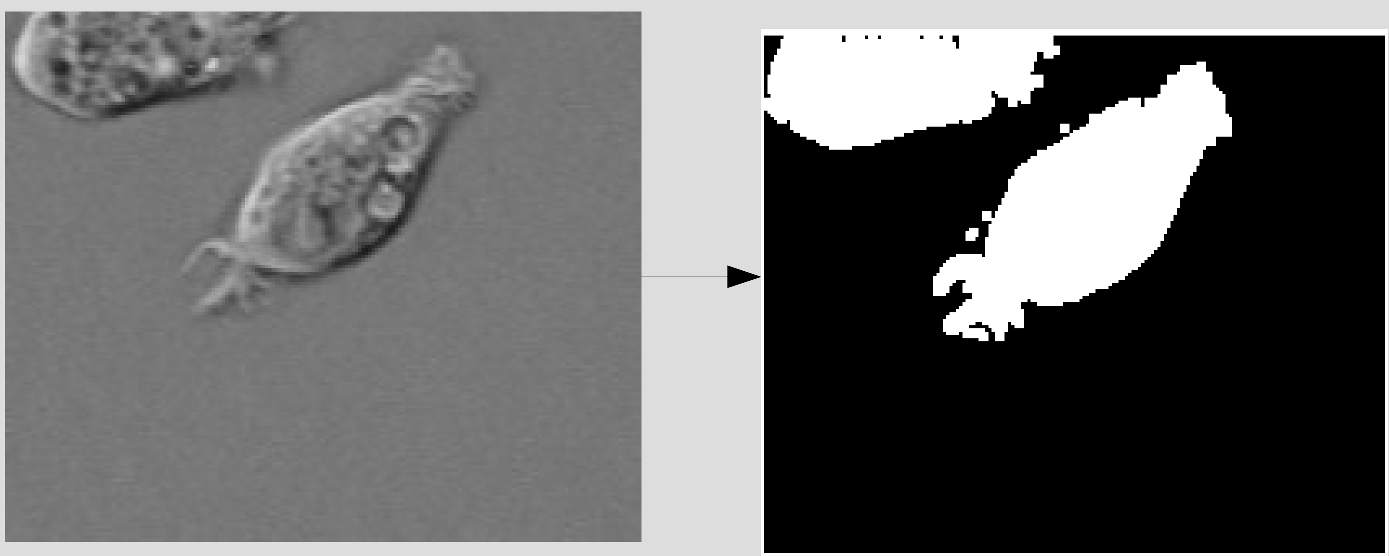
# SYDE 575: Introduction to Image Processing

Segmentation

# What is Segmentation?

- Underlying goal of image segmentation is to partition an image into multiple groups/regions



Source: The MathWorks

# Why segment?

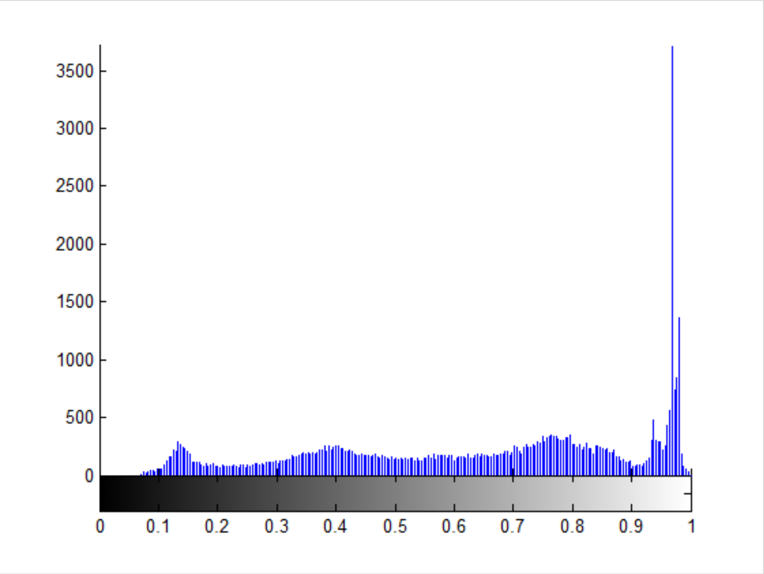
- Segmentation allows objects and regions to be analysed in a more meaningful manner.
- Some applications of segmentation:
  - Object tracking (e.g., people tracking for surveillance purposes)
  - Medical Image Analysis (e.g., tumor growth analysis)
  - Remote Sensing Analysis (e.g., determine the ratio of different types of sea-ice within a region)
  - Face recognition (e.g., partition face into individual parts for component recognition)

# Types of Segmentation Algorithms

- Some of the most common groups of segmentation algorithms are:
  - Histogram based segmentation
  - Clustering based segmentation
  - Region growing segmentation
  - Active contour based segmentation
  - Watershed based segmentation
  - Morphology based segmentation

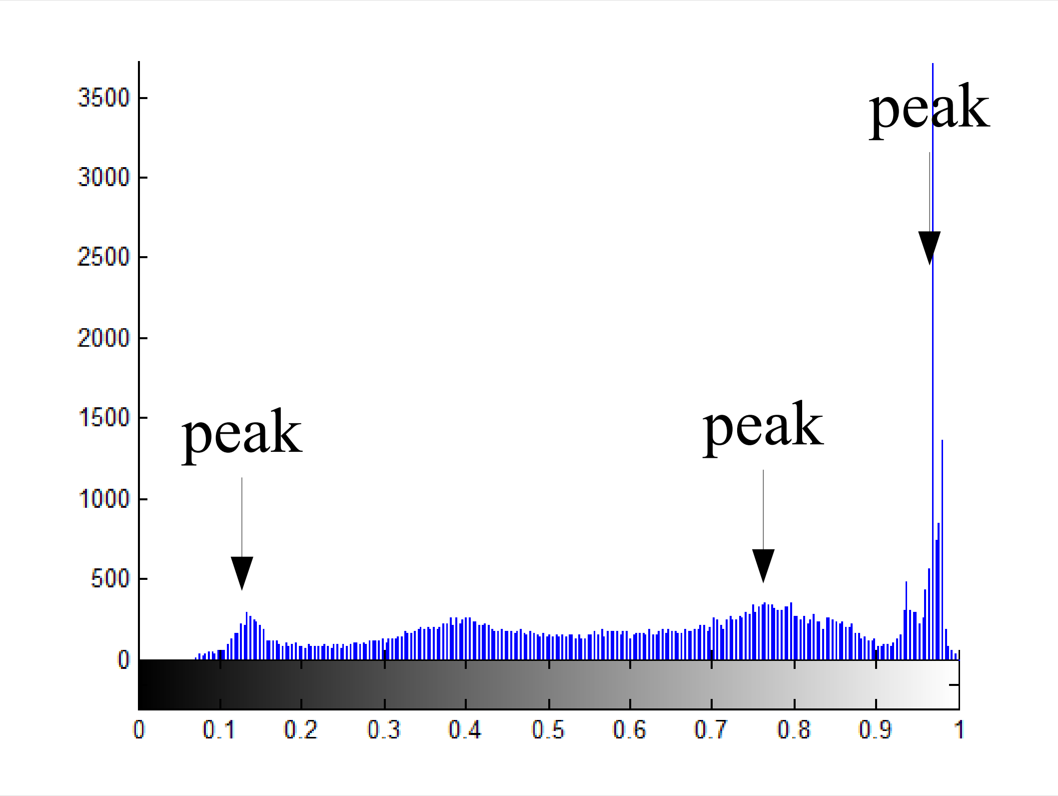
# Histogram based Segmentation

- One of the simplest and most efficient form of segmentation
- Steps:
  - Compute the histogram of the image



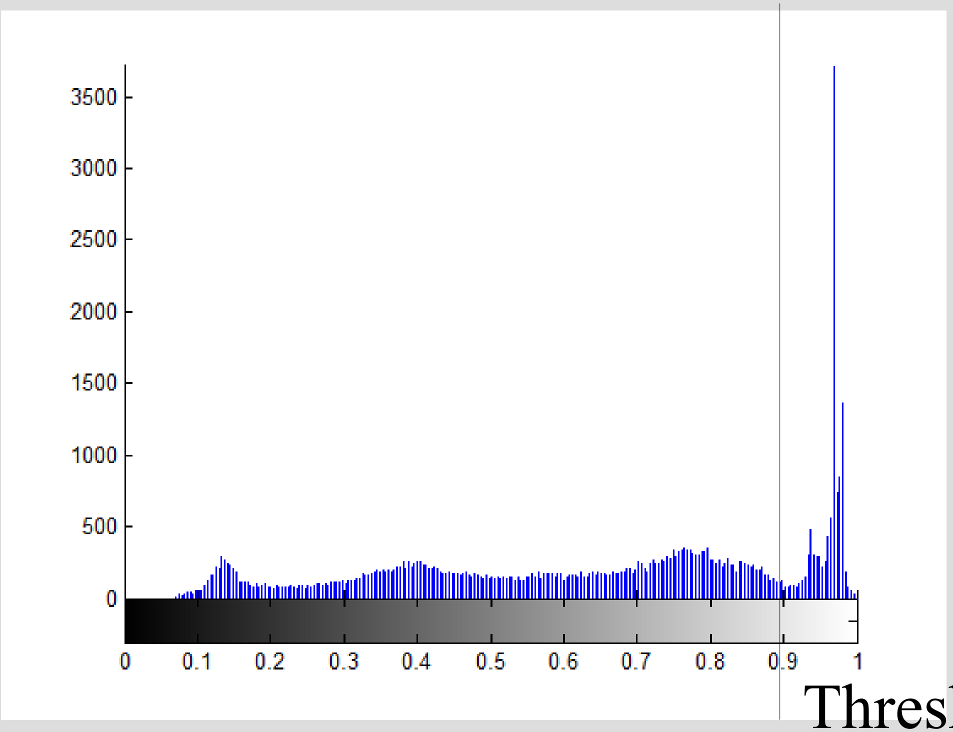
# Histogram based Segmentation

- Steps:
  - Analyse peaks of the histogram and determine an appropriate point of thresholding



# Histogram based Segmentation

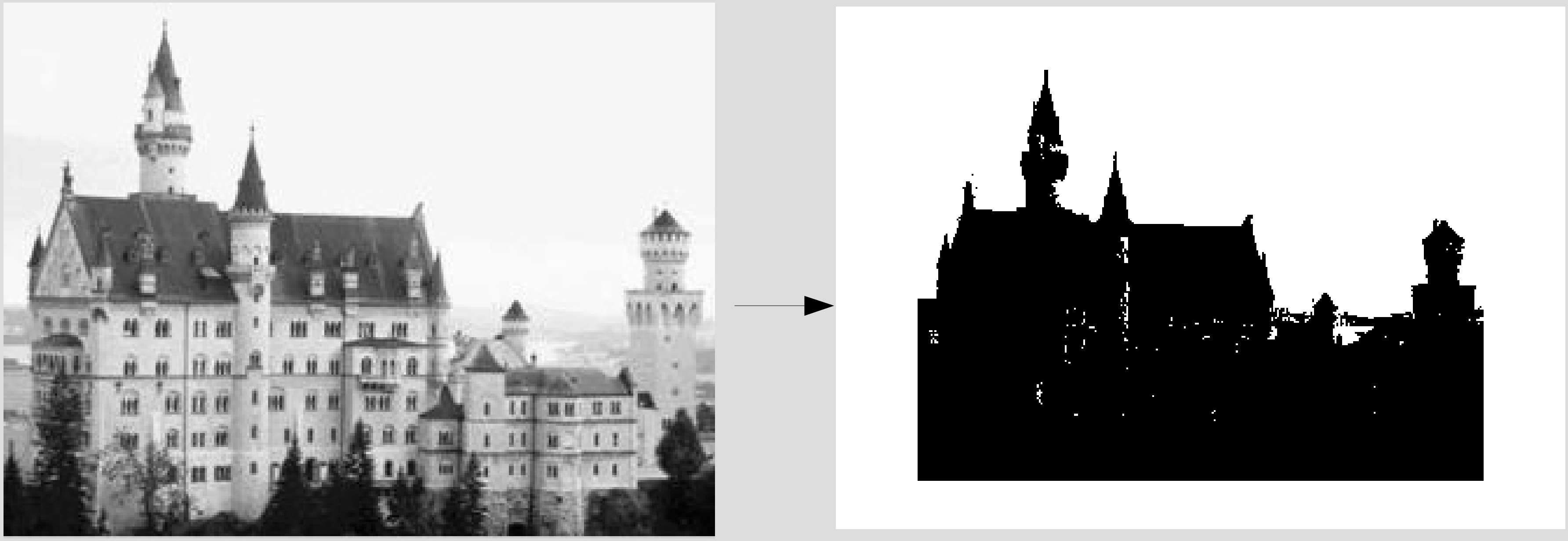
- Steps:
  - Determine an appropriate point of thresholding based on what we want (e.g., segment foreground and background)




Threshold

# Histogram based Segmentation

- Steps:
  - Set all pixels to a set of fixed values based on threshold



# Otsu's Method

- Goal:
  - Find threshold that minimizes intra-class variance
- What is intra-class variance?

$$\sigma^2{}_{intra}(T) = \sum_{i=0}^{T-1} p(i)\sigma^2{}_1(T) + \sum_{i=T}^{N-1} p(i)\sigma^2{}_2(T)$$

- Problem: Expensive to compute!

# Otsu's Method

- Solution: Minimizing intra-class variance equivalent to maximizing inter-class variance
- What is inter-class variance?

$$\sigma^2{}_{inter}(T) = \sigma^2{}_{total}(T) - \sigma^2{}_{inter}(T)$$

$$\sigma^2{}_{inter}(T) = \sum_{i=0}^{T-1} p(i)[\mu_1(T) - \mu]^2 + \sum_{i=T}^{N-1} p(i)[\mu_2(T) - \mu]^2$$

# Otsu's Method

- Since

$$\mu(T) = \sum_{i=0}^{T-1} p(i)\mu_1(T) + \sum_{i=T}^{N-1} p(i)\mu_2(T)$$

- The inter-variance can be expressed as

$$\sigma^2{}_{inter}(T) = \sum_{i=0}^{T-1} p(i) \sum_{i=T}^{N-1} p(i)[\mu_1(T) - \mu_2(T)]^2$$

# Otsu's Method

- Steps:
  - For each possible threshold T
    - 1. Determine the values within each of the clusters formed by T
    - 2. Find the mean of the clusters ($u_1$ and $u_2$)
    - 3. Compute the squared difference between the means
    - 4. Multiply result by the cumulative probability in cluster 1
    - 5. Multiply result by the cumulative probability in cluster 2

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# Finite Mixture Models

- Suppose we know that there are $m$ clusters/classes in the image
- Suppose that the probability distribution of each cluster/class can be modeled using a parametric model (e.g., Gaussian, Gamma, Cauchy, etc.)
- Idea: We can model the probability distribution of the image as a mixture of $m$ different probability distributions, one for each cluster/class

# Finite Mixture Models

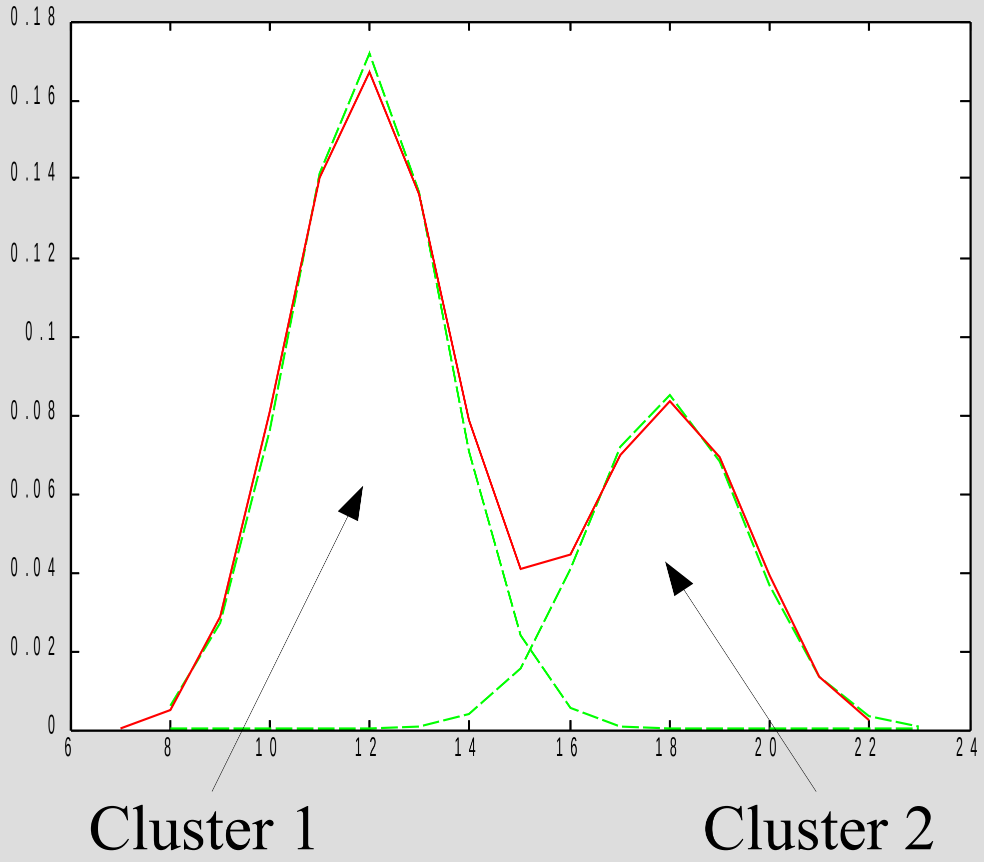
- Formulation:

$$f_X(x) = \sum_{i=1}^{m} a_i f_{Y_i}(x)$$

- Goal: Determine this set of *m* distributions and determine which pixel values belong to each cluster/class based on which of these distributions give the highest probability

# Finite Mixture Models

- Example



# Finite Mixture Models

- Steps:
  - Learn the parameters of the distribution models for the *m* clusters
    - e.g., for Gaussian, learn the mean and standard deviation
  - For each possible pixel
    - 1. Determine the probability that its pixel intensity belongs to each of the *m* clusters based on the distribution models
    - 2. Assign the pixel's cluster label to the cluster that provides the highest probability
  - Therefore, thresholds between clusters coincide with at points of equal probabilities

# Finite Mixture Models

- Example: Suppose we have two classes, modeled by two Gaussians (u1=3, σ1=1, u2=5, σ2=1)
- What is the threshold between these two classes?
  - Set up distribution equations for each class

$$f_{Y_1}(x) = \exp[-((x-3)^2)/(2(1)^2)]$$

$$f_{Y_2}(x) = \exp[-((x-5)^2)/(2(1)^2)]$$

# Finite Mixture Models

- Since threshold is at point of equal probabilities:

$$f_{Y_1}(x) = f_{Y_2}(x)$$

$$\exp[-((x-3)^2)/(2(1)^2)] = \exp[-((x-5)^2)/(2(1)^2)]$$

$$-((x-3)^2) = -((x-5)^2)$$

$$x^2 - 6x + 9 = x^2 - 10x + 25$$

$$4x = 16$$

$$x = 4$$

# Histogram based Segmentation

- Advantages:
  - Efficient (usually requires only one pass for simple segmentation cases)
- Disadvantages:
  - Often difficult to determine proper peaks in the histogram
  - Difficult in situations where intensity is not sufficient to distinguish between two partitions (e.g., textured regions containing different mixes of intensities)

# Clustering based Segmentation

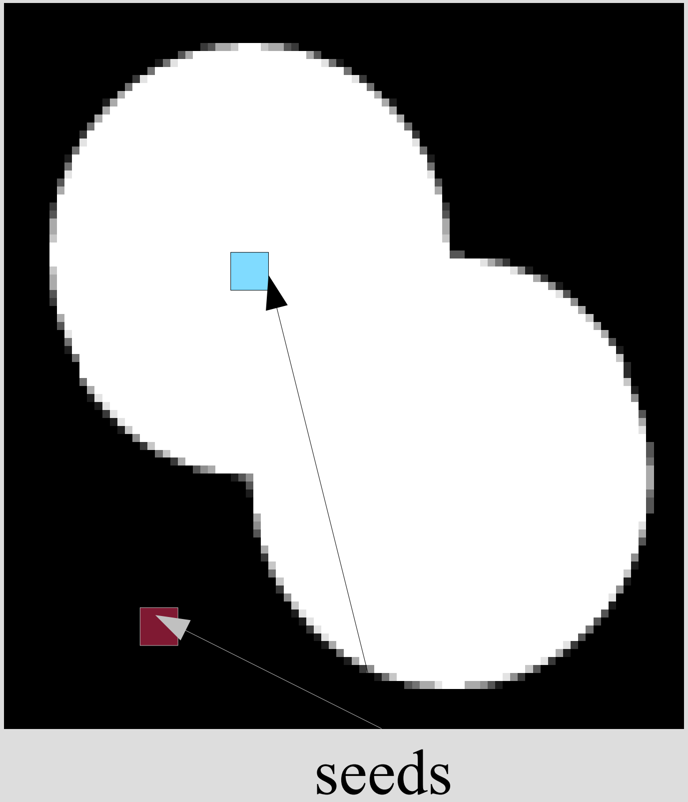
- Create partitions by grouping pixels into clusters
- Steps (for K-means clustering):
  - Pick k pixels in the image to act as the initial centers of the k clusters
  - For each pixel, find the cluster that minimizes your distance metric
    - Distance metric can be the differences in:
      - Pixel intensity
      - Location
      - Variance
      - Weighted combination of these differences

# Clustering based Segmentation

- Steps:
  - For each cluster, recalculate the cluster center based on the pixel locations within the cluster
  - Re-do all previous steps until convergence
- Advantages:
  - Good for segmentation where there are multiple distinct partitions
- Disadvantages:
  - Performs poorly when the regions have irregular shapes that mix into each other

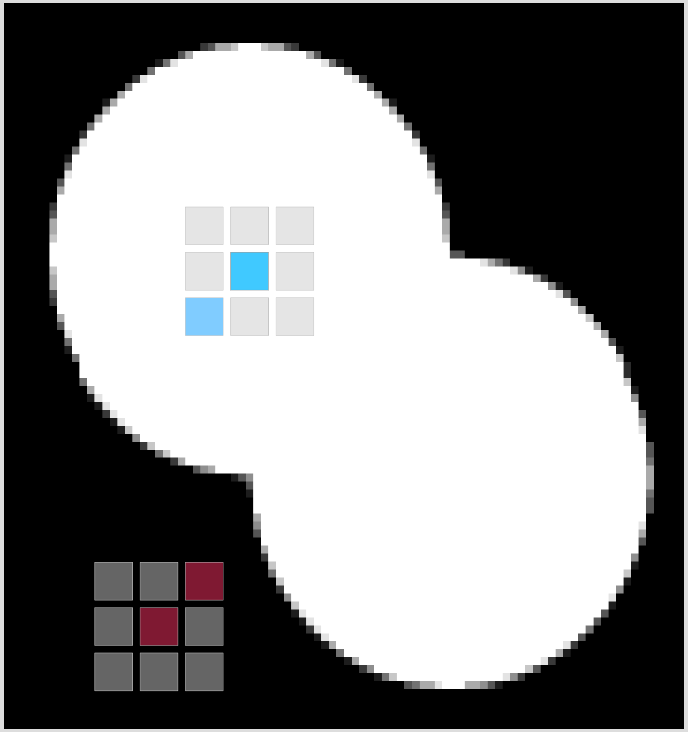
# Region Growing Segmentation

- Create partitions by continuously growing smaller regions until all pixels are accounted for.
- Steps:
  - Pick initial seeds that mark the individual regions who wish to segment



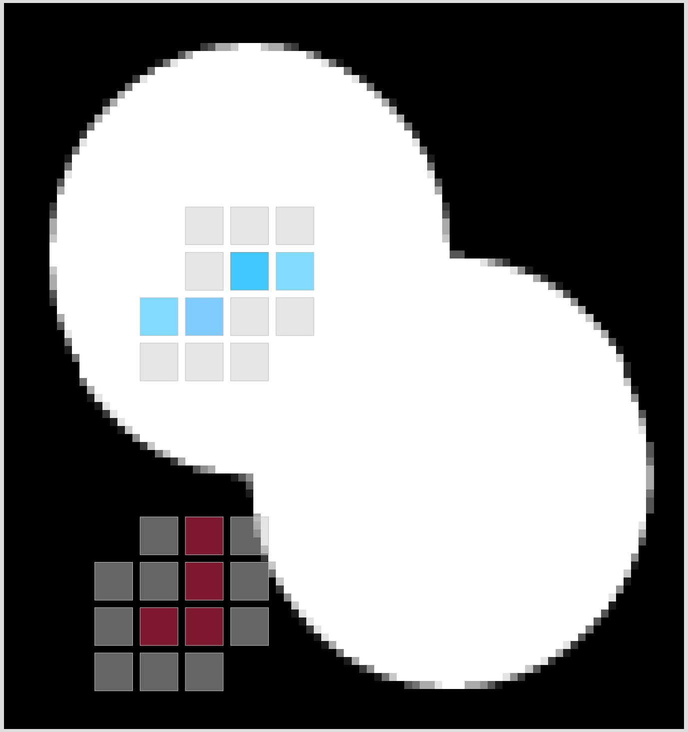
# Region Growing Segmentation

- Steps:
  - For all neighboring pixels to the seed, compare the similarity between the seed and the pixel
  - The pixel with the highest similarity is added to the seed to form a small region



# Region Growing Segmentation

- Steps:
  - For all neighboring pixels to the new regions, compare the similarity between the seed and the pixel
  - The pixel with the highest similarity is added to the small region to form a bigger region
  - Continue until all pixels in the image belong to a region

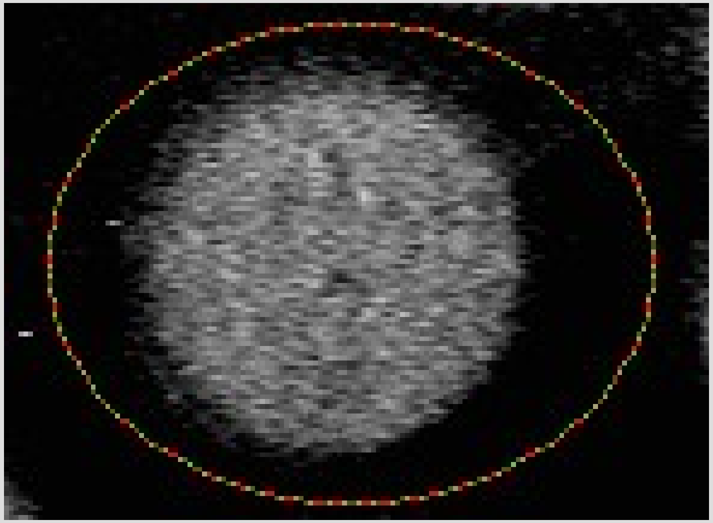


# Region Growing Segmentation

- Advantages:
  - Good for segmentation with irregular shapes
- Disadvantages:
  - Slow

# Active Contour Segmentation

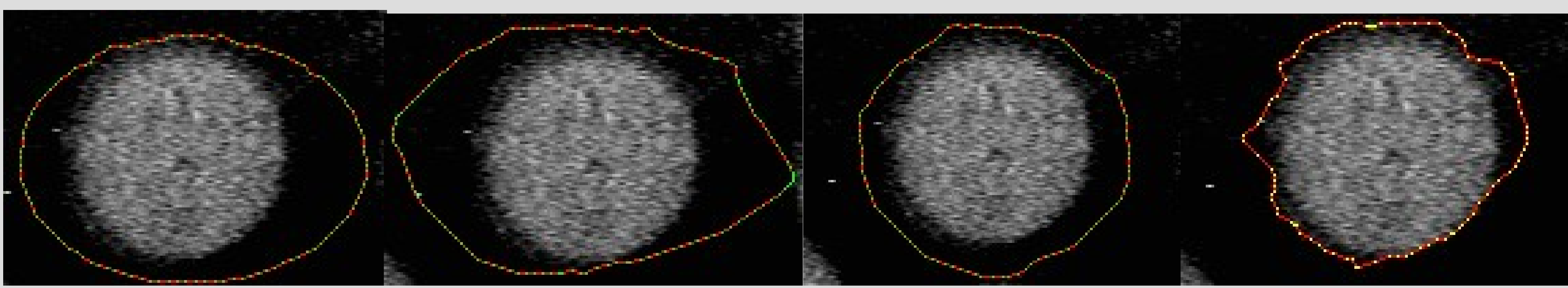
- Create partitions by forming rough boundaries around regions/objects of interest and refining the boundaries until it matches the actual boundaries of the objects
- Steps:
  - Create rough boundary around the object



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

# Active Contour Segmentation

- Steps:
  - Calculate energy gradient between the current location of the boundary and it's neighboring pixels
  - Expand or contract the boundary based on the gradient



i=1 i=5 i=20 i=50

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

# Active Contour Segmentation

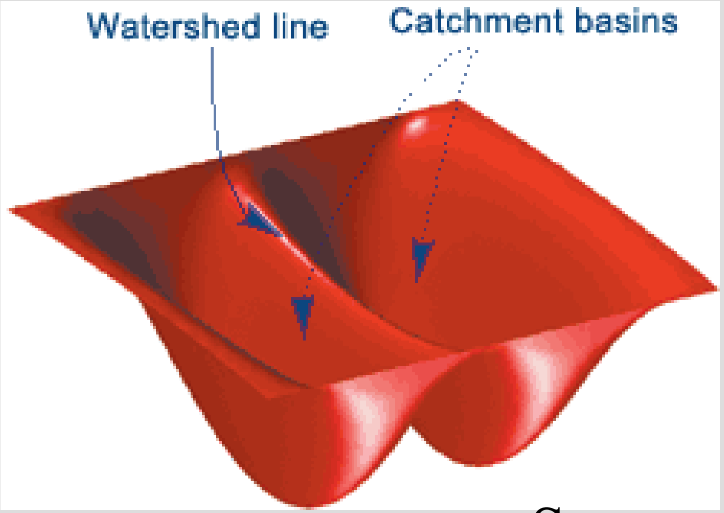
- Advantages:
  - Good for segmenting and tracking objects with deformable motion and clear boundaries
  - Motion information can be extracted from the contour
- Disadvantage:
  - Relatively slow
  - Ill-suited for situations where your regions do not have clearly defined boundaries

# Watershed Segmentation

- What is a watershed?
  - A ridge that divides different areas that different rivers and streams drain into
- What is a catchment basin?
  - An area that collects water within an area and drains into a body of water (e.g., sea, ocean, river, etc.)
- What does this have to do with segmentation?!

# Watershed Segmentation

- Idea:
  - Let's treat bright areas as having high elevation and dark areas as having low elevation
  - Let's treat boundaries between regions as watersheds and the local minimas of the regions as catchment basins




Source: The MathWorks

# Watershed Segmentation

- Idea:
  - Suppose we took a water hose and pour water into the catchment basins until they are full of water
  - Each of these filled catchment basins become the individual regions that you wish to segment!
  - Small regions can be merged into larger regions by continuing to pure water into the basins and overflow the smaller basins until they form a larger basin

# Watershed Segmentation

- Advantages:
  - Efficient
  - Simple conceptually
- Disadvantages:
  - How much water do I pour?
    - Too little water leads to over-segmentation (too many remaining regions)
    - Too much water leads to under-segmentation (keep pouring water and the whole image becomes one big region)