



图像分割

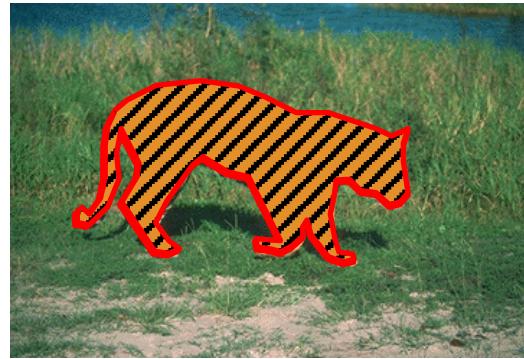
Image Segmentation

Ning Tang

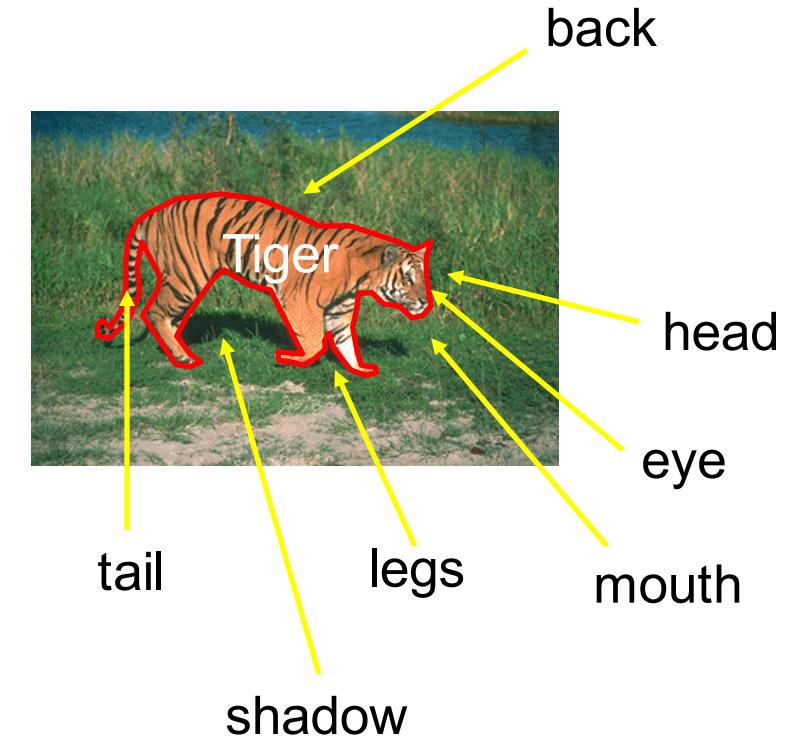
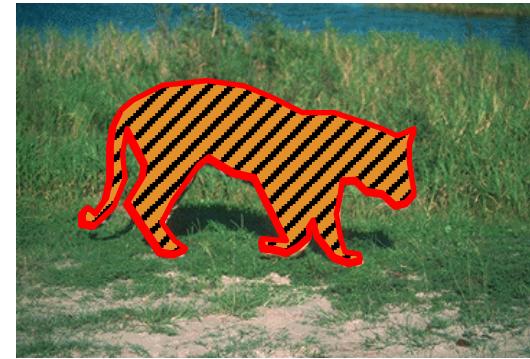
From Pixels to Perception



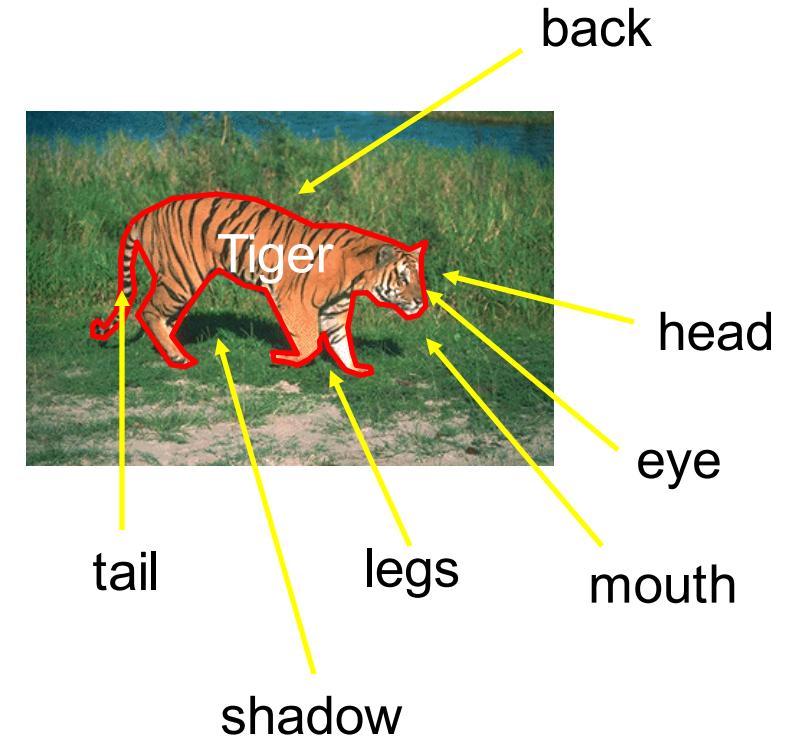
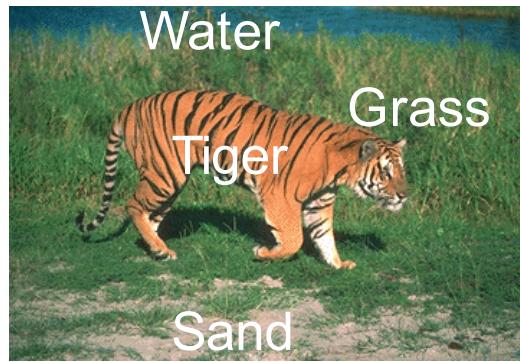
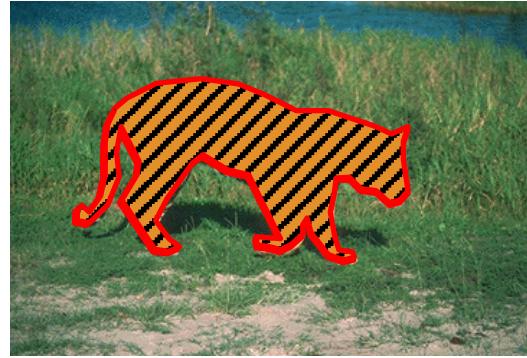
From Pixels to Perception



From Pixels to Perception



From Pixels to Perception

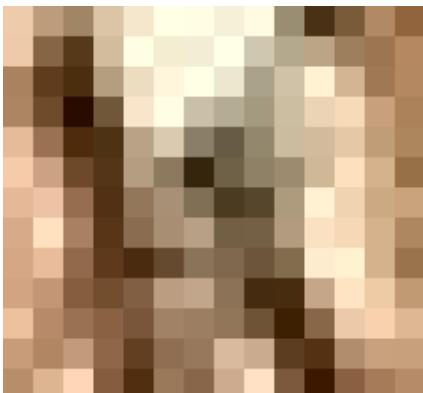


Visual Grouping

I stand at the window and see a house, trees, sky.
Theoretically I might say there were 327 brightnesses and
nuances of colour.

Do I have "327"?

No. I have sky, house, and trees.



---- Max Wertheimer, 1923

Human visual system

Computer Vision

Visual Grouping

Image Segmentation



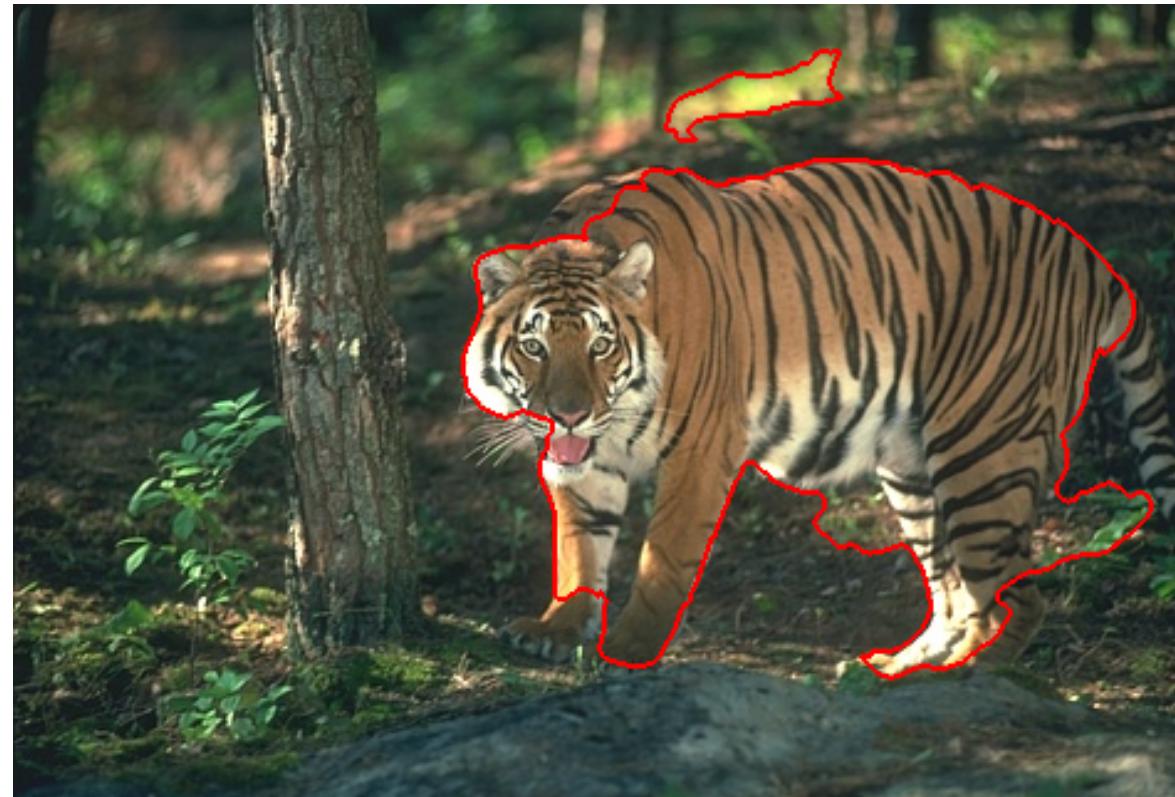
Image Segmentation

Image segmentation is the process of partitioning a image into multiple regions.

More precisely, **image segmentation** is the process of assigning a label to every pixel in an image so that pixels with the same label share certain characteristics (such as color, intensity, or texture).

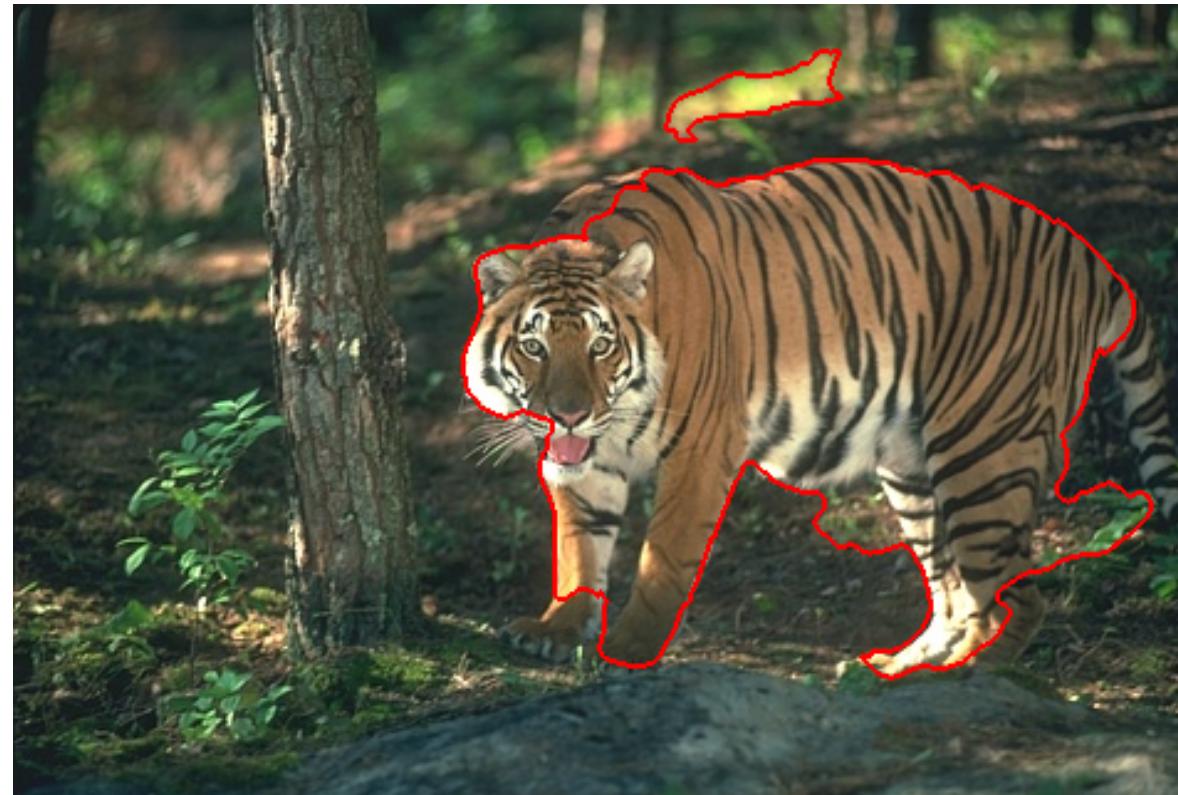
The Goal of Image Segmentation

Simplify the representation of an image into something that is more meaningful and easier to analyze.



The Goal of Image Segmentation

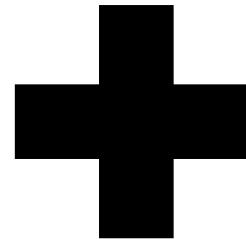
Simplify the representation of an image into something that is more meaningful and easier to analyze.



A pre-processing in Computer Vision

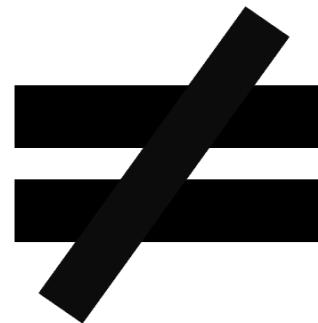
Image Segmentation Dataset

For image segmentation, we need :



Compare real segmentation result with ground-truth

real segmentation
result



ground-truth



Manual annotation for getting ground-truth



human
labeling



ground-truth



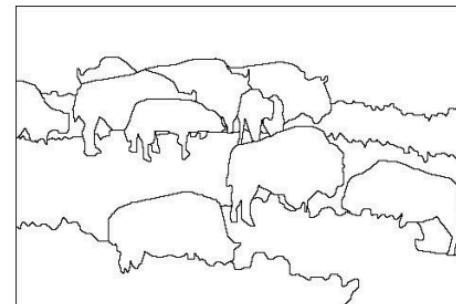
Some Common Datasets in Image Segmentation

- **BSDS500 :**

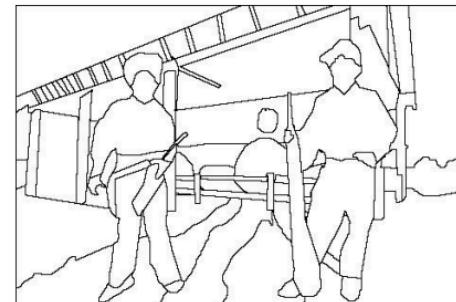
The dataset consists of 500 natural images (train, validation and test subsets) and ground-truth human annotations.



image



human segmentation



BSDS dataset:

<https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html>

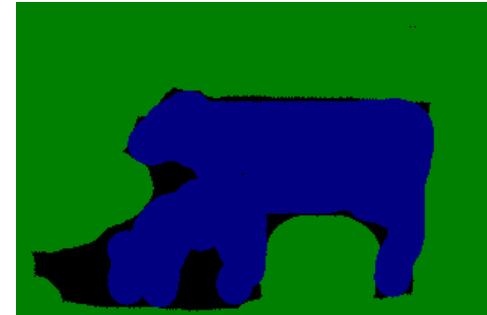
Some Common Datasets in Image Segmentation

- **MSRC :**

The dataset consists of 591 natural images and ground-truth human annotations.



image



human segmentation



MSRC dataset:

<https://www.microsoft.com/en-us/research/project/image-understanding/>

Some Common Datasets in Image Segmentation

- **PASCAL VOC2012 :**

The dataset consists of almost 10K natural images and ground-truth human annotations.



image



human segmentation

PASCAL dataset:

<http://host.robots.ox.ac.uk/pascal/VOC/voc2012/>

Image Segmentation Methods

- **Threshold Based Segmentation**
- **Edge Based Segmentation**
- **Region Based Segmentation**
- **Active Contour Based Segmentation**
- **Graph Based Segmentation**
-

Threshold Based Segmentation

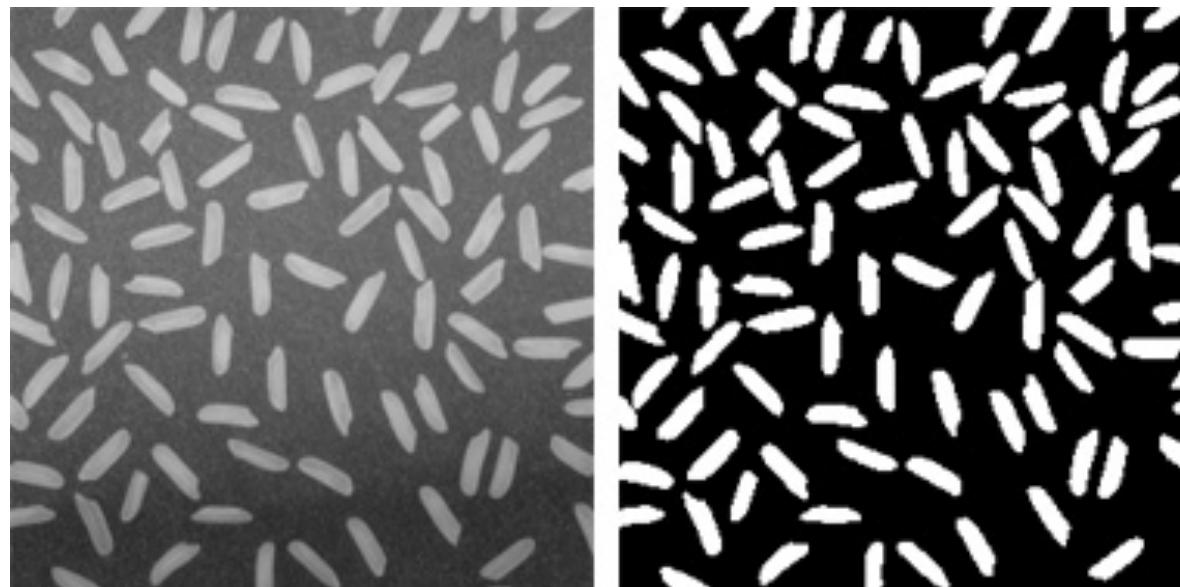
- The simplest image segmentation method
- Turn a gray-scale image $f(i, j)$ into a binary image $g(i, j)$

$$g(i, j) = \begin{cases} 1 & f(i, j) \geq T \\ 0 & f(i, j) < T \end{cases} \quad T : \text{threshold value}$$

The key of thresholding methods is to select a threshold value T

Otsu Thresholding

- Select the best threshold value to maximize the difference between background and target (maximize the inter-class variance)
- Global thresholding method



some images in BSDS500



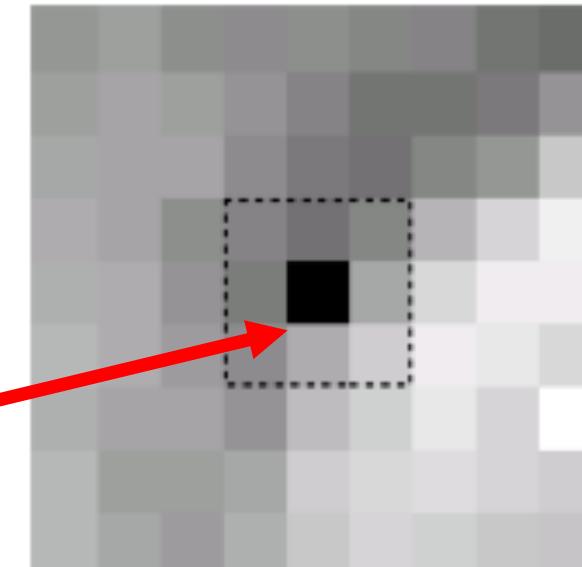
otsu



Adaptive Thresholding

- Finding the local threshold is to statistically examine the intensity values of the local neighborhood of each pixel
- Local thresholding method

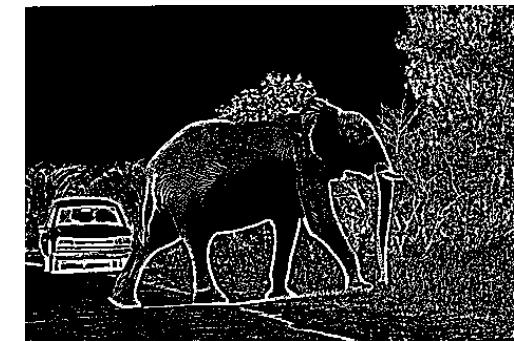
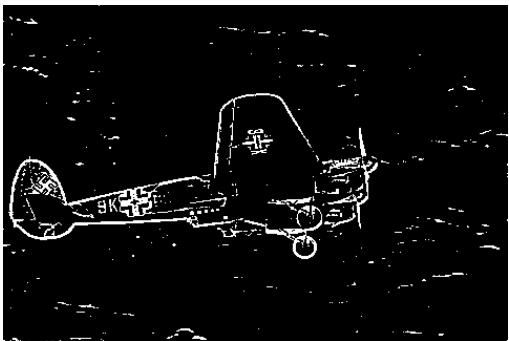
a pixel and its 3×3 neighborhood



images in BSDS500



adaptive

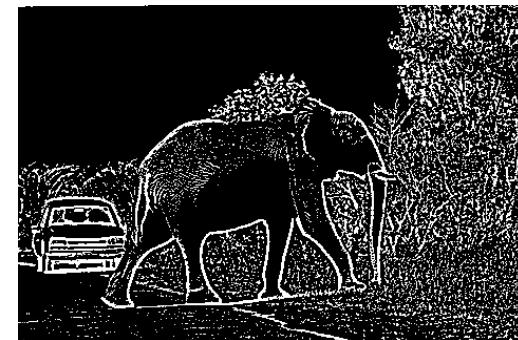
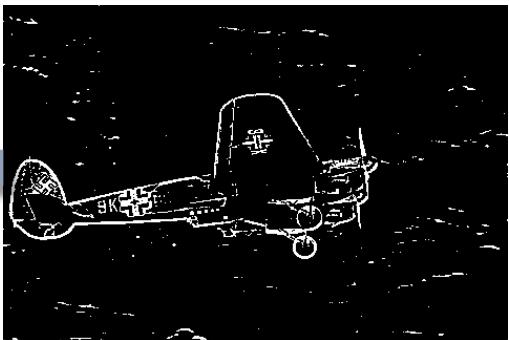


more local details

images in BSDS500

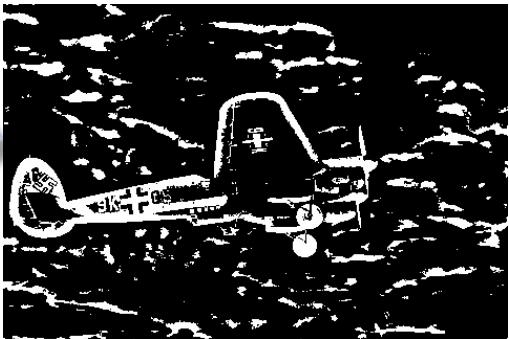


adaptive



more local details

in larger neighborhood



About Thresholding Methods

Advantages:

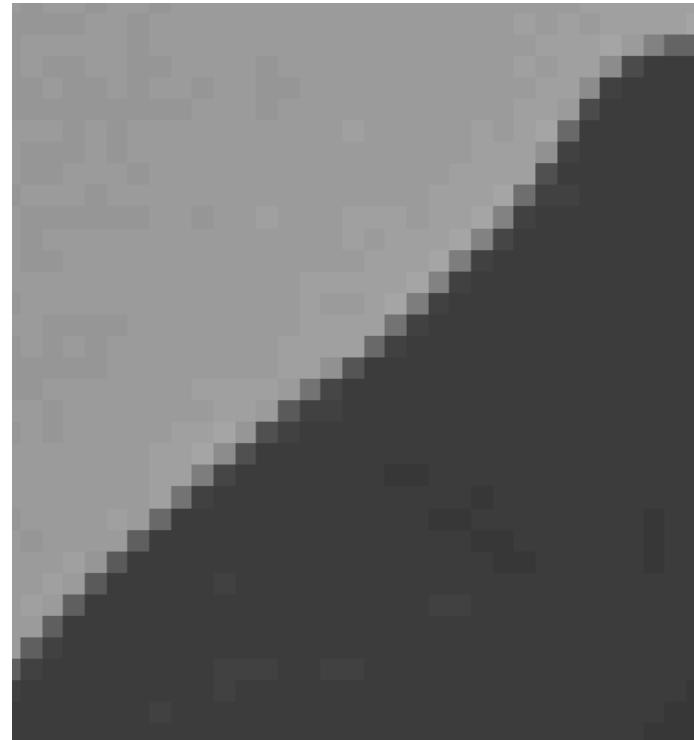
- Simplicity of calculation, fast

Disadvantages:

- Only consider gray-scale information
- Sensitive to noise

What is the edge?

An **edge** is the boundary between two regions with distinct properties (color, intensity, or texture).

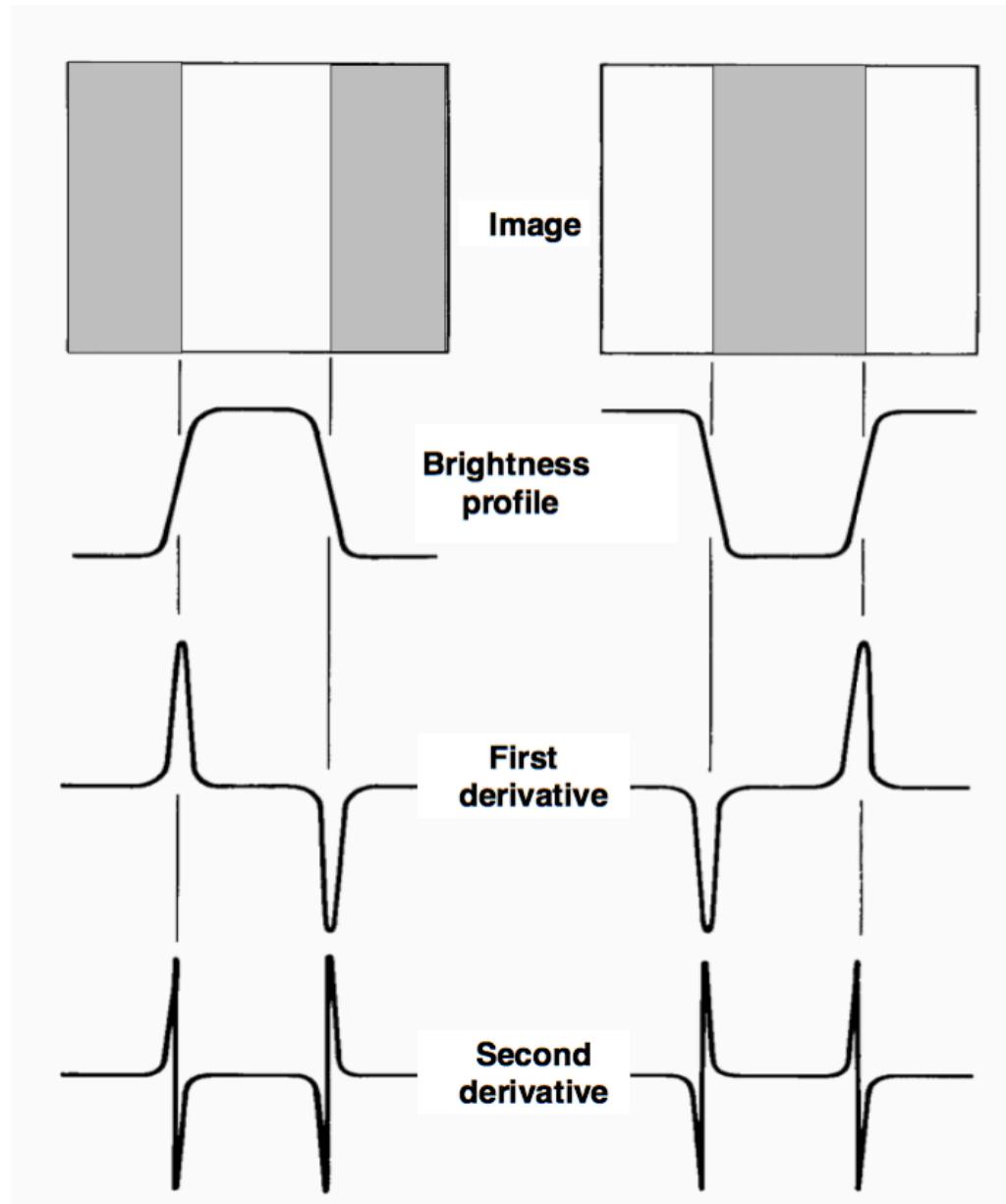


Edge Based Segmentation

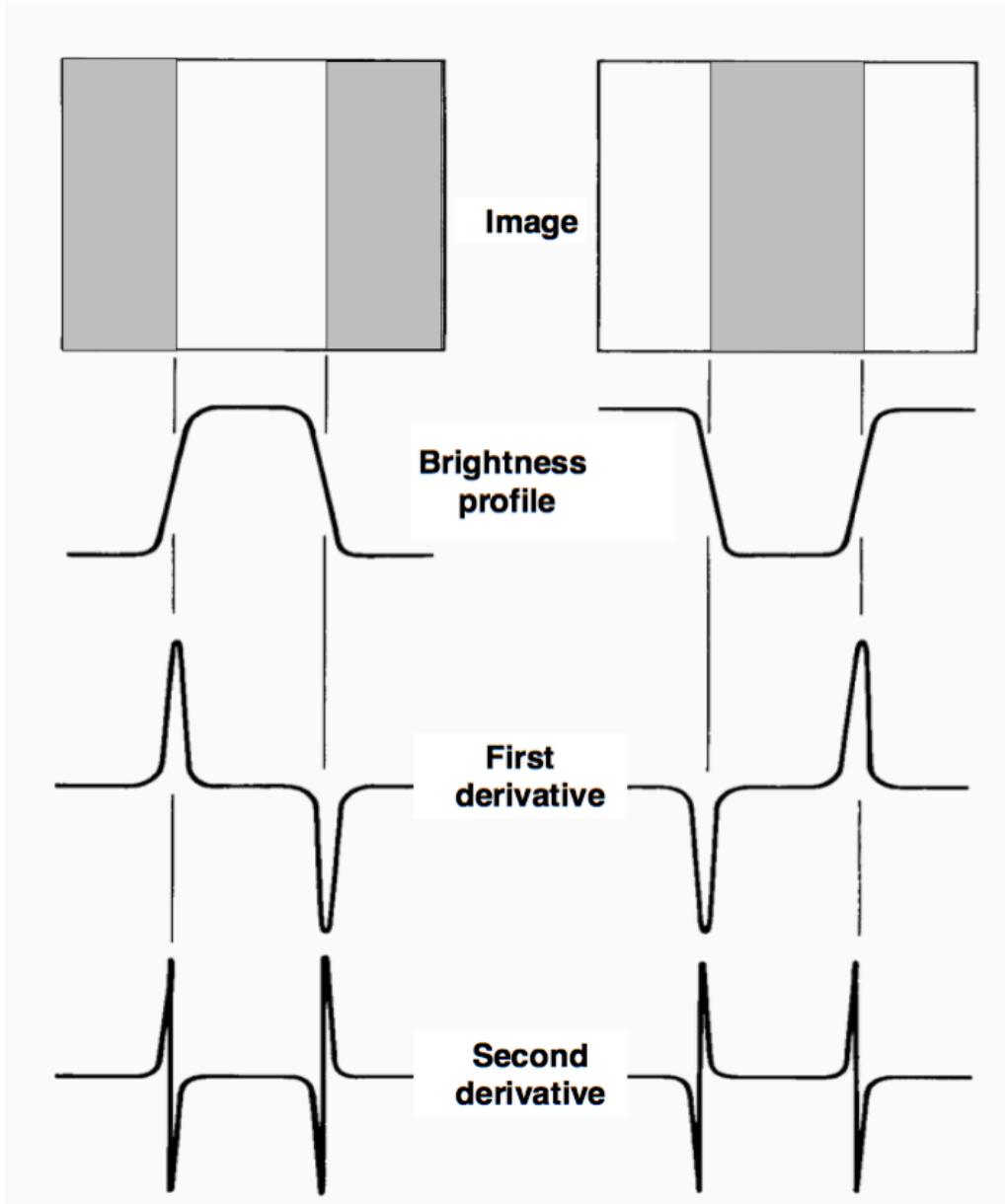
- Edges are **important features** in a image to separate regions
- Based on **discontinuity**
- Edge detection is the principal approaches to image segmentation



What is edge detection?

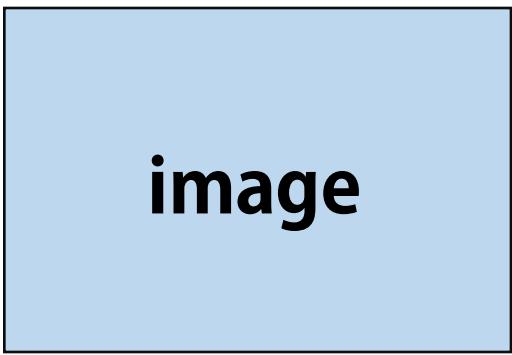


What is edge detection?



Edge detection by
means of gradient
operators

How gradient operators work?

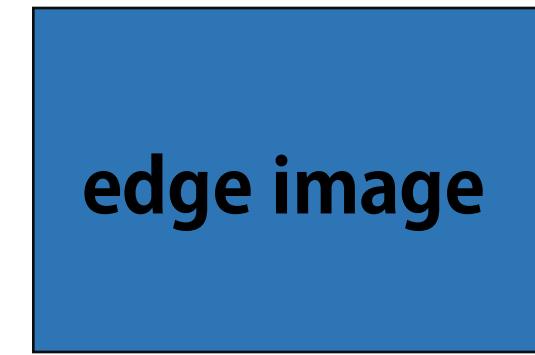


$$\text{image} * \begin{matrix} z_1 & z_2 & z_3 \\ z_4 & z_5 & z_6 \\ z_7 & z_8 & z_9 \end{matrix} = \text{edge image}$$

A mathematical expression showing the convolution of an "image" with a "gradient mask" to produce an "edge image". The gradient mask is a 3x3 matrix with elements labeled z_1 through z_9 . The multiplication symbol (*) is placed between the image box and the mask matrix, and the equals sign (=) is placed after the mask matrix.

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

gradient mask



Common Gradient Masks

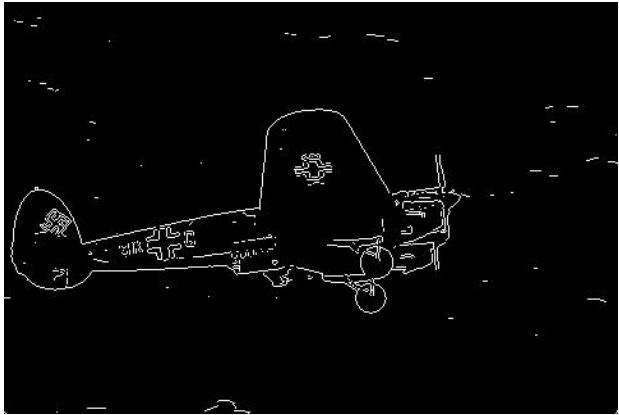
First order gradient masks :

- **Sobel**
- **Roberts**
- **Prewitt**
-

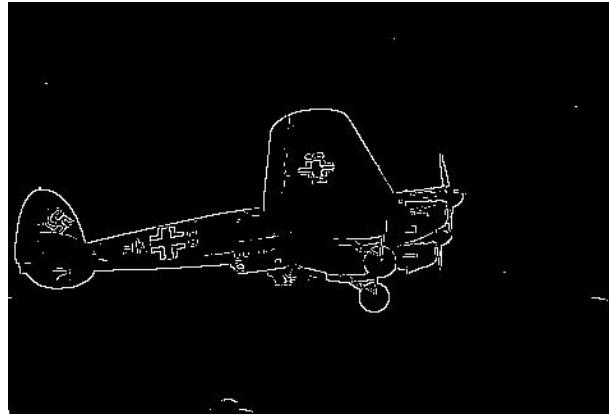
Second order gradient masks :

- **Canny**
- **LoG (Laplacian-Gauss)**
-

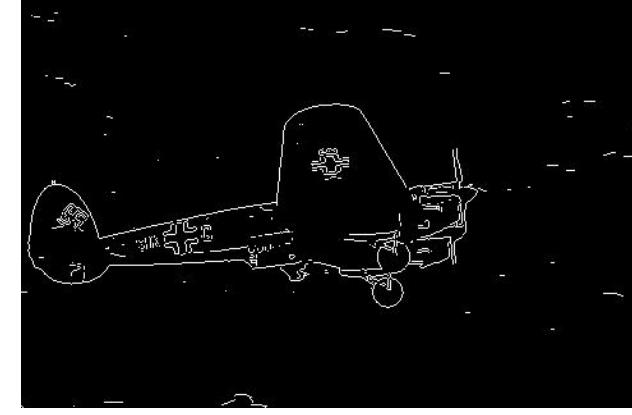
Sobel



Roberts



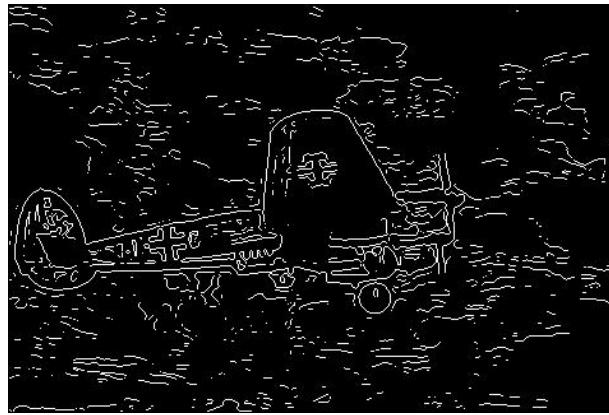
Prewitt



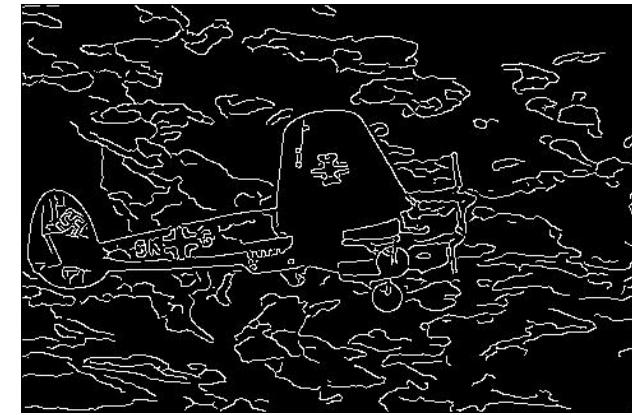
image



LoG



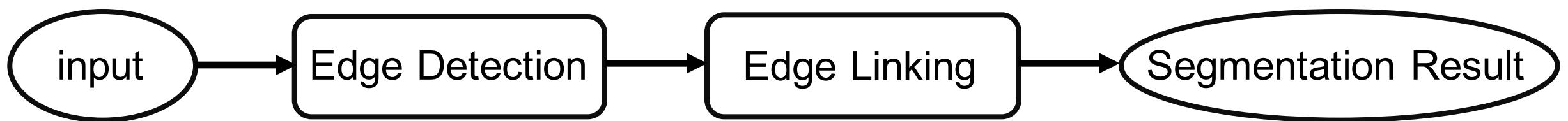
Canny



The Problem of Edge Detection

- **Noise and background affect the accurate of edge detection**
Edge presence in locations where there is no border, but no edge presence where a real border exists.
- **Edges are the sign of lack of continuity, and ending.**

The edges produced by edge detection can not be used directly, because edges are discontinuous.



From Edge to Region

The simplest way is some Morphological operations
to fill the edge

About Edge Based Segmentation Methods

Advantages:

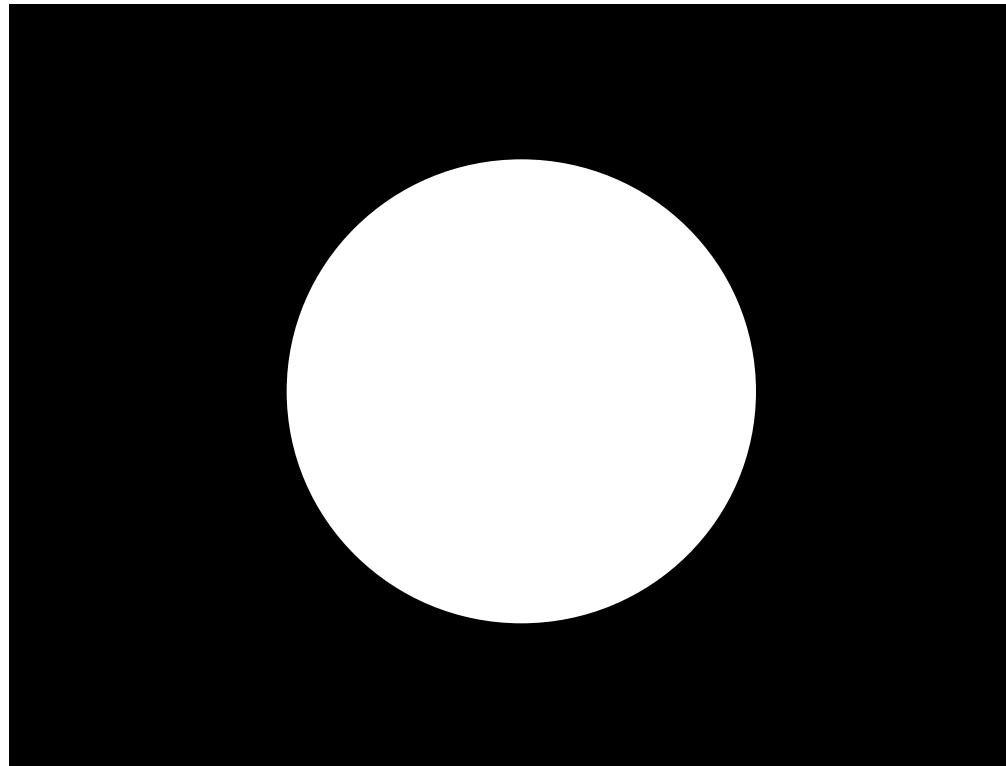
- Simplicity of calculation, fast
- Works well in images with good contrast between object and background

Disadvantages:

- Does not work well on images with smooth transitions and low contrast
- Sensitive to noise

What is a region?

A group of connected pixels with **similar properties**

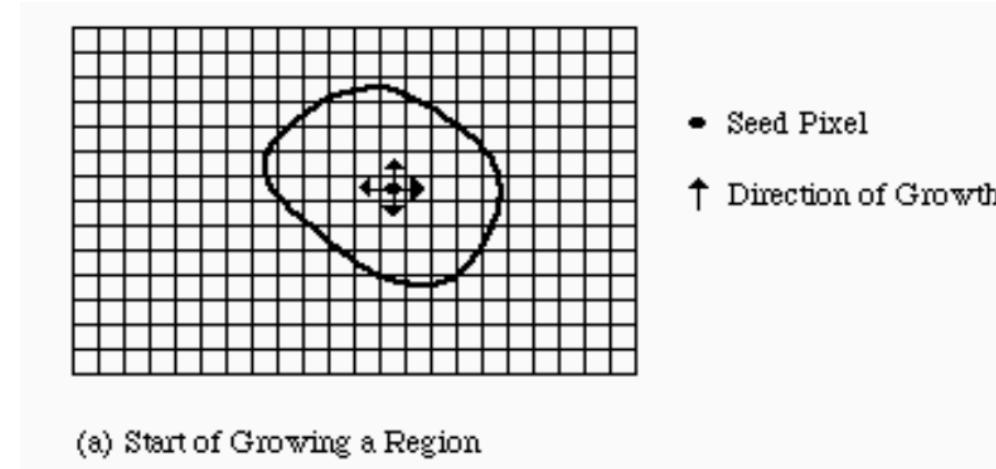


Region Based Segmentation

- Region is an important concept because regions may correspond to objects in a scene
 - Based on **similarity**
 - Those pixels that correspond to an object are grouped together and marked
 - Region based segmentation is a technique that allows us to determine the regions directly

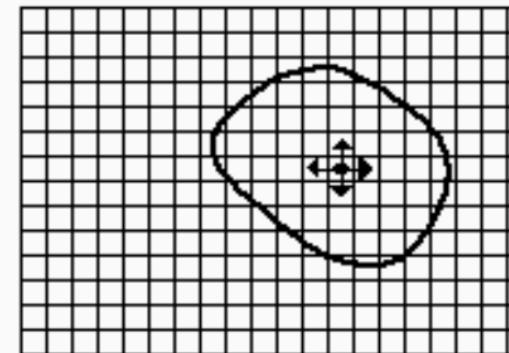
Region Growing Segmentation

- Start from some seed points to represent the property we want, then grow the region
- A bottom up method



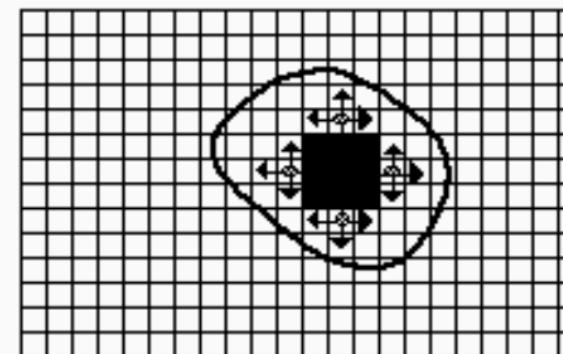
Region Growing Segmentation

- Start from some seed points to represent the property we want, then grow the region
- A bottom up method



- Seed Pixel
- ↑ Direction of Growth

(a) Start of Growing a Region

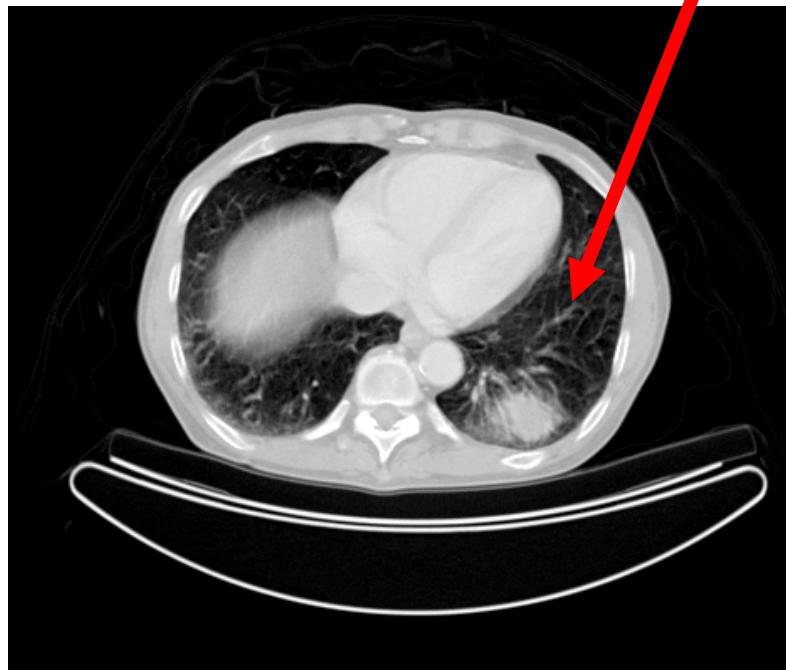


- Grown Pixels
- ~ Pixels Being Considered

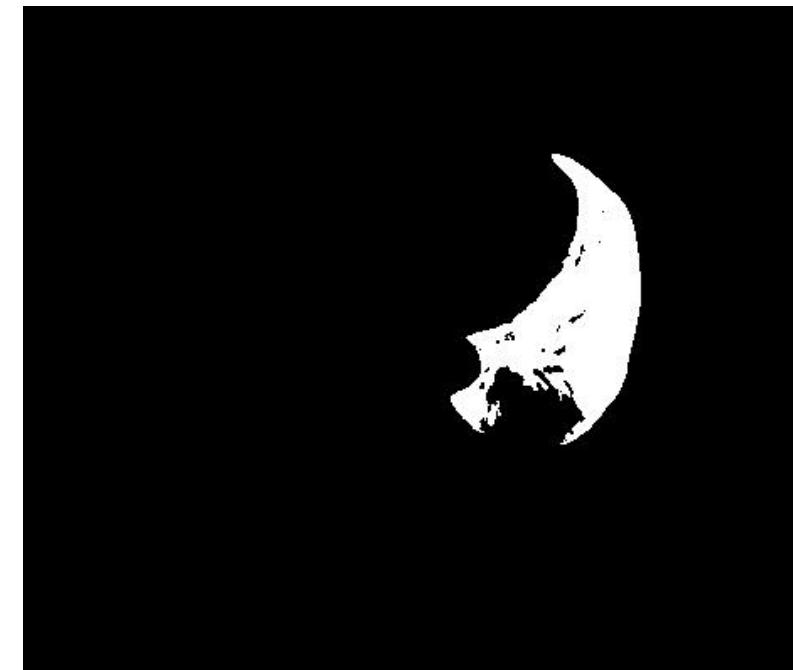
(b) Growing Process After a Few Iterations

An Example of Region Growing

set a seed around here



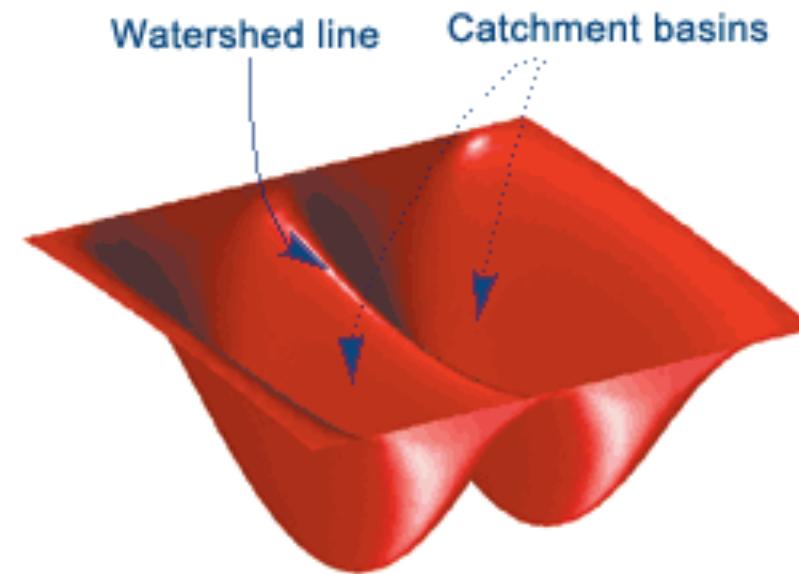
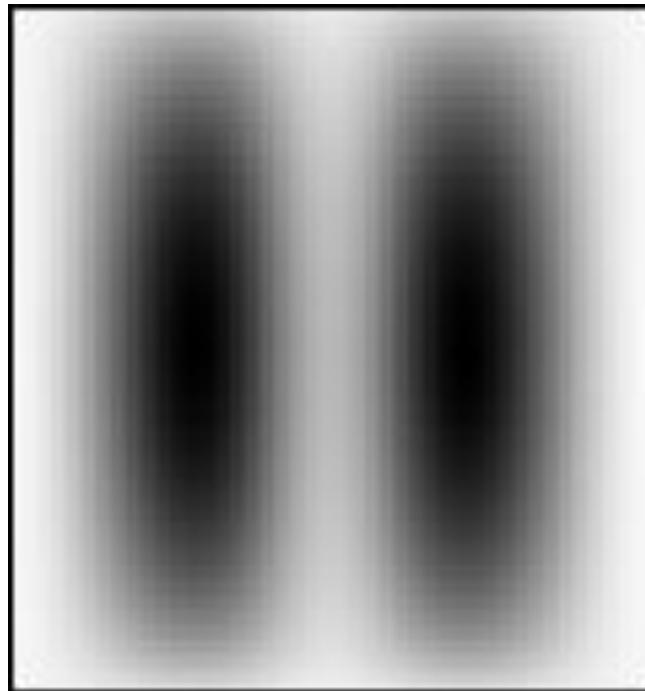
image



result

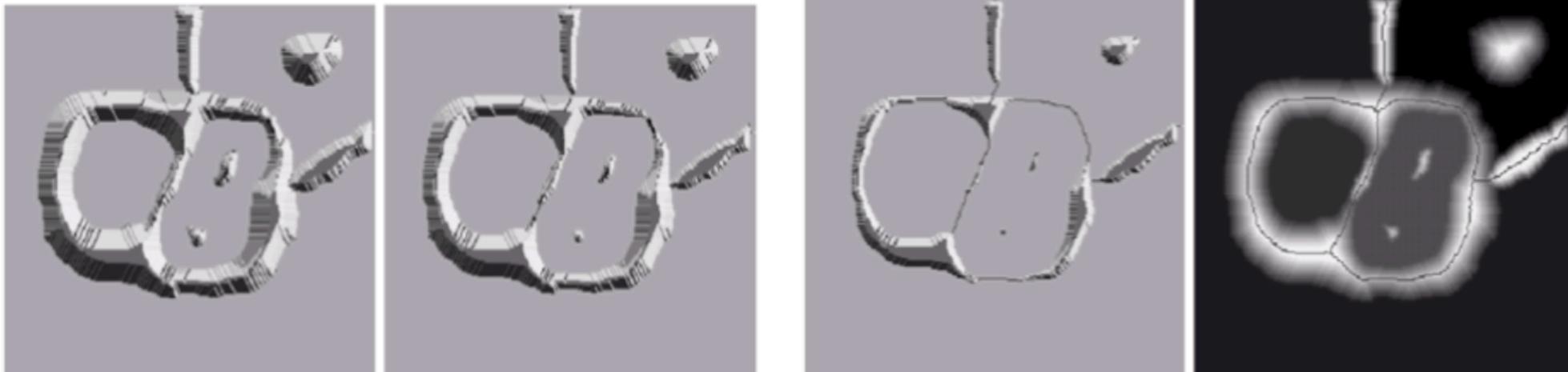
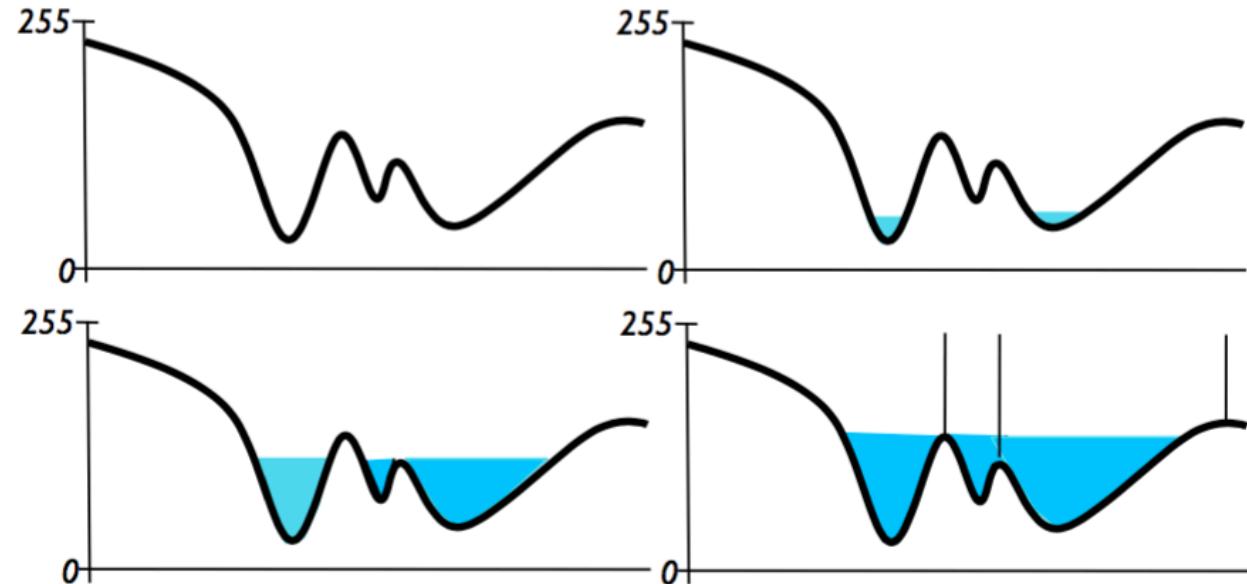
Watershed Segmentation

- An image is considered as a 3D topographic surface with valleys and mountains



Watershed Segmentation

- The goal of watershed segmentation:
To find the watershed lines
- Watershed lines are remained
by flooding water



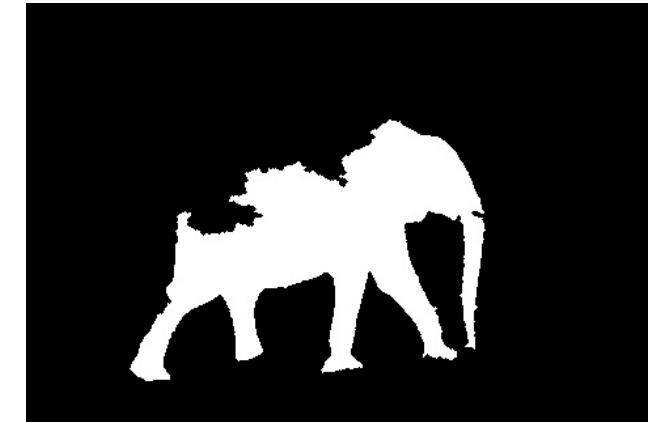
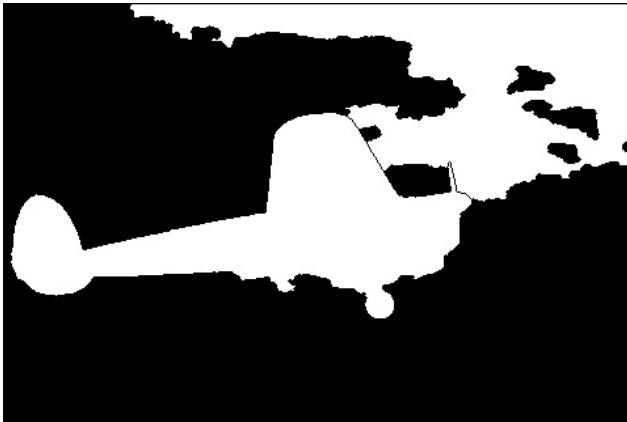
Watershed Segmentation

The difficulty of watershed segmentation is determining the masks as flooding water

image



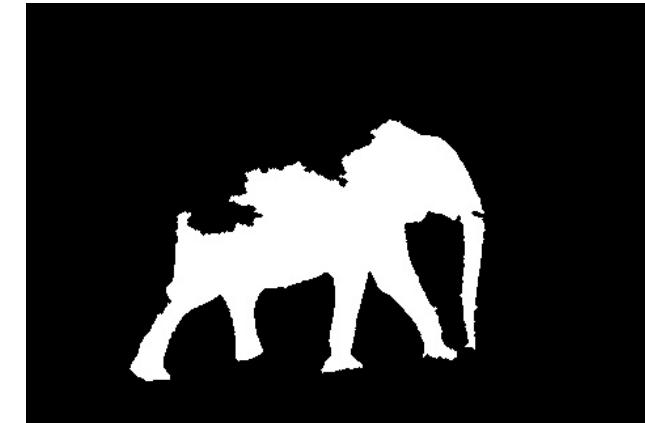
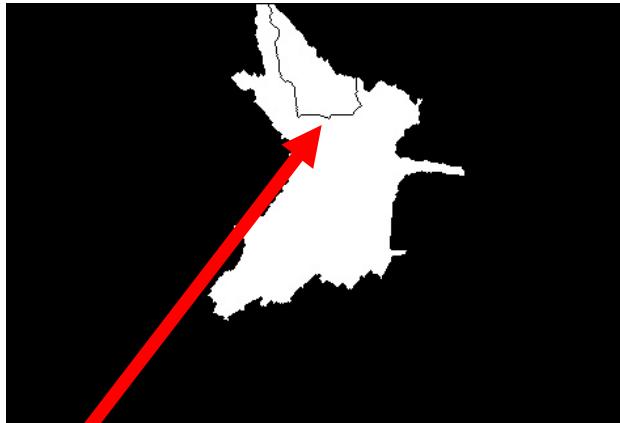
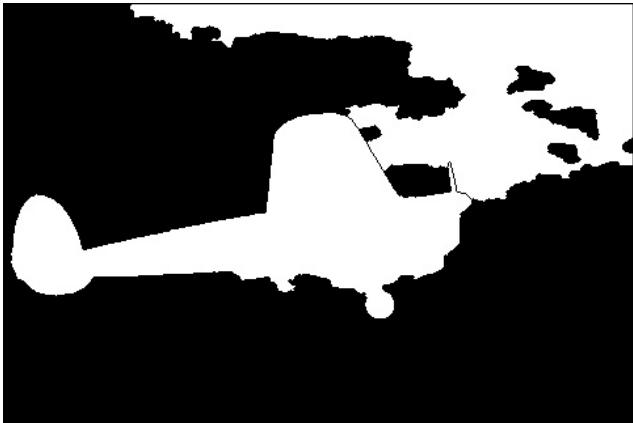
watershed



image



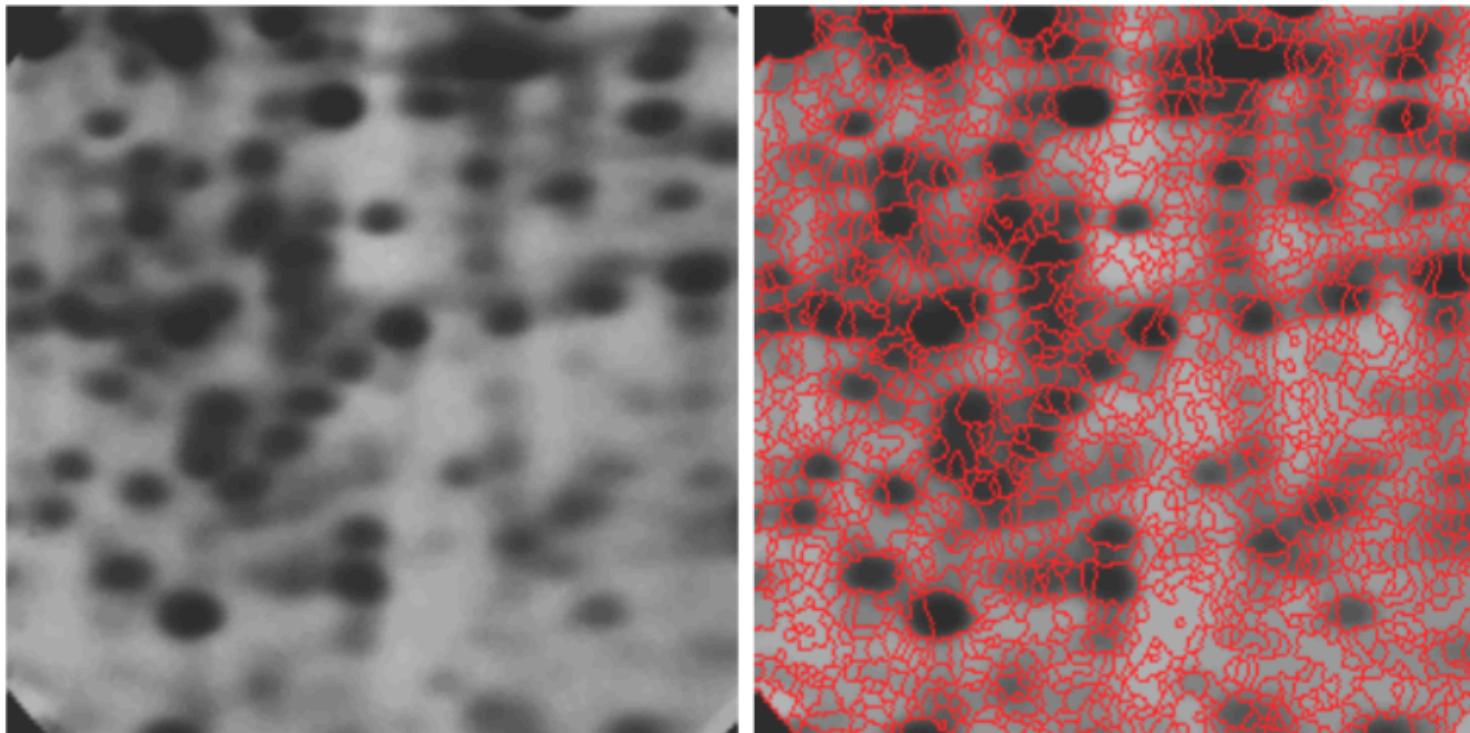
watershed



over-segmentation

Over-segmentation

A division into too many segments, as when attempting to recognize parts of an image.



About Region Based Segmentation Methods

Advantages:

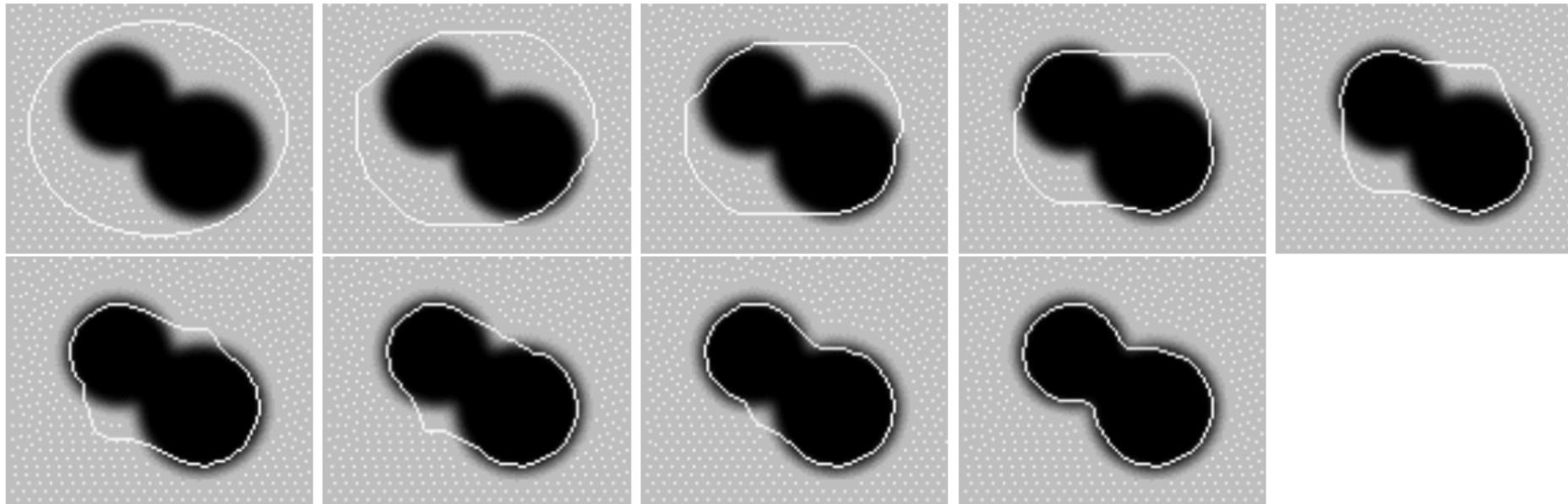
- **Simplicity of calculation, fast**

Disadvantages:

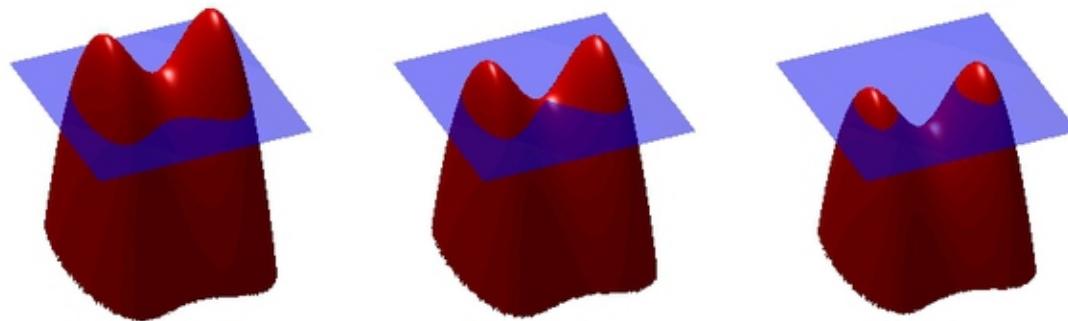
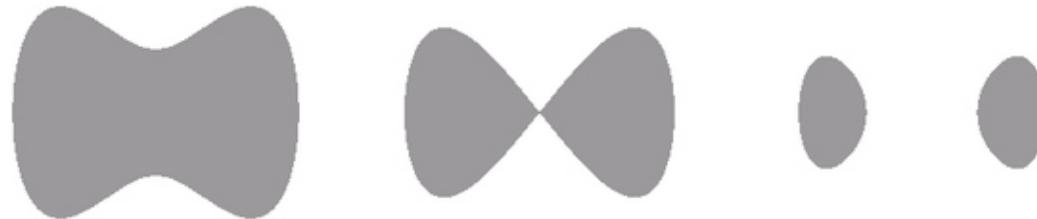
- **These two region based segmentation methods need human marks**
- **Sensitive to noise**
- **Watershed segmentation usually causes over-segmentation phenomenon**

Active Contour Based Segmentation

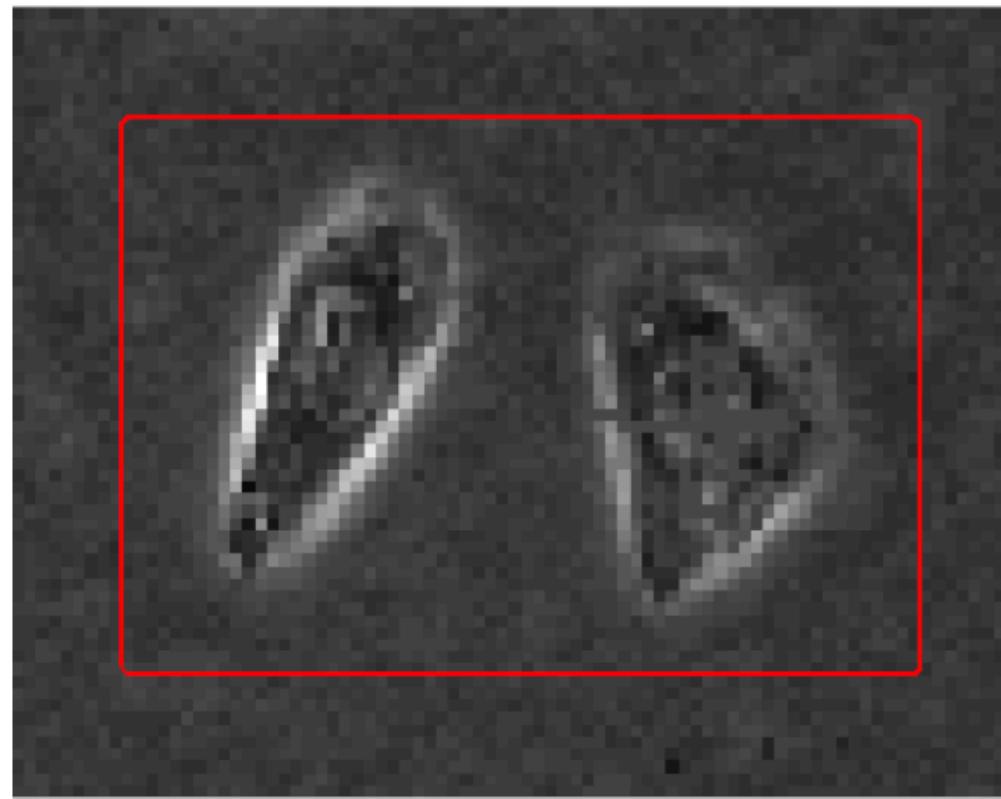
- Start from a contour
- Snake, Level set



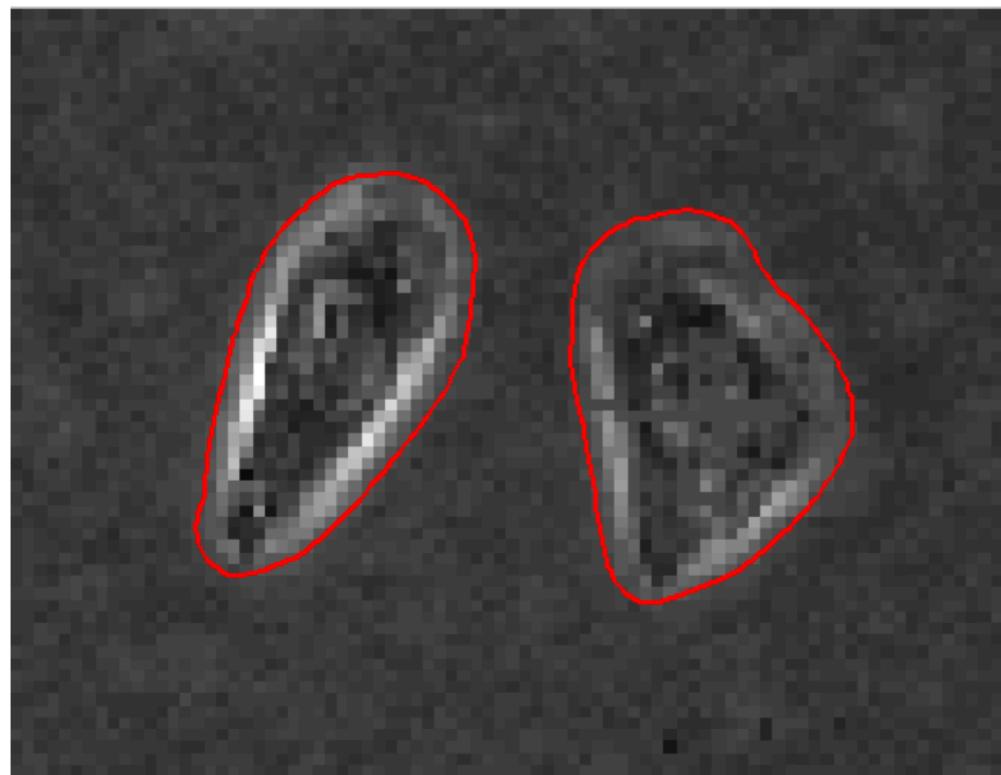
Level Set Segmentation



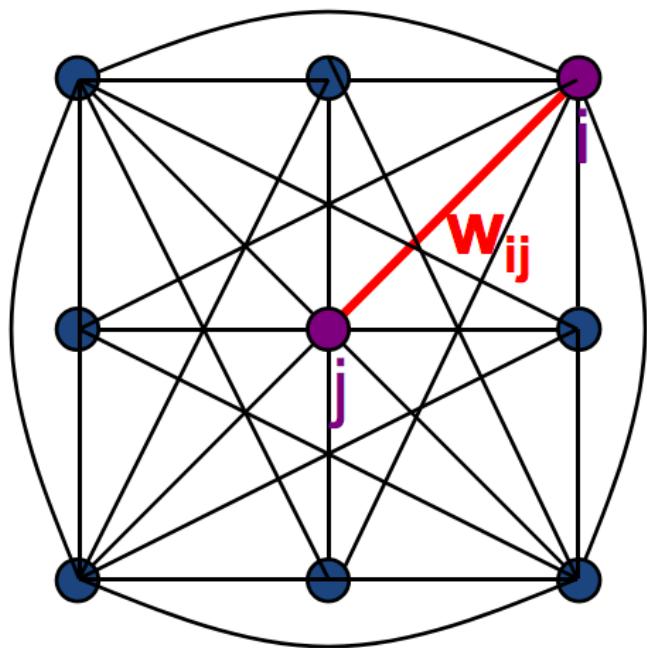
An Example of Level Set Segmentation



An Example of Level Set Segmentation



Graph Based Segmentation



Images as Graphs : $G = \{V, E\}$

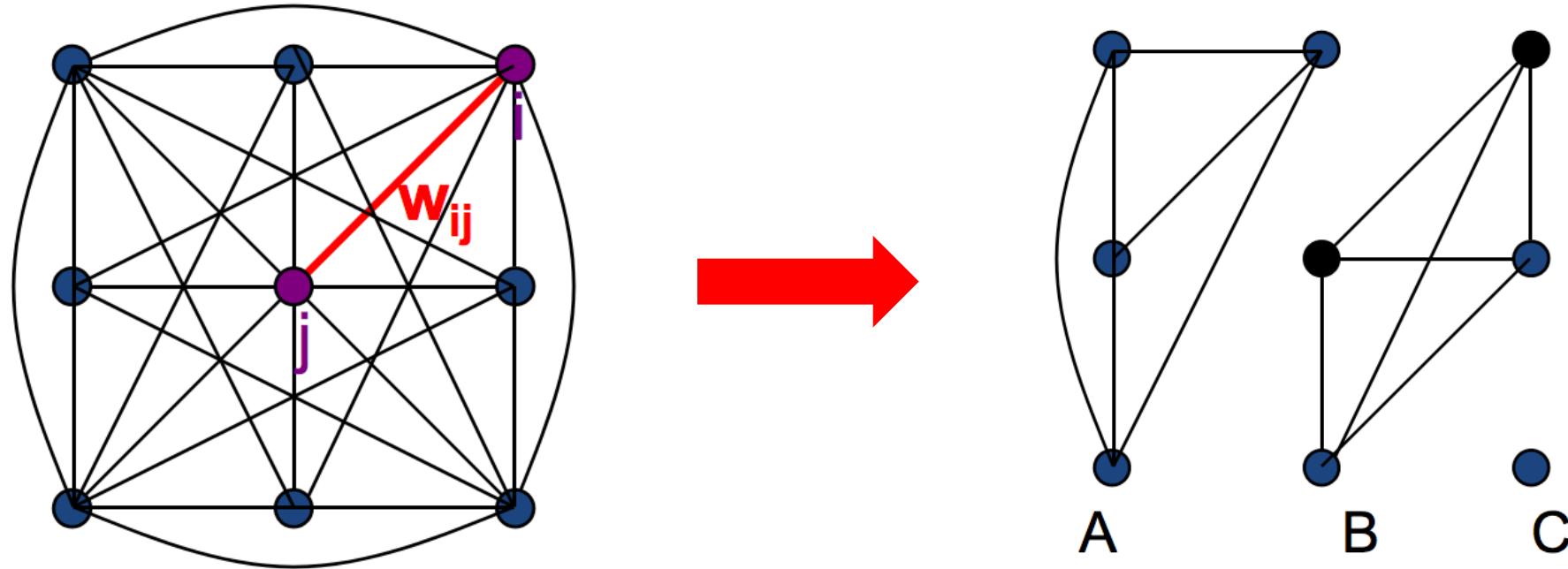


V (Vertex): graph nodes
E (Edge): edges connection nodes



Image = { pixels }
Pixel similarity

Break Graph into segments



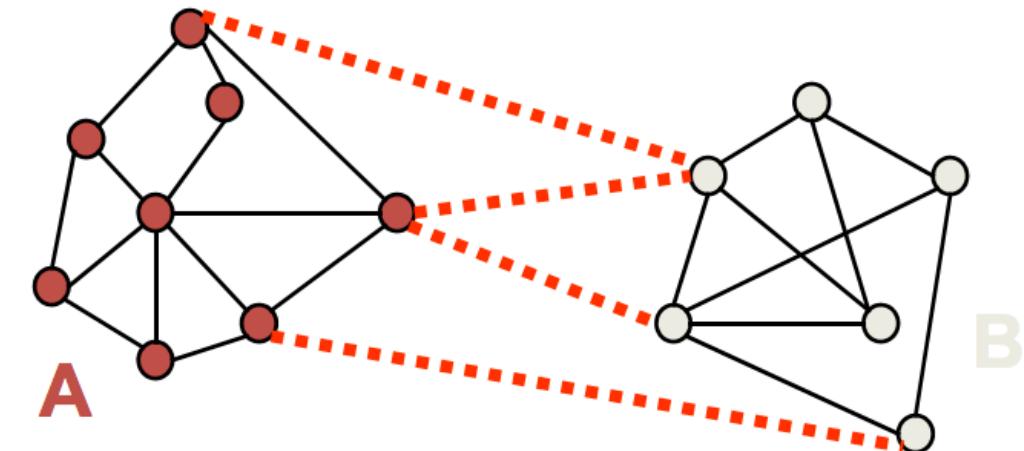
Delete links that cross between segments
Easiest to break links that have low cost (low similarity)

Cuts in a Graph

Link Cut

- set of links whose removal makes a graph disconnected
- cost of a cut:

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



One idea: find minimum Cut (Min Cut)

Two Interactive Min Cut Based Segmentation Methods

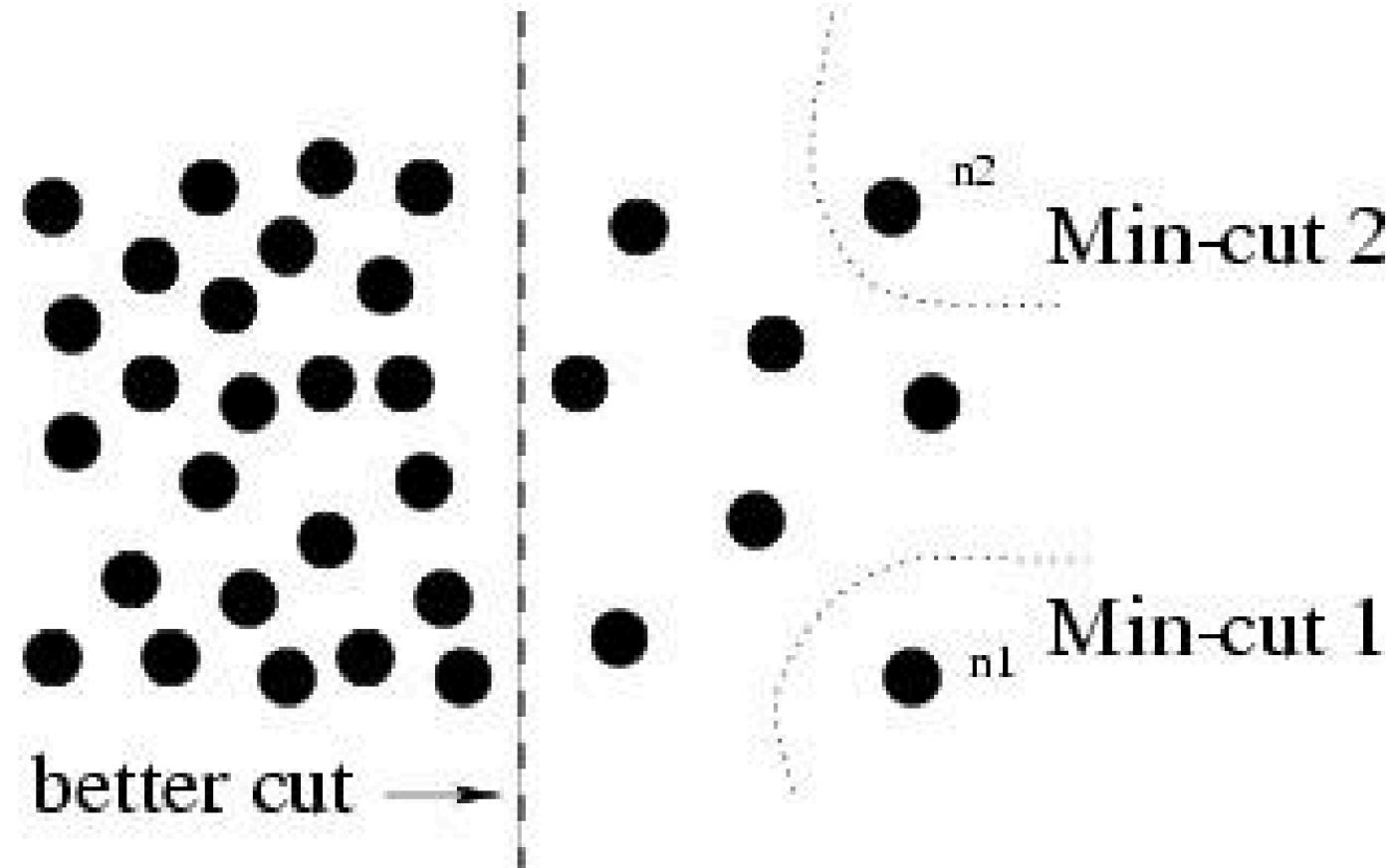
- Graph Cuts



- Grab Cuts



But Min Cut is not always the best Cut



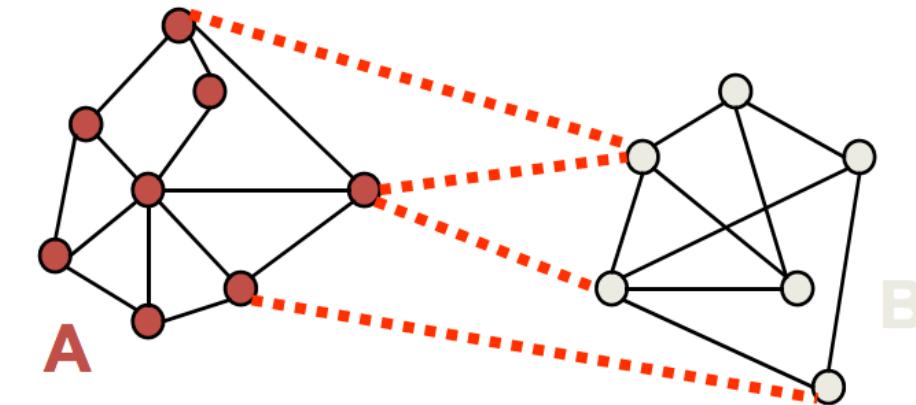
Normalized Cuts

- A cut penalizes large segments
- Fix by normalizing for size of segments

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

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

- **assoc(A,V) = sum of costs of all edges that touch A**



Normalized Cuts

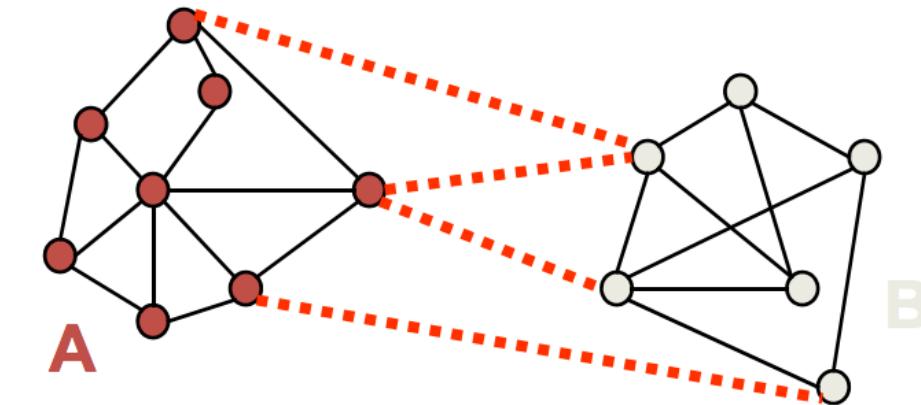
- A cut penalizes large segments
- Fix by normalizing for size of segments

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

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

minNcut(A, B) is NP—Hard

- **assoc(A, V) = sum of costs of all edges that touch A**



Solution

$\text{minNcut}(A, B)$



approximation

Solve for eigenvectors with the smallest eigenvalues:

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

$$D = \begin{bmatrix} \sum_j w(1, j) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sum_j w(N, j) \end{bmatrix}$$

$$W = \begin{bmatrix} w(1, 1) & \dots & w(1, N) \\ \vdots & \ddots & \vdots \\ w(N, 1) & \dots & w(N, N) \end{bmatrix}$$

Solution

$$(\mathbf{D} - \mathbf{W})\mathbf{y} = \lambda \mathbf{D}\mathbf{y}$$

- Use the eigenvector with the second smallest eigenvalue to bipartition the graph
- Recursively repartition the segmented parts if necessary

Some Normalized Cuts Results

need to set
the number of
segments (K)



Some Normalized Cuts Results

need to set
the number of
segments (K)
here, K=10



About Normalized Cuts

Advantages:

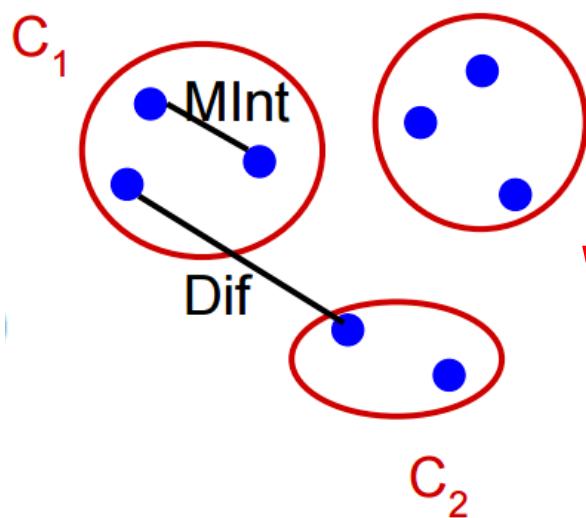
- **Generic framework, can be used with many different features and affinity formulations**

Disadvantages:

- **Need to chose number of segments**
- **High storage requirement and time complexity**

Efficient Graph-Based Image Segmentation

Predicate D determines whether there is a boundary for segmentation



$$D(C_1, C_2) = \begin{cases} \text{true} & \text{if } Dif(C_1, C_2) > MInt(C_1, C_2) \\ \text{false} & \text{otherwise} \end{cases}$$

Where

$Dif(C_1, C_2)$ is the difference between two components

$MInt(C_1, C_2)$ is the minimum internal different in the components C_1 and C_2

Efficient Graph-Based Image Segmentation Results

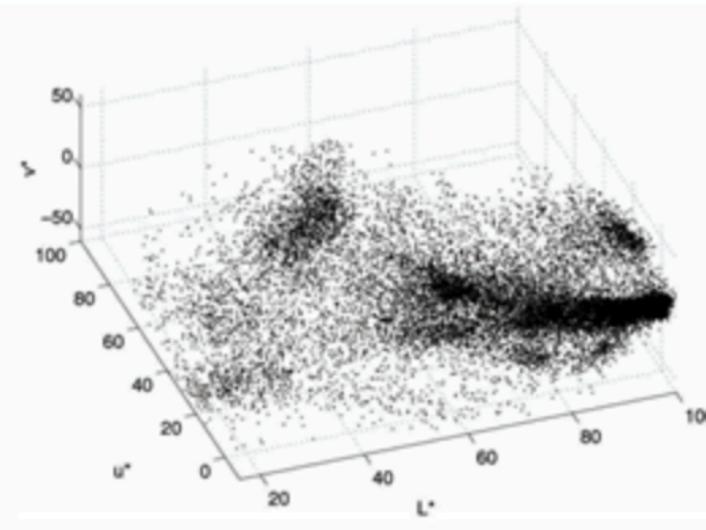


Need to tune parameters by hand



Mean Shift

- A feature space analysis method

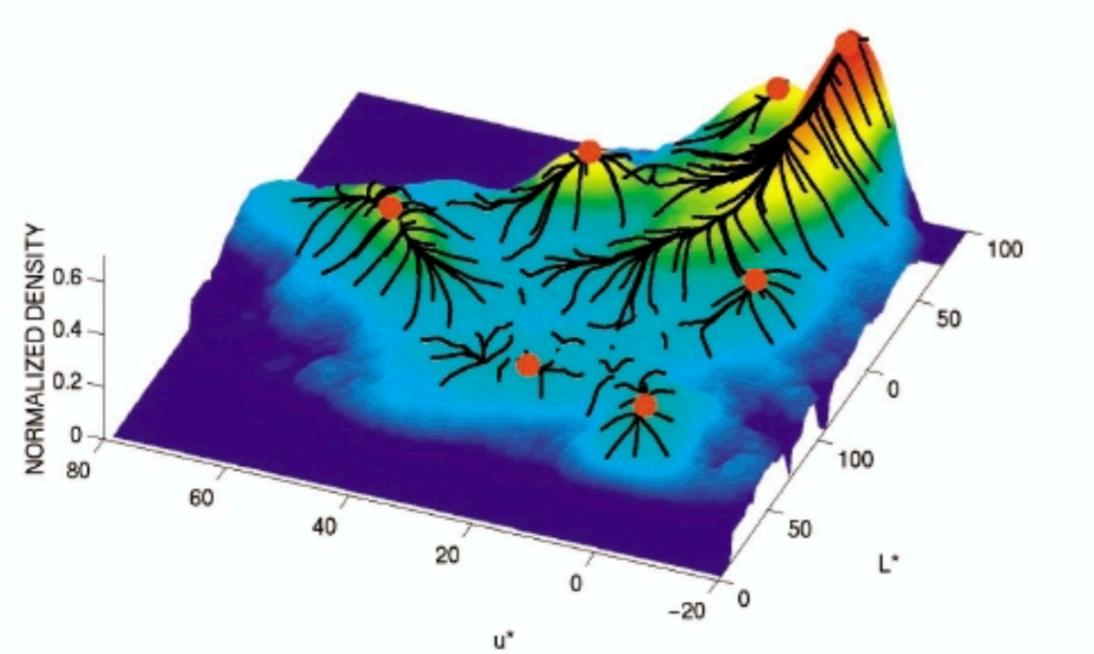


- Built on probabilistic intuitions

“Mean shift: a robust approach toward feature space analysis”, D. Comaniciu and P. Meer, PAMI, 2002

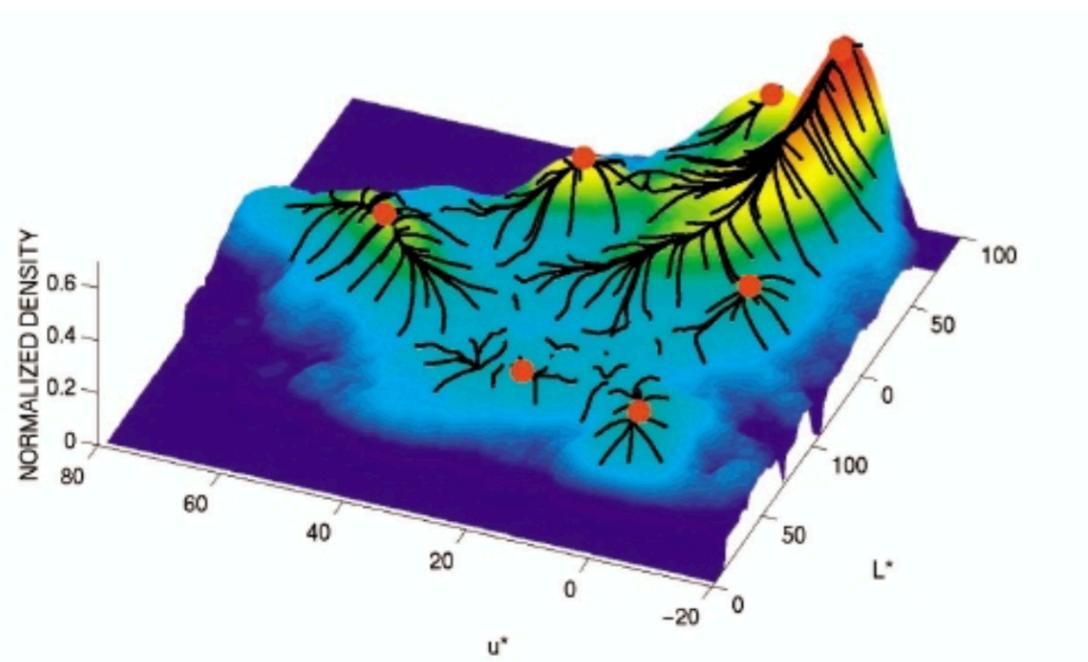
Non-Parametric Methods

- Basic Idea: Use the data to define the distribution
- Kernel-density estimates



What is Mean-Shift?

- The density will have peaks (also called modes)
- If we started at point and did gradient-ascent, we would end up at one of the modes
- Cluster based on which mode each point belongs to

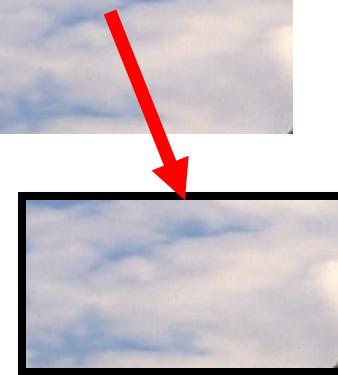


Gradient Ascent?

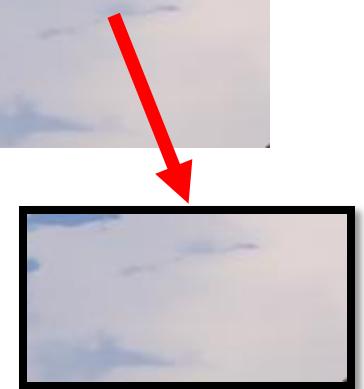
- **Actually, no**
- **A set of iterative steps can be taken that will monotonically converge to a mode**
 - **No worries about step sizes**
 - **This is an adaptive gradient ascent**

Mean Shift Result

image



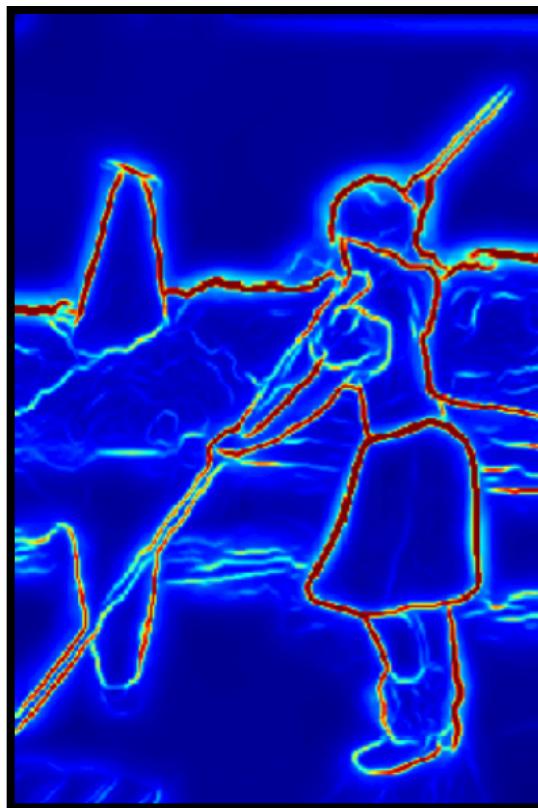
result



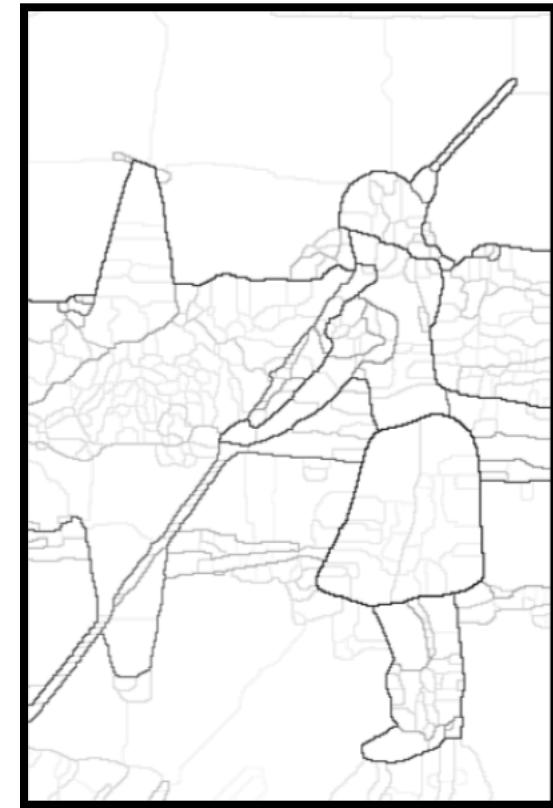
gPb-owt-ucm



Image



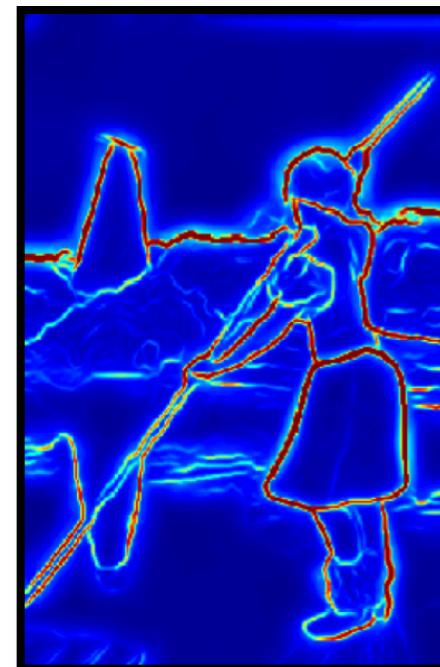
Contour



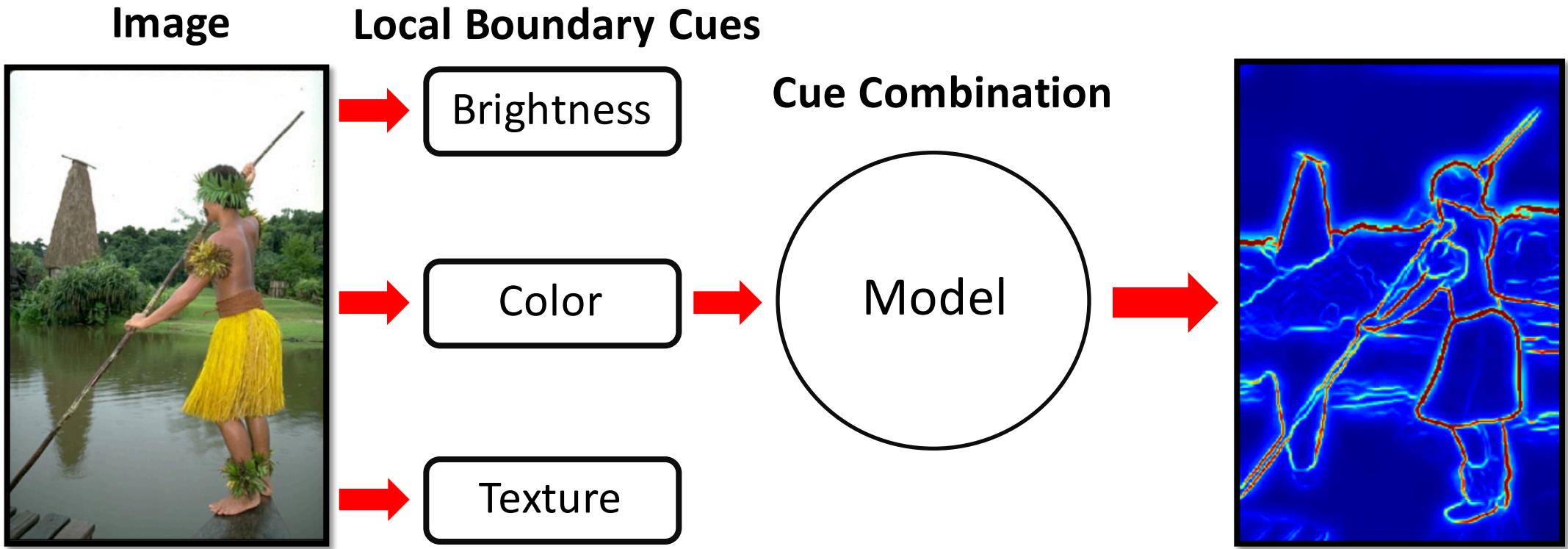
Segmentation

Contour Detection

- Learn local boundary cues
- Global framework to capture closure, continuity
- Local cues and global cues combination

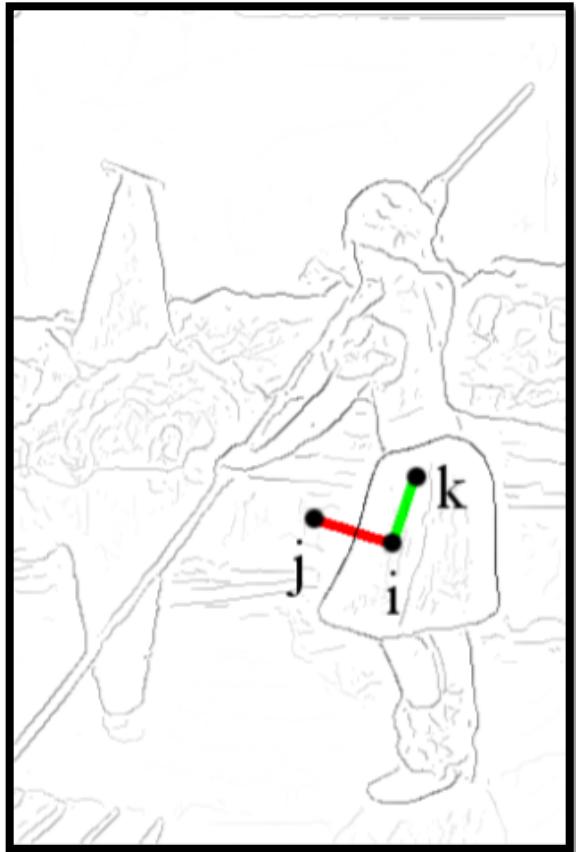


Learn Local Boundary Cues



$$mPb(x, y, \theta) = \sum_s \sum_i \alpha_{i,s} G_{i,\sigma(i,s)}(x, y, \theta)$$

Global framework



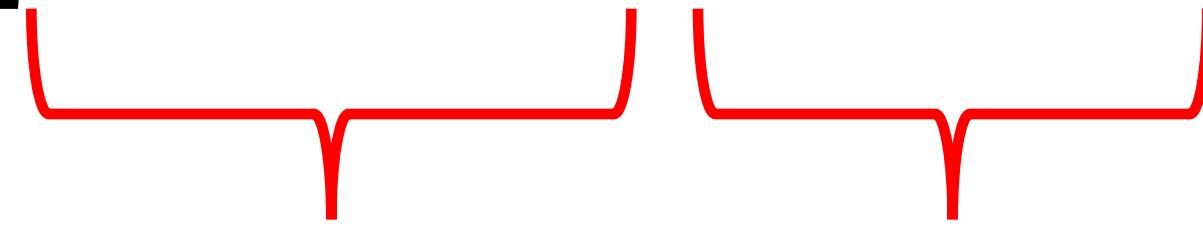
Build a weighted graph $G=(V,E)$ from image

$$W_{ij} = \exp \left(- \max_{p \in \bar{ij}} \{mPb(p)\} / \rho \right)$$

$$sPb(x, y, \theta) = \sum_{k=1}^n \frac{1}{\sqrt{\lambda_k}} \cdot \nabla_{\theta} \mathbf{v}_k(x, y)$$

Local cues and global cues combination

$$gPb(x, y, \theta) = \sum_s \sum_i \beta_{i,s} G_{i,\sigma(i,s)}(x, y, \theta) + \gamma \cdot sPb(x, y, \theta)$$



Local Cues

Global Cues

Hierarchical Segmentation

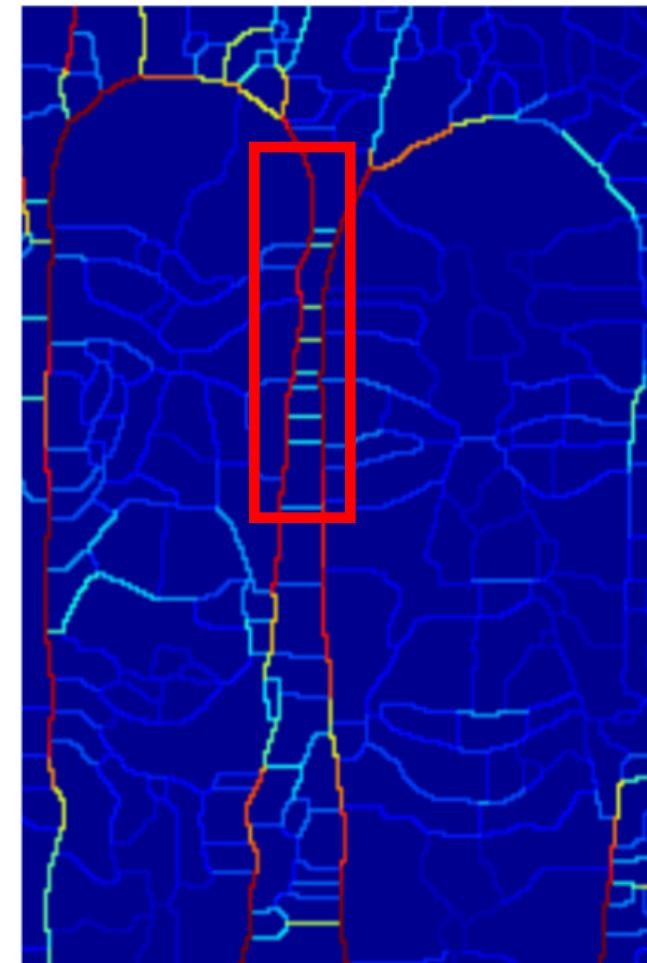
- Oriented Watershed Transform
- Ultrametric Contour Map

Watershed Transform

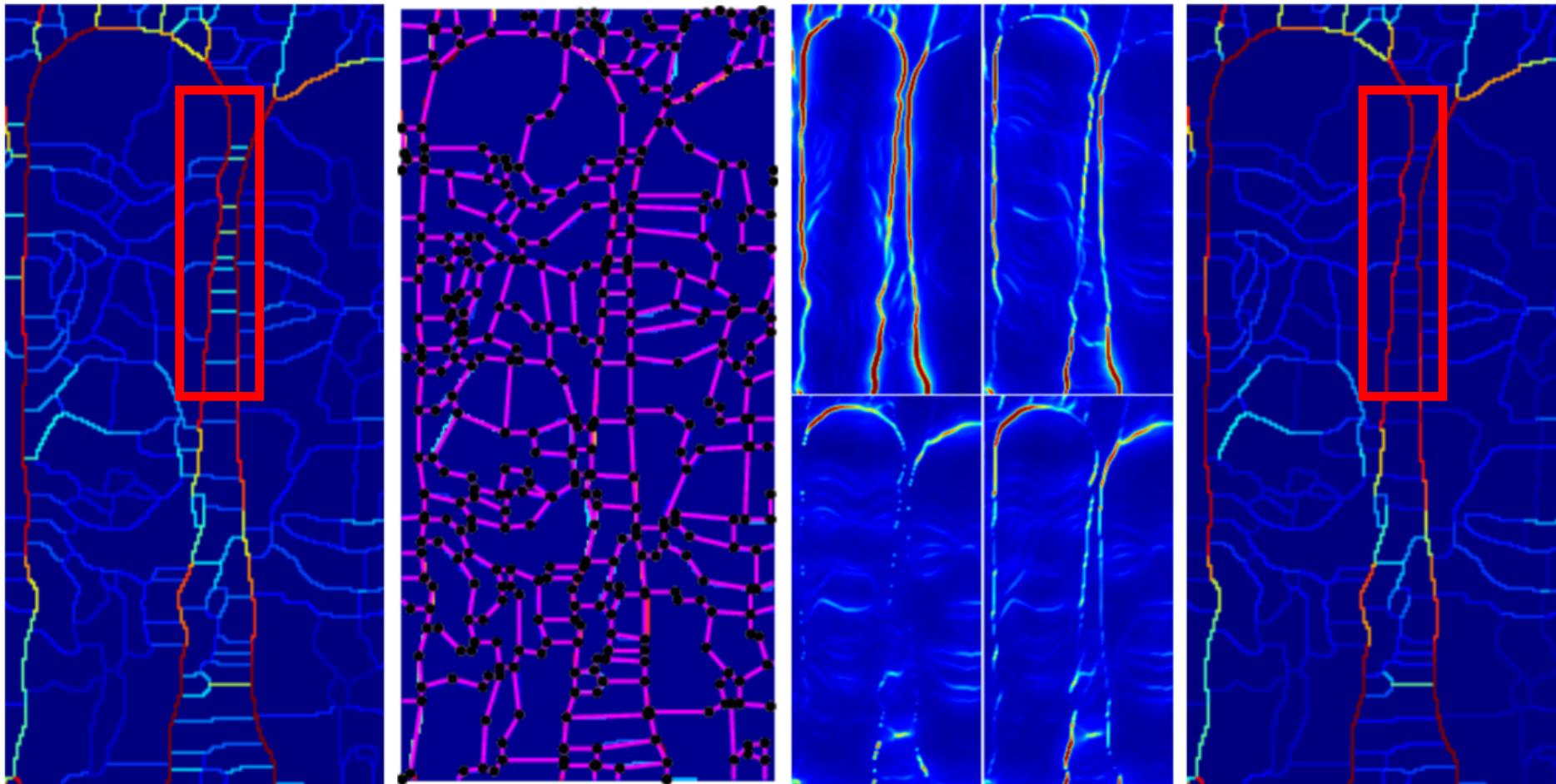
Image



Watershed

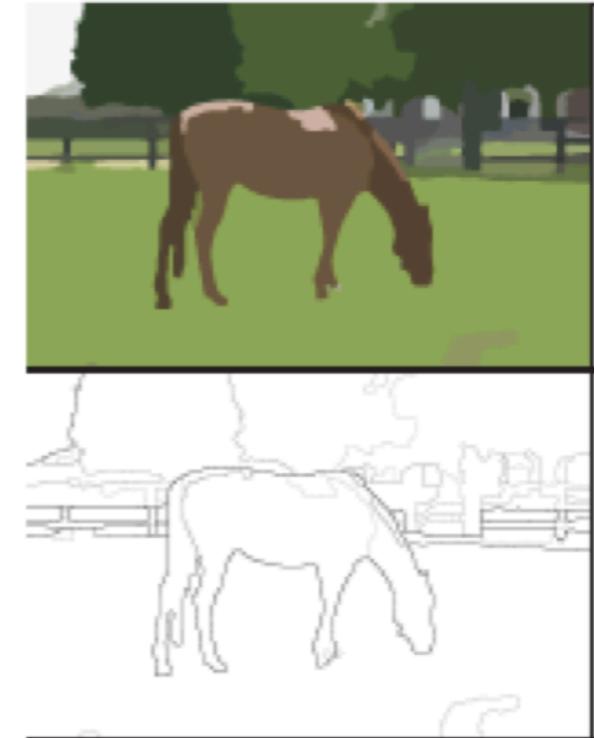
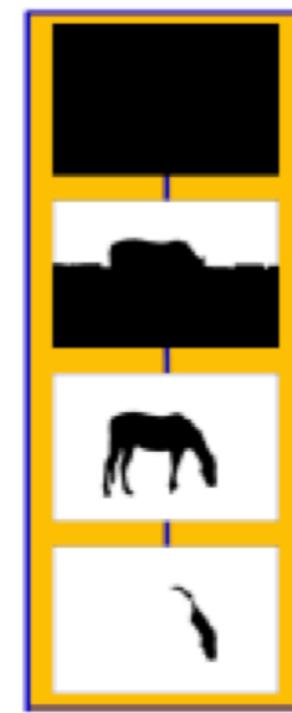
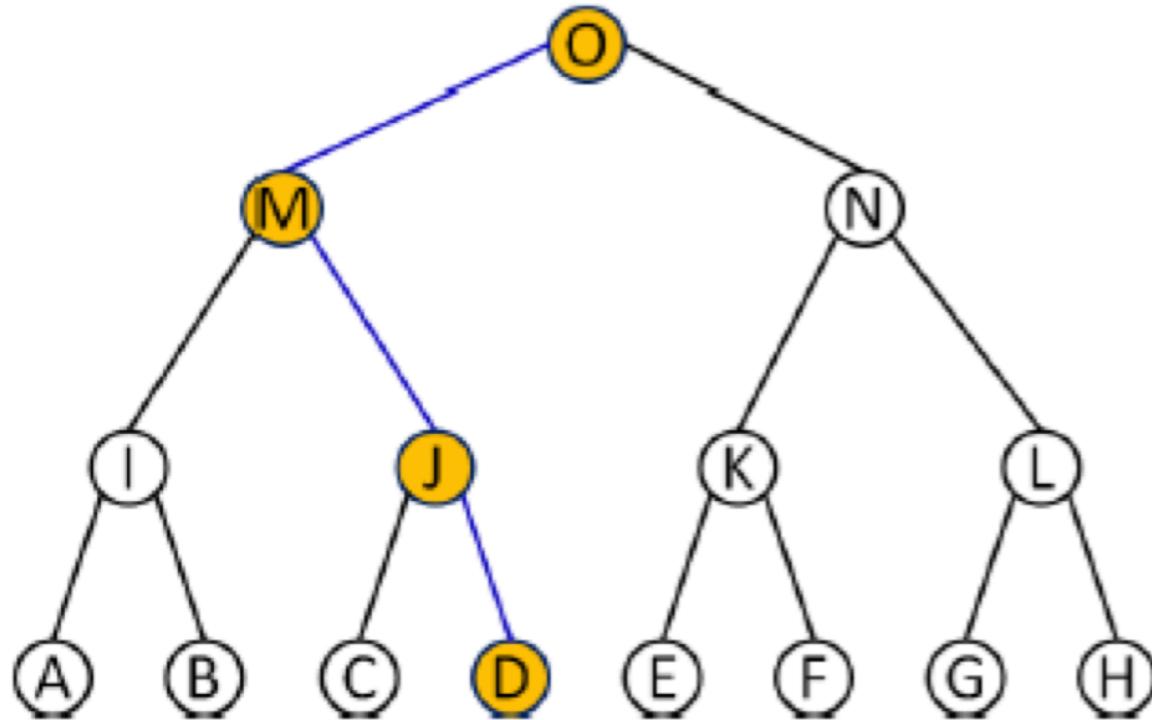


Oriented Watershed Transform

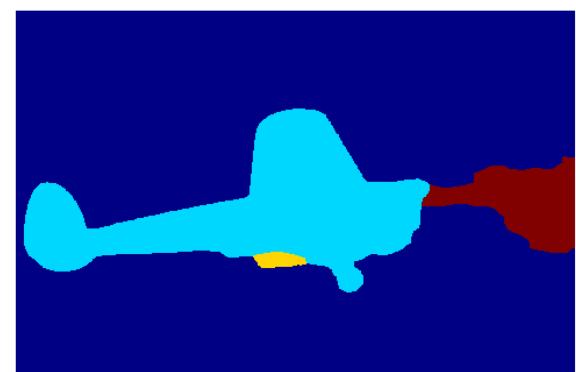
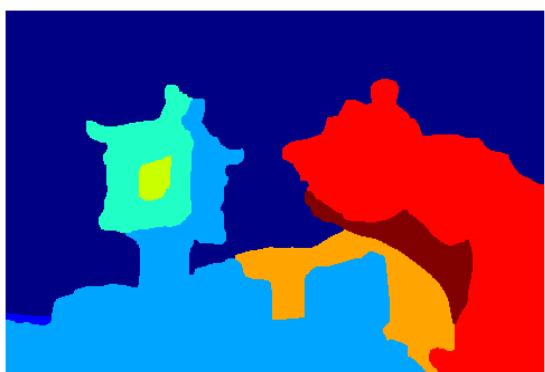
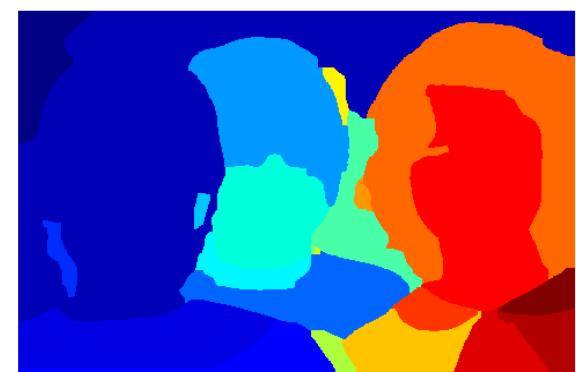
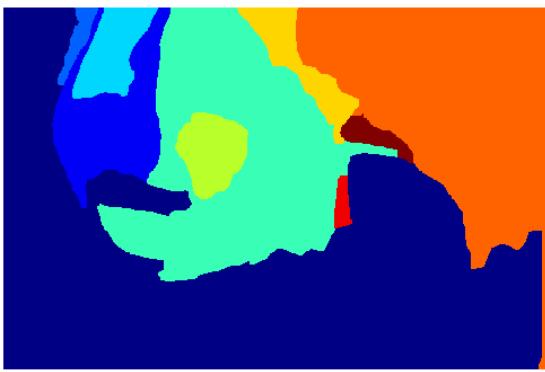


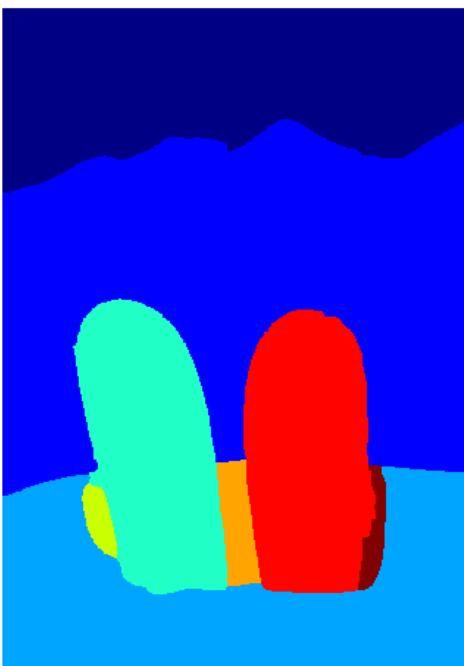
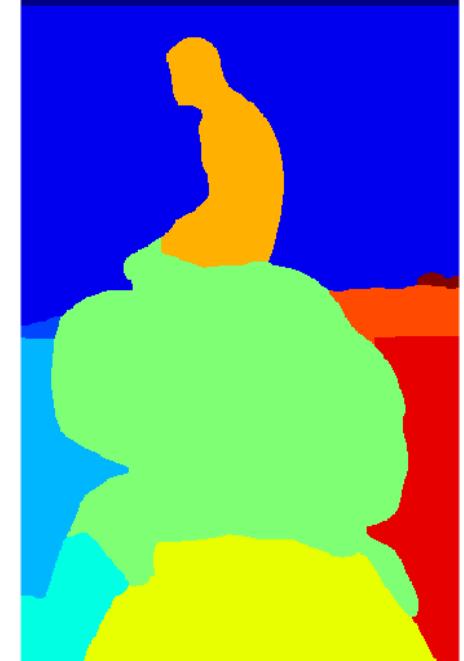
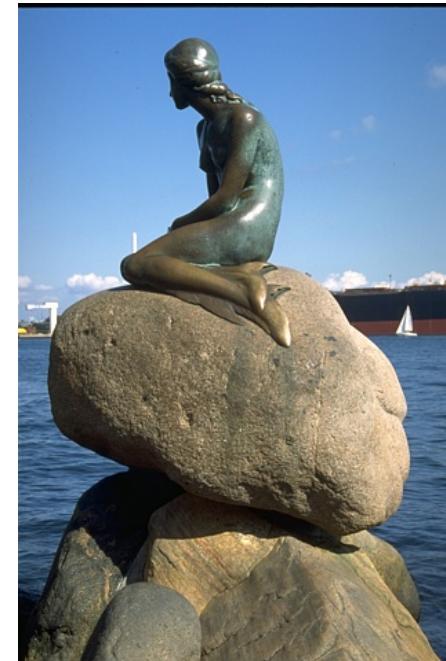
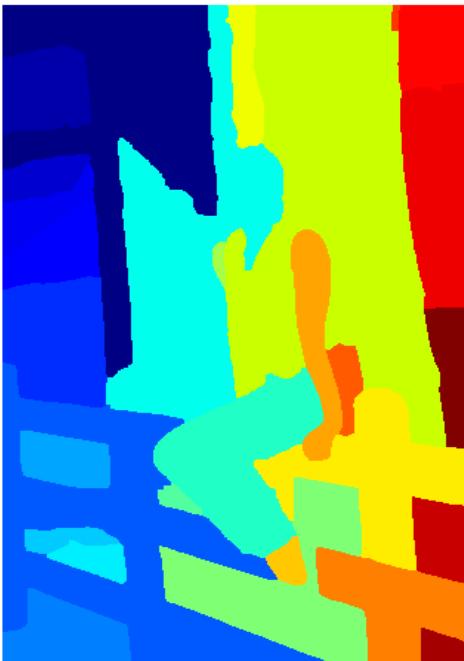
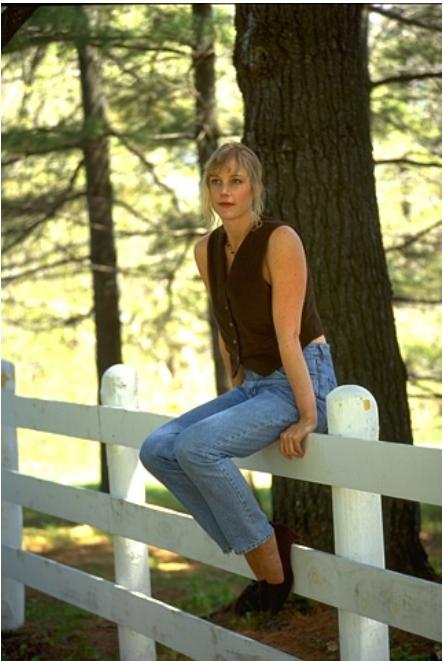
Ultrametric Contour Map

Iterative Merging



Some gPb-owt-ucm Results





Thanks