Grouping and Segmentation

Computer Vision
CS 543 / ECE 549
University of Illinois

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Announcements

• HW 3: due today
  – Graded by Tues after spring break

• HW 4: out soon
  1. Mean-shift segmentation
  2. EM problem for dealing with bad annotators
  3. Graph cuts segmentation
Today’s class

• Segmentation and grouping
  – Gestalt cues
  – By clustering (mean-shift)
  – By boundaries (watershed)
Gestalt grouping
Gestalt psychology or gestaltism

German: *Gestalt* - "form" or "whole"

Berlin School, early 20th century
Kurt Koffka, Max Wertheimer, and Wolfgang Köhler

View of brain:
• whole is more than the sum of its parts
• holistic
• parallel
• analog
• self-organizing tendencies
Gestaltism

The Muller-Lyer illusion
We perceive the interpretation, not the senses
Principles of perceptual organization

- Not grouped
- Proximity
- Similarity
- Similarity
- Common Fate
- Common Region

From Steve Lehar: The Constructive Aspect of Visual Perception
Principles of perceptual organization

- Parallelism
- Symmetry
- Continuity
- Closure
Gestaltists do not believe in coincidence
Emergence
Grouping by invisible completion

A

B

C

D

From Steve Lehar: The Constructive Aspect of Visual Perception
Grouping involves global interpretation

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Grouping involves global interpretation

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Gestalt cues

• Good intuition and basic principles for grouping

• Basis for many ideas in segmentation and occlusion reasoning

• Some (e.g., symmetry) are difficult to implement in practice
Image segmentation

Goal: Group pixels into meaningful or perceptually similar regions
Segmentation for feature support
Segmentation for efficiency

[Felzenszwalb and Huttenlocher 2004]

[Hoiem et al. 2005, Mori 2005]

[Shi and Malik 2001]
Segmentation as a result

Rother et al. 2004
Types of segmentations

- Oversegmentation
- Undersegmentation
- Multiple Segmentations
Major processes for segmentation

- **Bottom-up**: group tokens with similar features
- **Top-down**: group tokens that likely belong to the same object

[Levin and Weiss 2006]
Segmentation using clustering

• Kmeans

• Mean-shift
Feature Space

Source: K. Grauman
K-means clustering using intensity alone and color alone
K-Means pros and cons

• Pros
  – Simple and fast
  – Easy to implement

• Cons
  – Need to choose K
  – Sensitive to outliers

• Usage
  – Rarely used for pixel segmentation
Mean shift segmentation


- Versatile technique for clustering-based segmentation
Mean shift algorithm

- Try to find *modes* of this non-parametric density
Kernel density estimation

Data (1-D)
Estimated density
Kernel
Kernel density estimation

Kernel density estimation function

\[ \hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left( \frac{x - x_i}{h} \right) \]

Gaussian kernel

\[ K \left( \frac{x - x_i}{h} \right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-x_i)^2}{2h^2}}. \]
Mean shift

- Region of interest
- Center of mass
- Mean Shift vector

Slide by Y. Ukrainitz & B. Sarel
Mean shift

Region of interest
Center of mass
Mean Shift vector
Mean shift

Region of interest

Center of mass

Mean Shift vector

Slide by Y. Ukrainitz & B. Sarel
Mean shift
Mean shift
Mean shift

Slide by Y. Ukrainitz & B. Sarel
Simple Mean Shift procedure:
- Compute mean shift vector
- Translate the Kernel window by $\mathbf{m}(\mathbf{x})$

$$\mathbf{m}(\mathbf{x}) = \left[ \sum_{i=1}^{n} \mathbf{x}_i g \left( \frac{||\mathbf{x} - \mathbf{x}_i||^2}{h} \right) \right] / \left[ \sum_{i=1}^{n} g \left( \frac{||\mathbf{x} - \mathbf{x}_i||^2}{h} \right) \right]$$
Real Modality Analysis
Attraction basin

- **Attraction basin**: the region for which all trajectories lead to the same mode
- **Cluster**: all data points in the attraction basin of a mode
Attraction basin
Mean shift clustering

- The mean shift algorithm seeks *modes* of the given set of points
  1. Choose kernel and bandwidth
  2. For each point:
     a) Center a window on that point
     b) Compute the mean of the data in the search window
     c) Center the search window at the new mean location
     d) Repeat (b,c) until convergence
  3. Assign points that lead to nearby modes to the same cluster
Segmentation by Mean Shift

- Compute features for each pixel (color, gradients, texture, etc); also store each pixel's position
- Set kernel size for features $K_f$ and position $K_s$
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge modes that are within width of $K_f$ and $K_s$
Mean shift segmentation results

http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html
Mean-shift: other issues

• Speedups
  – Binned estimation – replace points within some “bin” by point at center with mass
  – Fast search of neighbors – e.g., k-d tree or approximate NN
  – Update all windows in each iteration (faster convergence)

• Other tricks
  – Use kNN to determine window sizes adaptively

• Lots of theoretical support
Doing mean-shift for HW 4

• Goal is to understand the basics of how mean-shift works
  – Just get something working that has the right behavior qualitatively
  – Don’t worry about speed

• Simplifications
  – Work with very small images (120x80)
  – Use a uniform kernel (compute the mean of color, position within some neighborhood given by $K_f$ and $K_s$)
  – Can use a heuristic for merging similar modes
Mean shift pros and cons

- **Pros**
  - Good general-purpose segmentation
  - Flexible in number and shape of regions
  - Robust to outliers

- **Cons**
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features

- **When to use it**
  - Oversegmentation
  - Multiple segmentations
  - Tracking, clustering, filtering applications

Watershed algorithm
Watershed segmentation

Image

Gradient

Watershed boundaries
Meyer’s watershed segmentation

1. Choose local minima as region seeds
2. Add neighbors to priority queue, sorted by value
3. Take top priority pixel from queue
   1. If all labeled neighbors have same label, assign that label to pixel
   2. Add all non-marked neighbors to queue
4. Repeat step 3 until finished (all remaining pixels in queue are on the boundary)

Matlab: `seg = watershed(bnd_im)`
Simple trick

- Use Gaussian or median filter to reduce number of regions
Watershed usage

• Use as a starting point for hierarchical segmentation
  – Ultrametric contour map (Arbelaez 2006)

• Works with any soft boundaries
  – Pb (w/o non-max suppression)
  – Canny (w/o non-max suppression)
  – Etc.
Watershed pros and cons

• Pros
  – Fast (< 1 sec for 512x512 image)
  – Preserves boundaries

• Cons
  – Only as good as the soft boundaries
  – Not easy to get variety of regions for multiple segmentations

• Usage
  – Preferred algorithm for hierarchical segmentation
Choices in segmentation algorithms

• Oversegmentation
  – Watershed + Pb ← my favorite
  – Felzenszwalb and Huttenlocher 2004 ← my favorite
    [Link](http://www.cs.brown.edu/~pff/segment/)
  – Turbopixels
  – Mean-shift

• Larger regions
  – Hierarchical segmentation (e.g., from Pb) ← my favorite
  – Normalized cuts
  – Mean-shift
  – Seed + graph cuts (discussed later)
Felzenszwalb and Huttenlocher: Graph-Based Segmentation

+ Good for thin regions
+ Fast
+ Easy to control coarseness of segmentations
+ Can include both large and small regions
- Often creates regions with strange shapes
- Sometimes makes very large errors

http://www.cs.brown.edu/~pff/segment/
Turbo Pixels: Levinstein et al. 2009


Tries to preserve boundaries like watershed but to produce more regular regions
Things to remember

- Gestalt cues and principles of organization

- Uses of segmentation
  - Efficiency
  - Better features
  - Want the segmented object

- Mean-shift segmentation
  - Good general-purpose segmentation method
  - Generally useful clustering, tracking technique

- Watershed segmentation
  - Good for hierarchical segmentation
  - Use in combination with boundary prediction
Further reading

• Nicely written mean-shift explanation (with math)
  http://saravananthirumuruganathan.wordpress.com/2010/04/01/introduction-to-mean-shift-algorithm/
  • Includes .m code for mean-shift clustering --- feel free to look at it but your code for segmentation will be different

• Mean-shift paper by Comaniciu and Meer
  http://www.caip.rutgers.edu/~comanici/Papers/MsRobustApproach.pdf

• Adaptive mean shift in higher dimensions

• Contours to regions (watershed): Arbelaez et al. 2009
Next class: EM algorithm

• Make sure to bring something to take notes (will include a long derivation)