extract something from image

LECTURE 08 IMAGE SEGMENTATION

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OBJECTIVES

- To understand segmentation fundamentals and its challenges
- To understand and be able to apply segmentation techniques to solve simple to intermediate complexity of problems
- To identify the limitation of different segmentation techniques

TODAY'S CONTENT

- Segmentation techniques
  - Discontinuity
  - Similarity
  - Region-based segmentation
  - Other segmentation techniques

WHAT IS SEGMENTATION?

WHAT IS SEGMENTATION?

Ref: Filip Malmberg

SEGMENTATION

- finding groups of pixels that “go together” -> Cluster analysis.
- subdivides an image into its constituent regions or objects.
- The level to which the subdivision is carried depends on the problem being solved.
- Segmentation accuracy determines the eventual success or failure of computerized analysis procedures.

Ref: Filip Malmberg

SEGMENTATION

- Accurate segmentation of objects of interest in an image greatly facilitates further analysis of these objects. For example, it allows us to:
  - Count the number of objects of a certain type.
  - Measure geometric properties (e.g., area, perimeter) of objects in the image.
  - Study properties of an individual object (intensity, texture, etc.)

semantic seg : แบ่งประเภท

Instance seg : นับจำนวน

panoptic seg : uncountable noun

Ref: Filip Malmberg

SEGMENTATION

- What would be correct segmentation of this image?

Ref: Filip Malmberg

SEGMENTATION

- What would be correct segmentation of this image?

Until we specify the target

"Segment the orange car from the background"

"Segment all road signs from the background"

Ref: Filip Malmberg

SEGMENTATION

- A segmentation can also be defined as a mapping from the set of pixels to some application dependent target set, e.g.
  - {Object, Background}
  - {Humans, Other objects}
  - {Healthy tissue, Tumors}
- To perform accurate segmentation, we (or our algorithms) need to somehow know how to differentiate between different elements of the target set.

Ref: Filip Malmberg

BASIC SEGMENTATION

- Two main properties of intensity values:
  - **Discontinuity** -> partition an image based on abrupt changes in intensity, such as edges.
  - **Similarity** -> partition an image into regions what are similar according to a set of pre-defined criteria, such as thresholding, region growing and region splitting.

BASIC SEGMENTATION ALGORITHMS

Thresholding *Similarity*

- Based on pixel intensities (shape of histogram is often used for automation).

Edge-based *Discontinuity*

- Detecting edges that separate regions from each other.

Region-based *Similarity*

- Grouping similar pixels (with e.g. region growing or merge & split).

Ref: Filip Malmberg

DISCONTINUITY

Using Discontinuity for segmentation

DETECTION OF DISCONTINUITIES

2

spatial / convo filtering

flip

- Basic types of gray-level discontinuities in a digital image:

1

- **Points**, **Lines**, and **Edges**

3

- Look at discontinuities -> apply 3x3 mask into an image.

ให้ผลลัพธ์เหมือนกัน, เมื่อเป็น symmetric

ω_1	ω_2	ω_3
ω_4	ω_5	ω_6
ω_7	ω_8	ω_9

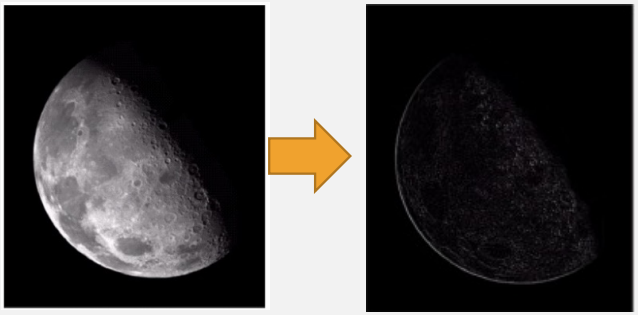
Mask coefficients

$$R = \sum_{i=1}^{mn} \omega_i z_i$$

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Image pixels

0	1	0
1	-4	1
0	1	0



Original image

Laplacian image

ω are mask coefficients

z : values of image gray levels corresponding those coefficients

mn: the total number of coefficients in the mask.

1 POINT DETECTION

- Detection of isolated points in an image can be detected using the mask below:
  - The idea of an isolated point is that gray level is significantly different from its background.

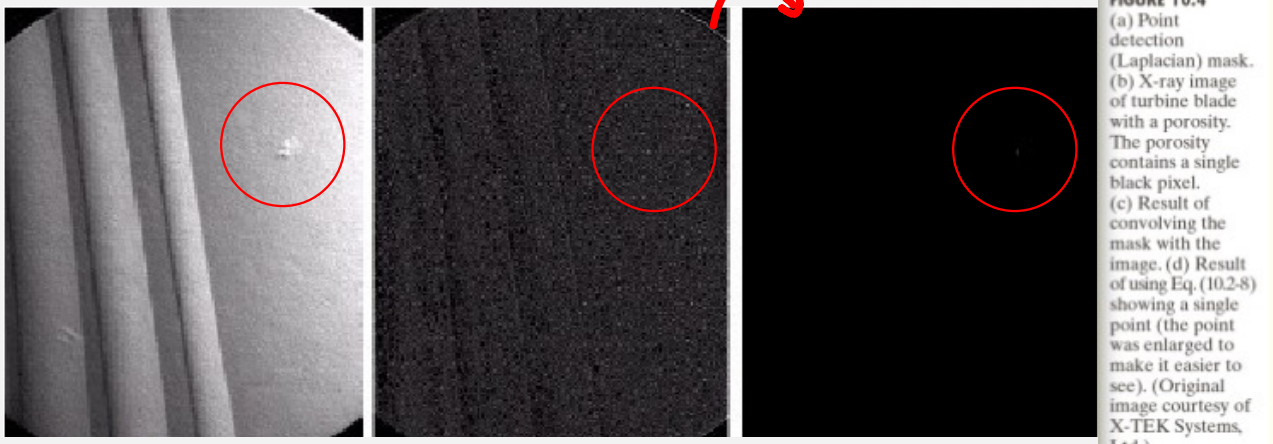
-1	-1	-1
-1	8	-1
-1	-1	-1

(a)

$$|R| \geq T$$

T: nonneg. Threshold

R: convolved image (image * mask)



(b) (c) (d)

FIGURE 10.4 (a) Point detection (Laplacian) mask. (b) X-ray image of turbine blade with a porosity. The porosity contains a single black pixel. (c) Result of convolving the mask with the image. (d) Result of using Eq. (10.2-8) showing a single point (the point was enlarged to make it easier to see). (Original image courtesy of X-TEK Systems, Ltd.)

2 LINE DETECTION

- The mask below will respond more strongly to lines (one pixel thick) oriented in horizontal, +45°, vertical, and -45° directions, respectively.

Line masks:

-1	-1	-1
2	2	2
-1	-1	-1

Horizontal

-1	-1	2
-1	2	-1
2	-1	-1

+45°

-1	2	-1
-1	2	-1
-1	2	-1

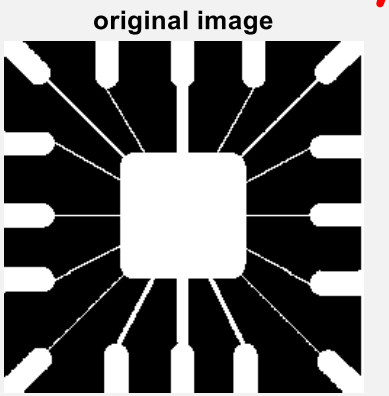
Vertical

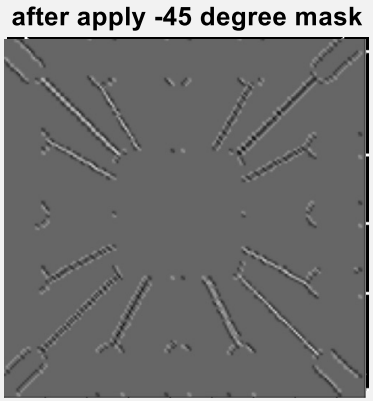
2	-1	-1
-1	2	-1
-1	-1	2

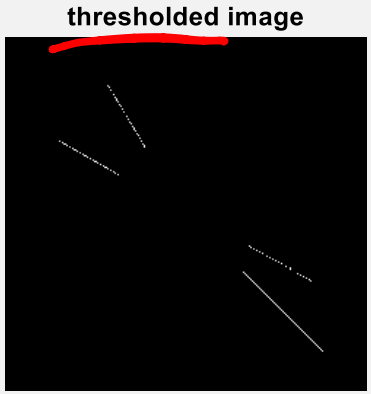
-45°

2 LINE DETECTION

- Digitized (binary) portion of a wire-bond mask for an electronic circuit (left).
- Absolute value of results after processing with -45° line detector (middle).
- Result of thresholding image (right).







2	-1	-1
-1	2	-1
-1	-1	2

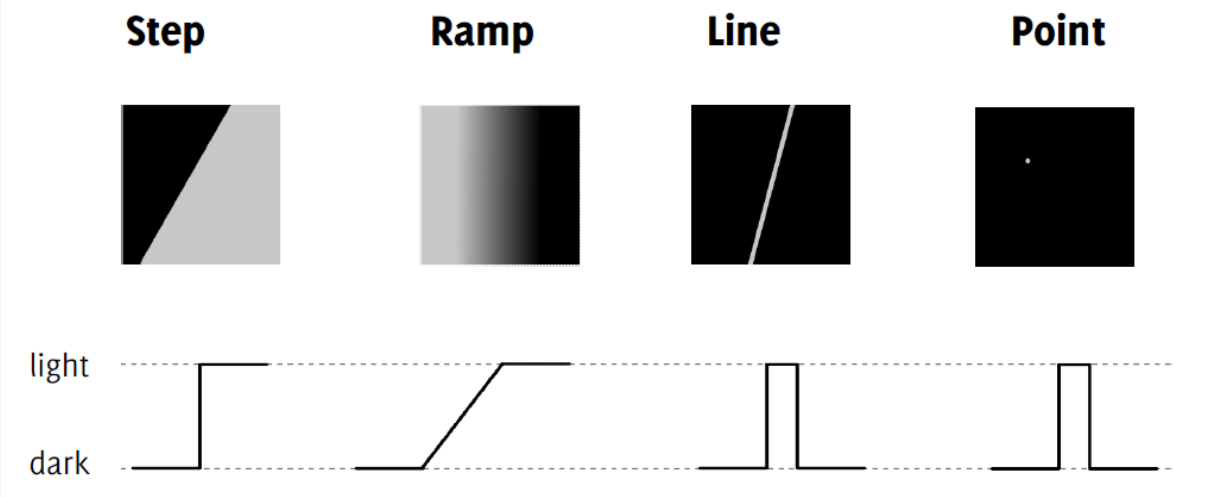
-45°

symmetric filter

3 EDGE DETECTION

- Intuitively, an edge is a set of connected pixels that lie on the boundary between two regions.
- A reasonable definition of “edge” requires the ability to measure gray-level transitions in a meaningful way.

Detecting sharp & local changes in intensity.

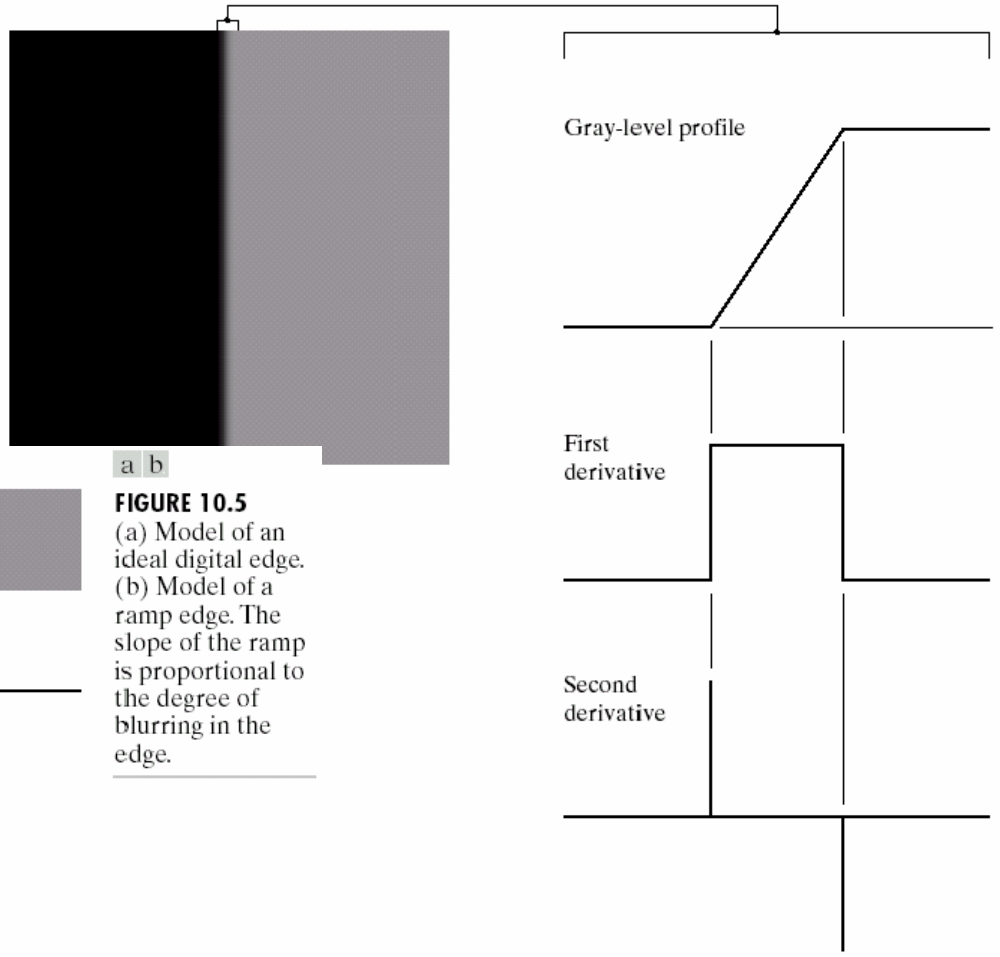


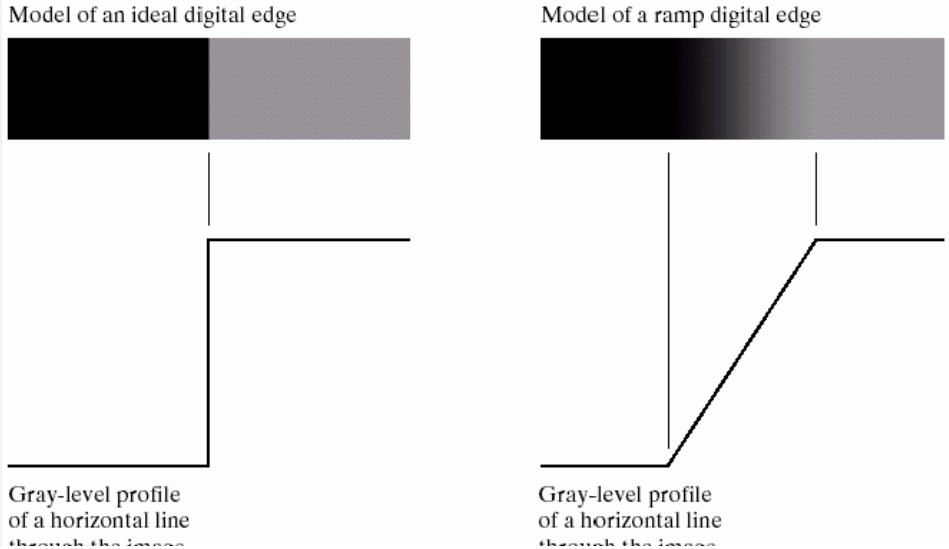
Ref: Filip Malmberg

3 EDGE DETECTION

a b

FIGURE 10.6
(a) Two regions separated by a vertical edge. (b) Detail near the edge, showing a gray-level profile, and the first and second derivatives of the profile.





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.

3 EDGE DETECTION

- **First derivatives:**
- The gradient of an image $f(x,y)$ at location (x,y) is defined as the *vector*

$$\nabla \boldsymbol{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \qquad \nabla f \approx |G_x| + |G_y|$$

- A weight value of 2 is used to achieve some smoothing by giving more importance to the center point, called the Sobel operators.

a
b c
d e
f g

FIGURE 10.8
A 3×3 region of an image (the z's are gray-level values) and various masks used to compute the gradient at point labeled z_5.

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	−1	0	1
0	0	0	−1	0	1
1	1	1	−1	0	1

Gx Prewitt Gy

−1	−2	−1	−1	0	1
0	0	0	−2	0	2
1	2	1	−1	0	1

Sobel

Gx (edges at x-direction)
Gy (edges in y-direction)

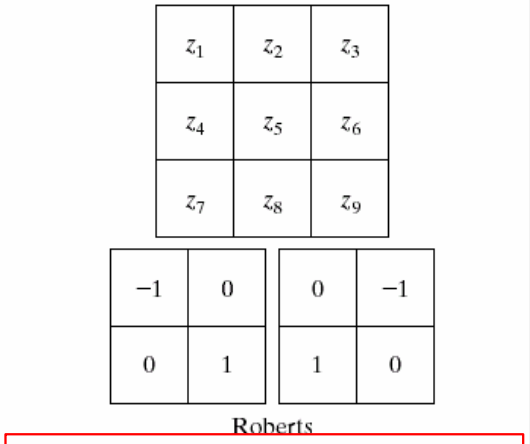
Image from Gonzalez & Woods, Digital Image Processing

3 EDGE DETECTION

- **First derivatives:**
- The Prewitt and Sobel operators are among the most used in practice for computing digital gradients.
- Prewitt masks are simpler to implement than the Sobel masks, but the latter have slightly superior **noise-suppression** characteristics, an important issue when dealing with derivatives.

a
b c
d e
f g

FIGURE 10.8
A 3×3 region of an image (the z's are gray-level values) and various masks used to compute the gradient at point labeled z_5.



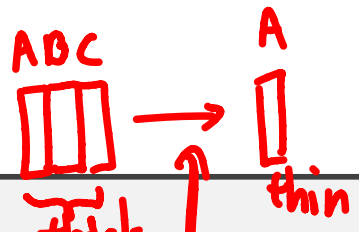
Might be opposite in the program

Gx (edges at x-direction)
Gy (edges in y-direction)

Image from Gonzalez & Woods, Digital Image Processing

3 EDGE DETECTION

- The Canny method has been developed by John F. Canny in 1986
- The Canny method finds edges by looking for **local maxima of the gradient of I.**
- This method uses two thresholds to detect strong and weak edges. By using two thresholds, the Canny method is less likely than the other methods to be fooled by **noise**, and more likely to **detect true weak edges.**
- **Steps:**
  1. **Noise Reduction** (remove noise with 5x5 Gaussian filter)
  2. **Finding Intensity Gradient of the Image** - Smoothened image is then filtered with a Sobel kernel in both horizontal and vertical direction

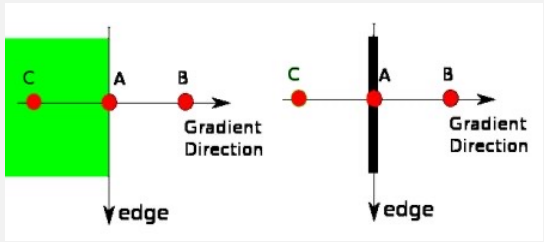


3 EDGE DETECTION

- The Canny method - multi-stage algorithm

3. Non-maximum Suppression – A full scan of image is done to remove any unwanted pixels which may not constitute the edge. Point A will be compared with B and C.

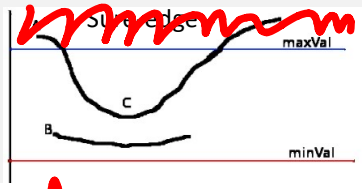
- if A is local maxima, A will be considered for the next stage.
- If not, suppressed. Remaining only **thin edges**.



A compared to C --- Yes
B > minVal but same with C – Not Edges

4. Hysteresis Thresholding – double thresholds

- Removes pixels whose gradients lower than the threshold noises on the assumption that edges are long lines
- Edge tracking by hysteresis - Weak edges that are connected to strong edges will be actual/real edges

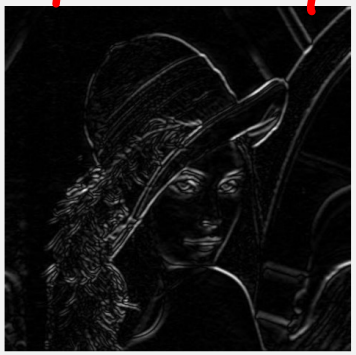


we finally get is strong edges in the image

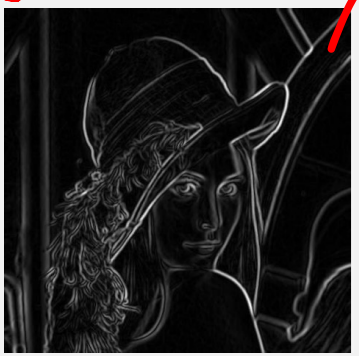
3 EDGE DETECTION

Gaussian Blur

Gx



Gy



Gradient Magnitude

Non-maxima Suppression

Double hysteresis

Edge tracking

Canny Edge detection

http://www.justin-liang.com/tutorials/canny/

3 EDGE DETECTION

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, $|G_x| + |G_y|$.

3 EDGE DETECTION

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1

FIGURE 10.13 Laplacian masks used to implement Eqs. (10.1-14) and (10.1-15), respectively.

- **Second derivatives:**
- The Laplacian of a 2-D function (x,y) is a second-order derivative defined as

$$\nabla^2 f = \frac{\partial^2 f}{\partial^2 x} + \frac{\partial^2 f}{\partial^2 y}$$

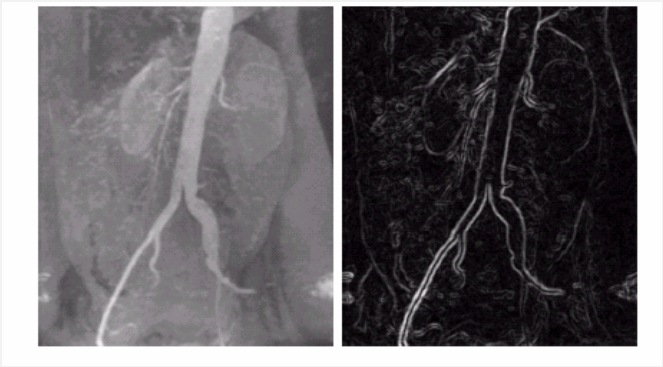
- As a second-order derivative, the Laplacian typically is unacceptably sensitive to noise.
- **Laplacian of a Gaussian (LoG)**
  - Laplacian combined with smoothing as a

    Precursor to finding edges via zero crossings.

0	0	−1	0	0
0	−1	−2	−1	0
−1	−2	16	−2	−1
0	−1	−2	−1	0
0	0	−1	0	0

3 EDGE DETECTION

- **Second derivatives:**
- One straightforward approach for approximating zero crossings is to threshold the LoG image by setting all its positive values to, say, white, and all negative values to black.



(a) (b)

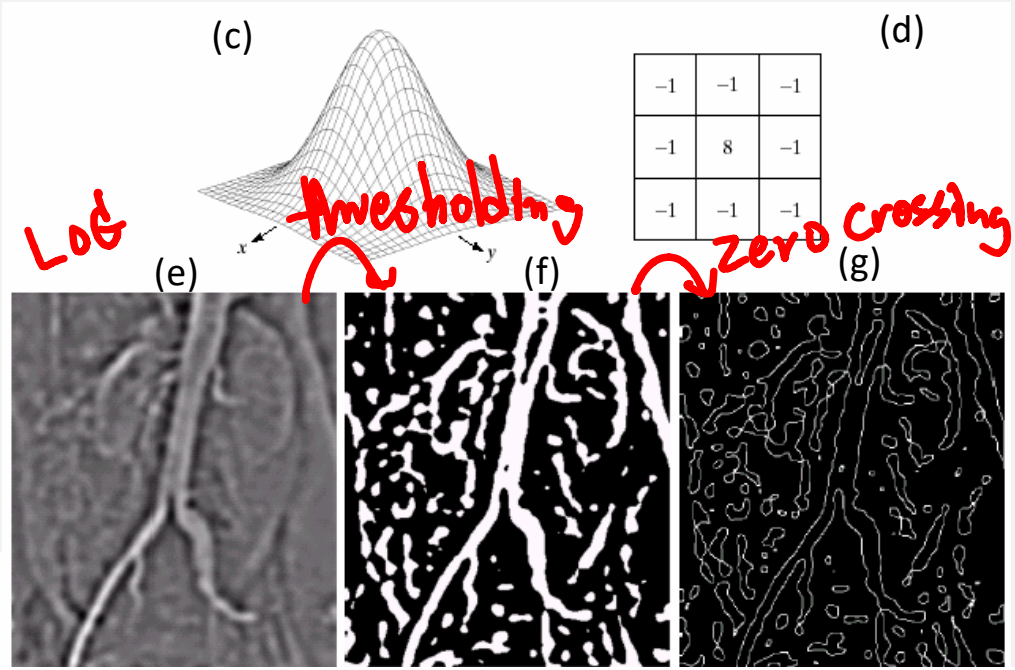


FIGURE 10.15 (a) Original image. (b) Sobel gradient (shown for comparison). (c) Spatial Gaussian smoothing function. (d) Laplacian mask. (e) LoG. (f) Thresholded LoG. (g) Zero crossings. (Original image courtesy of Dr. David R. Pickens, Department of Radiology and Radiological Sciences, Vanderbilt University Medical Center.)

3 EDGE DETECTION

Python

```
img = cv2.imread('cameraman.tif',0)

#canny
img_canny = ____________________________________

#sobel
img_sobelx = cv2.Sobel(img,cv2.CV_8U,1,0,ksize=3)
img_sobely = cv2.Sobel(img,cv2.CV_8U,0,1,ksize=3)
img_sobel = ____________________________________


#prewitt
kernelx = np.array([[-1,-1,-1],[0,0,0],[1,1,1]])
kernely = ____________________________________
img_prewittx = cv2.filter2D(img, -1, kernelx)
img_prewitty = ____________________________________
img_prewitt = ____________________________________
```

Org

void cv::Canny (InputArray image,
OutputArray edges,
double threshold1,
double threshold2,
int apertureSize = 3,
bool L2gradient = false

image	8-bit input image.
edges	output edge map; single channels 8-bit image, which has the same size as image
threshold1	first threshold for the hysteresis procedure.
threshold2	second threshold for the hysteresis procedure.
apertureSize	aperture size for the Sobel operator.
L2gradient	a flag, indicating whether a more accurate L_2 norm $= \sqrt{(dI/dx)^2 + (dI/dy)^2}$

3 EDGE DETECTION

```
#roberts
kernelx = ____________________________________
kernely = ____________________________________
img_robertsx = _____________________________________
img_robertsy = _____________________________________
img_roberts = ___________________________________


#Laplcian
laplacian = ____________________________________________
img_laplacian = _____________________________________
```

Display:

```
titles = ['Original Image','Canny','Sobel','Prewitt','Roberts',‘Laplacian']
images = [img, img_canny, img_sobel, img_prewitt, img_roberts, img_log]
for i in range(6):
   plt.subplot(2,3,i+1),plt.imshow(images[i],'gray')
   plt.title(titles[i])
   plt.xticks([]),plt.yticks([])
plt.show()
```

```
void cv::Canny ( InputArray  image,
                 OutputArray edges,
                 double      threshold1,
                 double      threshold2,
                 int         apertureSize = 3,
                 bool        L2gradient = false
               )
```

image	8-bit input image.
edges	output edge map; single channels 8-bit image, which has the same size as image
threshold1	first threshold for the hysteresis procedure.
threshold2	second threshold for the hysteresis procedure.
apertureSize	aperture size for the Sobel operator.
L2gradient	a flag, indicating whether a more accurate L_2 norm $= \sqrt{(dI/dx)^2 + (dI/dy)^2}$

4 HOUGH TRANSFORM

- Hough transform is generally used to detect whether a set of pixels lie on curves or lines of some specified objects.
- Patented by Paul Hough in 1962. The version of the method as it is used today was invented by Richard Duda and Peter Hart in 1972.

Richard Duda

Peter Hart

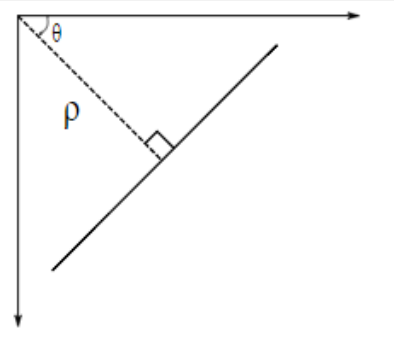
4 HOUGH TRANSFORM

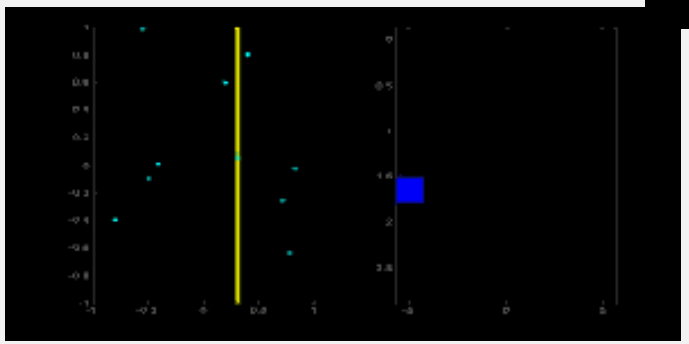
detect line

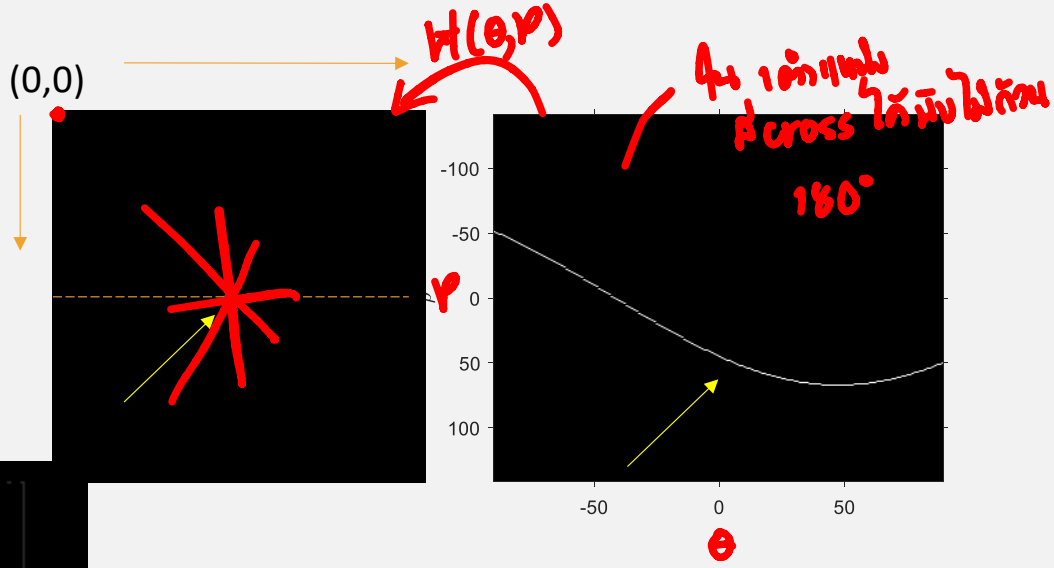
- **Hough Line transform** is to find every possible line that could fit a set of pixels in an image.

$$y = mx + c$$

$$\rho = x\cos\theta + y\sin\theta$$



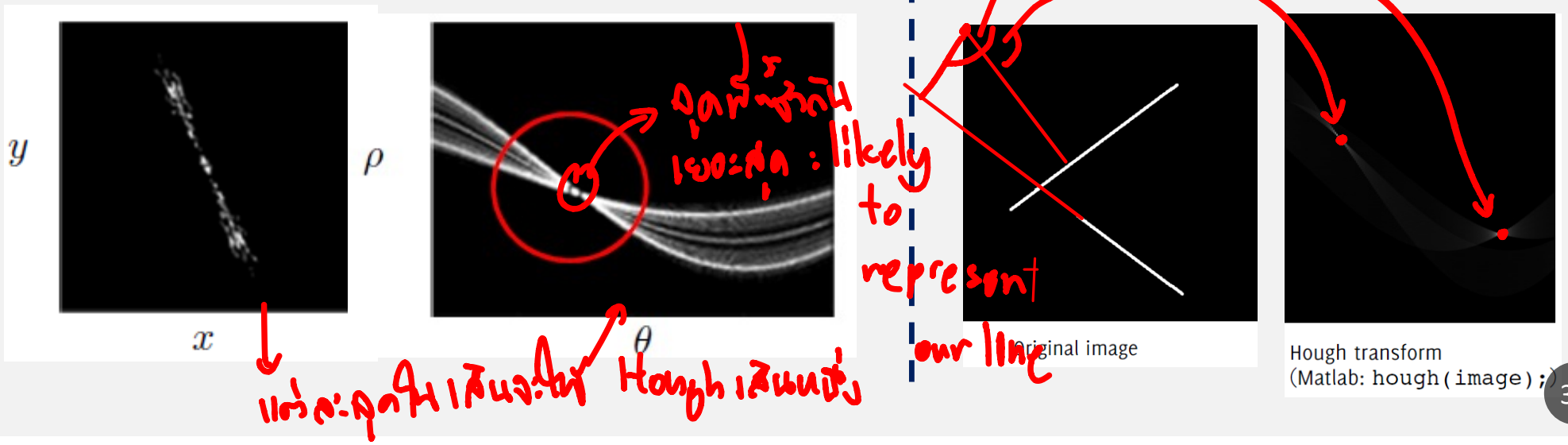




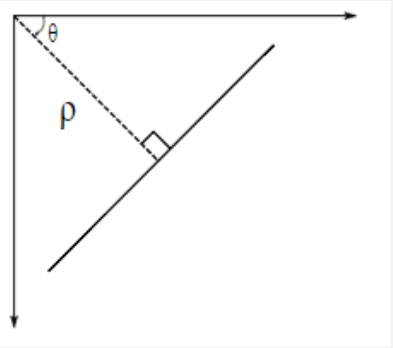
Ref. https://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_imgproc/py_houghlines/py_houghlines.html

4 HOUGH TRANSFORM

- The intersection point is usually the maximum magnitude resulted from the Hough transform.
- Performed after Edge Detection



4 HOUGH TRANSFORM

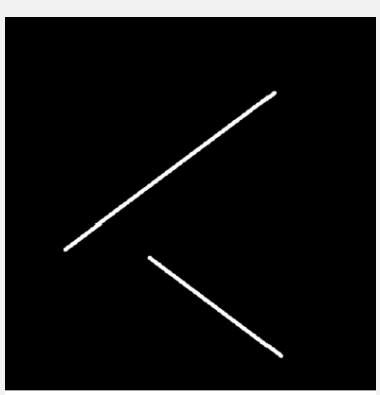


- **Hough Line Algorithm:**
- Typically use a different parameterization
  - ρ is the perpendicular distance from the line to the origin
  - θ is the angle this perpendicular makes with the x axis
- Basic Hough transform algorithm
  1. Initialize H[ρ, θ]=0 (H is an accumulator array)
  2. for each edge point I[x,y] in the image

     for θ = 0 to 180

     $$\rho = x\cos\theta + y\sin\theta$$

     H[ρ, θ] += 1
  3. Find the value(s) of (ρ, θ) where H[ρ, θ] is maximum
  4. The detected line in the image is given by



Original image

Hough transform
(Matlab: `hough(image);`)

$$\rho = x\cos\theta + y\sin\theta$$

HOUGH TRANSFORM [PYTHON]

- HoughLines

Python: `cv2.HoughLines`(image, rho, theta, threshold[, lines[, srn[, stn]]]) → lines

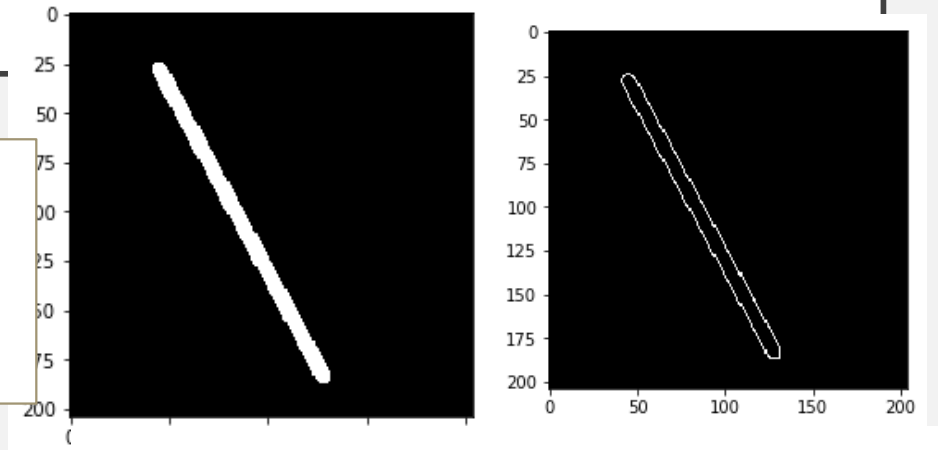
Parameters:

- **image** – 8-bit, single-channel binary source image. The image may be modified by the function.
- **lines** – Output vector of lines. Each line is represented by a two-element vector (ρ, θ) . ρ is the distance from the coordinate origin $(0, 0)$ (top-left corner of the image). θ is the line rotation angle in radians ($0 \sim \text{vertical line}, \pi/2 \sim \text{horizontal line}$).
- **rho** – Distance resolution of the accumulator in pixels.
- **theta** – Angle resolution of the accumulator in radians.
- **threshold** – Accumulator threshold parameter. Only those lines are returned that get enough votes ($>$ `threshold`).
- **srn** – For the multi-scale Hough transform, it is a divisor for the distance resolution `rho` . The coarse accumulator distance resolution is `rho` and the accurate accumulator resolution is `rho/srn` . If both `srn=0` and `stn=0` , the classical Hough transform is used. Otherwise, both these parameters should be positive.
- **stn** – For the multi-scale Hough transform, it is a divisor for the distance resolution `theta`.

https://docs.opencv.org/2.4/modules/imgproc/doc/feature_detection.html

HOUGH TRANSFORM [PYTHON]

```
#HoughLines
img = cv2.imread('line.png')
gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
edges = cv2.Canny(gray,50,150,apertureSize = 3)
lines = cv2.HoughLines(edges,10,np.pi/180,100)
```

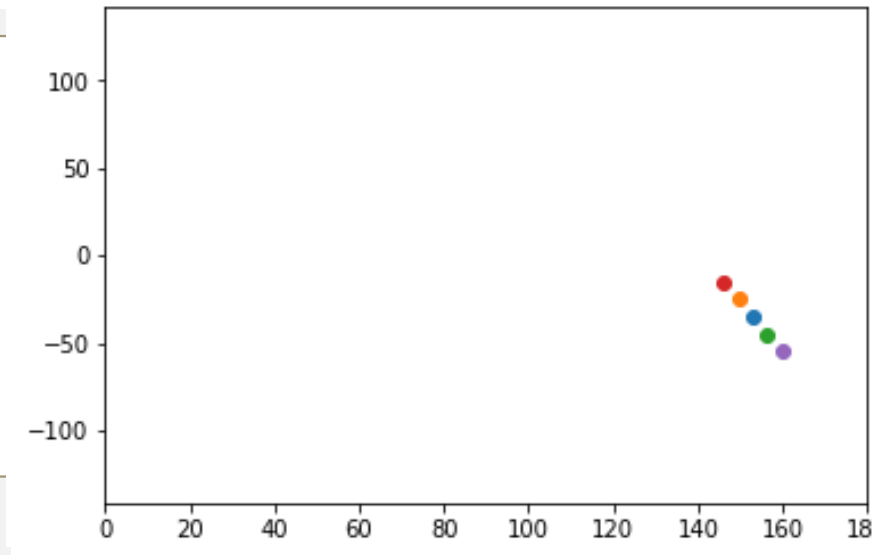


To display:

```
#Change radian to degree
linesdegree = lines.copy()
linesdegree[:,0:1,1:2] =linesdegree[:,0:1,1:2]*180/np.pi

# use scatter plot
for i in range(0,len(linesdegree)):
    plt.scatter(linesdegree[i,0:1,1:2],linesdegree[i,0:1,0:1])

# set x,y limits
plt.xlim(0, 180)
plt.ylim(-100*np.sqrt(2), 100*np.sqrt(2))
```



https://docs.opencv.org/2.4/modules/imgproc/doc/feature_detection.html

4 OTHER HOUGE TRANSFORM

- The equation has three parameters for circle Hough transform– x_0, y_0, ρ
- Hough circle / lines -> opencv
- Hough circle / lines / ellipse -> scikit-image

Analytic Form	Parameters	Equation
Line	ρ, θ	$xcos\theta + ysin\theta = \rho$
Circle	x_0, y_0, ρ	$(x - x_0)^2 + (y - y_0)^2 = \rho^2$
Parabola	x_0, y_0, ρ, θ	$(y - y_0)^2 = 4\rho(x - xo)$
Ellipse	x_0, y_0, a, b, θ	$(x - xo)2/a^2 + (y - y_0)^2/b^2 = 1$

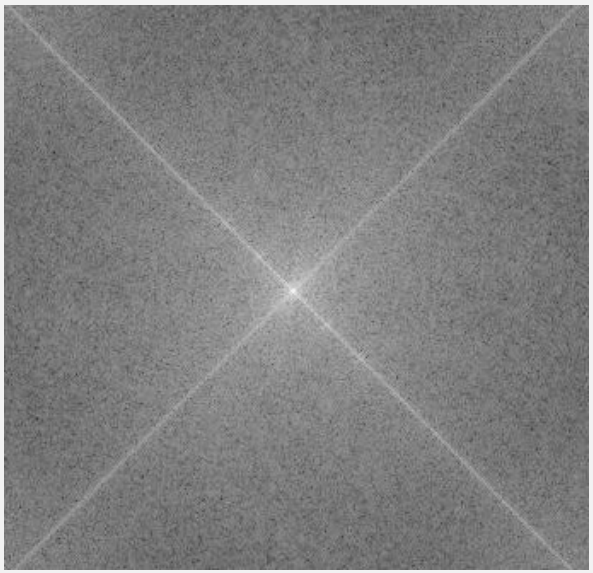
EXERCISE #2 HOUGH LINE TRANSFORM

- Exercise #2 Find main lines in this image and describe the lines:
  - What are the main ρ (s), and θ (s) of this image?

clock2.jpg

ASSIGNMENT

- Find main lines in this image and describe the lines:



findLine.png

EXERCISE #3 HOUGH CIRCLE

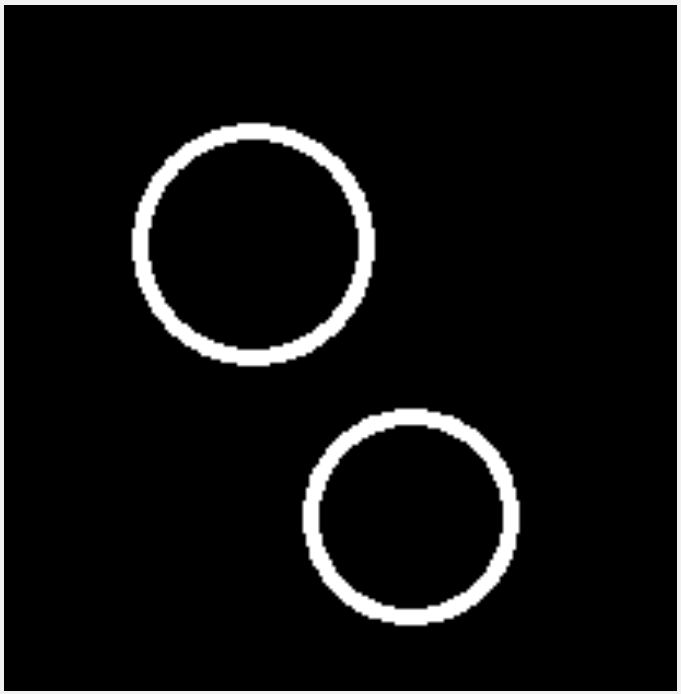
- Exercise #3 Read circle.png to detect circle using Hough transform

◆ HoughCircles()

```
void cv::HoughCircles ( InputArray  image,
                        OutputArray circles,
                        int         method,
                        double      dp,
                        double      minDist,
                        double      param1 = 100 ,
                        double      param2 = 100 ,
                        int         minRadius = 0 ,
                        int         maxRadius = 0
                      )
```

Python:

```
cv.HoughCircles( image, method, dp, minDist[, circles[, param1[, param2[, minRadius[, maxRadius]]]]] ) -> circles
```



SIMILARITY

Using Similarity for segmentation

THRESHOLDING

- Isolate objects from their background.
- The success of these operations depends very much on choosing an appropriate threshold level.
  - Too low -> reduce object size
  - Too high -> include extraneous background

- Automatic method for choosing a best threshold is needed!!!!

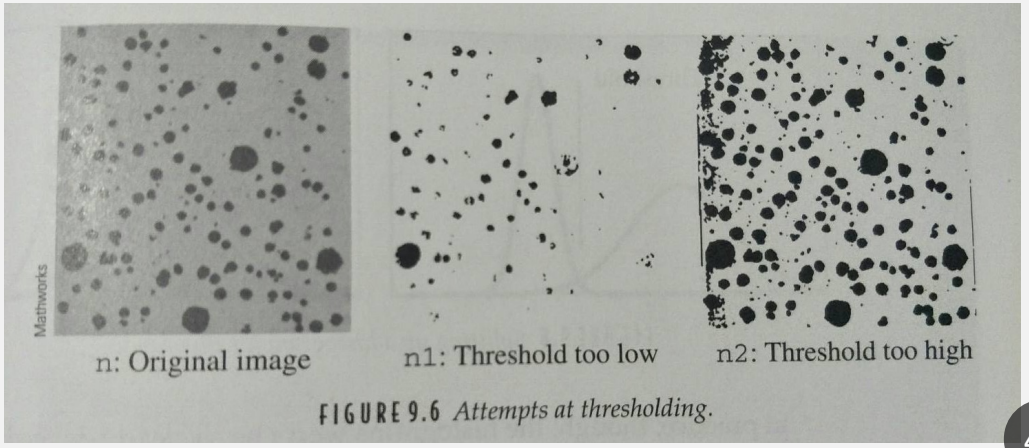


FIGURE 9.6 *Attempts at thresholding.*

THRESHOLDING

- Good threshold:

Which pixels belong to the object?

Optimal threshold

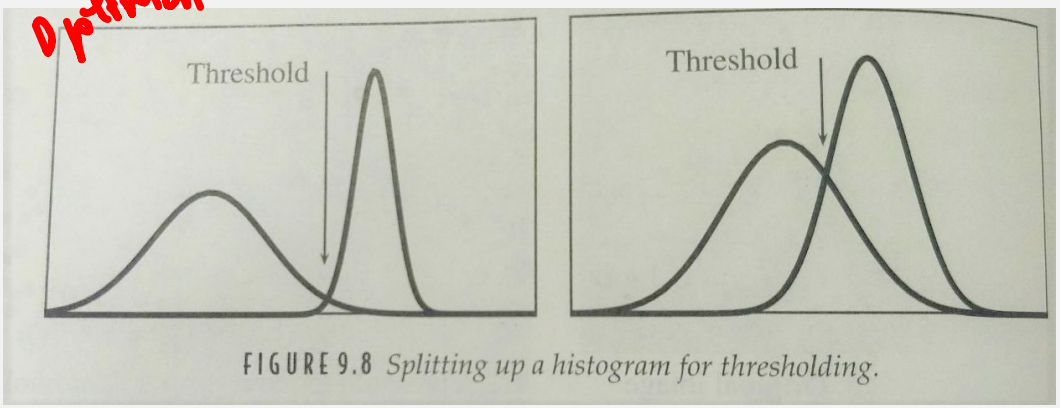


FIGURE 9.8 *Splitting up a histogram for thresholding.*

A threshold T, a gray level intensity, classifies every pixel as belonging to objects (foreground) or background. (Or rather, {dark objects, bright objects}).

Ref: Filip Malmberg

THRESHOLDING

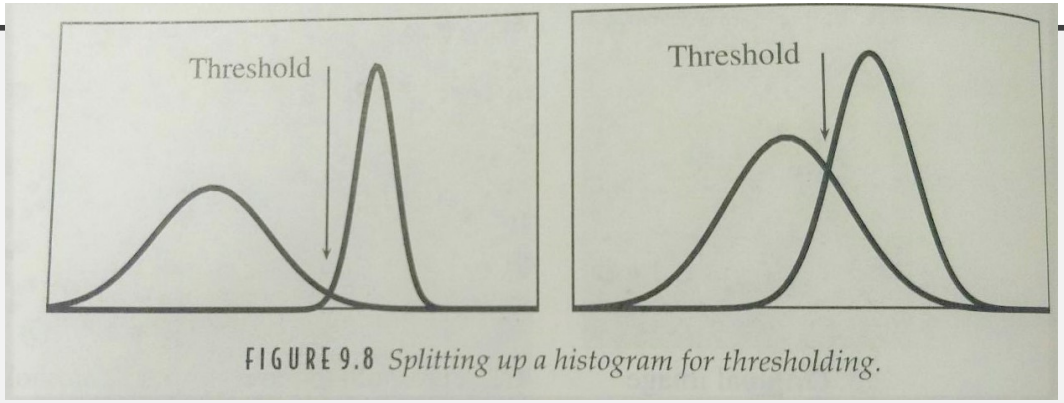


FIGURE 9.8 *Splitting up a histogram for thresholding.*

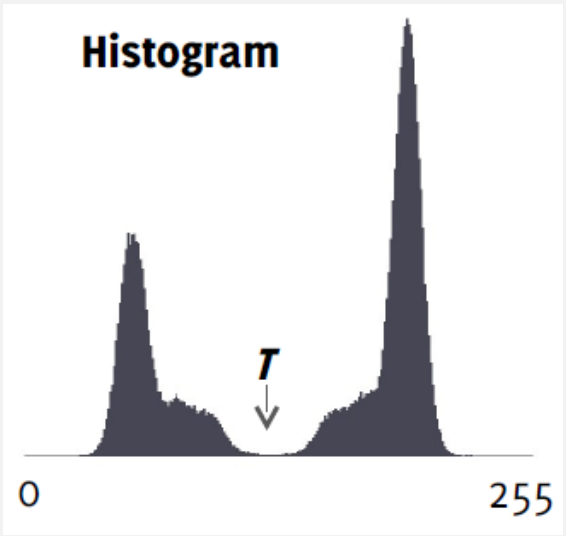
1. **Global threshold**
   - The same value is used for the whole image.

   Optimal global threshold
   - Based on the shape of the current image histogram. Searching for valleys, Gaussian distribution etc.

2. **Local (or dynamic) threshold**
   - The image is divided into non-overlapping sections, which are thresholded one by one.

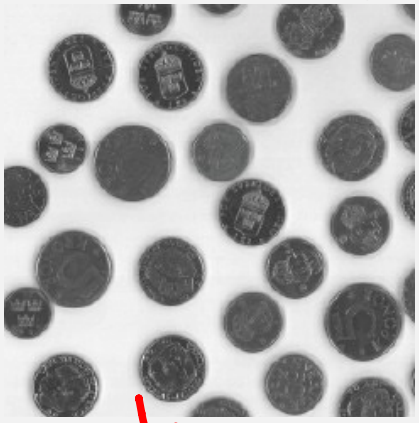
THRESHOLDING

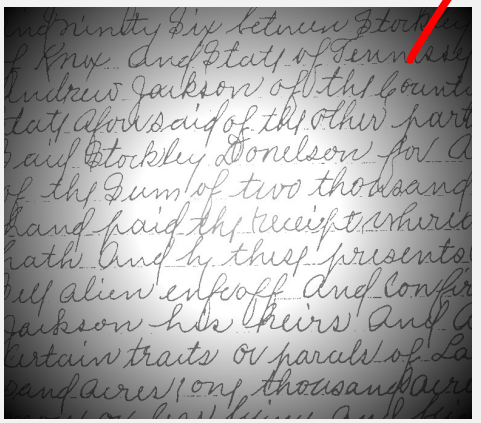
- We chose a threshold T midway between the two gray value distributions.

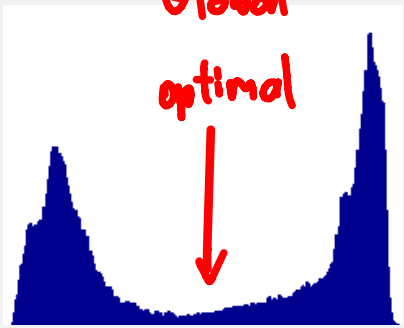


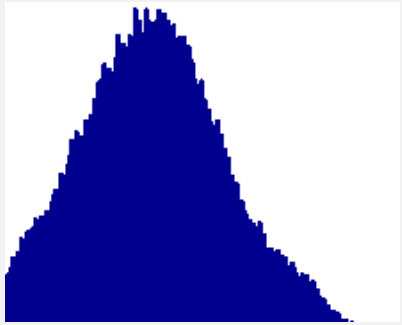
THRESHOLDING

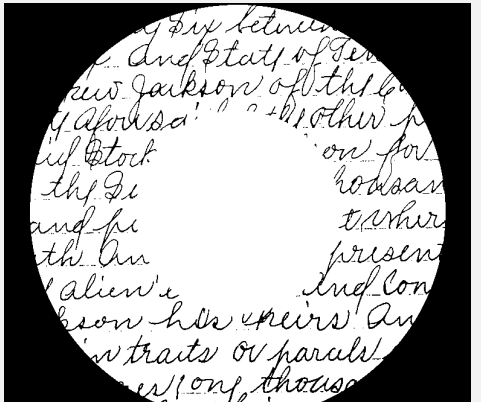
- When does intensity based thresholding work?





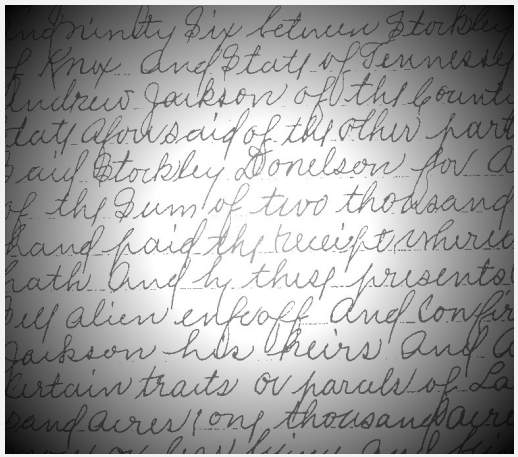
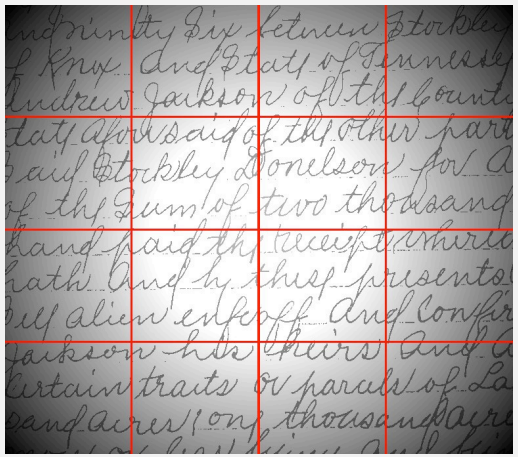
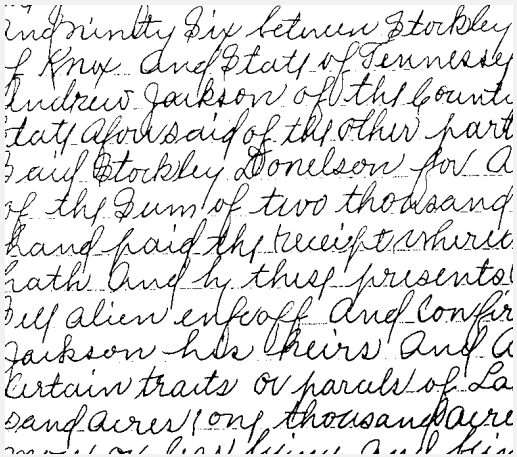






THRESHOLDING

- **Local thresholding:**

Subdivide image into non-overlapping rectangles. These rectangles are chosen small enough so that the illumination of each is approximately uniform. Then determine a global threshold for each subimage.

THRESHOLDING

§ threshold()

```
double cv::threshold ( InputArray  src,
                       OutputArray dst,
                       double      thresh,
                       double      maxval,
                       int         type
                     )
```

fixed threshold

Python:

```
retval, dst = cv.threshold( src, thresh, maxval, type[, dst] )
```

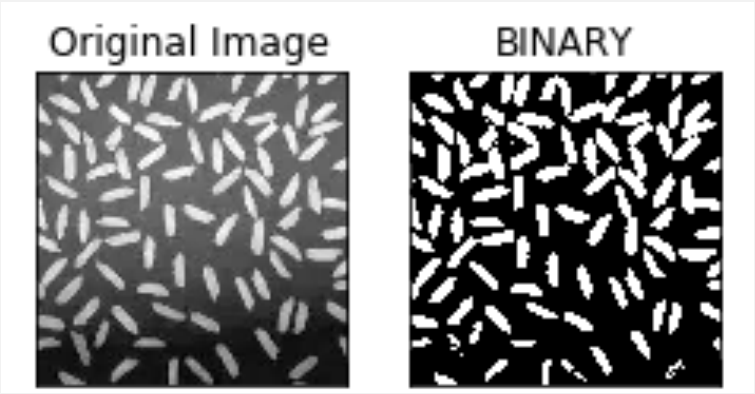
- **Python:**
- Simple Threshold:

```
img = cv2.imread("bacteria.png",0)
ret,thresh1 = cv2.threshold(img,100,255,cv2.THRESH_BINARY)
```

To display:

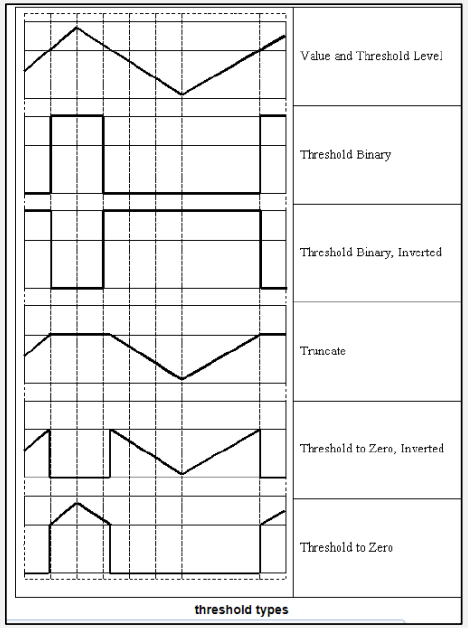
```
plt.subplot(1,2,1),plt.imshow(img,'gray')
plt.title("Original")
plt.subplot(1,2,2),plt.imshow(thresh1,'gray')
plt.title("Original")
plt.show()
```

What is the best **thresh**?
Todo: try to change them



THRESHOLDING

- **Python:**
- Threshold Type
  https://docs.opencv.org/3.4.0/d7/d1b/group__imgproc__misc.html#gaa9
  5576



Enumerator	
THRESH_BINARY Python: cv.THRESH_BINARY	$\texttt{dst}(x,y) = \begin{cases} \texttt{maxval} & \text{if } \texttt{src}(x,y) > \texttt{thresh} \\ 0 & \text{otherwise} \end{cases}$
THRESH_BINARY_INV Python: cv.THRESH_BINARY_INV	$\texttt{dst}(x,y) = \begin{cases} 0 & \text{if } \texttt{src}(x,y) > \texttt{thresh} \\ \texttt{maxval} & \text{otherwise} \end{cases}$
THRESH_TRUNC Python: cv.THRESH_TRUNC	$\texttt{dst}(x,y) = \begin{cases} \texttt{threshold} & \text{if } \texttt{src}(x,y) > \texttt{thresh} \\ \texttt{src}(x,y) & \text{otherwise} \end{cases}$
THRESH_TOZERO Python: cv.THRESH_TOZERO	$\texttt{dst}(x,y) = \begin{cases} \texttt{src}(x,y) & \text{if } \texttt{src}(x,y) > \texttt{thresh} \\ 0 & \text{otherwise} \end{cases}$
THRESH_TOZERO_INV Python: cv.THRESH_TOZERO_INV	$\texttt{dst}(x,y) = \begin{cases} 0 & \text{if } \texttt{src}(x,y) > \texttt{thresh} \\ \texttt{src}(x,y) & \text{otherwise} \end{cases}$
THRESH_MASK Python: cv.THRESH_MASK	
THRESH_OTSU Python: cv.THRESH_OTSU	flag, use Otsu algorithm to choose the optimal threshold value
THRESH_TRIANGLE Python: cv.THRESH_TRIANGLE	flag, use Triangle algorithm to choose the optimal threshold value

§ threshold()

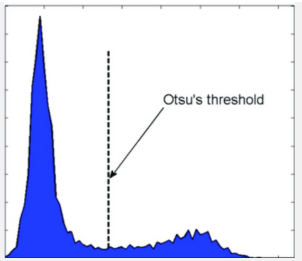
```
double cv::threshold ( InputArray  src,
                       OutputArray dst,
                       double      thresh,
                       double      maxval,
                       int         type
                     )
```

Python:

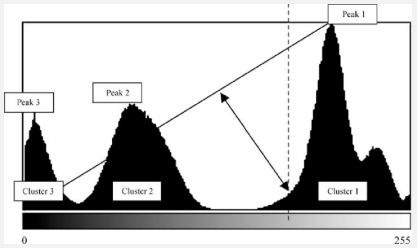
```
retval, dst = cv.threshold( src, thresh, maxval, type[, dst] )
```

Parameters

src	input array (multiple-channel, 8-bit or 32-bit floating point).
dst	output array of the same size and type and the same number of channels as src.
thresh	threshold value.
maxval	maximum value to use with the THRESH_BINARY and THRESH_BINARY_INV thresholding types.
type	thresholding type (see the cv::ThresholdTypes).



Segmentation of Rice Seedlings Using the YCrCb Color Space and an Improved Otsu Method, Juan Liao et al. (2018)



Automatic and Accurate Extraction of Road Intersections from Raster Maps, Yao-Yi Chiang et al. (2009)

THRESHOLDING

§ threshold()

```
double cv::threshold ( InputArray  src,
                       OutputArray dst,
                       double      thresh,
                       double      maxval,
                       int         type
                     )
```

Python:

```
retval, dst = cv.threshold( src, thresh, maxval, type[, dst] )
```

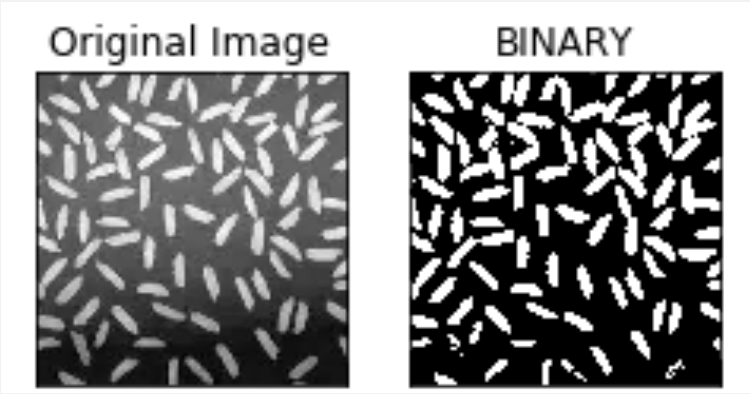
- **Python:**
- Simple Threshold:

```
img = cv2.imread("bacteria.png",0)
ret,thresh1 = cv2.threshold(img,127,255,cv2.THRESH_BINARY)
```

To display:

```
plt.subplot(1,2,1),plt.imshow(img,'gray')
plt.title("Original")
plt.subplot(1,2,2),plt.imshow(thresh1,'gray')
plt.title("Original")
plt.show()
```

What is the best **thresh**?
Todo: try to change them



THRESHOLDING

§ threshold()

```
double cv::threshold ( InputArray  src,
                       OutputArray dst,
                       double      thresh,
                       double      maxval,
                       int         type
                     )
```

Python:

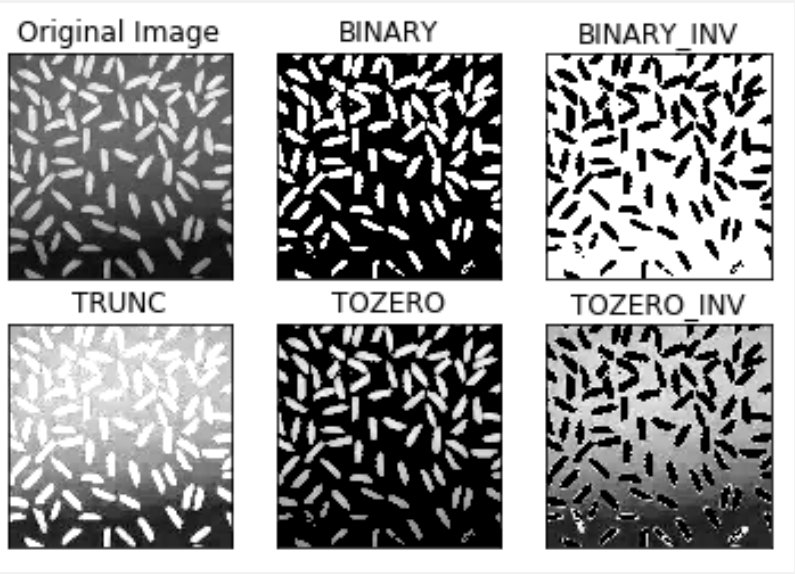
```
retval, dst = cv.threshold( src, thresh, maxval, type[, dst] )
```

- **Python:**
- Simple Threshold:

```
img = cv2.imread("bacteria.png",0)
ret,thresh1 = cv2.threshold(img,127,255,cv2.THRESH_BINARY)
ret,thresh2 = cv2.threshold(img,127,255,cv2.THRESH_BINARY_INV)
ret,thresh3 = cv2.threshold(img,127,255,cv2.THRESH_TRUNC)
ret,thresh4 = cv2.threshold(img,127,255,cv2.THRESH_TOZERO)
ret,thresh5 = cv2.threshold(img,127,255,cv2.THRESH_TOZERO_INV)
```

To display:

```
titles = ['Original
Image','BINARY','BINARY_INV','TRUNC','TOZERO','TOZERO_INV']
images = [img, thresh1, thresh2, thresh3, thresh4, thresh5]
for i in range(6):
    plt.subplot(2,3,i+1),plt.imshow(images[i],'gray')
    plt.title(titles[i])
    plt.xticks([]),plt.yticks([])
plt.show()
```



THRESHOLDING

- **Otsu's thresholding:**
  - An automatic method for choosing a best threshold.
  - Image histogram as a probability distribution

$$p_i = n_i/N$$

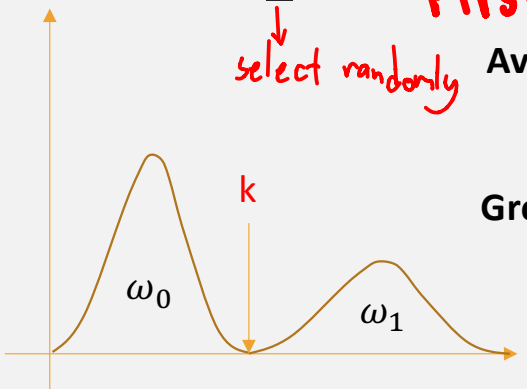
n_i is the number of pixels with gray level I
N is the total number of pixels
p_i probability of a pixel having gray level i

Normalized Histogram

  - If we threshold at ***k***

select randomly

Intensity
Group#1:
0 to k
Group#2:
k+1 to maxval



Average mean: $\mu_T = \sum_{i=0}^{L-1} ip_i$

Group#1 mean: $\mu_0(k) = \sum_{i=0}^{k} ip_i$

Group#2mean: $\mu_1(k) = \sum_{i=k+1}^{L-1} ip_i$

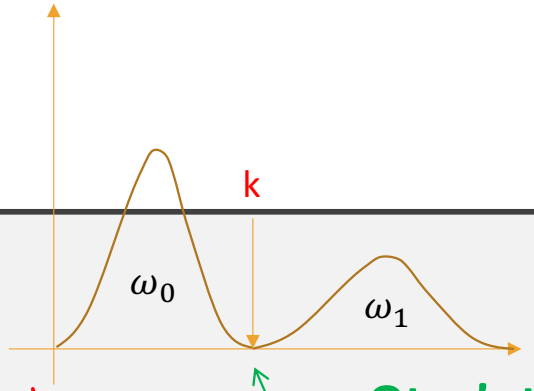
Sum of pdf group #1:

$$\omega_0(k) = \sum_{i=0}^{k} p_i$$

Sum of pdf group #2:

$$\omega_1(k) = \sum_{i=k+1}^{L-1} p_i$$

THRESHOLDING



- **Otsu's thresholding:**
  - Best ***k*** → $k\ which\ maximize(\sigma_B^2)$

Otsu's threshold

$$\text{Between-class variance } (\sigma_B^2(\text{k})) = \frac{(\mu_T \omega_0(k) - \mu_0(k))^2}{\omega_0(k)(1-\omega_0(k))}$$

sum pdf g#1 — mean group #1 — $\omega_1(k)$ — sum pdf g#2

Algorithm [WIKIPEDIA]

1. Compute histogram and probabilities of each intensity level
2. Step through all possible thresholds k=(minimum intensity),.. to... (maximum intensity – 1)
   1. Update ω_i and μ_i
   2. Compute σ_B^2
3. Desired threshold corresponds to the maximum σ_B^2(k)

group 1 = 0 ถึง k

group 2 = k+1 ถึงสุด

Ref: Otsu, N., "A Threshold Selection Method from Gray-Level Histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 9, No. 1, 1979, pp. 62-66.

THRESHOLDING

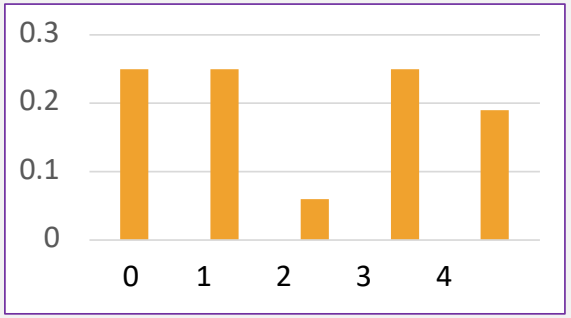
- Otsu's thresholding
  - Intensity level in range [0,4]

Find best threshold at k for segmenting this Image

0	4	3	1
0	1	0	3
1	0	2	4
3	1	3	4

Gray	0	1	2	3	4
n_i					
$p_i = n_i/N$					

$\sum = 1$



THRESHOLDING

k ควรอยู่ใน 0 - 4-1

- Otsu's thresholding

Find best threshold at k for segmenting this Image

Gray	0	1	2	3	4
n_i	4	4	1	4	3
$p_i = n_i/N$	0.25	0.25	0.06	0.25	0.19

Between-class variance $= \dfrac{(\mu_T \omega_0(k) - \mu_0(k))^2}{\omega_0(k)\omega_1(k)}$

$$\mu_T = 0 * 0.25 + 1 * 0.25 + 2 * 0.06 + 3 * 0.25 + 4 * 0.19 = 1.88$$

k = 0 $\omega_0(0) = 0.25$, $\omega_1(0) = 0.75$ $\mu_0(0) = 0*0.25$

bc variance = (1.88*0.25-0)^2 / (0.25*0.75) = 1.1781

k = 1 $w_0(1) = 0.5$, $w_1(1) = 0.5$, $\mu_0(1) = 0*0.25 + 1*0.25 = 0.25$

bc variance = 1.9044

k = 2 $w_0(2) = 0.56$, $w_1(2) = 0.44$, $\mu_0(2) = 1*0.25 + 2*0.06 = 0.37$

bc = 1.892

k = 3 $w_0(3) = 0.81$, $w_1(3) = 0.19$, $\mu_0(3) = 0.37 + 3 \times 0.25 = 1.12$

bc = 1.0543

THRESHOLDING

k is the best threshold, *L* is number of gray level .

$$f_{binary}(x,y) = \begin{cases} 0 \; if \; 1 \le f(x,y) \le k \\ 1 \; if \; k < f(x,y) \le L \end{cases}$$

- k = 1
- Group 1: 1,…., k -> gray level 0,1 -> **0**
- Group 2: k+1,… N -> gray level 2,3,4 3 -> **1**

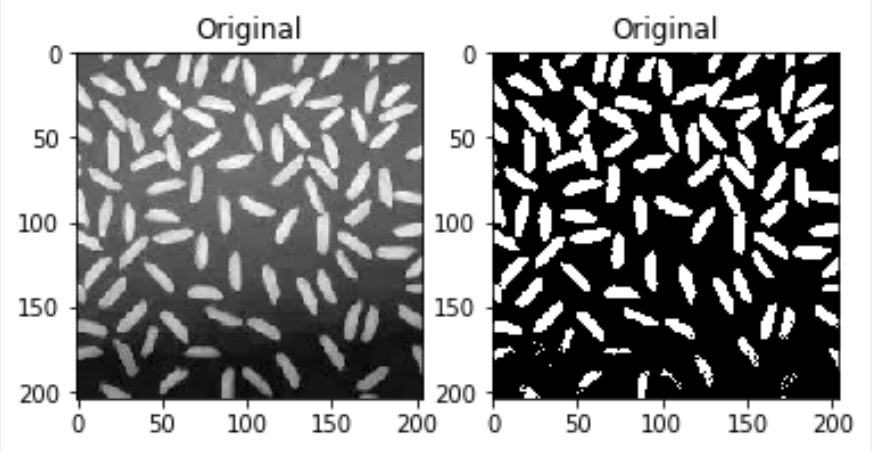
0	4	3	1
0	1	0	3
1	0	2	4
3	1	3	4

Binary image

THRESHOLDING

- **Python:**
- Otsu's Threshold:

```
img = cv2.imread("bacteria.png",0)
ret2,th2 = cv2.threshold(img,0,255,cv2.THRESH_OTSU)
```



Advantages or disadvantages?

THRESHOLDING

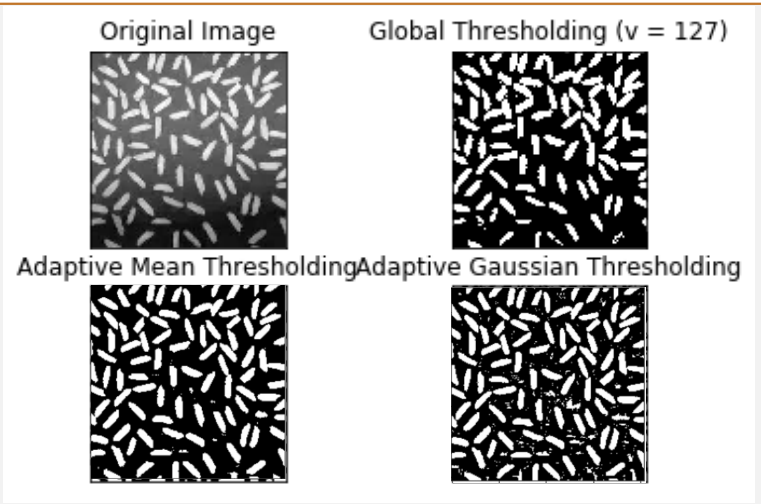
- **Python:**
- Adaptive Threshold:

local threshold

```
img = cv2.imread("bacteria.png",0)
ret,th1 = cv2.threshold(img,127,255,cv2.THRESH_BINARY)
th2 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_MEAN_C,\
            cv2.THRESH_BINARY,21,0)
th3 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,\
            cv2.THRESH_BINARY,21,0)
```

mean of local − C

Gaussian mean of local − C



§ adaptiveThreshold()

```
void cv::adaptiveThreshold ( InputArray  src,
                             OutputArray dst,
                             double      maxValue,
                             int         adaptiveMethod,
                             int         thresholdType,
                             int         blockSize,
                             double      C
                           )
```

Python:

```
dst = cv.adaptiveThreshold( src, maxValue, adaptiveMethod, thresholdType, blockSize, C[, dst] )
```

https://docs.opencv.org/3.4.0/d7/d1b/group__imgproc__misc.html#ga72b913f352e4a1b1b397736707afcde3

Parameters

src	Source 8-bit single-channel image.
dst	Destination image of the same size and the same type as src.
maxValue	Non-zero value assigned to the pixels for which the condition is satisfied
adaptiveMethod	Adaptive thresholding algorithm to use, see **cv::AdaptiveThresholdTypes**. The BORDER_REPLICATE | BORDER_ISOLATED is used to process boundaries.
thresholdType	Thresholding type that must be either THRESH_BINARY or THRESH_BINARY_INV, see **cv::ThresholdTypes**.
blockSize	Size of a pixel neighborhood that is used to calculate a threshold value for the pixel: 3, 5, 7, and so on.
C	Constant subtracted from the mean or weighted mean (see the details below). Normally, it is positive but may be zero or negative as well.

Enumerator	
ADAPTIVE_THRESH_MEAN_C Python: cv.ADAPTIVE_THRESH_MEAN_C	the threshold value $T(x, y)$ is a mean of the **blockSize** × **blockSize** neighborhood of (x, y) minus C
ADAPTIVE_THRESH_GAUSSIAN_C Python: cv.ADAPTIVE_THRESH_GAUSSIAN_C	the threshold value $T(x, y)$ is a weighted sum (cross-correlation with a Gaussian window) of the **blockSize** × **blockSize** neighborhood of (x, y) minus C . The default sigma (standard deviation) is used for the specified blockSize . See **cv::getGaussianKernel**

Increase or decrease blockSize?

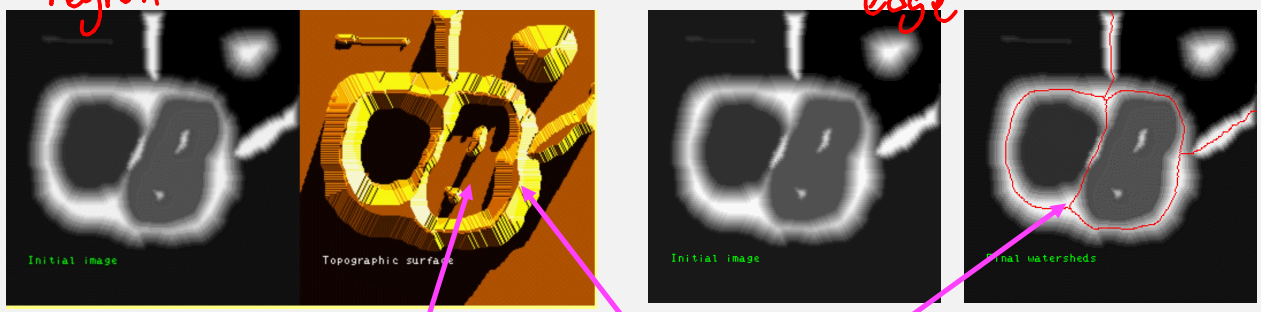
SEGMENTATION PART II

- Region-based segmentation
- K-means clustering
- Deep learning-based Techniques

REGION-BASED SEGMENTATION

REGION GLOWING

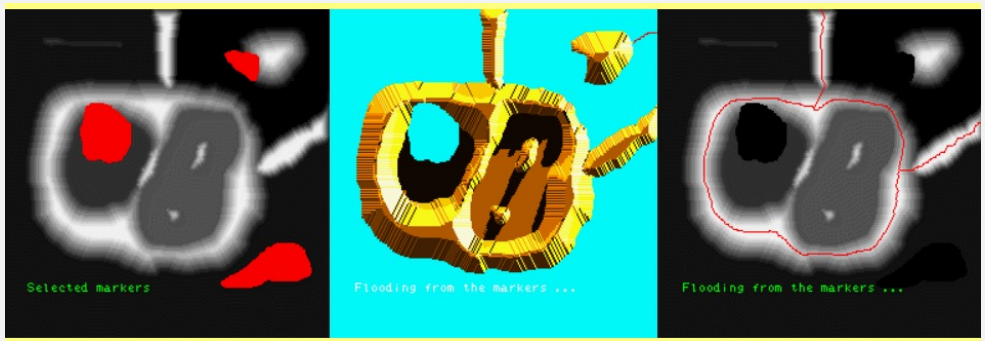
- If you have an image, how to select the most prominent contours?
  - Watershed transform - If we flood this surface from its minima and, if we prevent the merging of the waters coming from different sources, we partition the image into two different sets: the catchment basins and the watershed lines.

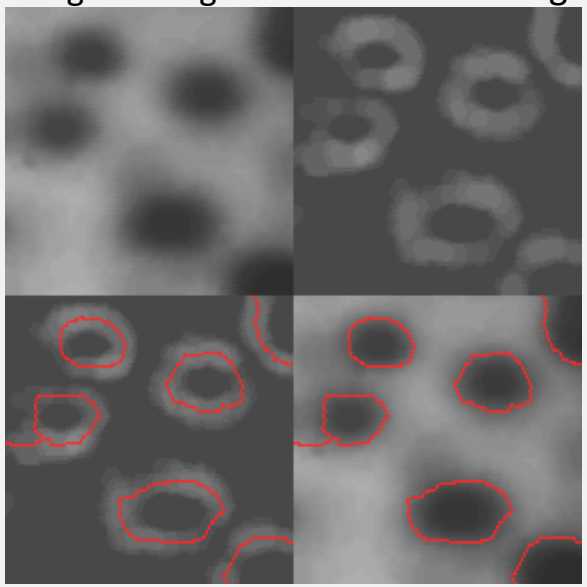


References: Serge Beucher, IMAGE SEGMENTATION AND MATHEMATICAL MORPHOLOGY, https://people.cmm.minesparis.psl.eu/users/beucher/wtshed.html

REGION GLOWING

- If you have an image, how to select the most prominent contours?
  - Watershed transform - If we apply this transformation to the image gradient, the catchment basins should theoretically correspond to the homogeneous grey level regions of this image.
  - Marker-controlled watershed - A major enhancement of the watershed transformation consists in flooding the topographic surface from a previously defined set of markers.





References: Serge Beucher, IMAGE SEGMENTATION AND MATHEMATICAL MORPHOLOGY, https://people.cmm.minesparis.psl.eu/users/beucher/wtshed.html

REGION GLOWING

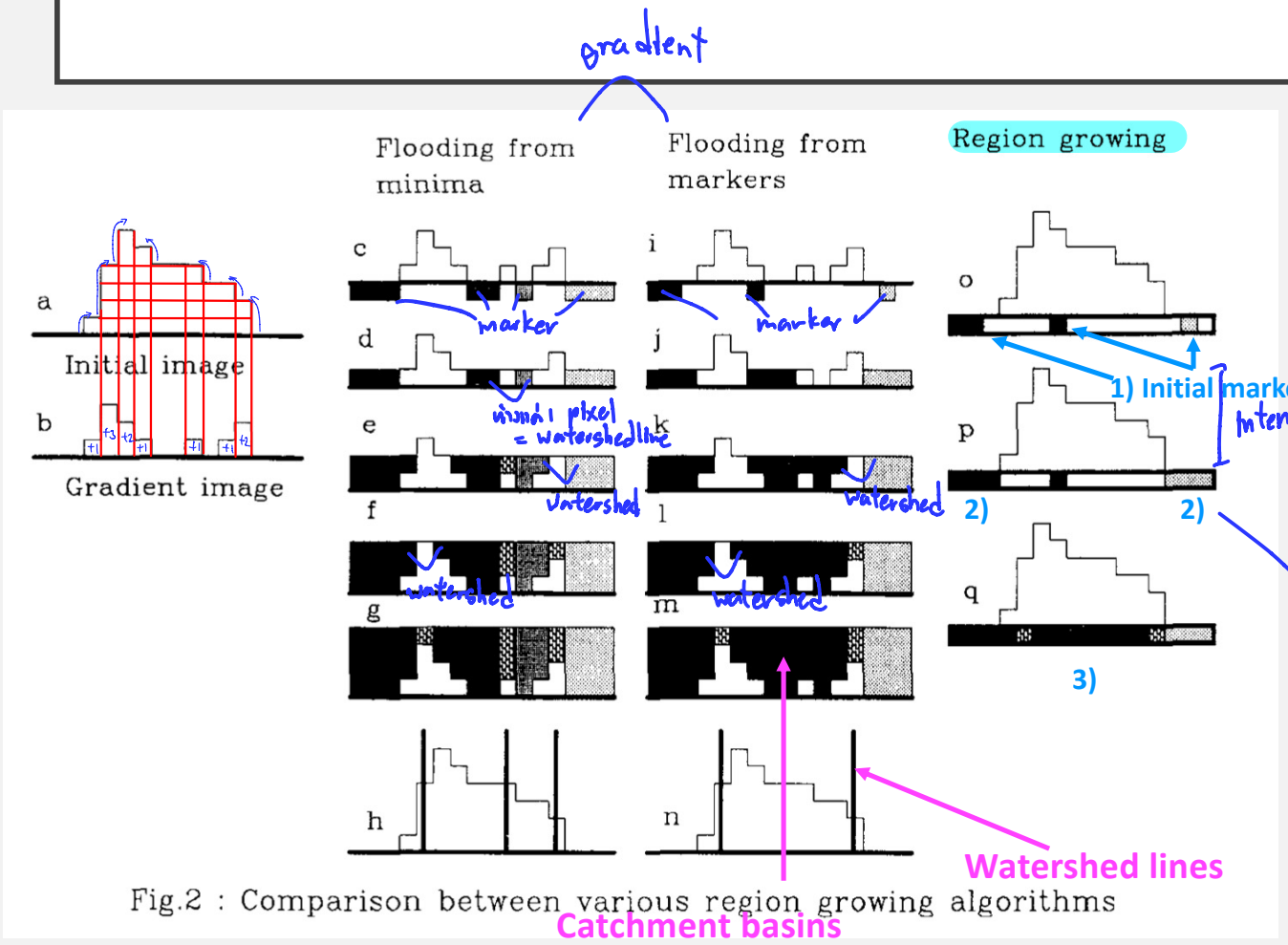
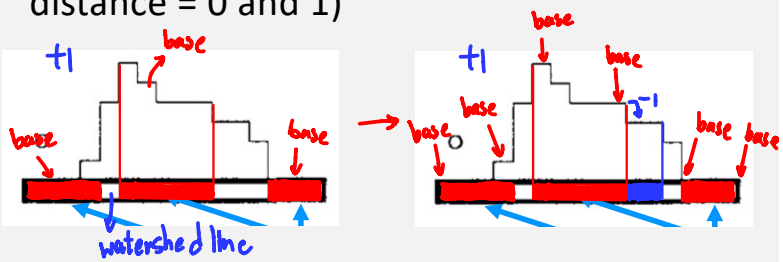


Fig.2 : Comparison between various region growing algorithms

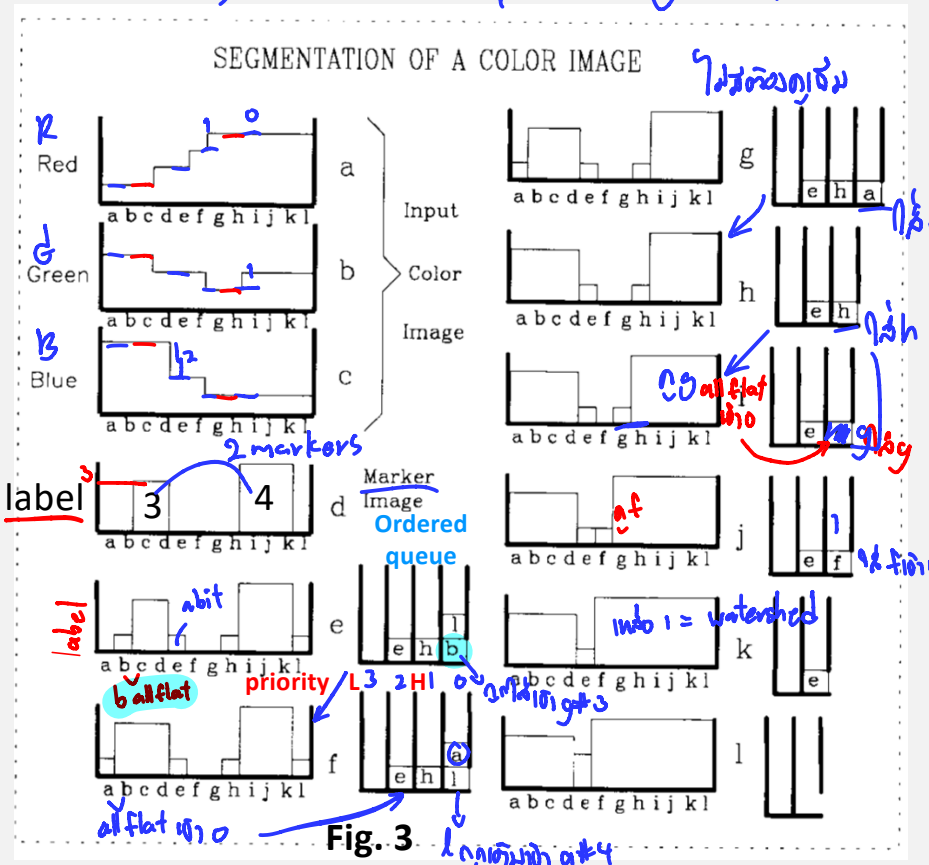
Region growing step:

1) Starting points - Fig. 2o: gives initial position of the markers
2) The expansion amonst points with zero distance to fill up background same intensity
3) Futher expansion by the point with distance = 1 (aggregate all points at distance = 0 and 1)



Reference: Fernand Meyer. Color image segmentation. In *Image Processing and its Applications, 1992*

REGION GLOWING



Region growing step for color image:

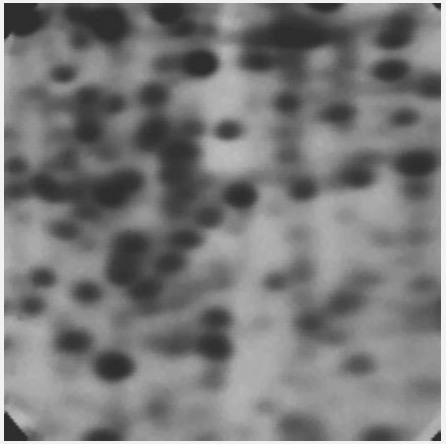
1) RGB from Fig. 3a-c, markers are defined in Fig. 3d
2) Similarity between the point already in the markers and its neighbors. If $(r1, g1, b1)$ and $(r2, g2, b2)$ are RGB for pixel #1 and pixel #2, respectively, The color difference defined by
$$Max(|r1 - r2|, |g1 - g2|, |b1 - b2|)$$
3) An ordered queue with four levels is created, e.g., h and i (in the labelled region) is difference by 1, h will be put in the priority 1.
4) First point to be extracted from the ordered queue is b which will get the same label with c (label = 3), a which is a neighbour of b is put into highest priority.
5) Next to consider is l will have the same label as k (label = 4), and a has a label = 3.
6) Now highest priority is empty and then suppressed, consider the next priority. h has label = 4, g, f are put in label = 4.
7) e already in the queue and has neighbours of 2 distinct labelled regions, e is a frontier point.

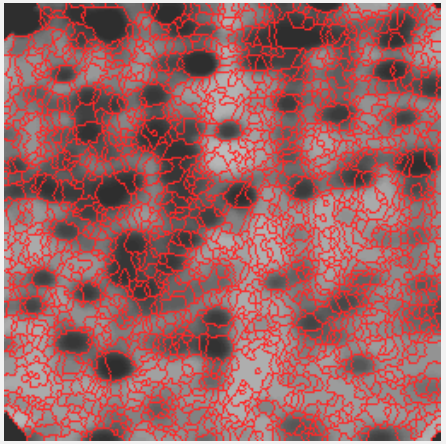
Label = 1 is always assigned with a point in the queue, label = 2 is the frontier point (watershed line)

Fernand Meyer. Color image segmentation. In *Image Processing and its Applications, 1992*

MARKER-BASED WATERSHED

- Apply transformation on image gradient (can be over-segmentation)
- *Marker-controlled watershed*
- **we prevent any over-segmentation.**

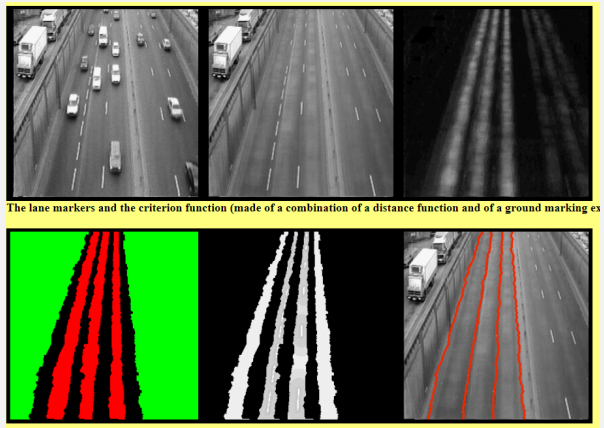


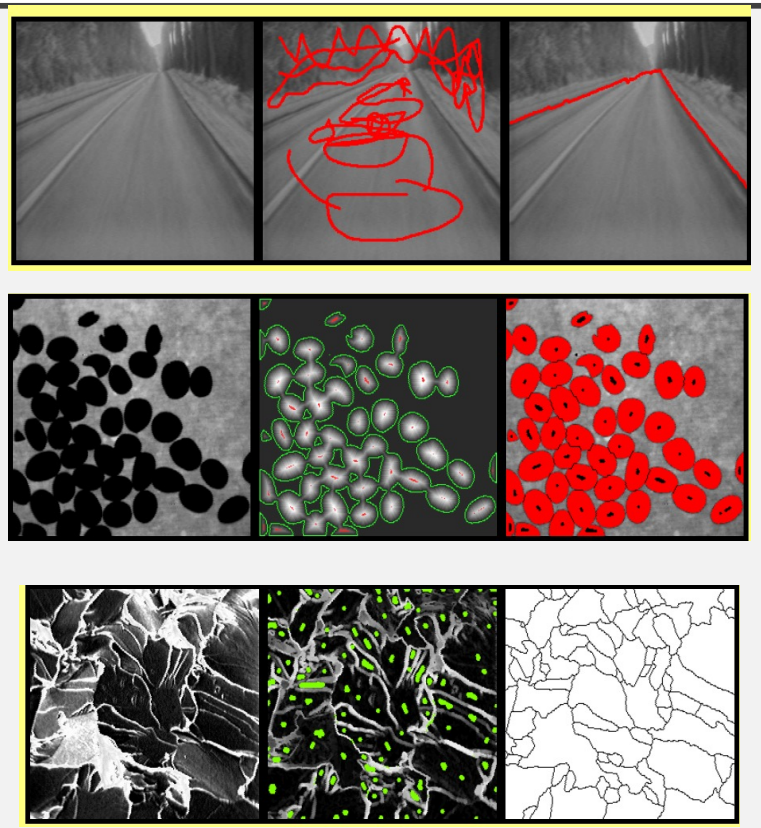


http://cmm.ensmp.fr/~beucher/wtshed.html

MARKER-BASED WATERSHED

- Applications:
  - **Road segmentation**
  - **Coffee beans separation**
  - **Traffic monitoring**
  - **Cleavage fracture in steel**





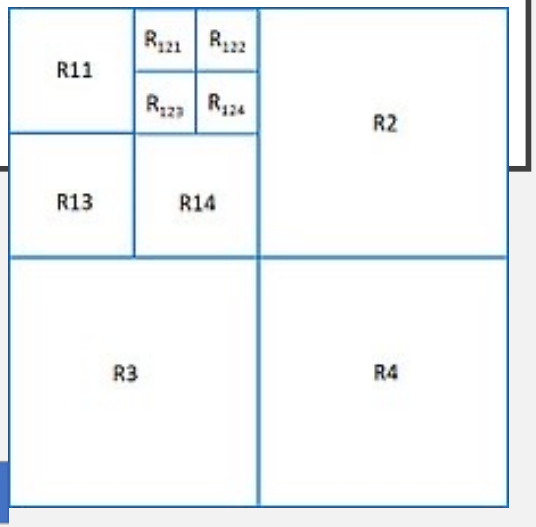
http://cmm.ensmp.fr/~beucher/wtshed.html

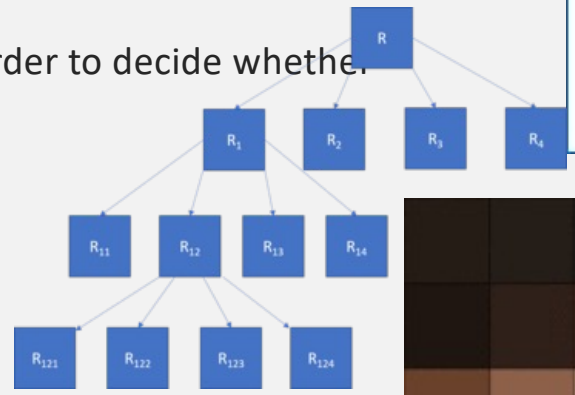
REGION SPLITTING AND MERGING

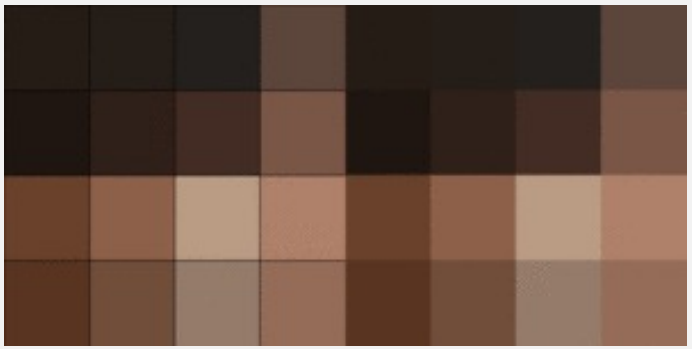
- In **Region splitting**, the whole image is first taken as a single region.
- If the region does not follow the predefined rules, then it is further divided into multiple regions (usually 4 quadrants).
- the predefined rules are carried out on those regions in order to decide whether to further subdivide or to classify that as a region.
- An example of a predefined rule:

$$|Z_{max} - Z_{min}| \leq T$$

where Z_{max} and Z_{min} are the maximum and minimum pixel intensity values, respectively. T is a threshold.



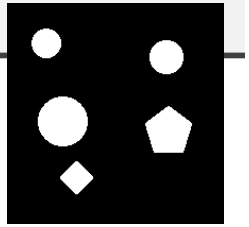


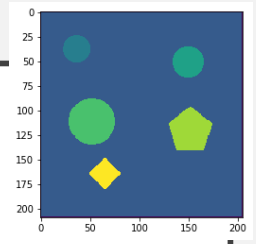


- In **Region merging** technique, we consider every pixel as an individual region.
- We select a region as the seed region to check if adjacent regions are similar based on predefined rules.
- If they are similar, we merge them into a single region and move ahead in order to build the segmented regions of the whole image.

References:
https://en.wikipedia.org/wiki/Split_and_merge_segmentation
https://towardsdatascience.com/image-segmentation-part-2-8959b609d268

DEMO: REGION GROWING (MARKER-BASED WATERSHED)

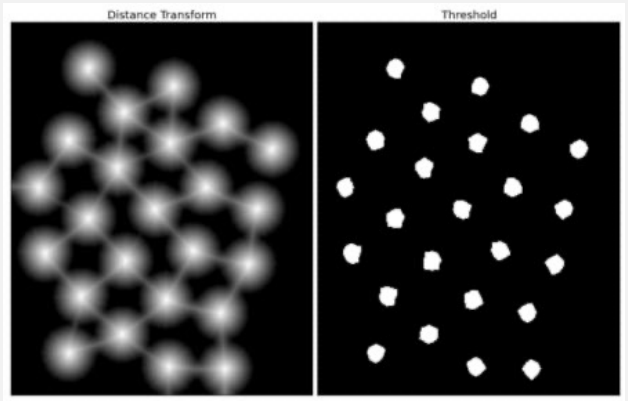




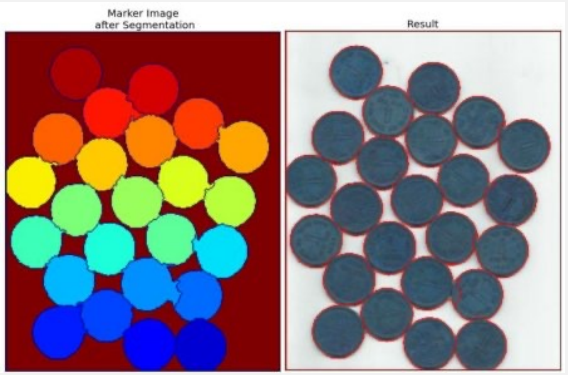
- A topographic surface where high intensity denotes peaks and hills while low intensity denotes valleys
  - To partition the image into two different sets:

    the catchment basins and the watershed lines.

Use morphology to find marker areas



Use watershed techniques



https://docs.opencv.org/3.1.0/d3/db4/tutorial_py_watershed.html

Fernand Meye, The watershed concept and its use in segmentation (2012)

◆ watershed()

```
void cv::watershed ( InputArray        image,
                     InputOutputArray  markers
                   )
```

Python:

```
cv.watershed( image, markers ) -> markers
```

```
#include <opencv2/imgproc.hpp>
```

Performs a marker-based image segmentation using the watershed algorithm.

The function implements one of the variants of watershed, non-parametric marker-based segmentation algorithm, described in [169] .

Before passing the image to the function, you have to roughly outline the desired regions in the image markers with positive (>0) indices. So, every region is represented as one or more connected components with the pixel values 1, 2, 3, and so on. Such markers can be retrieved from a binary mask using **findContours** and **drawContours** (see the watershed.cpp demo). The markers are "seeds" of the future image regions. All the other pixels in markers , whose relation to the outlined regions is not known and should be defined by the algorithm, should be set to 0's. In the function output, each pixel in markers is set to a value of the "seed" components or to -1 at boundaries between the regions.

Note

Any two neighbor connected components are not necessarily separated by a watershed boundary (-1's pixels); for example, they can touch each other in the initial marker image passed to the function.

Parameters

image	Input 8-bit 3-channel image.
markers	Input/output 32-bit single-channel image (map) of markers. It should have the same size as image .

See also

findContours

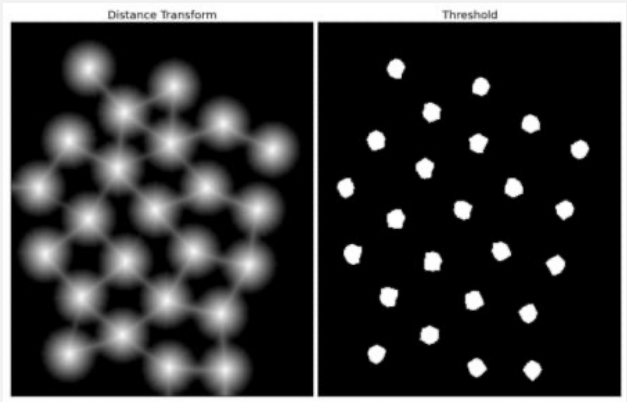
Examples:

samples/cpp/watershed.cpp.

https://docs.opencv.org/4.5.3/d3/d47/group__imgproc__segmentation.html#ga3267243e4d3f95165d55a618c65ac6e1

DEMO: REGION GROWING (MARKER-BASED WATERSHED)

- Distance Transform:

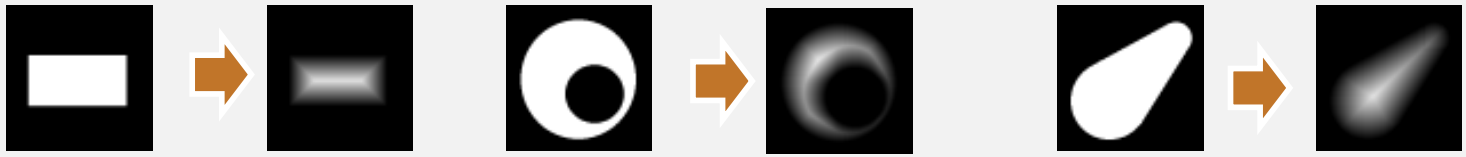


- The distance transform is an operator normally only applied to binary images.
- The result of the transform is a grey level image that looks similar to the input image, except that the grey level intensities of points inside foreground regions are changed to show **the distance to the closest boundary from each point**.

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0

→

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	2	2	2	2	1	0
0	1	2	3	3	2	1	0
0	1	2	2	2	2	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0



References: Pedro Felzenszwalb and Daniel Huttenlocher. Distance transforms of sampled functions. Technical report, Cornell University, 2004.
https://homepages.inf.ed.ac.uk/rbf/HIPR2/distance.htm