Final project guidelines posted

Milestones

- October 27: Abstract due
- December 1, 3: Project presentations
- December 13: Final report due

Final project is graded as two homework assignments

- The scope of the project should be roughly equal to two homework assignments.
- Scales linearly with the team size.
- Form your own teams.

Alternatively, you can do a literature survey (solo)
• What are grouping problems in vision?

• Inspiration from human perception
  • Gestalt properties

• Bottom-up segmentation via clustering
  • Algorithms:
    - Mode finding and mean shift: k-means, mean-shift
    - Graph-based: graph cuts, normalized cuts
  • Features: color, texture, …
    - Quantization for texture summaries
Grouping in vision

- **Goals:**
  - Gather features that belong together
  - Obtain an intermediate representation that compactly describes key image or video parts for further processing
    - This is a computational complexity argument
Examples of grouping in vision

Determine image regions

Group video frames into shots

Figure-ground

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 application
What are the groups?
Questions …

- What things should be grouped?
- What cues indicate grouping?
• 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)
Similarity can occur in the form of shape, color, shading or other qualities.
Symmetry

http://themetapicture.com/the-average-woman-from-each-country/
Common fate

Image credit: Arthus-Bertrand (via F. Durand)
Proximity
Illusory/subjective contours

Interesting tendency to explain by occlusion

In Vision, D. Marr, 1982
Continuity, explanation by occlusion
Grouping phenomena in real life

Forsyth & Ponce, Figure 14.7
Grouping phenomena in real life

Forsyth & Ponce, Figure 14.7
• Gestalt: whole or group
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• Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)

• Inspiring observations/explanations; challenge remains how to best map to algorithms.
What are grouping problems in vision?

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The goals of segmentation

Separate image into coherent “objects”

Source: Lana Lazebnik
The goals of segmentation

Separate image into coherent “objects”

Group together similar-looking pixels for efficiency of further processing

“superpixels”

• 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 $c_i$:

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

recall $k$-means
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)
quantization of the feature space; segmentation label map
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.
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…
Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **texture** similarity

Feature space: filter bank responses (e.g., 24-d)
Recall: texture representation example

Windows with primarily horizontal edges

Windows with small gradient in both directions

Dimension 1 (mean d/dx value)

Dimension 2 (mean d/dy value)

Both

Windows with primarily vertical edges

statistics to summarize patterns in small windows

Kristen Grauman
Segmentation with texture features

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


Adapted from Lana Lazebnik
Image segmentation example

Texture-based regions

Color-based regions
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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
Mean shift algorithm

- The mean shift algorithm seeks *modes* or local maxima of density in the feature space

**Image**

**Feature space**
(L* u* v* color values)
Mean shift

- Search window
- Center of mass
- Mean Shift vector
Mean shift

Center of mass

Search window

Mean Shift vector
Mean shift

- Search window
- Center of mass

Mean Shift vector

Slide by Y. Ukrainitz & B. Sarel
Mean shift

Search window
Center of mass

Mean Shift vector
Mean shift

Search window

Center of mass

Mean Shift vector
Mean shift

Search window
Center of mass

Slide by Y. Ukrainitz & B. Sarel
Mean Shift procedure:
For each point, repeat till convergence:
• Compute mean shift vector
• Translate the Kernel window by \( m(x) \)

\[
\text{Computing the Mean Shift}
\]

\[
m(x) = \frac{\sum_{i=1}^{n} x_i g \left( \frac{\|x - x_i\|^2}{h} \right)}{\sum_{i=1}^{n} g \left( \frac{\|x - x_i\|^2}{h} \right)}
\]

\[
\exp \left( -\frac{\|x - x_i\|^2}{h} \right)
\]
Mean shift clustering

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

- Find features (color, gradients, texture, etc)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode
Mean shift segmentation results

http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html
Mean shift clustering results
Mean shift

- **Pros:**
  - Does not assume shape on clusters
  - One parameter choice (window size)
  - Generic technique
  - Find multiple modes

- **Cons:**
  - Selection of window size
  - Is rather expensive: $O(dN^2)$ per iteration
  - Does not work well for high-dimensional features