Image Segmentation: Basic Techniques

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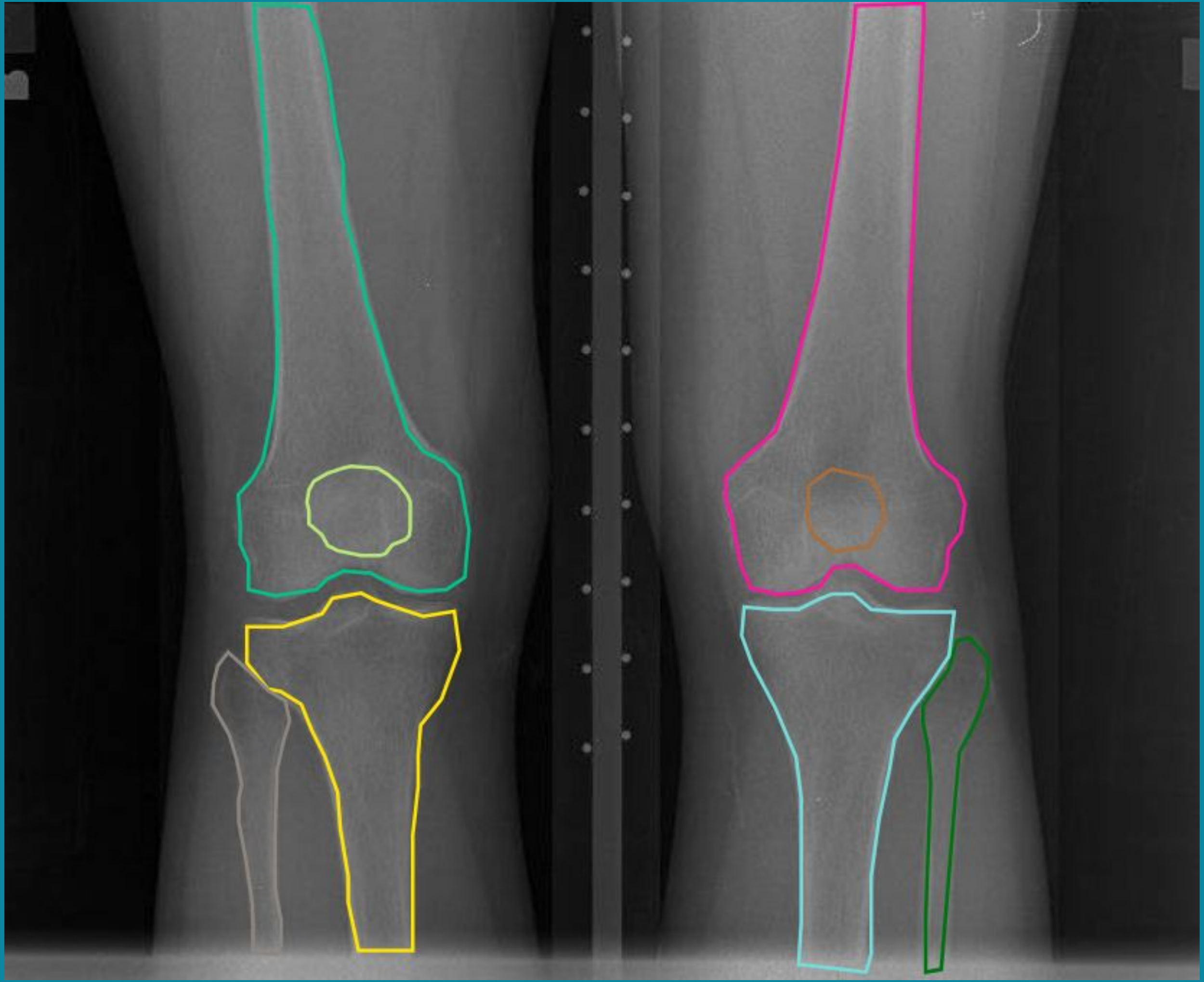
Image Segmentation

What is the basic idea?

Image Segmentation

Basic idea: Partitioning image into segments that share common attributes

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



Basic Segmentation Techniques

- Binary Thresholding Method
- Otsu’s Method of Thresholding
- Watershed Algorithm
- K-means clustering

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Binary Thresholding Method Based on Histogram of Pixel Intensities

- Two main regions of interest
  - Background and object

- Strategy
  - Make a histogram of pixel intensities
  - Pick a threshold intensity
  - Set the pixels above threshold to 0 (black)
  - Set the pixels below threshold to 255 (white)
  - Leads to a background and object in white and black colors

- If peaks in the histogram are not clear (not distinctly separated by zero density)
  - Pick the two intensities that seem to peak on the histogram, call them p_1 and p_2
  - Threshold = $(p_1 + p_2) / 2$

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Otsu's Method

Maximizes the variance between segments/classes of the image

- Same as minimizing the variance within each class

Steps

- Create histogram of pixel intensities in the image
- If the image has two segments (i.e., bimodal histogram) based on threshold t, call them c_1 + c_2
    - Variance between c_1 and c_2 is

$$var(C_1, C_2) = P(C_1)(u_1 - u)^2 + P(C_2)(u_2 - u)^2$$

$$var(C_1, C_2) = P(C_1)(u_1 - u)^2 + P(C_2)(u_2 - u)^2$$

$$u_1 = \sum_{i=0}^{t} P(i)i \quad u_2 = \sum_{i=t+1}^{L-1} P(i)i \quad u = \sum_{i=0}^{L-1} P(i)i$$

$$P(C_1) = \sum_{i=0}^{t} P(i) \quad P(C_2) = \sum_{i=t+1}^{L-1} P(i)$$

- $\boldsymbol{\mu}_1$ is the mean intensity of segment 1

- $\boldsymbol{\mu}_2$ is the mean intensity of segment 2

- p(i) = count(i) / M
  - M = number of pixels within each segment
  - I = intensity level

- $p(c_1)$ = probability of an intensity level below threshold t

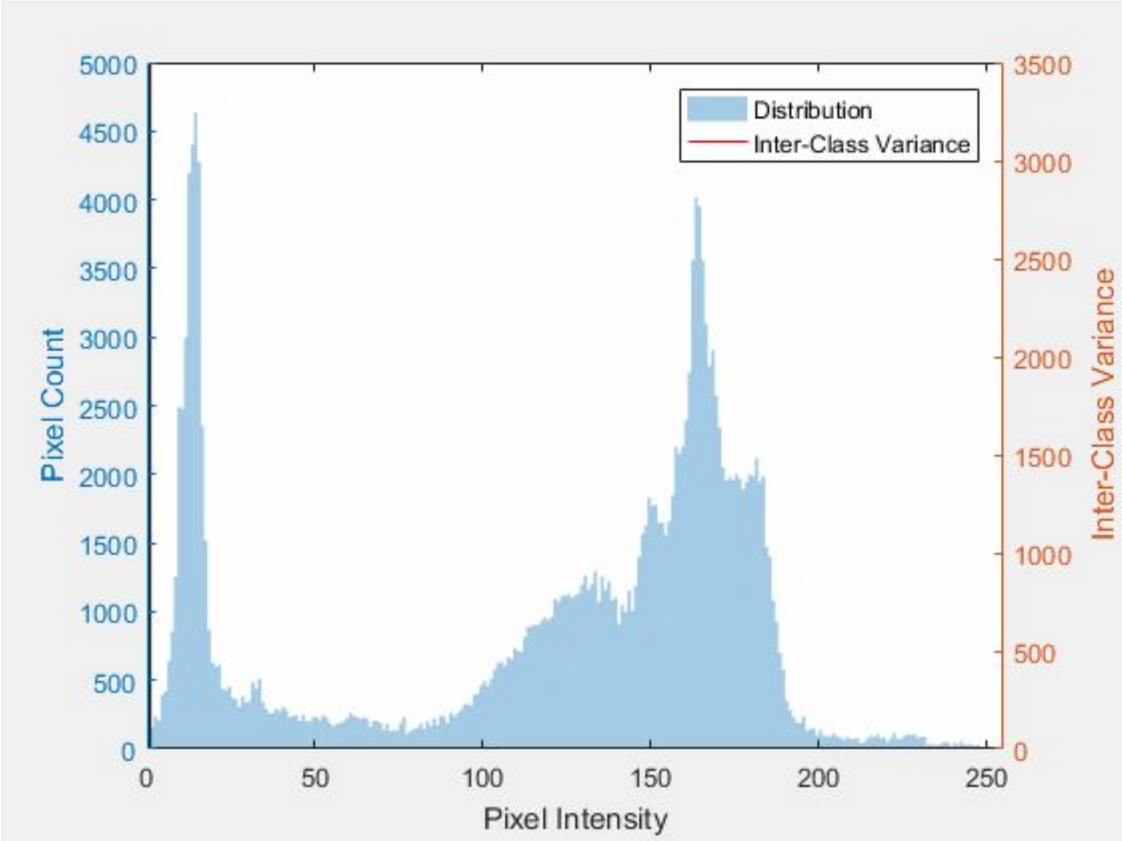
- $p(c_2)$ = probability of an intensity level above threshold t

- $\boldsymbol{\mu}$ = Global mean

- goal : maximize the equation

$$var(C_{1,}C_2) = P(C_{1,})(u_1 - u)^2 + P(C_2)(u_2 - u)^2$$

- End result is a threshold t that maximizes the variance between the segments of the image


Distribution
Inter-Class Variance
Pixel Count
Inter-Class Variance
Pixel Intensity
0
50
100
150
200
250
500
1000
1500
2000
2500
3000
3500
4000
4500
5000

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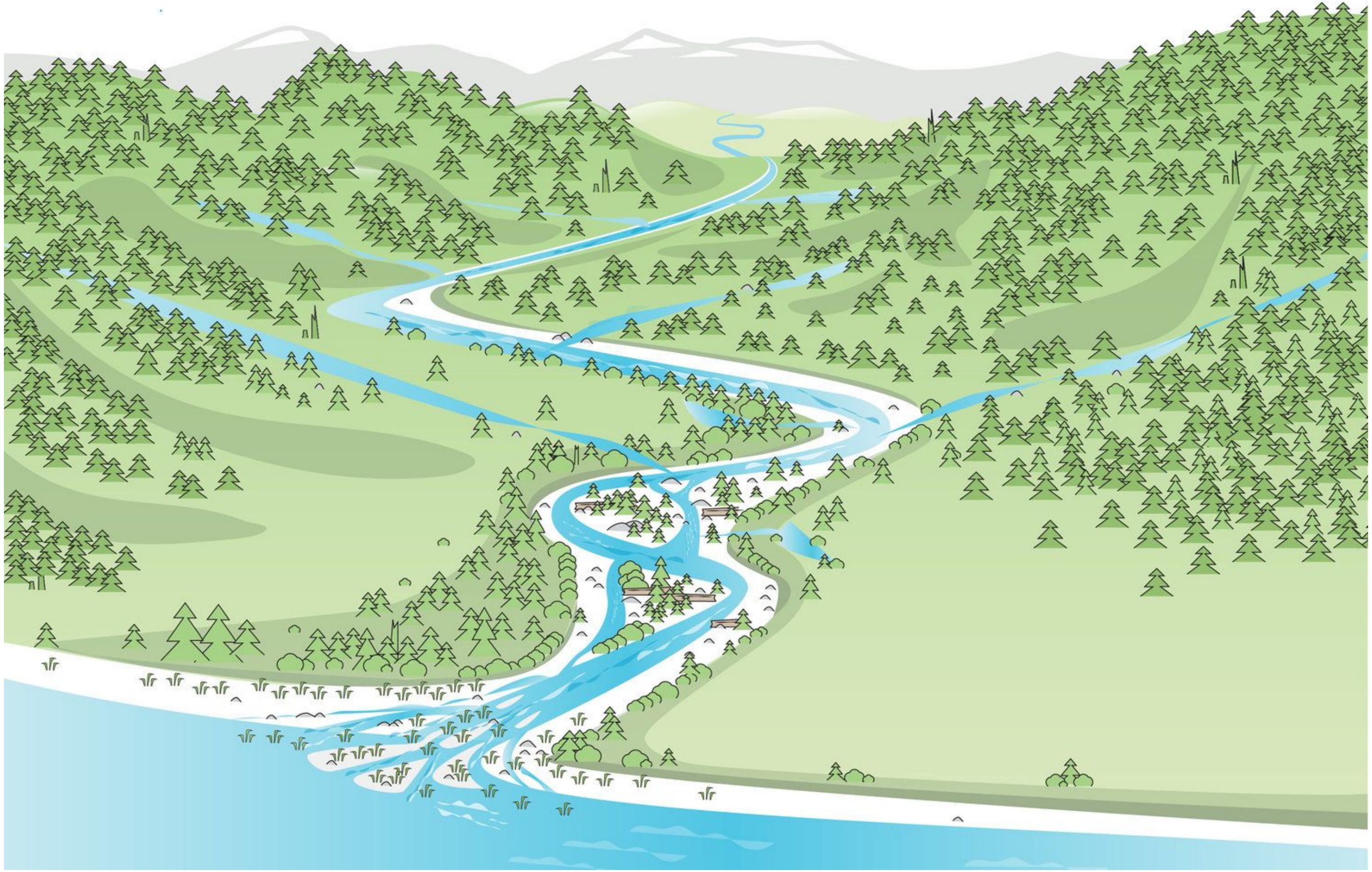
Watershed Algorithm

In watershed segmentation, an image is regarded as a topographic landscape with ridges and valleys.

Watershed Algorithm

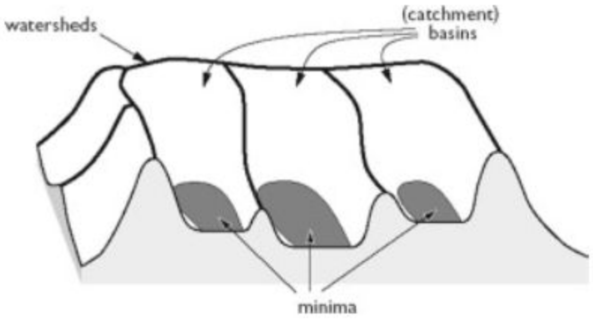
Watersheds are one of the typical regions in the field of topography.

- A watershed is an area or ridge of land that separates waters flowing to different bodies of water.



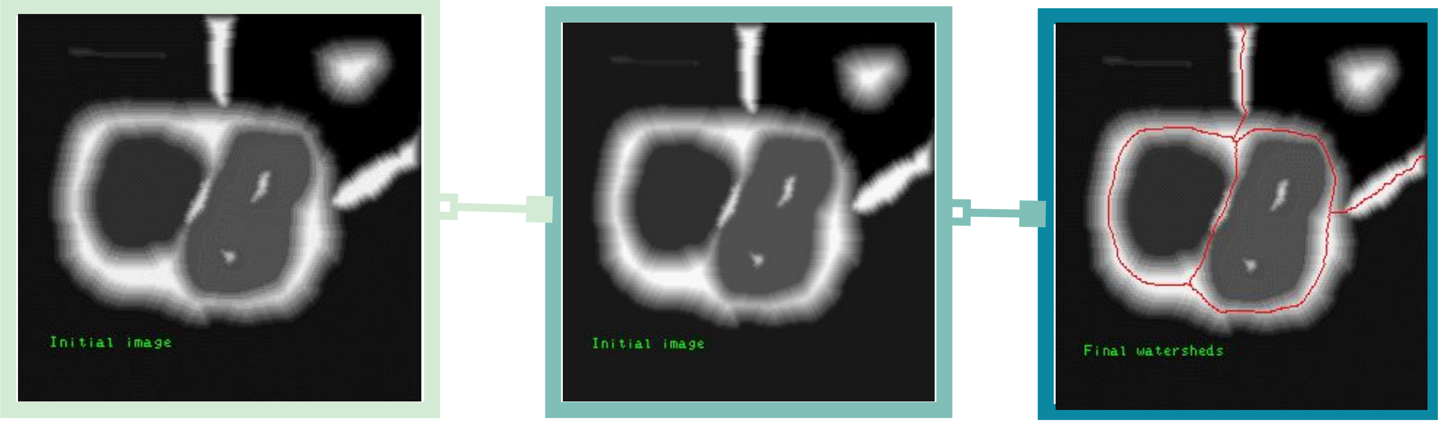
Philosophy of Watershed Algorithm

Any grayscale image can be viewed as a topographic surface where high intensity denotes peaks while low intensity denotes valleys. We start filling every isolated valleys (local minima) with different colored water (labels). As the water rises, water from different valleys (with different colors) will begin to merge. To avoid this, we build barriers in the locations where water merges.

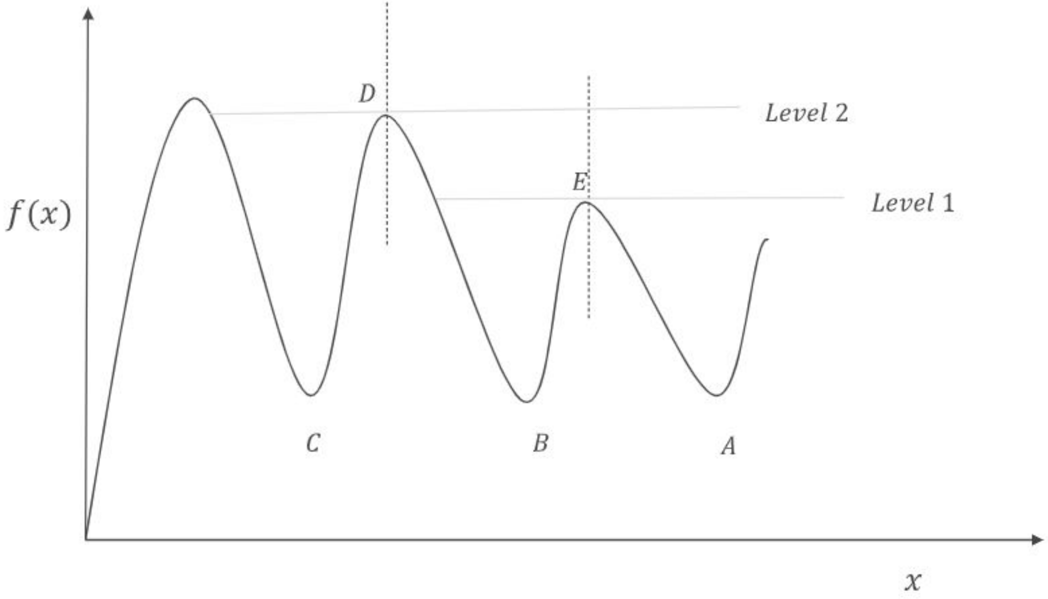


Philosophy of Watershed Algorithm

We continue the work of filling water and building barriers until all the peaks are under water. The barriers created give us the segmentation result.



http://www.cmm.mines-paristech.fr/~beucher/wtshed.html



A, B, C $-$ *Minima of Catchment Basins*
D, E $-$ *Peaks or Maximas where watersheds need to be constructed*

Figure 6-3. *Watershed algorithm illustration*

Benefits

The Watershed algorithm is particularly useful in detecting objects when there is overlap between them. Thresholding techniques are unable to determine distinct object boundaries.

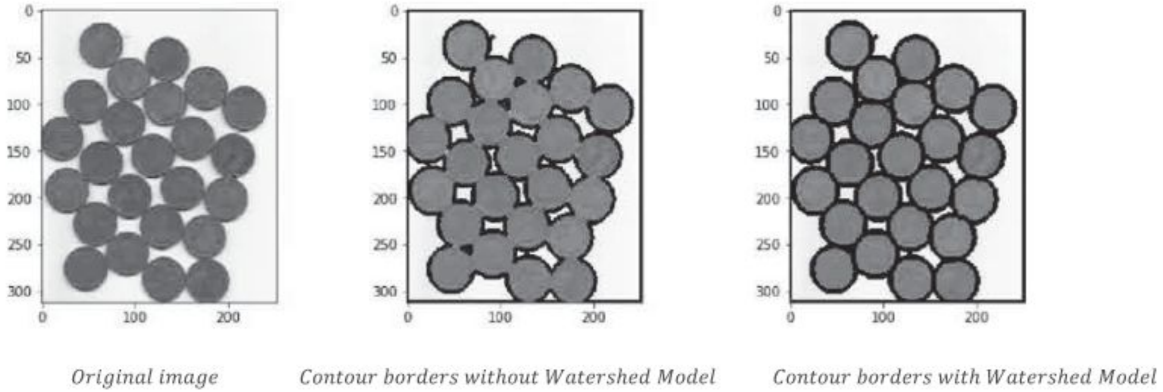


Figure 6-4. *Illustration of Watershed algorithm for image segmentation)*

Problems with Oversegmentation

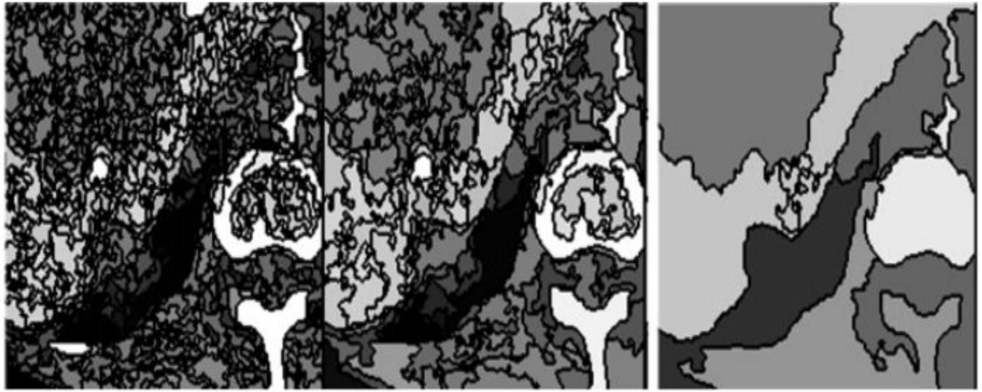


Figure 4.14. Illustration of the over-segmentation problem of the watershed transform applied to an axial slice of a CT image. Individual basins are merged to form successively larger regions.

(Courtesy of Thomas Schindewolf, Fraunhofer MEVIS Bremen)

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K-means Clustering

This algorithm partitions the given data into K-clusters or parts based on the K-centroids.

K-means Clustering

The objective of K-Means clustering is to minimize the sum of squared distances between all points and the cluster center.

number of clusters

number of cases

centroid for cluster *j*

case *i*

objective function

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \underbrace{\left\| x_i^{(j)} - c_j \right\|^2}_{\text{Distance function}}$$

K-means Clustering Steps

1. Choose the number of clusters K.
2. Select at random K points, the centroids(not necessarily from your dataset).
3. Assign each data point to the closest centroid → that forms K clusters.
4. Compute and place the new centroid of each cluster.
5. Reassign each data point to the new closest centroid. If any reassignment took place, go to step 4, otherwise, the model is ready.

K-means Clustering: Color Clusters

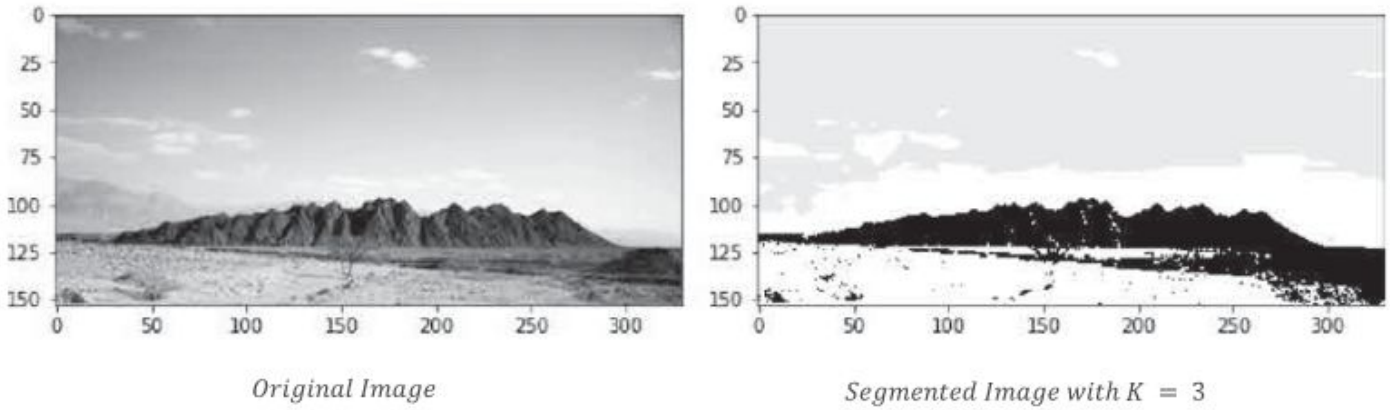

Figure 6-5. *Illustration of segmentation through the K-means algorithm*

K-means Clustering: Color Clusters

- Categorizing the original image into three dominant colors

Image Segmentation when K=3