Edges and Binary Image Analysis

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Previously

- Filters allow local image neighborhood to influence our description and features
  - Smoothing to reduce noise
  - Derivatives to locate contrast, gradient
- Seam carving application:
  - use image gradients to measure “interestingness” or “energy”
  - remove 8-connected seams so as to preserve image’s energy

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Review: Partial derivatives of an image

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

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

-1	1

-1	? or	1
1		-1

Which shows changes with respect to x?

(showing filters for correlation)

Slide credit: Kristen Grauman

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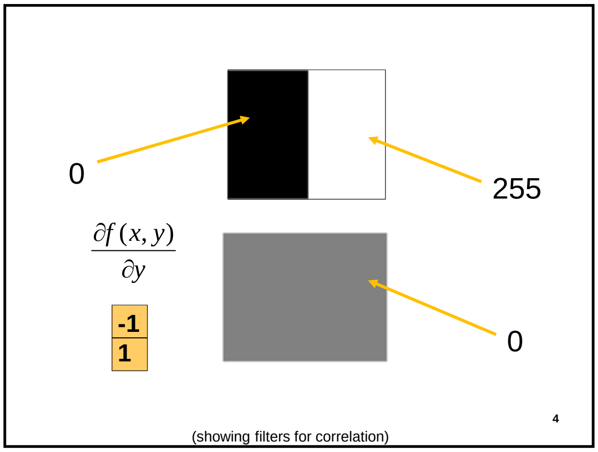

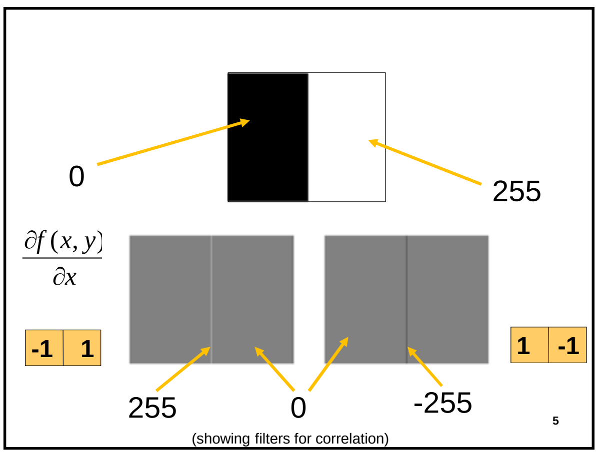

Today

- Edge detection and matching
  - process the image gradient to find curves/contours
  - comparing contours
- Binary image analysis
  - blobs and regions

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Edge detection

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

Figure from D. Lowe

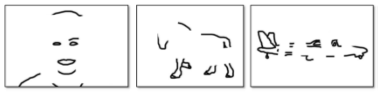

Figure from J. Shotton et al., PAMI 2007

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

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Slide credit: Kristen Grauman

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

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Slide credit: Kristen Grauman

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)

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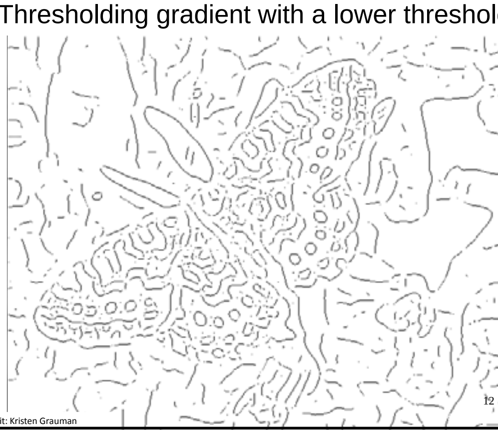
Slide credit: Kristen Grauman

Original image

Slide credit: Kristen Grauman

Gradient magnitude image

Thresholding gradient with a lower threshold



Slide credit: Kristen Grauman

Thresholding gradient with a higher threshold

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Slide credit: Kristen Grauman

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`

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Slide credit: David Lowe, Fei-Fei Li

The Canny edge detector

original image (Lena)

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Slide credit: Steve Seitz

The Canny edge detector

gradient magnitude

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Slide credit: Kristen Grauman

Compute Gradients

X-Derivative of Gaussian Y-Derivative of Gaussian Gradient Magnitude

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Slide credit: Svetlana Lazebnik

The Canny edge detector

gradient magnitude

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Slide credit: Kristen Grauman

The Canny edge detector

thresholding

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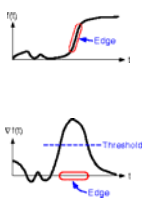
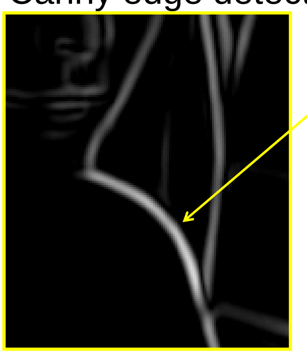
Slide credit: Kristen Grauman

The Canny edge detector





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

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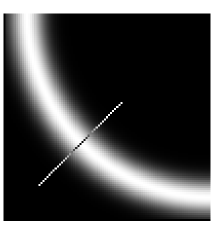
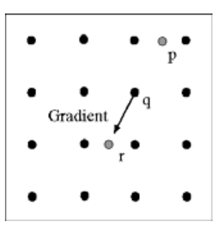
Slide credit: Kristen Grauman

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

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Slide credit: Kristen Grauman

The Canny edge detector

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

thinning
(non-maximum suppression)

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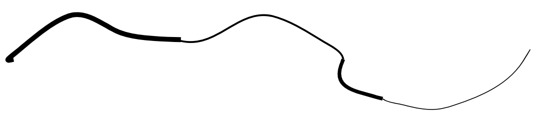
Slide credit: Kristen Grauman

Hysteresis thresholding

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



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Slide credit: Steve Seitz

Hysteresis thresholding

original image

high threshold (strong edges) | low threshold (weak edges) | hysteresis threshold

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Slide credit: Fei-Fei Li

Hysteresis thresholding

http://users.ecs.soton.ac.uk/msn/book/new_demo/thresholding/

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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`

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Slide credit: David Lowe, Fei-Fei Li

Low-level edges vs. perceived contours

Background Texture Shadows

Slide credit: Kristen Grauman

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Low-level edges vs. perceived contours

image | **human segmentation** | **gradient magnitude**

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

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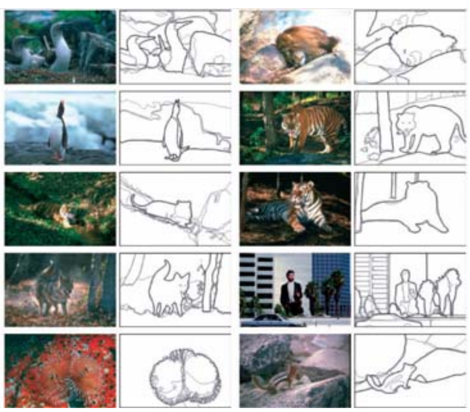
Slide credit: Svetlana Lazebnik

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

[D. Martin et al. PAMI 2004]



Human-marked segment boundaries

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Slide credit: Kristen Grauman

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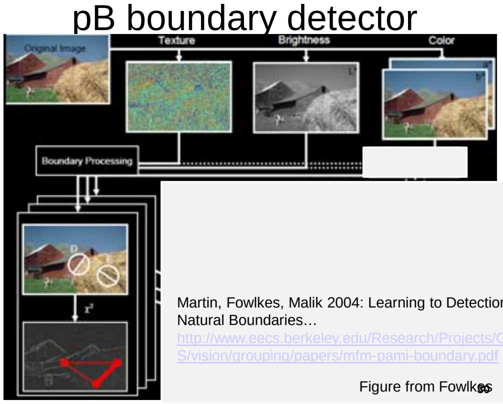
pB boundary detector



Martin, Fowlkes, Malik 2004: Learning to Detection Natural Boundaries…
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/papers/mfm-pami-boundary.pdf

Figure from Fowlkes

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pB Boundary Detector

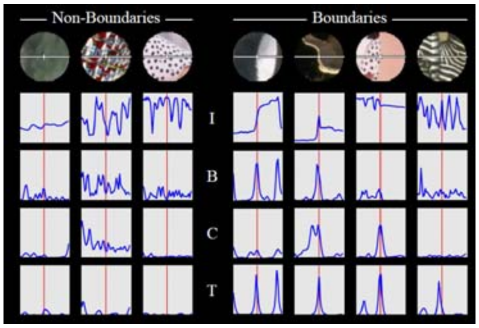

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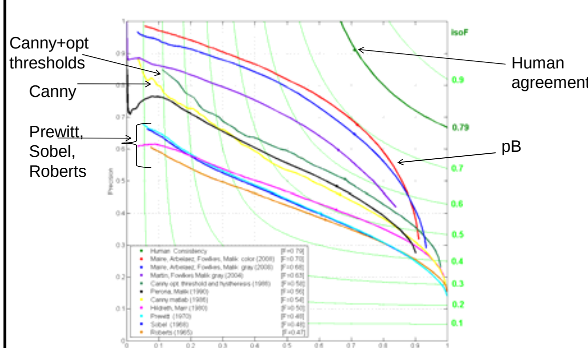
Figure from Fowlkes

Slide credit: Kristen Grauman [D. Martin et al. PAMI 2004] 32

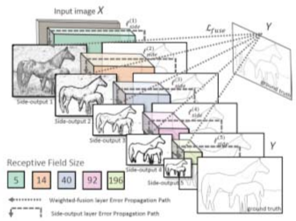
State-of-the-Art in Contour Detection



Source: Jitendra Malik: http://www.cs.berkeley.edu/~malik/malik-talks-ptrs.html 33

Holistically-Nested Edge Detection (Xie, Tu ICCV 2015)

1. holistic image training and prediction
2. multi-scale and multi-level feature learning
3. Deeply-supervised fully-convolutional network



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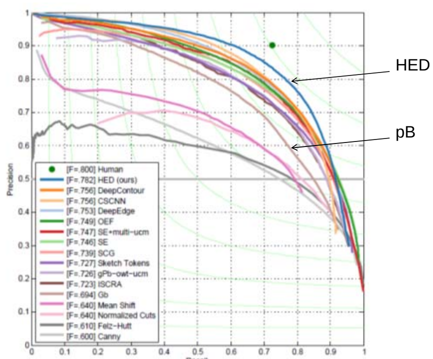
State-of-the-Art in Contour Detection



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Today

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- Binary image analysis
  - blobs and regions

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Slide credit: Kristen Grauman

Fig. 1. Examples of two handwritten digits. In terms of pixel-to-pixel comparisons, these two images are quite different, but to the human observer, the shapes appear to be similar.

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Figure from Belongie et al.

Chamfer distance

- Average distance to nearest feature/edge

$$D_{chamfer}(T, I) \equiv \frac{1}{|T|} \sum_{t \in T} d_I(t)$$

I = Set of edge points in image

T = Set of edge points on (shifted) template

$d_I(t)$ = Minimum distance between point t and some point in I

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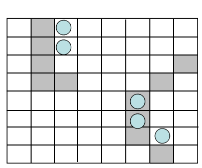
Chamfer distance



$$D_{chamfer}(T, I) \equiv \frac{1}{|T|} \sum_{t \in T} d_I(t)$$

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Slide credit: Kristen Grauman

Chamfer distance

- Average distance to nearest feature

$$D_{chamfer}(T,I) \equiv \frac{1}{|T|}\sum_{t \in T} d_I(t)$$

How is the measure different than just filtering with a mask having the shape points?

How expensive is a naïve implementation?

Edge image

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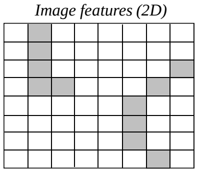
Slide credit: Kristen Grauman

Distance transform

Image features (2D)



Distance Transform

1	0	1	2	3	4	3	2
1	0	1	2	3	3	2	1
1	0	1	2	3	2	1	0
1	0	0	1	2	1	0	1
2	1	1	2	1	0	1	2
3	2	2	2	1	0	1	2
4	3	3	2	1	0	1	2
5	4	4	3	2	1	0	1

Distance Transform is a function $D(\cdot)$ that for each image pixel p assigns a non-negative number $D(p)$ corresponding to distance from p to the nearest feature in the image I

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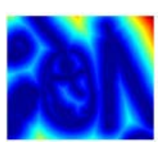
Slide credit: Yuri Boykov

Distance transform

original

edges



distance transform

Value at (x,y) tells how far that position is from the nearest edge point (or other binary image structure)

```
>> help bwdist
```

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Slide credit: Kristen Grauman

Distance transform (1D)

Two pass O(n) algorithm for 1D L_1 norm

1. Initialize: For all j
   $D[j] \leftarrow 1_P[j]$ // 0 if j is in **P**, infinity otherwise

Image features (edges)

0	1	0	1	0	0	0	1	0

Distance transform

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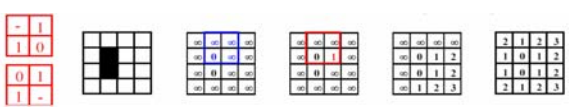
Slide adapted from Dan Huttonlocher

Distance Transform (2D)

- 2D case analogous to 1D
  - Initialization
  - Forward and backward pass
    - Fwd pass finds closest above and to left
    - Bwd pass finds closest below and to right



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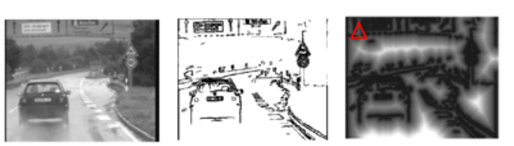
Slide credit: Dan Huttonlocher

Chamfer distance

- Average distance to nearest feature

$$D_{chamfer}(T,I) \equiv \frac{1}{|T|}\sum_{t\in T} d_I(t)$$



Edge image | Distance transform image

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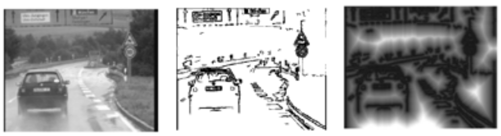
Slide credit: Kristen Grauman

Chamfer distance



Edge image Distance transform image

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Fig from D. Gavrila, DAGM 1999

Chamfer distance: properties

- Sensitive to scale and rotation
- Tolerant of small shape changes, clutter
- Need large number of template shapes
- Inexpensive way to match shapes

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Slide credit: Kristen Grauman

Today

- Edge detection and matching
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  - comparing contours
- Binary image analysis
  - blobs and regions

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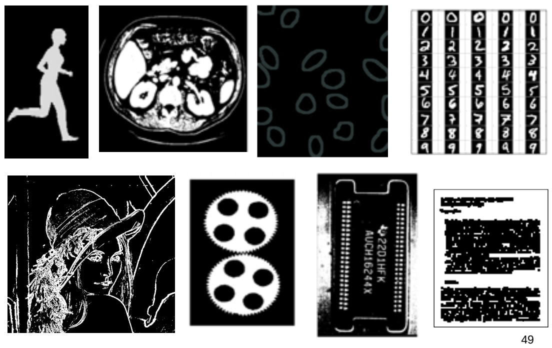
Slide credit: Kristen Grauman

Binary images



Slide credit: Kristen Grauman

Binary image analysis: basic steps

- Convert the image into binary form
  - Thresholding
- Clean up the thresholded image
  - Morphological operators
- Extract separate blobs
  - Connected components
- Describe the blobs with region properties

Slide credit: Kristen Grauman

Binary images

- Two pixel values
  - Foreground and background
  - Mark region(s) of interest

1	1	0	1	1	1	0	1
1	1	0	1	0	1	0	1
1	1	1	1	0	0	0	1
0	0	0	0	0	0	0	1
1	1	1	1	0	1	0	1
0	0	0	1	0	1	0	1
1	1	0	1	0	0	0	1
1	1	0	1	0	1	1	1

Slide credit: Kristen Grauman

Thresholding

- Grayscale -> binary mask
- Useful if object of interest's intensity distribution is distinct from background

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

$$F_T[i,j] = \begin{cases} 1 & \text{if } T_1 \leq F[i,j] \leq T_2 \\ 0 & otherwise. \end{cases}$$

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

- Example
  http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/FITZGIBBON/simplebinary.html

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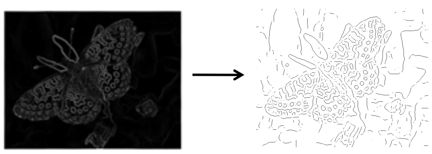
Slide credit: Kristen Grauman

Thresholding

- Given a grayscale image or an intermediate matrix → threshold to create a binary output.

Example: edge detection



Gradient magnitude

`fg_pix = find(gradient_mag > t);`

Looking for pixels where gradient is strong.

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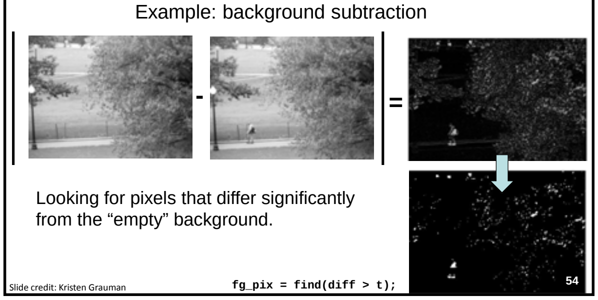
Slide adapted from Kristen Grauman

Thresholding

- Given a grayscale image or an intermediate matrix → threshold to create a binary output.

Example: background subtraction



Looking for pixels that differ significantly from the "empty" background.

Slide credit: Kristen Grauman

`fg_pix = find(diff > t);`

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Thresholding

- Given a grayscale image or an intermediate matrix → threshold to create a binary output.

Example: intensity-based detection

`fg_pix = find(im < 65);`

Looking for dark pixels

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Slide credit: Kristen Grauman

Thresholding

- Given a grayscale image or an intermediate matrix → threshold to create a binary output.

Example: color-based detection

`fg_pix = find(hue > t1 & hue < t2);`

Looking for pixels within a certain hue range.

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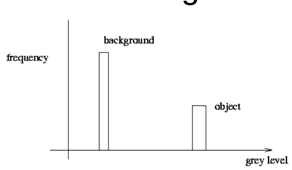
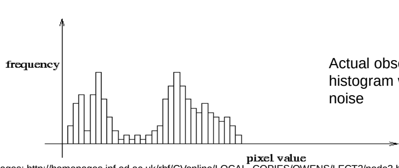
Slide credit: Kristen Grauman

A nice case: bimodal intensity histograms



Ideal histogram, light object on dark background



Actual observed histogram with noise

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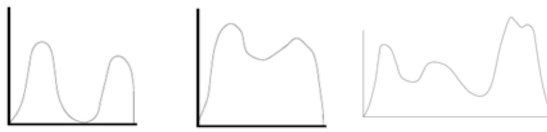
Images: http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/OWENS/LECT2/node3.html

Not so nice cases



Two distinct modes   Overlapped modes

Slide credit: Shapiro and Stockman

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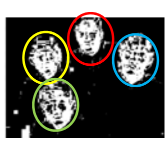
Issues

- What to do with “noisy” binary outputs?
  - Holes
  - Extra small fragments

- How to demarcate multiple regions of interest?
  - Count objects
  - Compute further features per object



Slide credit: Kristen Grauman

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Morphological operators

- Change the shape of the foreground regions via intersection/union operations between a scanning structuring element and binary image
- Useful to clean up result from thresholding
- Basic operators are:
  - Dilation
  - Erosion

Slide credit: Kristen Grauman

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Dilation

- Expands connected components
- Grow features
- Fill holes

Before dilation

After dilation

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Slide credit: Kristen Grauman

Erosion

- Erode connected components
- Shrink features
- Remove bridges, branches, noise

Before erosion

After erosion

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Slide credit: Kristen Grauman

Structuring elements

- **Masks** of varying shapes and sizes used to perform morphology, for example:

- Scan mask across foreground pixels to transform the binary image

```
>> help strel
```

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Slide credit: Kristen Grauman

Dilation vs. Erosion

At each position:

- **Dilation**: if **current pixel** is 1, then set all the output pixels corresponding to structuring element to 1.

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Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1								

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Slide credit: Adapted by Kristen Grauman from T. Moeslund

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1								

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0							

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0	0						

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0	1	1	1				

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0	1	1	1	1			

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0	1	1	1	1	1		

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0	1	1	1	1	1		

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Slide credit: Kristen Grauman

Example for Dilation

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

1	1	0	1	1	1	1	1	1	1

Note that the object gets bigger and holes are filled.

```
>> help imdilate
```

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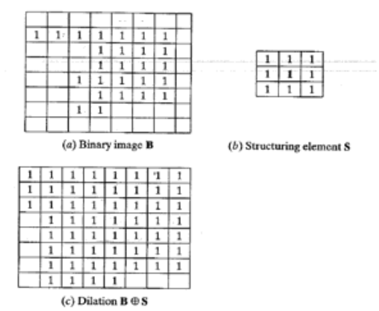
Slide credit: Kristen Grauman

2D example for dilation



(a) Binary image B

(b) Structuring element S

(c) Dilation B ⊕ S

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Slide credit: Shapiro & Stockman

Dilation vs. Erosion

At each position:

- **Dilation**: if **current pixel** is 1, then set all the output pixels corresponding to structuring element to 1.
- **Erosion**: if **every pixel** under the structuring element is 1, then set the output pixel corresponding to the current pixel to 1.

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Example for Erosion (1D)

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

0									

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Slide credit: Kristen Grauman

Example for Erosion (1D)

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

0	0								

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Slide credit: Kristen Grauman

Example for Erosion

Input image

1	0	0	0	1	1	1	0	1	1

Structuring Element

1	**1**	**1**

Output Image

0	0	0							

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element			**1**	**1**	**1**					
Output Image	0	0	0	0						

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element				**1**	**1**	**1**				
Output Image	0	0	0	0	0					

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element					**1**	**1**	**1**			
Output Image	0	0	0	0	0	1				

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element						**1**	**1**	**1**		
Output Image	0	0	0	0	0	1	0			

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element							**1**	**1**	**1**	
Output Image	0	0	0	0	0	1	0	0		

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element								**1**	**1**	**1**
Output Image	0	0	0	0	0	1	0	0	0	

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Slide credit: Kristen Grauman

Example for Erosion

Input image	1	0	0	0	1	1	1	0	1	1
Structuring Element									1	1
Output Image	0	0	0	0	0	1	0	0	0	1

Note that the object gets smaller

`>> help imerode`

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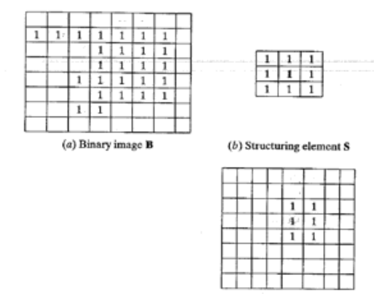
Slide credit: Kristen Grauman

2D example for erosion



(a) Binary image B

(b) Structuring element S

(d) Erosion B ⊖ S

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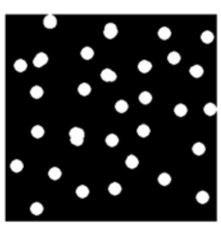
Slide credit: Shapiro & Stockman

Opening

- Erode, then dilate
- Remove small objects, keep original shape

Before opening



After opening

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Slide credit: Kristen Grauman

Closing

- Dilate, then erode
- Fill holes, but keep original shape

Before closing

After closing

Applet: http://bigwww.epfl.ch/demo/jmorpho/start.php

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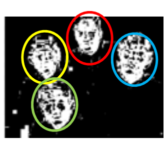
Slide credit: Kristen Grauman

Issues

- What to do with "noisy" binary outputs?
  - Holes
  - Extra small fragments

- How to demarcate multiple regions of interest?
  - Count objects
  - Compute further features per object



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Slide credit: Kristen Grauman

Connected components

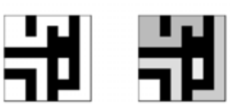
- Identify distinct regions of "connected pixels"

1	1	0	1	1	1	0	1
1	1	0	1	0	1	0	1
1	1	1	1	0	0	0	1
0	0	0	0	0	0	0	1
1	1	1	1	0	1	0	1
0	0	0	1	0	1	0	1
1	1	0	1	0	0	0	1
1	1	0	1	0	1	1	1

a) binary image

1	1	0	1	1	1	0	2
1	1	0	1	0	1	0	2
1	1	1	1	0	0	0	2
0	0	0	0	0	0	0	2
3	3	3	3	0	4	0	2
0	0	0	3	0	4	0	2
5	5	0	3	0	0	0	2
5	5	0	3	0	2	2	2

b) connected components labeling



c) binary image and labeling, expanded for viewing

>> L = bwlabel(BW,conn)

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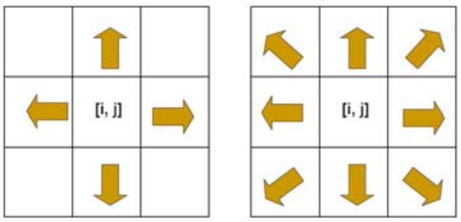
Connectedness

- Defining which pixels are considered neighbors



4-connected   8-connected

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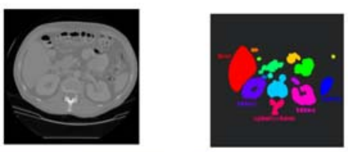
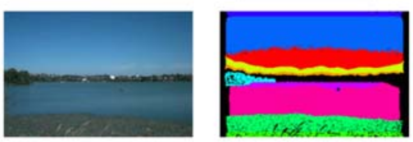
Slide credit: Chaitanya Chandra

Connected components



connected components of 1's from thresholded image



connected components of cluster labels

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Slide credit: Pinar Duygulu

Region properties

- Given connected components, can compute simple features per blob, such as:
  - Area (num pixels in the region)
  - Centroid (average x and y position of pixels in the region)
  - Bounding box (min and max coordinates)

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Slide credit: Kristen Grauman

Binary image analysis: basic steps (recap)

- Convert the image into binary form
  - Thresholding
- Clean up the thresholded image
  - Morphological operators
- Extract separate blobs
  - Connected components
- Describe the blobs with region properties

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Slide credit: Kristen Grauman

Matlab

- `L = bwlabel (BW,8);`
- `STATS = regionprops(L,PROPERTIES) ;`
  - `'Area'`
  - `'Centroid'`
  - `'BoundingBox'`
  - `'Orientation', …`
- `IM2 = imerode(IM,SE);`
- `IM2 = imdilate(IM,SE);`
- `IM2 = imclose(IM, SE);`
- `IM2 = imopen(IM, SE);`

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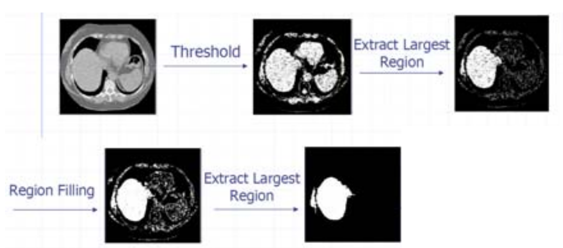
Slide adapted from Kristen Grauman

Example using binary image analysis: segmentation of a liver



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Slide credit: Li Shen

Application by Jie Zhu, Cornell University

Binary images

- Pros
  - Can be fast to compute, easy to store
  - Simple processing techniques available
  - Lead to some useful compact shape descriptors
- Cons
  - Hard to get “clean” silhouettes
  - Noise common in realistic scenarios
  - Can be too coarse of a representation

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Slide credit: Kristen Grauman

Summary

- Operations, tools
  - Derivative filters
  - Smoothing, morphology
  - Thresholding
  - Connected components
  - Matching filters
  - Histograms
- Features, representations
  - Edges, gradients
  - Blobs/regions
  - Local patterns
  - Textures (next)
  - Color distributions

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Coming up

- Texture
  - Read Szeliski 10.5

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Questions?

See you Thursday!

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