Bioimage Informatics

Lecture 15, Spring 2012

Bioimage Data Analysis (IV)

Image Segmentation (part 4)

Announcement

- There will be no lecture on Mar-21.

- Watching the following two videos is required:
  - http://ibioseminar.hhmi.org/
  - Kurt Thorn, *Optical Sectioning and Confocal Microscopy* (27 minutes)
  - Nico Stuurman, *Fluorescence Microscopy* (46 minutes)

- A one-page summary of the videos due on Mar-26.

- Recommended but not required:
  - Jennifer Lippincott-Schwartz, *Breakthroughs in Intracellular Fluorescent Imaging* (1 hour 30 minutes)

Outline

- Review of segmentation techniques covered
- Region-based image segmentation
- Concept of perceptual organization
- Graph-cut based image segmentation
- Active contour based image segmentation

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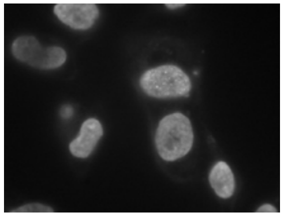
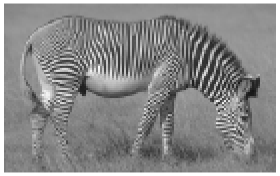
Segmentation Techniques Covered (I)





- Intensity thresholding based image segmentation
  - Essentially a mode finding technique
  - Simplicity; Robustness
  - Lack of spatial information

- Mean shift image segmentation is another commonly used mode finding technique.

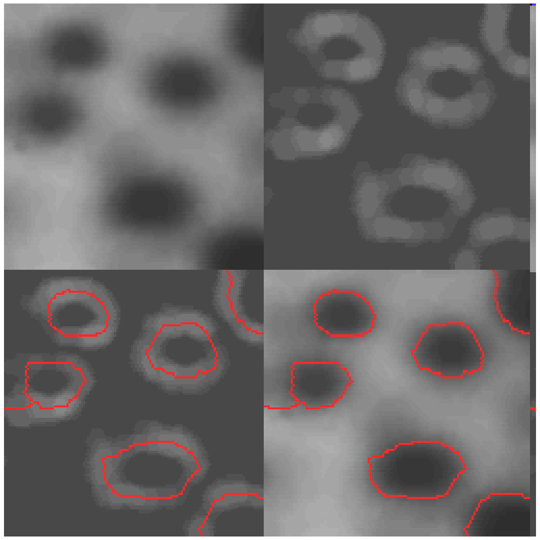
Comaniciu D. and Meer P. *Mean shift: a robust approach toward feature space analysis*, PAMI, 24(5):603-619.

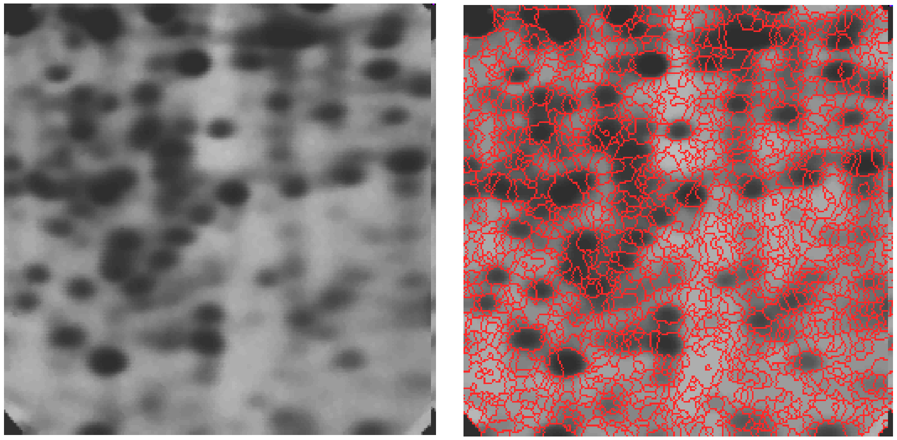
Paris S. and Durand E. *A topological approach to hierarchical segmentation using mean shift*, CVPR 2007,

Watershed Segmentation (I)

- Watershed is usually applied to gradient images.

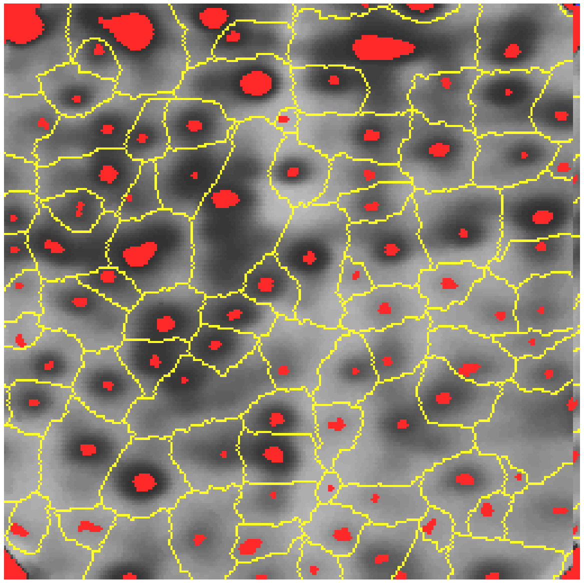
- Image noise often causes oversegmentation because of false local minima caused by noise.

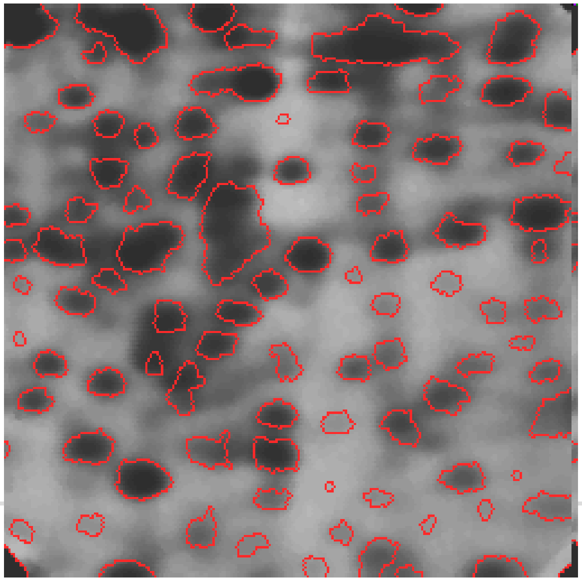




Watershed Segmentation (II)

- Oversegmentation can be minimized by using markers.
- Markers are the only allowed local minima.
- Construction of markers
  - Low-pass smoothing of the original image
  - Identify connected local minimum regions as markers





Segmentation Techniques Covered (II)

- Watershed segmentation

  - <u>Essentially a seeded region growth (merging) technique</u>

  - Conceptually simple

  - Sensitive to image noise

  - Boundary localization accuracy may be low

  - Often used in an interactive fashion

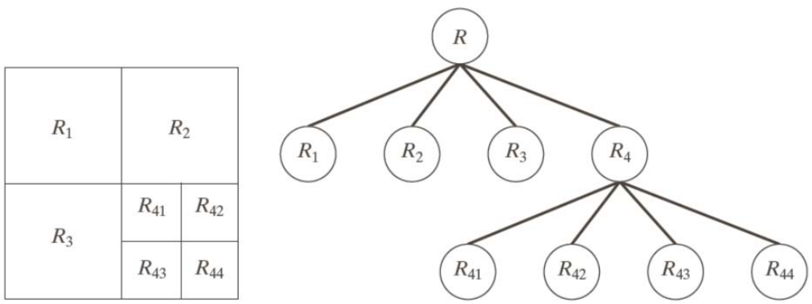
- Review of segmentation techniques covered
- Region-based image segmentation
- Concept of perceptual organization
- Graph-cut based image segmentation
- Active contour based image segmentation

Region-Based Segmentation (I)

- Segmentation based on splitting/merging

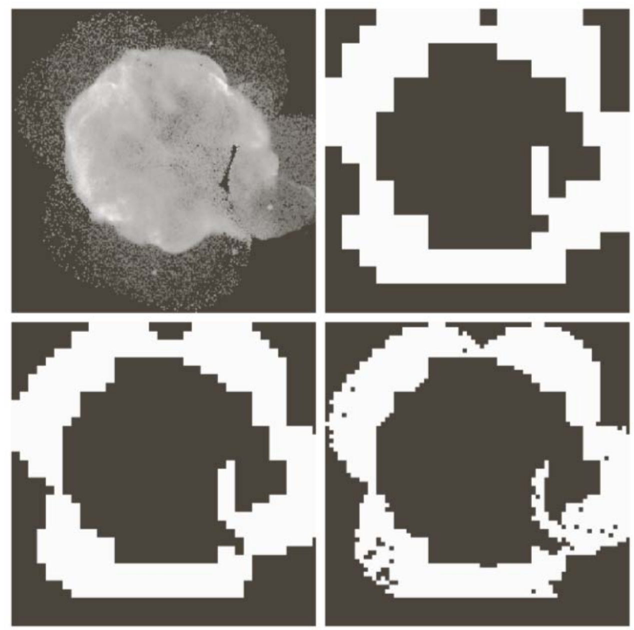
  Starting with subdividing images into several regions, recursive adjust regions through splitting/merging based on

  1) Dissimilarities; 2) Connectivity & adjacency



a b

FIGURE 10.52 (a) Partitioned image. (b) Corresponding quadtree. R represents the entire image region.



a b
c d

FIGURE 10.53 (a) Image of the Cygnus Loop supernova, taken in the X-ray band by NASA's Hubble Telescope. (b)–(d) Results of limiting the smallest allowed quadregion to sizes of 32×32, 16×16, and 8×8 pixels, respectively. (Original image courtesy of NASA.)

Region-Based Segmentation (II)

- Segmentation based on seeded region growth

  Starting with seeds, recursive grow from the seeds based on

  1) Similarities; 2) Connectivity or adjacency

- Seed selection

  - Strong evidence
  - Random sampling

- Criteria for stopping the iteration

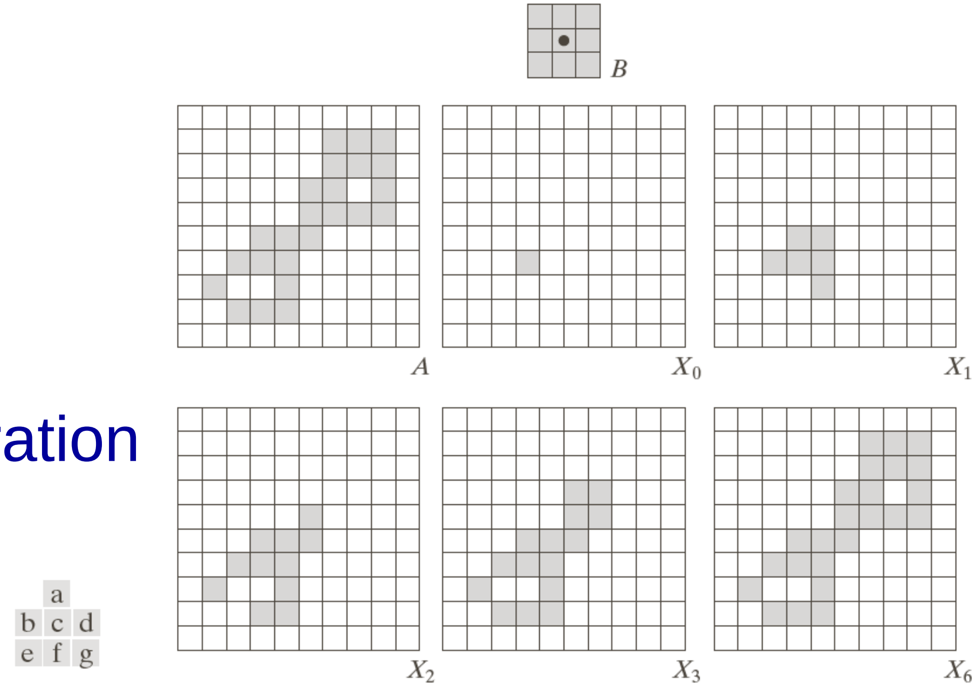
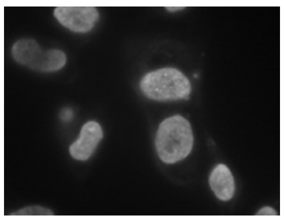
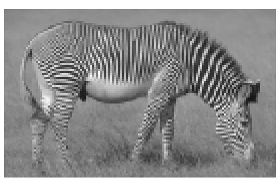


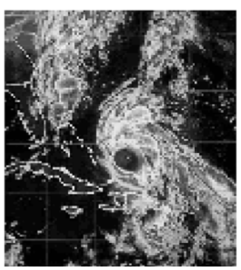
FIGURE 9.17 Extracting connected components. (a) Structuring element. (b) Array containing a set with one connected component. (c) Initial array containing a 1 in the region of the connected component. (d)–(g) Various steps in the iteration of Eq. (9.5-3).

Region-Based Segmentation (III)

- Some generic examples







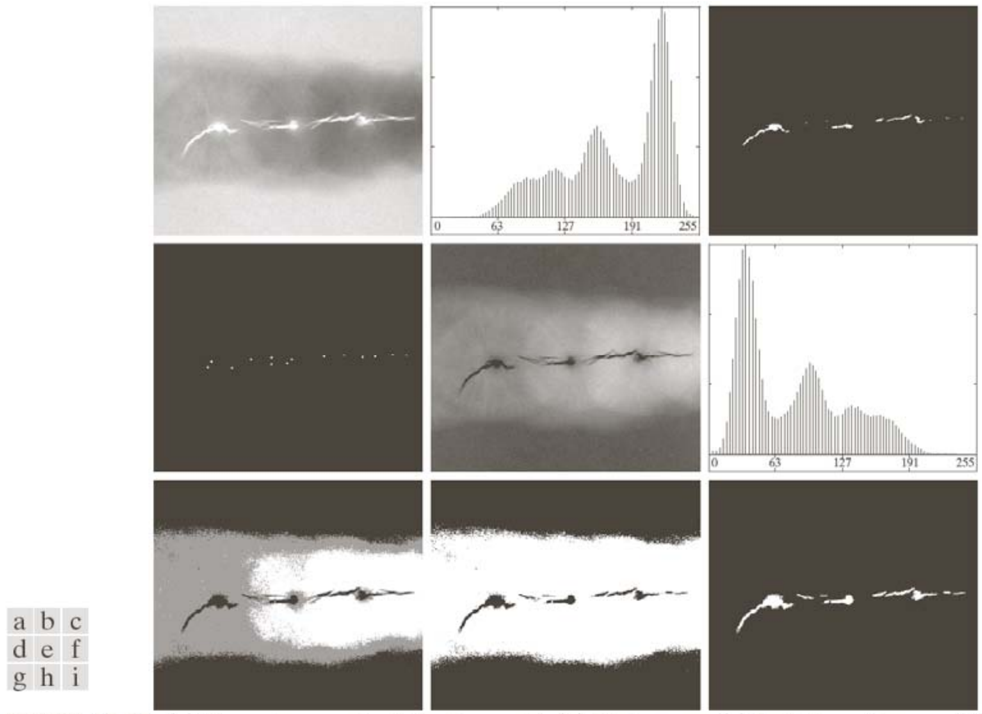
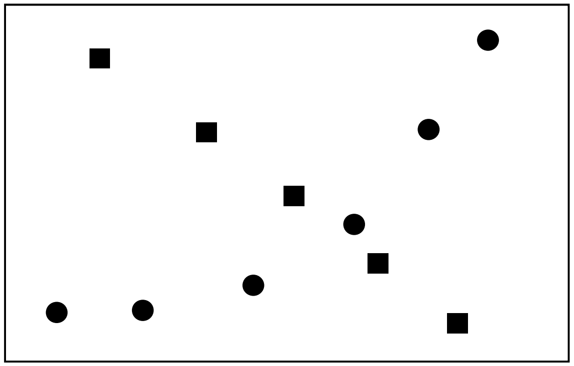


FIGURE 10.51 (a) X-ray image of a defective weld. (b) Histogram. (c) Initial seed image. (d) Final seed image (the points were enlarged for clarity). (e) Absolute value of the difference between (a) and (c). (f) Histogram of (e). (g) Difference image thresholded using dual thresholds. (h) Difference image thresholded with the smallest of the dual thresholds. (i) Segmentation result obtained by region growing. (Original image courtesy of X-TEK Systems, Ltd.)

Region-Based Segmentation (IV)

- Fundamental limitations of region-based segmentation
  - Decision is typically based on local measures; No global information



- Related MATLAB functions from DIP are deposited at the Blackboard site for this class.

- Review of segmentation techniques covered
- Region-based image segmentation
- Concept of perceptual organization
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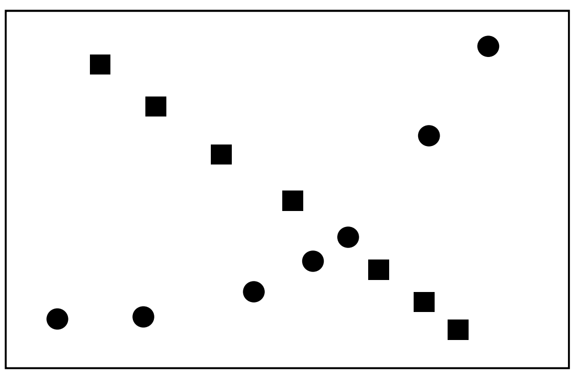
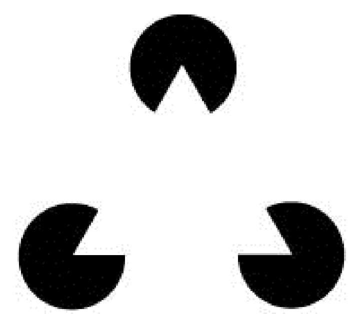
Perceptual Organization in Human Vision (I)

- A basic goal or idea of computer vision is to first understand human vision and then to emulate its functions using computation.
- Human vision system tends to perceptually organize individual objects perceived into groups. This is referred to as perceptual organization or perceptual grouping.
- The key idea here is to recognize organization in images over large scales.



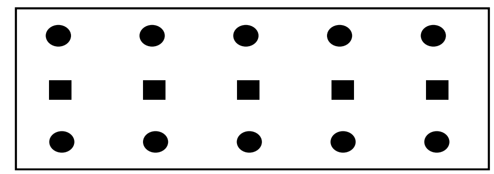


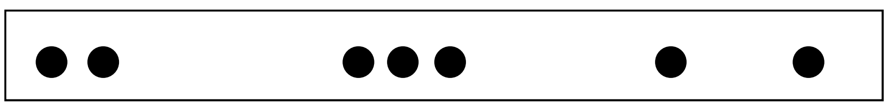
Perceptual Organization in Human Vision (II)

- The Gestalt school of psychology originated in 1920s-1930s in recognition of the role of perceptual organization in human vision.

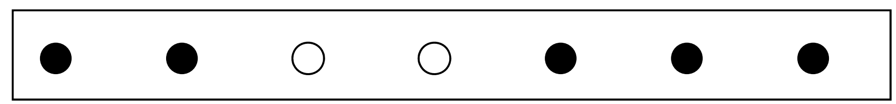
- Gestalt: a German word meaning "form" or "whole"

- Some basic principles of perceptual organization

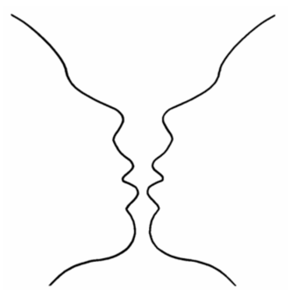




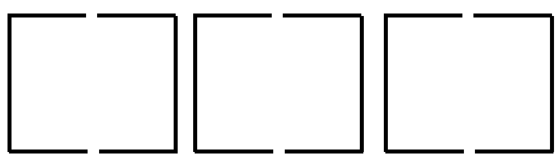
proximity



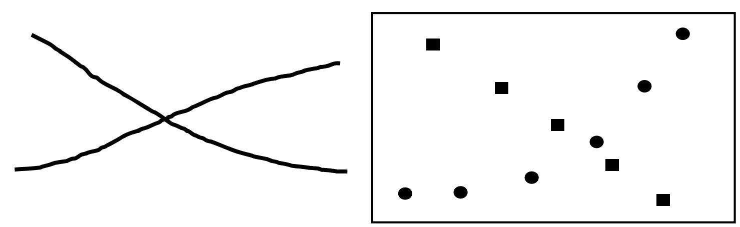
similarity



symmetry



closure

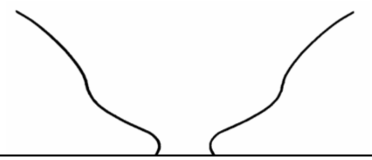


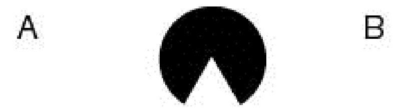
continuity

Perceptual Organization in Human Vision (III)

- Some fundamental questions

    - Example: The law of closure





What to compute?
How to compute?

- Review of segmentation techniques covered
- Region-based image segmentation
- Concept of perceptual organization
- **Graph-cut based image segmentation**
- Active contour based image segmentation

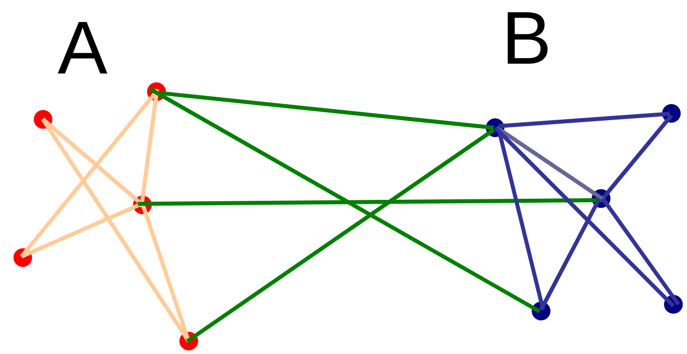
Basic Concept of Graph Cuts (I)

- A graph G = (V, E) can be partitioned into two disjoint sets A, B

$$A \bigcup B = V \qquad A \bigcap B = \varnothing$$

- Each vertex represents a pixel within the image.

- The weight of the edge connecting two vertices represents their similarity.

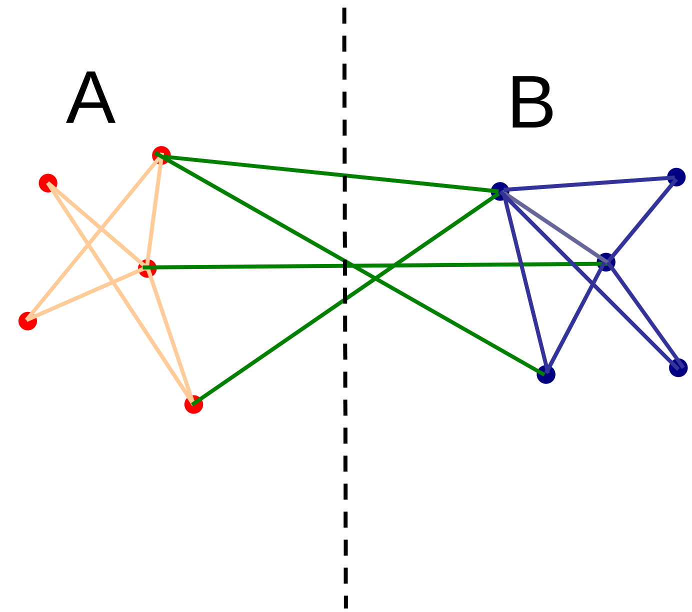


Shi & Malik, PAMI, 22:888-905, 2000

Basic Concept of Graph Cuts (II)

- A graph cut is defined as

$$cut(A,B) = \sum_{u \in A, v \in B} w(u,v)$$



- The goal is to find a partition that minimizes the cut.

- But there is a catch: minimum cut favors small sets of isolated nodes.

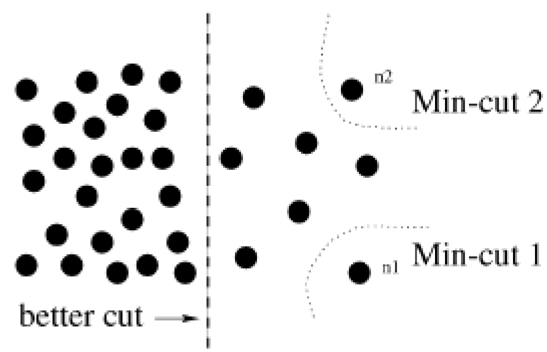


Fig. 1. A case where minimum cut gives a bad partition.

Formulation of Normalized Cut (I)

- Definition of normalized cut

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

$$\text{where } assoc(A,V) = \sum_{u \in A, t \in V} w(u,t) = assoc(A,A) + cut(A,B)$$

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

Formulation of Normalized Cut (II)

- Definition of normalized association

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

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

$$= 2 - \left(\frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \right)$$

$$\boxed{Nassoc(A,B) = 2 - Ncut(A,B)}$$

Solution of Normalized Cut (I)

- Matrix formulation

$$Ncut(A,B) = \frac{\sum_{(x_i>0,x_j<0)} -w_{ij}x_ix_j}{\sum_{x_i>0} d_i} + \frac{\sum_{(x_i<0,x_j>0)} -w_{ij}x_ix_j}{\sum_{x_i<0} d_i}$$

$$d(i) = \sum_j w(i,j)$$

- Reformulate the problem into a matrix form

$$D = \begin{bmatrix} d_1 & 0 & 0 & 0 & 0 \\ 0 & d_2 & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & d_{N-1} & 0 \\ 0 & 0 & 0 & 0 & d_N \end{bmatrix} \text{where } d_i = \sum_j w(i,j) \quad W(i,j) = w(i,j)$$

Solution of Normalized Cut (II)

- Exact solution of normalized cut is NP-complete.

$$min_x \; Ncut(x) = min_y \frac{y^T (D - W) y}{y^T D y}$$

$$\text{where} \quad y = (1 + x) - b(1 - x), \qquad b = \frac{k}{1-k} \;\; \text{and } k = \frac{\sum_{x_i > 0} d_i}{\sum d_i}$$

$$s.t. \quad y_i \in \{1, -b\} \qquad y^T D 1 = 0$$

Solution of Normalized Cut (III)

- Reformulate the problem into a matrix form

$$D = \begin{bmatrix} d_1 & 0 & 0 & 0 & 0 \\ 0 & d_2 & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & d_{N-1} & 0 \\ 0 & 0 & 0 & 0 & d_N \end{bmatrix} \text{ where } d_i = \sum_j w(i,j) \quad W(i,j) = w(i,j)$$

- A key relaxation is to allow y to take on continuous real values. Now y can be determined as the solution of

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

- After a further transformation, y is the solution of the following equation

$$D^{-\frac{1}{2}}(D-W)D^{-\frac{1}{2}}z = \lambda z \text{ where } y = D^{-\frac{1}{2}}z$$

- A key relaxation is to allow y to take on real values.

$$\min_x Ncut(x) = \min_y \frac{y^T(D-W)y}{y^T Dy}$$

$$\Updownarrow$$

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

$$\Updownarrow$$

$$D^{\frac{1}{2}}(D-W)D^{-\frac{1}{2}}z = \lambda z \quad z = D^{\frac{1}{2}}y$$

Summary of the Solution Procedure

- Step 1: Solve the eigenvector of the following equation

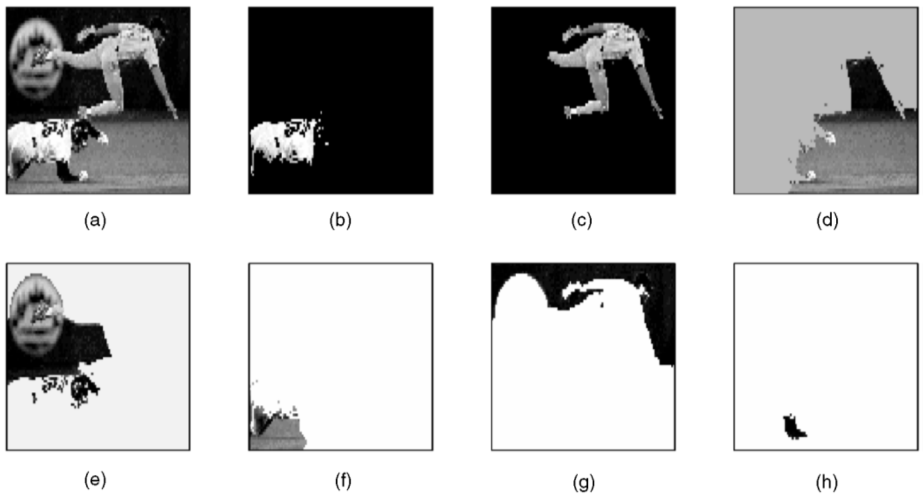
$$D^{-\frac{1}{2}}(D-W)D^{-\frac{1}{2}}z = \lambda z$$

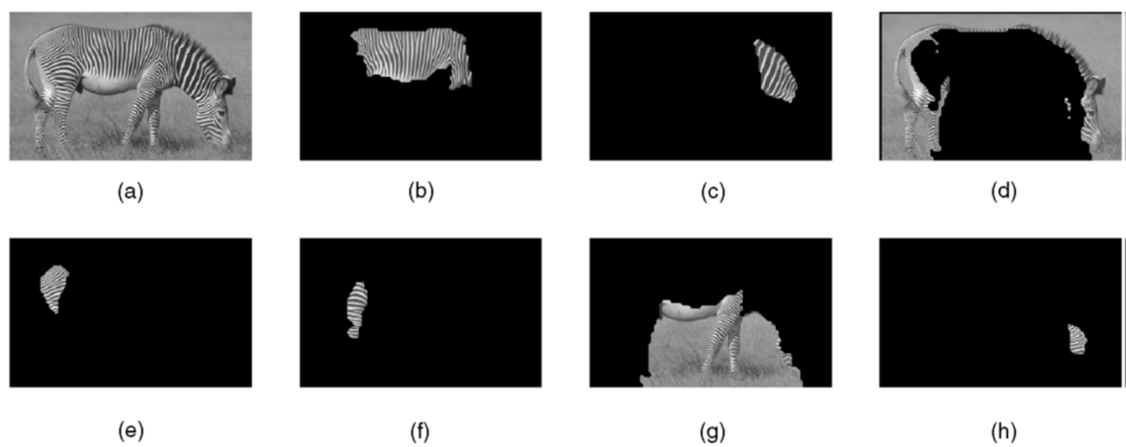
- Step 2: Take the eigenvector corresponding to the second smallest eigenvalue and calculated

$$y = D^{-\frac{1}{2}}z$$

- Step 3: Partition y
  - By taking zero or the median as the splitting point
  - Search for the splitting point that minimizes Ncut

Results





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Basic Idea of Active Contour (I)

- The basic idea is to start with an initial contour and iteratively update through an energy minimization process such that the contour will actively converge to the

$$E = E_{\text{Internal}} + E_{\text{external}}$$

$$E_{\text{internal}} = \int_0^1 \alpha \left| X'(s) \right|^2 + \beta \left| X''(s) \right|^2$$

$$= \sum \alpha \left\| X_i - X_j \right\| + \beta \left\| X_{i-1} - 2X_i + X_{i+1} \right\|$$

$$E_{\text{external}} = \int_0^1 - \left| \nabla G_\sigma \left(x(s), y(s) \right) * I \left(x(s), y(s) \right) \right|^2$$

Basic Idea of Active Contour (II)

- This approach is rather general and can be used to detect both open and closed edges and curves.

- Two simple demonstrations

  - An implementation of the classic approach

    http://www.markschulze.net/snakes/

  - An implementation of the GVF approach

    http://www.iacl.ece.jhu.edu/static/gvf/

Questions?