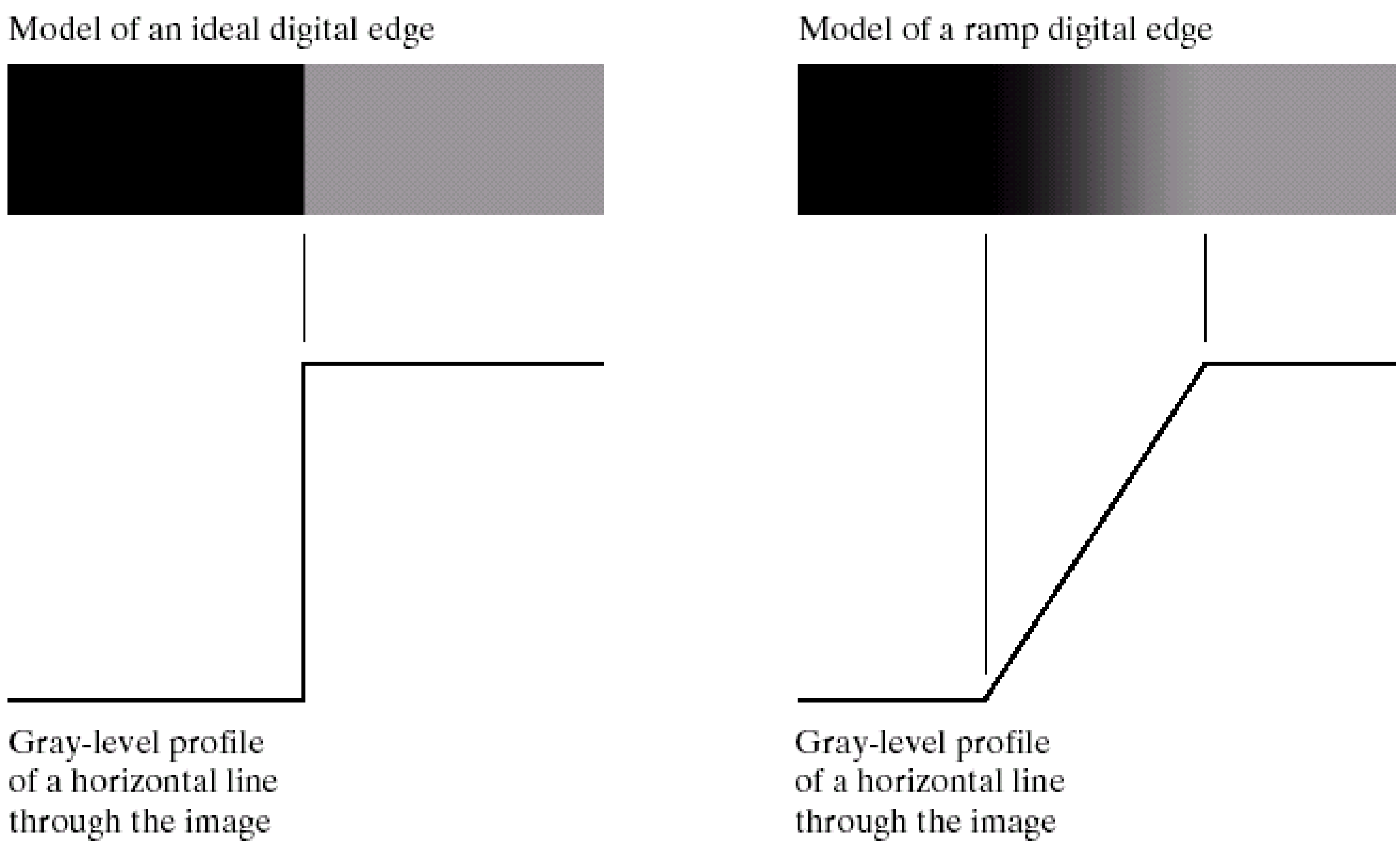
Digital Image Processing

Lecture # 6
Edge Detection and Segmentation

Edge Detection

- Edge detectors can be based on the first and second derivatives which can detect abrupt intensity changes.
- Derivates of digital functions are defined in terms of differences
- See approximations on using first and second derivatives in Gonzalez section 10.2.1

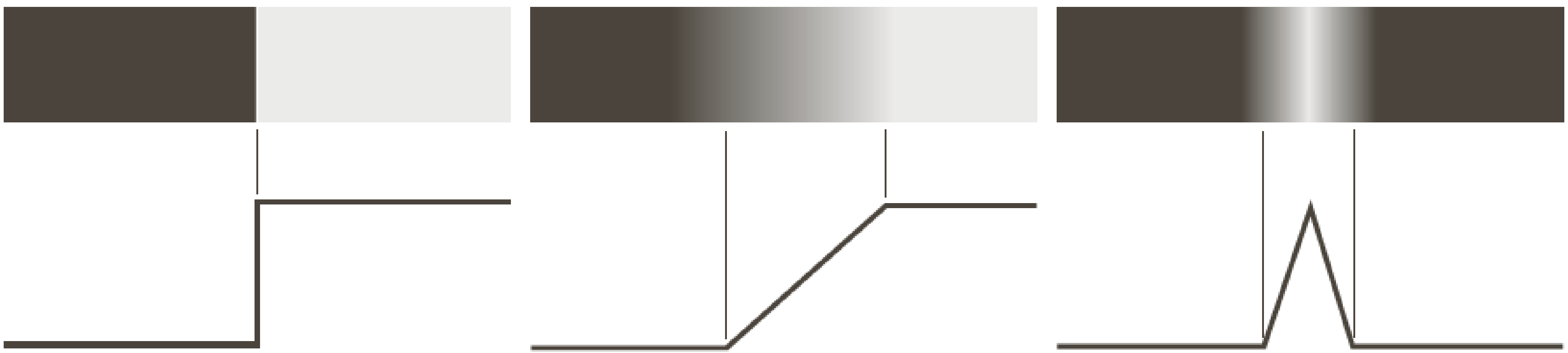
Edge Detection



a b

FIGURE 10.5 (a) Model of an ideal digital edge. (b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.

Edges



a b c

FIGURE 10.8
From left to right, models (ideal representations) of a step, a ramp, and a roof edge, and their corresponding intensity profiles.

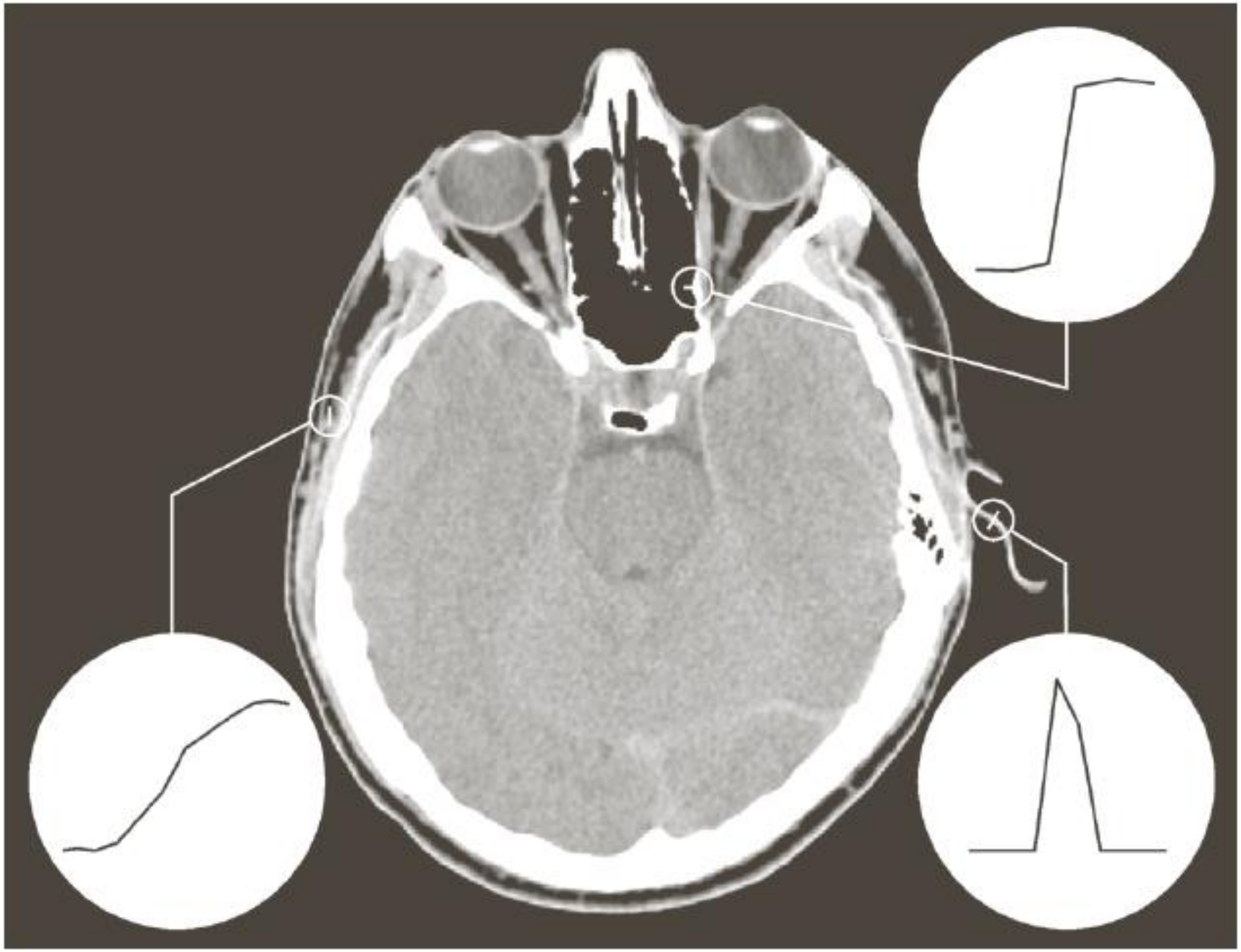


FIGURE 10.9 A 1508 $\times$ 1970 image showing (zoomed) actual ramp (bottom, left), step (top, right), and roof edge profiles. The profiles are from dark to light, in the areas indicated by the short line segments shown in the small circles. The ramp and "step" profiles span 9 pixels and 2 pixels, respectively. The base of the roof edge is 3 pixels. (Original image courtesy of Dr. David R. Pickens, Vanderbilt University.)

Use of first derivatives for image enhancement: The Gradient

- The **gradient** of a function f(x,y) is defined as

$$\nabla \mathrm{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix}$$

Gradient Operators

Sobel Operator

-1	**-2**	**-1**
0	**0**	**0**
1	**2**	**1**

Extract horizontal edges

-1	**0**	**1**
-2	**0**	**2**
-1	**0**	**1**

Extract vertical edges

Emphasize more the current point (y direction)

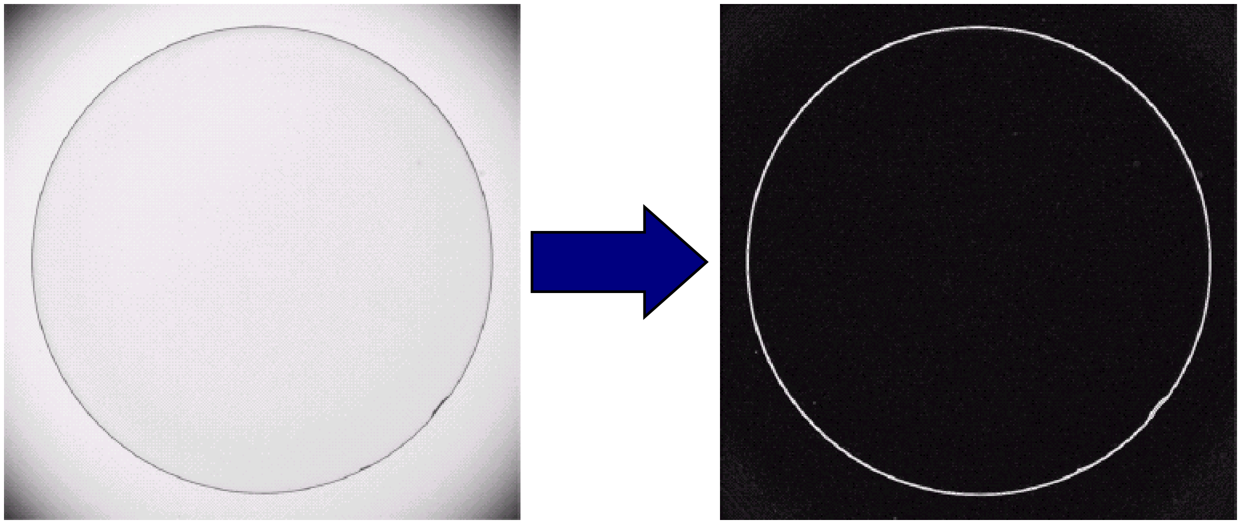
$$\nabla f \approx \left|(z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)\right| + \left|(z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)\right|$$

Emphasize more the current point (x direction)

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Pixel Arrangement

Sobel Operator: Example



An image of a contact lens which is enhanced in order to make defects more obvious

Sobel filters are typically used for edge detection

Gradient Operators

Some common gradient operators

- Roberts and Prewitt masks are the simplest but not robust against noise
- Sobel edge detection masks are the most common and give satisfactory results in presence of noise

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

−1	0
0	1

0	−1
1	0

Roberts

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Prewitt

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

Sobel

a	
b	c
d	e
f	g

FIGURE 10.14 A 3 × 3 region of an image (the z's are intensity values) and various masks used to compute the gradient at the point labeled z_5.

Gradient Operators

0	1	1
−1	0	1
−1	−1	0

−1	−1	0
−1	0	1
0	1	1

Prewitt

0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Sobel

a	b
c	d

FIGURE 10.15 Prewitt and Sobel masks for detecting diagonal edges.

Gradient Operators

- Most common differentiation operator is the gradient vector.

$$\nabla f(x,y) = \begin{bmatrix} \dfrac{\partial f(x,y)}{\partial x} \\ \dfrac{\partial f(x,y)}{\partial y} \end{bmatrix} = \begin{bmatrix} G_x \\ G_y \end{bmatrix}$$

Magnitude:

$$\left|\nabla f(x,y)\right| = \left[G_x^{\,2} + G_y^{\,2}\right]^{1/2} \approx \left|G_x\right| + \left|G_x\right|$$

Direction:

$$\angle f(x,y) = \tan^{-1}\left[\frac{G_y}{G_x}\right]$$

Direction of an Edge

- The direction of an edge at a point is orthogonal to the direction of the gradient vector at the point

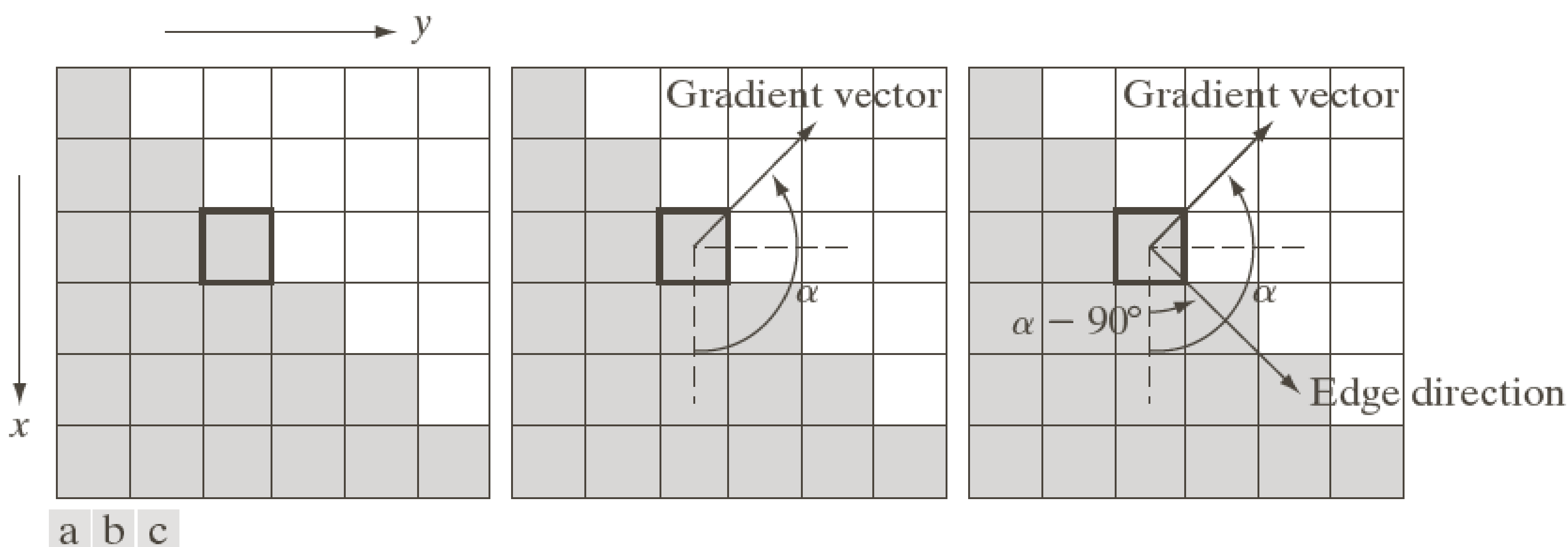


FIGURE 10.12 Using the gradient to determine edge strength and direction at a point. Note that the edge is perpendicular to the direction of the gradient vector at the point where the gradient is computed. Each square in the figure represents one pixel.

a b
c d

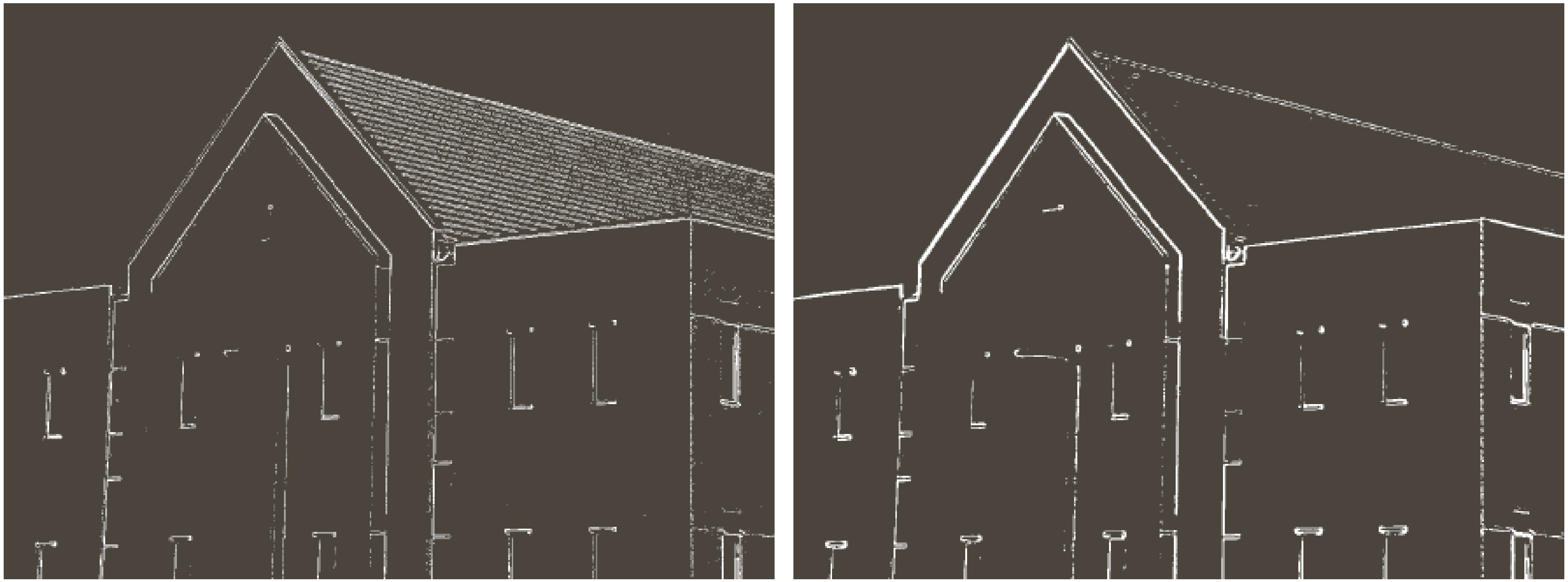
FIGURE 10.16 (a) Original image of size 834×1114 pixels, with intensity values scaled to the range [0, 1]. (b) $|g_x|$, the component of the gradient in the x-direction, obtained using the Sobel mask in Fig. 10.14(f) to filter the image. (c) $|g_y|$, obtained using the mask in Fig. 10.14(g). (d) The gradient image, $|g_x| + |g_y|$.

a b
c d

FIGURE 10.18 Same sequence as in Fig. 10.16, but with the original image smoothed using a 5×5 averaging filter prior to edge detection.

a b

FIGURE 10.19 Diagonal edge detection. (a) Result of using the mask in Fig. 10.15(c). (b) Result of using the mask in Fig. 10.15(d). The input image in both cases was Fig. 10.18(a).



a b

FIGURE 10.20 (a) Thresholded version of the image in Fig. 10.16(d), with the threshold selected as 33% of the highest value in the image; this threshold was just high enough to eliminate most of the brick edges in the gradient image. (b) Thresholded version of the image in Fig. 10.18(d), obtained using a threshold equal to 33% of the highest value in that image.

Canny Edge Detector

(*J. Canny'1986*)

Original image

↓

Smoothing by Gaussian convolution

↓

Differential operators along x and y axis

↓

Non-maximum suppression
finds peaks in the image gradient

↓

Hysteresis thresholding locates edge strings

↓

Edge map

Canny Edge Detector (smoothing and enhancement)

CANNY_ENHANCER

Given image I

1. Apply Gaussian Smoothing to I.
2. For each pixel (i, j):
    1. Compute the gradient components $I_x = \frac{\partial I}{\partial x}, I_y = \frac{\partial I}{\partial y}$
    2. Estimate the edge strength $\sqrt{I_x^2 + I_y^2}$
    3. Estimate the orientation of the edge normal

$$tan^{-1}\frac{I_x}{I_y}$$

Canny Edge Detector (Nonmaximum suppression)

The input is the output of CANNY_ENHANCER. We need to thin the edges. Given Es, Eo, the edge strength and orientation images. For each pixel (i, j),

1. Find the direction best approximate the direction Eo(i, j).
2. If Es(i, j) is smaller than at least one of its two neighbors along this direction, suppress this pixel.

The output is an image of the thinned edge points after suppressing nonmaxima edge points.

Canny Edge Detector (Hysteresis Thresholding)

Performs edge tracking and reduces the probability of false contours.

Input I is the output of nonmaximum_suppression, Eo and two threshold parameters

Scan I in a fixed order:

$$\tau_l < \tau_h$$

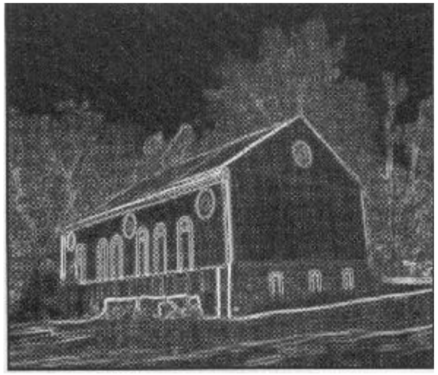
1. Locate the next unvisited edge pixel (i, j) such that I(i, j) $> \tau_h$
2. Starting from (I, j), follow the chains of connected local maxima in both directions perpendicular to the edge normal as long as I $> \tau_l$
3. Marked all visited points and save a list of the locations of all points in the connected contour found.

Hysteresis thresholding

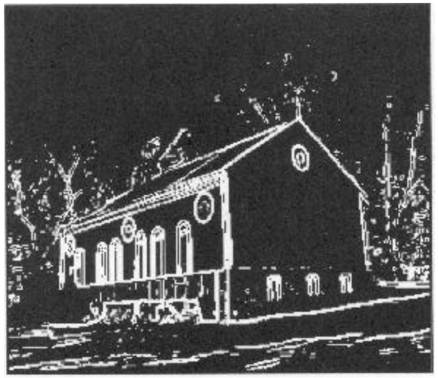
- Standard thresholding:

  - Can only select "strong" edges.
  - Does not guarantee "continuity".

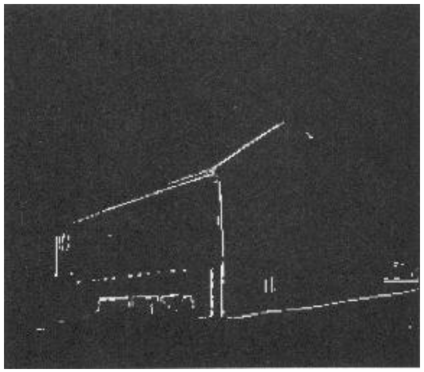
gradient magnitude



low threshold



high threshold



Hysteresis thresholding (cont'd)

- Hysteresis thresholding uses two thresholds:

  - low threshold t_l
  - high threshold t_h (usually, $t_h = 2t_l$)

$$\|\nabla f(x,y)\| \geq t_h \quad \text{definitely an edge}$$

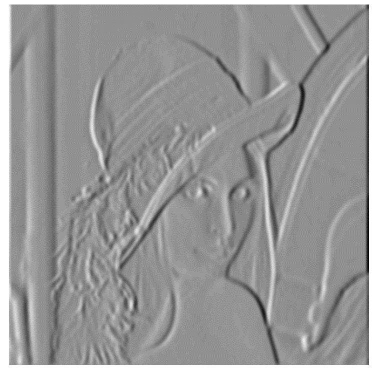
$$t_l \geq \|\nabla f(x,y)\| < t_h \quad \text{maybe an edge, depends on context}$$

$$\|\nabla f(x,y)\| < t_l \quad \text{definitely not an edge}$$

- For "maybe" edges, decide on the edge if <u>neighboring</u> pixel is a strong edge.

Canny Edge Detector Example

original image



vertical edges

horizontal edges

norm of the gradient

after thresholding

after thinning

Image Segmentation

Image Segmentation

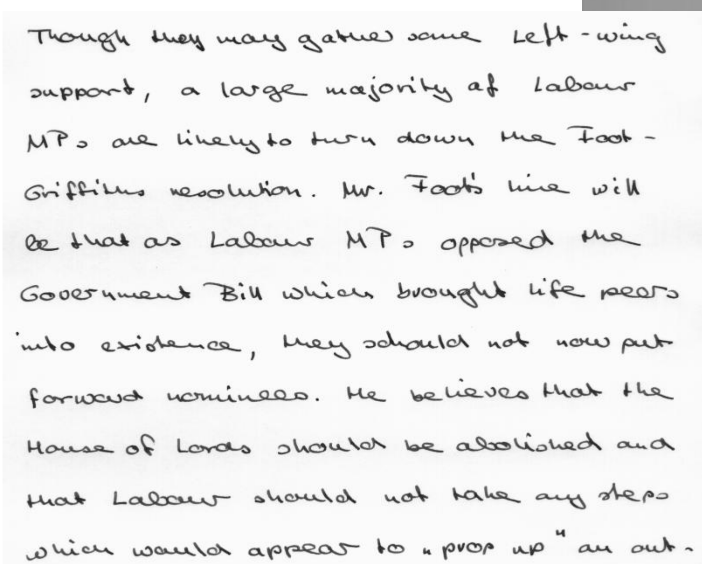
- Group similar components (such as, pixels in an image, image frames in a video)
- Applications: Finding tumors, veins, etc. in medical images, finding targets in satellite/aerial images, finding people in surveillance images, summarizing video, etc.

Image Segmentation

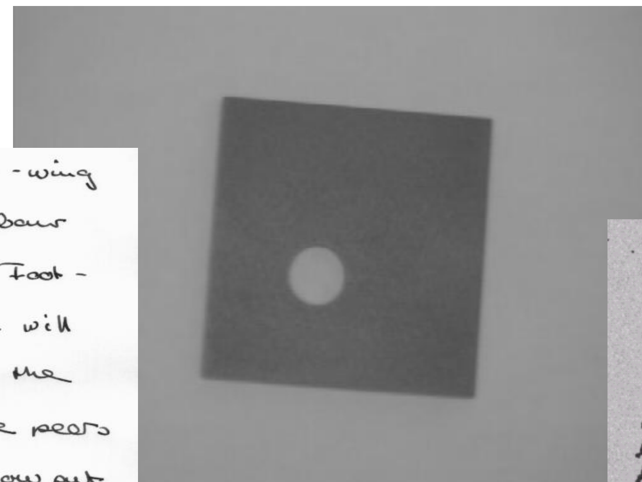
- Segmentation algorithms are based on one of two basic properties of gray-scale values:
  - Discontinuity
    - Partition an image based on abrupt changes in gray-scale levels.
    - Detection of isolated points, lines, and edges in an image.
  - Similarity
    - Thresholding, region growing, and region splitting/merging.

Thresholding

- Segmentation into two classes/groups
  - Foreground (Objects)
  - Background



Though they may gather some Left-wing
support, a large majority of Labour
MPs are likely to turn down the Foot-
Griffiths resolution. Mr. Foot's line will
be that as Labour MPs opposed the
Government Bill which brought life peers
into existence, they should not now put
forward nominees. He believes that the
House of Lords should be abolished and
that Labour should not take any steps
which would appear to "prop up" an out-



Thresholding

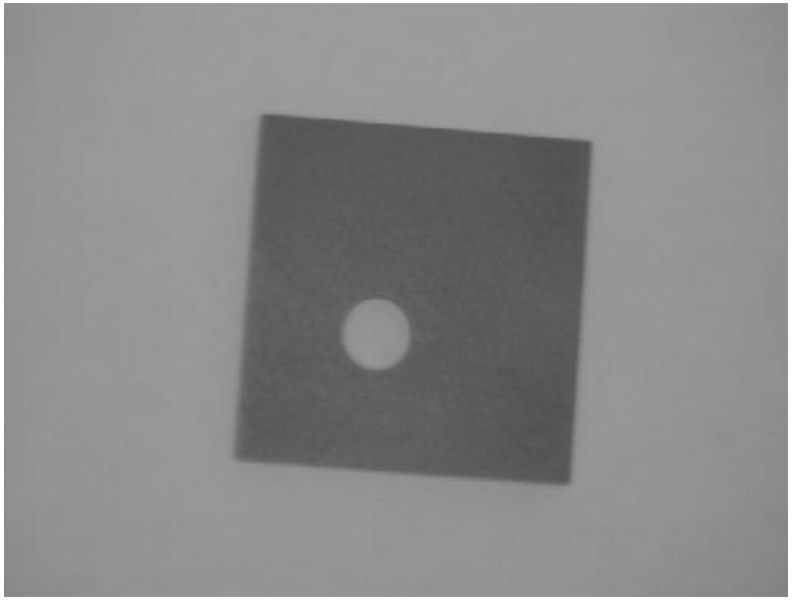
$$g(x,y)=\begin{cases}1 & if \;\; f(x,y)>T \\ 0 & if \;\; f(x,y)\le T\end{cases}$$

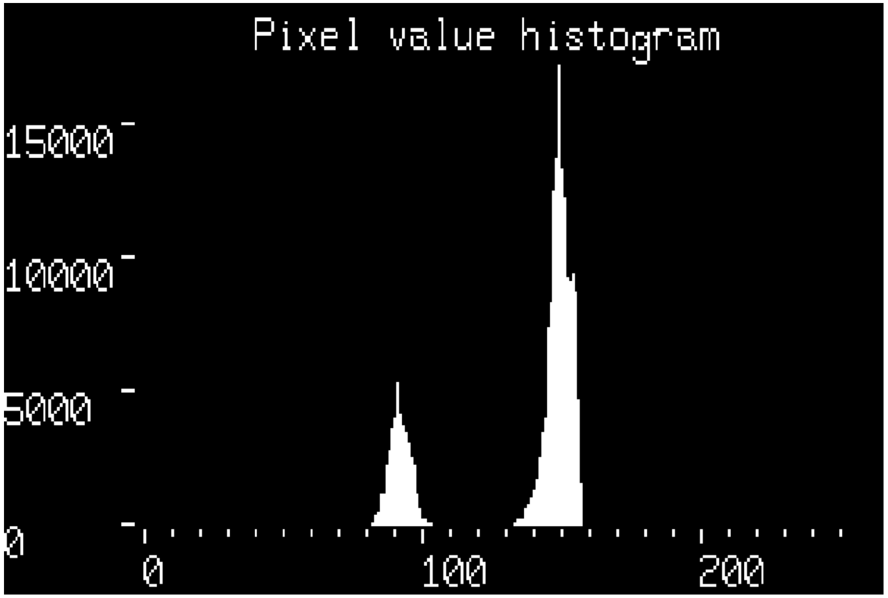
Objects & Background

- Global Thresholding
- Local/Adaptive Thresholding

Global Thresholding

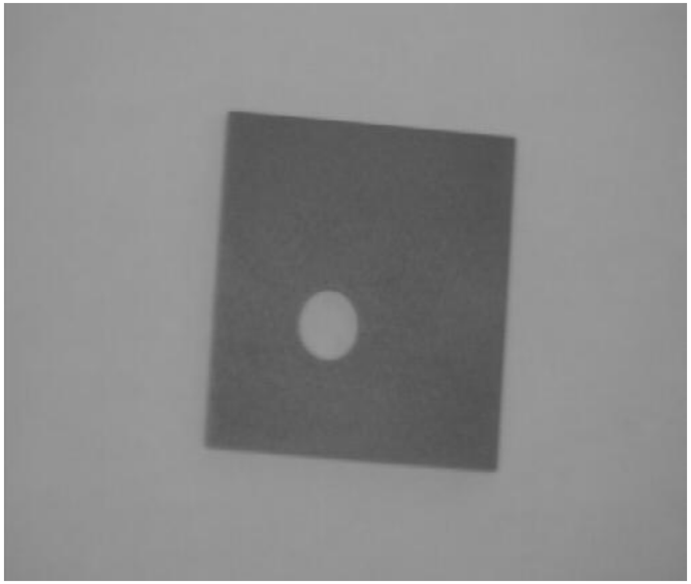
- Single threshold value for entire image
- Fixed ?
- Automatic
  - Intensity histogram

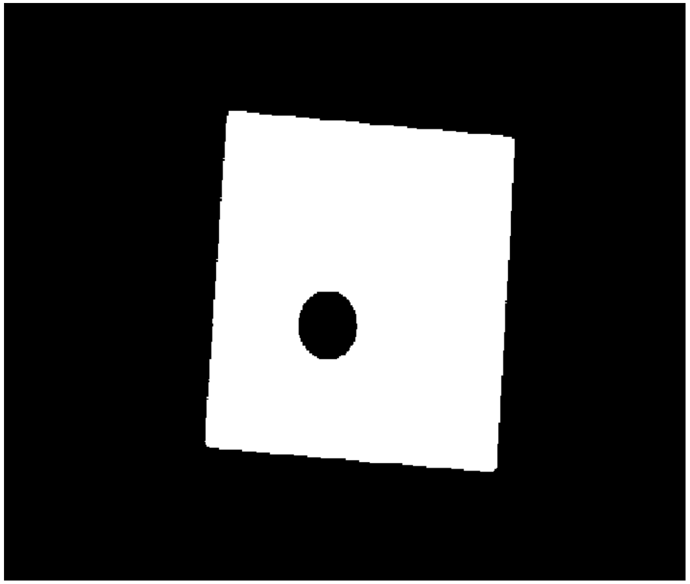




Global Thresholding

- Single threshold value for entire image
- Fixed ?
- Automatic
  - Intensity histogram

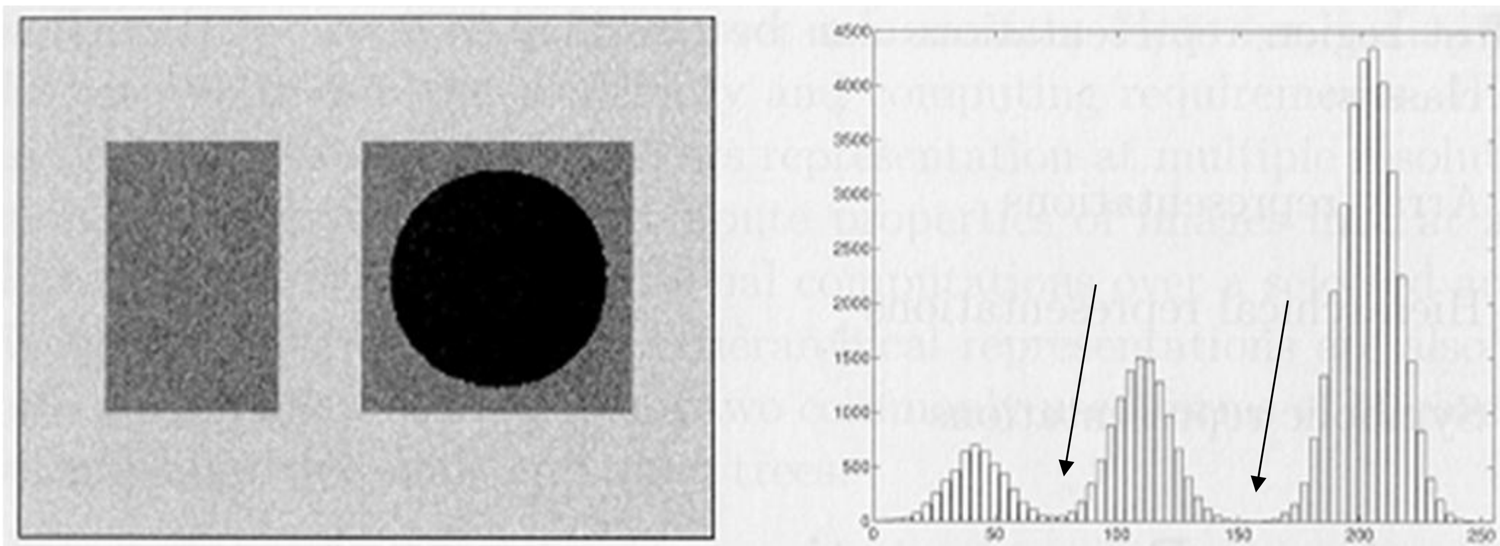




Global Thresholding

- Estimate an initial T
- Segment Image using T: Two groups of pixels G1 and G2
- Compute average gray values m1 and m2 of two groups
- Compute new threshold value T=1/2(m1+m2)
- Repeat steps 2 to 4 until: abs(T_i – T_{i-1})<epsilon

Global Thresholding

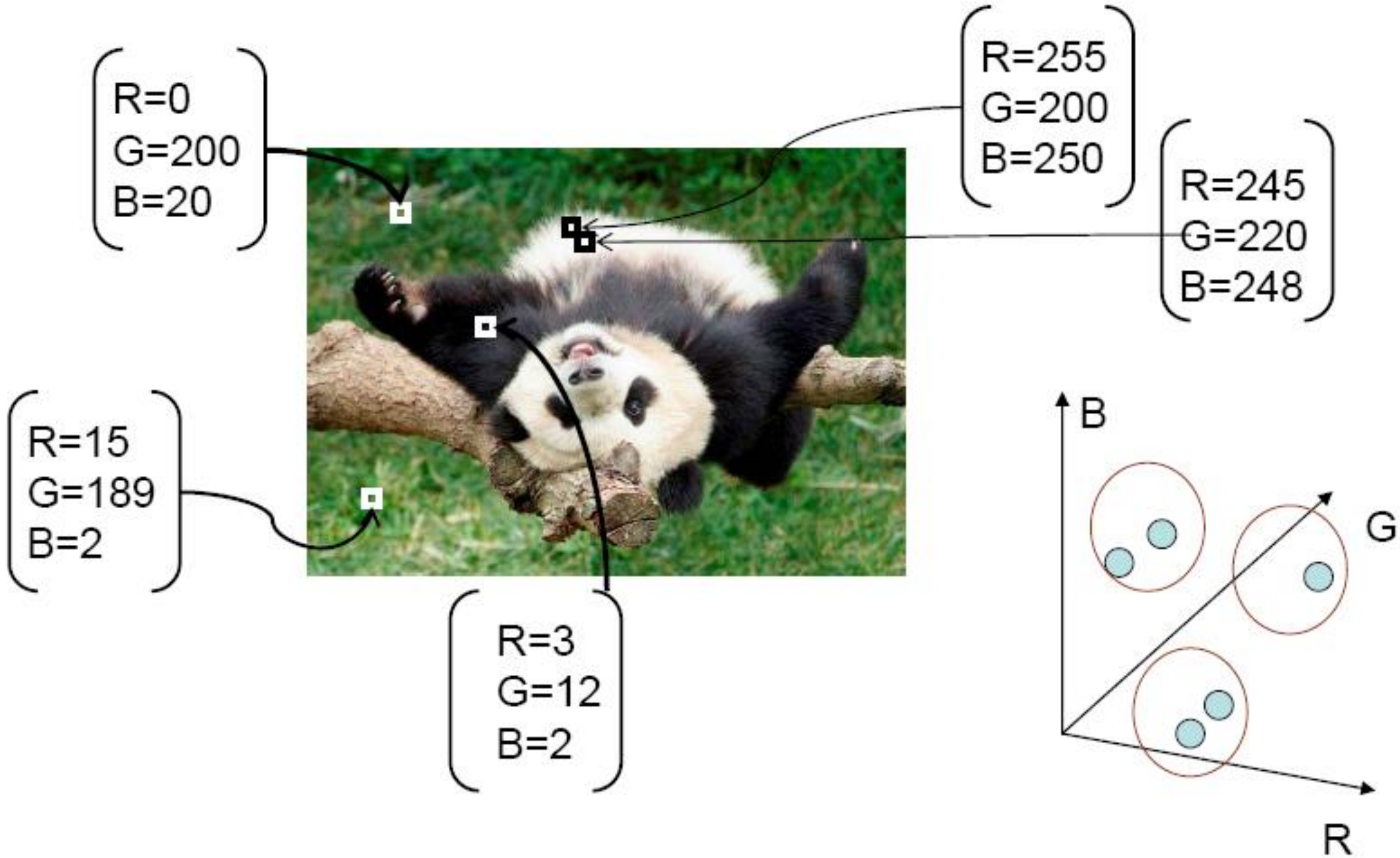


Multilevel thresholding

Cluster Analysis

Segmentation as clustering

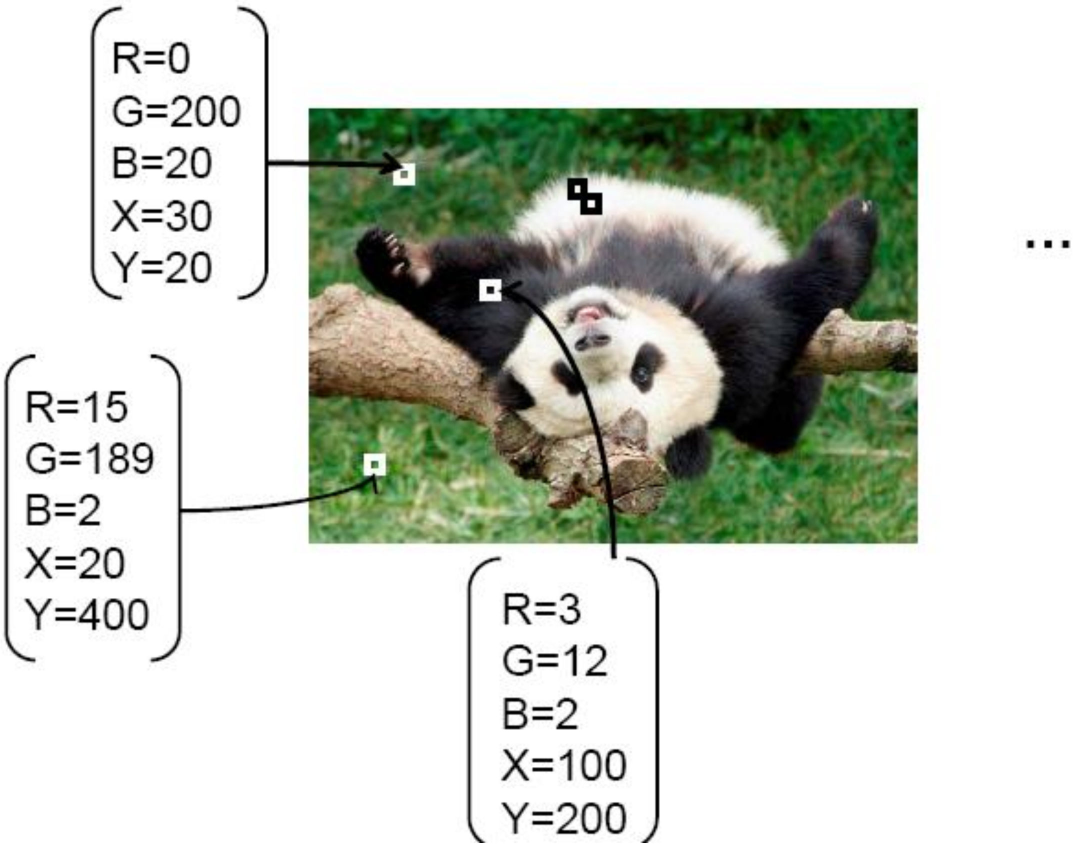
- Cluster similar pixels (features) together



Source: K. Grauman

Segmentation as clustering

- Cluster similar pixels (features) together

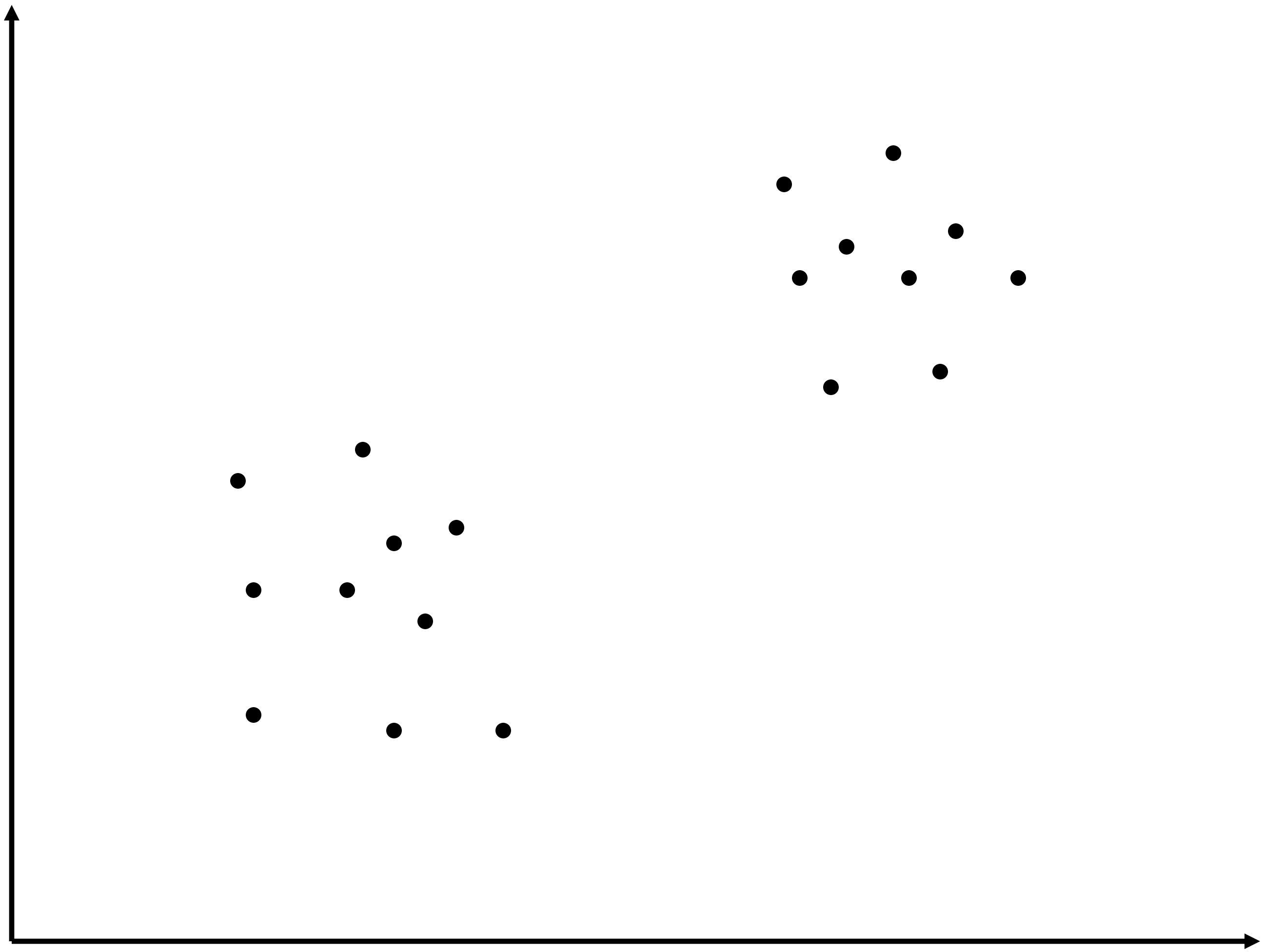


Source: K. Grauman

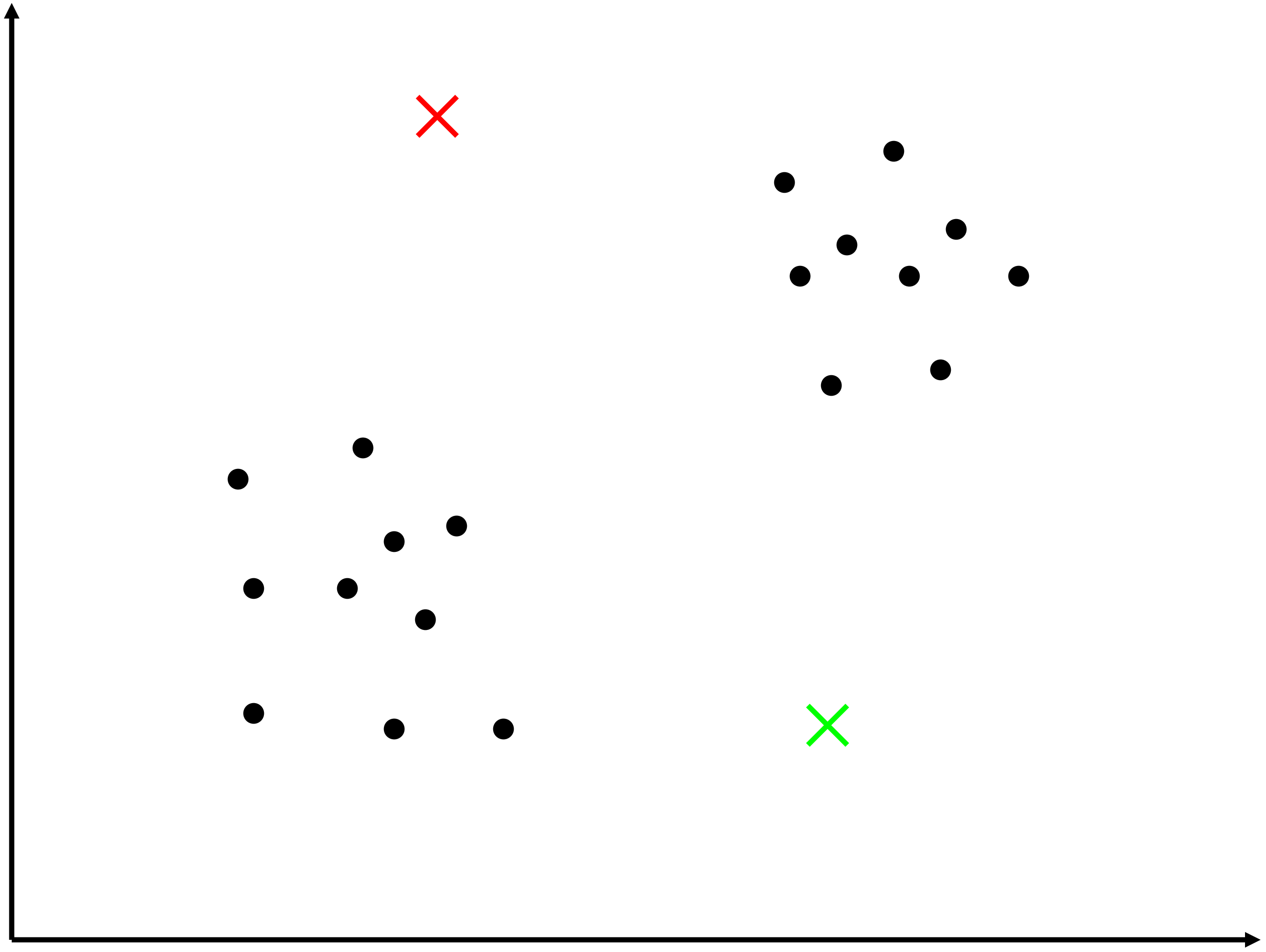
K-Means Clustering

1. Chose the number (K) of clusters and randomly select the centroids of each cluster.
2. For each data point:
   - Calculate the distance from the data point to each cluster.
   - Assign the data point to the closest cluster.
3. Recompute the centroid of each cluster.
4. Repeat steps 2 and 3 until there is no further change in the assignment of data points (or in the centroids).

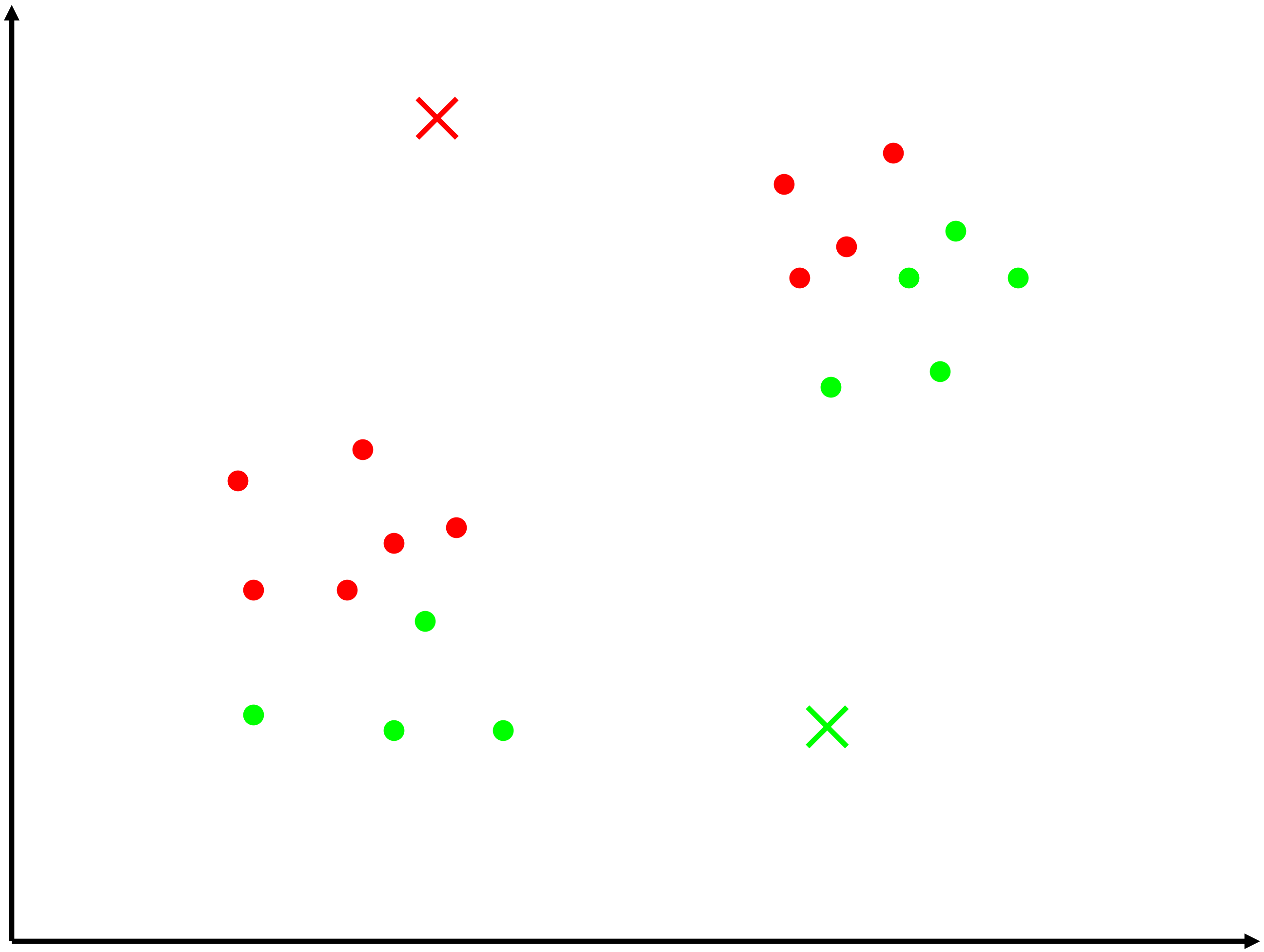
K-Means Clustering



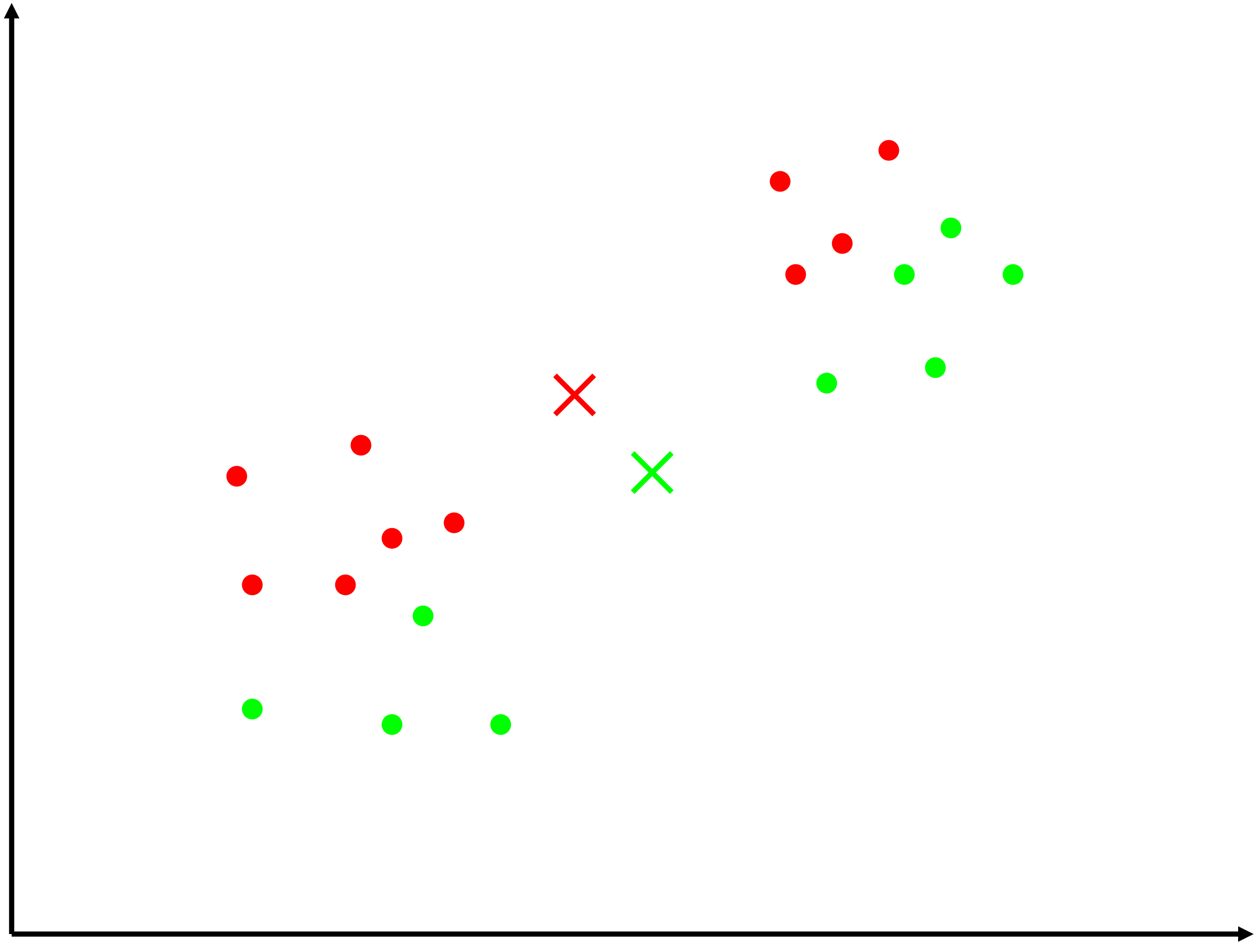
K-Means Clustering



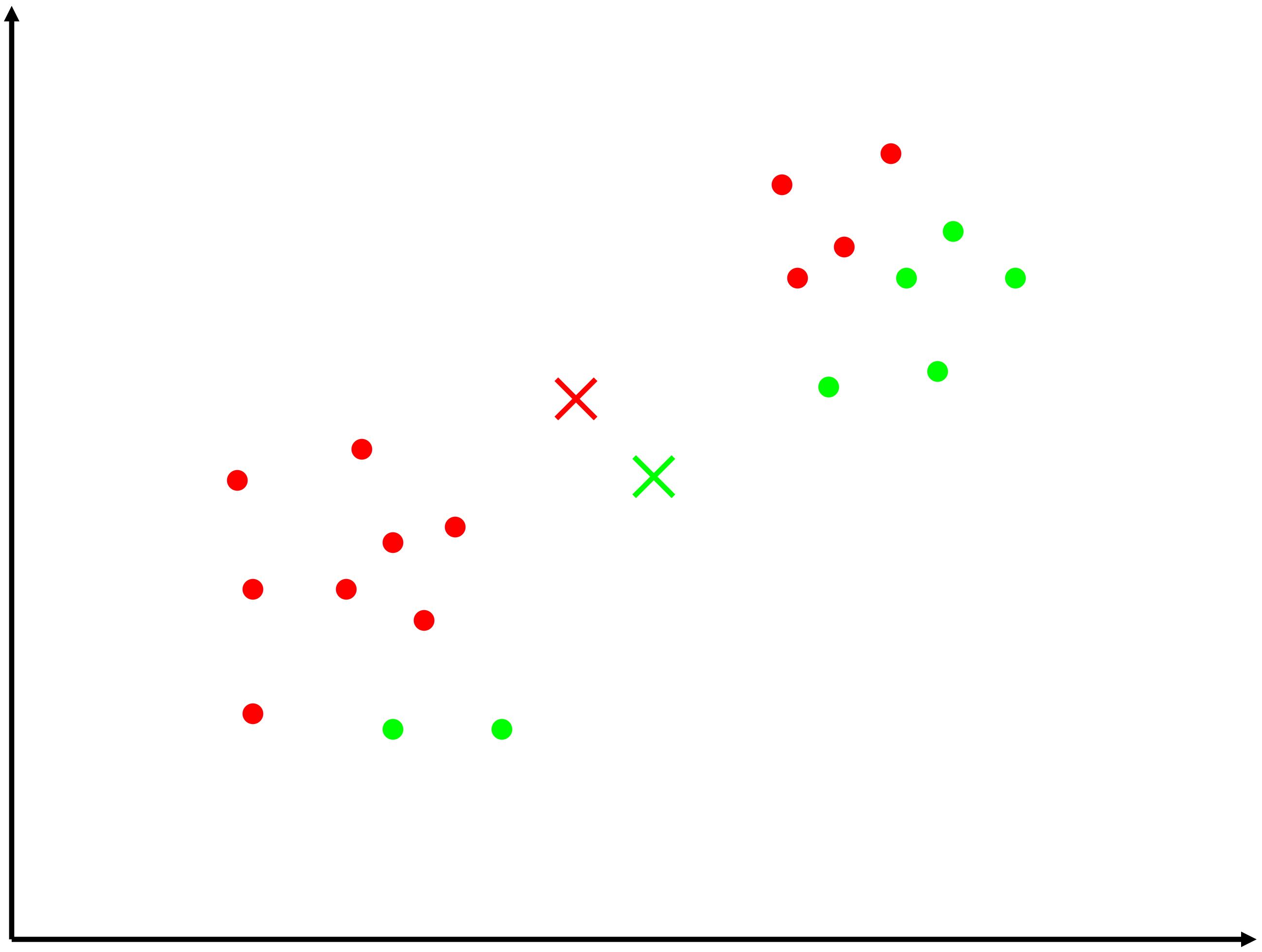
K-Means Clustering



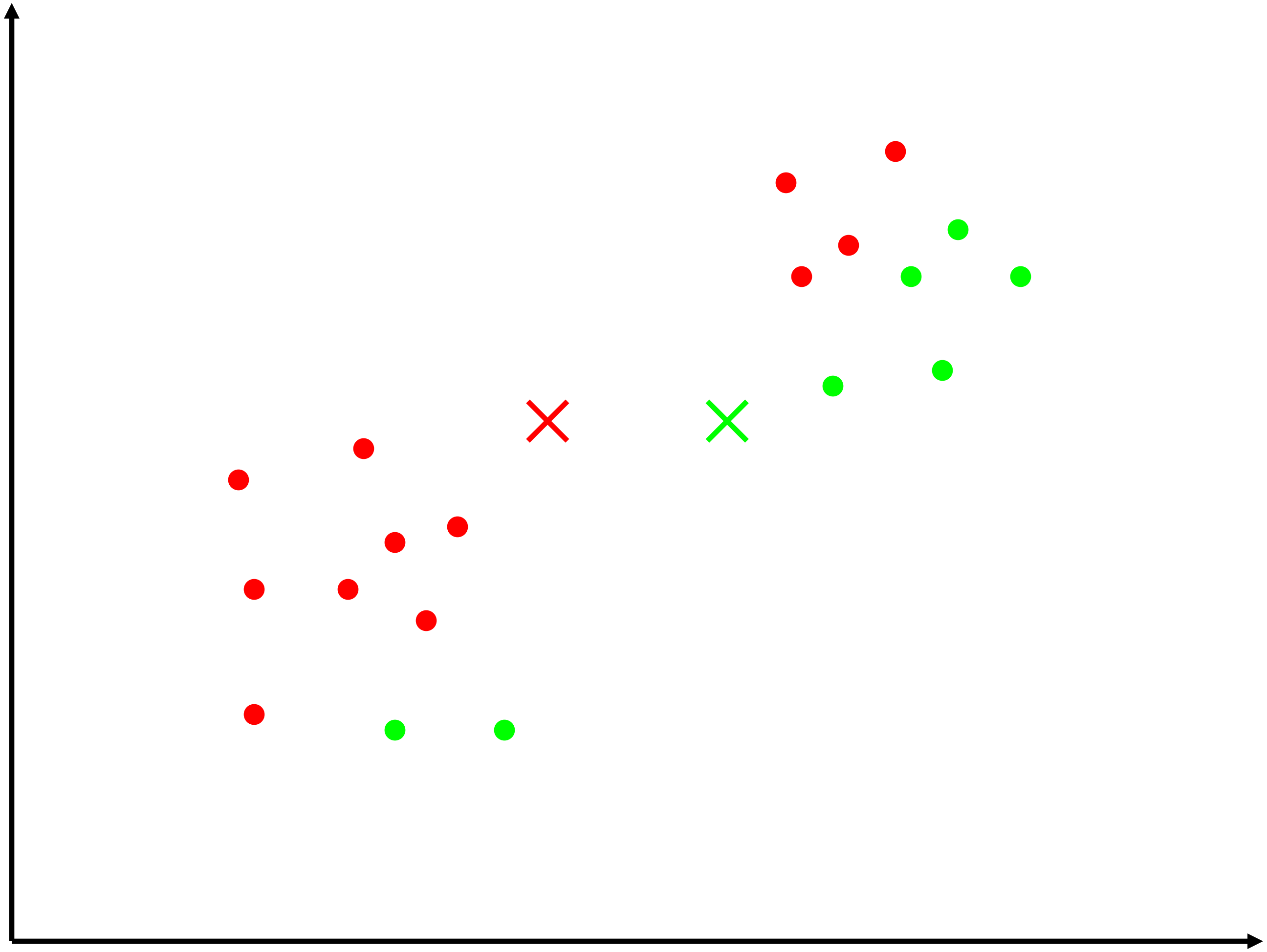
K-Means Clustering



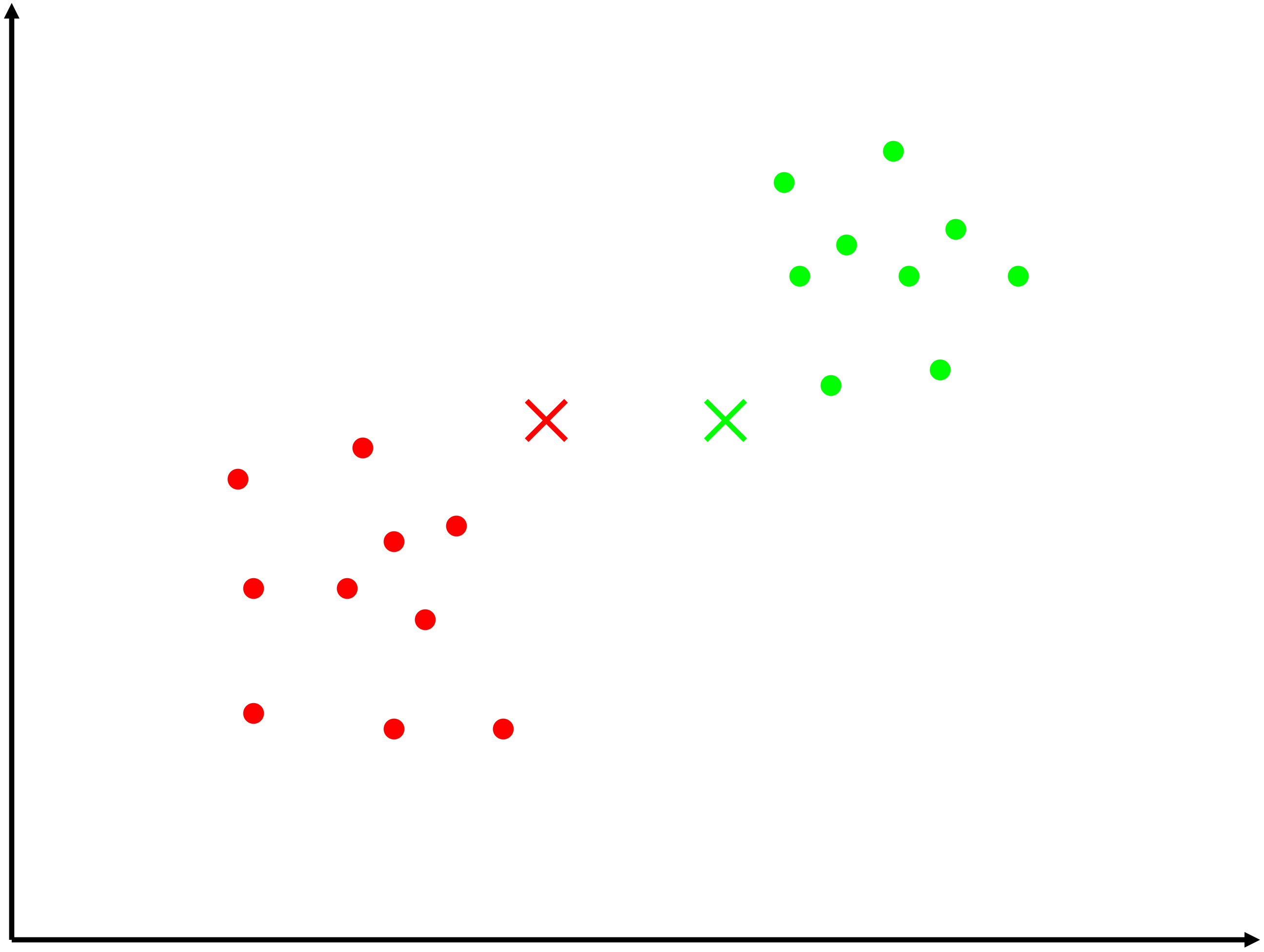
K-Means Clustering



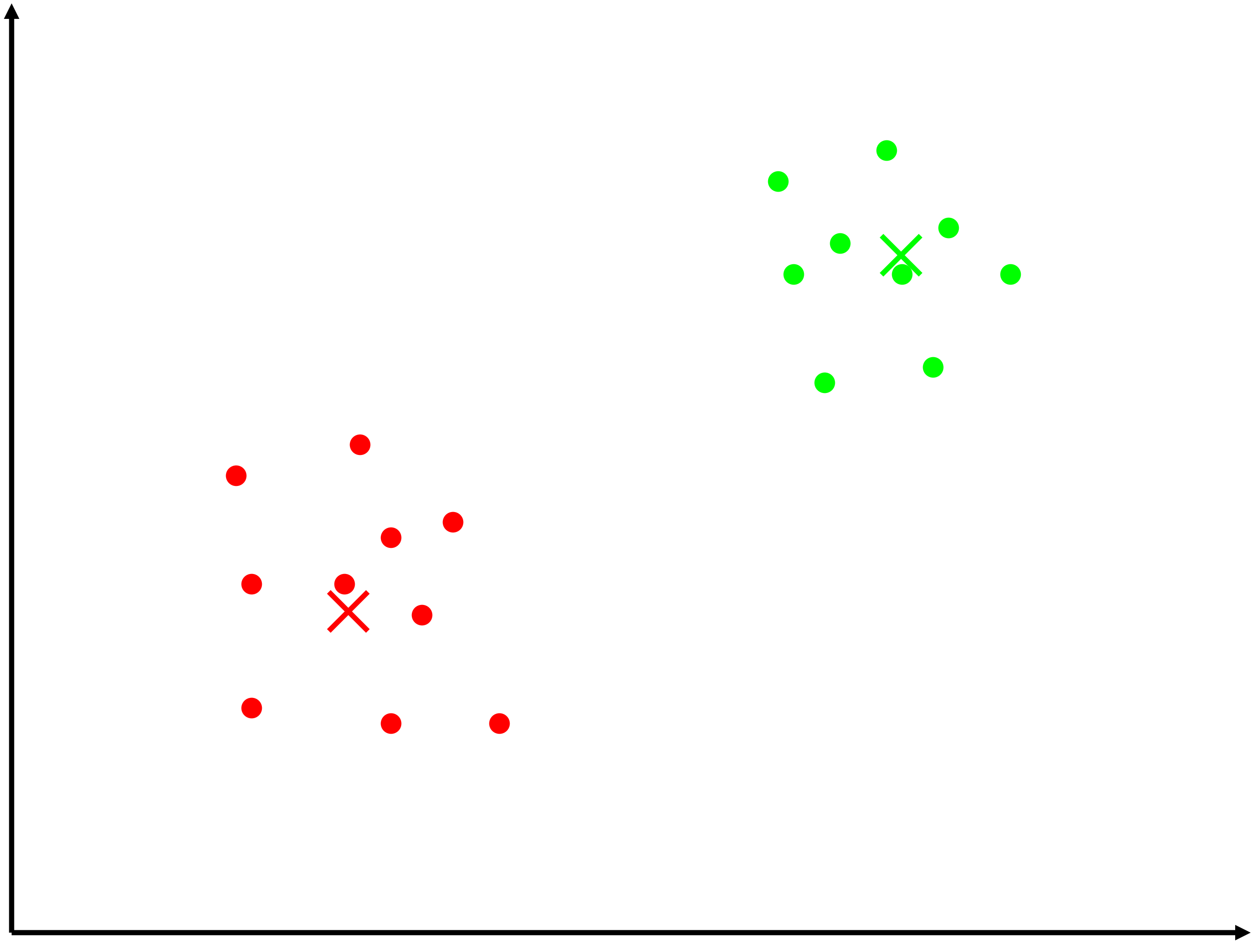
K-Means Clustering



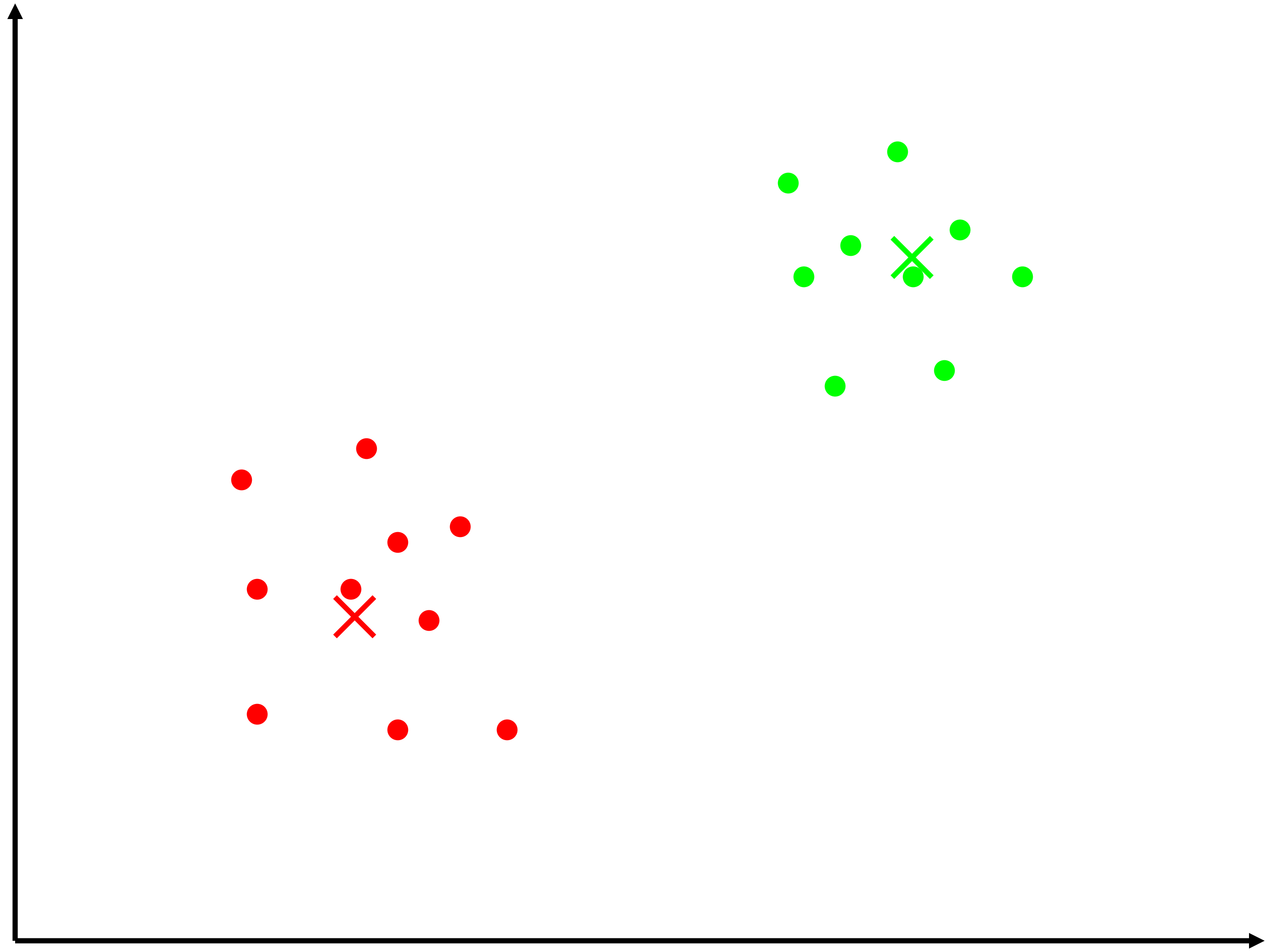
K-Means Clustering



K-Means Clustering

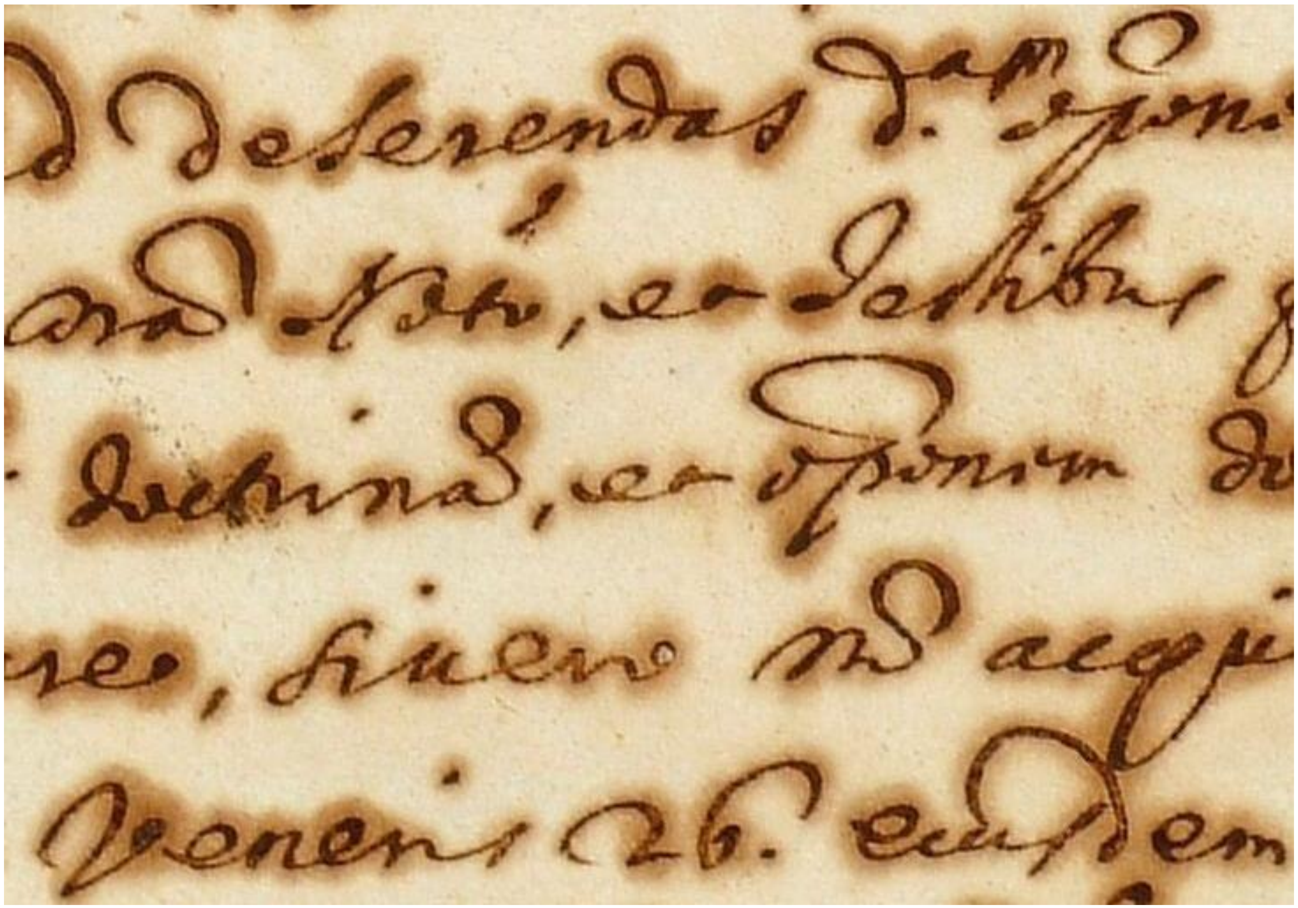


K-Means Clustering



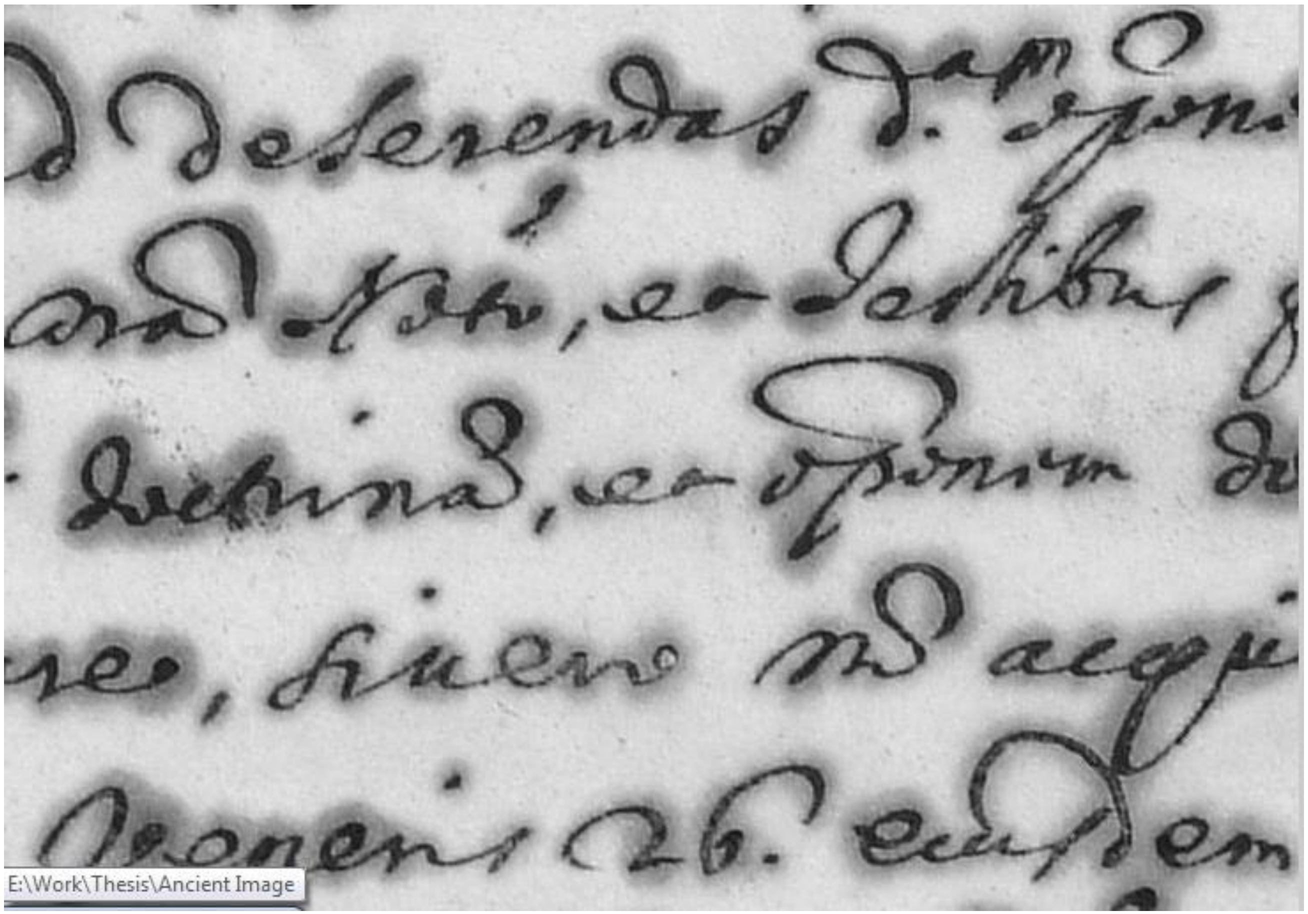
Clustering

- Example



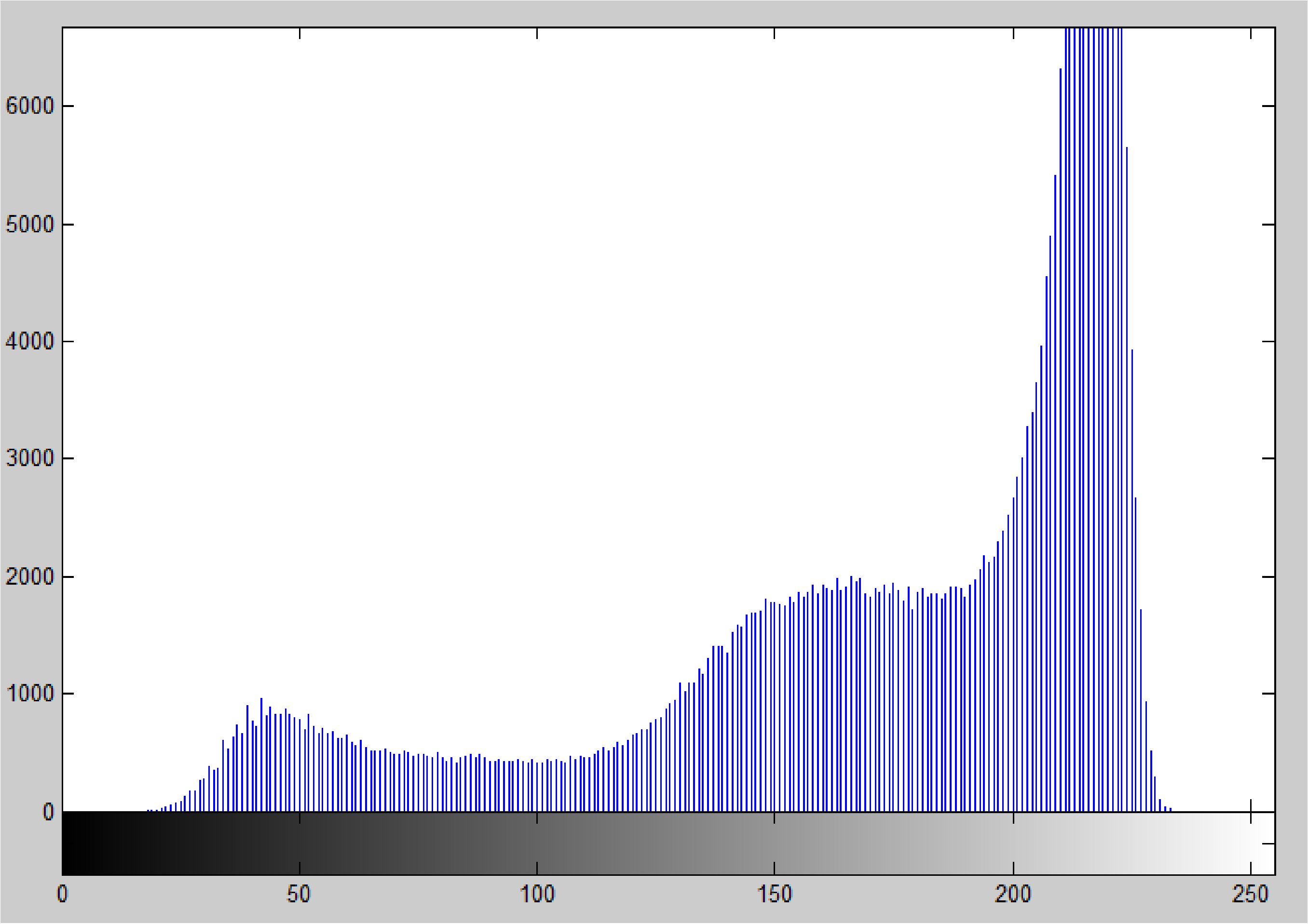
Clustering

- Example



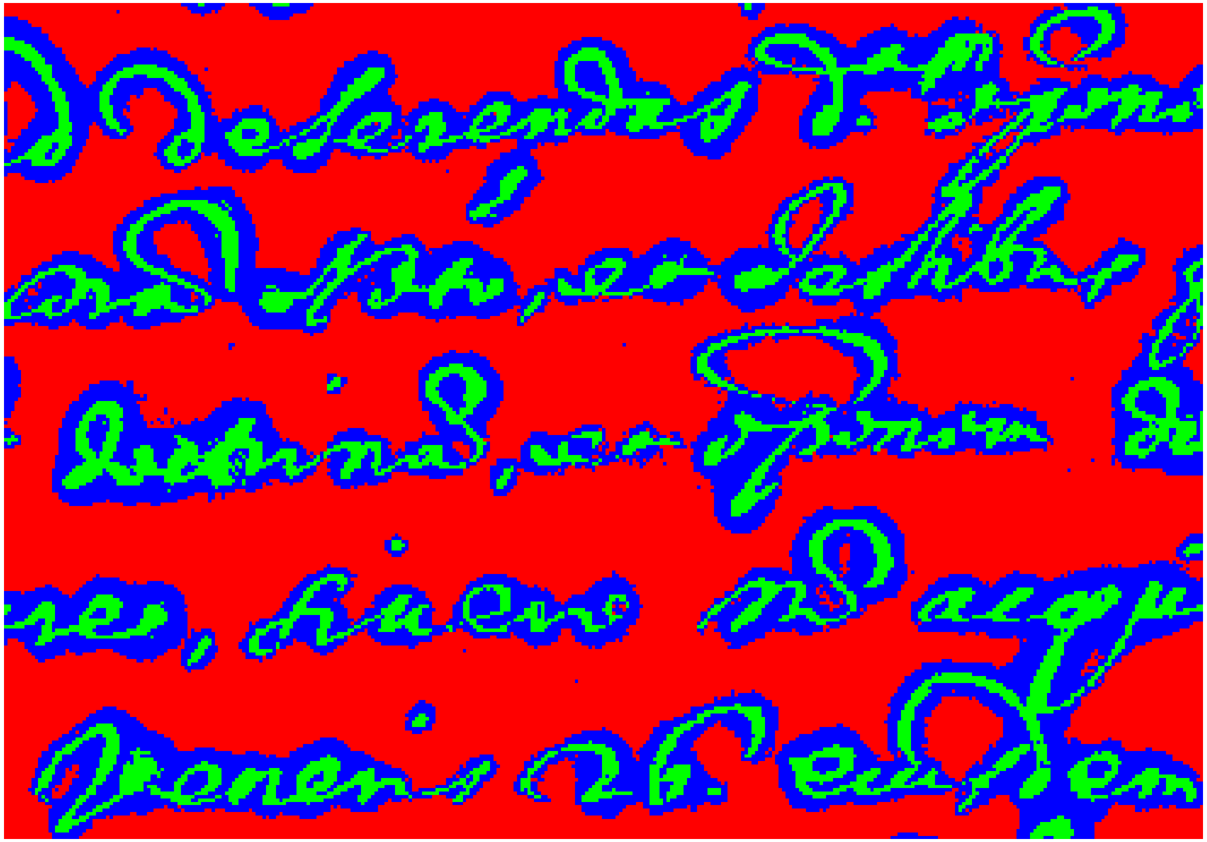
Clustering

- Example



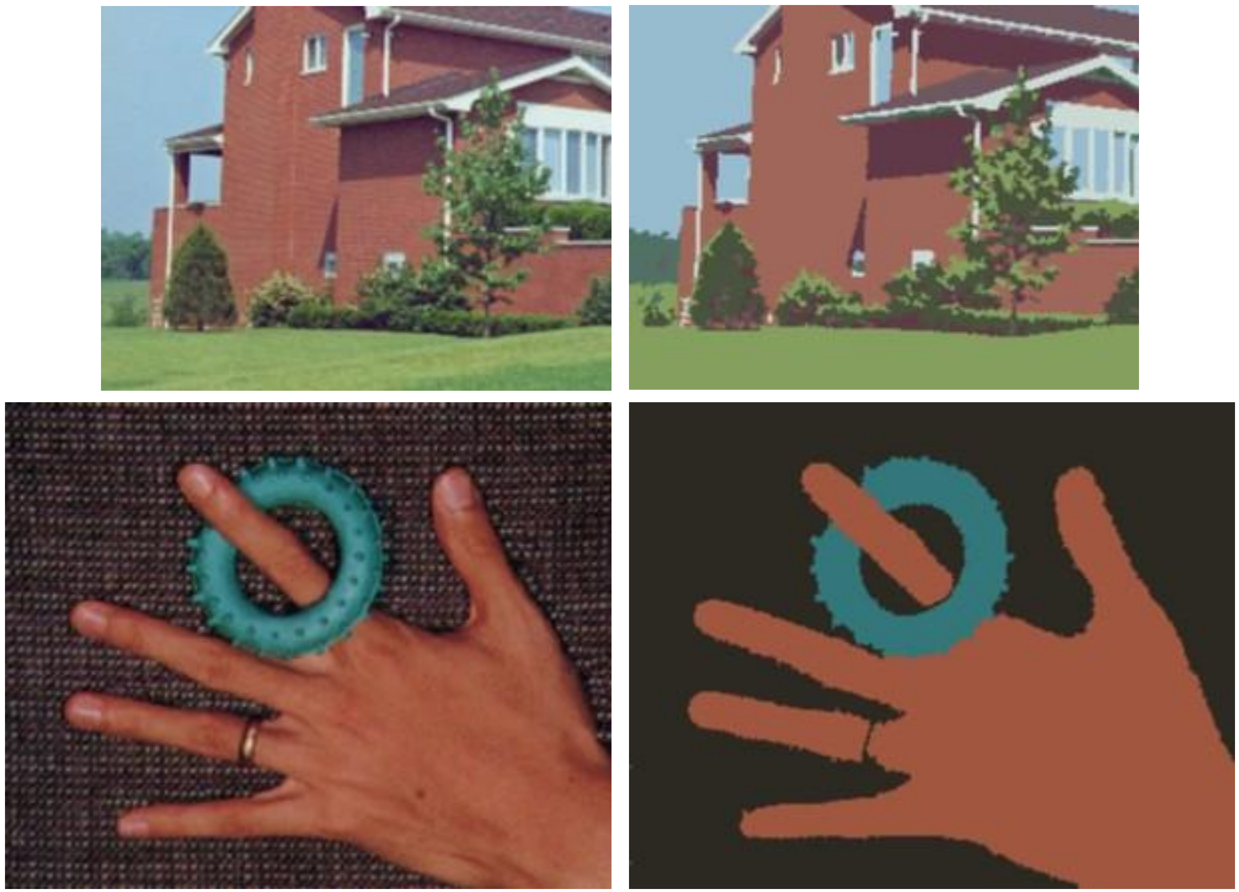
Clustering

- Example



Clustering

- Example



D. Comaniciu and P. Meer, *Robust Analysis of Feature Spaces: Color Image Segmentation*, 1997.

K-Means Clustering

- Example

Original

K=5

K=11