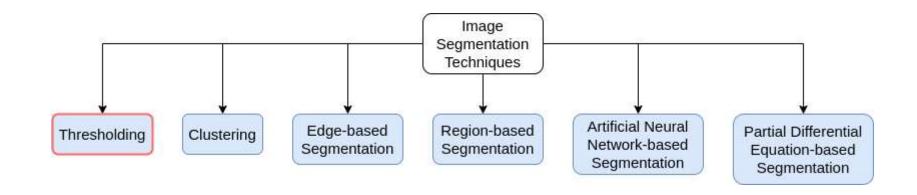
Yih-Lon Lin (林義隆)

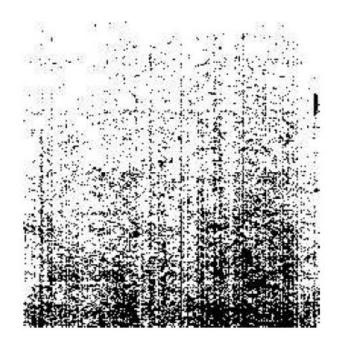
Associate Professor,

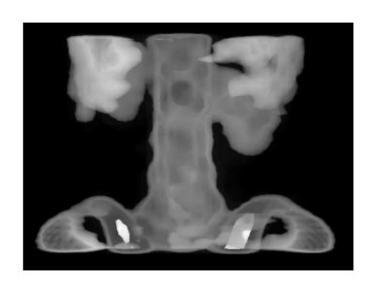
Department of Computer Science and Information Engineering, National Yunlin University of Science and Technology

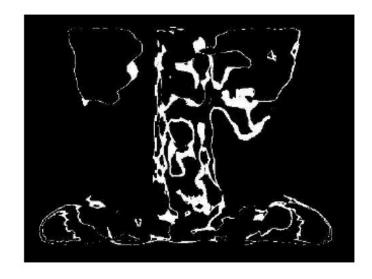


https://learnopencv.com/otsu-thresholding-with-opencv/





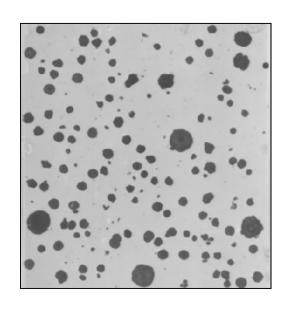


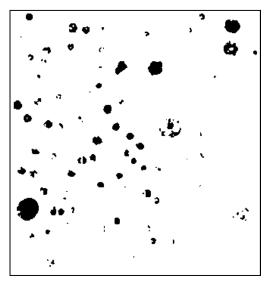


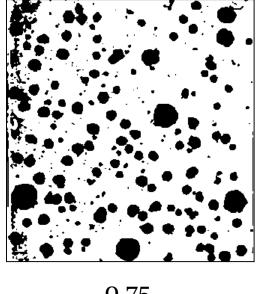
Text Running To Locate A Known To Locate A Known Target in an Image Direction

Cross Correlation Used
To Locate A Known
Target in an Image

Direction
Direction

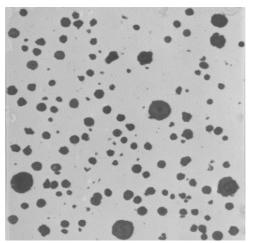


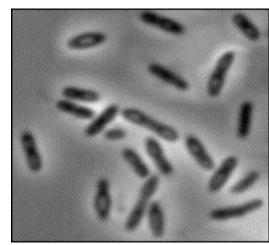




Original Image

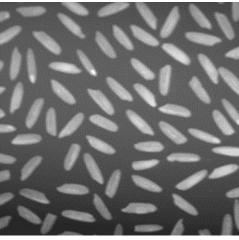
nodules1.tif





bacteria.tif

rice.tif

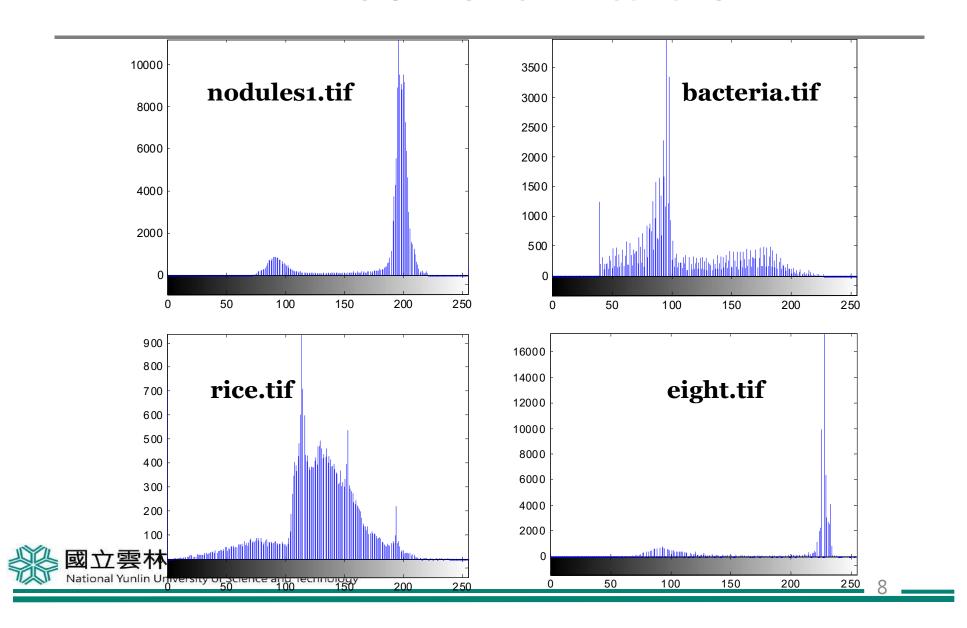




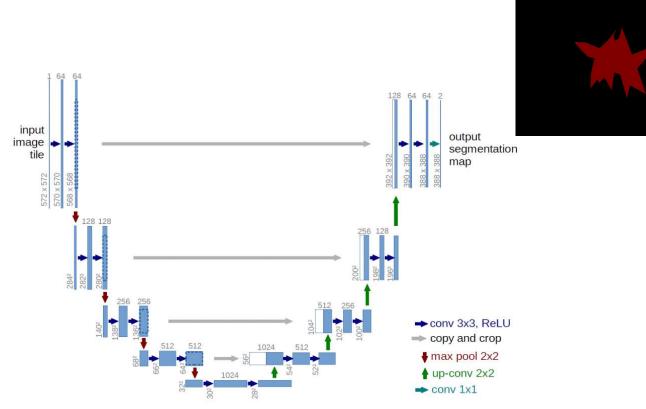
eight.tif



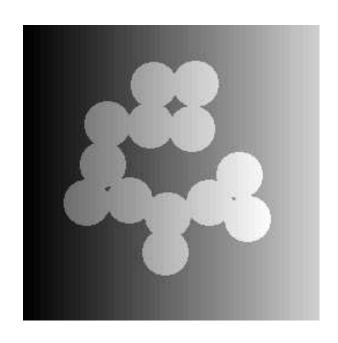
Threshold Value

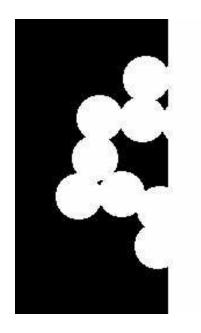




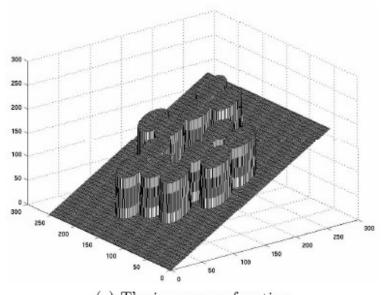


Adaptive Thresholding

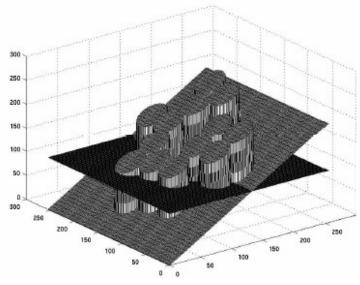




Adaptive Thresholding

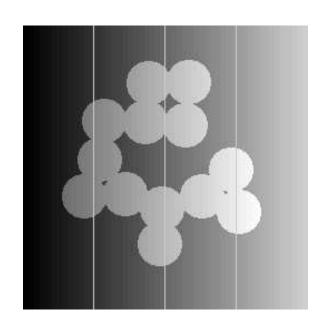


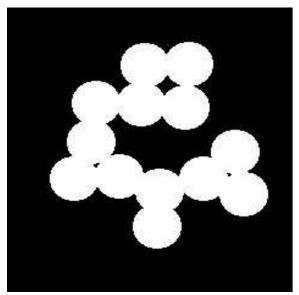
(a) The image as a function



(b) Thresholding attempt

Adaptive Thresholding





Otsu's Method

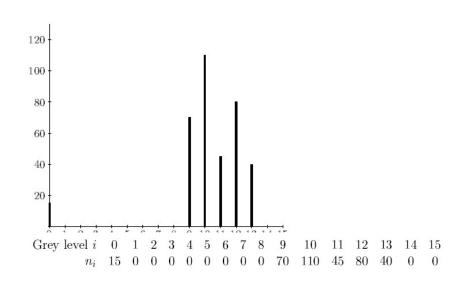
Automatic global thresholding algorithms usually have following steps.

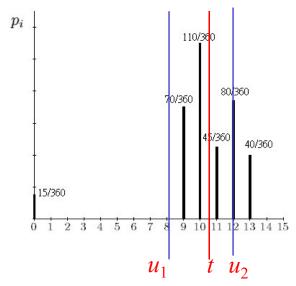
- 1. Process the input image
- 2. Obtain image histogram (distribution of pixels)
- 3. Compute the threshold value T

Replace image pixels into white in those regions, where saturation is greater than T and into the black in the opposite cases.

Usually, different algorithms differ in step 3

Otsu's Method





$$\sigma_{w}^{2}(t) = w_{1}(t)\sigma_{1}^{2}(t) + w_{2}(t)\sigma_{2}^{2}(t)$$

$$w_1(t) = \sum_{i=1}^{t} p(i)$$
 $w_2(t) = \sum_{i=t+1}^{I} p(i)$

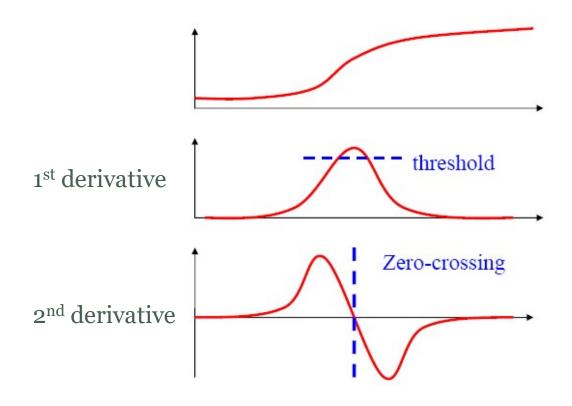
$$\mu_1(t) = \sum_{i=1}^{t} \frac{ip(i)}{w_1(t)}$$
 $\mu_2(t) = \sum_{i=t+1}^{t} \frac{ip(i)}{w_2(t)}$

$$\sigma_1^2(t) = \sum_{i=1}^t [i - \mu_1(t)]^2 \frac{p(i)}{w_1(t)} \quad \sigma_2^2(t) = \sum_{i=t+1}^I [i - \mu_2(t)]^2 \frac{p(i)}{w_2(t)}$$

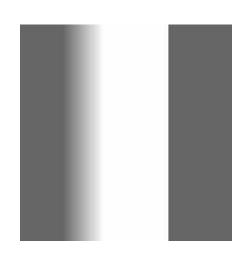
Edge Detection

- 1st derivatives operators
 - Prewitt operator
 - Sobel operator
 - Directional edge detection
- 2nd derivative operators
 - Laplacian
 - High-order finite difference approximation

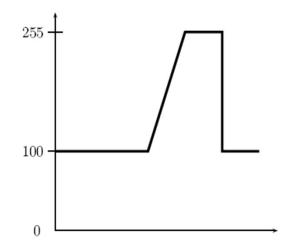
Derivative Operators

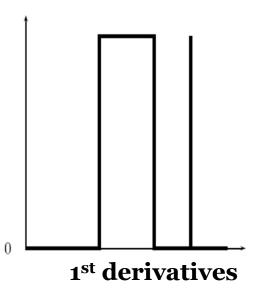


Derivative Operators



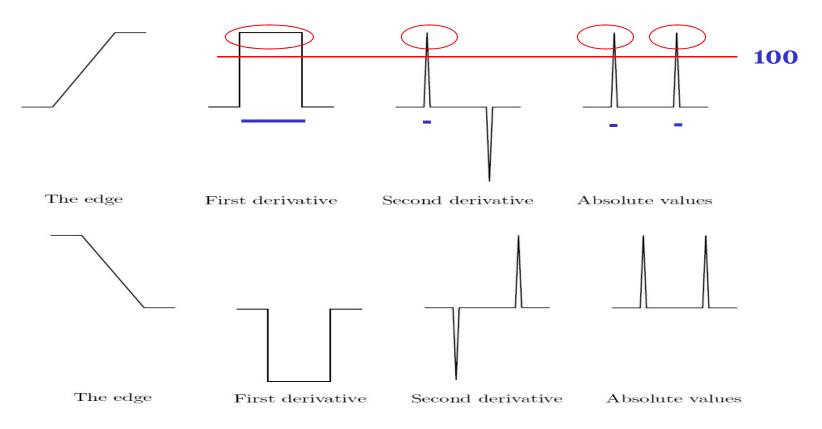
ramp edge step edge (ideal edge)





Derivative Operators

Fundamental definitions



The definition of the 1st derivative

$$\frac{df}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$
$$f(x+1) - f(x)$$

$$\lim_{h \to 0} \frac{f(x) - f(x - h)}{h}, \qquad \lim_{h \to 0} \frac{f(x + h) - f(x - h)}{2h}$$

$$f(x) - f(x-1),$$
 $(f(x+1) - f(x-1))/2.$

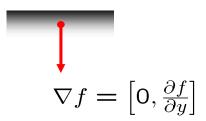
Derivatives and Edges

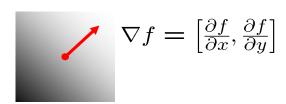
• The gradient of an image:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

 The gradient points in the direction of most rapid change in intensity

$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$





• The gradient direction is given by:

$$\theta = \tan^{-1} \left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x} \right)$$

• The edge strength is given by the gradient magnitude: $\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$



Some edge detection filters

• Using the expression f(x+1) - f(x-1) for the derivative, produces horizontal and vertical filters:

$$\begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$
 and $\begin{bmatrix} -1 & 0 & 1 \\ 1 & 1 \end{bmatrix}$

Prewitt filters

$$P_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad P_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$\sqrt{p_x^2 + p_y^2}$$
. $\max\{|p_x|, |p_y|\}$ or $|p_x| + |p_y|$.

Some edge detection filters

Roberts cross-gradient filters

$$\left[egin{array}{ccc} 1 & 0 & 0 \ 0 & -1 & 0 \ 0 & 0 & 0 \end{array}
ight] \ {
m and} \ \left[egin{array}{ccc} 0 & 1 & 0 \ -1 & 0 & 0 \ 0 & 0 & 0 \end{array}
ight]$$

Sobel filters:

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \text{ and } \begin{bmatrix} -1 & -2 & 1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Second Derivatives

The Laplacian

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

$$\cong \left[f(x+1, y) - 2f(x, y) + f(x-1, y) \right]$$

$$+ \left[f(x, y+1) - 2f(x, y) + f(x, y-1) \right]$$

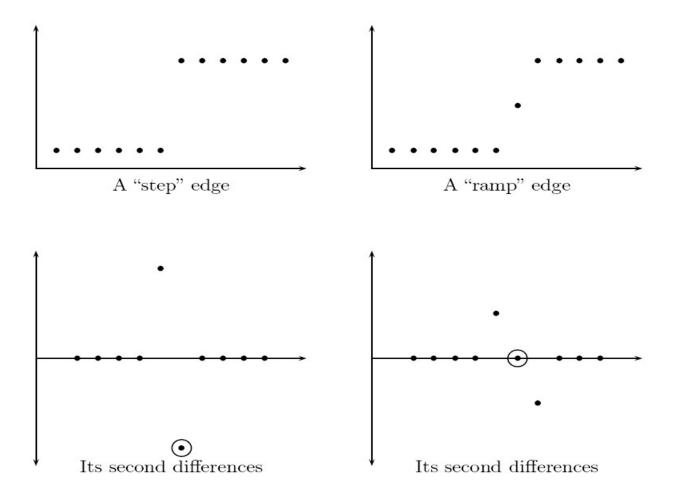
$$\nabla^2 f(x, y) \cong \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Other Laplacian masks

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix} \text{ and } \begin{bmatrix} -2 & 1 & -2 \\ 1 & 4 & 1 \\ -2 & 1 & -2 \end{bmatrix}$$

$$\frac{1}{\alpha+1} \left[\begin{array}{cccc} \alpha & 1-\alpha & \alpha \\ 1-\alpha & -4 & 1-\alpha \\ \alpha & 1-\alpha & \alpha \end{array} \right]$$

Zero Crossings



Zero Crossings

50	50	50	50	50	50	50	50	50	50
50	50	50	50	50	50	50	50	50	50
50	50	200	200	200	200	200	200	50	50
50	50	200	200	200	200	200	200	50	50
50	50	200	200	200	200	200	200	50	50
50	50	200	200	200	200	200	200	50	50
50	50	50	50	200	200	200	200	50	50
50	50	50	50	200	200	200	200	50	50
50	50	50	50	50	50	50	50	50	50
50	50	50	50	50	50	50	50	50	50

(a) A simple image

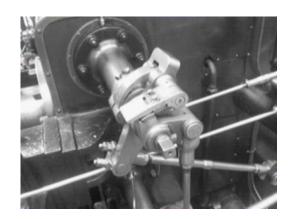
-100	-50	-50	-50	-50	-50	-50	-50	-50	-100
-50	0	150	150	150	150	150	150	0	-50
-50	150	- 300	-150	- 150	- 150	-150	- 300	150	-50
-50	150	- 150	0	0	0	0	- 150	150	-50
-50	150	– 150	0	0	0	0	- 150	150	-50
-50	150	- 300	-150	0	0	0	- 150	150	-50
-50	0	150	300	- 150	0	0	- 150	150	-50
-50	0	0	150	- 300	- 150	-150	- 300	150	-50
-50	0	0	0	150	150	150	150	0	-50
-100	-50	-50	-50	-50	-50	-50	-50	-50	-100

(b) After laplace filtering

Step 1: noise reduction

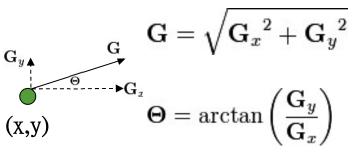
the Canny edge detector uses a filter based on the first derivative of a Gaussian.

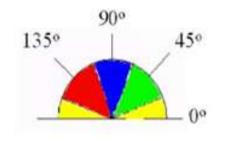
$$\mathbf{B} = \frac{1}{159} \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} * \mathbf{A} \quad \sigma = 0.4$$

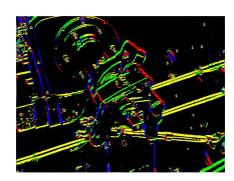


• Step 2: Finding the intensity gradient of the image.

An edge in an image may point in a variety of directions, so the Canny algorithm uses four filters to detect horizontal, vertical and diagonal edges in the blurred image. The edge direction angle is **rounded** to one of four angles representing vertical, horizontal and the two diagonals (0, 45, 90 and 135 degrees for example).



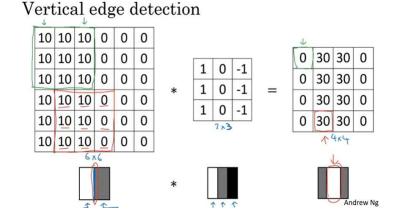




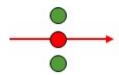
Andrew Ng

Vertical edge detection 3x1+1x1 +2x1+0x0+5x0+7x0+ 1x-1+8x-1+2x-1=-5 consolution (2) 5 8 9 3 1 0 2 (5) 1 3 * 0 0 6 -2 | -3 | -16 5 2 3 9 filter python: coar-forward torsorfins: tf.nn.conild

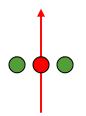
Keras: Conv20



• Step 3:Non-maximum suppression (local maximum)



Given estimates of the image gradients, a search is then carried out to determine if the gradient magnitude assumes a local maximum in the gradient direction.



if the rounded angle is **zero** degrees the point will be considered to be on the edge if its intensity (gradient magnitude) is greater than the intensities in the **north and south** directions,

 if the rounded angle is 90 degrees the point will be considered to be on the edge if its intensity is greater than the intensities in the west and east directions,



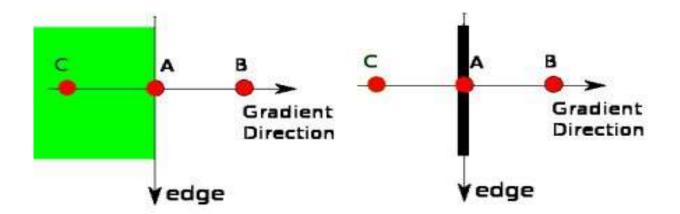
 if the rounded angle is 135 degrees the point will be considered to be on the edge if its intensity is greater than the intensities in the north east and south west directions,

if the rounded angle is 45 degrees the point will be considered to be on the edge if its intensity is greater than the intensities in the north west and south east directions.

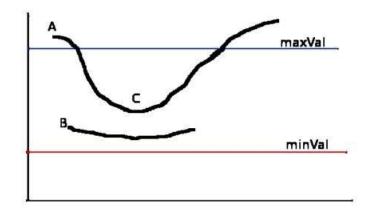




• Step 3:Non-maximum suppression (local maximum)



- Step 4: Tracing edges through the image and hysteresis thresholding
 - Thresholding with hysteresis requires two thresholds high and low.
 - Making the assumption that important edges should be along continuous curves in the image allows us to follow a faint section of a given line and to discard a few noisy pixels that do not constitute a line but have produced large gradients.
 - Once this process is complete we have a binary image where each pixel is marked as either an edge pixel or a non-edge pixel.



Step 1



Step 2

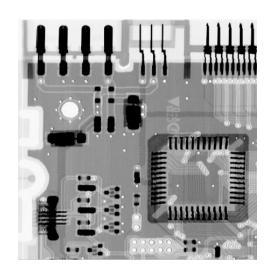


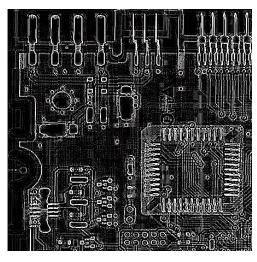
Step 3



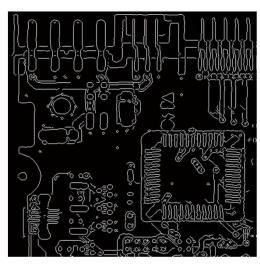
Step 4







Sobel



Canny Edge