JAIPUR ENGINEERING COLLEGE AND RESEARCH CENTRE

Department of Computer Science & Engineering

Digital Image Processing(6CS3-01)

COURSE OUTCOMES

CO4: Evaluate various coding algorithms used in image processing and compression

Topics Covered:

Introduction of image segmentation
Detection of discontinuities
Point detection
Line detection
Edge Detection
Thresholding
Adaptive Thresholding
Thresholding based on boundary characteristics

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VISION & MISSION OF DEPARTMENT

VISION: To become renowned Centre of excellence in computer science and engineering and make competent engineers & professionals with high ethical values prepared for lifelong learning.

MISSION:

- M1: To impart outcome based education for emerging technologies in the field of computer science and engineering.
- M2: To provide opportunities for interaction between academia and industry.
- M3: To provide platform for lifelong learning by accepting the change in technologies
- M4: To develop aptitude of fulfilling social responsibilities

Course Outcomes

- Understand the fundamental aspects of image processing
- Apply the mathematical foundations of coloring and image enhancement in spatial and frequency domains
- Compare and Implement filters for various types of noise.
- Evaluate various coding algorithms used in image processing and compression

Image Segmentation

Image Segmentation

Image segmentation divides an image into regions that are connected and have some similarity within the region and some difference between adjacent regions.

The goal is usually to find individual objects in an image.

For the most part there are fundamentally two kinds of approaches to segmentation: discontinuity and similarity.

- ❑ Discontinuity: Approach is to partition image based on abrupt changes in intensities (edges).
- ❑ Similarity: Approach is to partition the image based on similar regions according to predefined criteria. Such as Thresholding, region growing, region splitting & merging.

How to achieve segmentation?

- Image is divided into separate regions that are homogeneous with respect to a chosen property such as color, brightness, texture, etc.
- Segmentation algorithms generally are based on 2 basic properties of gray level values: Discontinuity and Similarity

- **Segmentation methods:**

1. Global approaches such as thresholding
2. Edge-based segmentation
3. Region-based segmentation

Detection of Discontinuities

- There are 3 basic types of discontinuities: points, lines and edges.
- The detection is based on convoluting the image with a spatial mask.
- A general 3x3 mask

$$\begin{bmatrix} w_{-1,-1} & w_{-1,0} & w_{-1,1} \\ w_{0,-1} & w_{0,0} & w_{0,1} \\ w_{1,-1} & w_{1,0} & w_{1,1} \end{bmatrix}$$

- The response of the mask at any point (x,y) in the image is $R_{x,y} = \sum_{i=-1}^{1} \sum_{j=-1}^{1} p(x-i, y-j)\, w(i,j)$

Point Detection

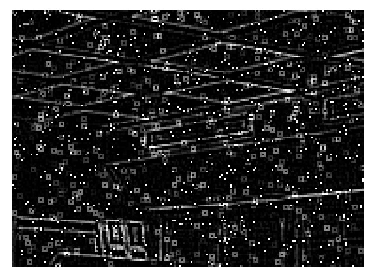
- A point has been detected at the location p(i,j) on which the mask is centered if |R |>T, where T is a nonnegative threshold, and R is obtained with the following mask.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

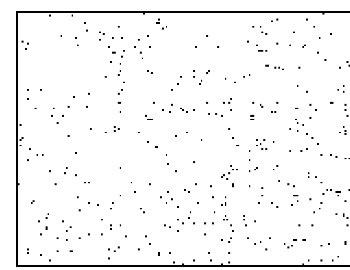
- The idea is that the gray level of an isolated point will be quite different from the gray level of its neighbors.

Original

Noise Added



Filtered O/P



Threshold Output

- If, at a certain point in the image, $|R_i|>|R_j|$ for all $j \neq i$, that point is said to be more likely associated with a line in the direction of mask i.

Line Detection masks:

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

Horizontal

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

+45°

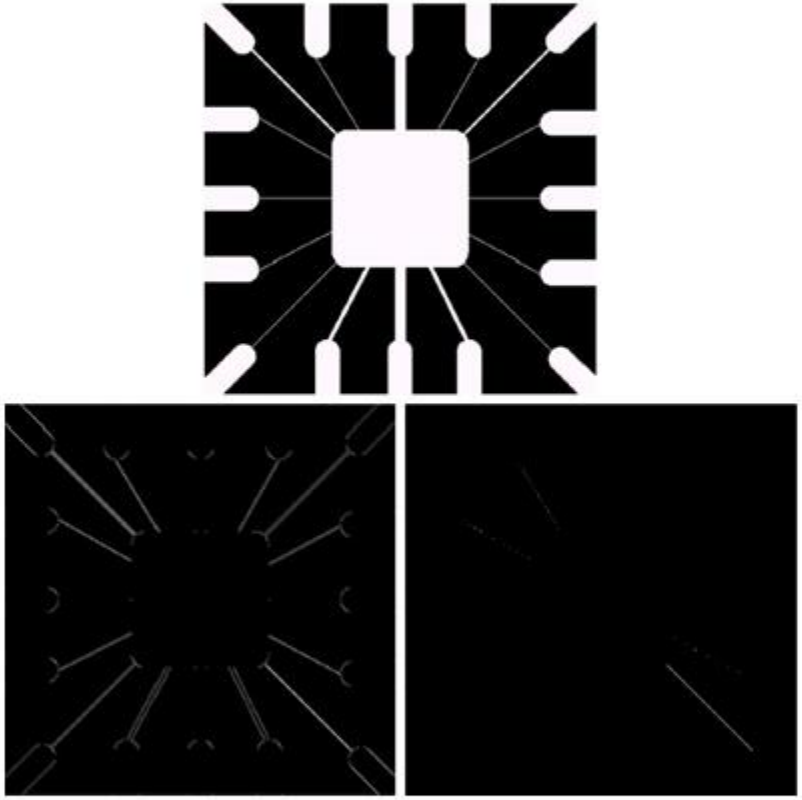
-1	2	-1
-1	2	-1
-1	2	-1

Vertical

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

- 45°

Line Detection masks:

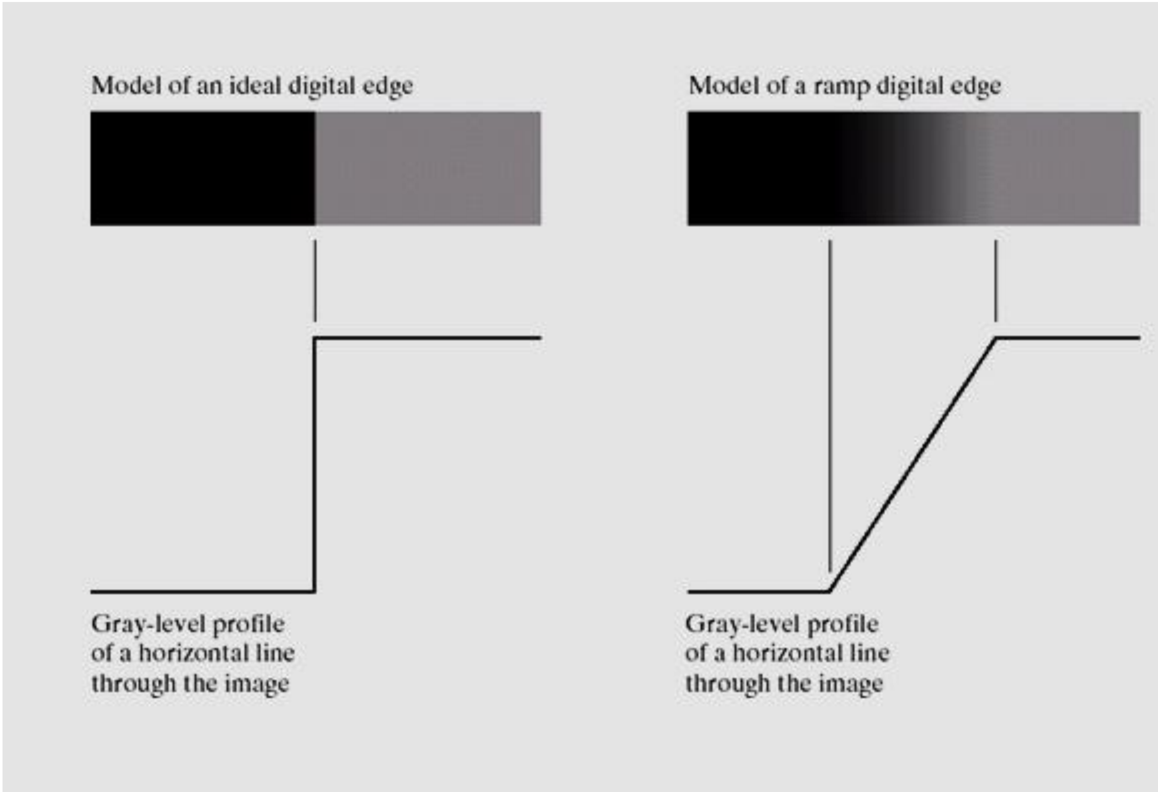


(a) Binary wire-bond mask.
(b) Absolute value of result after processing with −45° line detector.
(c) Result of thresholding image (b).

Edge detection

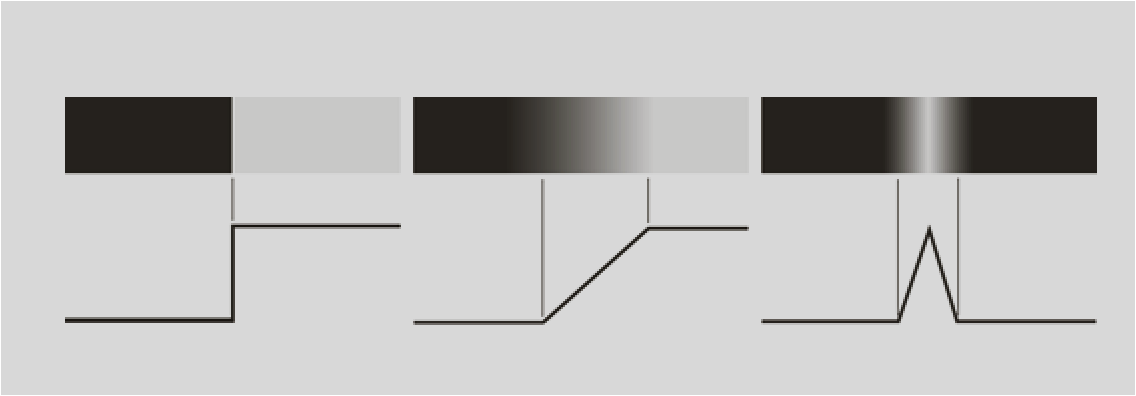
- It locates sharp changes in the intensity function.
- Edges are pixels where brightness changes abruptly.
- A change of the image function can be described by a gradient that points in the direction of the largest growth of the image function.
- An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of the pixel.
- Magnitude of the first derivative detects the presence of the edge.
- Sign of the second derivative determines whether the edge pixel lies on the dark sign or light side.

Edge detection



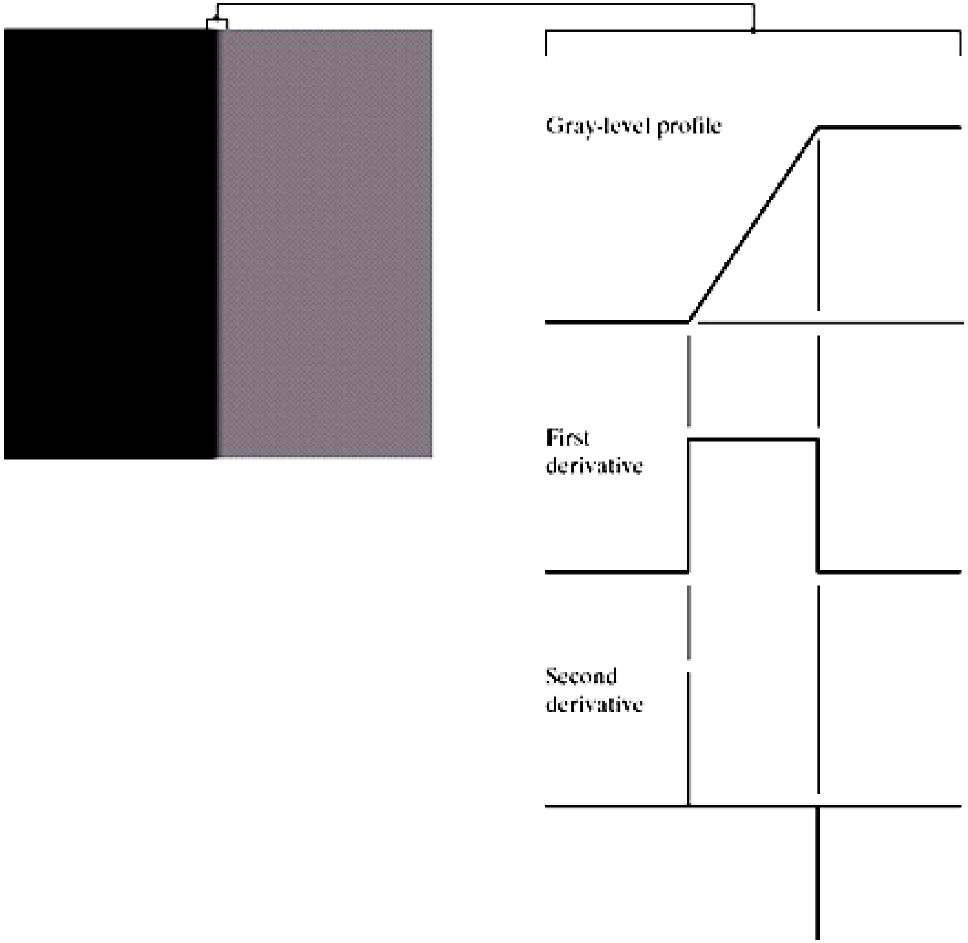
(a) Model of an ideal digital edge. (b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.

Edge detection



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

Edge detection



(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.

Detection of Discontinuities

- **Gradient Operators**

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

$$\nabla \mathbf{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

  - The magnitude of this vector: $\nabla f = \text{mag}(\nabla \mathbf{f}) = \left[G_x^2 + G_y^2\right]^{1/2}$

  - The direction of this vector: $\alpha(x, y) = \tan^{-1}\left(\frac{G_x}{G_y}\right)$

– It points in the direction of the greatest rate of change of f at location (x,y)

Detection of Discontinuities

- **Gradient Operators**

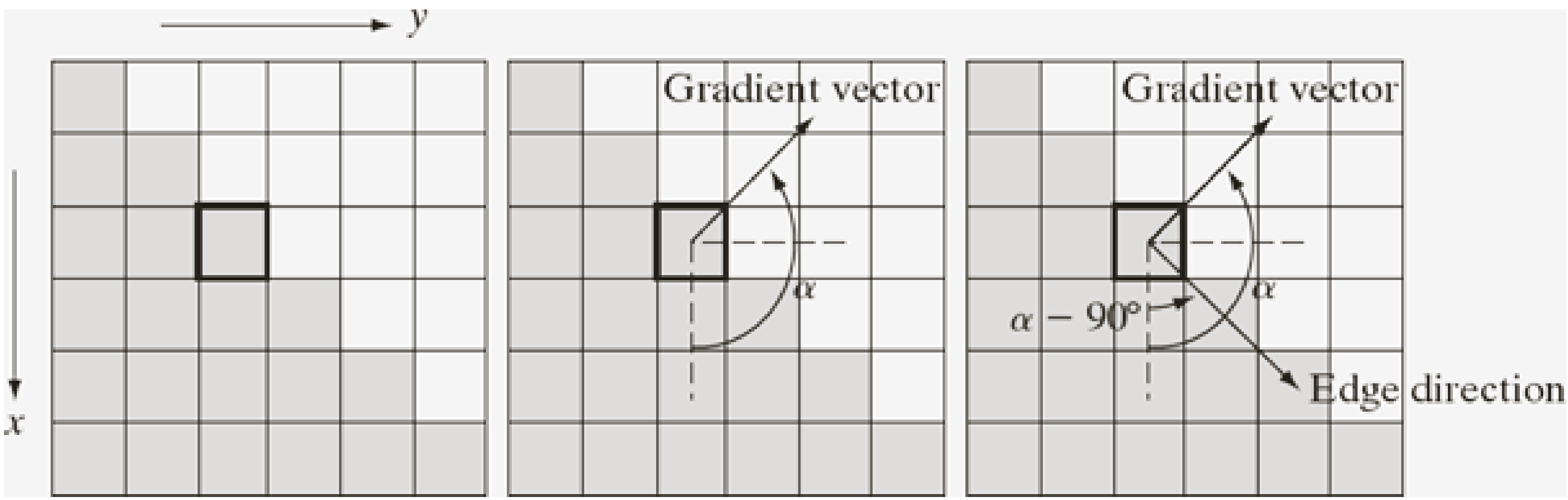


FIGURE Using the gradient to determine edge strength and direction at a point. Note that the edge is perpendicular to the direction of the gradient vector at the point where the gradient is computed. Each square in the figure represents one pixel.

Detection of Discontinuities

- **Gradient Operators**

Roberts cross-gradient operators

−1	0	0	−1
0	1	1	0

Roberts

Prewitt operators

−1	−1	−1	−1	0	1
0	0	0	−1	0	1
1	1	1	−1	0	1

Prewitt

Sobel operators

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

Sobel

Detection of Discontinuities

- **Gradient Operators**

Prewitt masks for detecting diagonal edges

0	1	1		−1	−1	0
−1	0	1		−1	0	1
−1	−1	0		0	1	1

Prewitt

Sobel masks for detecting diagonal edges

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

Sobel

a	b
c	d

Detection of Discontinuities Gradient Operators: Example

(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, $|G_x| + |G_y|$.

$$\nabla f \approx |G_x| + |G_y|$$

Detection of Discontinuities Gradient Operators: Example

0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Diagonal edge detection.

Detection of Discontinuities
Gradient Operators

Second Order Derivative

- The Laplacian of a 2D function f(x,y) is a 2nd-order derivative defined as

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

- The Laplacianhas the same properties in all directions and is therefore invariant to rotation in the image.
- It can also be implemented in digital form in various ways.
- For a 3x3 region, the mask is given as

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

- It is seldom used in practice for edge detection for the following reasons:

1. As a 2nd-order derivative, it is unacceptably sensitive to noise.
2. It produces double edges and is unable to detect edge direction.

- The Laplacian usually plays the secondary role of detector for establishing whether a pixel is on the dark or light side of an edge.

Thresholding

- Suppose that an image, f(x,y), is composed of light objects on a dark background, and the following figure is the histogram of the image.

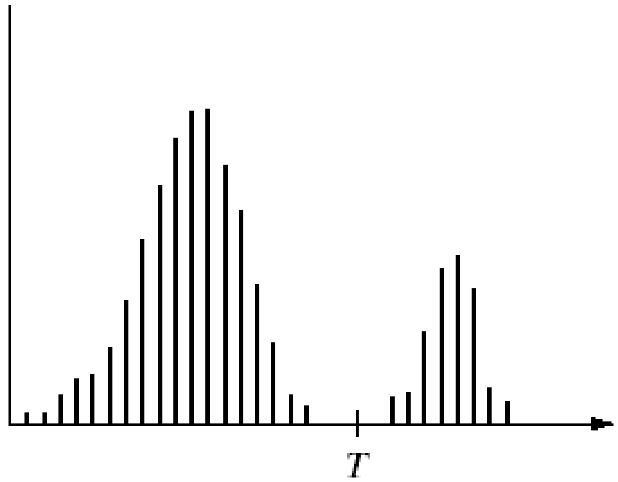


image with dark background and a light object

- Then, the objects can be extracted by comparing pixel values with a threshold T.

Thresholding

- One way to extract the objects from the background is to select a threshold ***T*** that separates object from background.
- Any point *(x,y)* for which ***f(x,y) > T*** is called an object point; otherwise the point is called a background point.

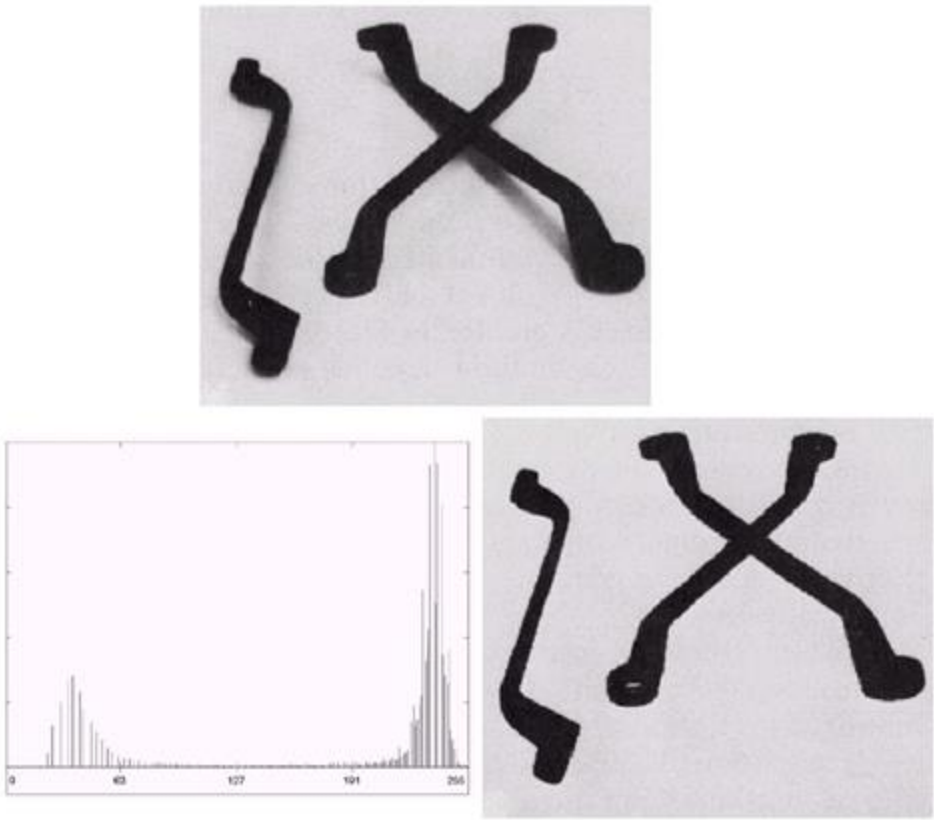
$$g(x, y) = \begin{cases} 1 & if \quad f(x,y) > T \\ 0 & f \quad f(x, y) \leq T \end{cases}$$

- When ***T*** is a constant applicable over an entire image, then the above process is called as *Global thresholding*.

Thresholding

- When the value of ***T*** changes over an image
- Then that process is referred as *Variable thresholding*.
- Sometimes it is also termed as *local* or *regional thresholding.*
- Where, the value of ***T*** at any point (x,y) in an image depends on properties of a *neighborhood of* (x,y).
- If ***T*** depends on the spatial coordinates (x,y) themselves, then variable thresholding is often referred to as *dynamic* or *adaptive thresholding*.

Thresholding



(a) Original image. (b) Image histogram. (c) Result of global thresholding with *T* midway between the maximum and minimum gray levels.

Multilevel Thresholding

- It is also possible to extract objects that have a specific intensity range using multiple thresholds.

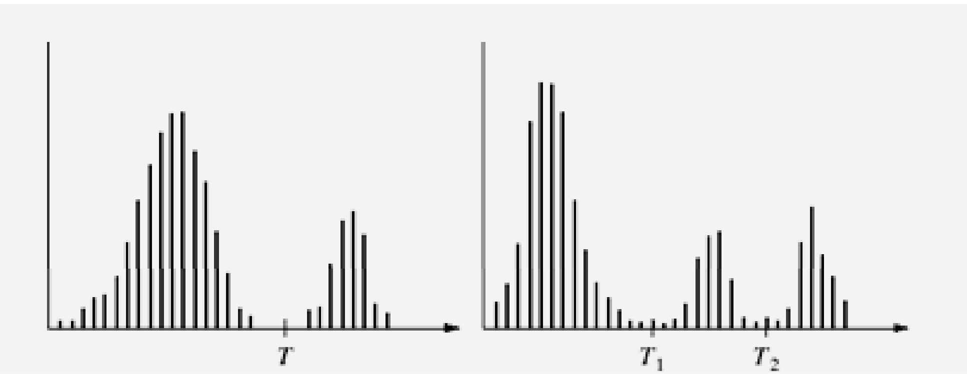


image with dark background
and two light objects

a b

FIGURE (a) Gray-level histograms that can be partitioned by (a) a single threshold, and (b) multiple thresholds.

Extension to color images is straightforward: There are three color channels, in each one specify the intensity range of the object… Even if objects are not separated in a single channel, they might be with all the channels… Application example: Detecting/Tracking faces based on skin color…

Multilevel Thresholding

- A point (x,y) belongs
  - to an object class if $T_1 < f(x,y) \leq T_2$
  - to another object class if $f(x,y) > T_2$
  - to background if $f(x,y) \leq T_1$

$$g(x, y) = \begin{cases} a & \text{if } f(x,y) > T_2 \\ b & \text{if } T_1 \leq f(x, y) \leq T_2 \\ c & \text{if } f(x, y) \leq T_1 \end{cases}$$

Thresholding

Segmentation problems requiring multiple thresholds are best solved using region growing methods

Thresholding can be viewed as

$$T = T[\,x,\, y,\, p(x,y),\; f(x,y)\,],$$

where $f(x,y)$ is gray-level at (x,y) and $p(x,y)$ denotes some local property, for example average gray level in neighbourhood

Thresholding

A thresholded image $g(x, y)$ is defined as

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

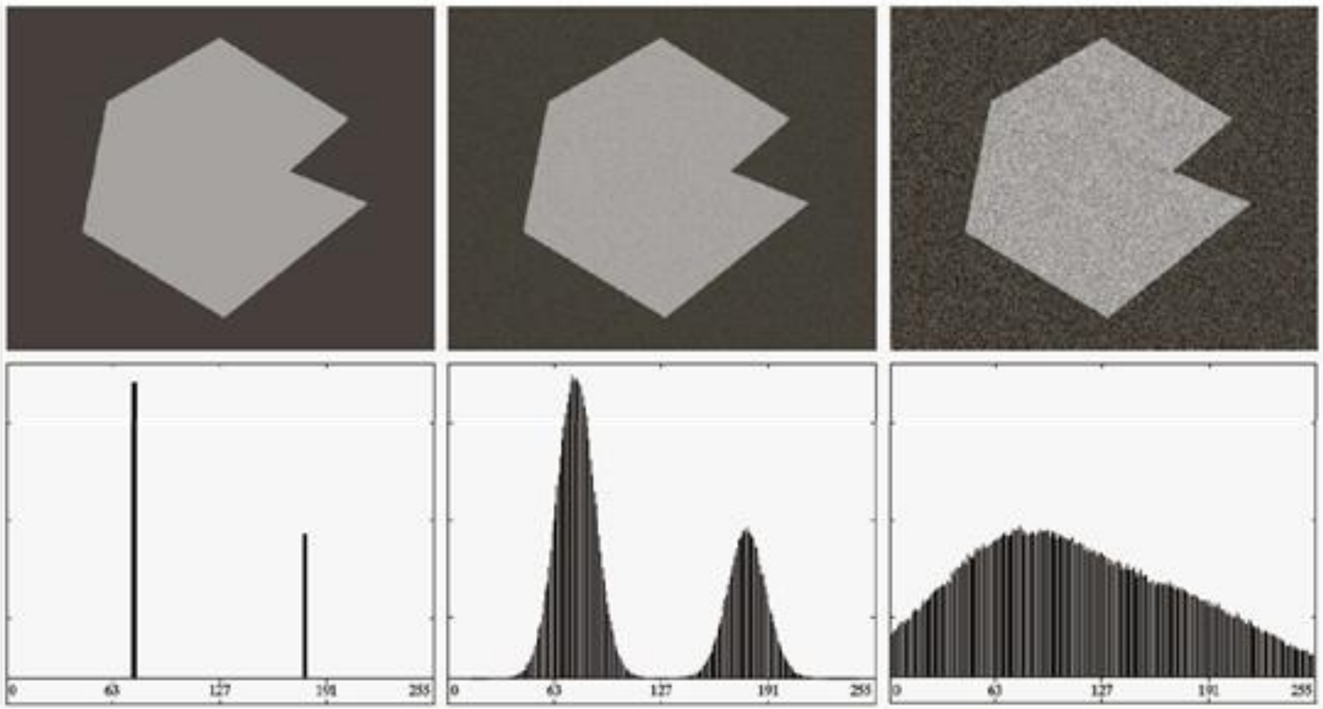
where 1 is object and 0 is background

When $T = T[\, f(x,y)\,]$, threshold is **global**

When $T = T[\, p(x,y),\ f(x,y)\,]$, threshold is **local**

When $T = T[\, x,\ y,\ p(x,y),\ f(x,y)\,]$, threshold is **dynamic** or **adaptive**

Role of Noise in Image Thresholding



a b c
d e f

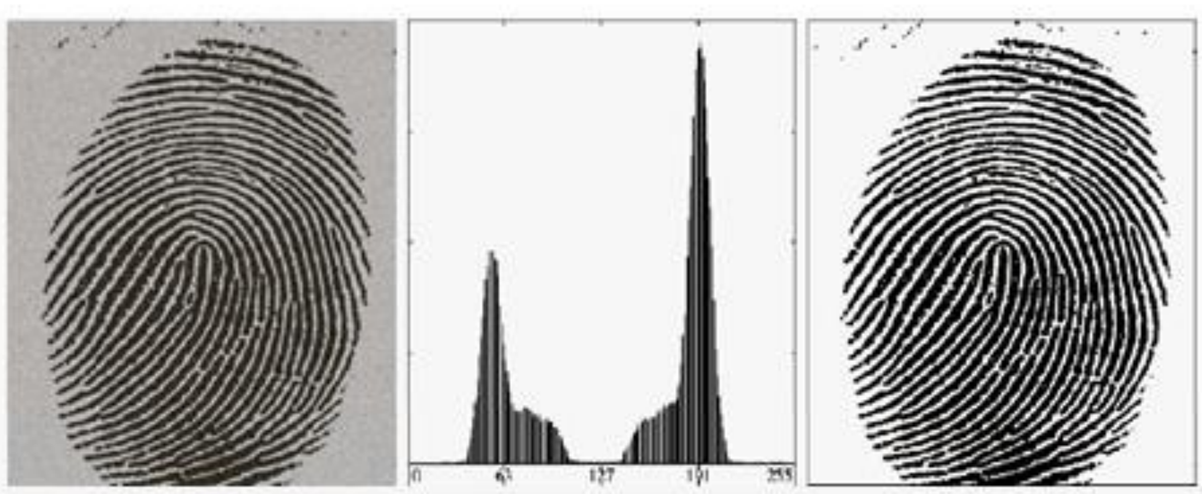
FIGURE (a) Noiseless 8-bit image. (b) Image with additive Gaussian noise of mean 0 and standard deviation of 10 intensity levels. (c) Image with additive Gaussian noise of mean 0 and standard deviation of 50 intensity levels. (d)–(f) Corresponding histograms.

Basic Global thresholding

Based on visual inspection of histogram

1. Select an initial estimate for **T**.
2. Segment the image using **T.** This will produce two groups of pixels: G_1 consisting of all pixels with gray level values > **T** and G_2 consisting of pixels with gray level values ≤ **T**
3. Compute the average gray level values μ_1 and μ_2 for the pixels in regions G_1 and G_2
4. Compute a new threshold value
5. **T** = 0.5 ($\mu_1 + \mu_2$)
6. Repeat steps 2 through 4 until the difference between the values of **T** in successive iterations is smaller than a predefined parameter **ΔT**.

Basic Global thresholding



Note: the clear valley of the histogram and the segmentation between object and background

a b c

FIGURE (a) Noisy fingerprint. (b) Histogram. (c) Segmented result using a global threshold (the border was added for clarity). (Original courtesy of the National Institute of Standards and Technology.)

Initially T= average intensity of image $T_0 = 0$
3 iterations
with result T = 125

Basic Global thresholding

1. Works well in situations where there is a reasonably clear valley between the modes of the histogram related to objects and background.
2. ΔT is used to control the number of iterations.
3. Initial threshold must be chosen greater than the minimum and less than the maximum intensity level in the image
4. The average intensity of the image is a good initial choice for T.

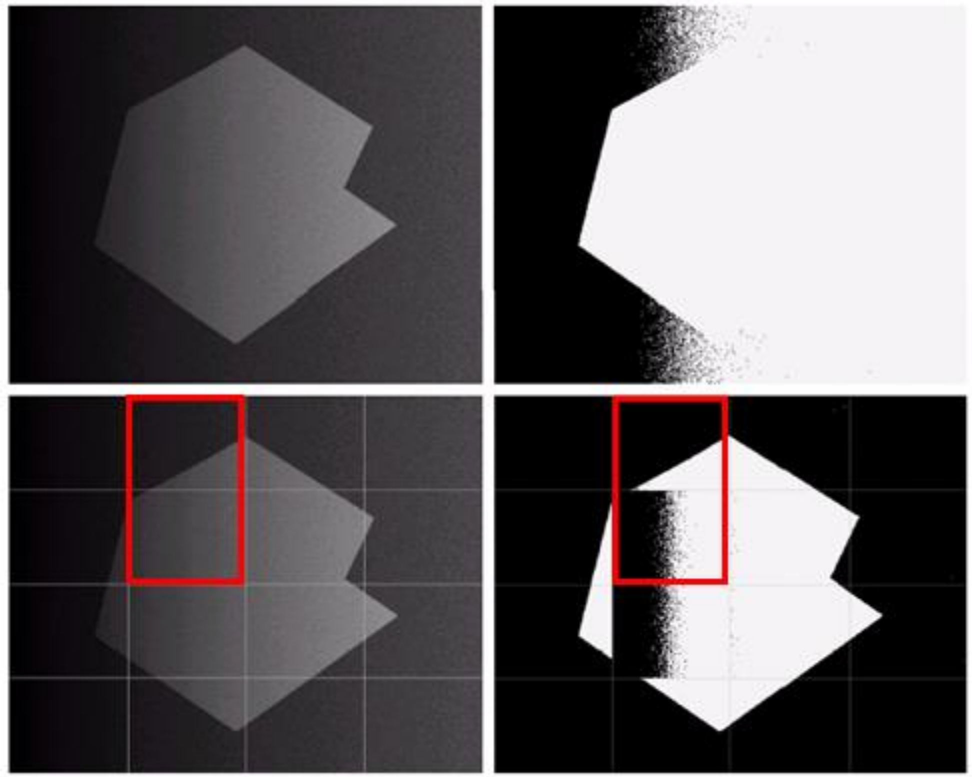
Basic Adaptive Thresholding

- subdivide original image into small areas.
- utilize a different threshold to segment each subimages.
- since the threshold used for each pixel depends on the location of the pixel in terms of the subimages, this type of thresholding is adaptive.

Example of Adaptive Thresholding

a b
c d

FIGURE
(a) Original image. (b) Result of global thresholding. (c) Image subdivided into individual subimages. (d) Result of adaptive thresholding.



Edge & Boundary Linking

- Set of pixels from edge detecting algorithms, seldom define a boundary completely because of noise, breaks in the boundary etc.
- Therefore, Edge detecting algorithms are typically followed by linking and other detection procedures, designed to assemble edge pixels into meaningful boundaries.
- 2 types – local and global

Analyse the characteristics of pixels in a small neighbourhood (3x3, or 5x5) about every point that has undergone edge detection. All points that are similar are linked, forming a boundary of pixels that share some common properties.

Local Processing

- 2 main properties for establishing similarity of edge pixels:-
  - strength of the response of the gradient operator used to produce the edge pixel
  - direction of the gradient.
  - A point in the predefined neighbourhood of (x,y) is linked to the pixel at (x,y) if both magnitude and direction criteria are satisfied. This process is repeated for every location in the image.

Edge & Boundary Linking by Hough Transforms

➢ *The* <u>*Hough transform*</u> *is a technique which can be used to isolate features of a particular shape within an image.*

❖ Hough transform is most commonly used for the detection of regular curves such as lines, circles, ellipses, *etc*.

❖ The main advantage of the Hough transform technique is that it is tolerant of gaps in feature boundary descriptions and is relatively unaffected by image noise.

The line equation is $y = mx + c$

However, the problem is that there are infinite line passing through one points

Therefore, an edge point in an x-y plane is transformed to a c-m plane Now equation of line is $c = (-x)m + y$

- **Hough Transform steps:**

1) Load the image
2) Find the edges of the image using any edge detector
3) Quantize the parameter space P
4) Repeat the following for all the pixels of the image: if the pixel is an edge pixel, then

   (a) $c = (-x)m + y$ *or calculate* ρ

   (b) $P(c,m) = P(c,m) + 1$ *or increment position in P*
5) Show the Hough Space
6) Find the local maxima in the parameter space
7) Draw the line using the local maxima

- The major problem with this algorithm is that it does not work for vertical lines, as they have a slope of infinity
- Convert line into polar coordinates $\rho = x \cos\Theta + y\sin\Theta$, where Θ is the angle between the line and x-axis, and ρ is the diameter

Example of Hough Transform

Q. Using hough transform, show that the points (1,1), (2,2), (3,3) are collinear . Find the equation of line.

Sol: Note: **Three or more points that lie on the same line are collinear points**

The equation of line is y=mx+c , where m=slope and c=intercept

To perform hough transform, we need to convert line from (x,y) plane to (m,c) plane.

The equation of line in (m,c) plane is

c=-mx+y…….(eq.1)

Now

1. For (x,y)= (1,1) ; c=-m+1…..(eq.2)

Now we will consider two conditions i.e if c=0, in eq.1 means 0=-m+1 i.e m=1

if m=0 in eq.2 then c=1

Therefore we can write (m,c)= (1,1)

2. Now for (x,y) = (2,2)

c= -2m+2 …..(eq.3) from eq.1

Again we will consider two condition

If c=0 in eq.3 then 0=-2m+2 i.e m=1

If m=0 in eq.3 then c=2 therefore (m,c)=(1,2)

3. Now for (x,y) =(3,3)

C= -3m+3…….(eq.4)

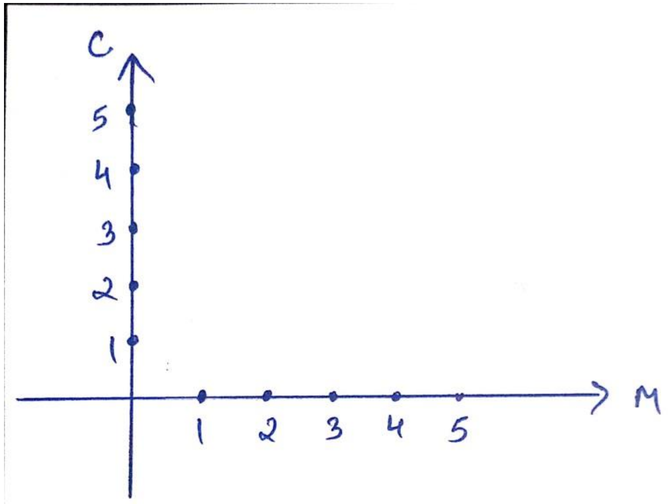
Again we will consider two condition

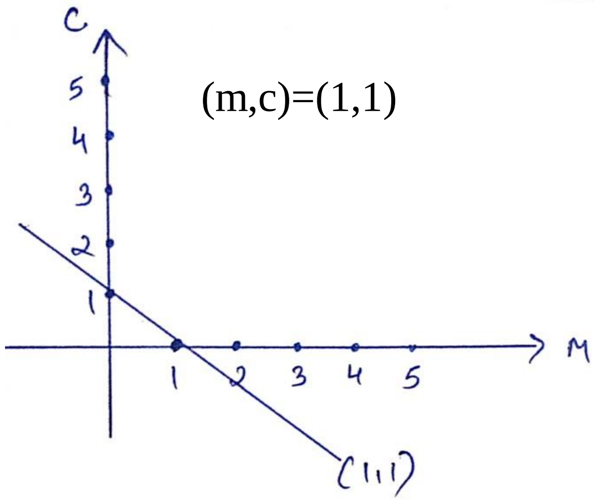
If c=0 in eq.4 then 0=-3m+3 i.e m=1

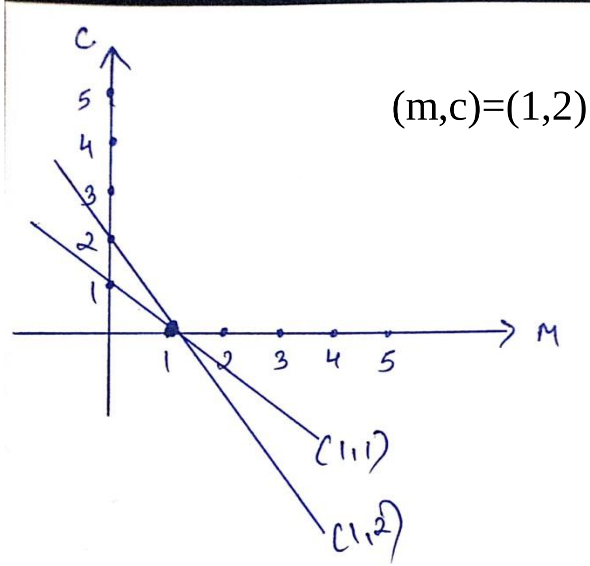
If m=0 in eq.4 then c=3 therefore (m,c)=(1,3)

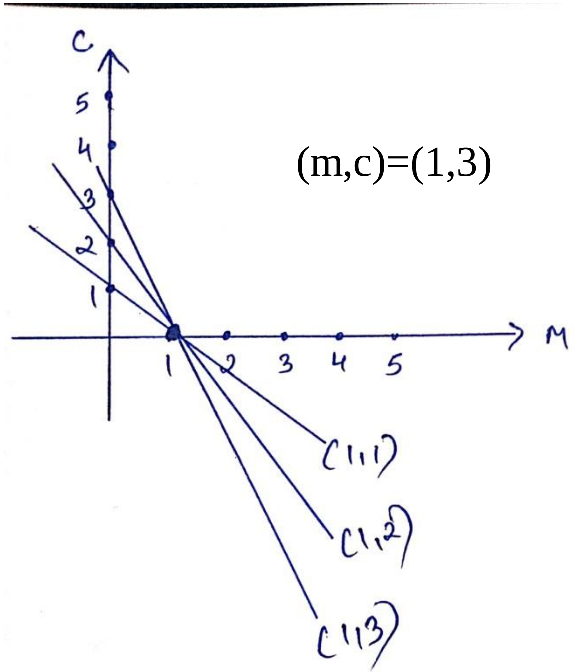
Now we have (m,c)= (1,1) , (1,2) , (1,3)

Now plot these values









So , by seeing this diagram we have to see the point at which all these 3 lines meet at same point.
So this point is m=1 and c=0
i.e (m,c)= (1,0)

Now original equation of line is y=mx+c
Put the value (m,c)= (1,0) in this equation we will get
y=x
Therefore final equation of line is y=x

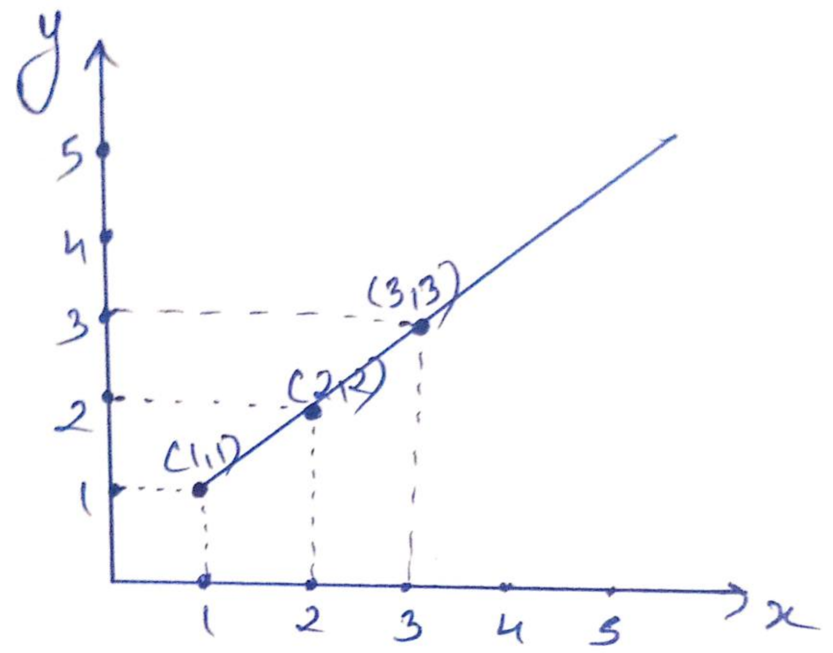
- Now we have to show that points are collinear or not

The final line of equation is y=x

So for (1,1) (2,2) (3,3)

x=1, y=1 x=2, y=2 x=3, y=3

Plot these values



So it shows that points are collinear