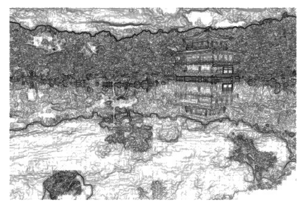
Image gradients and edges

Tues Jan 24, 2017

Kristen Grauman

UT-Austin



Announcements

- Slides are posted for lecture the night before
- Office hours on homepage
  - Tues 11-12 + appointment (me)
  - Tues 3-4 and Wed 4-5 (Nick)
  - Mon 2:30-3:30 and Thurs 3:30-4:30 (Paul)
- Reminder: no laptops, phones, tablets, etc. open in class.
- Class is 100% full with registered students. Please reserve chairs for those on the roster.

Last time

- Various models for image “noise”
- Linear filters and convolution useful for
  – Image smoothing, removing noise
    - Box filter
    - Gaussian filter
    - Impact of scale / width of smoothing filter
- Separable filters more efficient
- Median filter: a non-linear filter, edge-preserving

Image filtering

- Compute a function of the local neighborhood at each pixel in the image
  – Function specified by a “filter” or mask saying how to combine values from neighbors.
- Uses of filtering:
  – Enhance an image (denoise, resize, etc)
  – Extract information (texture, edges, etc)
  – Detect patterns (template matching)

Today

Adapted from Derek Hoiem

Edge detection

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

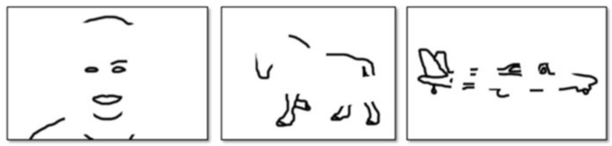
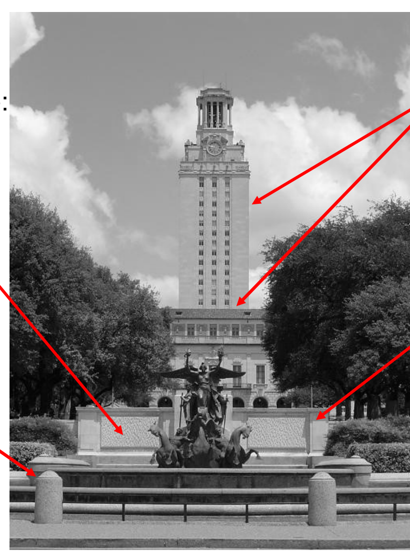


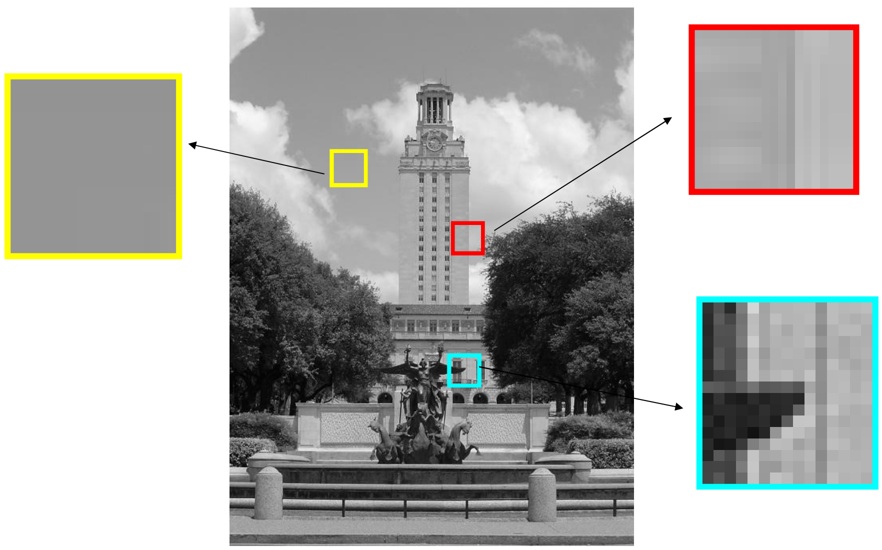
Figure from J. Shotton et al., PAMI 2007

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

What causes an edge?

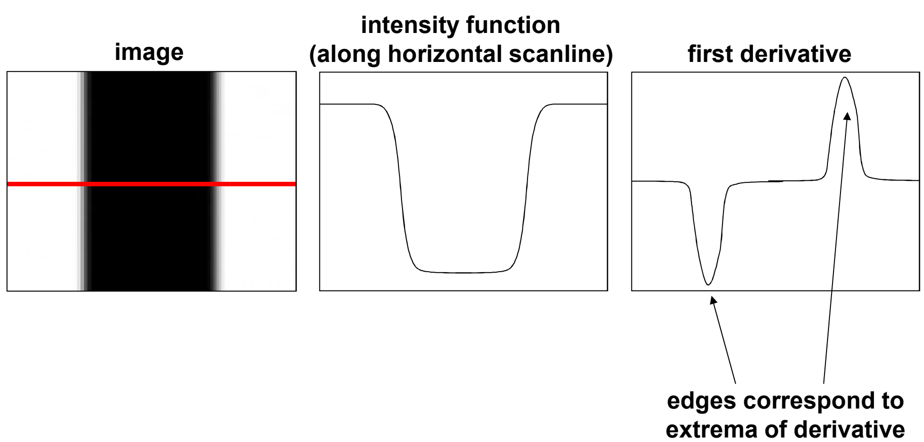


Edges/gradients and invariance



Derivatives and edges

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



Source: L. Lazebnik

Derivatives with convolution

For 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 using finite differences:

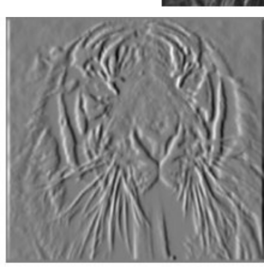
$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1, y) - f(x,y)}{1}$$

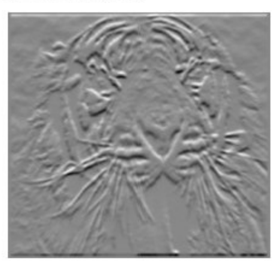
To implement above as convolution, what would be the associated filter?

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?

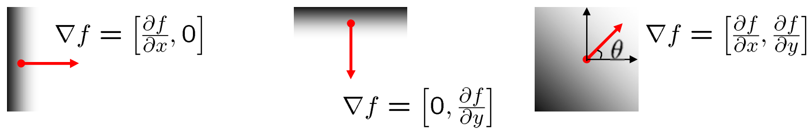
(showing filters for correlation)

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 change in intensity



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

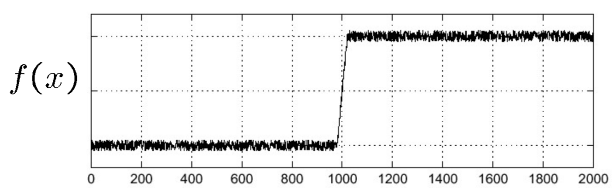
$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

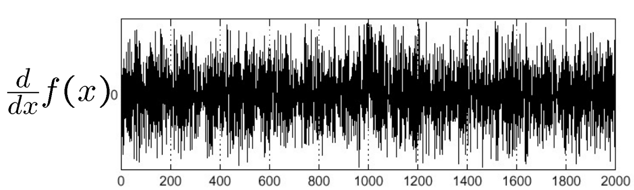
Slide credit Steve Seitz

Effects of noise

Consider a single row or column of the image

- Plotting intensity as a function of position gives a signal





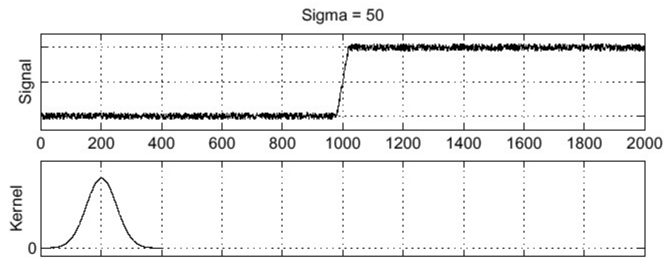
Where is the edge?

Slide credit Steve Seitz

Solution: smooth first

f

h



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

Derivative theorem of convolution

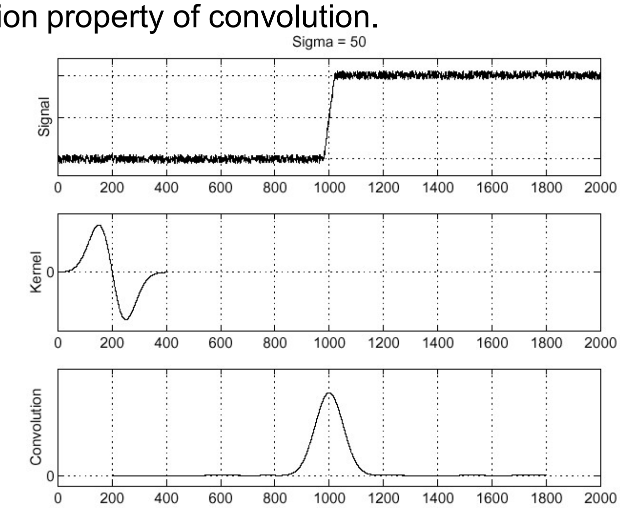
$$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$$

Differentiation property of convolution.

f

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

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

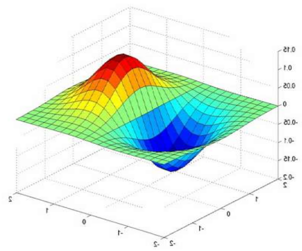


Slide credit Steve Seitz

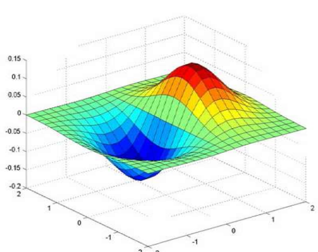
Derivative of Gaussian filters

$$(I \otimes g) \otimes h = I \otimes (g \otimes h)$$

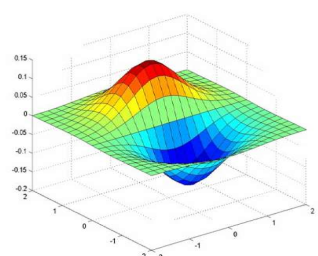
$$\begin{bmatrix} 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0219 & 0.0983 & 0.1621 & 0.0983 & 0.0219 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \end{bmatrix} \otimes \begin{bmatrix} 1 & -1 \end{bmatrix}$$



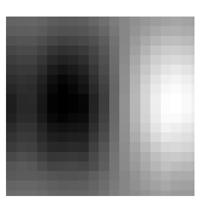
Derivative of Gaussian filters

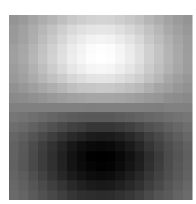


***x*-direction**



***y*-direction**





Source: L. Lazebnik

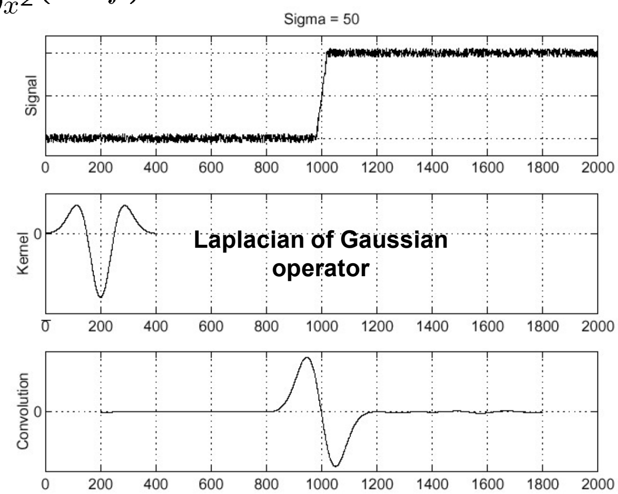
Laplacian of Gaussian

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

f

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

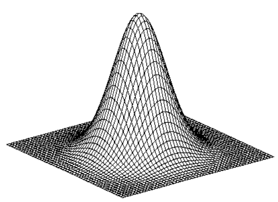
$(\frac{\partial^2}{\partial x^2}h) \star f$



Where is the edge? Zero-crossings of bottom graph

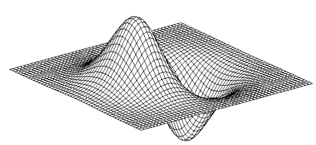
Slide credit: Steve Seitz

2D edge detection filters



Gaussian

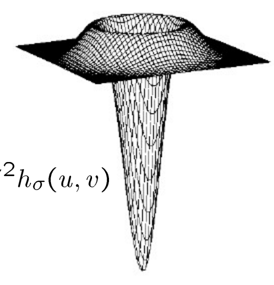
$$h_\sigma(u,v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



derivative of Gaussian

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

Laplacian of Gaussian



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

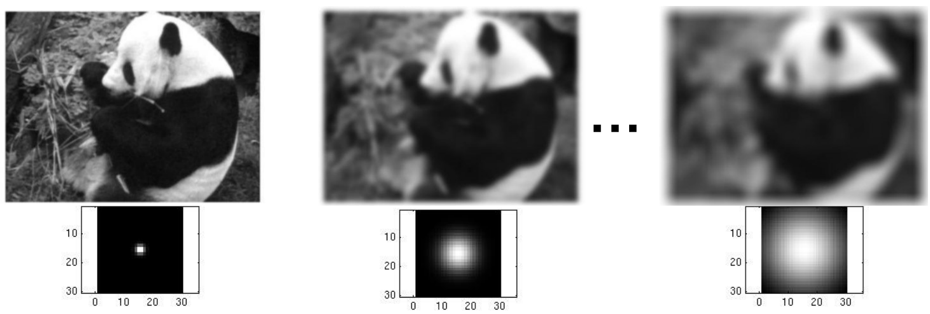
- ∇^2 is the Laplacian operator:

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

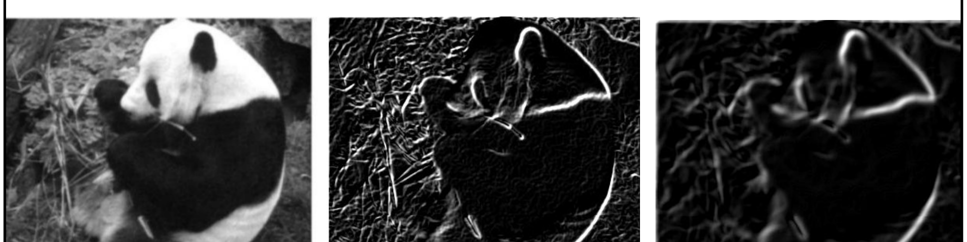
Slide credit: Steve Seitz

Smoothing with a Gaussian

Recall: parameter σ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.



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

So, what scale to choose?

It depends what we're looking for.

Mask properties

- Smoothing
  - Values positive
  - Sum to 1 → constant regions same as input
  - Amount of smoothing proportional to mask size
  - Remove "high-frequency" components; "low-pass" filter
- Derivatives
  - ___________ signs used to get high response in regions of high contrast
  - Sum to ___ → no response in constant regions
  - High absolute value at points of high contrast

Seam carving: main idea

[Shai & Avidan, SIGGRAPH 2007]

Seam carving: main idea

Content-aware resizing

Traditional resizing

[Shai & Avidan, SIGGRAPH 2007]

Seam carving: main idea

Real image example

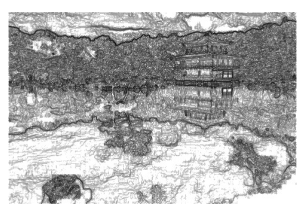
Seam carving: main idea

Content-aware resizing

Intuition:

- Preserve the most "interesting" content
  → Prefer to remove pixels with low gradient energy
- To reduce or increase size in one dimension, remove irregularly shaped "seams"
  → Optimal solution via dynamic programming.

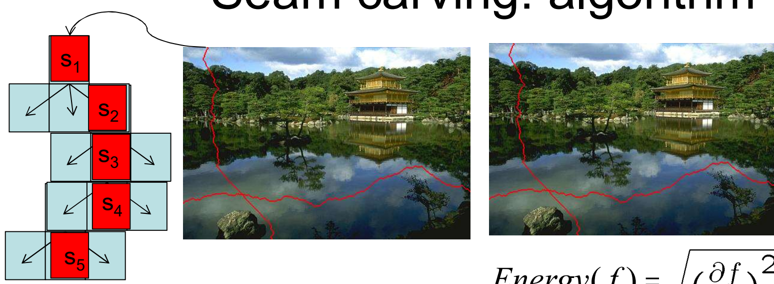
Seam carving: main idea



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

- Want to remove seams where they won't be very noticeable:
  - Measure "energy" as gradient magnitude
- Choose seam based on **minimum total energy path** across image, subject to 8-connectedness.

Seam carving: algorithm



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

Let a vertical seam **s** consist of *h* positions that form an 8-connected path.

Let the cost of a seam be: $Cost(\mathbf{s}) = \sum_{i=1}^{h} Energy(f(s_i))$

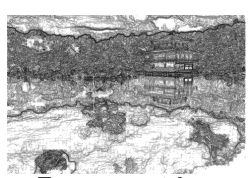
Optimal seam minimizes this cost: $\mathbf{s}^* = \min_{\mathbf{s}} Cost(\mathbf{s})$

Compute it efficiently with dynamic programming.

How to identify the minimum cost seam?

- First, consider a **greedy** approach:

1	3	$\boxed{0}$
2	$\boxed{8}$	9
5	$\boxed{2}$	6

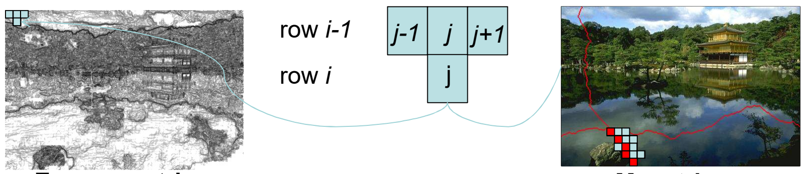


Energy matrix (gradient magnitude)

Seam carving: algorithm

- Compute the cumulative minimum energy for all possible connected seams at each entry *(i,j)*:

$$\mathbf{M}(i,j) = Energy(i,j) + \min\left(\mathbf{M}(i-1,j-1), \mathbf{M}(i-1,j), \mathbf{M}(i-1,j+1)\right)$$



Energy matrix (gradient magnitude)

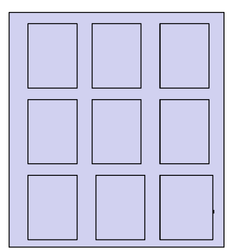
M matrix: cumulative min energy (for vertical seams)

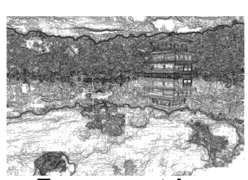
- Then, min value in last row of **M** indicates end of the minimal connected vertical seam.
- Backtrack up from there, selecting min of 3 above in **M**.

Example

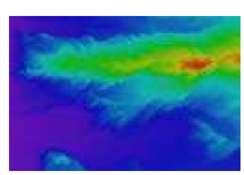
$$\mathbf{M}(i,j) = Energy(i,j) + \min\left(\mathbf{M}(i-1,j-1), \mathbf{M}(i-1,j), \mathbf{M}(i-1,j+1)\right)$$

1	3	0
2	8	9
5	2	6





Energy matrix (gradient magnitude)

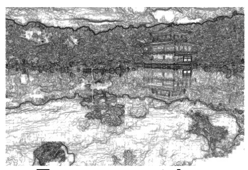


M matrix (for vertical seams)

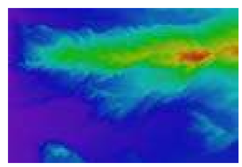
Example

$$\mathbf{M}(i,j) = Energy(i,j) + \min\big(\mathbf{M}(i-1,j-1), \mathbf{M}(i-1,j), \mathbf{M}(i-1,j+1)\big)$$

$$\begin{matrix} \boxed{1} & 3 & 0 \\ \boxed{2} & 8 & 9 \\ 5 & \boxed{2} & 6 \end{matrix} \qquad \begin{matrix} \boxed{1} & 3 & 0 \\ \boxed{3} & 8 & 9 \\ 8 & \boxed{5} & 14 \end{matrix}$$



Energy matrix (gradient magnitude)

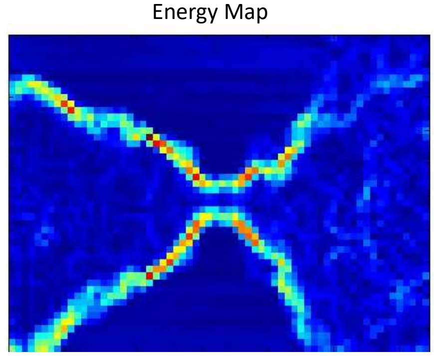


M matrix (for vertical seams)

Real image example

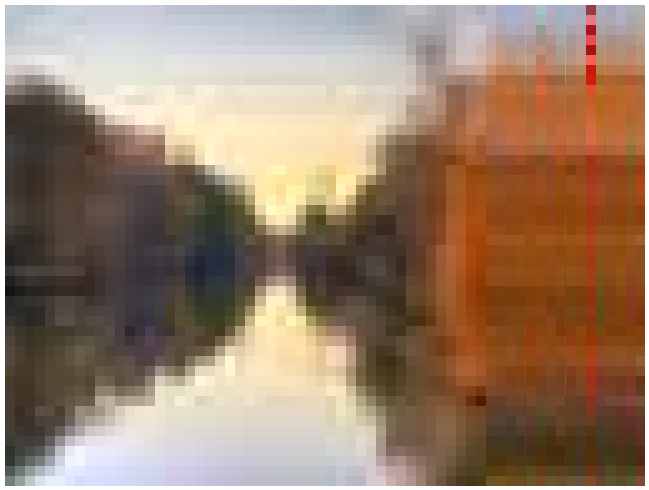
Original Image

Energy Map



Blue = low energy
Red = high energy

Real image example



Other notes on seam carving

- Analogous procedure for horizontal seams
- Can also insert seams to *increase* size of image in either dimension
  - Duplicate optimal seam, averaged with neighbors
- Other energy functions may be plugged in
  - E.g., color-based, interactive,…
- Can use combination of vertical and horizontal seams

Example results from prior classes

(a) Original input

(b) Content-aware resizing

(c) Image from 'imresize'

Results from Eunho Yang

Original image

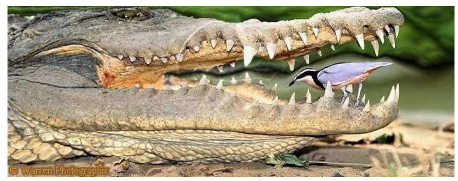
Conventional resize

Seam carving result

Results from Martin Becker

Original image

Conventional resize



Seam carving result

Results from Martin Becker

Original image (599 by 799)

Conventional resize (399 by 599)

Seam carving (399 by 599)

Results from Jay Hennig

Removal of a marked object

(a) Selected an area.

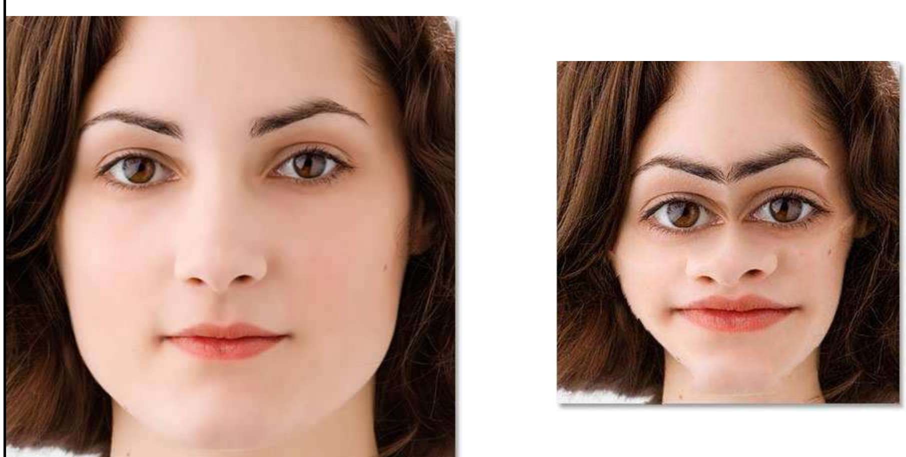
Removal of a marked object

Results from Eunho Yang

“Failure cases” with seam carving

By Donghyuk Shin

“Failure cases” with seam carving



By Suyog Jain

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

   - Threshold, Thin

Thresholding

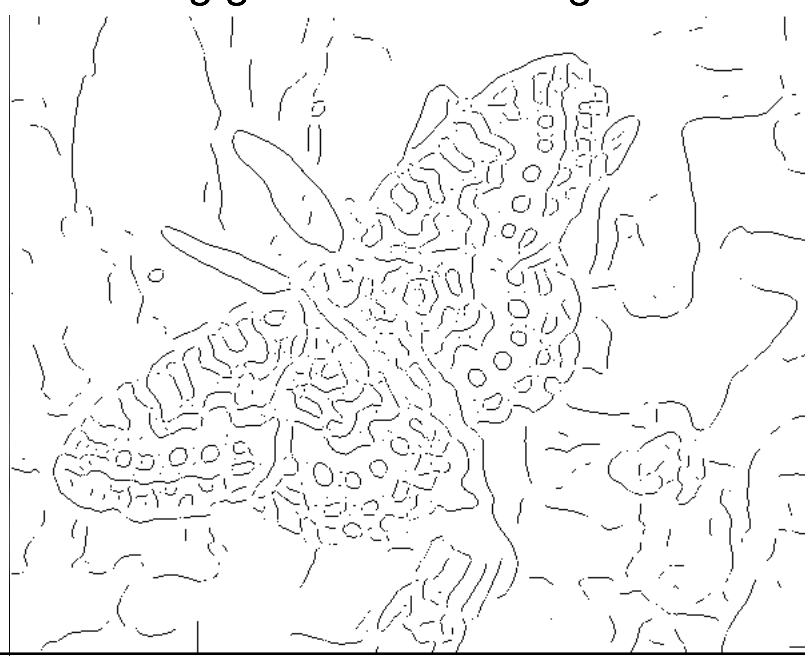
- Choose a threshold value t
- Set any pixels less than t to zero (off)
- Set any pixels greater than or equal to t to one (on)

Original image

Gradient magnitude image

Thresholding gradient with a lower threshold

Thresholding gradient with a higher threshold



Canny edge detector

- Filter image with derivative of Gaussian
- Find magnitude and orientation of gradient
- **Non-maximum suppression**:
  - Thin wide "ridges" down to single pixel width
- **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

The Canny edge detector

original image (Lena)

Slide credit: Steve Seitz

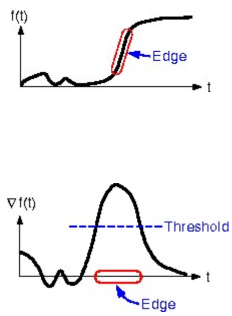
The Canny edge detector

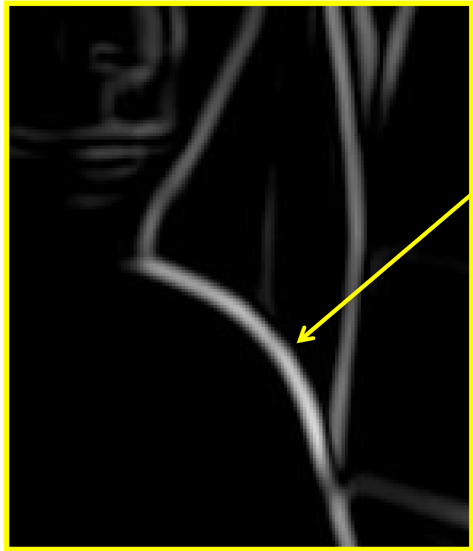
norm of the gradient

The Canny edge detector

thresholding

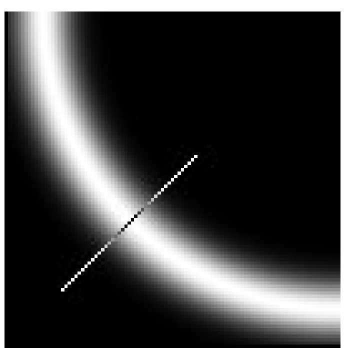
The Canny edge detector

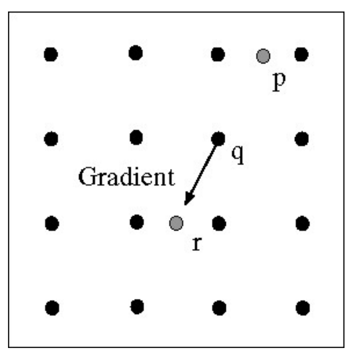




How to turn these thick regions of the gradient into curves?

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

The Canny edge detector

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

thinning
(non-maximum suppression)

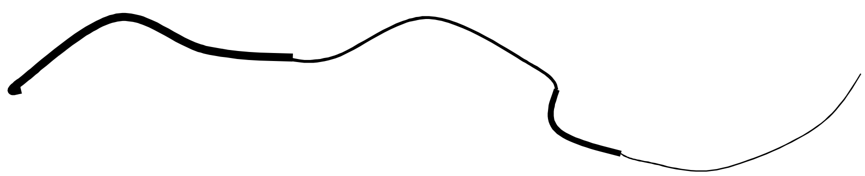
Hysteresis thresholding

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

Credit: James Hays

Hysteresis thresholding

- Use a high threshold to start edge curves, and a low threshold to continue them.



Source: Steve Seitz

Final Canny Edges

Credit: James Hays

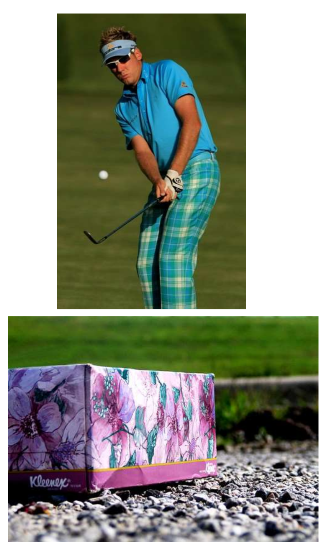
Recap: Canny edge detector

- Filter image with derivative of Gaussian
- Find magnitude and orientation of gradient
- **Non-maximum suppression**:
  – Thin wide “ridges” down to single pixel width
- **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

Low-level edges vs. perceived contours

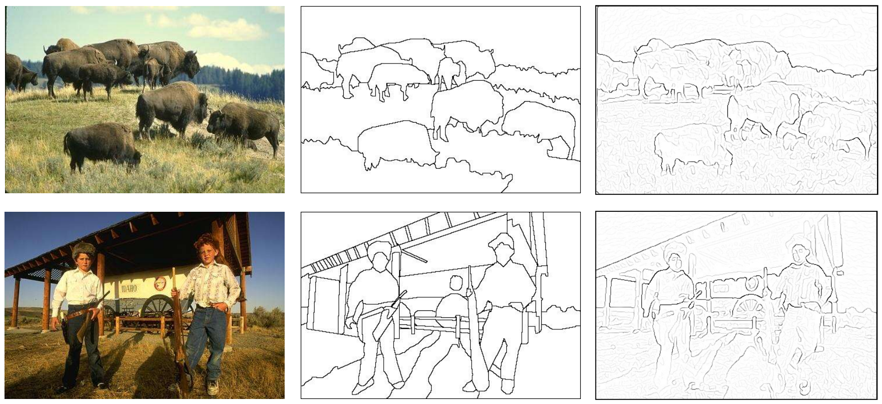
Background



Texture

Shadows

Low-level edges vs. perceived contours



Berkeley segmentation database:

http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

Source: L. Lazebnik

Protocol

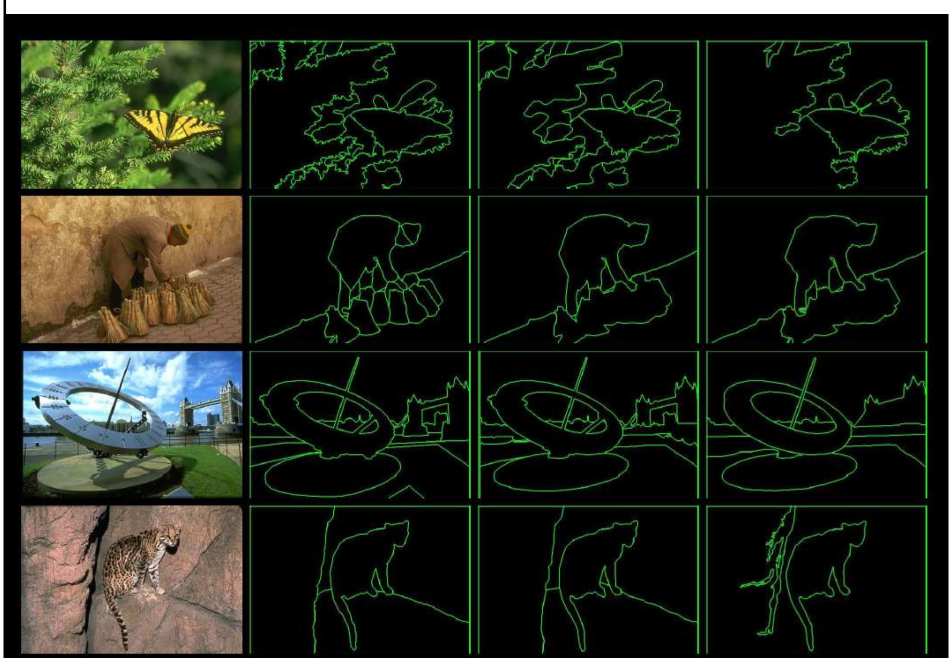
You will be presented a photographic image. Divide the image into some number of segments, where the segments represent "things" or "parts of things" in the scene. The number of segments is up to you, as it depends on the image. Something between 2 and 30 is likely to be appropriate. It is important that all of the segments have approximately equal importance.

- Custom segmentation tool
- Subjects obtained from work-study program (UC Berkeley undergraduates)

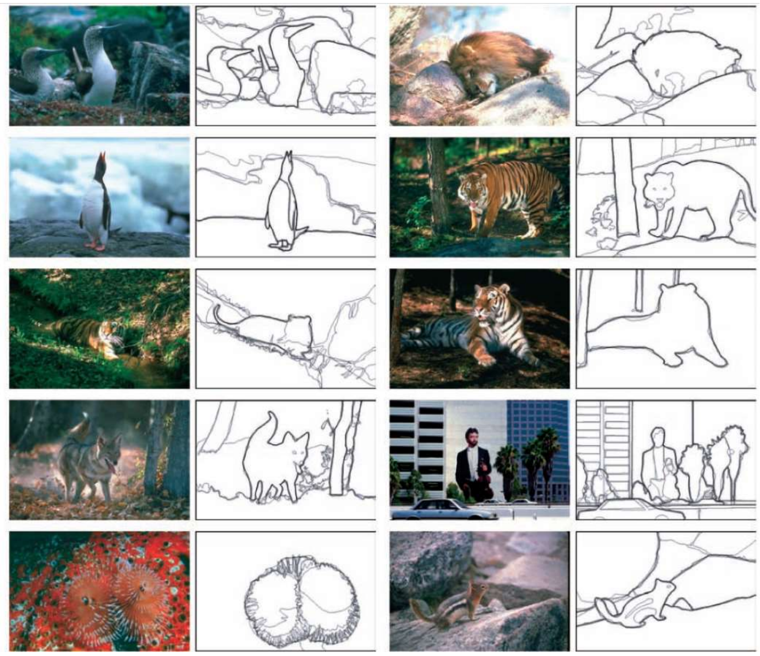
Berkeley Segmentation Data Set
David Martin, Charless Fowlkes, Doron Tal, Jitendra Malik

Credit: David Martin

P◯ST



Learn from humans which combination of features is most indicative of a "good" contour?



[D. Martin et al. PAMI 2004] Human-marked segment boundaries

Dataflow

Image

Boundary Cues

- Brightness
- Color
- Texture

Cue Combination

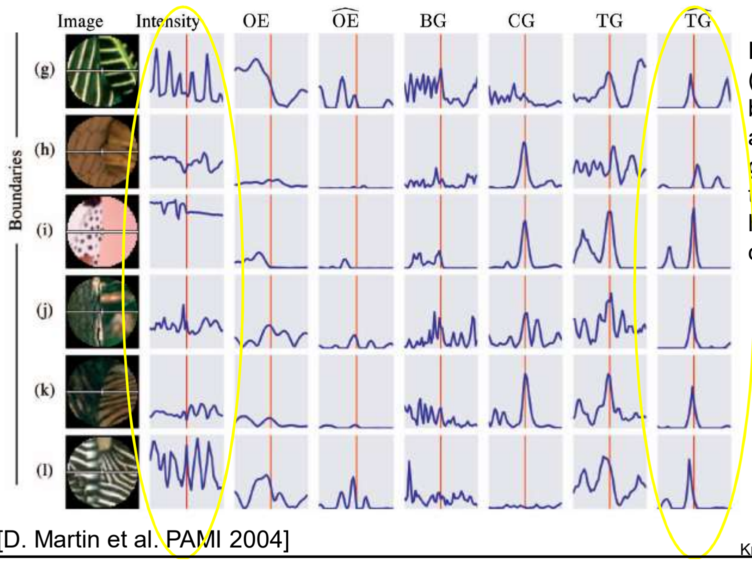
Model

P_b

Challenges: texture cue, cue combination

Goal: learn the posterior probability of a boundary $P_b(x,y,\theta)$ from local information only

What features are responsible for perceived edges?

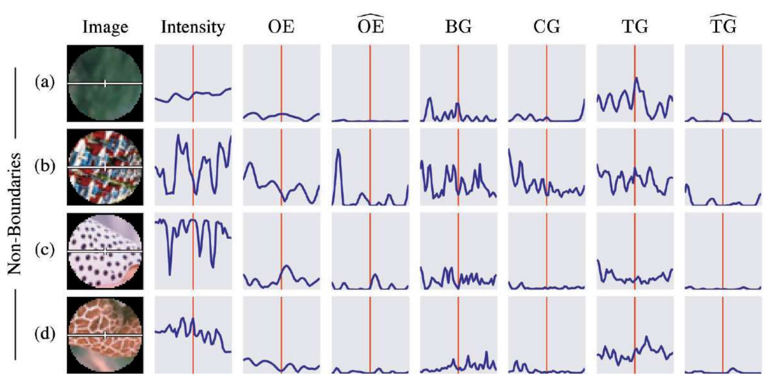


Feature profiles (oriented energy, brightness, color, and texture gradients) along the patch's horizontal diameter

[D. Martin et al. PAMI 2004]

Kristen Grauman, UT-Austin

What features are responsible for perceived edges?



Feature profiles (oriented energy, brightness, color, and texture gradients) along the patch's horizontal diameter

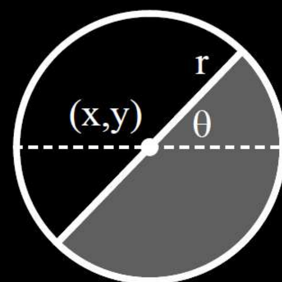
[D. Martin et al. PAMI 2004]

Kristen Grauman, UT-Austin

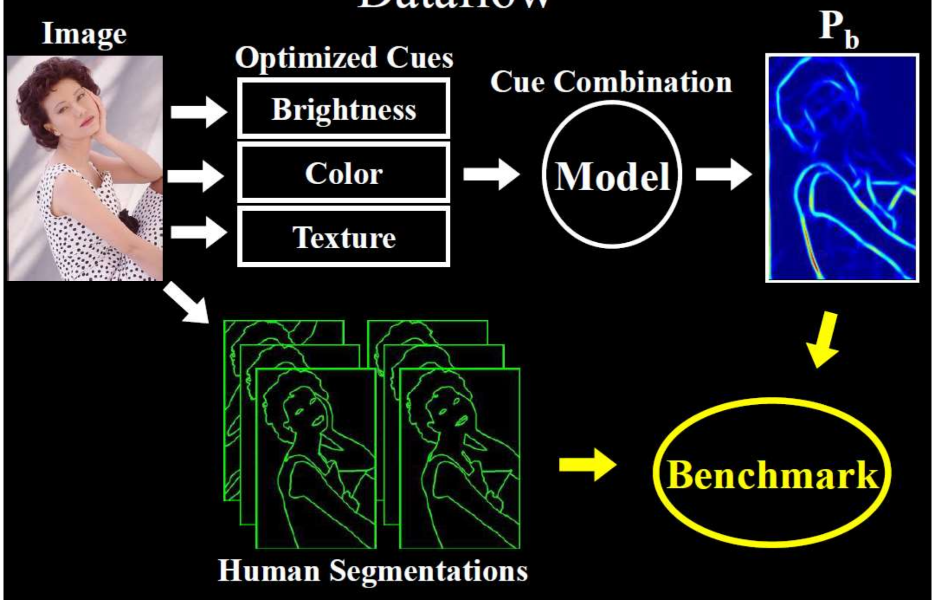
Brightness and Color Features

- 1976 CIE L*a*b* colorspace
- Brightness Gradient BG(x,y,r,θ)
  - χ^2 difference in L* distribution
- Color Gradient CG(x,y,r,θ)
  - χ^2 difference in a* and b* distributions

$$\chi^2(g,h) = \frac{1}{2}\sum_i \frac{(g_i - h_i)^2}{g_i + h_i}$$

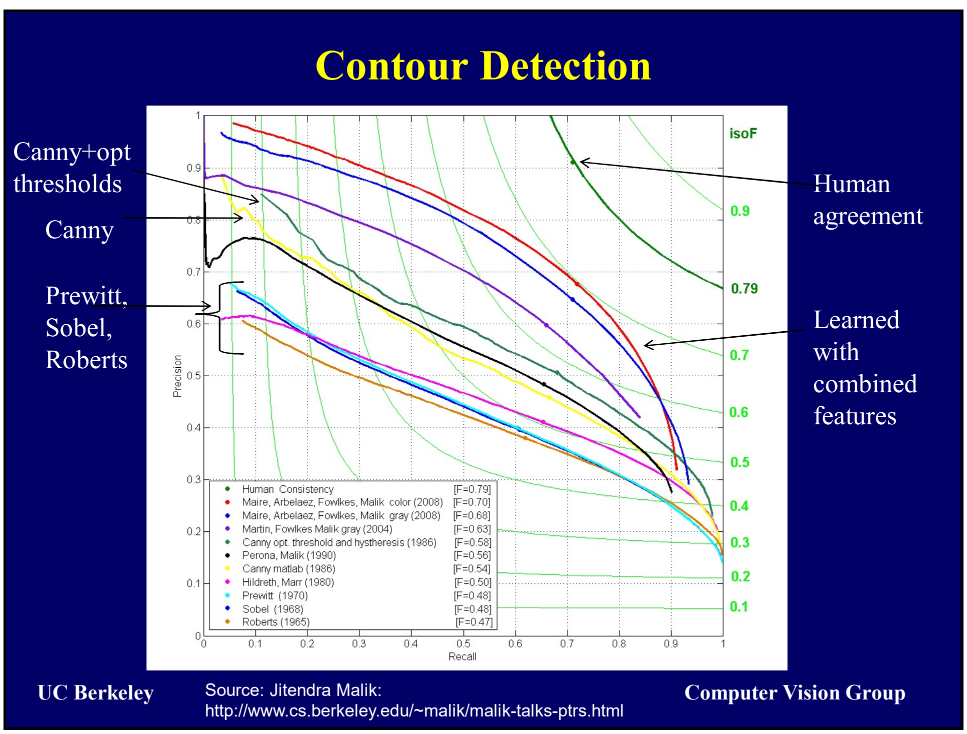


Dataflow



Credit: David Martin


Image
BG+CG+TG
Human
[D. Martin et al. PAMI 2004]
Kristen Grauman, UT-Austin


Contour Detection
Canny+opt thresholds
Canny
Prewitt, Sobel, Roberts
Human agreement
Learned with combined features
isoF
0.9
0.79
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Precision
Recall
Human Consistency [F=0.79]
Maire, Arbelaez, Fowlkes, Malik color (2008) [F=0.70]
Maire, Arbelaez, Fowlkes, Malik gray (2008) [F=0.68]
Martin, Fowlkes Malik gray (2004) [F=0.63]
Canny opt. threshold and hystheresis (1986) [F=0.58]
Perona, Malik (1990) [F=0.56]
Canny matlab (1986) [F=0.54]
Hildreth, Marr (1980) [F=0.50]
Prewitt (1970) [F=0.48]
Sobel (1968) [F=0.48]
Roberts (1965) [F=0.47]
UC Berkeley
Source: Jitendra Malik:
http://www.cs.berkeley.edu/~malik/malik-talks-ptrs.html
Computer Vision Group

Recall: image filtering

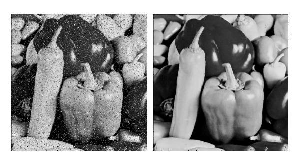
- Compute a function of the local neighborhood at each pixel in the image
  – Function specified by a “filter” or mask saying how to combine values from neighbors.

- Uses of filtering:
  – Enhance an image (denoise, resize, etc)
  – Extract information (texture, edges, etc)
  – Detect patterns (template matching)

Adapted from Derek Hoiem

Filters for features

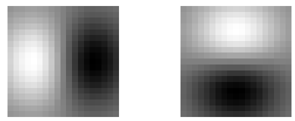
- Map raw pixels to an intermediate representation that will be used for subsequent processing



- Goal: reduce amount of data, discard redundancy, preserve what’s useful

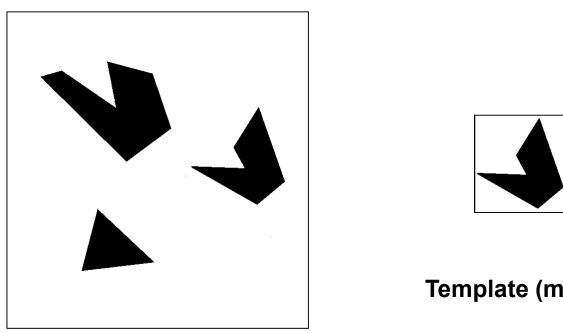
Template matching

- Filters as **templates**:
  Note that filters look like the effects they are intended to find --- "matched filters"



- Use normalized cross-correlation score to find a given pattern (template) in the image.
- Normalization needed to control for relative brightnesses.

Template matching

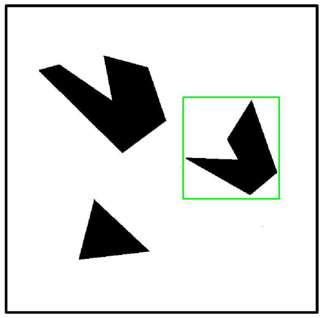


Template (mask)

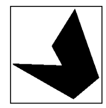
Scene

A toy example

Template matching

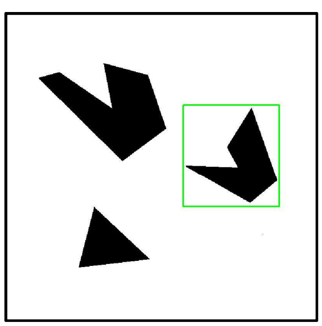


Detected template

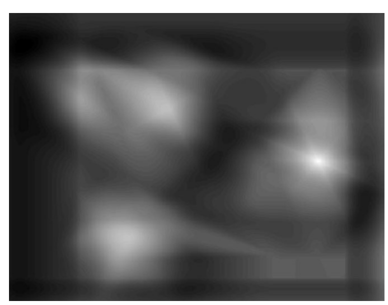


Template

Template matching



Detected template



Correlation map

Where’s Waldo?

Scene

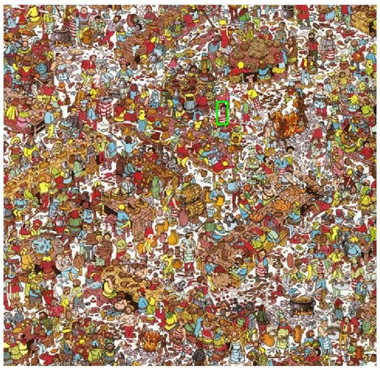
Template

Where’s Waldo?

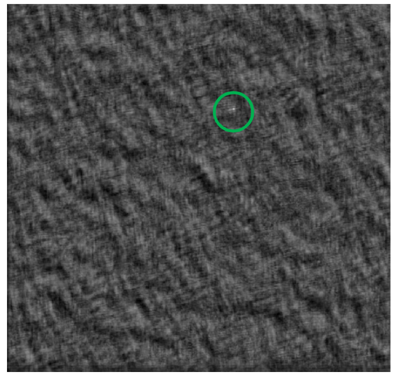
Detected template

Template

Where's Waldo?



Detected template



Correlation map

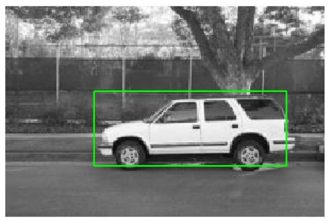
Template matching

Scene

Template

What if the template is not identical to some subimage in the scene?

Template matching



Template

Detected template

Match can be meaningful, if scale, orientation, and general appearance is right.

How to find at any scale?

Recap: Mask properties

- Smoothing
  - Values positive
  - Sum to 1 → constant regions same as input
  - Amount of smoothing proportional to mask size
  - Remove "high-frequency" components; "low-pass" filter
- Derivatives
  - Opposite signs used to get high response in regions of high contrast
  - Sum to 0 → no response in constant regions
  - High absolute value at points of high contrast
- Filters act as templates
  - Highest response for regions that "look the most like the filter"
  - Dot product as correlation

Summary

- Image gradients
- Seam carving – gradients as “energy”
- Gradients → edges and contours
- Template matching
  - Image patch as a filter
  - Chamfer matching
    - Distance transform

Coming up

- A1 out tonight, due in 2 weeks
- Thursday: binary image analysis
- Friday: A0 due