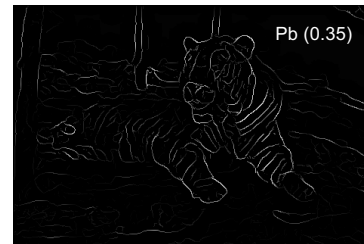
- Score = confidence of edge
- For humans, this is averaged across multiple participants



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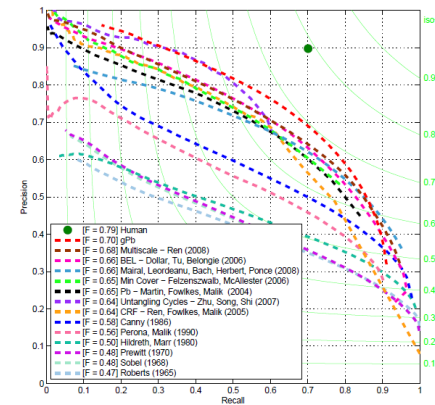
- Score = confidence of edge
- For humans, this is averaged across multiple participants



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45 years of boundary detection



Source: Arbelaez, Maire, Fowlkes, and Malik. TPAMI 2011 (pdf)

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State of edge detection

- Local edge detection works well
 - But 'False positives' from illumination and texture edges
- Some methods consider longer contours
 - But could probably do better
- Modern methods that learn from data
- Poor use of object and high-level information

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Canny edge detector

- Probably the most widely used edge detector in computer vision
- Theoretical model: step-edges corrupted by additive Gaussian noise
- Canny showed 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.

Citation: 35420!

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Example



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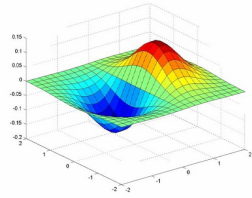
Canny edge detector

1. Filter image with x, y derivatives of Gaussian

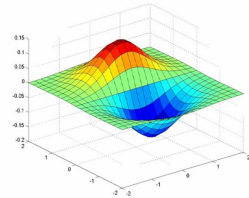
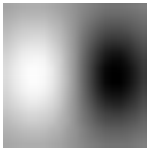
32



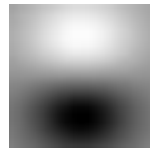
Derivative of Gaussian filter



x-direction



y-direction



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Compute Gradients (DoG)



X-Derivative of Gaussian



Y-Derivative of Gaussian

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Canny edge detector

1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradients



Compute gradient magnitude

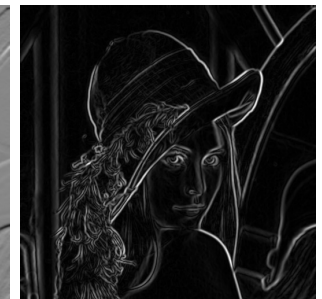
$$\sqrt{\text{DoG}_x(I)^2 + \text{DoG}_y(I)^2} = \text{gradient magnitude}$$



X-Derivative of Gaussian



Y-Derivative of Gaussian



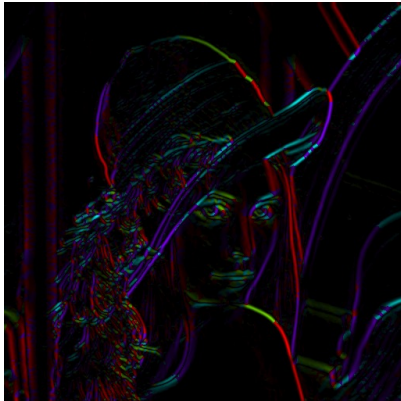
Gradient Magnitude

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Compute gradient orientation



- Threshold at minimum level

- Get orientation via

$$\theta = \tan^{-1} \frac{\text{DoG}_y I}{\text{DoG}_x I}$$

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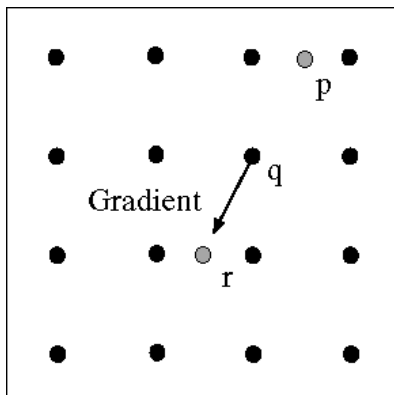
Canny edge detector

1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradients
3. Non-maximum suppression:
 - Thin multi-pixel wide 'ridges' to single pixel width

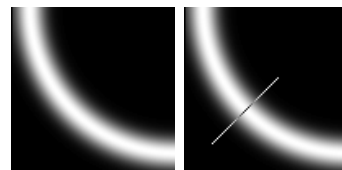
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Non-maximum suppression for each orientation



At q , we have a maximum if the value is larger than those at both p and at r . Interpolate to get these values.

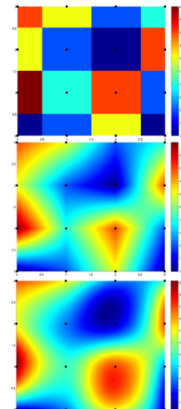


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Sidebar: interpolation options

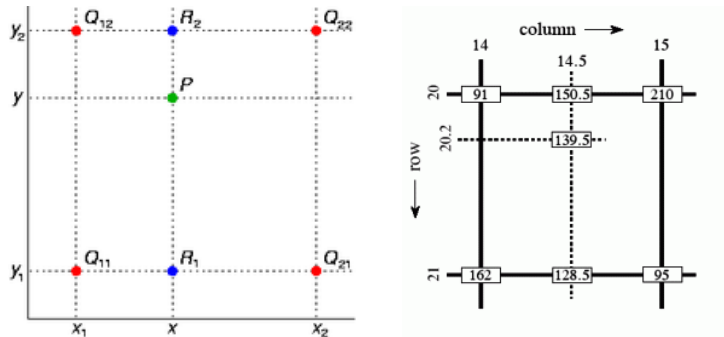
- **Nearest**
 - Copy value from nearest known
 - Very fast but creates blocky edges
- **Bilinear**
 - Weighted average from four nearest known pixels
 - Fast and reasonable results
- **Bicubic**
 - Non-linear smoothing over larger area (4x4)
 - Slower, visually appealing, may create negative pixel values



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Sidebar: bilinear interpolation



$$f(x, y) \simeq \begin{bmatrix} 1-x & x \end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}$$

http://en.wikipedia.org/wiki/Bilinear_interpolation

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Before non-maximum suppression



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After non-maximum suppression



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Canny edge detector

1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradients
3. Non-maximum suppression:
 - Thin multi-pixel wide 'ridges' to single pixel width
4. Thresholding and linking

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Thresholding and linking

- Threshold at low/high levels to get weak/strong edge pixels
- Do connected components, starting from strong edge pixels

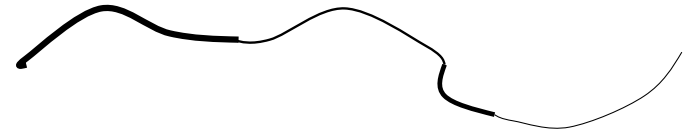


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Thresholding and linking

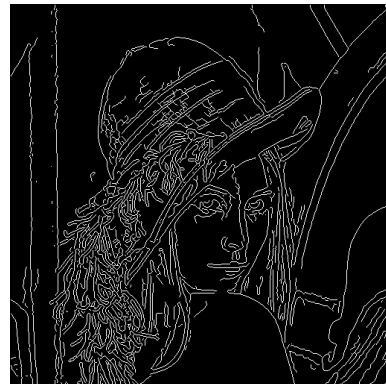
- Two thresholds → high and low
 - Grad. mag. > high threshold? = **strong edge**
 - Grad. mag. < low threshold? **noise**
 - In between = weak edge
- 'Follow' edges starting from strong edge pixels
 - Continue them into weak edges
 - Connected components (Szeliski 3.3.4)



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Find canny edges



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Canny edge detector

1. Filter image with x, y derivatives of Gaussian
2. Find magnitude and orientation of gradients
3. Non-maximum suppression:
 - Thin multi-pixel wide 'ridges' to single pixel width
4. Thresholding and linking
 - Define two thresholds: low and high
 - Use the high threshold to start edge curves and the low threshold to continue them

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Effect of σ (Gaussian kernel size)



The choice of σ depends on desired behavior

- large σ detects large scale edges
- small σ detects fine features

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Questions?

- Edge detection: goal and ideal output
- Characteristics of edge
- What is a good edge detector
- Canny edge detector

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