## CSSE463: Image Recognition

- This week
- Today:
- Graph-theoretic approach to segmentation
- Tuesday: Project workday
- Thursday: Test 2
- Friday: status reports due
- Next week:
- Monday - Friday: presentations
- Questions?


## Segmentation

- Goal: we want the pixels in each region to be similar to each other, but different than ones in other regions.
- Measures of affinity:
- Color, distance, edges, texture, etc.


## Graph-theoretic segmentation

- J Shi and J Malik, Normalized Cuts and Image Segmentation, IEEE TPAMI, 22(8), Aug 2000.
- Posted in Angel > Papers in Angel
- Much of the next set of slides is from Forsyth \& Ponce, section 14.5.
- But first, what's a graph? (on board)
- Undirected vs. directed
- Weight matrices


## What's graph-based segmentation?

- From images to graphs:
- Each pixel is a vertex
- Each edge represents an affinity between pixels
- Color, texture, distance, edges, etc.
- Cut the graph into two subgraphs (regions) with high affinity within each subgraph and low affinity across subgraphs
- Recurse
- How?
- An exact solution is NP-complete.

Split such that large weights (affinity) within cluster, low weights between clusters


## Weight matrix



Brighter = Larger weights
Ordered such that each cluster (blocks) is on the diagonal. Cutting the graph gives two separate blocks

## Measuring Affinity

- Recall: goal is for similar pixels to have higher affinity

Intensity

$$
\operatorname{aff}(x, y)=\exp \left\{-\left(1 / 2 \sigma_{i}^{2}\right)\left(|I(x)-I(y)|^{2}\right)\right\}
$$

Distance

$$
\operatorname{aff}(x, y)=\exp \left\{-\left(1 / 2 \sigma_{d}^{2}\right)\left(\left(x-y \|^{2}\right)\right\}\right.
$$

Color
What if $c(x)==c(y)$ ?
What if they are very different?

$$
\operatorname{aff}(x, y)=\exp \left\{-\left(1 / 2 \sigma_{t}^{2}\right)\left(\|c(x)-c(y)\|^{2}\right)\right\}
$$

## Scale affects affinity



Affinity by distance with $\sigma_{d}=0.1, \sigma_{d}=0.2, \sigma_{d}=1$

## How to segment

- There are some techniques that ignore across-cluster distance (and only use within-cluster affinity).
- We'll ignore these
- Want to minimize the cut between clusters A and B :
- In this graph, cut(left, right) =

$$
\begin{aligned}
& \operatorname{cut}(A, B)=\sum_{\substack{u \in A \\
v \in B}} w(u, v) \\
& =
\end{aligned}
$$

- This creates two segments like discussed above. However, it favors small regions


## The normalized cuts (ncuts) approach minimizes affinities between clusters and maximizes affinities within clusters

- Weight the cut by the total association with the whole graph

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

- Example.


$$
\operatorname{assoc}(A, V)=\sum_{\substack{u \in A \\ v \in V}} w(u, v)
$$

This summation double-counts the affinities within a cluster, which is OK.

Ncut(left, right) $=0.2 /[2(0.1+0.1+2(2+2+5+2))]+$ $0.2 /[2(0.1+0.1+2(1+2+3+4+7+1))]$

## How do we find min Ncut()?

- Let W be the matrix of weights
- Let d be the total affinity of pixel d with the rest of the image (row sums of W), and D be a matrix with the $\mathrm{d}(\mathrm{i})$ on the diagonal

- Let x be a vector whose elements are 1 if item is in A , -1 if it's in B,
- Let $\mathrm{y}=\mathrm{f}(\mathrm{x}, \mathrm{d})$ defined in the paper.
- 1 is the vector with all ones.
- Criterion becomes
subject to the constraint

$$
\begin{gathered}
\min _{\mathrm{y}}\left(\frac{y^{T}(D-W) y}{y^{T} D y}\right) \\
y^{T} D 1=0
\end{gathered}
$$

See p. 890, Shi and Malik for details

## Normalized cuts

- To do this, we can solve the generalized eigenvalue problem

$$
\max _{y}\left(y^{T}(D-W) y\right) \text { subject to }\left(y^{T} D y=1\right)
$$

- which gives

$$
(D-W) y=\lambda D y
$$

- The authors showed that the solution, y , corresponding to the second smallest eigenvalue solves this problem (the smallest is a trivial solution).
- When y is discrete, this is np-hard.
- Solution: assume y is continuous, solve, then threshold to give the clusters (approximation)
- Recursively split clusters until we pass a threshold on the cut value.


## Results with color + texture



Figure from "Image and video segmentation: the normalised cut framework", by Shi and Malik, copyright IEEE, 1998

## Results with motion



Figure from "Normalized cuts and image segmentation," Shi and Malik, copyright IEEE, 2000

## This uses distances too

