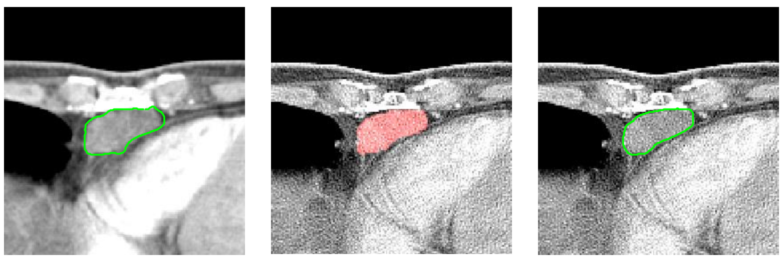
Medical Image Processing and Analysis

- Image Segmentation
- Data Analysis (Pattern recognition): Clustering and Classification
- Image Measurement and Meaning
- Image Registration

Segmentation

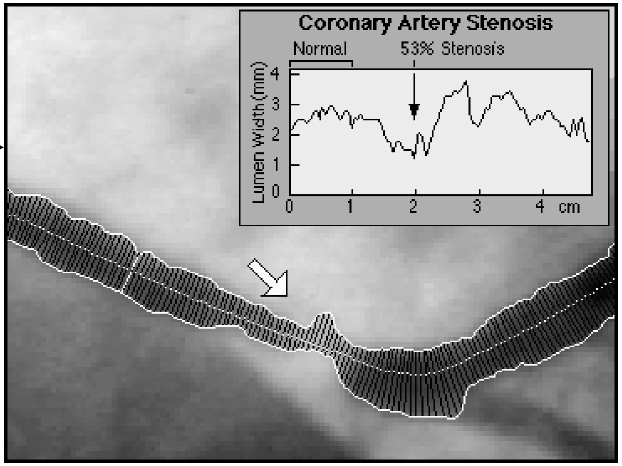
Definition: Spatial partitioning of an image into its constituent parts, or isolating specific objects in an image.

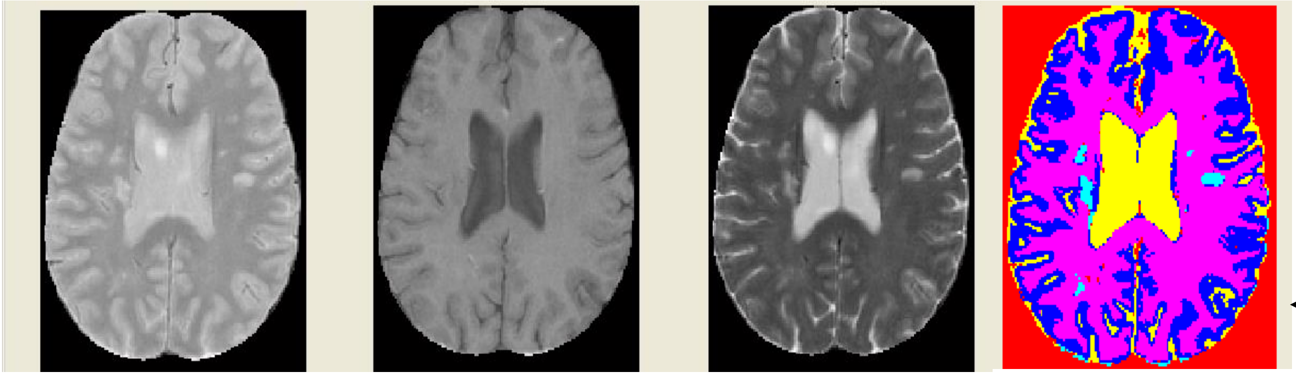
- Extract Region-of-Interest (ROI)
- Measurements – e.g. tracking volume over time, lesion burden



Lymph node segmentation (CT)

Coronary vessel segmentation (Angiograms)





Brain tissue and lesion segmentation (MRI)

Three general types of segmentation techniques:

Manual:

time consuming, error prone, subjective, not reproducible

may be the most accurate approach if an expert is doing the work

(non-fatigued + good interactive tools).

Automatic:

Algorithms to segment and partition an image entirely automatically, with no human intervention. Computer intensive; Error prone due to large variety of image types and image characteristics.

Semi-automatic:

Combination of computer processing and human intervention. The expert can initialize the process by selecting initial boundaries or starting information.

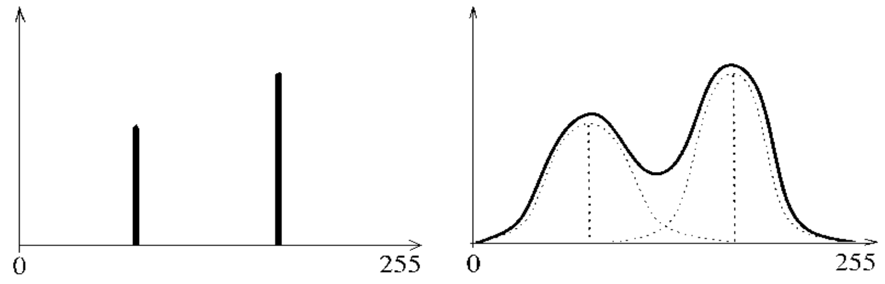
At the end of the process, the expert can correct erroneous results.

Variety of works in the field:

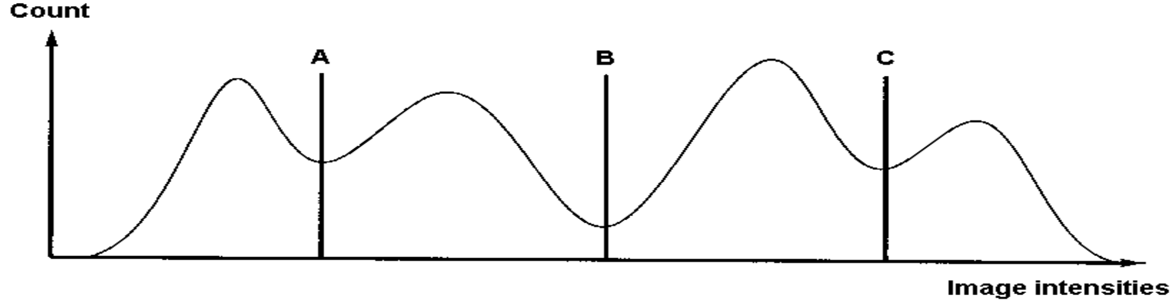
- Manual methods
- Thresholding
  - Shape-based histogram techniques
  - Non-parametric & parametric optimal thresholding
- Edge-based techniques
  - Border tracing
  - Graph searching
- Region-based techniques
  - Region growing
  - Region splitting and merging
  - Connected component labeling
- Morphology operators

Segmentation via Thresholding

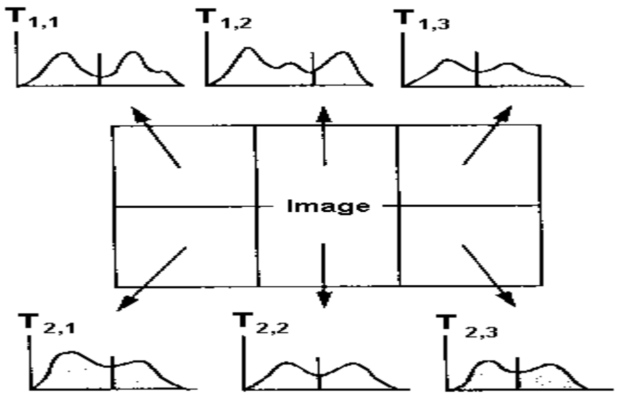
Object Vs. Background



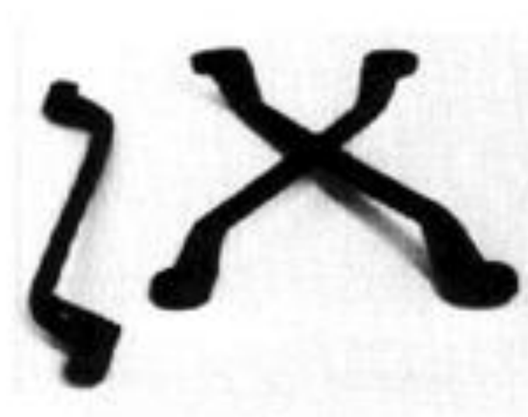
Several objects in image



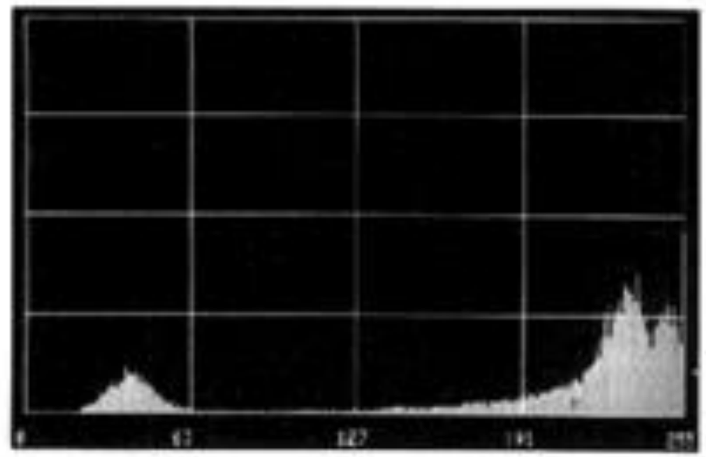
Adaptive Thresholding



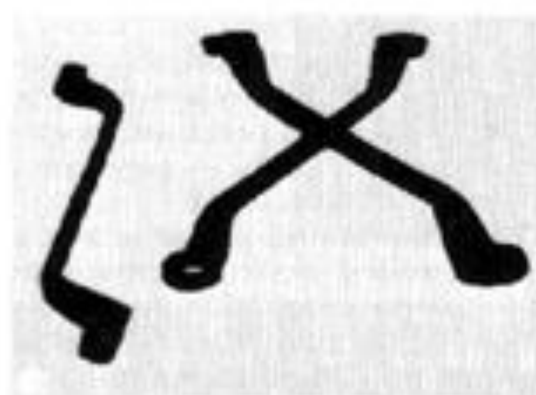
Simple Global Thresholding

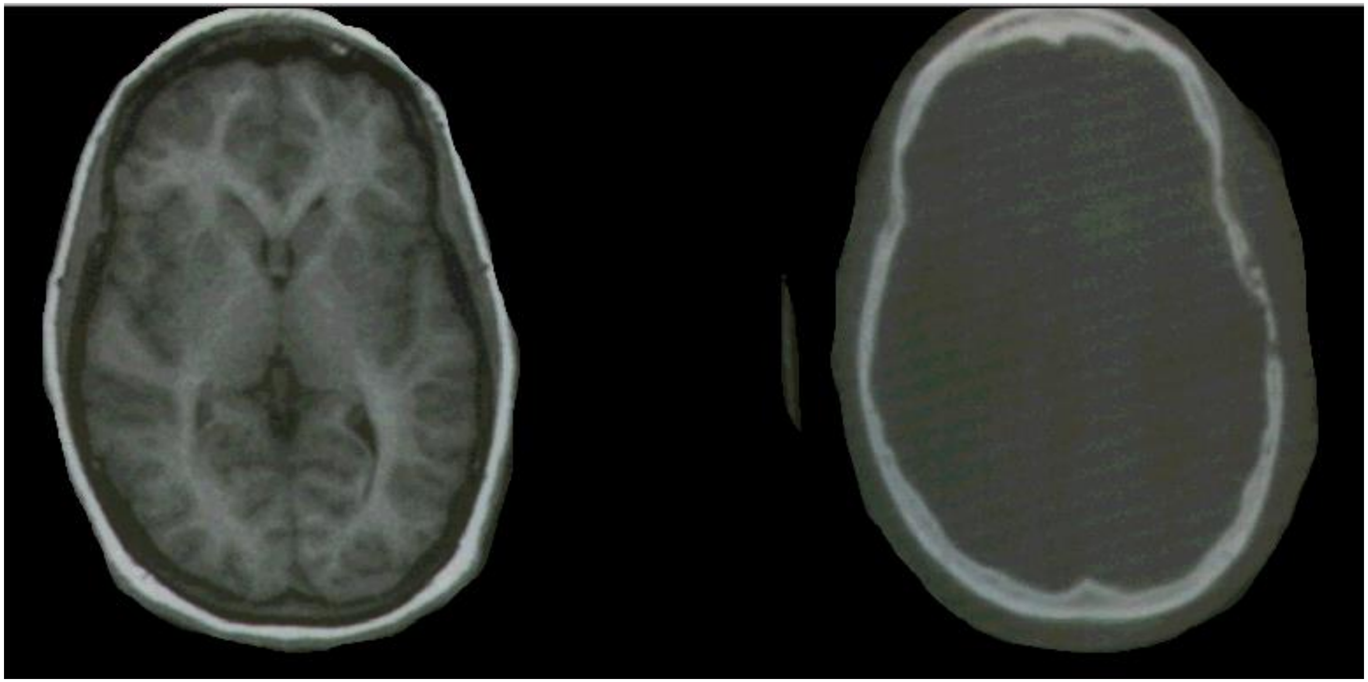


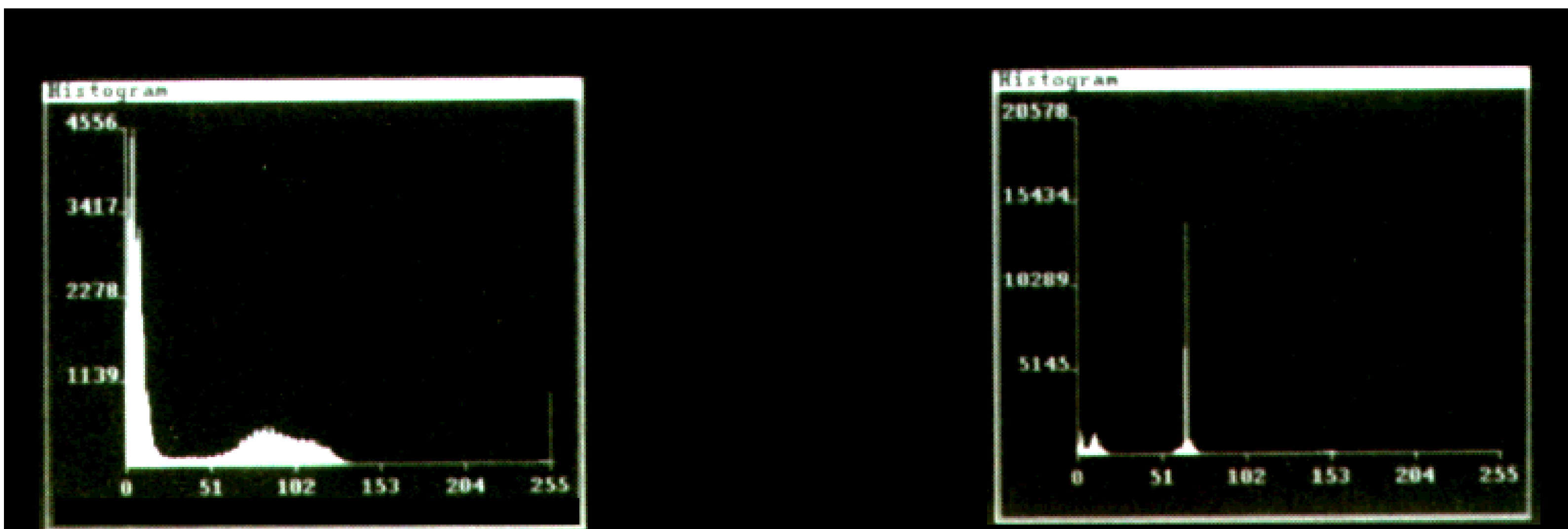
(a)



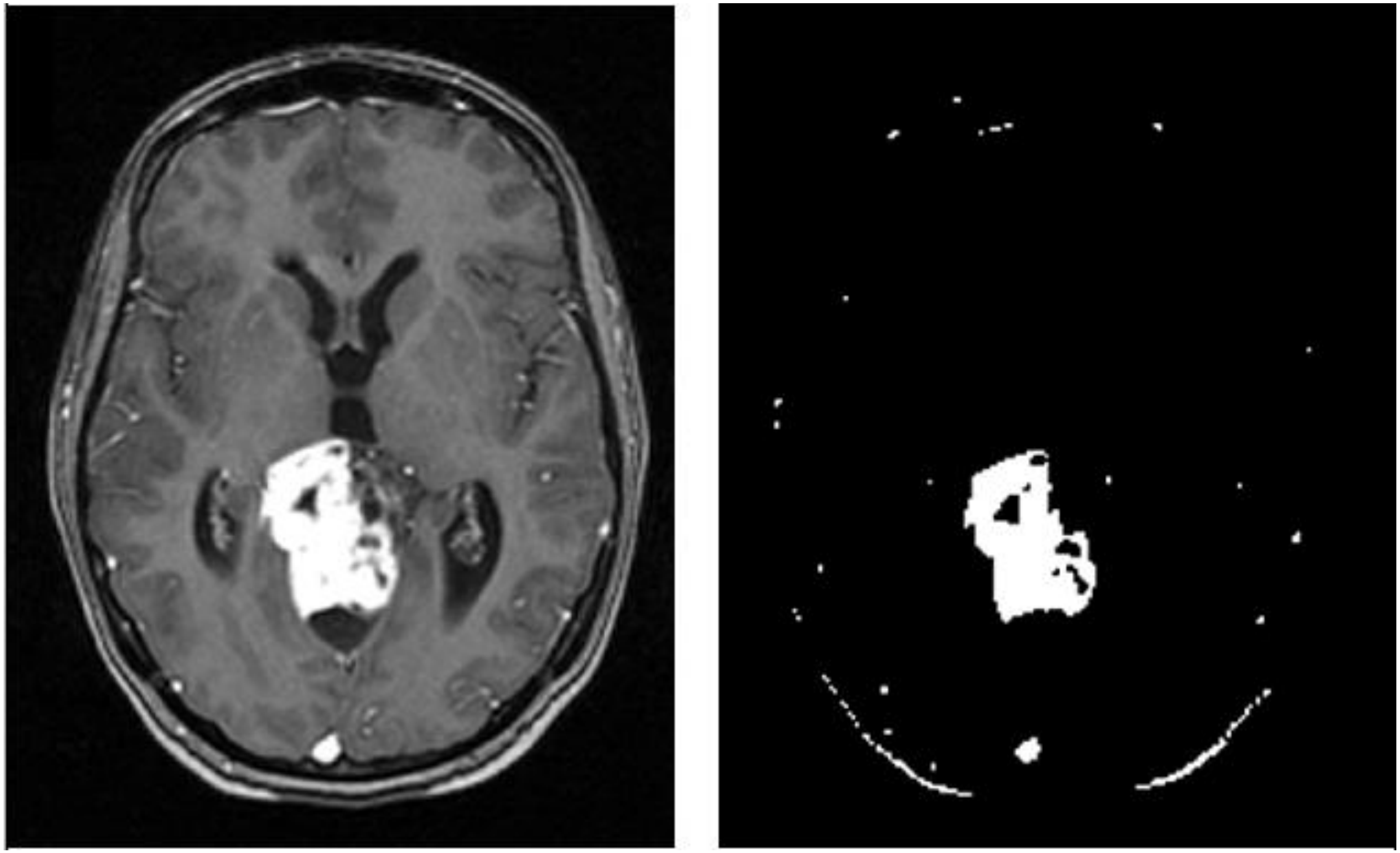
(b)






Histogram
4556
3417
2278
1139
0
51
102
153
204
255
Histogram
20578
15434
10289
5145
0
51
102
153
204
255

MRI CT



MRI segmentation using thresholding

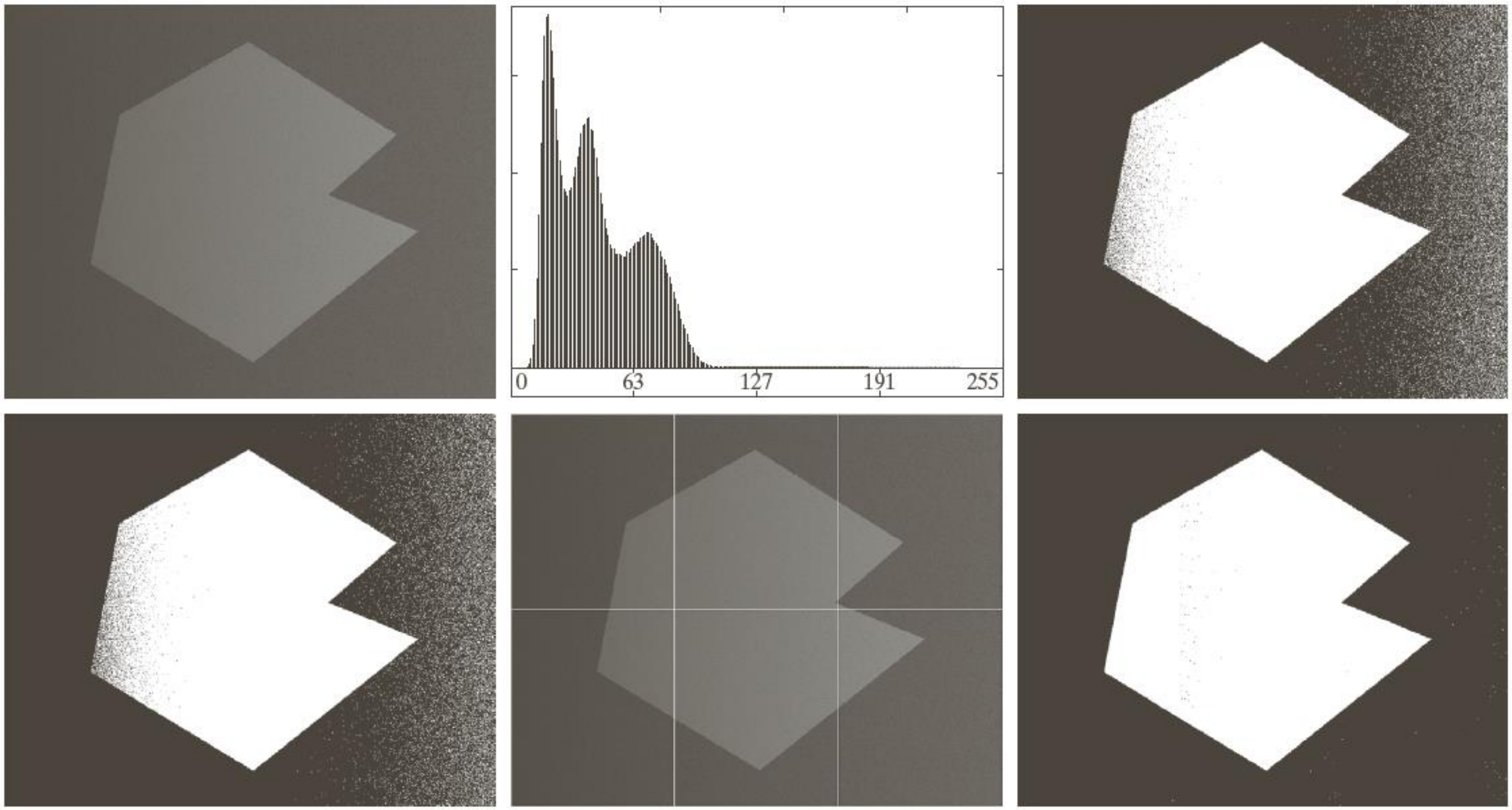
Thresholding

- Algorithm: Iterative threshold selection
  1. *Select an initial estimate of the threshold, T. A good initial value is the average intensity of the image.*
  2. *Partition the image into 2 groups:* R_1 *and* R_2 *using the threshold T.*
  3. *Calculate the mean gray values* μ_1 *and* μ_2 *of the partitions* R_1 *and* R_2*.*
  4. *Select a new threshold:* $T = \frac{1}{2}(\mu_1 + \mu_2)$
  5. *Repeat steps 2-4 until the mean values* μ_1 *and* μ_2 *in successive iterations do not change.*

Input (noisy, shaded)

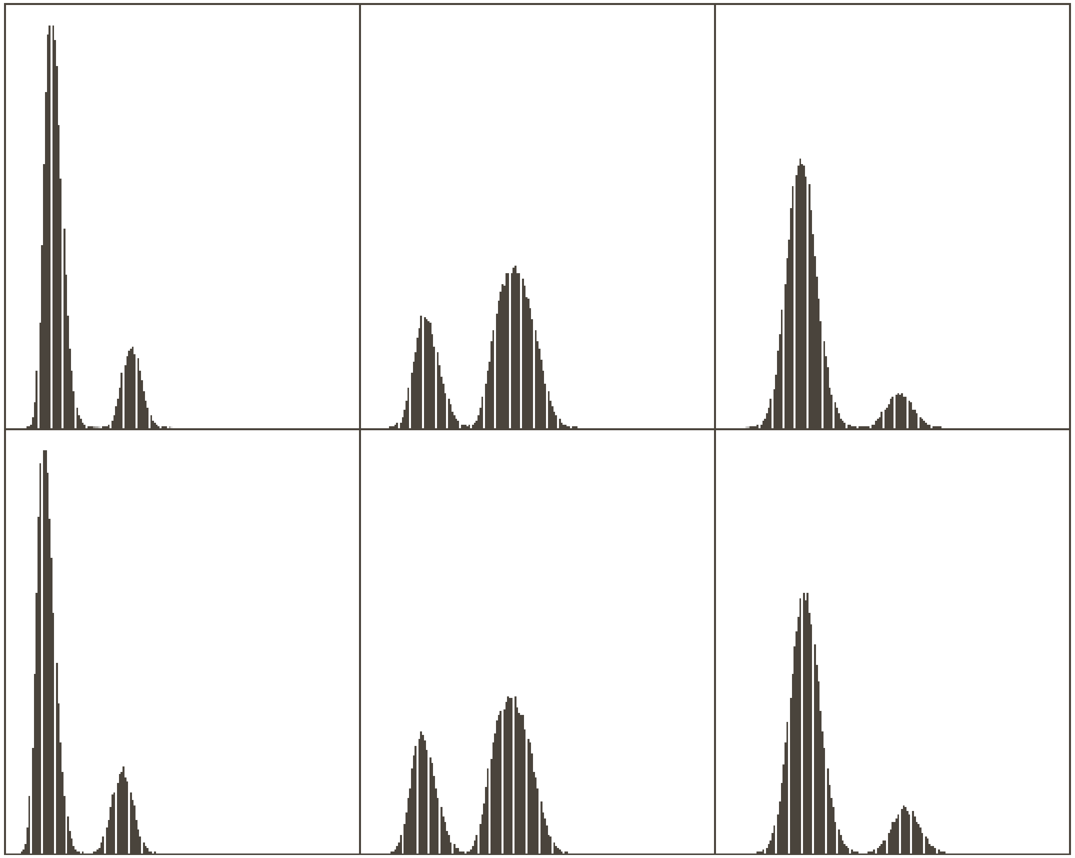
Histogram

Segmented image
Global HistogramThresholding



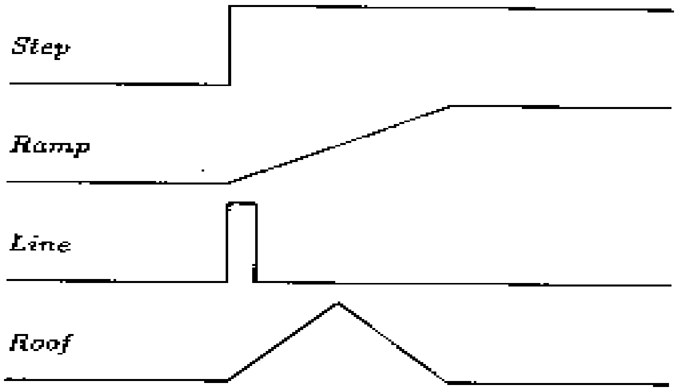
Local processing

Segmented image
Adaptive HistogramThresholding

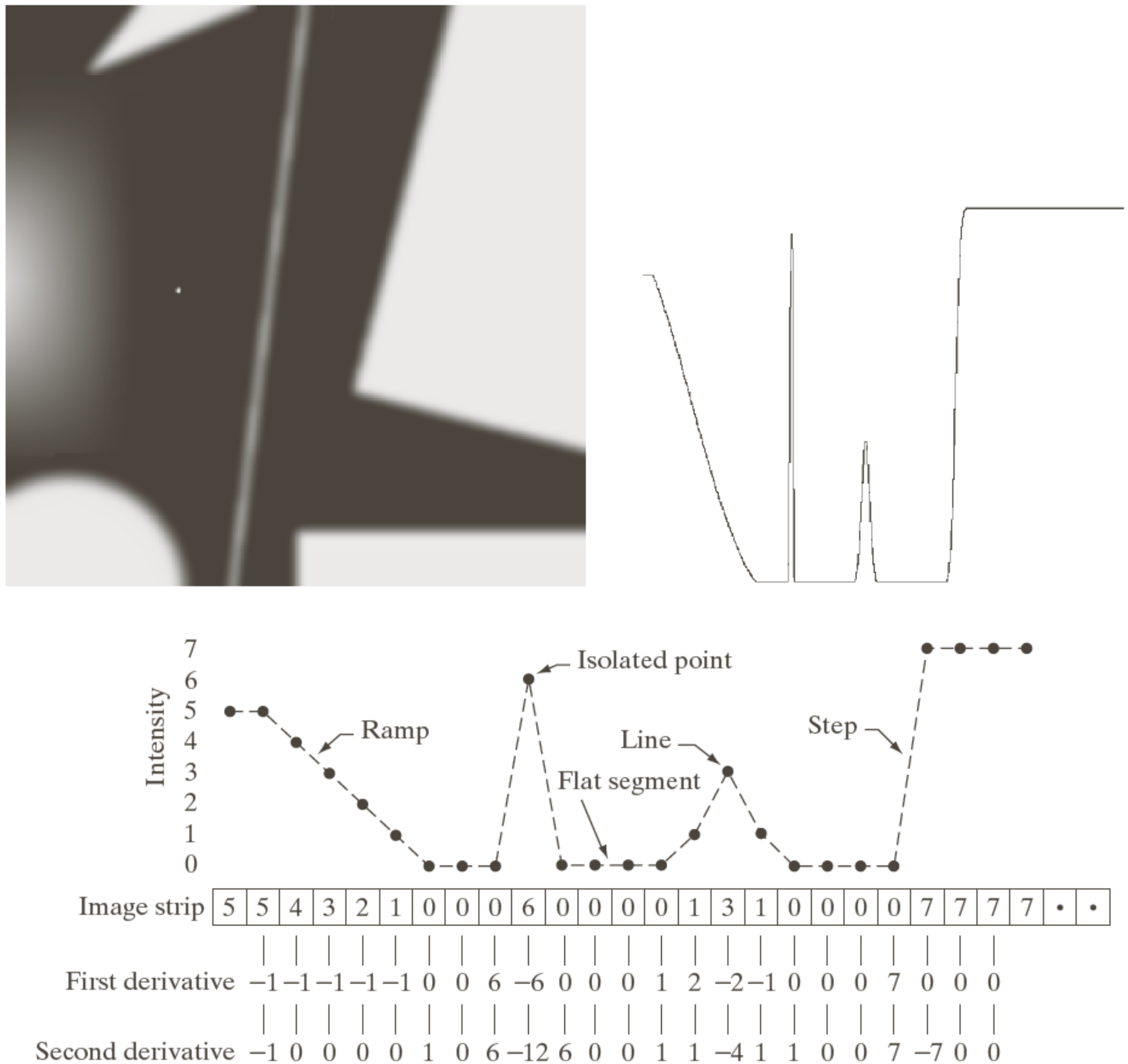


Edge Detection

- Edge = Local change in intensity between 2 image regions
- The idea behind most edge-detection algorithms is the computation of a local derivative operator.

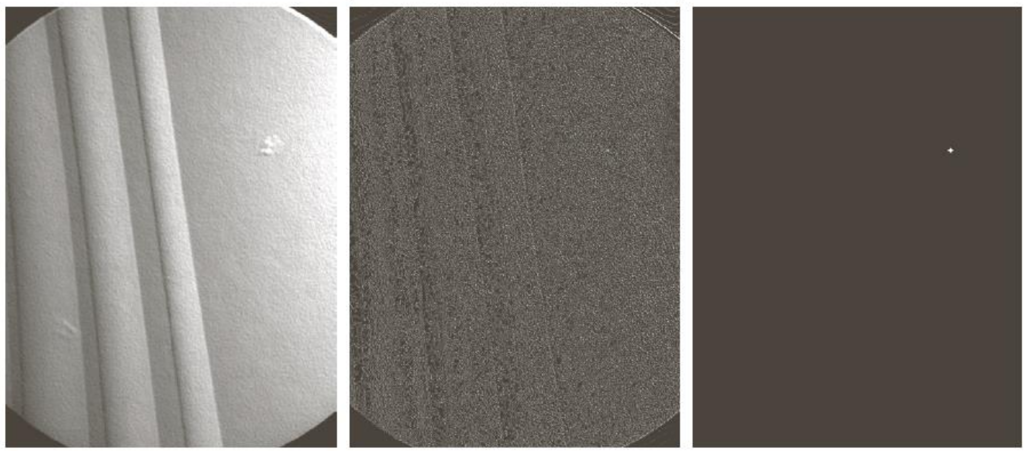


One-dimensional edge profiles



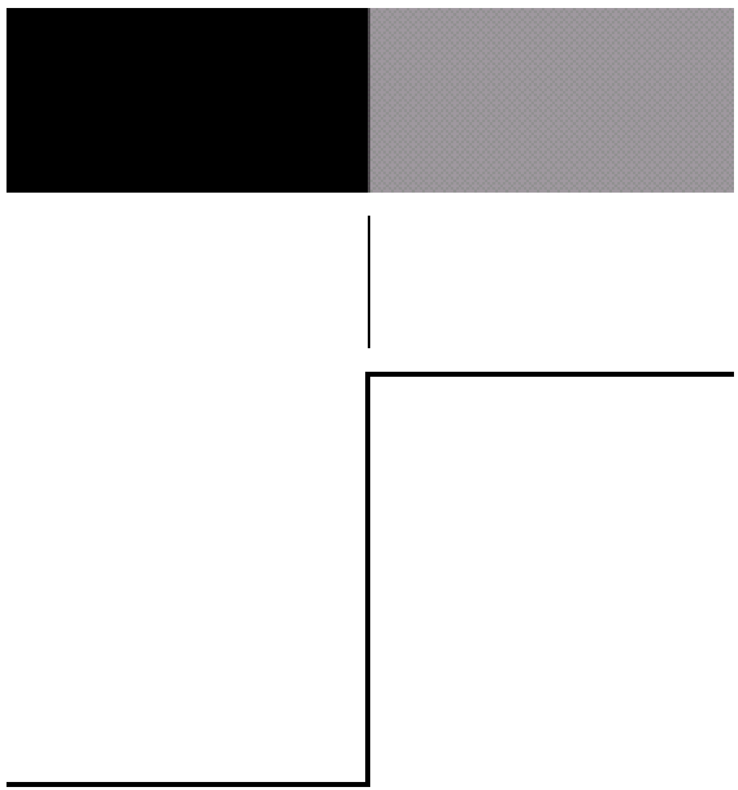
Isolated point
Ramp
Line
Step
Flat segment
Intensity
7 6 5 4 3 2 1 0
Image strip 5 5 4 3 2 1 0 0 0 6 0 0 0 0 1 3 1 0 0 0 0 7 7 7 7 • •
First derivative −1 −1 −1 −1 −1 0 0 6 −6 0 0 0 1 2 −2 −1 0 0 0 7 0 0 0
Second derivative −1 0 0 0 0 1 0 6 −12 6 0 0 1 1 −4 1 1 0 0 7 −7 0 0

1	1	1
1	−8	1
1	1	1



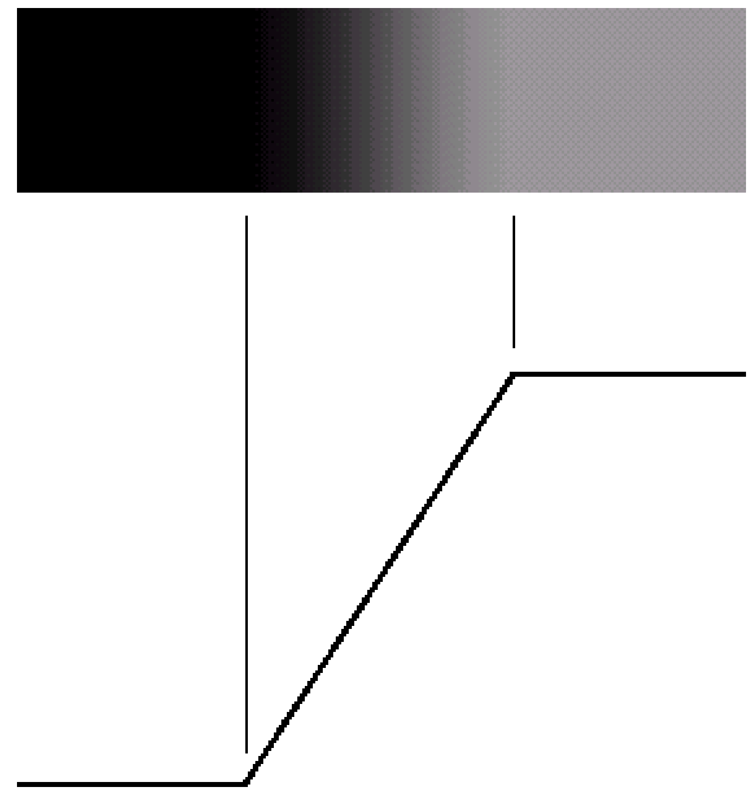
Detection of Isolated Points

Model of an ideal digital edge

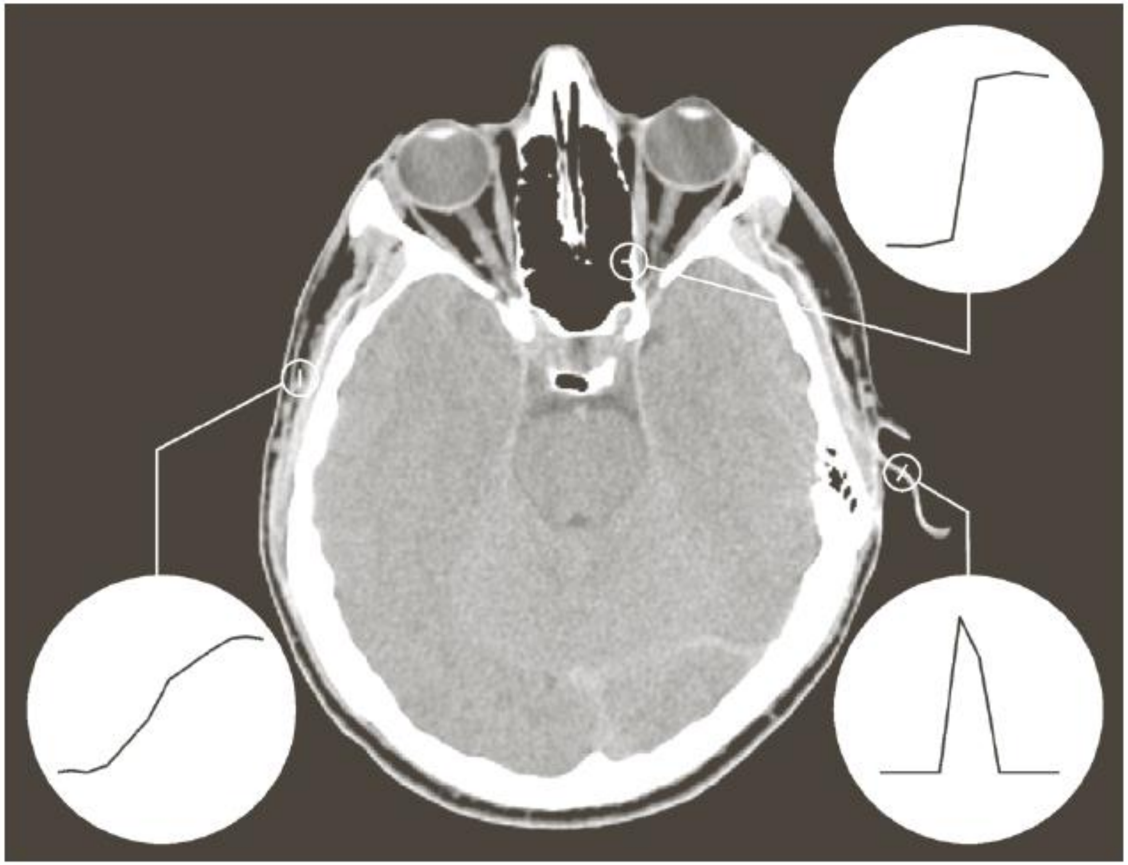


Gray-level profile
of a horizontal line
through the image

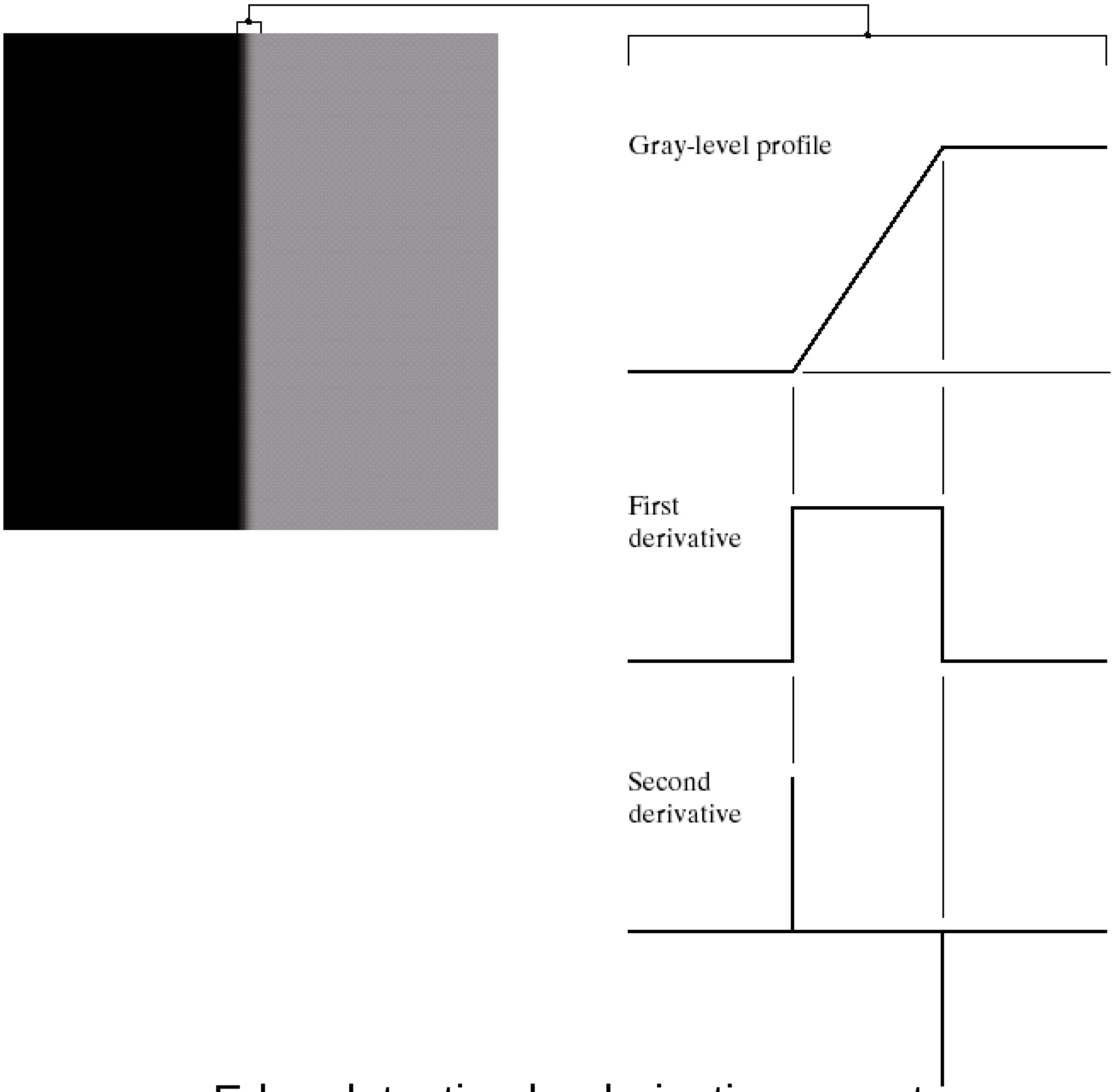
Model of a ramp digital edge



Gray-level profile
of a horizontal line
through the image



1508x1970 image showing 3 different edge types:
“ramp” (bottom, left), “step” (top, right), “roof” (bottom, right)



Edge detection by derivative operators

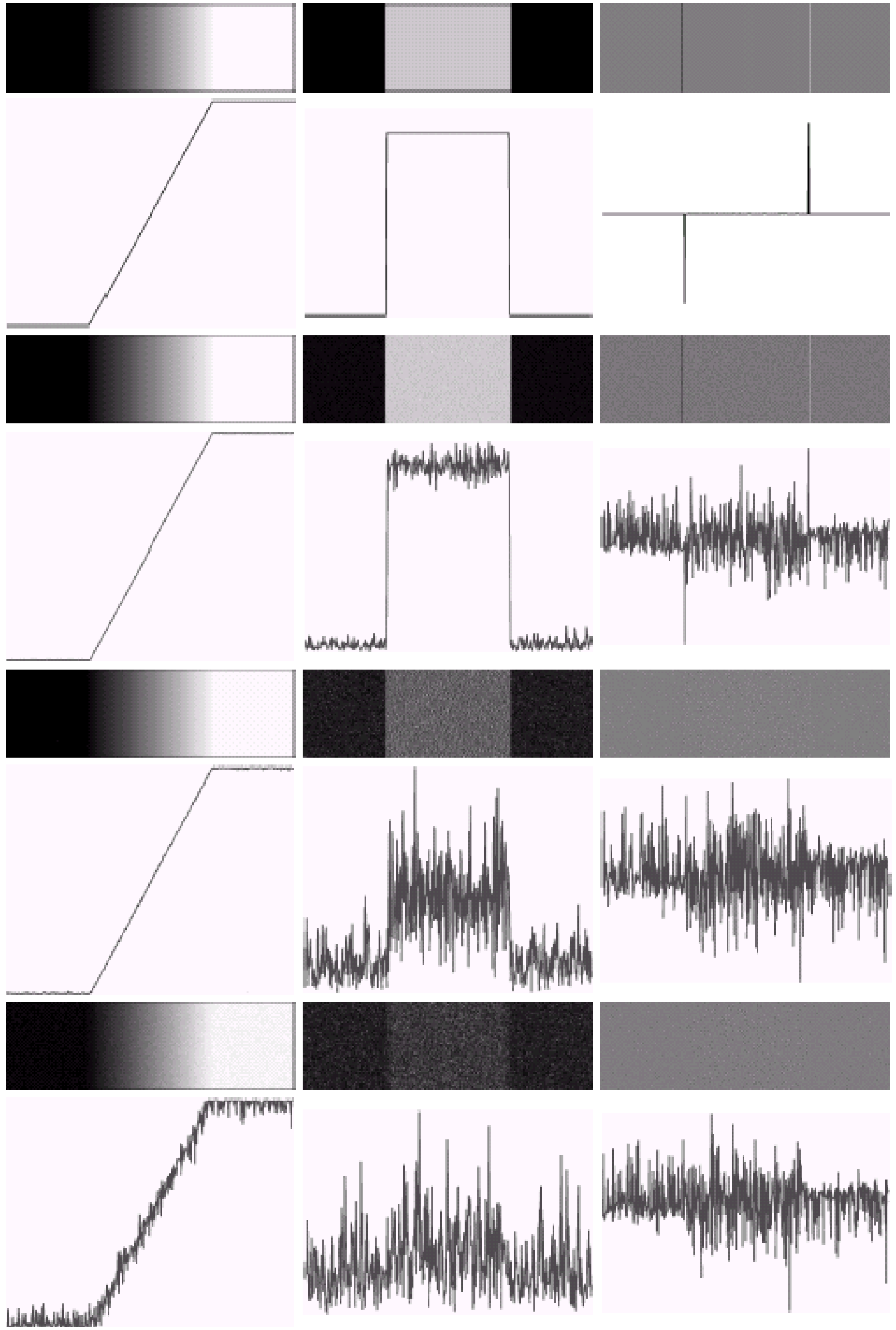


Image Gradient

- The 2-D equivalent of the first derivative.

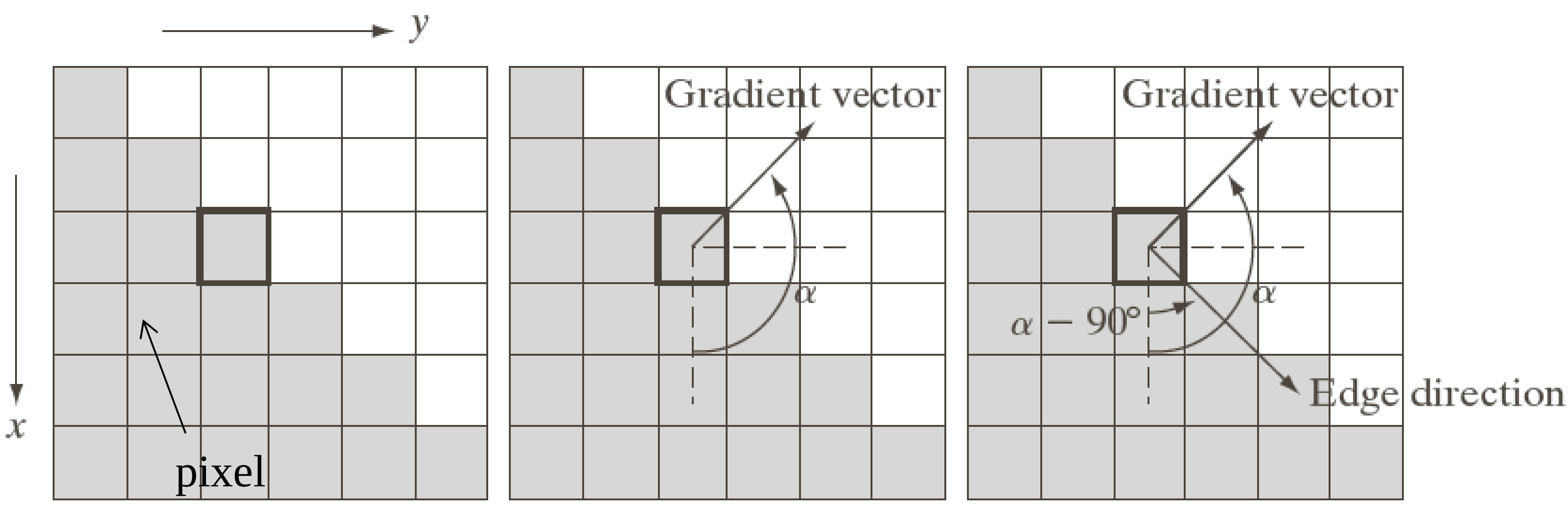
$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

- Magnitude of the gradient

$$\nabla f = \sqrt{G_x^2 + G_y^2} \approx |G_x| + |G_y|$$

- Direction of the gradient

$$\alpha(x, y) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$



Gradient Operators:Prewitt, Sobel

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

−1	0
0	1

0	−1
1	0

Roberts

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Prewitt

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

Sobel

0	1	1
−1	0	1
−1	−1	0

−1	−1	0
−1	0	1
0	1	1

Prewitt

0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Sobel

2D Gradient Image

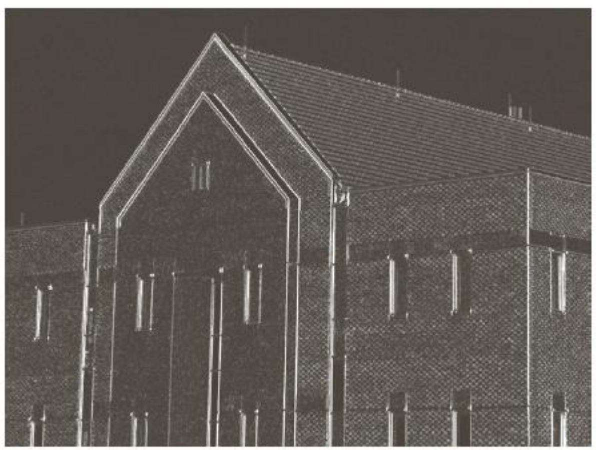
Original Image

Filtered Image (Sobel)

$|G_x|$

Filtered Image (Sobel)

$|G_y|$



Gradient Image (Sobel)

$|G_x| + |G_y|$

2D Gradient Image –
Smoothing prior to Gradient filtering

Original Image

Filtered Image (Sobel)

$|G_x|$

Filtered Image (Sobel)

$|G_y|$

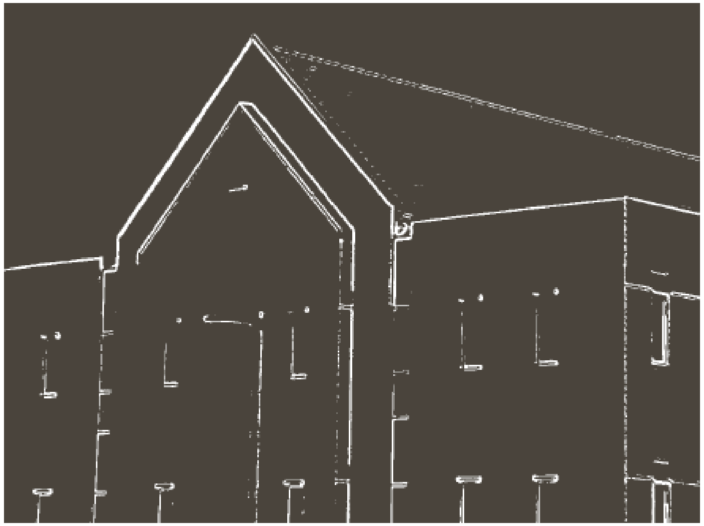
Gradient Image (Sobel)

$|G_x| + |G_y|$

Diagonal Edge Detection

Combining Gradient with Thresholding

Gradient, no smoothing

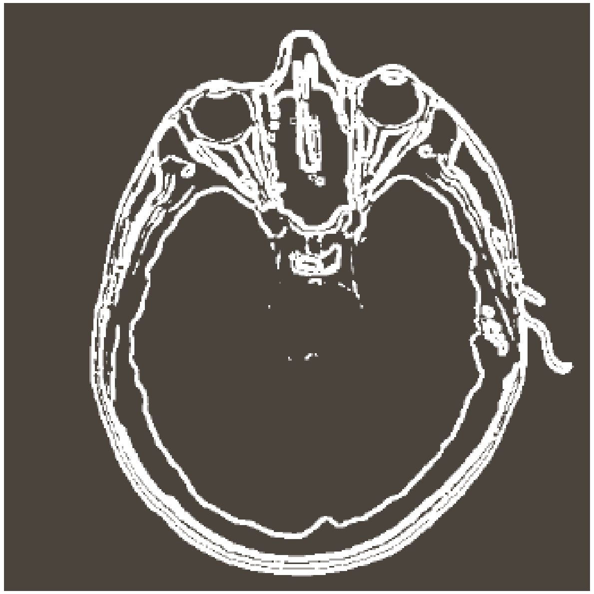


Gradient, with smoothing

Threshold = 33% of highest value in image

Edge detection on head CT image

512x512
Input Image



Thresholded Gradient
Image

Marr-Hildreth Edge Detector

- The Laplacian operator:
  the 2-D equivalent of the second derivative.

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

- Laplacian of Gaussian

$$h(x, y) = \exp\left[-\frac{x^2 + y^2}{2\sigma^2}\right]$$

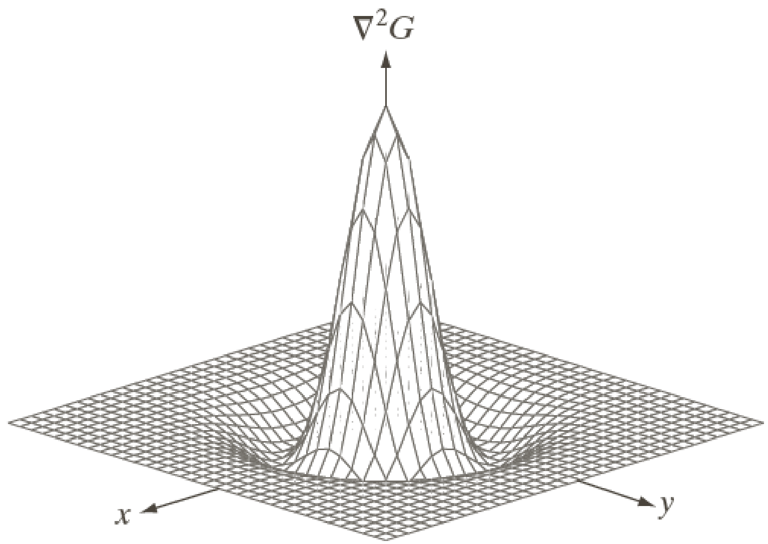
$$\nabla^2\left[h(x, y) \otimes f(x, y)\right] = \left[\nabla^2 h(x, y)\right] \otimes f(x, y)$$

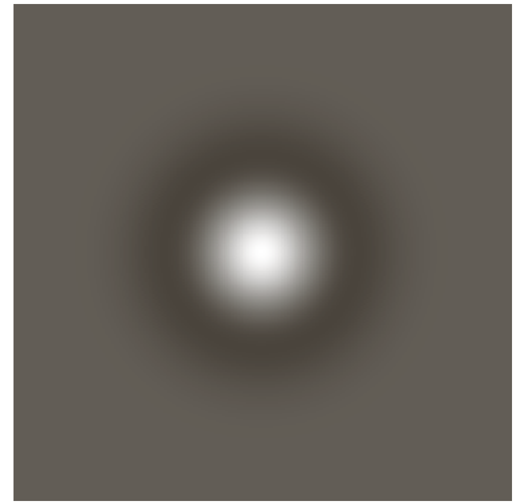
$$LoG = \nabla^2 h(x, y) = \left(\frac{x^2 + y^2 - 2\sigma^2}{\sigma^4}\right)\exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) =$$

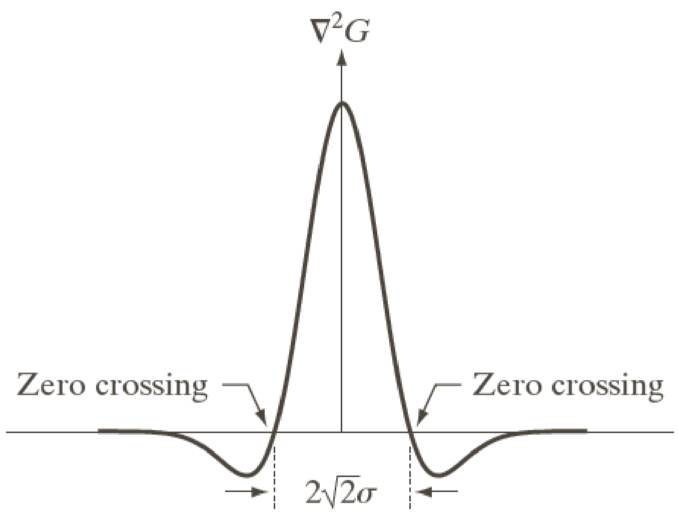
$$= \left(\frac{r^2 - \sigma^2}{\sigma^4}\right)\exp\left(\frac{-r^2}{2\sigma^2}\right)$$

Mexican hat operator

Laplacian of Gaussian







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

5x5 Laplacian of Gaussian mask

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

17x17 Laplacian of Gaussian mask

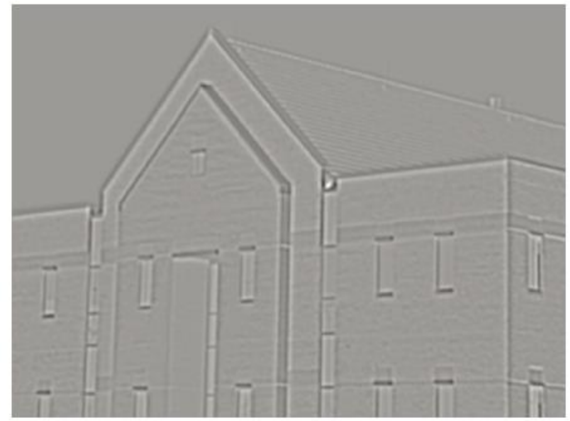
0	0	0	0	0	0	−1	1	1	−1	1	0	0	0	0	0	0
0	0	0	0	−1	−1	−1	−1	−1	−1	−1	−1	−1	0	0	0	0
0	0	−1	−1	−1	−2	−3	−3	−3	−3	−3	−2	−1	1	−1	0	0
0	0	−1	−1	−2	3	3	−3	−3	−3	−3	−3	−2	−1	−1	0	0
0	−1	−1	−2	−3	−3	−3	−2	−3	−2	−3	−3	−3	−2	−1	−1	0
0	−1	−2	−3	−3	3	0	2	1	2	0	−3	−3	−3	−2	−1	0
1	−1	−3	−3	−3	0	4	10	12	10	4	0	−3	−3	−3	−1	−1
−1	−1	−3	−3	−2	2	10	18	21	18	10	2	−2	−3	−3	−1	−1
−1	1	3	−3	−3	4	12	21	21	21	12	4	−3	−3	−3	−1	−1
−1	−1	−3	−3	−2	2	10	18	21	18	10	2	−2	3	−3	−1	−1
−1	−1	3	−3	−3	0	4	10	12	10	4	0	−3	−3	−3	−1	−1
0	−1	−2	−3	−3	−3	0	2	4	2	0	−3	−3	−3	−2	−1	0
0	−1	−1	−2	−3	−3	−3	2	3	−2	3	−3	−3	−2	−1	−1	0
0	0	−1	−1	−2	−3	−3	−3	−3	−3	−3	−3	−2	−1	−1	0	0
0	0	−1	−1	−1	−2	−3	−3	−3	−3	−3	−2	1	−1	−1	0	0
0	0	0	0	−1	−1	−1	−1	−1	−1	−1	−1	−1	0	0	0	0
0	0	0	0	0	0	−1	−1	−1	−1	−1	0	0	0	0	0	0

Marr-Hildreth Edge Detection

Original
Image

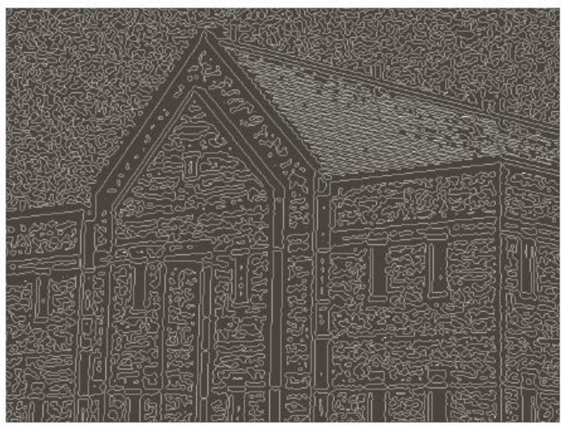
LoG

(σ =4, n=25)



ZC

Thresh=0

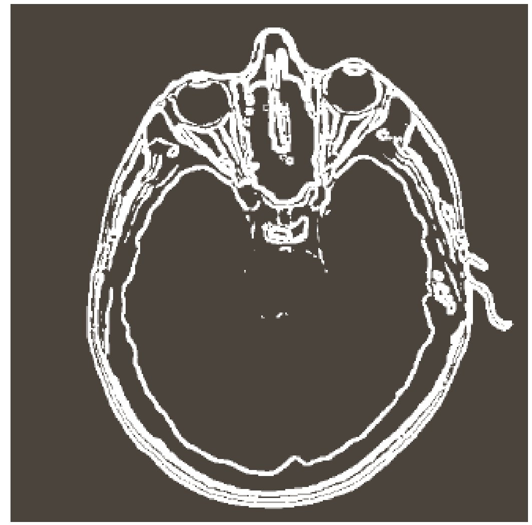


ZC

Thresh=4%
Max value of
LoG image

Edge detection methods on head CT image

512x512
Input Image



Thresholded
Gradient of
Smoothed
Image

Marr-Hildreth
Edge Detection

Edge Linking & Boundary Detection

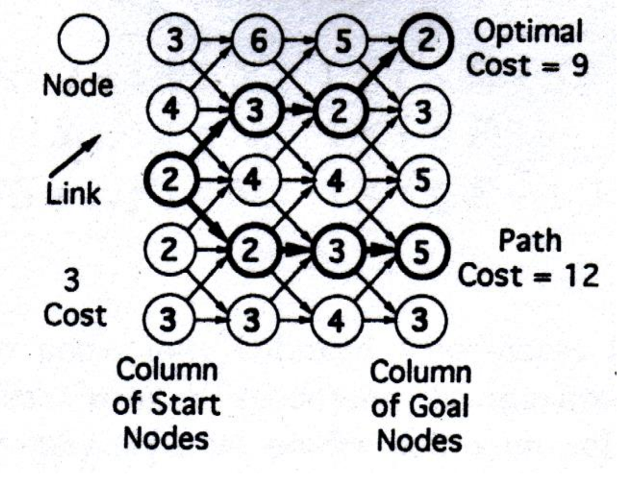
Pixel neighborhood & connectivity

Border Tracing

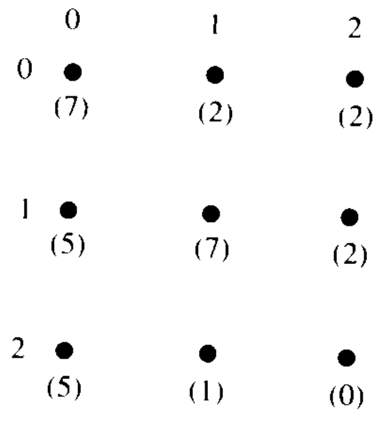
Graph Searching

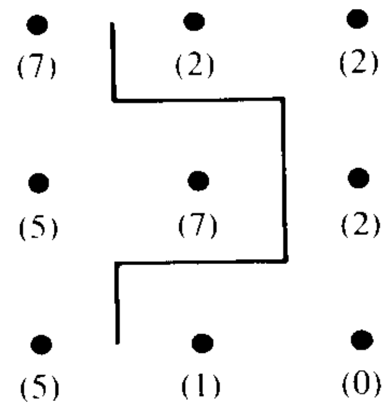
Graph Searching Algorithms

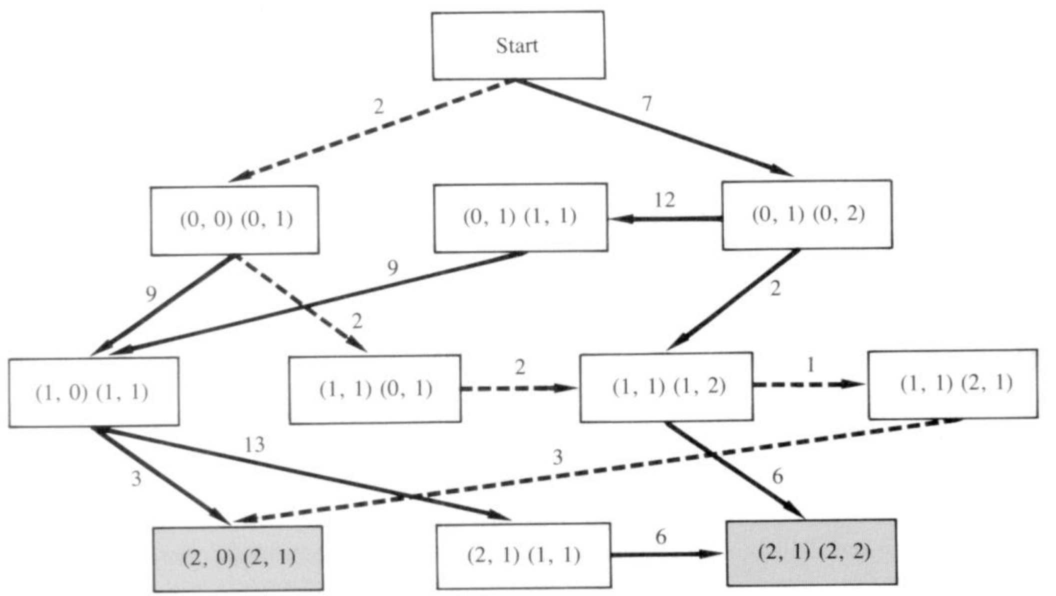
- An object constructed from **nodes**, and **vertices**.
- A **cost** function can be associated with every vertex or every node.
- A **path** is set of connected nodes, linking a start node to an end node.



Graph Searching Algorithms







Open Issues

- Cost function design:
  - Intensity & Gradients.
  - Distance from previous contours.
  - Smoothness.
  - Orientation smoothness.
  - Morphology operators.
- Different representation of images as graphs.