Segmentation & Grouping

Thursday, Sept 17
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UT-Austin

Last time

- Texture is a useful property that is often indicative of materials, appearance cues
- **Texture representations** attempt to summarize repeating patterns of local structure
- **Filter banks** useful to measure redundant variety of structures in local neighborhood
  - Feature spaces can be multi-dimensional
  - Distance in feature space to compare descriptors

Review questions

- When describing texture, why do we collect filter response statistics within a window?
- What is the Markov assumption?
  - And why is it relevant for the texture synthesis technique of Efros & Leung?

Outline

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Algorithms: k-means, graph-based
    - Quantization for texture summaries
  - Features: color, texture, …

Grouping in vision

- Goals:
  - Gather features that belong together
  - Obtain an intermediate representation that compactly describes key image or video parts

Examples of grouping in vision

[Figure by J. Shi]

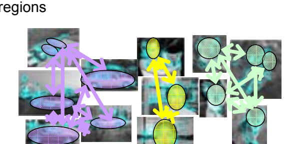
Determine image regions

[http://poseidon.csd.auth.gr/LAB_RESEARCH/Latest/imgs/SpeakDepVidIndex_img2.jpg]

Group video frames into shots

[Figure by Wang & Suter]

Figure-ground



[Figure by Grauman & Darrell]

Object-level grouping

Grouping in vision

- Goals:
  - Gather features that belong together
  - Obtain an intermediate representation that compactly describes key image (video) parts
- Top down vs. bottom up segmentation
  - Top down: pixels belong together because they are from the same object
  - Bottom up: pixels belong together because they look similar
- Hard to measure success
  - What is interesting depends on the app.

What things should be grouped?
What cues indicate groups?

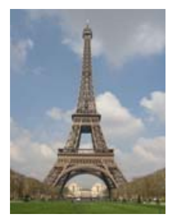
Similarity




http://chicagoist.com/attachments/chicagoist_alicia/GEESE.jpg, http://wwwdelivery.superstock.com/WI/223/1532/PreviewComp/SuperStock_1532R-0831.jpg

Symmetry



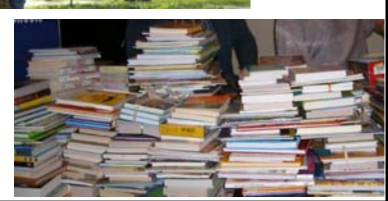



http://seedmagazine.com/news/2006/10/beauty_is_in_the_processingtim.php

Common fate


Image credit: Arthus-Bertrand (via F. Durand)

Proximity

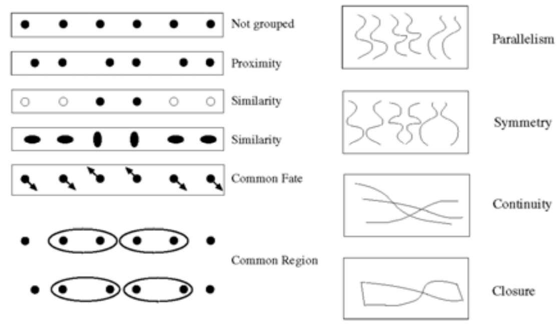



http://www.capital.edu/Resources/Images/outside6_035.jpg

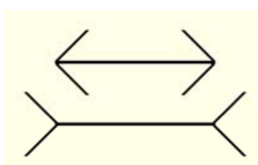
Gestalt

- Gestalt: whole or group
  - Whole is greater than sum of its parts
  - Relationships among parts can yield new properties/features
- Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)

Some Gestalt factors

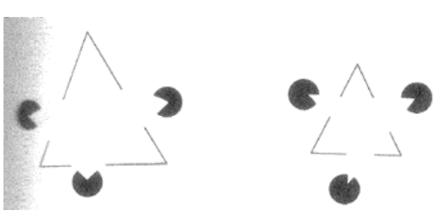


Muller-Lyer illusion



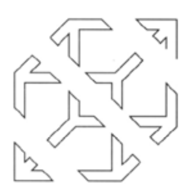
Gestalt principle: grouping key to visual perception.

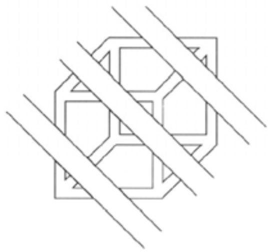
Illusory/subjective contours



Interesting tendency to explain by occlusion

In *Vision*, D. Marr, 1982

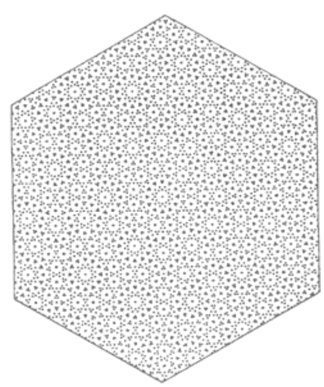




Continuity, explanation by occlusion

D. Forsyth

Figure-ground



In *Vision*, D. Marr, 1982; from J. L. Marroquin, "Human visual perception of structure", 1976.

Gestalt

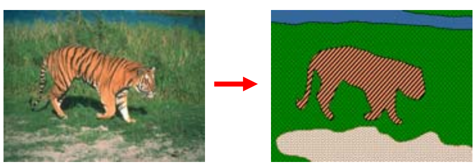
- Gestalt: whole or group
  - Whole is greater than sum of its parts
  - Relationships among parts can yield new properties/features
- Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)
- **Inspiring observations/explanations, but not necessarily directly useful for algorithms.**

Outline

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Algorithms: k-means, graph-based
    - Quantization for texture summaries
  - Features: color, texture, …

Image segmentation

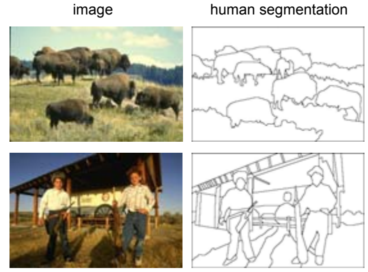
- Goal: identify groups of pixels that go together.



The goals of segmentation

Separate image into coherent "objects"

image — human segmentation



Source: Lana Lazebnik

The goals of segmentation

Separate image into coherent "objects"

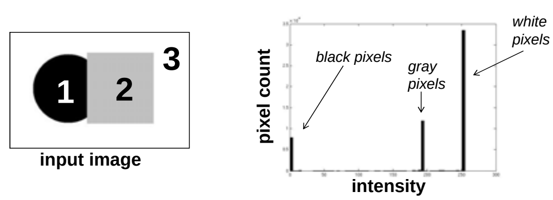
Group together similar-looking pixels for efficiency of further processing

"superpixels"

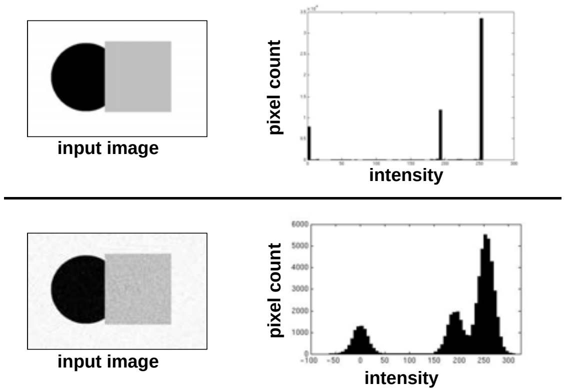
X. Ren and J. Malik. Learning a classification model for segmentation. ICCV 2003.

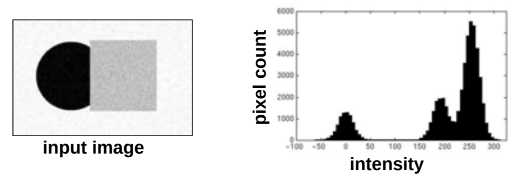
Source: Lana Lazebnik

Image segmentation: toy example

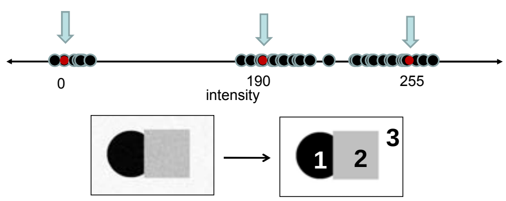


- These intensities define the three groups.
- We could label every pixel in the image according to which of these primary intensities it is.
  - i.e., *segment* the image based on the intensity feature.
- What if the image isn't quite so simple?





- Now how to determine the three main intensities that define our groups?
- We need to ***cluster.***

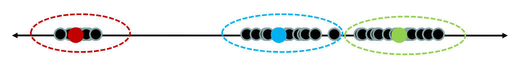


- Goal: choose three "centers" as the representative intensities, and label every pixel according to which of these centers it is nearest to.
- Best cluster centers are those that minimize SSD between all points and their nearest cluster center c_i:

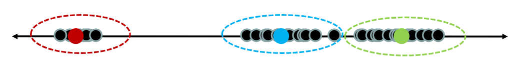
$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} \|p - c_i\|^2$$

Clustering

- With this objective, it is a "chicken and egg" problem:
  - If we knew the **cluster centers**, we could allocate points to groups by assigning each to its closest center.



  - If we knew the **group memberships**, we could get the centers by computing the mean per group.



K-means clustering

- Basic idea: randomly initialize the *k* cluster centers, and iterate between the two steps we just saw.
  1. Randomly initialize the cluster centers, $c_1, ..., c_K$
  2. Given cluster centers, determine points in each cluster
     - For each point p, find the closest c_i. Put p into cluster i
  3. Given points in each cluster, solve for c_i
     - Set c_i to be the mean of points in cluster i
  4. If c_i have changed, repeat Step 2

Properties
- Will always converge to *some* solution
- Can be a "local minimum"
  - does not always find the global minimum of objective function:

$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} \|p - c_i\|^2$$

Source: Steve Seitz

K-means clustering

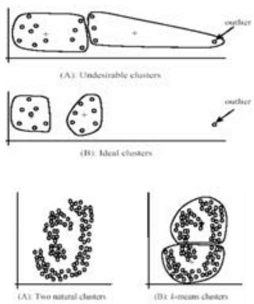
- Java demo:

  http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html

K-means: pros and cons

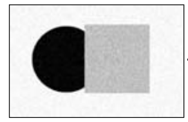
Pros
- Simple, fast to compute
- Converges to local minimum of within-cluster squared error

Cons/issues
- Setting k?
- Sensitive to initial centers
- Sensitive to outliers
- Detects spherical clusters
- Assuming means can be computed

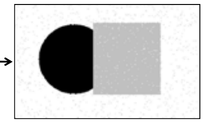


An aside: Smoothing out cluster assignments

- Assigning a cluster label per pixel may yield outliers:



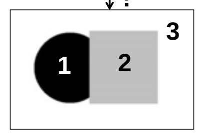
original



labeled by cluster center's intensity

?

- How to ensure they are spatially smooth?



Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity** similarity

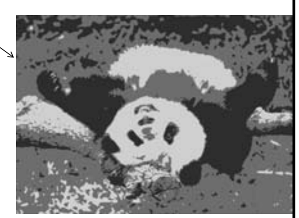
Feature space: intensity value (1-d)

K=2

K=3

quantization of the feature space; segmentation label map

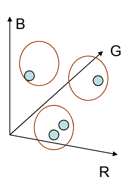
```
img_as_col = double(im(:));
cluster_membs = kmeans(img_as_col, K);

labelim = zeros(size(im));
for i=1:k
   inds = find(cluster_membs==i);
   meanval = mean(img_as_column(inds));
   labelim(inds) = meanval;
end
```

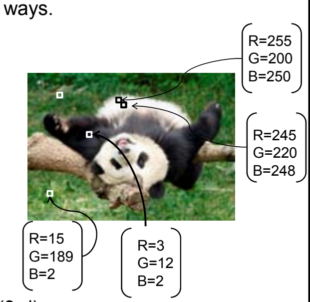


Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **color** similarity





Feature space: color value (3-d)

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

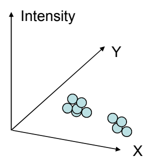
Grouping pixels based on **intensity** similarity

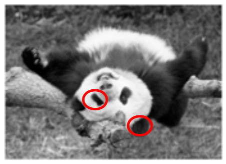
Clusters based on intensity similarity don't have to be spatially coherent.

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity+position** similarity





Both regions are black, but if we also include **position (x,y),** then we could group the two into distinct segments; way to encode both similarity & proximity.

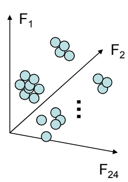
Segmentation as clustering

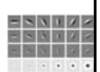
- Color, brightness, position alone are not enough to distinguish all regions…

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **texture** similarity

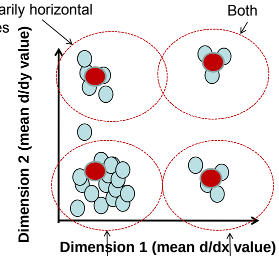


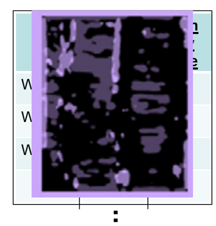


Filter bank of 24 filters

Feature space: filter bank responses (e.g., 24-d)

Recall: texture representation example

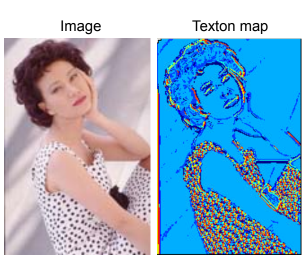


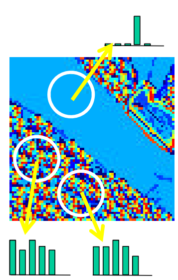


statistics to summarize patterns in small windows

Segmentation with texture features

- Find "textons" by **clustering** vectors of filter bank outputs
- Describe texture in a window based on *texton histogram*





Malik, Belongie, Leung and Shi. IJCV 2001.

Adapted from Lana Lazebnik

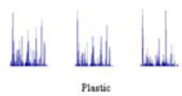
Material classification example

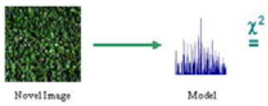
For an image of a single texture, we can classify it according to its global (image-wide) texton histogram.

Figure from Varma & Zisserman, IJCV 2005

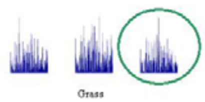
Material classification example

Nearest neighbor classification: label the input according to the nearest known example's label.





$$\chi^2(h_i, h_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}$$



Manik Varma
http://www.robots.ox.ac.uk/~vgg/research/texclass/with.html

Pixel properties vs. neighborhood properties

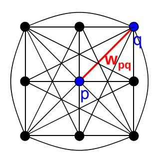
These look very similar in terms of their color distributions (histograms).

How would their *texture* distributions compare?

Outline

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Algorithms: k-means, graph-based
  - Features: color, texture, …

Images as graphs



Fully-connected graph
- node (vertex) for every pixel
- link between *every* pair of pixels, **p,q**
- affinity weight w_{pq} for each link (edge)
  - w_{pq} measures *similarity*
    - » similarity is *inversely proportional* to difference (in color and position…)

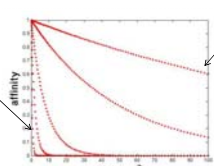
Source: Steve Seitz

Measuring affinity

- One possibility:

$$aff(x, y) = \exp\left\{-\left(\frac{1}{2\sigma_d^2}\right)\left(\|x - y\|^2\right)\right\}$$

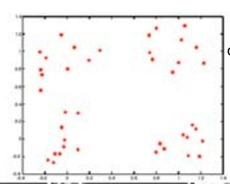
Small sigma: group only nearby points



Large sigma: group distant points

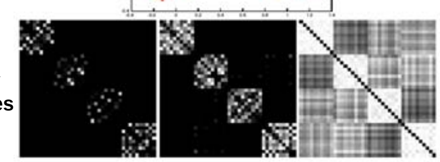
Measuring affinity

Data points



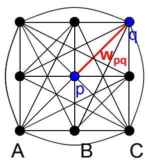
σ=.2

Affinity matrices



σ=.1 σ=.2 σ=1

Segmentation by Graph Cuts

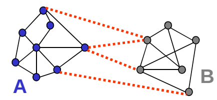


Break Graph into Segments

- Want to delete links that cross **between** segments
- Easiest to break links that have low similarity (low weight)
  - similar pixels should be in the same segments
  - dissimilar pixels should be in different segments

Source: Steve Seitz

Cuts in a graph: Min cut



Link Cut

- set of links whose removal makes a graph disconnected
- cost of a cut: $cut(A,B) = \sum_{p \in A, q \in B} w_{p,q}$

Find minimum cut

- gives you a segmentation
- fast algorithms exist for doing this

Source: Steve Seitz

Minimum cut

- Problem with minimum cut:
  Weight of cut proportional to number of edges in the cut; tends to produce small, isolated components.

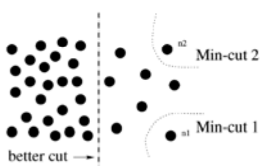
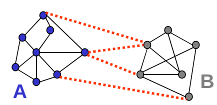


Fig. 1. A case where minimum cut gives a bad partition.

[Shi & Malik, 2000 PAMI]

Cuts in a graph: Normalized cut



Normalized Cut

- fix bias of Min Cut by **normalizing** for size of segments:

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

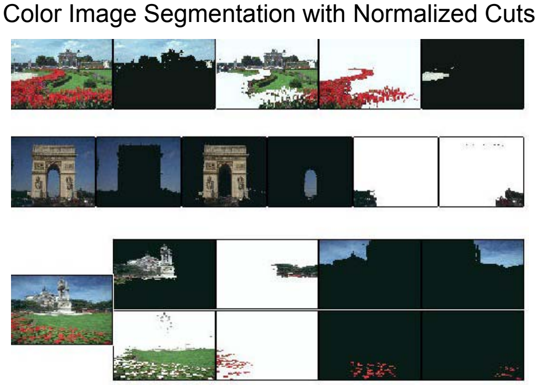
assoc(A,V) = sum of weights of all edges that touch A

- Approximate solution for minimizing the Ncut value : generalized eigenvalue problem.

J. Shi and J. Malik, Normalized Cuts and Image Segmentation, CVPR, 1997

Source: Steve Seitz

Color Image Segmentation with Normalized Cuts



J. Shi and J. Malik, Normalized Cuts and Image Segmentation, CVPR, 1997

Example results

Results: Berkeley Segmentation Engine

http://www.cs.berkeley.edu/~fowlkes/BSE/

Normalized cuts: pros and cons

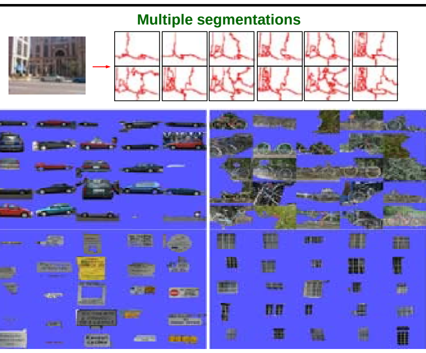
Pros:

- Generic framework, flexible to choice of function that computes weights ("affinities") between nodes
- Does not require model of the data distribution

Cons:

- Time complexity can be high
  - Dense, highly connected graphs → many affinity computations
  - Solving eigenvalue problem
- Preference for balanced partitions

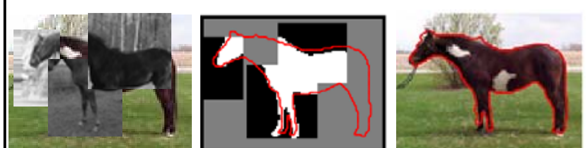
Segments as primitives for recognition



B. Russell et al., "Using Multiple Segmentations to Discover Objects and their Extent in Image Collections," CVPR 2006

Slide credit: Lana Lazebnik

Top-down segmentation

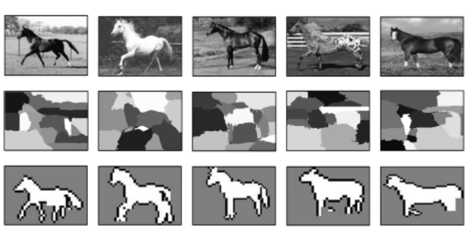


E. Borenstein and S. Ullman, "Class-specific, top-down segmentation," ECCV 2002

A. Levin and Y. Weiss, "Learning to Combine Bottom-Up and Top-Down Segmentation," ECCV 2006.

Slide credit: Lana Lazebnik

Top-down segmentation



Normalized cuts

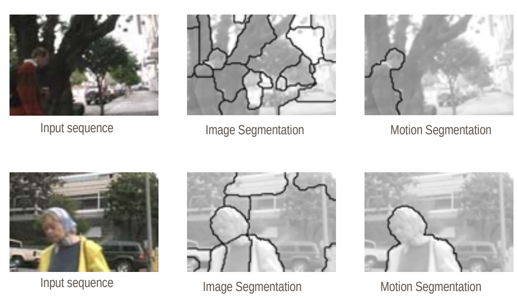
Top-down segmentation

E. Borenstein and S. Ullman, "Class-specific, top-down segmentation," ECCV 2002

A. Levin and Y. Weiss, "Learning to Combine Bottom-Up and Top-Down Segmentation," ECCV 2006.

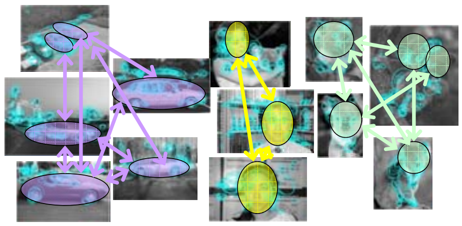
Slide credit: Lana Lazebnik

Motion segmentation



A.Barbu, S.C. Zhu. Generalizing Swendsen-Wang to sampling arbitrary posterior probabilities, *IEEE Trans. PAMI,* August 2005.

Image grouping



Build a graph of images, with edges weighted by some feature matching score. Partition the graph to “discover” categories of objects.

K. Grauman & T. Darrell, Unsupervised Learning of Categories from Sets of Partially Matching Image Features, CVPR 2006.

Summary

- Segmentation to find object boundaries or mid-level regions, tokens.
- Bottom-up segmentation via clustering
  - General choices -- features, affinity functions, and clustering algorithms
- Grouping also useful for quantization, can create new feature summaries
  - Texton histograms for texture within local region
- Example clustering methods
  - K-means
  - Graph cuts, normalized cuts
  - Tradeoffs

Next

- Pset 1 due Mon 11:59 PM
- Fitting
  - Read F&P Chapter 15.1: Hough Transform