22 - Segmentasi Citra (Bagian 1)

IF4073 Interpretasi dan Pengolahan Citra

Oleh: Rinaldi Munir

Program Studi Teknik Informatika
Sekolah Teknik Elektro dan Informatika
Institut Teknologi Bandung
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Segmentasi Citra

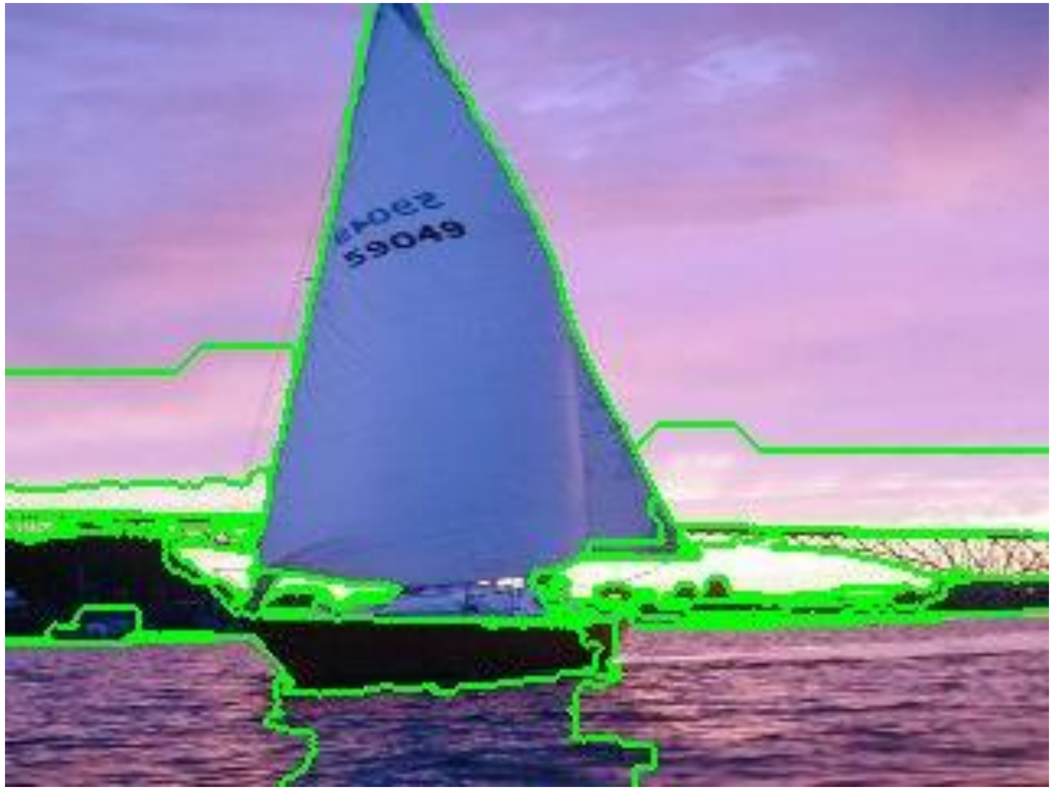
Segmentasi citra adalah operasi mempartisi citra menjadi sebuah koleksi yang terdiri dari sekumpulan pixel yang terhubung satu sama lain

1. menjadi region-region, yang biasanya mencakup keseluruhan citra

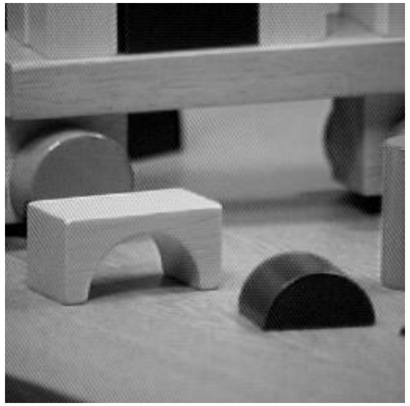
2. menjadi struktur linier, seperti
   - segmen garis
   - segmen kurva

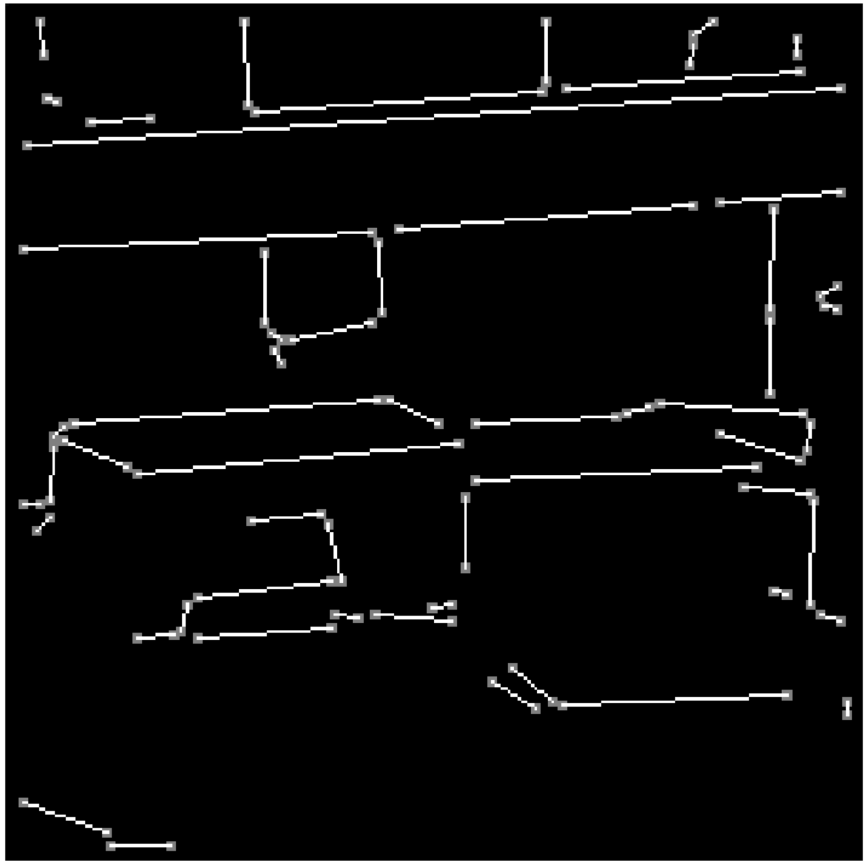
3. Menjadi bentuk-bentuk 2D, seperti
   - lingkaran
   - elips
   - kotak, dll

Contoh 1: Region



Contoh 2: Garis lurus



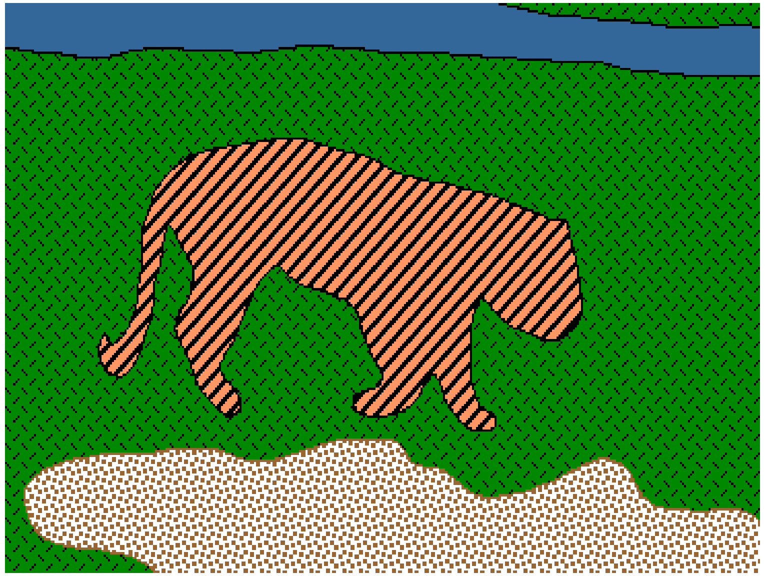


Metode:
- Edge detection
- Hough transformation

Contoh 2:
Garis dan lingkaran

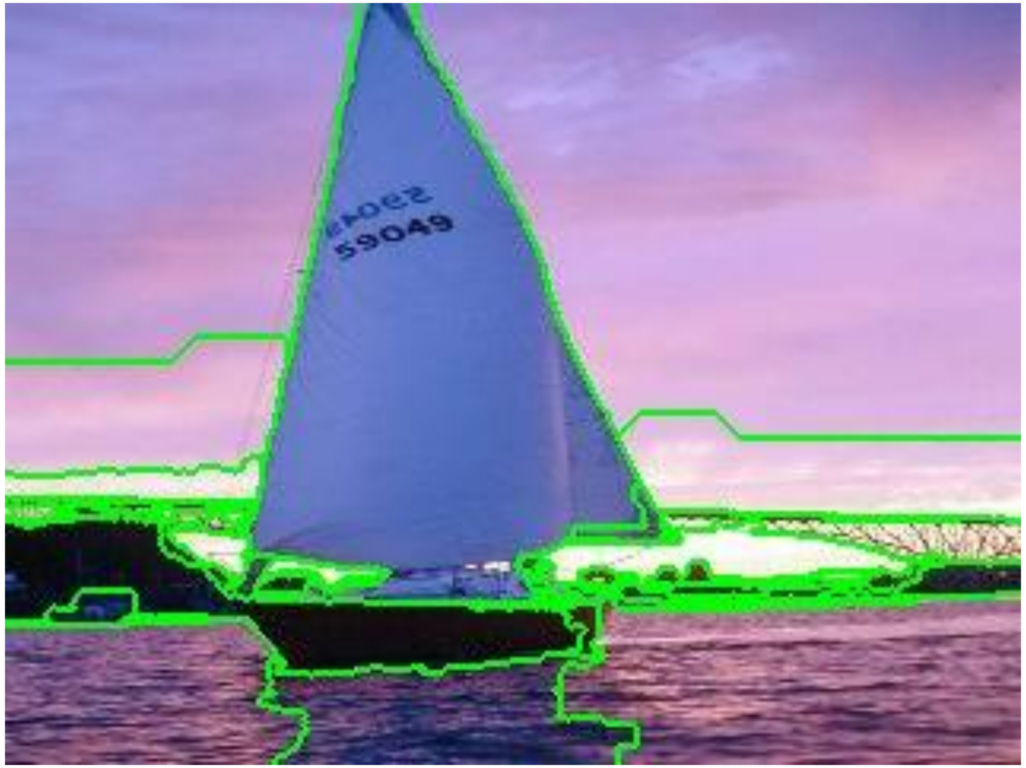
Metode:
- Edge detection
- Hough transformation

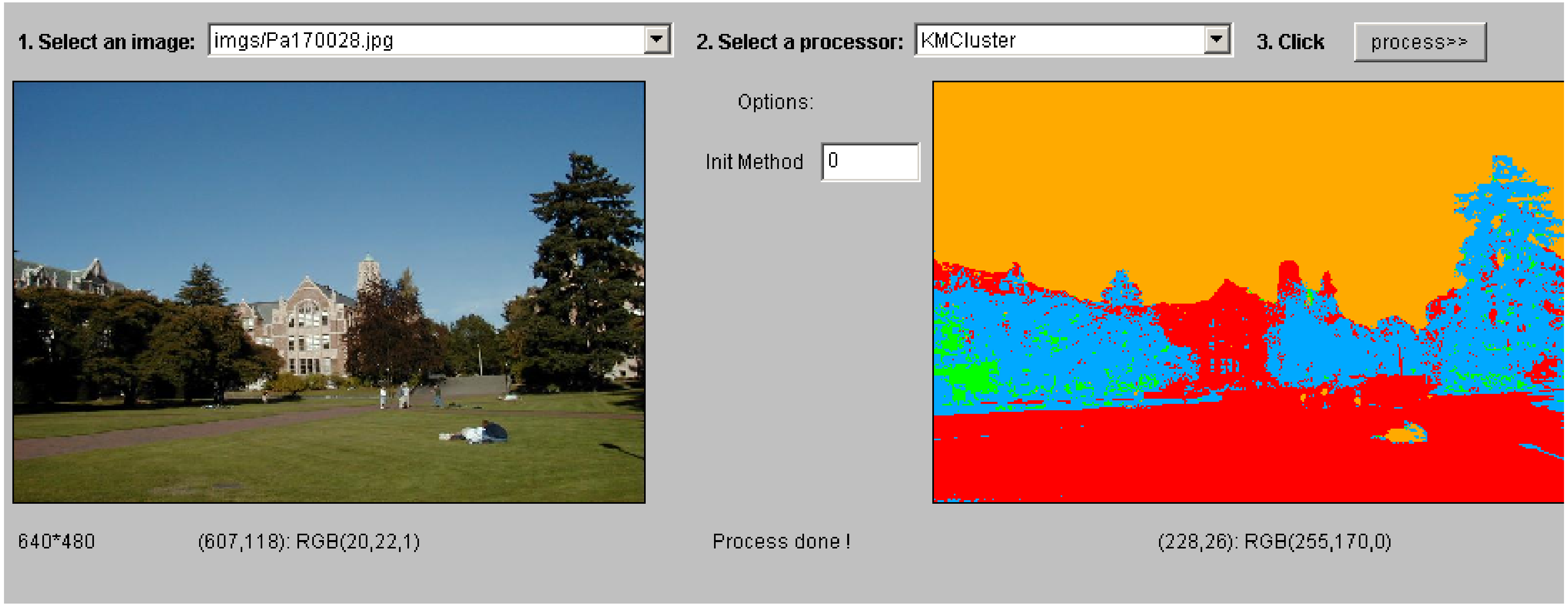
- Segmentasi citra (*image segmentation*) menjadi sejumlah region bertujuan untuk:
  1. membagi citra menjadi semen-segmen atau objek-objek yang berbeda.
  2. memisahkan objek dengan latar belakang

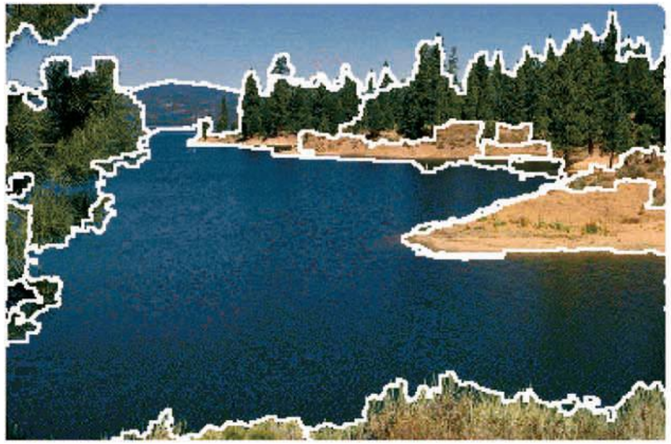


- Dengan membagi citra menjadi sejumlah segmeb, kita dapat memproses hanya segmen penting atau segmen tertentu di dalam citra daripada memproses seluruh bagian citra

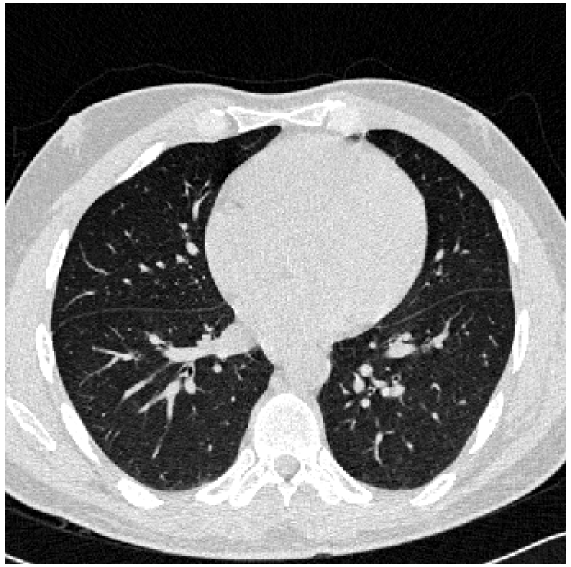
- Goal segmentasi citra adalah menemukan bagian citra yang koheren atau objek spesifik.
- Citra disegmentasi berdasarkan properti yang dipilih seperti kecerahan, warna, tekstur, dan sebagainya.
- Segmentasi membagi citra menjadi sejumlah region yang terhubung, tiap region bersifat homogen berdasarkan properti yang dipilih.
- Segmentasi citra merupakan tahapan sebelum melakukan *image/object recognition*, *image understanding*, dll.




1. Select an image:
imgs/Pa170028.jpg
2. Select a processor:
KMCluster
3. Click
process>>
Options:
Init Method
0
640*480
(607,118): RGB(20,22,1)
Process done !
(228,26): RGB(255,170,0)



Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation



Citra medis

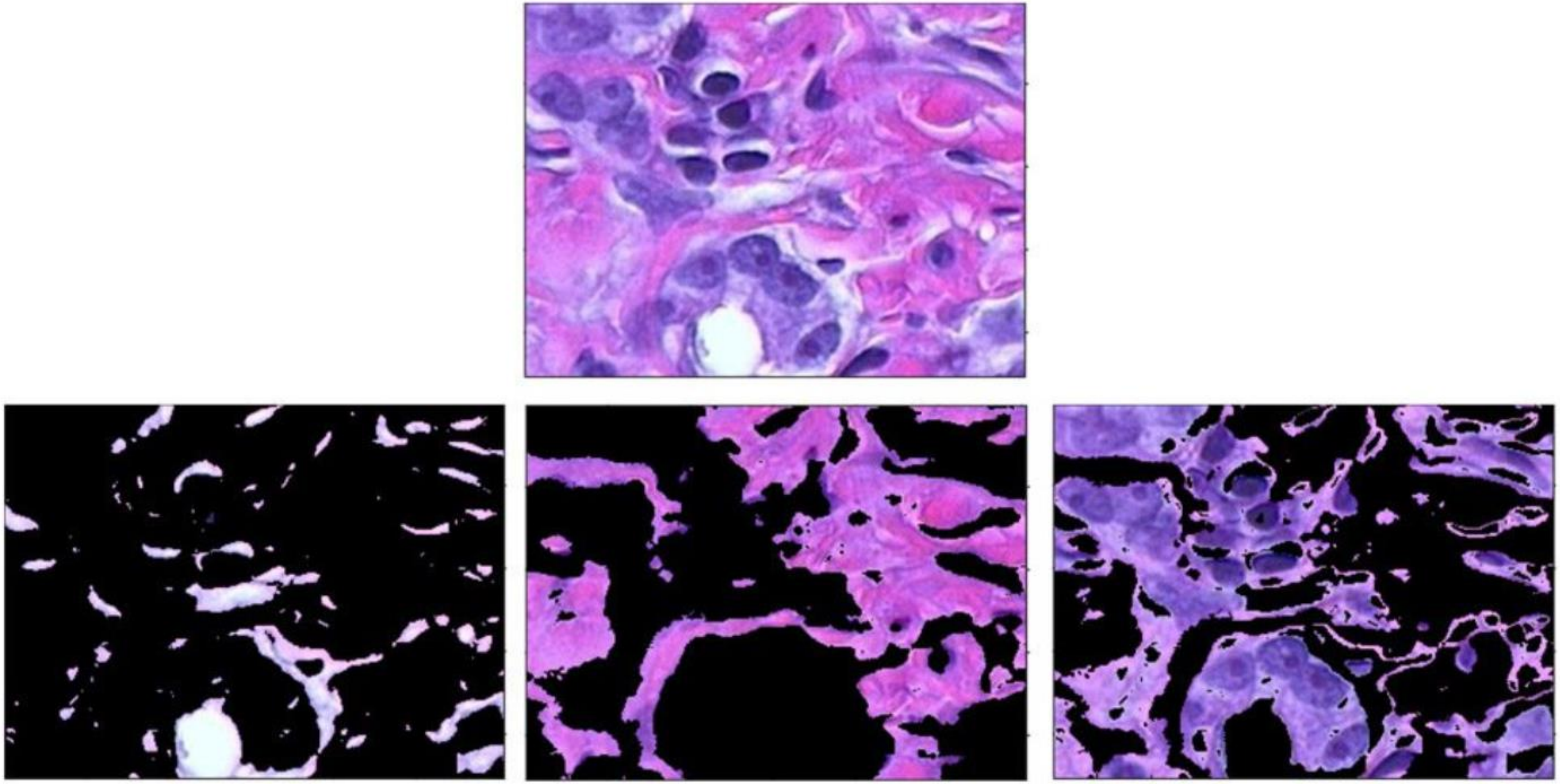
Hasil segmentasi

Beberapa aplikasi segmentasi citra

1. **Medical imaging**

   Selama diagnosis medis untuk kanker, ahli patologi menginjeksi jaringan tubuh dengan hematoxylin dan eosin (H&E) untuk membedakan jenis jaringan.

   Mereka kemudian menggunakan teknik segmentasi gambar yang disebut clustering untuk mengidentifikasi jenis jaringan tersebut dalam gambar mereka.



Menggunakan clustering untuk membedakan jenis jaringan (bawah) pada citra jaringan tubuh (atas) yang diwarnai dengan hematoxylin dan eosin (H&E).

Sumber: https://www.mathworks.com/discovery/image-segmentation.html

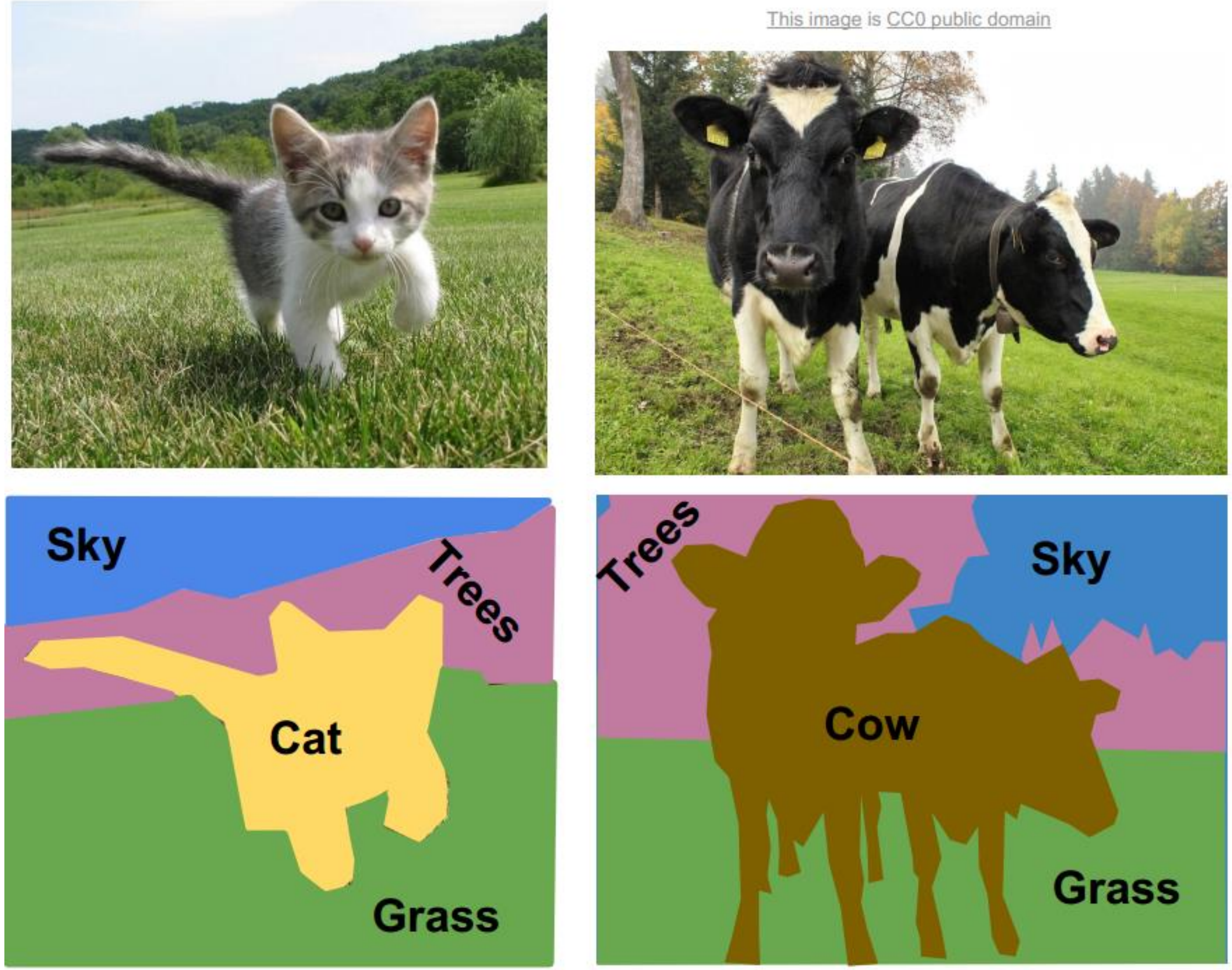
2. Autonomous Vehicle

Saat merancang persepsi untuk kendaraan otonom, seperti mobil self-driving, segmentasi citra digunakan untuk membantu sistem mengidentifikasi dan menemukan kendaraan dan objek lain di jalan.

Menggunakan segmentasi citra untuk mengaitkan setiap piksel gambar dengan label kelas (seperti mobil, jalan, langit, pejalan kaki, atau sepeda).

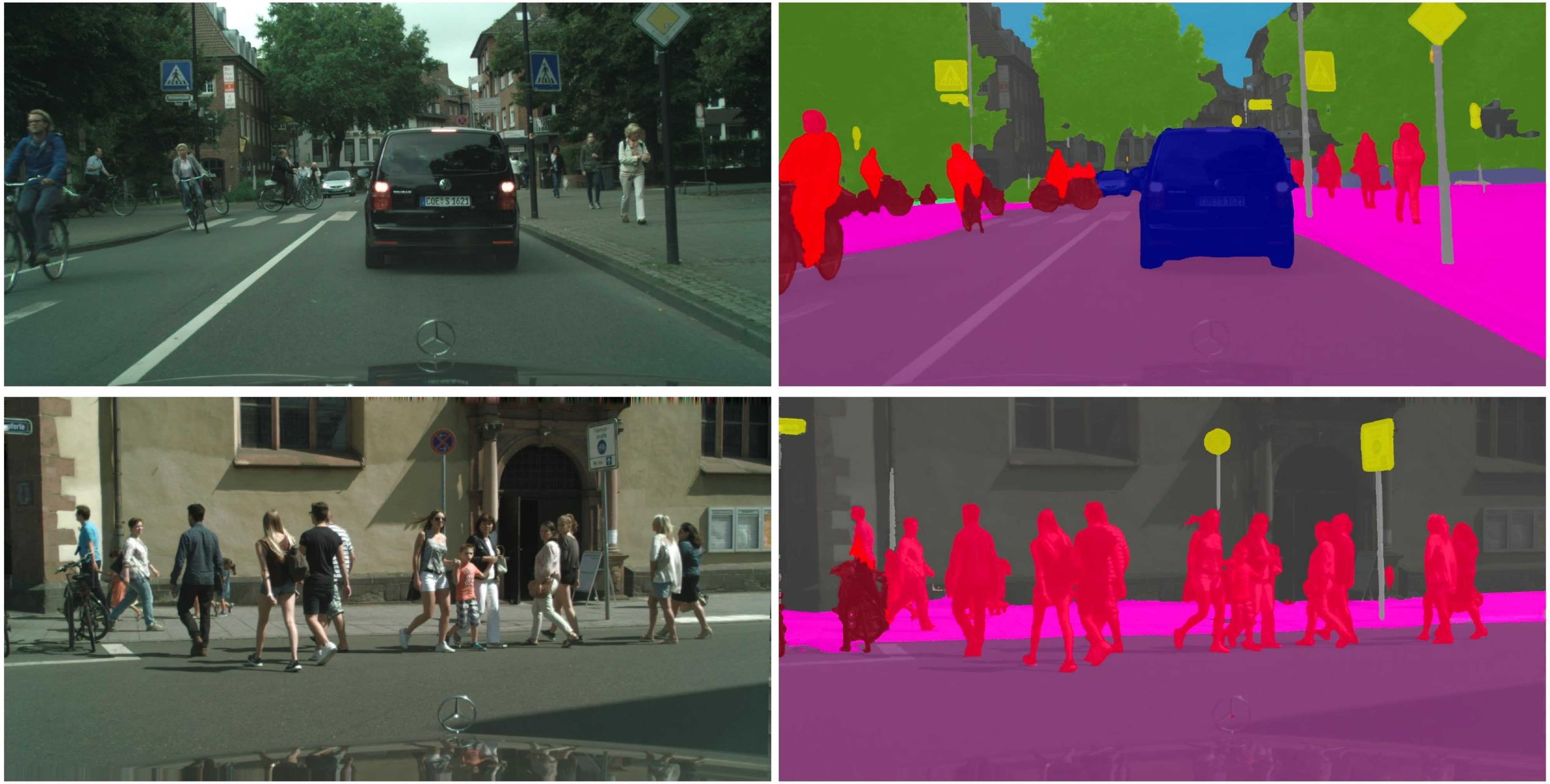
Sumber: https://www.mathworks.com/discovery/image-segmentation.html

3. Object recognition



3. Scene understanding

Mesin dapat memahami apa yang “dilihatnya”



Kriteria Segmentasi

- Menurut Pavlidis:

Segmentasi adalah partisi citra I menjadi sejumlah region S_1, S_2, … S_m
yang memenuhi persyaratan:

1. $\cup S_i = S$ — Partisi mencakup keseluruhan *pixel* di dalam citra.
2. $S_i \cap S_j = \phi$, $i \neq j$ — Tidak ada region yang beririsan.
3. $\forall S_i$, $P(S_i)$ = true — P = Predikat homogenitas, dipenuhi oleh setiap region
4. $P(S_i \cup S_j)$ = false, $i \neq j$, S_i adjacent S_j — Gabungan region bertetangga tidak memenuhi predikat

- Jadi, yang harus dilakukan adalah mendefinisikan dan mengimplementasikan predikat *similarity.*
- Misalnya, *similarity* didasarkan pada pixel-pixel di dalam rentang nilai yang sama.

Metode segmentasi citra

Metode segmentasi citra umumnya dikelompokkan berdasarkan dua pendekatan:

1. *Diskontinuitas*

   Mempartisi citra berdasarkan perubahan nilai intensitas *pixel* yang cepat seperti tepi (*edge detection*)

2. *Similarity*

   Mempartisi citra berdasarkan kemiripan area menurut properti yang ditentukan

   Metode segmentasi citra yang termasuk ke dalam pendekatan ini:

   a) Pengambangan (*thresholding*)

   b) *Region growing*

   c) *Split and merge*

   d) *Clustering*

- Pendeteksian tepi dapat digunakan untuk melakukan segmentasi citra.
- Metode-metode deteksi tepi sudah dibahas pada materi sebelumnya, seperti metode berbasis gradien (Sobel, Prewit, Canny, Roberts, Laplacian, LoG, dll)

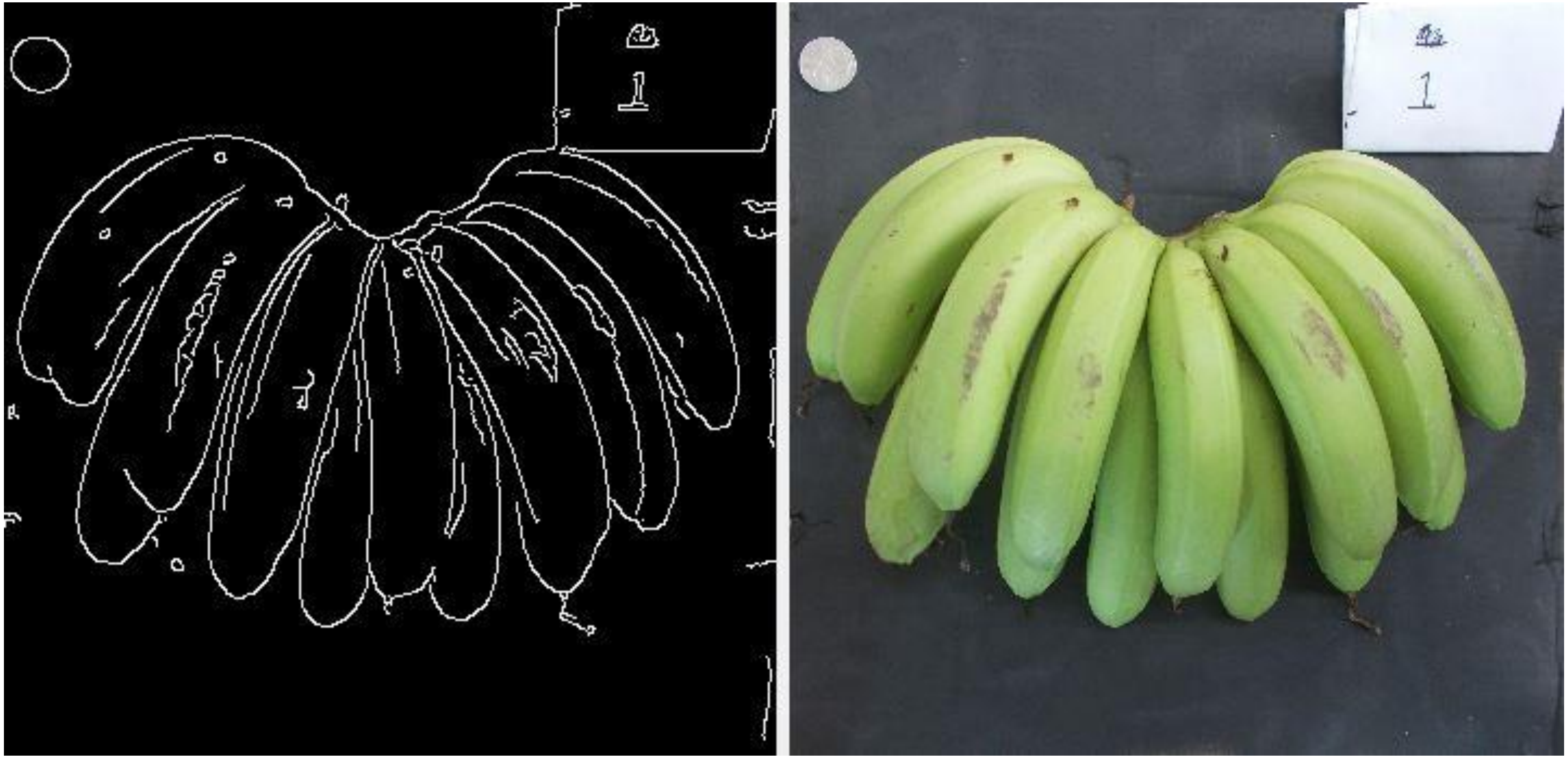
a b
c d

FIGURE 10.10 (a) Original image. (b) $|G_x|$, component of the gradient in the x-direction. (c) $|G_y|$, component in the y-direction. (d) Gradient image, $|G_x| + |G_y|$.



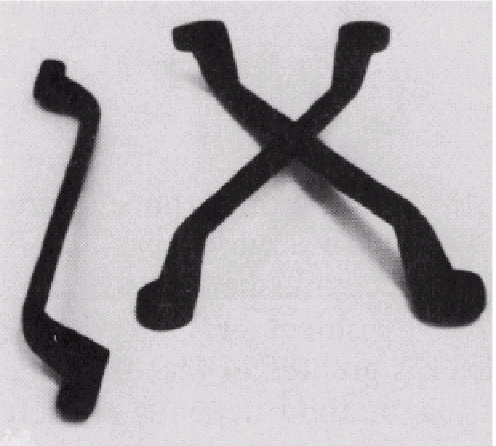

a) Complemented Image b) Edged Image

Figure 3. Complemented Image and Edged Image

Segmentasi citra berdasarkan *similarity*

- Cara paling sederhana menemukan bagian citra yang koheren adalah berdasarkan nilai intensitas pixel atau warna



Perkakas menjadi bagian yang koheren

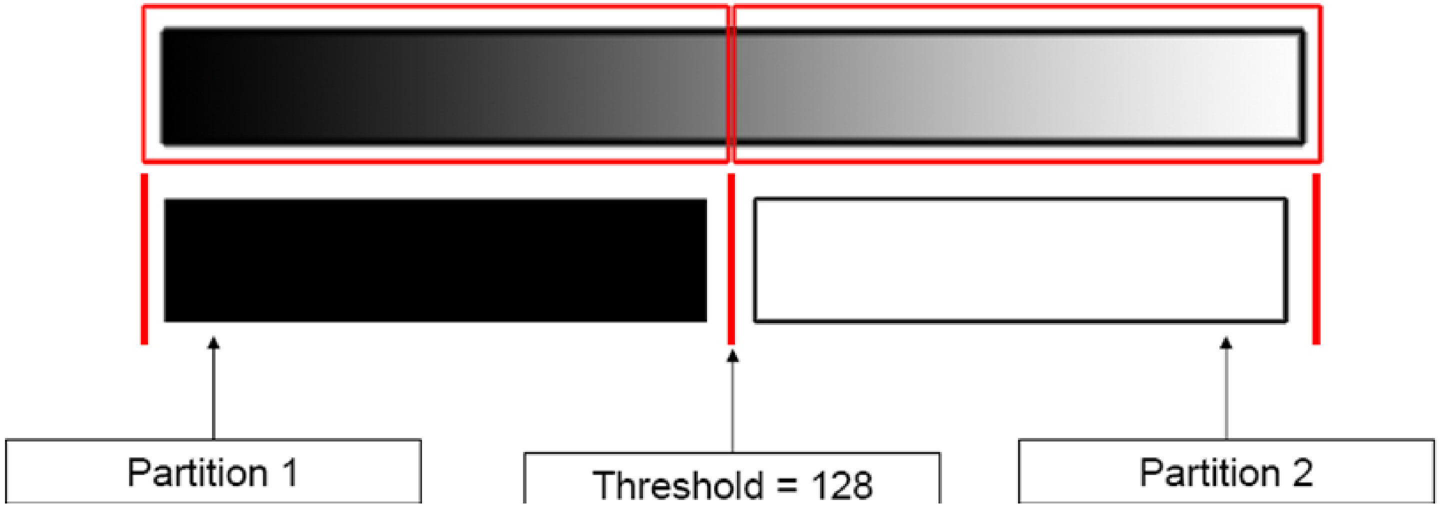
Rumah, rumput, dan langit membentuk bagian koheren yang berbeda

- Metode segmentasi berbasis *similarity*: pengambangan (*thresholding*), *region growing*, *split and merge*, dan *clustering*.

Sumber: CS 4487/9587 Algorithms for Image Analysis

1. Pengambangan

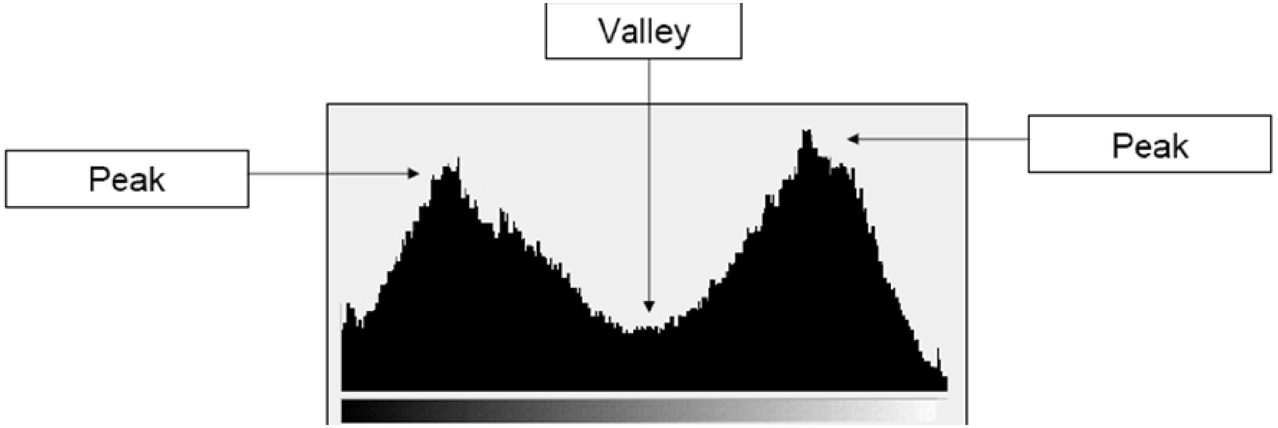
- Sudah dijelaskan pada materi sebelumnya (lihat materi Citra Biner)
- Segmentasi citra didasarkan pada nilai intensitas pixel-pixel dan nilai ambang T.
- Salah satu cara untuk mengekstrak objek dari latar belakang adalah dengan memilih ambang T.
- Setiap pixel (x, y) pada citra di mana f (x, y)> T disebut titik objek, jika tidak maka akan disebut latar belakang.
- Hasil segmentasi adalah berupa citra biner



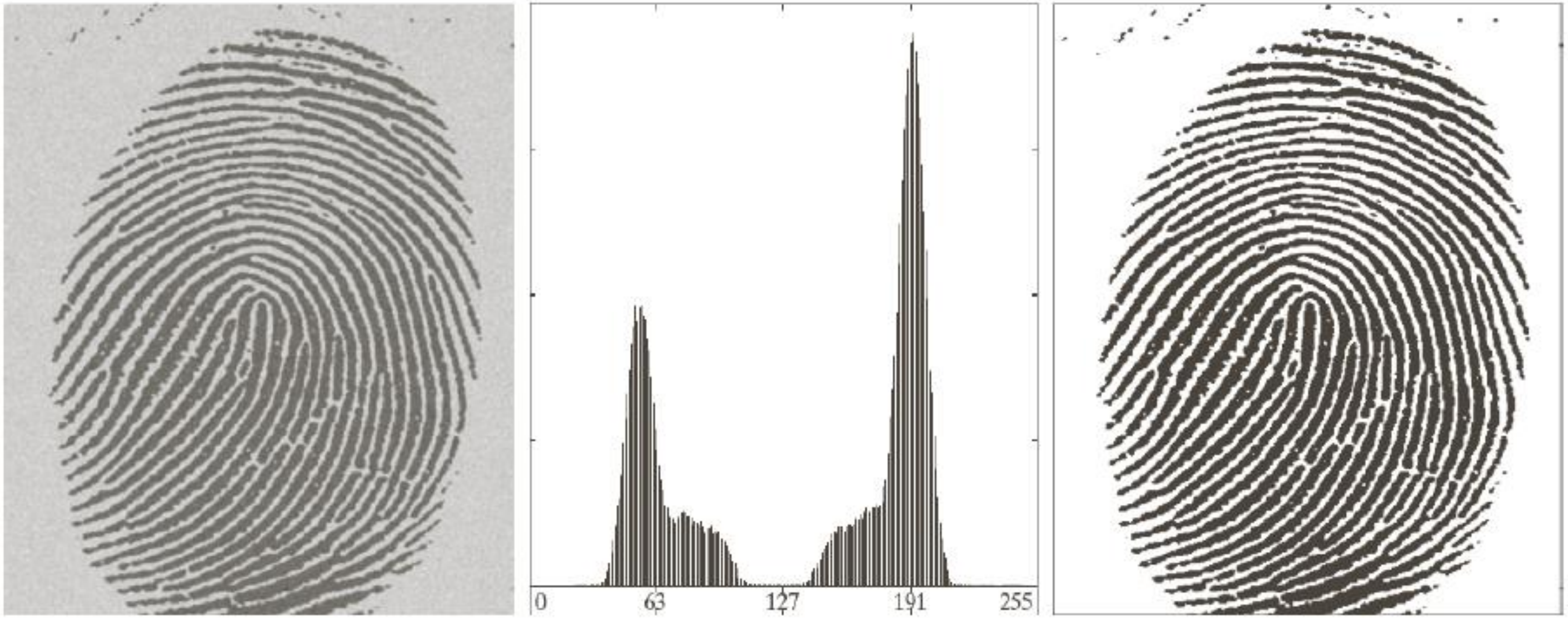
Pilih nilai ambang T

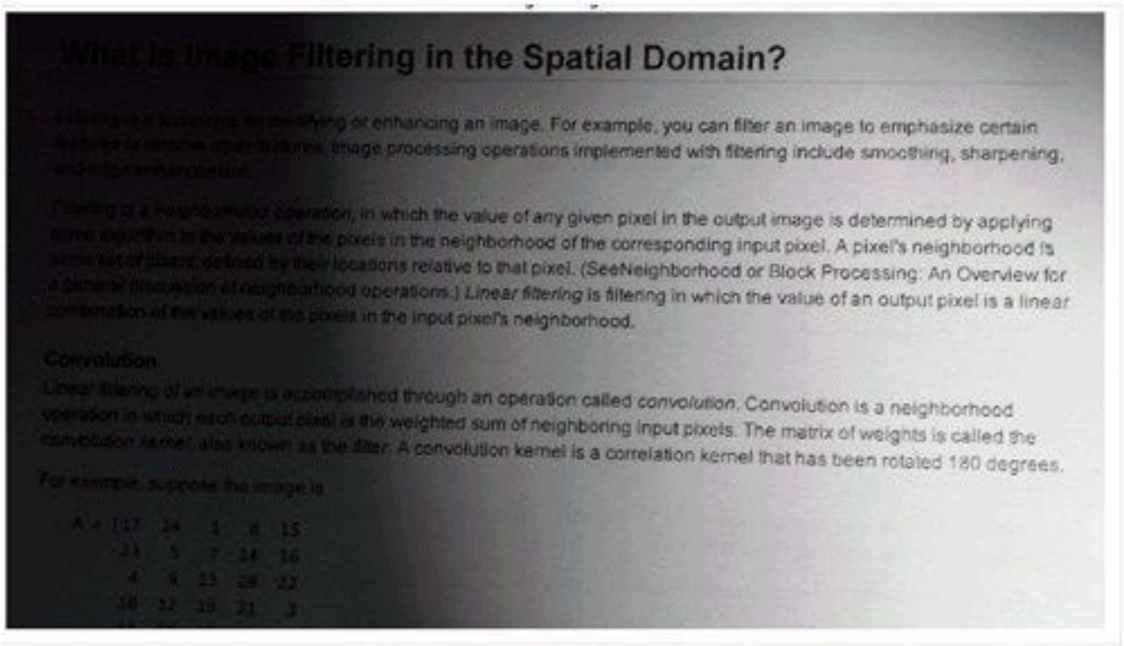
1. Pixel-pixel di atas nilai ambang mendapatkan intensitas baru A.
2. Pixels di bawah nilai ambang mendapatkan intensitas baru B.

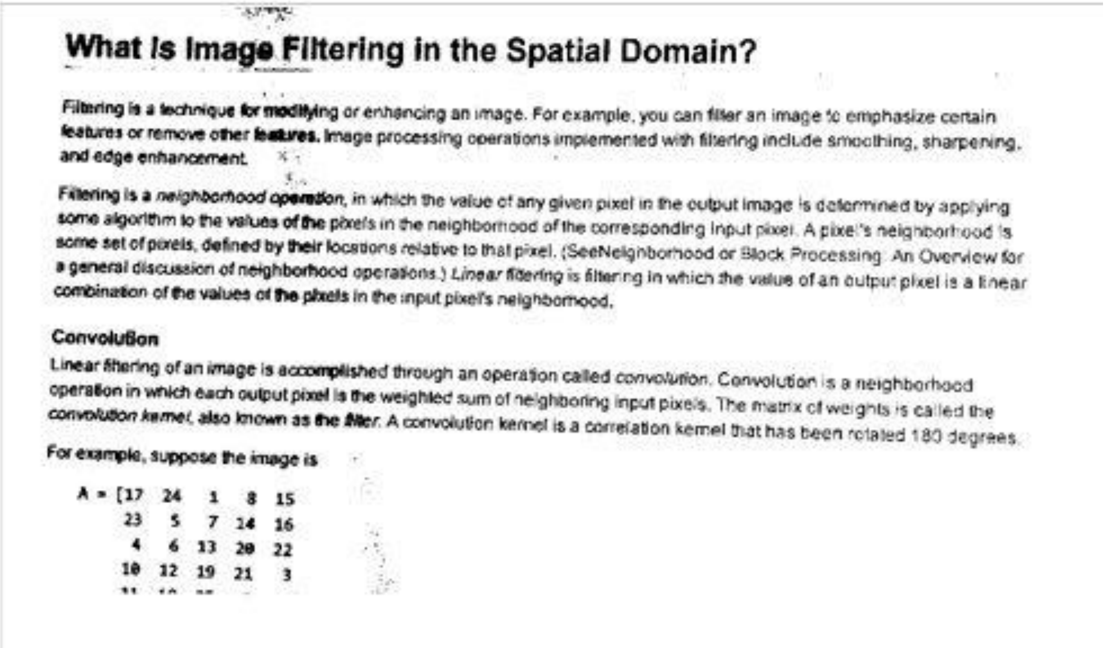
- Untuk mendapatkan nilai ambang T, analisis histogram citra lalu identifikasi puncak dan lembah.



- Nilai *grayscale* pada lembah terdalam di antara dua bukit menyatakan nilai T.


0
63
127
191
255





What Is Image Filtering in the Spatial Domain?

Filtering is a technique for modifying or enhancing an image. For example, you can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement.

Filtering is a *neighborhood operation*, in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is some set of pixels, defined by their locations relative to that pixel. (SeeNeighborhood or Block Processing: An Overview for a general discussion of neighborhood operations.) *Linear filtering* is filtering in which the value of an output pixel is a linear combination of the values of the pixels in the input pixel's neighborhood.

Convolution

Linear filtering of an image is accomplished through an operation called *convolution*. Convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the *convolution kernel*, also known as the *filter*. A convolution kernel is a correlation kernel that has been rotated 180 degrees.

For example, suppose the image is

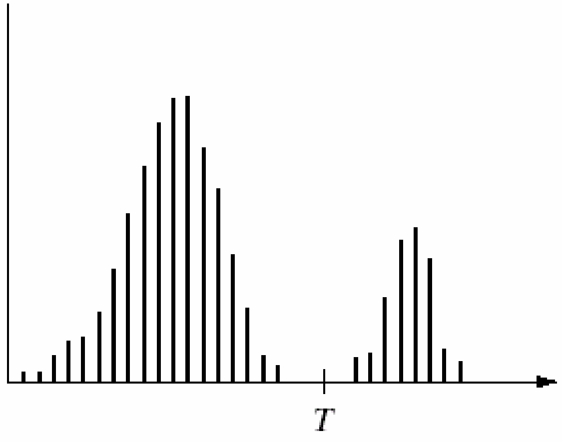
```
A = [17  24   1   8  15
     23   5   7  14  16
      4   6  13  20  22
     10  12  19  21   3
```

Menggunakan pengambangan untuk mengonversi ke gambar biner untuk meningkatkan keterbacaan teks dalam gambar.

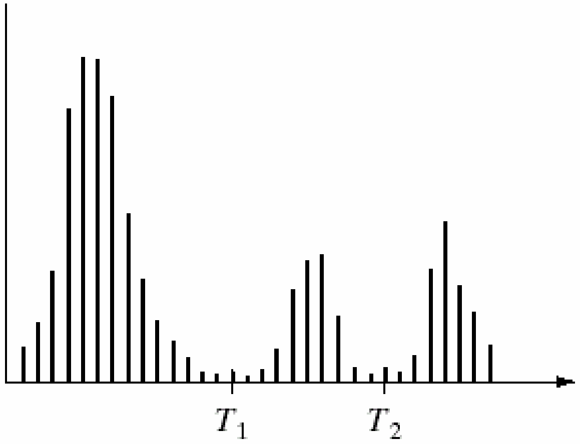
Sumber: https://www.mathworks.com/discovery/image-segmentation.html

- Mencari nilai T dengan cara sederhana di atas hanya tepat jika histogram bersifat bimodal (mempunyai dua puncak dan satu lembah). Misalnya segmentasi teks dengan latar belakangnya.

- Jika terdapat multimodal di dalam citra, maka diperlukan beberapa nilai ambang.



bimodal



multimodal

- Teknik pengambangan dibagi menjadi:

  1. *Global thresholding*

     Nilai ambang bergantung pada keseluruhan nilai-nilai *pixel*

  2. *Local thresholding*

     Nilai ambang bergantung pada *pixel-pixe*l bertetangga, hanya untuk sekelompok *pixel* saja.

  3. *Adaptive thresholding*

     Nilai ambang berubah secara dinamis bergantung pada perubahan pencahayaan di dalam citra

Sumber: Image segmentation
Stefano Ferrari
Universit`a degli Studi di Milano
stefano.ferrari@unimi.it

Global thresholding

A simple algorithm:

1. Initial estimate of T
2. Segmentation using T:
   - G_1, pixels brighter than T;
   - G_2, pixels darker than (or equal to) T.
3. Computation of the average intensities m_1 and m_2 of G_1 and G_2.
4. New threshold value:

$$T_{\text{new}} = \frac{m_1 + m_2}{2}$$

5. If $|T - T_{\text{new}}| > \Delta T$, back to step 2, otherwise stop.

Pengambangan dengan Metode Otsu

Otsu's method

- Otsu's method is aimed in finding the optimal value for the global threshold.
- It is based on the interclass variance maximization.
  - Well thresholded classes have well discriminated intensity values.
- $M \times N$ image histogram:
  - L intensity levels, $[0, \ldots, L-1]$;
  - n_i #pixels of intensity i:

$$MN = \sum_{i=0}^{L-1} n_i$$

- Normalized histogram:

$$p_i = \frac{n_i}{MN}$$

$$\sum_{i=0}^{L-1} p_i = 1, \quad p_i \geq 0$$

Sumber: *Image Segmentation*, by Stefano Ferrari

Otsu's method (2)

- Using k, $0 < k < L-1$, as threshold, $T = k$:
  - two classes: C_1 (pixels in $[0, k]$) and C_2 (pixels in $[k+1, L-1]$)
  - $P_1 = P(C_1) = \sum_{i=0}^{k} p_i$, probability of the class C_1
    - $P_2 = P(C_2) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1$, probability of the class C_2
  - m_1, mean intensity of the pixels in C_1:

$$
\begin{aligned}
m_1 &= \sum_{i=0}^{k} i \cdot P(i|C_1) \\
&= \sum_{i=0}^{k} i \frac{P(C_1|i)P(i)}{P(C_1)} \\
&= \frac{1}{P_1} \sum_{i=0}^{k} i \cdot p_i
\end{aligned}
$$

where $P(C_1|i) = 1$, $P(i) = p_i$ e $P(C_1) = P_1$.

Otsu's method (3)

- Similarly, m_2, mean intensity of the pixels in C_2:

$$m_2 = \frac{1}{P_2} \sum_{i=k+1}^{L-1} i \cdot p_i$$

- Mean global intensity, m_G:

$$m_G = \sum_{i=0}^{L-1} i \cdot p_i$$

- while the mean intensity up to the k level, m:

$$m = \sum_{i=0}^{k} i \cdot p_i$$

- Hence:

$$P_1 m_1 + P_2 m_2 = m_G$$

$$P_1 + P_2 = 1$$

Otsu's method (4)

- The global variance σ_G^2:

$$\sigma_G^2 = \sum_{i=0}^{L-1} (i - m_G)^2 \cdot p_i$$

- The *between-class variance*, σ_B, can be defined as:

$$\begin{aligned}
\sigma_B^2 &= P_1(m_1 - m_G)^2 + P_2(m_2 - m_G)^2 \\
&= P_1 P_2 (m_1 - m_2)^2 \\
&= \frac{(m_G P_1 - m)^2}{P_1(1 - P_1)} x
\end{aligned}$$

- The *goodness* of the choice $T = k$ can be estimated as the ratio η:

$$\eta = \frac{\sigma_B^2}{\sigma_G^2}$$

Otsu's method (5)

- The quantities required for the computation of η, can be obtained from the histogram:
- Hence, for each value of k, $\eta(k)$ can be computed:

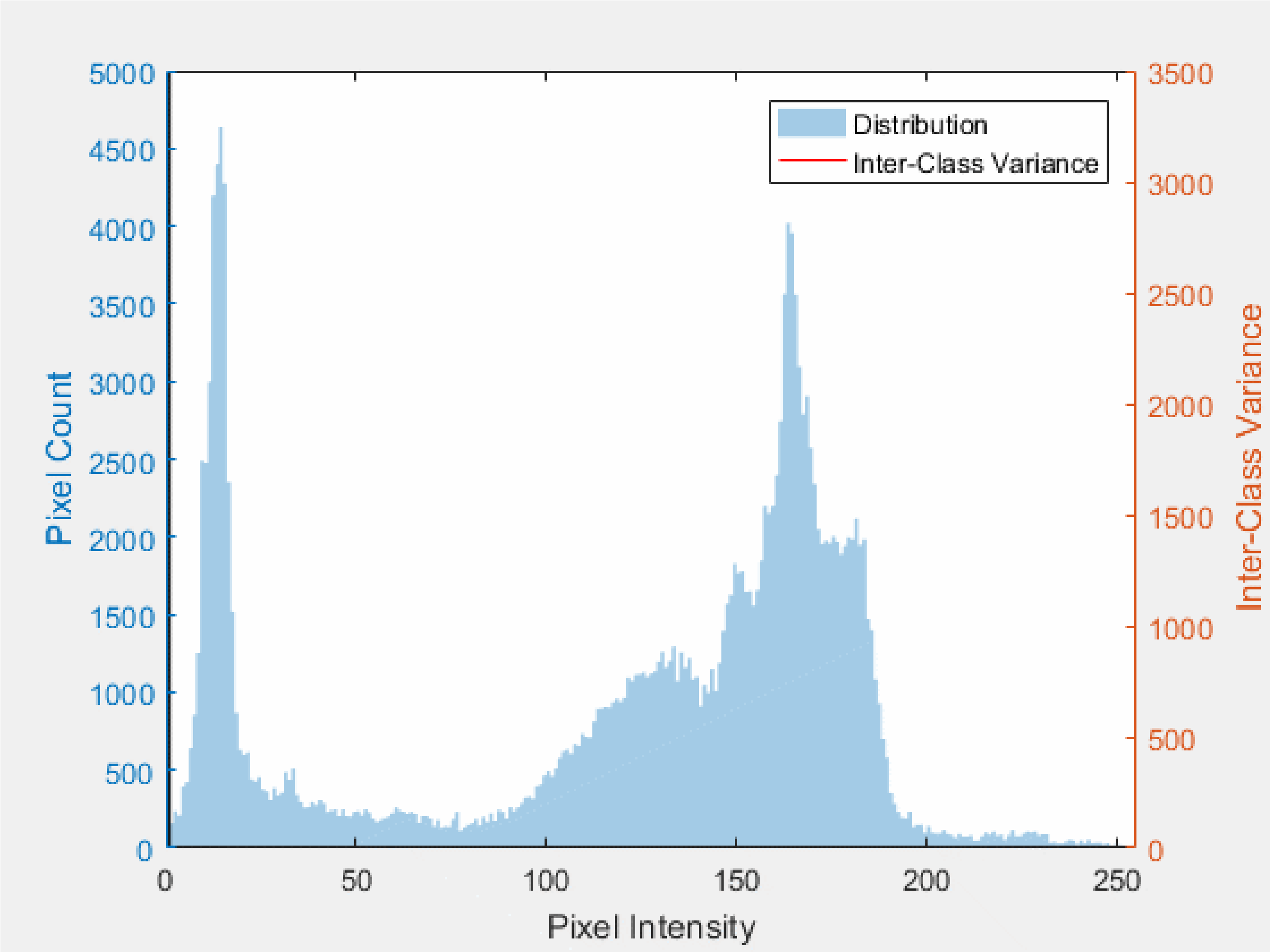
$$\eta(k) = \frac{\sigma_B^2(k)}{\sigma_G^2}$$

where

$$\sigma_B^2(k) = \frac{(m_G P_1(k) - m(k))^2}{P_1(k)(1 - P_1(k))}$$

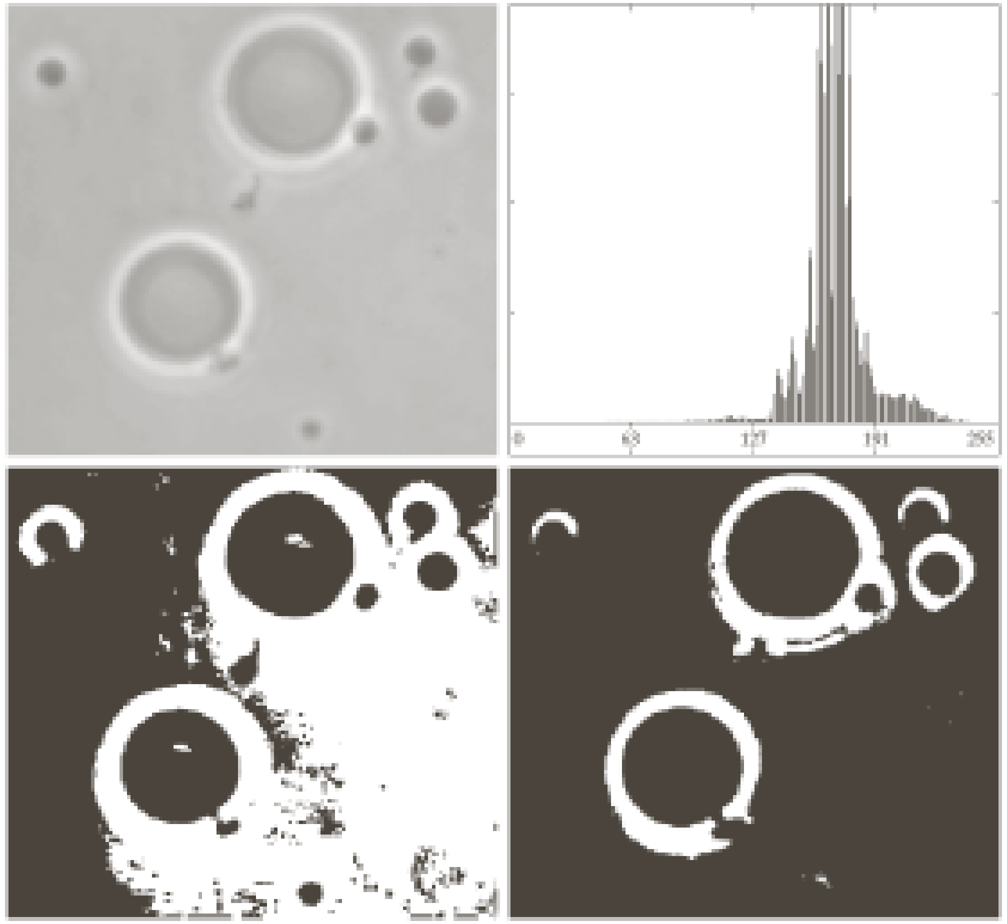
- The optimal threshold value, k^*, satisfies:

$$\sigma_B^2(k^*) = \max_{0<k<L-1} \sigma_B^2(k)$$



Visualisasi metode Otsu (Sumber: Wikipedia)

Otsu's method: an example



a	b
c	d

(a) original image;

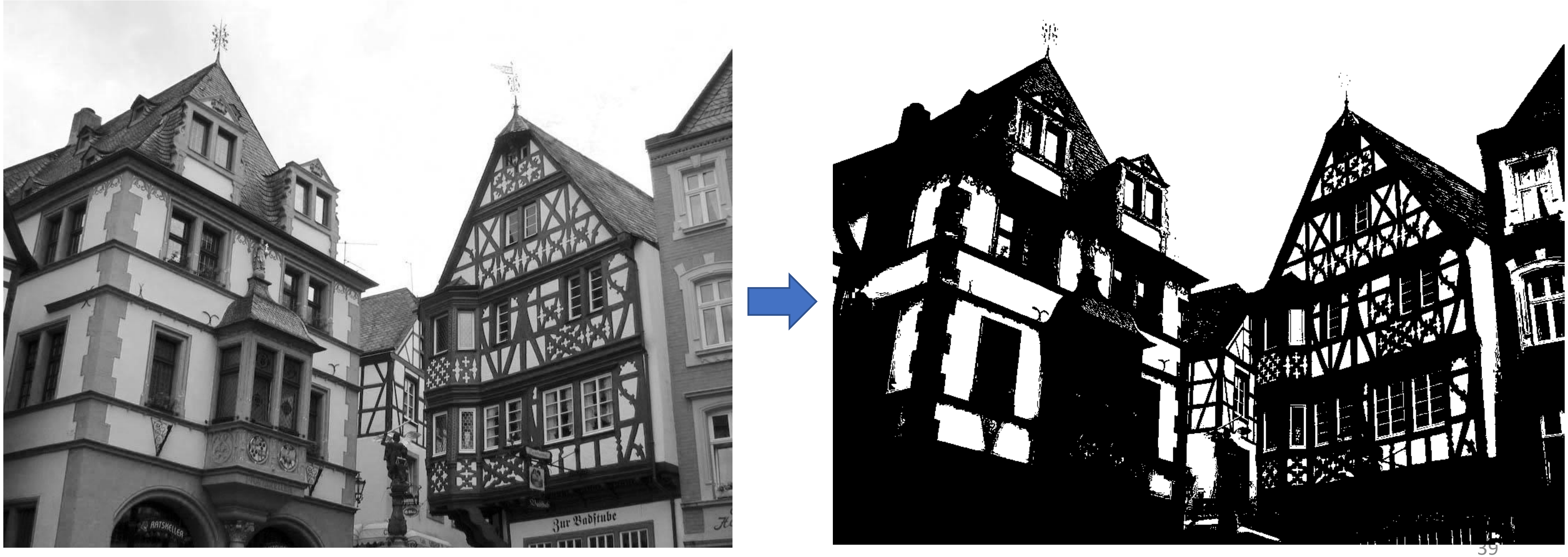
(b) histogram of (a);

(c) global threshold: $T = 169$, $\eta = 0.467$;

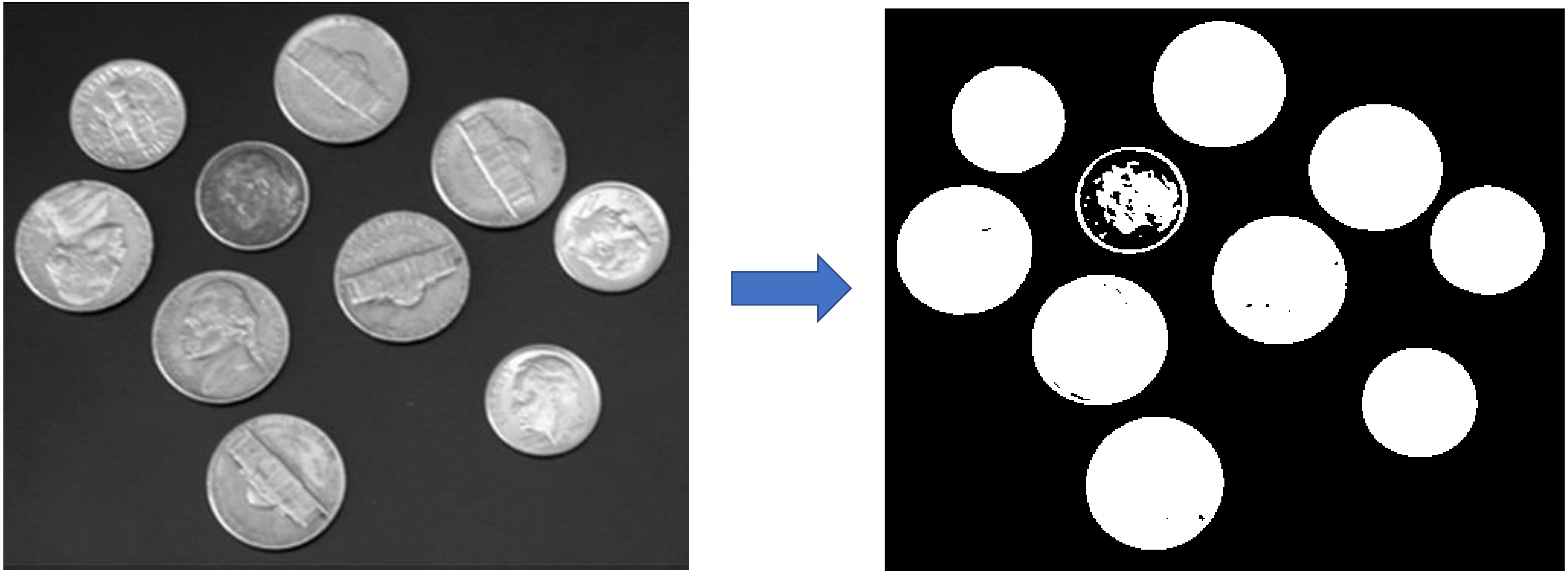
(d) Otsu's method: $T = 181$, $\eta = 0.944$.

- Matlab memiliki fungsi `graythresh()` untuk melakukan pengambangan dengan metode Otsu.

```
I = imread('house.jpg');
T = graythresh(I);
BW = im2bw(I, T);
imshow(I);
figure; imshow(BW)
```

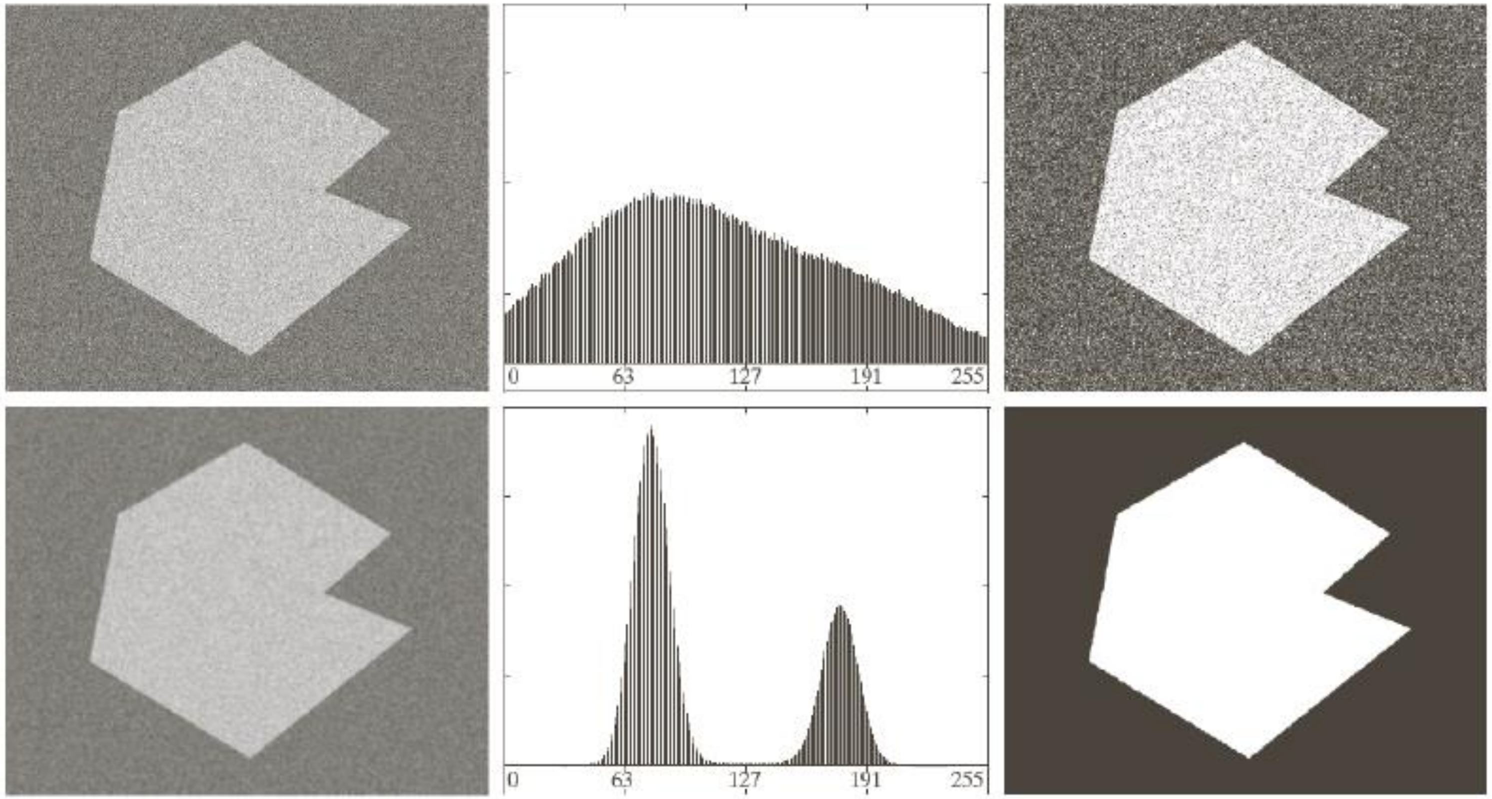


```
I = imread('coins.bmp');
T = graythresh(I);
BW = im2bw(I, T);
imshow(I);
figure; imshow(BW)
```



Hasil pengambangan dengan metode Otsu

Smoothing



- Otsu's method may not work in presence of noise.
- Smoothing can produce a histogram with separated peaks.

Multiple thresholds Otsu's method

- The Otsu's method can be applied also for the multiple thresholds segmentation (generally, double threshold).
- Between-class variance:

$$\sigma_B^2(k_1,\, k_2) = P_1(m_1 - m_G)^2 + P_2(m_2 - m_G)^2 + P_3(m_3 - m_G)^2$$

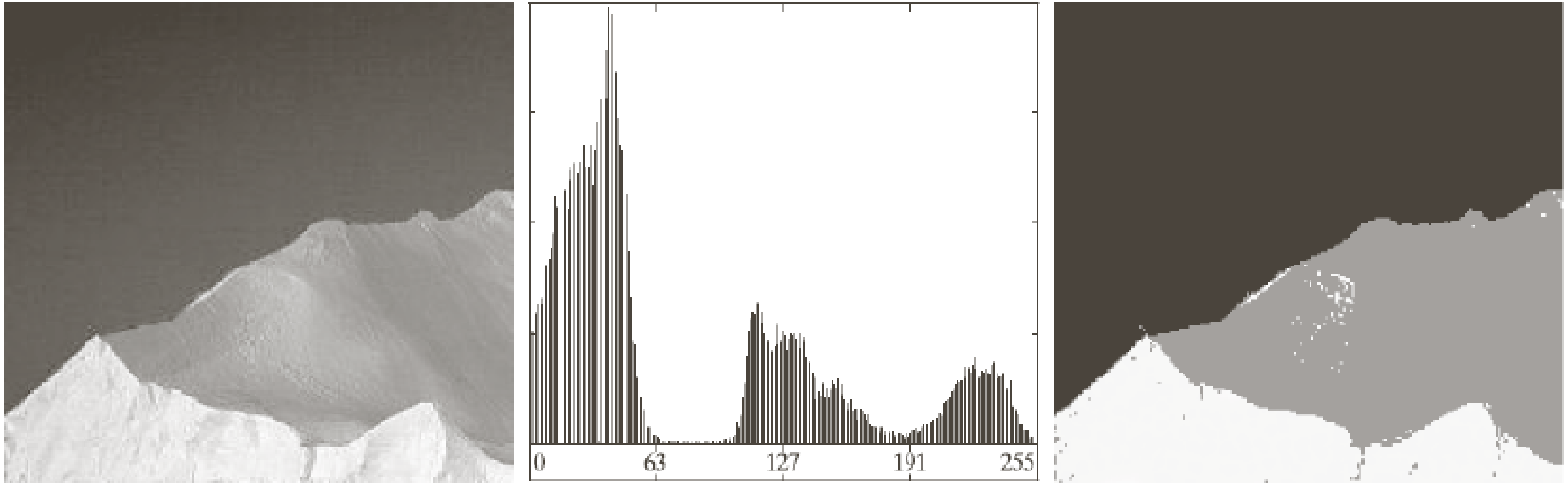
- The optimal thresholds k_1^* and k_2^* can be computed as:

$$\sigma_B^2(k_1^*,\, k_2^*) = \max_{0<k_1<k_2<L-1} \sigma_B^2(k_1,\, k_2)$$

- The separability degree can be measured as:

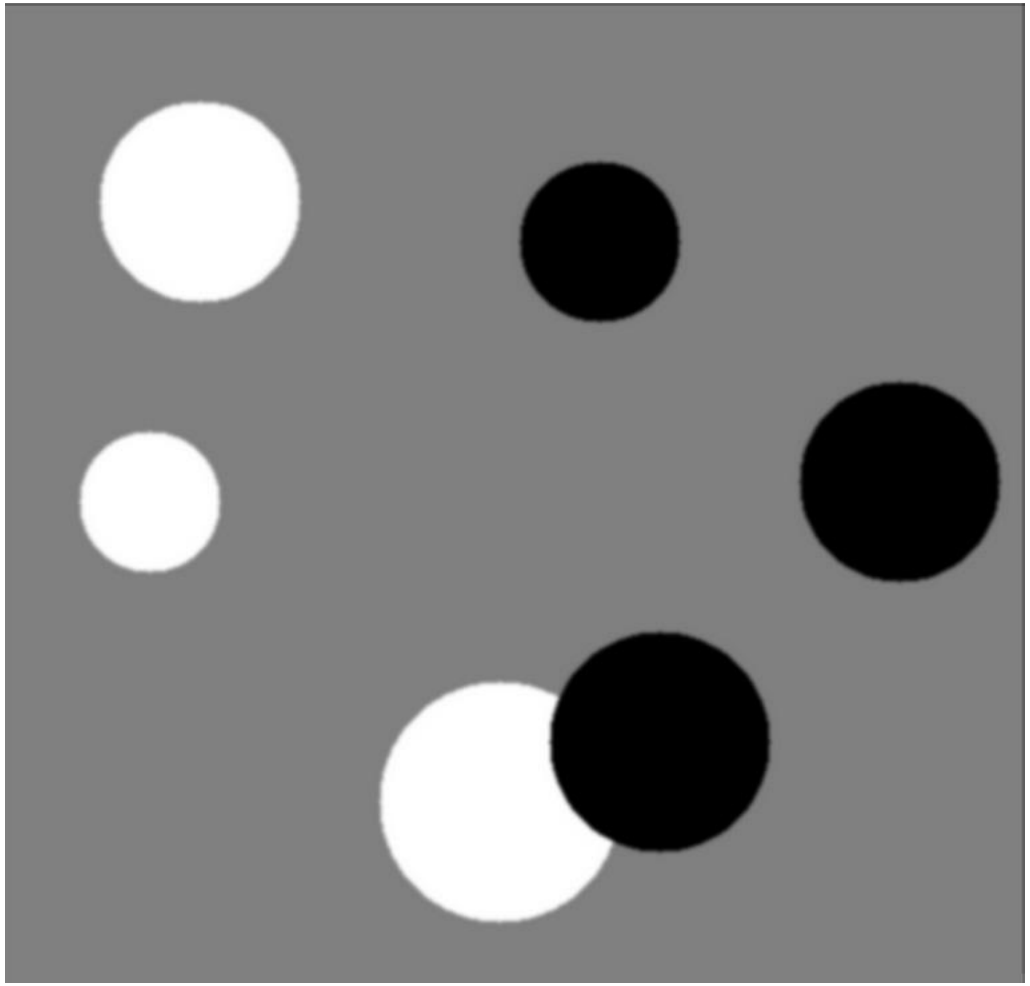
$$\eta(k_1^*,\, k_2^*) = \frac{\sigma_B^2(k_1^*,\, k_2^*)}{\sigma_G^2}$$

Multiple thresholds Otsu's method: an example

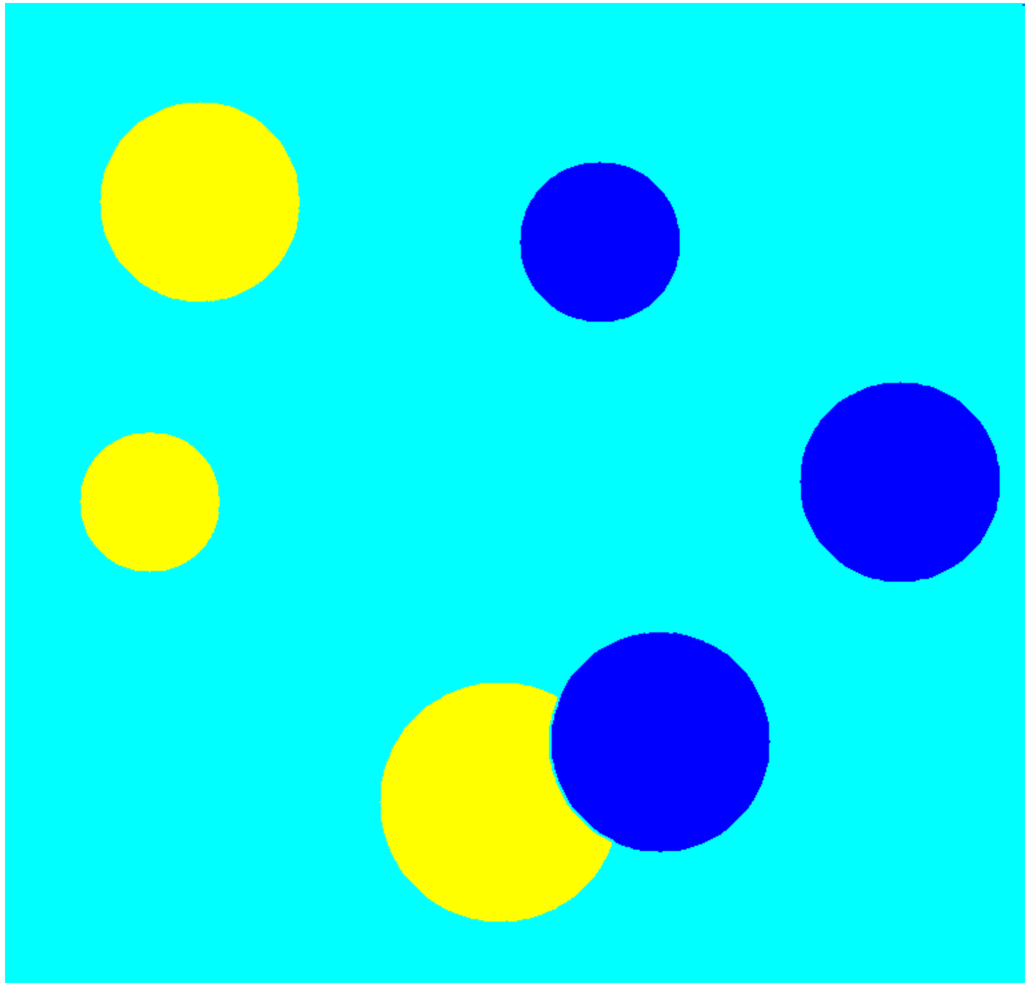


- Di dalam Matlab, fungsi `multithresh()` digunakan untuk melakukan *multiple threshold* dengan metode Otsu.

```
% Baca citra
I = imread('circle.jpg');

% Tampilkan citra
imshow(I);

% Hitung dua buah nilai ambang
thresh = multithresh(I, 2);

%Segmentasi citra menjadi tiga level dengan fungsi imquantize
seg_I = imquantize(I,thresh);

% Konversi citra yang disegmentasi menjadi citra berwarna dengan
% menggunakan fungsi label2rgb dan tampilkan
RGB = label2rgb(seg_I);
figure;  imshow(RGB)
axis off
title('RGB Segmented Image')
```



RGB Segmented Image



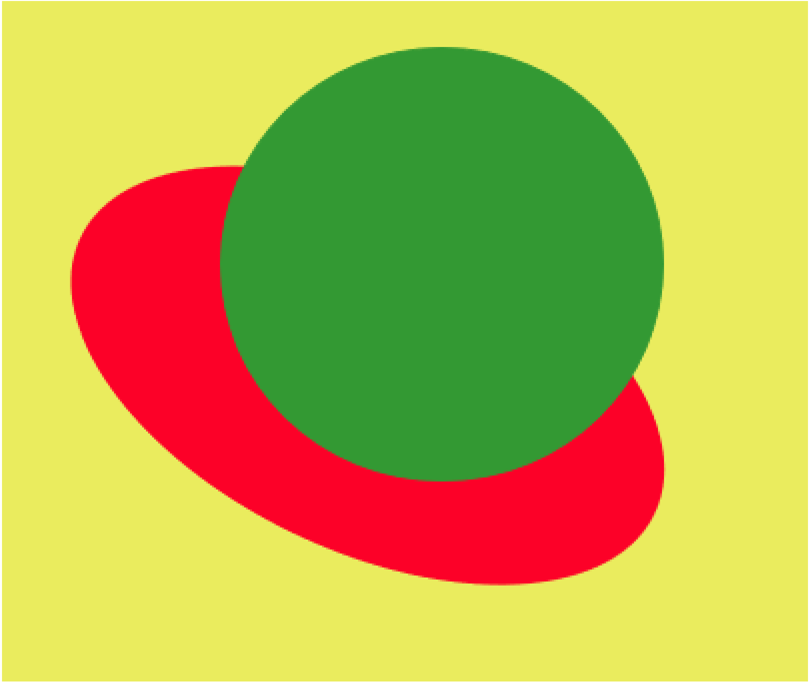
2. Region Growing

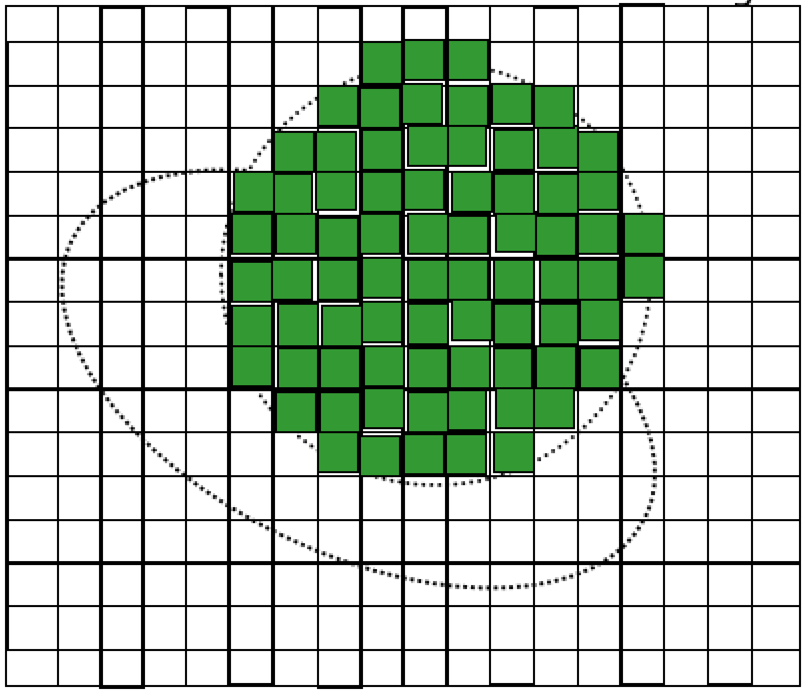
- *Region growing*: kelompok *pixel* atau sub-region yang tumbuh menjadi region yang lebih besar.

- Algoritma: Mulai dengan "umpan (*seed*)" yang berisi himpunan beranggota satu atau lebih *pixel* dari region yang potensial, dan dari sini *region* berkembang dengan menambahkan pada umpan *pixel-pixel* tetangga yang memiliki properti yang mirip dengan umpan, lalu berhenti jika *pixel-pixel* tetangga tidak mirip lagi.

- Biasanya uji statistik digunakan untuk memutuskan apakah sebuah *pixel* dapat digabungkan ke dalam region atau tidak.

- Keuntungan: memiliki keterhubungan yang bagus antar pixel di dalam region
- Kelemahan: - pemilihan umpan yang tepat
  - kriteria berhenti
  - mengkonsumsi waktu yang lama





Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

Unseeded Region Growing

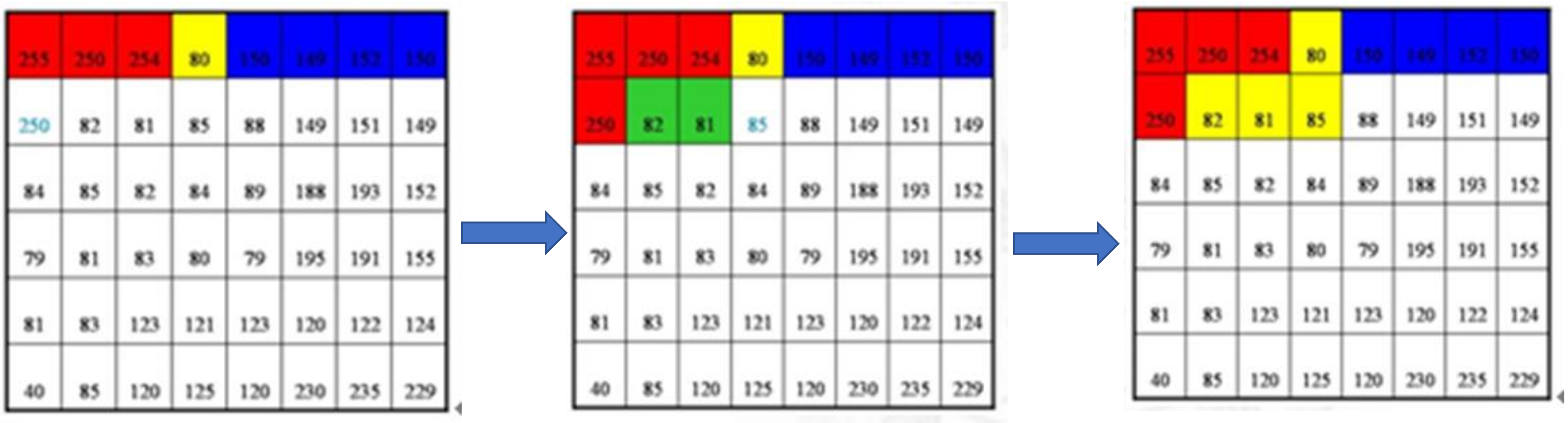
- Metode *region growing* tanpa spesifikasi umpan
- Menggunakan algoritma *fast scanning*

255	250	254	80	150	149	152	150
250	82	81	85	88	149	151	149
84	85	82	84	89	188	193	152
79	81	83	80	79	195	191	155
81	83	123	121	123	120	122	124
40	85	120	125	120	230	235	229

255	250	254	80	150	149	152	150
250	82	81	85	88	149	151	149
84	85	82	84	89	188	193	152
79	81	83	80	79	195	191	155
81	83	123	121	123	120	122	124
40	85	120	125	120	230	235	229

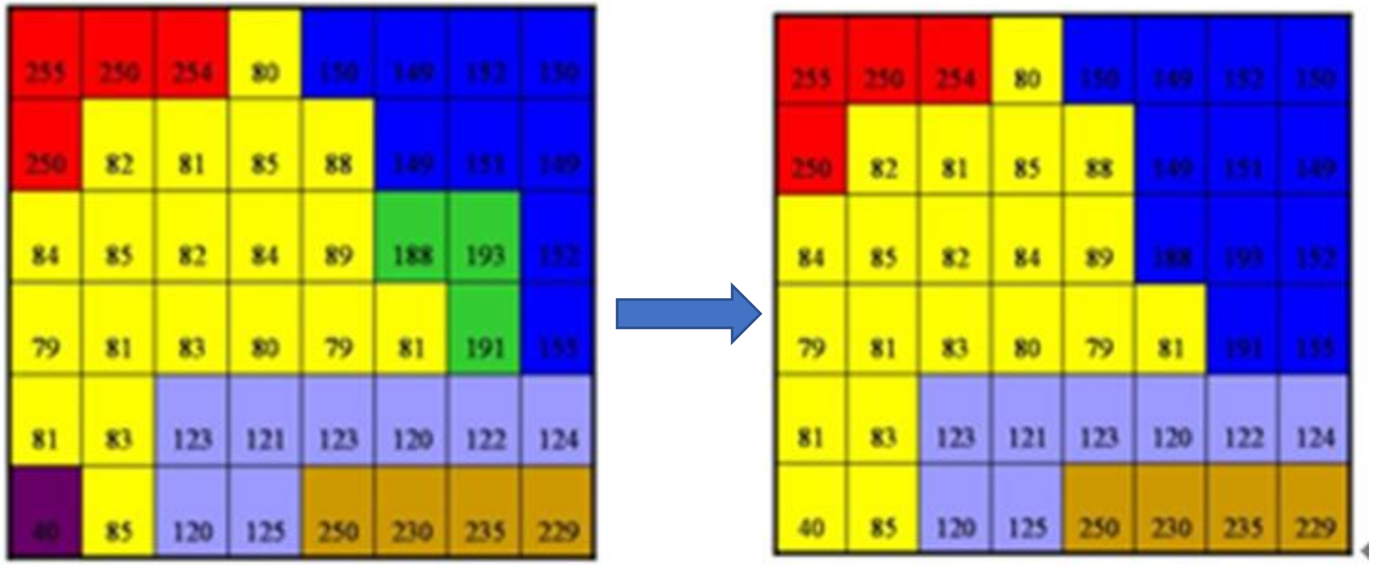
255	250	254	80	150	149	152	150
250	82	81	85	88	149	151	149
84	85	82	84	89	188	193	152
79	81	83	80	79	195	191	155
81	83	123	121	123	120	122	124
40	85	120	125	120	230	235	229

Sumber:主講人:張緯德, Image segmentation, Representation, and Description



Langkah terakhir:

Gabungkan (*merge*) region kecil menjadi region besar



Sumber:主講人:張緯德, Image segmentation, Representation, and Description

Seeded Region Growing (segmentasi.m)

```
% read image
reg_maxdist = 0.2;
I = im2double(imread('lada-gray.bmp'));
subplot(121);
imshow(I);
% let the user pick one point
[x,y] = ginput(1);
% round to integer to match required input by regiongrowing function
x = round(x);
y = round(y);
% plot point on original image
hold on;
plot(x,y,'xg','MarkerSize',20,'LineWidth',2);
hold off;
% get region from seed point
J = regiongrowing(I,y,x,reg_maxdist);
% plot region
subplot(122);
imshow(J);
```

Sumber: https://stackoverflow.com/questions/44234856/region-growing-in-matlab

(regiongrowing.m)

```
function J=regiongrowing(I,x,y,reg_maxdist)
% This function performs "region growing" in an image from a specified
% seedpoint (x,y)
%
% J = regiongrowing(I,x,y,t)
% % I : input image
% J : logical output image of region
% x,y : the position of the seedpoint (if not given uses function getpts)
% t : maximum intensity distance (defaults to 0.2)
%
% The region is iteratively grown by comparing all unallocated neighbouring pixels to
the region.
% The difference between a pixel's intensity value and the region's mean,
% is used as a measure of similarity. The pixel with the smallest difference
% measured this way is allocated to the respective region.
% This process stops when the intensity difference between region mean and
% new pixel become larger than a certain treshold (t)
%
% Example:
%
% I = im2double(imread('medtest.png'));
% x=198; y=359;
% J = regiongrowing(I,x,y,0.2);
% figure, imshow(I+J);
%
% Author: D. Kroon, University of Twente
```

```
if(exist('reg_maxdist','var')==0), reg_maxdist=0.2; end
if(exist('y','var')==0), figure, imshow(I,[]); [y,x]=getpts;
y=round(y(1)); x=round(x(1)); end
J = zeros(size(I)); % Output
Isizes = size(I); % Dimensions of input image
reg_mean = I(x,y); % The mean of the segmented region
reg_size = 1; % Number of pixels in region
% Free memory to store neighbours of the (segmented) region
neg_free = 10000; neg_pos=0;
neg_list = zeros(neg_free,3);
pixdist=0; % Distance of the region newest pixel to the regio mean
% Neighbor locations (footprint)
neigb=[-1 0; 1 0; 0 -1;0 1];
% Start regiogrowing until distance between regio and posible new
pixels become
% higher than a certain treshold
```

```
while(pixdist<reg_maxdist&&reg_size<numel(I))
    % Add new neighbors pixels
    for j=1:4,
        % Calculate the neighbour coordinate
        xn = x +neigb(j,1); yn = y +neigb(j,2);

        % Check if neighbour is inside or outside the image
        ins=(xn>=1)&&(yn>=1)&&(xn<=Isizes(1))&&(yn<=Isizes(2));

        % Add neighbor if inside and not already part of the segmented area
        if(ins&&(J(xn,yn)==0))
                neg_pos = neg_pos+1;
                neg_list(neg_pos,:) = [xn yn I(xn,yn)]; J(xn,yn)=1;
        end
    end
    % Add a new block of free memory
    if(neg_pos+10>neg_free), neg_free=neg_free+10000;
neg_list((neg_pos+1):neg_free,:)=0; end
```

```
% Add pixel with intensity nearest to the mean of the region, to the region
    dist = abs(neg_list(1:neg_pos,3)-reg_mean);
    [pixdist, index] = min(dist);
    J(x,y)=2; reg_size=reg_size+1;

    % Calculate the new mean of the region
    reg_mean= (reg_mean*reg_size + neg_list(index,3))/(reg_size+1);

    % Save the x and y coordinates of the pixel (for the neighbour add
proccess)
    x = neg_list(index,1); y = neg_list(index,2);

    % Remove the pixel from the neighbour (check) list
    neg_list(index,:)=neg_list(neg_pos,:); neg_pos=neg_pos-1;
end
% Return the segmented area as logical matrix
J=J>1;
```

Sumber: https://www.mathworks.com/matlabcentral/fileexchange/19084-region-growing

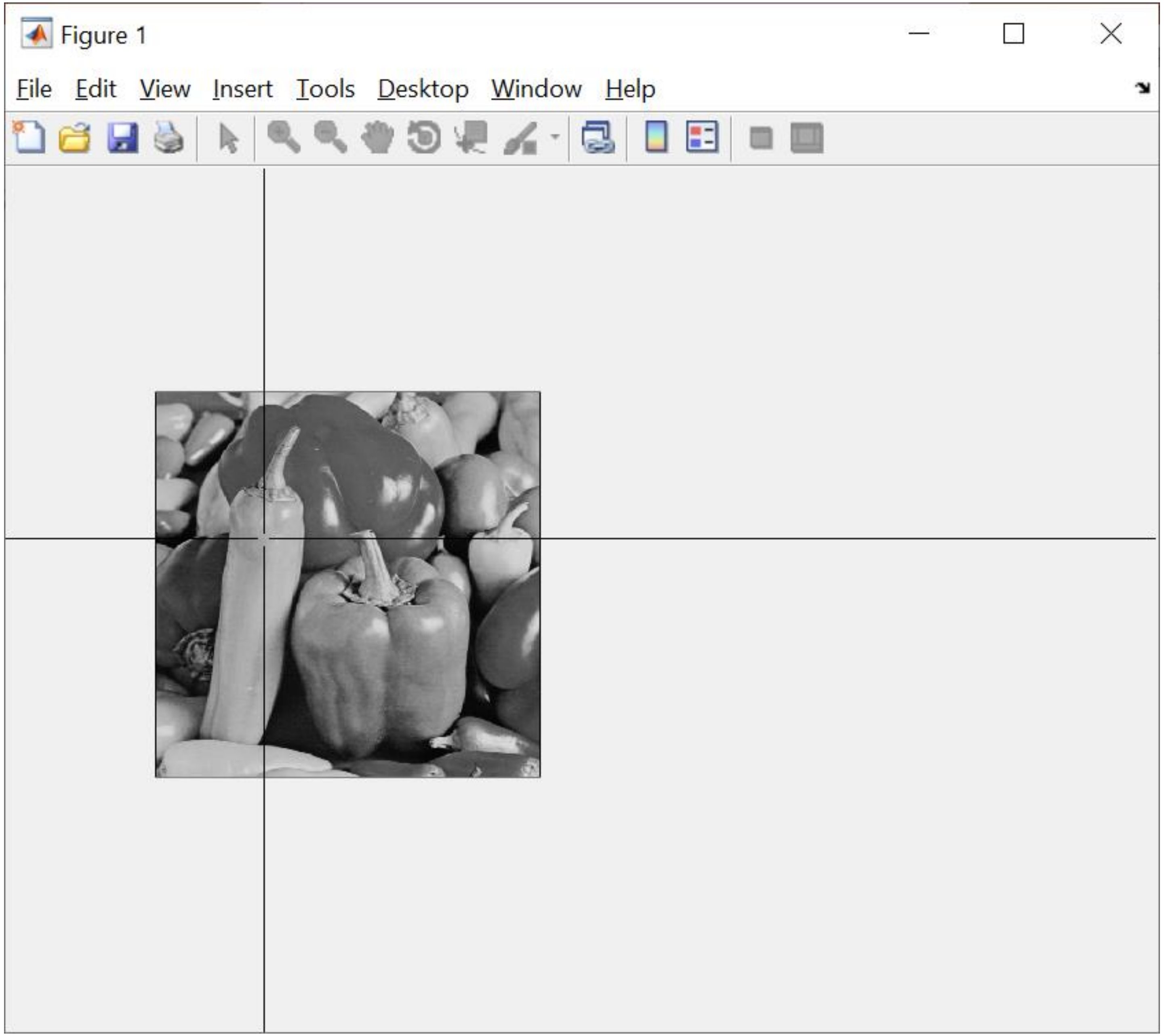


Figure 1
File Edit View Insert Tools Desktop Window Help

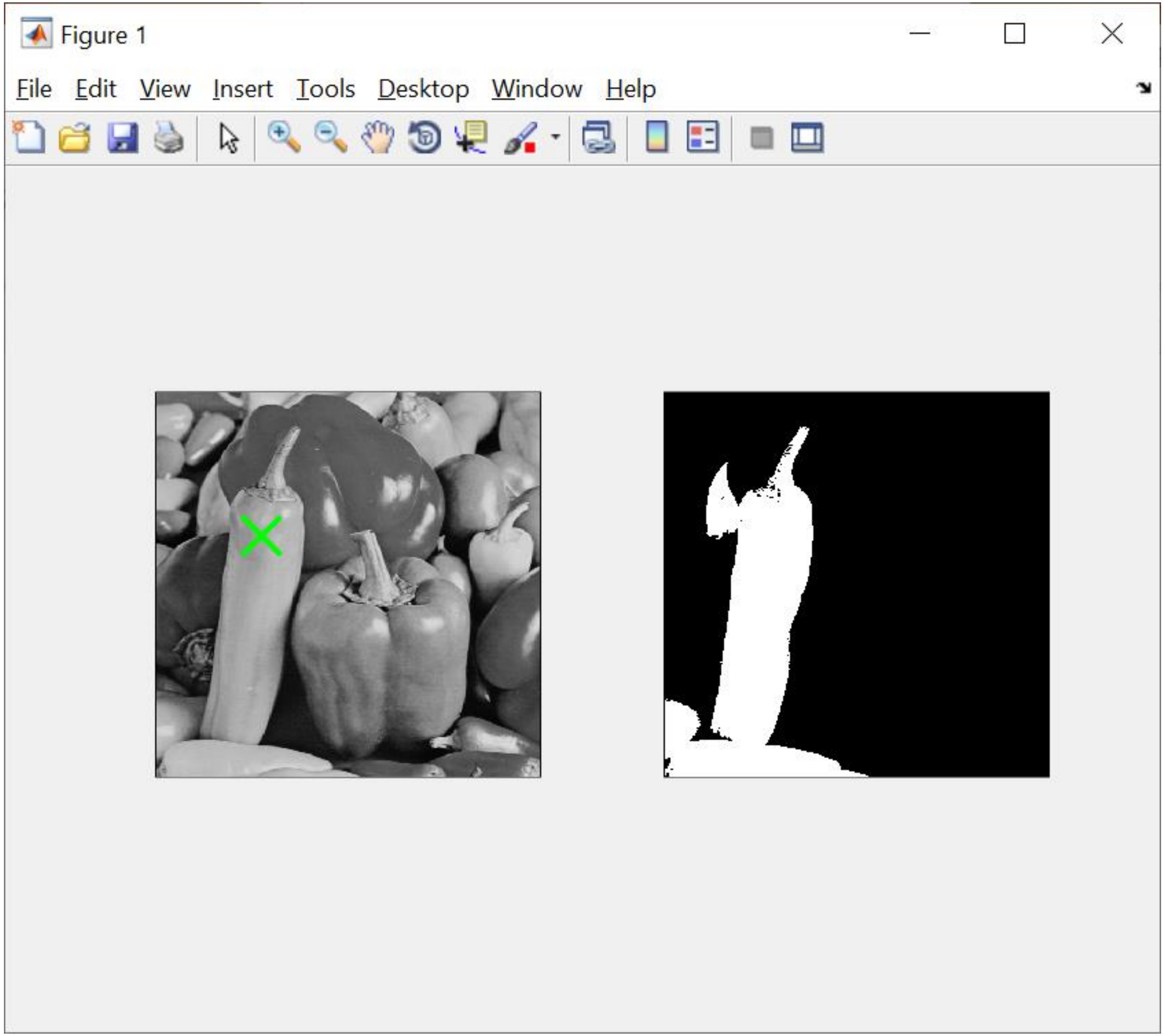
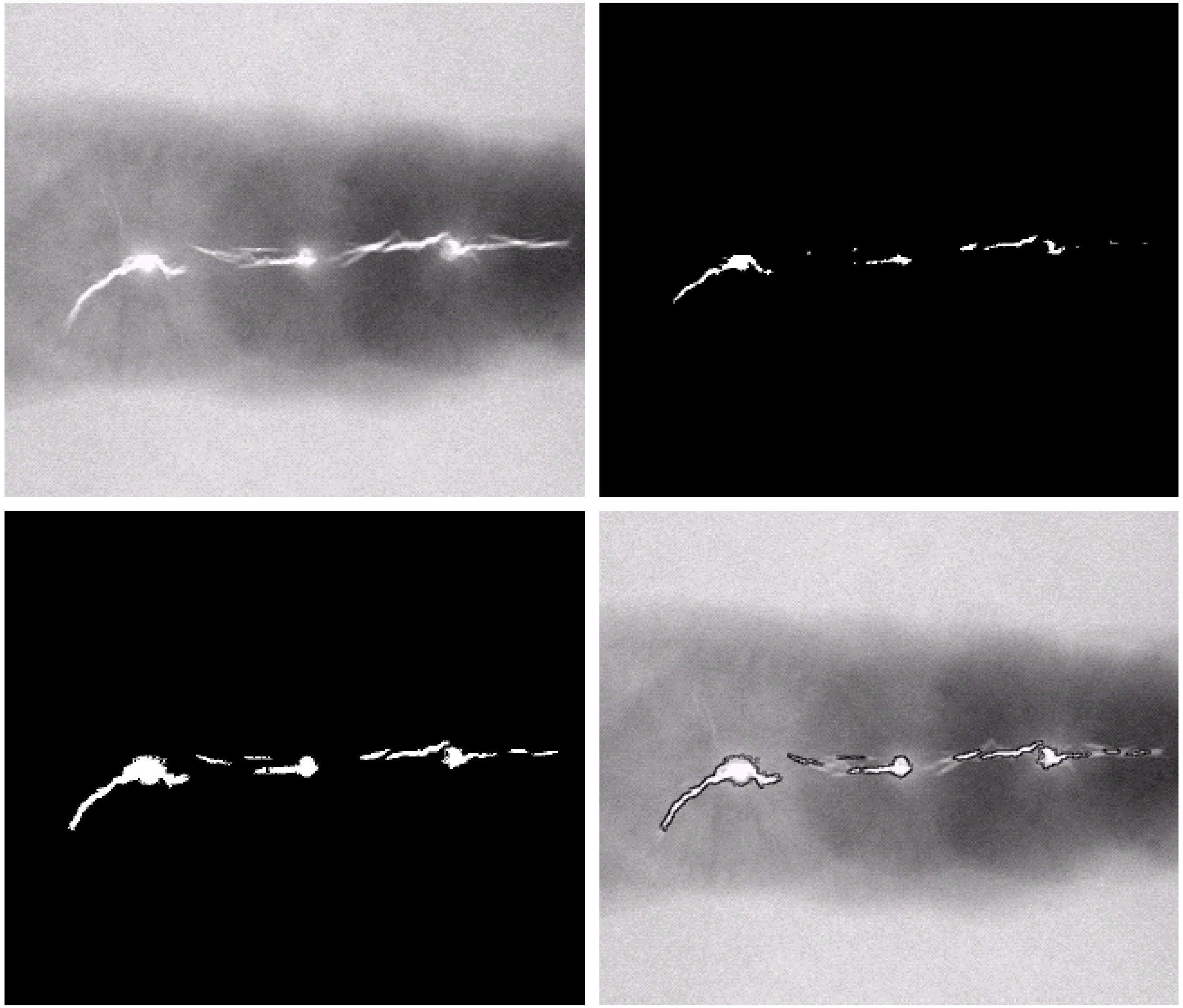


Figure 1
File Edit View Insert Tools Desktop Window Help



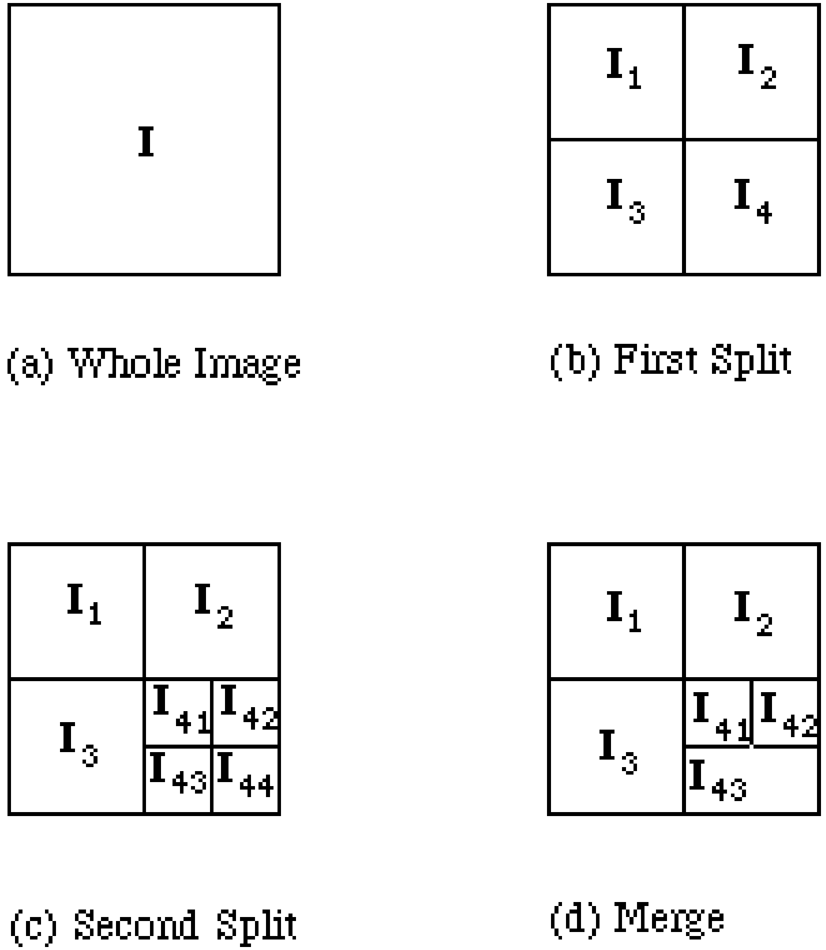
a b
c d

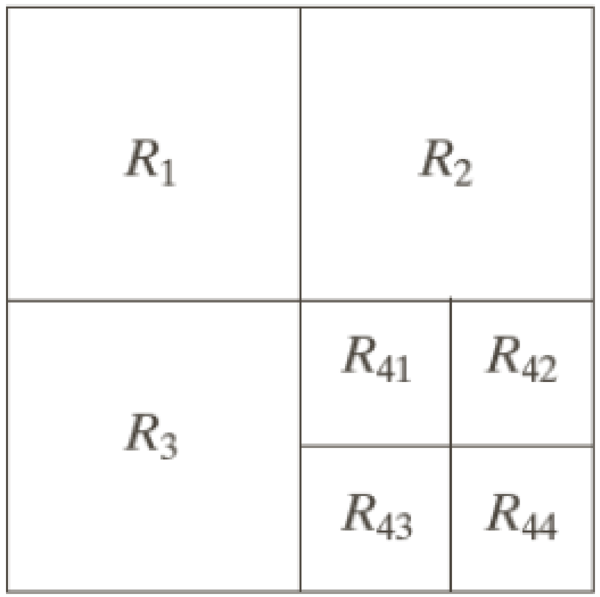
FIGURE 10.40 (a) Image showing defective welds. (b) Seed points. (c) Result of region growing. (d) Boundaries of segmented defective welds (in black). (Original image courtesy of X-TEK Systems, Ltd.).

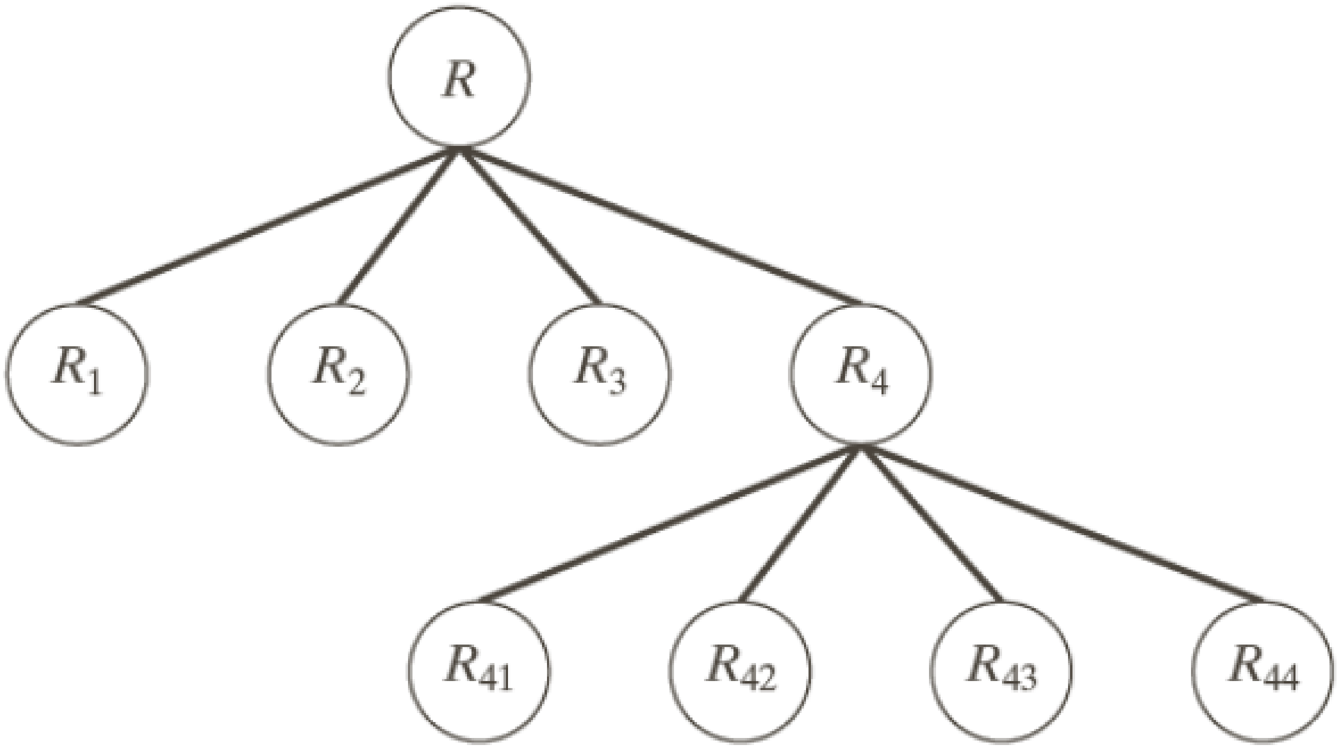
3. Split and Merge

- Mengggunakan algoritma *divide and conquer*
- Citra dibagi (split) menjadi sejumlah region yang *disjoint*

- Gabung (*merge*) region-region bertetangga yang homogen




R_1
R_2
R_3
R_{41}
R_{42}
R_{43}
R_{44}

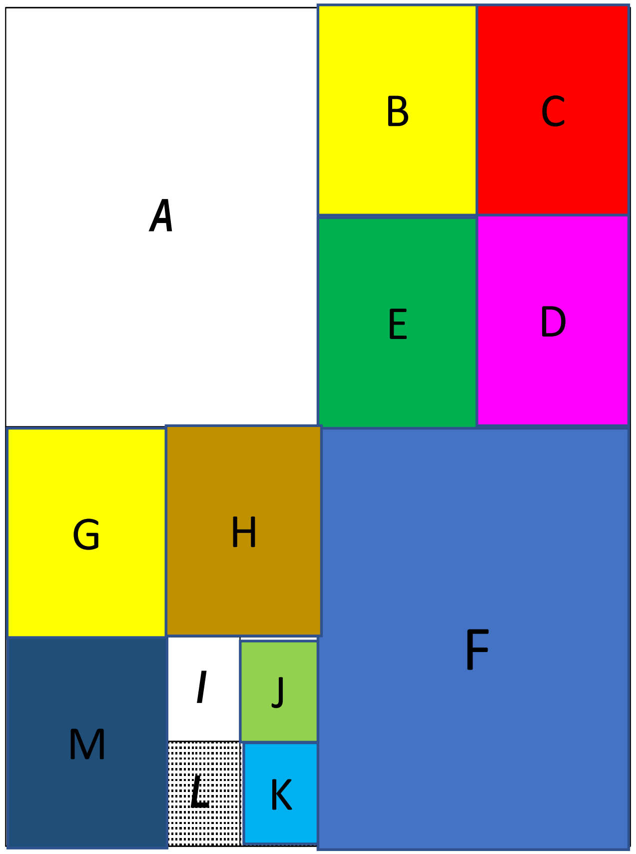

R
R_1
R_2
R_3
R_4
R_{41}
R_{42}
R_{43}
R_{44}

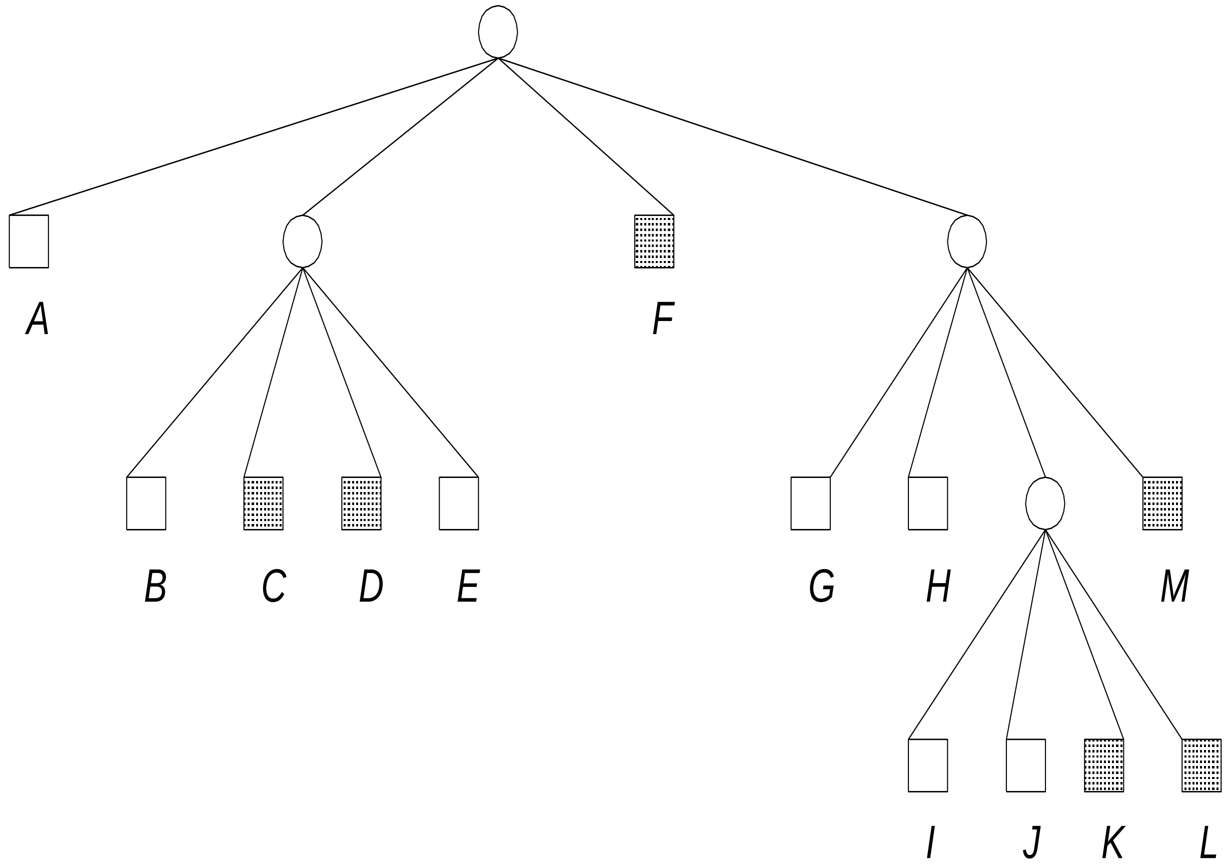
Algoritma *Split & Merge*

Given an image f and a predicate Q, the basic algorithm is:

1. $R_1 = f$
2. Subdivision in quadrants of each region R_i for which $Q(R_i) = \text{FALSE}$.
3. If $Q(R_i) = \text{TRUE}$ for every regions, merge those adjacent regions R_i and R_j such that $Q(R_i \cup R_j) = \text{TRUE}$; otherwise, repeat step 2.
4. Repeat the step 3 until no merging is possible.

Sumber: Image segmentation
Stefano Ferrari
Universit`a degli Studi di Milano
stefano.ferrari@unimi.it


A
B
C
E
D
G
H
F
I
J
M
L
K

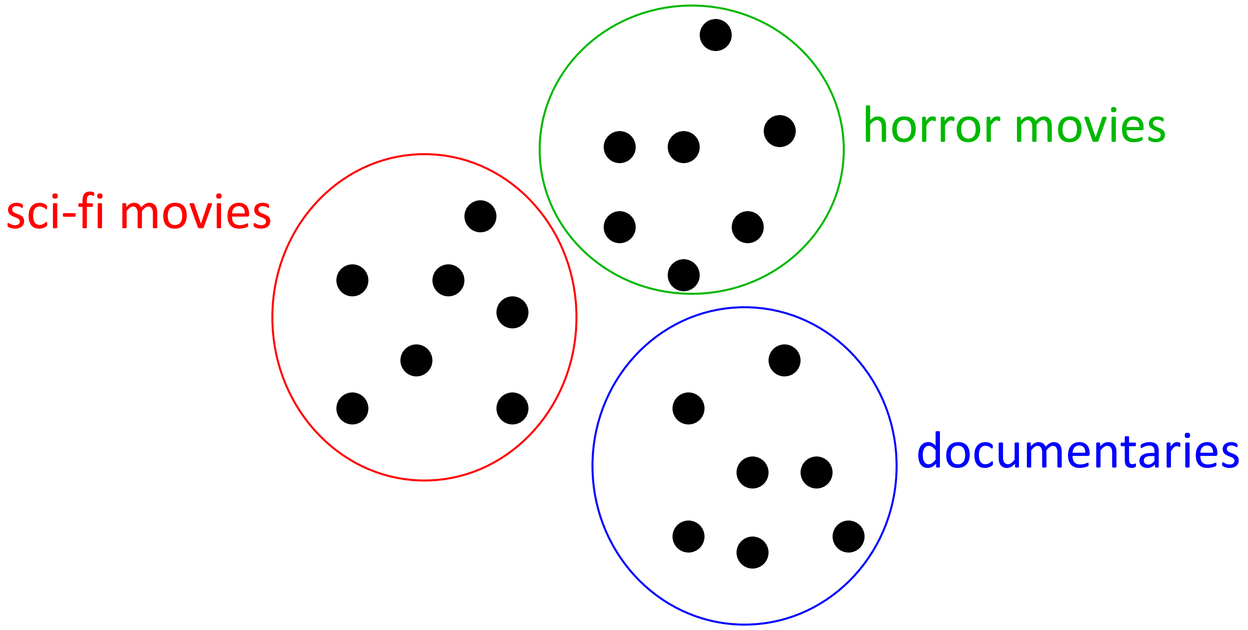

A
F
B
C
D
E
G
H
M
I
J
K
L

Sumber: Image Segmentation, by Dr. Rajeev Srivastava

4. Clustering

Prinsip *clustering* secara umum

- Misalkan terdapat N buah titik data (terokan, vektor fitur, dll), $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N$
- Kelompokkan (*cluster*) titik-titik yang mirip dalam kelompok yang sama



Bagaimana kaitan *clustering* pada segmentasi citra?

- Nyatakan citra sebagai vektor fitur $\boldsymbol{x}_1,\ldots,\mathbf{x}_n$
  - Sebagai contoh, setiap *pixel* dapat dinyatakan sebagai vektor:
    - Intensitas → menghasilkan vektor dimensi satu
    - Warna → menghasilkan vektor berdimensi tiga (R, G, B)
    - Warna + koordinat, → menghasilkan vektor berdimensi lima

- Kelompokkan vektor-vektor fitur ke dalam ***k*** kluster

Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

citra input

9 4 2	7 3 1	8 6 8
8 2 4	5 8 5	3 7 2
9 4 5	2 9 3	1 4 4

Vektor fitur untuk clustering berdasarkan warna

[9 4 2]   [7 3 1]   [8 6 8]

[8 2 4]   [5 8 5]   [3 7 2]

[9 4 5]   [2 9 3]   [1 4 4]

RGB (or LUV) space clustering

Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

citra input

9 4 2	7 3 1	8 6 8
8 2 4	5 8 5	3 7 2
9 4 5	2 9 3	1 4 4

Vektor fitur untuk clustering berdasarkan warna dan koordinat pixel

[9 4 2 0 0] [7 3 1 0 1] [8 6 8 0 2]

[8 2 4 1 0] [5 8 5 1 1] [3 7 2 1 2]

[9 4 5 2 0] [2 9 3 2 1] [1 4 4 2 2]

RGBXY (or LUVXY) space clustering

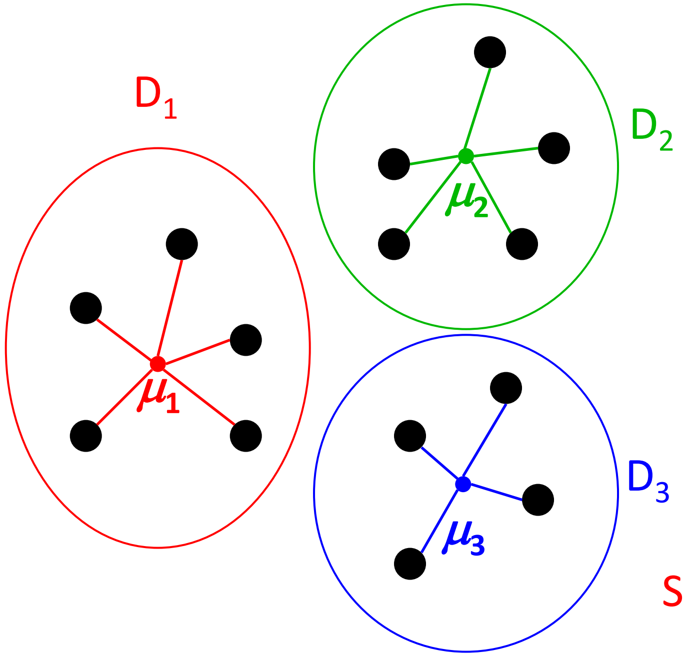
Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

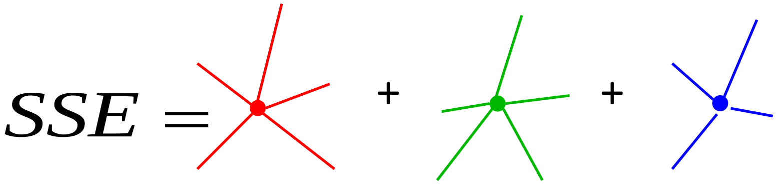
K-Means Clustering

- *K-means clustering* merupakan algoritma *clustering* yang paling populer
- Asumsikan jumlah cluster adalah *k*
- Mengooptimalkan (secara hampiran) fungsi objektif berikut untuk variabel D_i dan μ_i

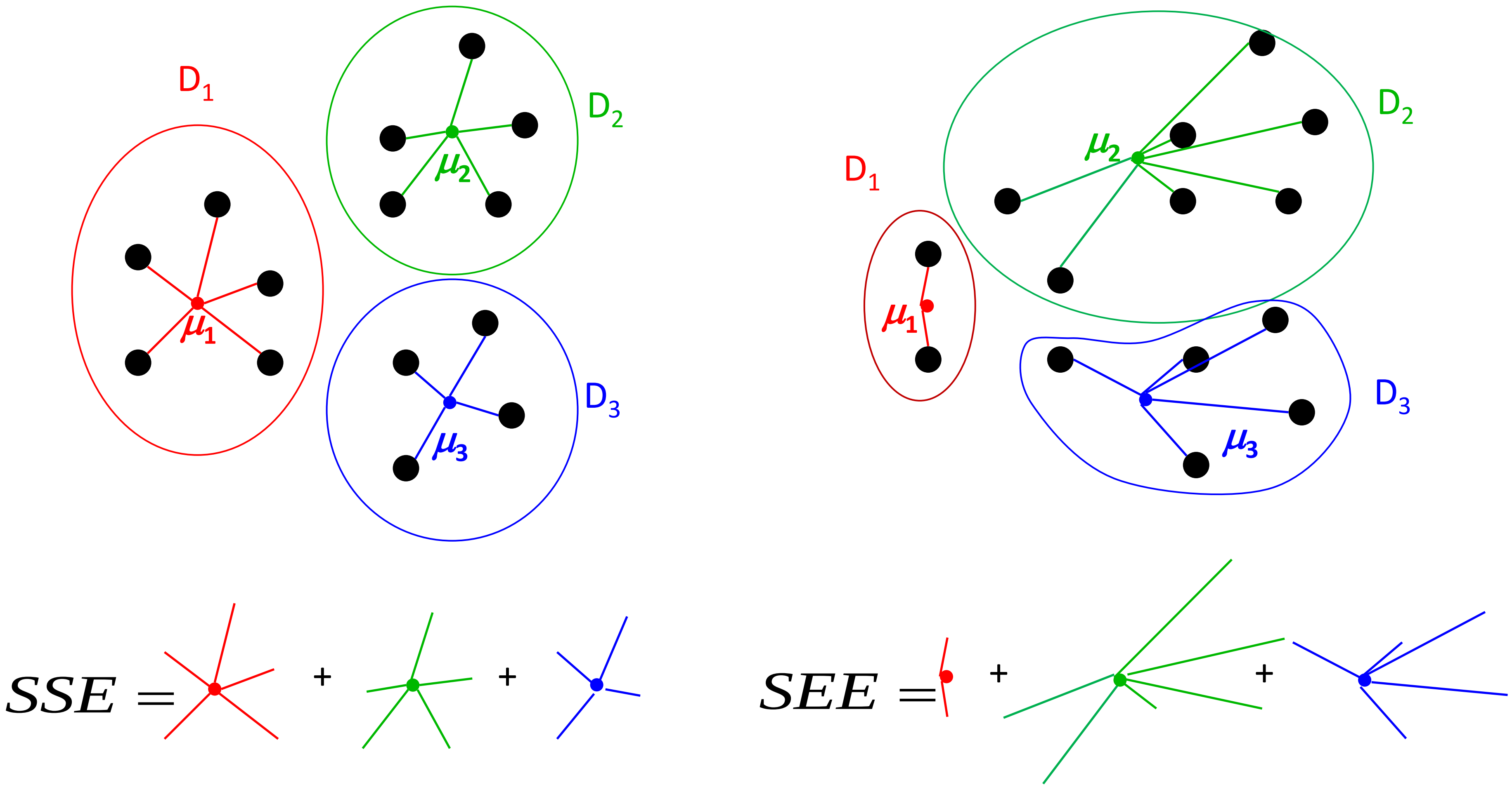
$$E_k = SSE = \sum_{i=1}^{k} \sum_{x \in D_i} \left\| x - \mu_i \right\|^2$$

sum of squared errors dari kluster dengan pusat μ_i





Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

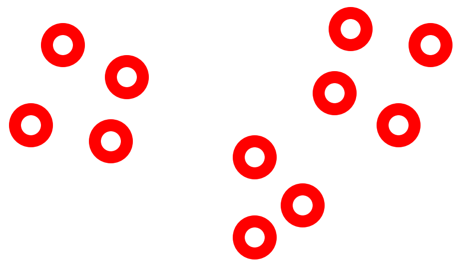


Good (tight) clustering
smaller value of SSE

Bad (loose) clustering
larger value of *SSE*

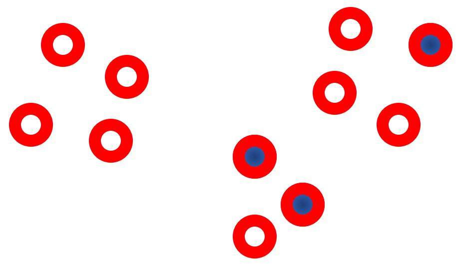
Algoritma K-means Clustering

- Initialization step
  1. pick ***k*** cluster centers randomly



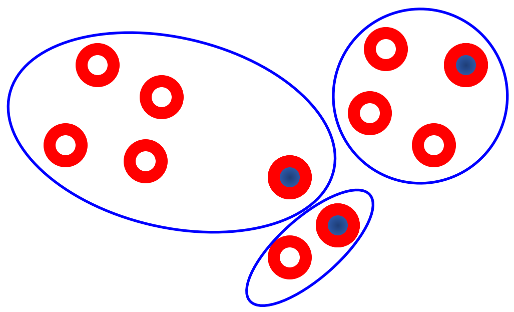
Algoritma K-means Clustering

- Initialization step
  1. pick ***k*** cluster centers randomly



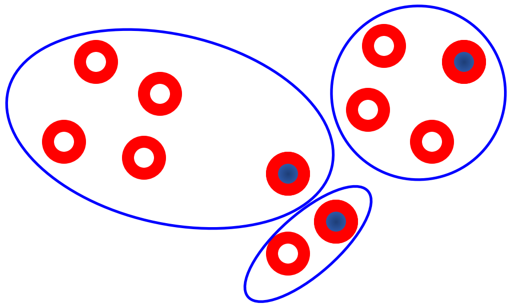
Algoritma K-means Clustering

- Initialization step
  1. pick ***k*** cluster centers randomly
  2. assign each sample to closest center

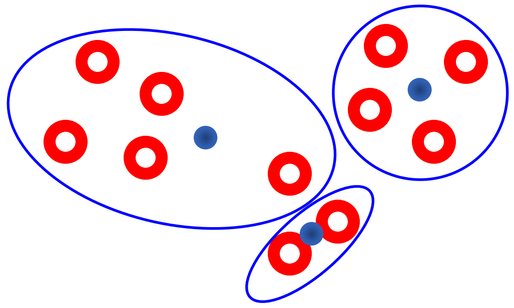


Algoritma K-means Clustering

- Initialization step
  1. pick ***k*** cluster centers randomly
  2. assign each sample to closest center



Algoritma K-means Clustering

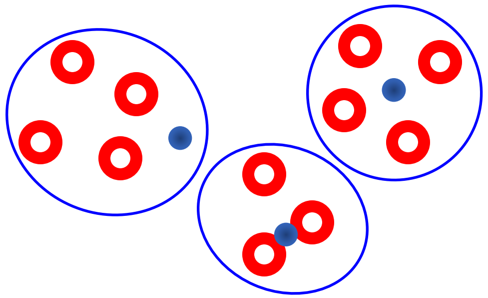


- Initialization step
  1. pick ***k*** cluster centers randomly
  2. assign each sample to closest center

- Iteration steps
  1. compute means in each cluster $\mu_i = \frac{1}{|D_i|}\sum_{x \in D_i} x$

Algoritma K-means Clustering

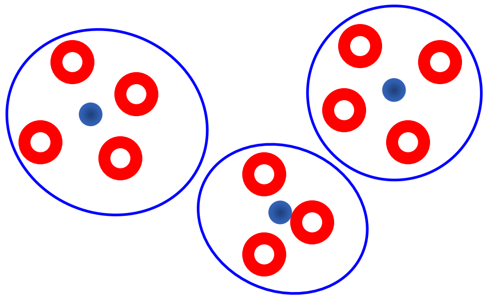
- Initialization step
  1. pick ***k*** cluster centers randomly
  2. assign each sample to closest center



- Iteration steps
  1. compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$
  2. re-assign each sample to the closest mean

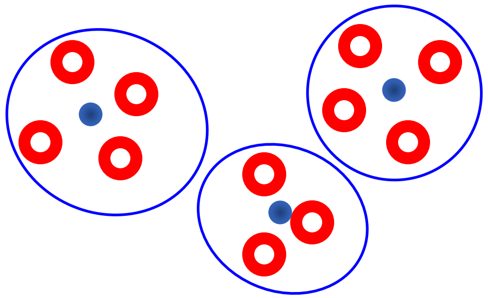
Algoritma K-means Clustering

- Initialization step
  1. pick ***k*** cluster centers randomly
  2. assign each sample to closest center



- Iteration steps
  1. compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$
  2. re-assign each sample to the closest mean
- Iterate until clusters stop changing

Algoritma K-means Clustering



- Initialization step
  1. pick ***k*** cluster centers randomly
  2. assign each sample to closest center

- Iteration steps
  1. compute means in each cluster $\mu_i = \frac{1}{|D_i|} \sum_{x \in D_i} x$
  2. re-assign each sample to the closest mean
- Iterate until clusters stop changing

- This procedure decreases the value of the objective function

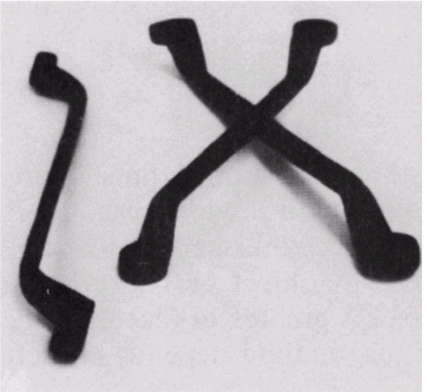
$$E_k(D, \mu) = \sum_{i=1}^{k} \sum_{x \in D_i} \|x - \mu_i\|^2$$

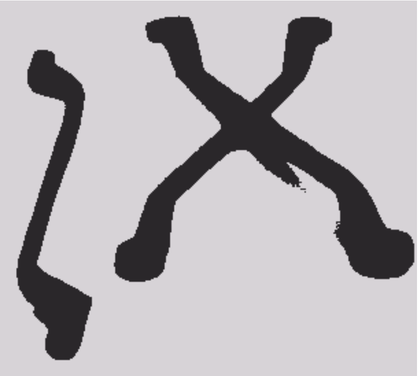
optimization variables

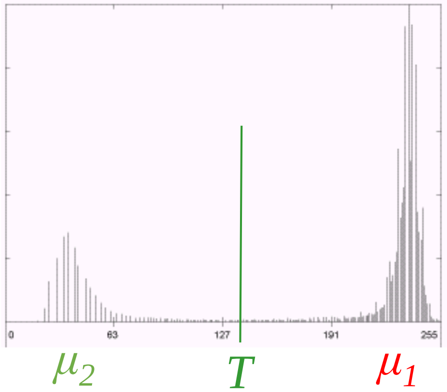
$$D = (D_1, \ldots, D_k)$$
$$\mu = (\mu_1, \ldots, \mu_k)$$

block-coordinate descent: step 1 optimizes μ, step 2 optimizes D

Contoh hasil *K-means clustering*



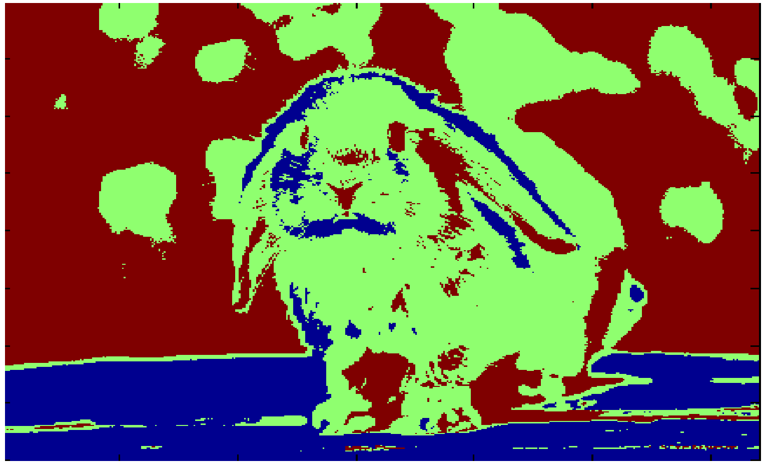




K-means menghasilkan
Pengelompokan yang kompak

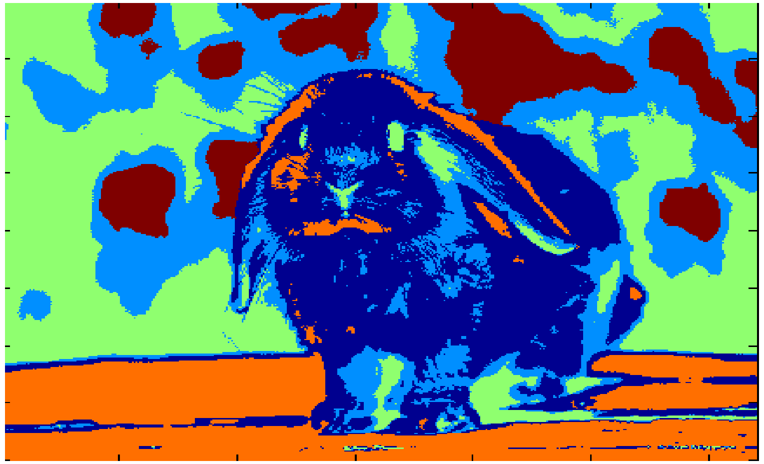
Pada kasus ini, K-means (K=2) secara otomatis menemukan nilai ambang yang bagus (antara 2 cluster

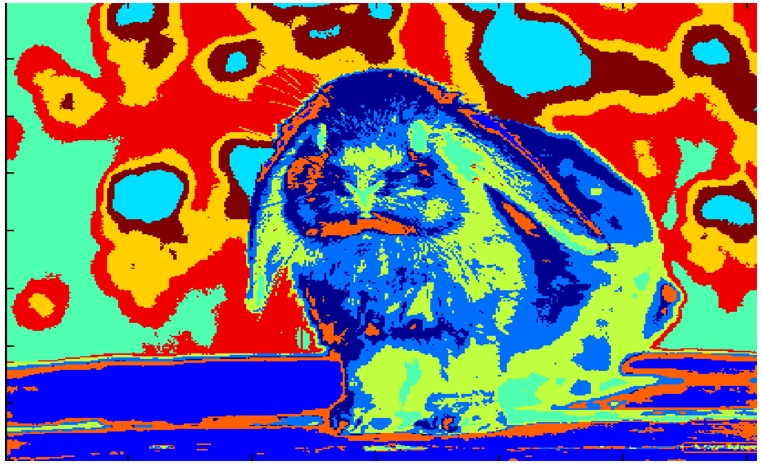
Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

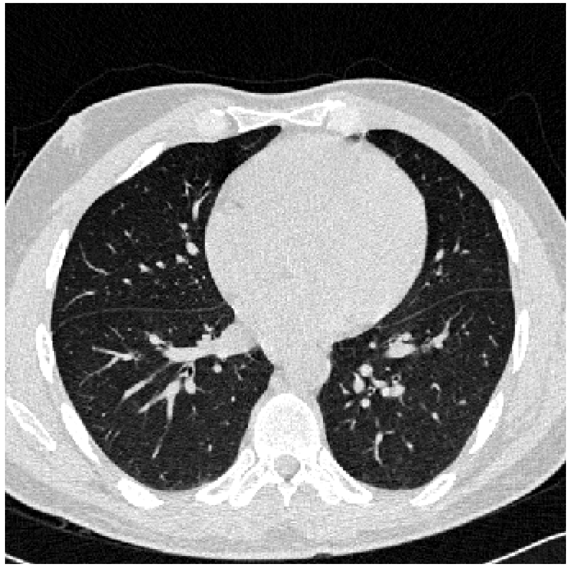


***k* = 3**

(random colors are used to better show segments/clusters)

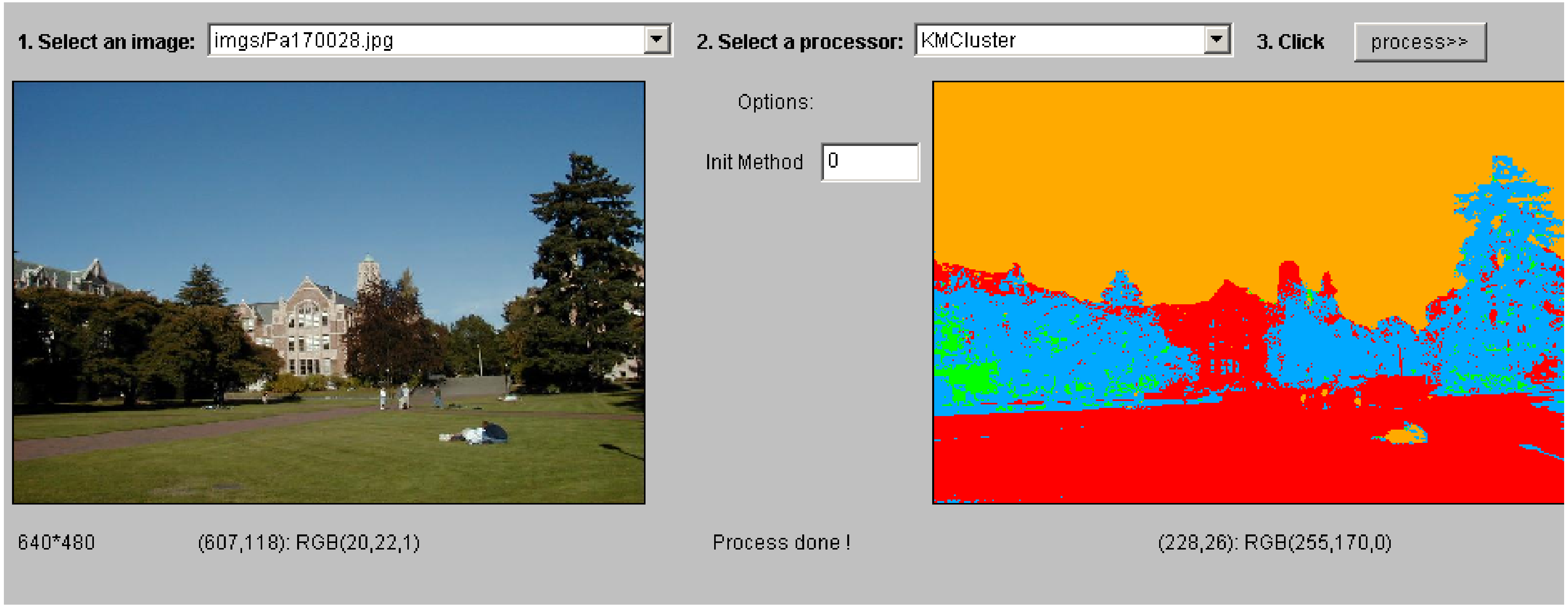


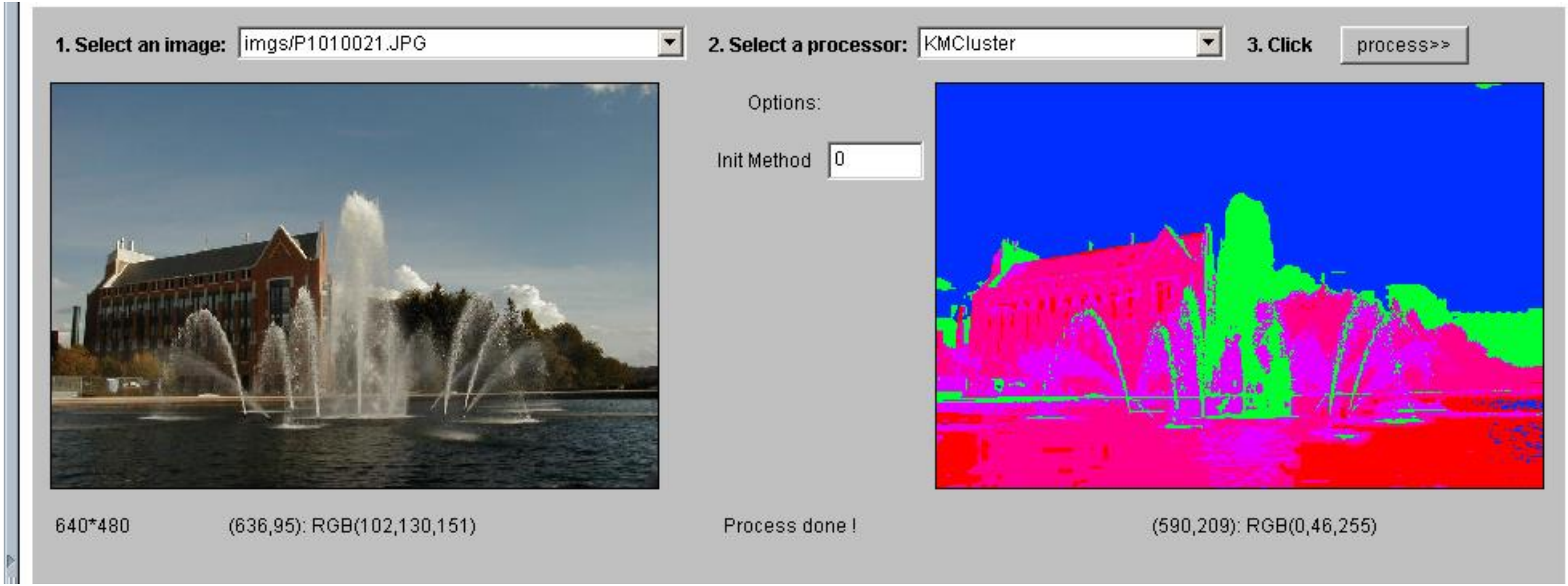




An image(I)

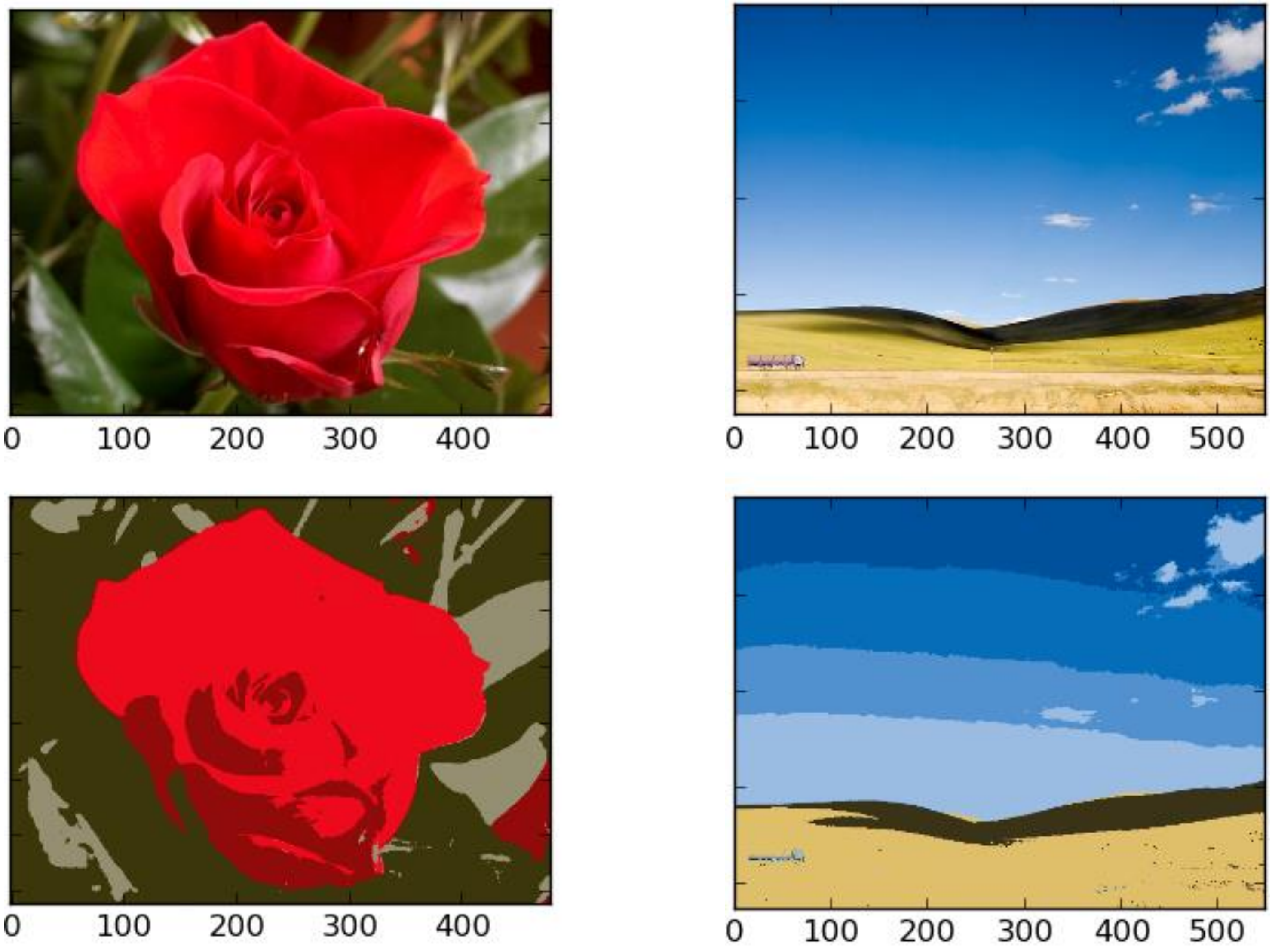
Three cluster image (J)on gray values of I


1. Select an image:
imgs/Pa170028.jpg
2. Select a processor:
KMCluster
3. Click
process>>
Options:
Init Method
0
640*480
(607,118): RGB(20,22,1)
Process done !
(228,26): RGB(255,170,0)


1. Select an image:
imgs/P1010021.JPG
2. Select a processor:
KMCluster
3. Click
process>>
Options:
Init Method
0
640*480
(636,95): RGB(102,130,151)
Process done !
(590,209): RGB(0,46,255)

Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

Contoh hasil *K-means clustering (berdasarkan warna)*



Contoh hasil *K-means clustering (berdasarkan warna + koordinat)*

color quantization

RGB features

superpixels

RGBXY features

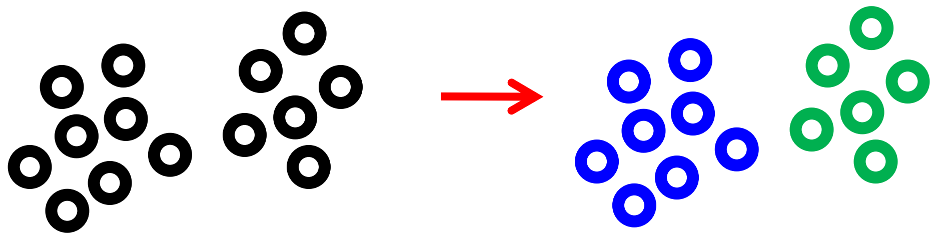
Voronoi cells

XY features only

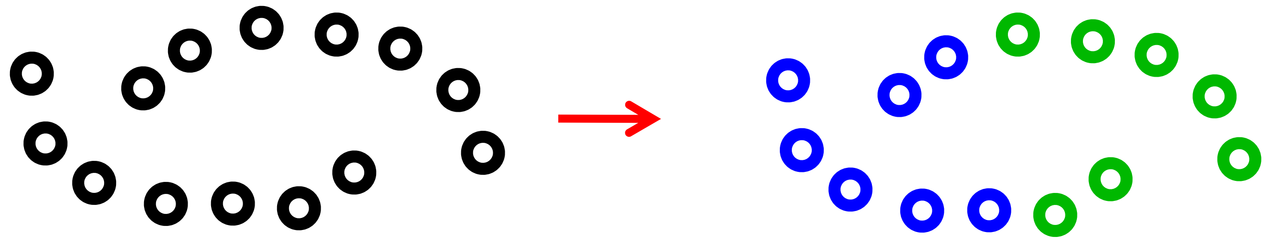
Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

Sifat-sifat K-means

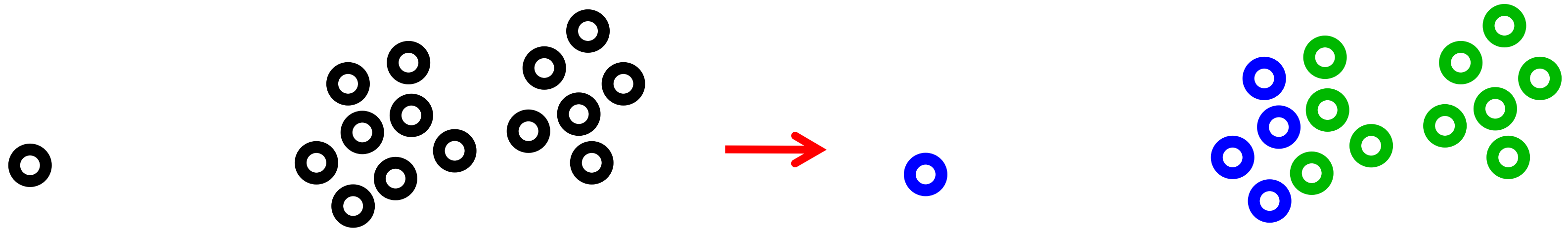
- Works best when clusters are spherical (blob like)



- Fails for elongated clusters
  - SSE is not an appropriate objective function in this case



- Sensitive to outliers



maximum likelihood (ML) fitting
of parameters μ_i (means) of Gaussian distributions

$$E_k = \sum_{i=1}^{k} \sum_{x \in D_i} \|x - \mu_i\|^2$$

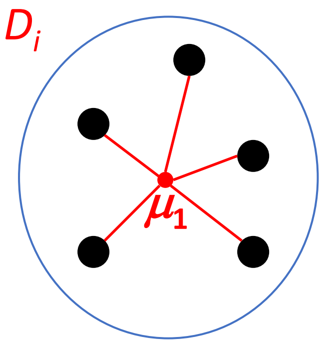
equivalent (easy to check)

$$E_k \sim -\sum_{i=1}^{k} \sum_{x \in D_i} \log P(x \mid \mu_i) \quad + const$$

Gaussian distribution $P(x \mid \mu_i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(- \frac{\| x - \mu_i \|^2}{2\sigma^2} \right)$

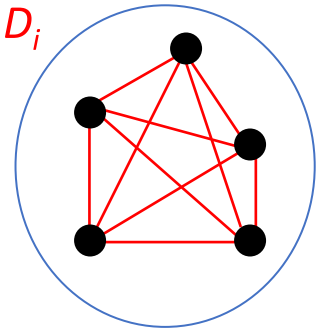
Sumber: CS 4487/9587 Algorithms for Image Analysis: Basic Image Segmentation

just plug-in expression $\mu_i = \frac{1}{|D_i|} \sum_{y \in D_i} y$



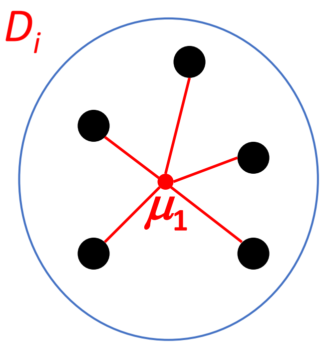
$$E_k = \sum_{i=1}^{k} \sum_{x \in D_i} \|x - \mu_i\|^2$$

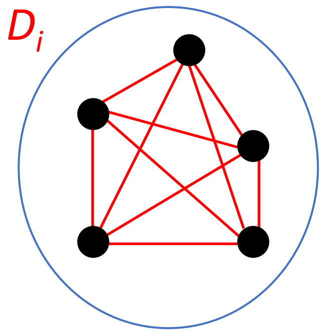
equivalent (easy to check)



$$E_k = \sum_{i=1}^{k} \sum_{x,y \in D_i} \frac{\| x - y \|^2}{2 \cdot | D_i |}$$

sample variance: $\mathrm{var}(D_i) = \frac{1}{|D_i|} \sum_{x \in D_i} \| x - \mu_i \|^2 = \frac{1}{2|D_i|^2} \sum_{x,y \in D_i} \| x - y \|^2$





both formulas can be written as

$$E_k = \sum_{i=1}^{k} |D_i| \cdot \mathrm{var}(D_i)$$

sample variance: $\mathrm{var}(D_i) = \frac{1}{|D_i|}\sum_{x\in D_i} \| x-\mu_i \|^2 = \frac{1}{2|D_i|^2}\sum_{x,y\in D_i} \| x-y \|^2$

Rangkuman K-means

- Advantages
  - Principled (objective function) approach to clustering
  - Simple to implement (the approximate iterative optimization)
  - Fast
- Disadvantages
  - Only a local minimum is found (sensitive to initialization)
  - May fail for non-blob like clusters
  - Sensitive to outliers
  - Sensitive to choice of ***k***

K-means fits Gaussian models

Quadratic errors are such

Can add sparsity term and make *k* an additional variable

$$E = \sum_{i=1}^{k} \sum_{x \in D_i} \|x - \mu_i\|^2 \; + \; \gamma \cdot |k|$$

Akaike Information Criterion (AIC) or
Bayesian Information Criterion (BIC)