Announcement

Quiz #10 is available in Blackboard.

Due date: 11:59pm EST, Thursday, April 17^{th}

Open book and open notes

Today

Image segmentation

Image Segmentation

(a) $\bigcup_{i=1}^{n} R_i = R$

(b) R_i is a connected set, $i = 1, \ldots, n$

(c) $R_i \cap R_j = \phi, \forall i \neq j$

(d) $Q(R_i) = TRUE$

(e) $Q(R_i \cup R_j) = FALSE$ for adjacent regions R_i and R_j

Two categories based on intensity properties:

- **Discontinuity** – edge-based algorithms
- **Similarity** – region-based algorithms

Edge Linking and Boundary Detection

All edge detection algorithms can only detect fragments of boundaries, due to image noise, non-uniform illuminations, or other effects

Edge linking: link edges into longer meaningful edges or a full region boundaries

Three classic methods:

- Local processing
- Regional Processing
- Hough transform

Note

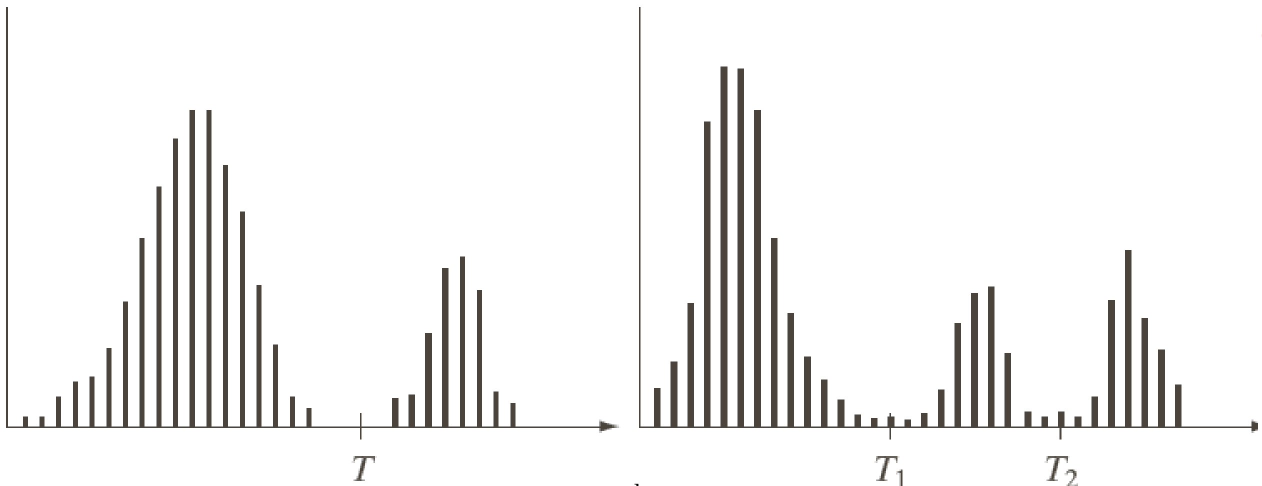
Thresholding is required to get edge pixels and realize edge-based segmentation

Boundary detection (edge linking) is still a hot research topic in image processing and computer vision

Incorporate domain knowledge:

- Psychology rules on the boundary: smooth, convex, symmetry, closed, complete, etc
- Template shape information: hand, stomach, lip, etc
- Appearance information: region-based texture, intensity/color, etc.

Edge-based Segmentation -- Intensity Thresholding



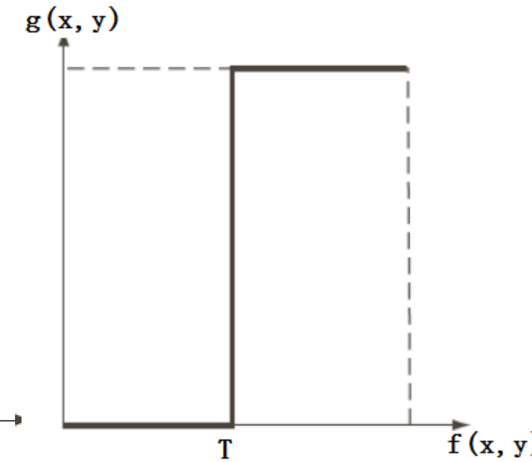


Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

Object/background segmentation:

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

- A constant T - global thresholding
- A variable T - local/regional thresholding; adaptive thresholding
- Multiple T - multiple thresholding

Key Factors Affect Thresholding

- Separation between peaks
- Noise level
- Relative sizes of objects and background
- Uniformity of the illumination source
- Uniformity of the reflectance of the image

The Role of Noise in Image Thresholding

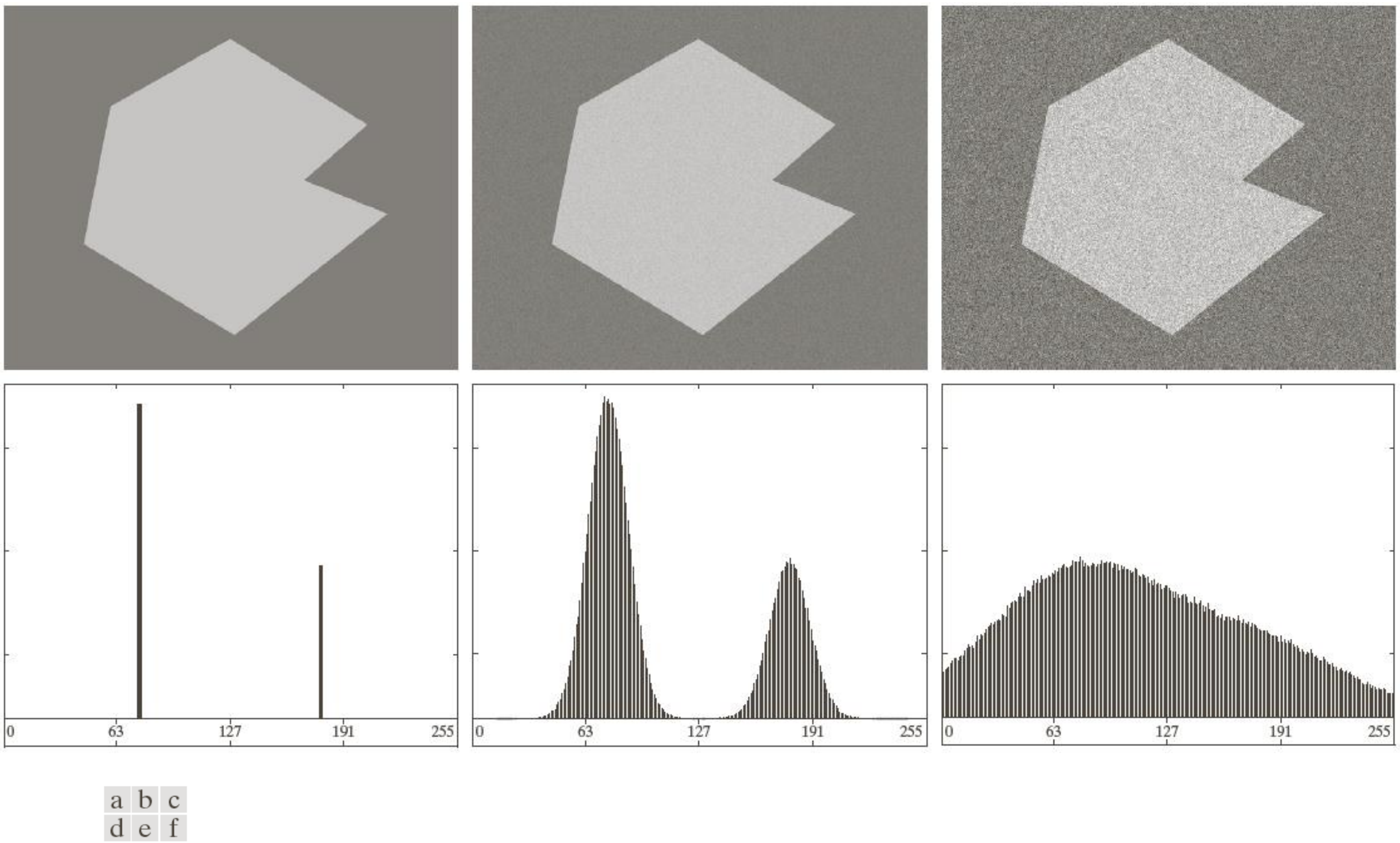


FIGURE 10.36 (a) Noiseless 8-bit image. (b) Image with additive Gaussian noise of mean 0 and standard deviation of 10 intensity levels. (c) Image with additive Gaussian noise of mean 0 and standard deviation of 50 intensity levels. (d)–(f) Corresponding histograms.

Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

The Role of Illumination in Thresholding

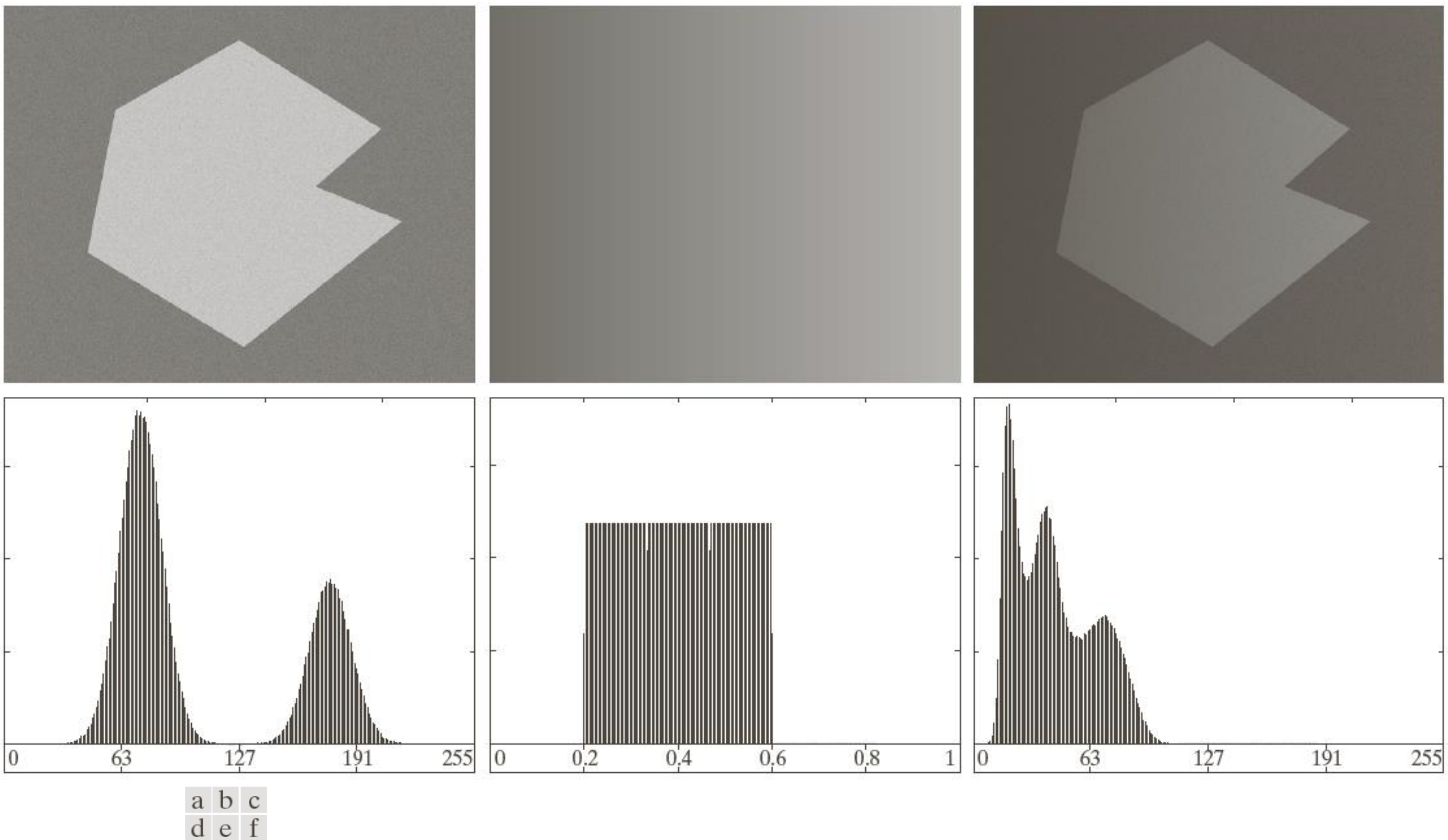


FIGURE 10.37 (a) Noisy image. (b) Intensity ramp in the range [0.2, 0.6]. (c) Product of (a) and (b). (d)–(f) Corresponding histograms.

Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

How to Pick the Threshold

1. Select an initial estimate for the global threshold, T.
2. Segment the image using T by producing two groups of pixels
3. Compute the mean of these two groups of pixels, say m_1 and m_2.
4. Update the threshold $T=(m_1 + m_2)/2$
5. Repeat Steps 2 through 4 until convergence

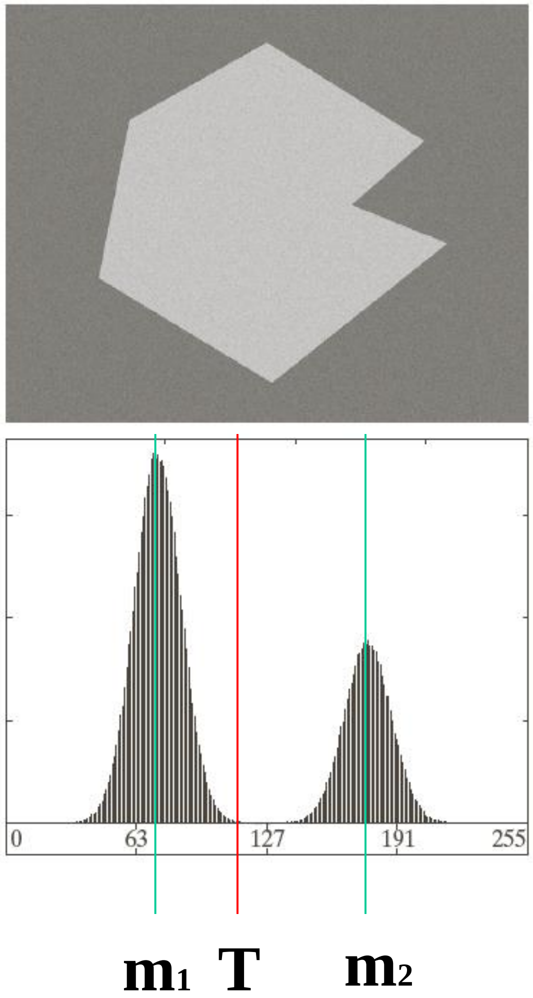


Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

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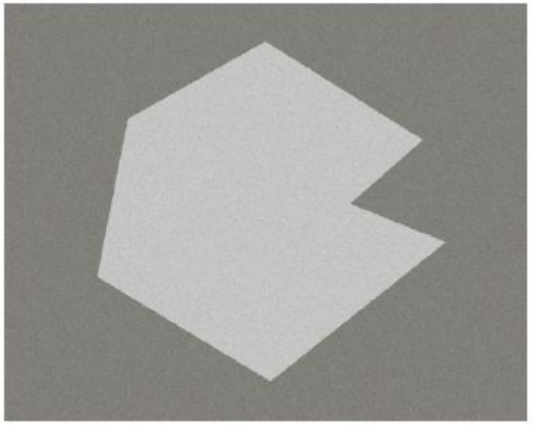


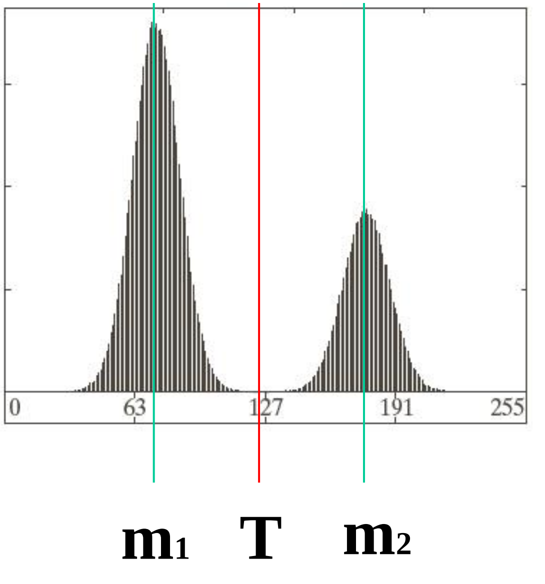
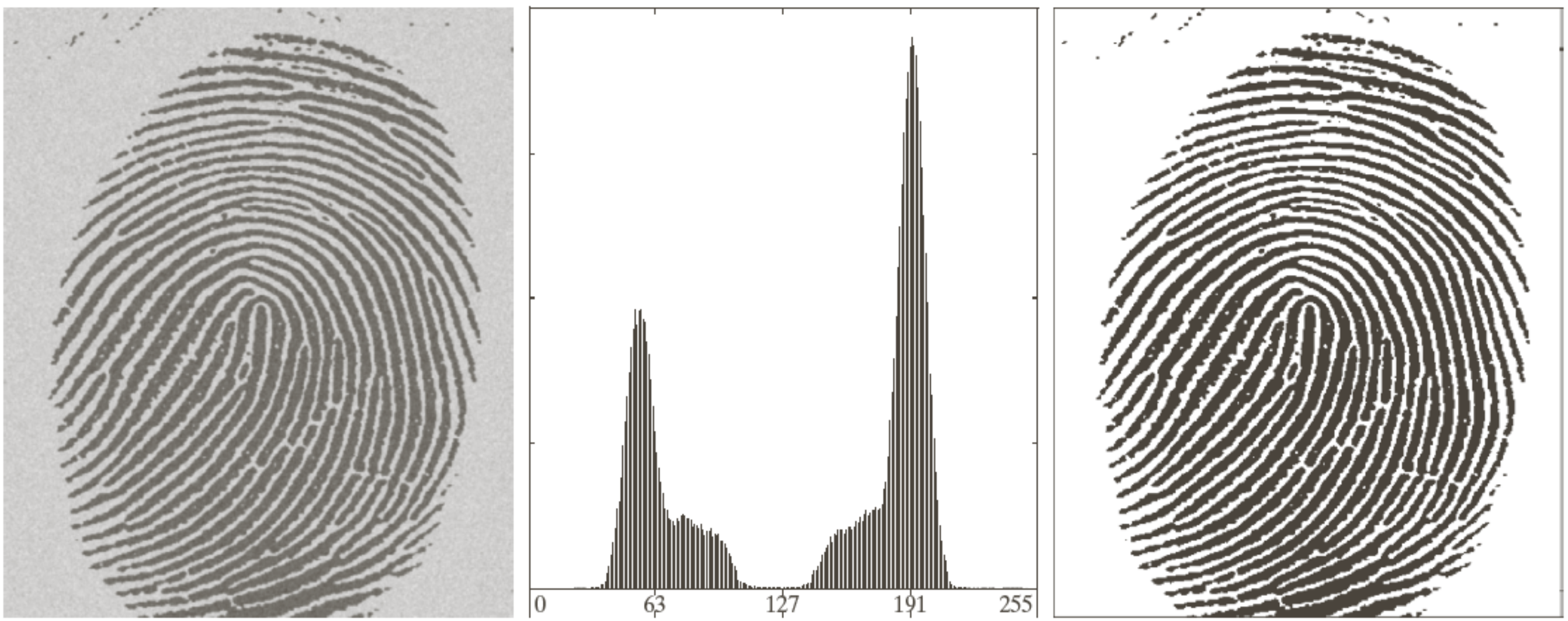


Figure from “Digital Image Processing”, 3rd edition, Gonzalez and Woods

An Example



a b c

FIGURE 10.38 (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.)

Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

Image Segmentation

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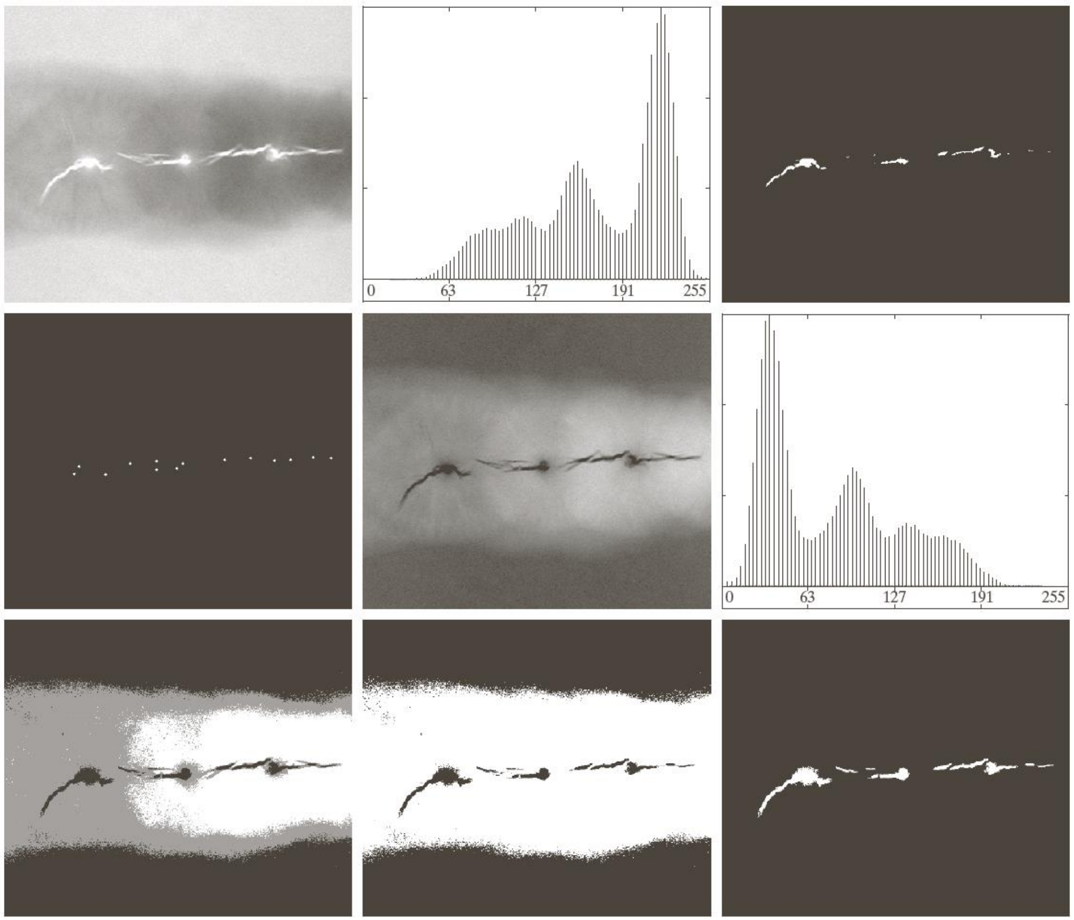
Region-Based Segmentation

- Region growing
- Region splitting and merging

Region Growing Algorithm

- A procedure that groups pixels or subregions into larger regions based on predefined criteria for growth
- Start with a set of “seed” points and grow regions by appending neighboring pixels that satisfy the given criteria
  - Connectivity
  - Stopping rules
    - Local criteria: intensity values, textures, color
    - Prior knowledge: size and shape of the object

An Example



a b c
d e f
g h i

FIGURE 10.51 (a) X-ray image of a defective weld. (b) Histogram. (c) Initial seed image. (d) Final seed image (the points were enlarged for clarity). (e) Absolute value of the difference between (a) and (c). (f) Histogram of (e). (g) Difference image thresholded using dual thresholds. (h) Difference image thresholded with the smallest of the dual thresholds. (i) Segmentation result obtained by region growing. (Original image courtesy of X-TEK Systems, Ltd.)

$$Q = \begin{cases} True & if\ |I_{seed} - I(x,y)| \le T \\ False & otherwise \end{cases}$$

Figure from “Digital Image Processing”, 3rd edition, Gonzalez and Woods

Region-Splitting and Merging Algorithm

Step1: Keep splitting the region while $Q(R_i) = FALSE$ and $R_i > \min Size$

Step 2: Merge the subregions while $Q(R_i \cup R_j) = TRUE$

a b

FIGURE 10.52 (a) Partitioned image. (b) Corresponding quadtree. R represents the entire image region.

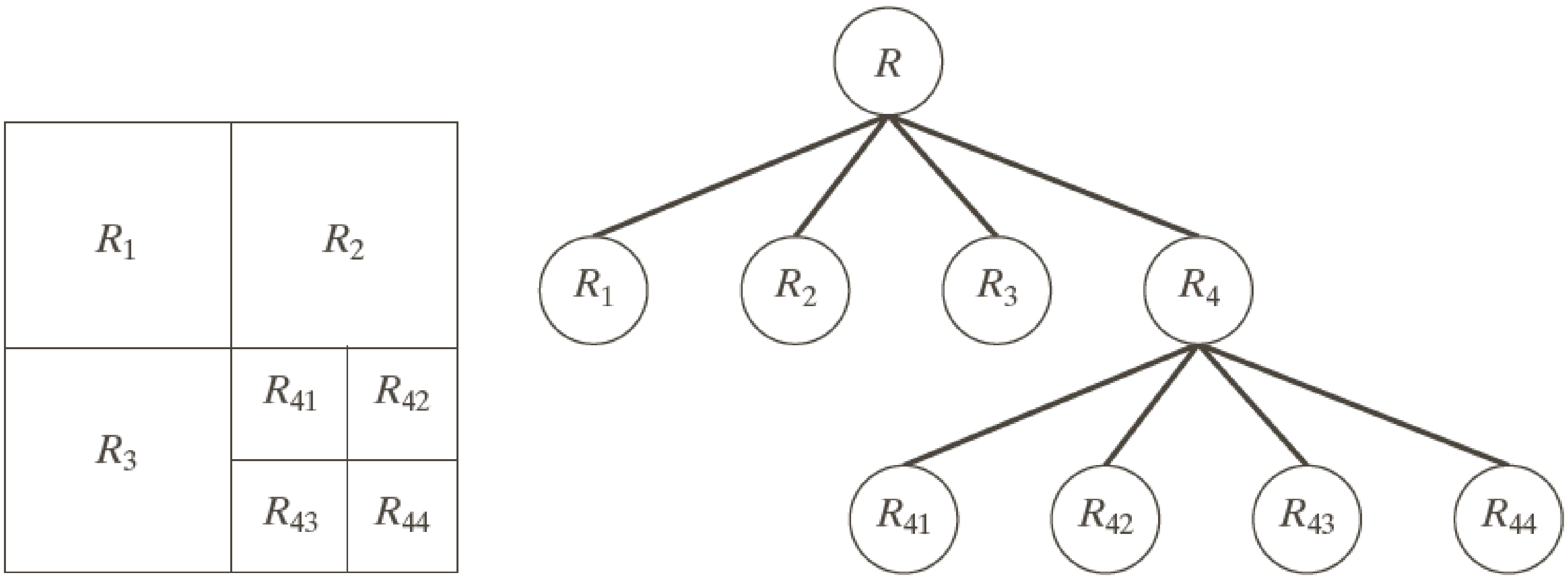
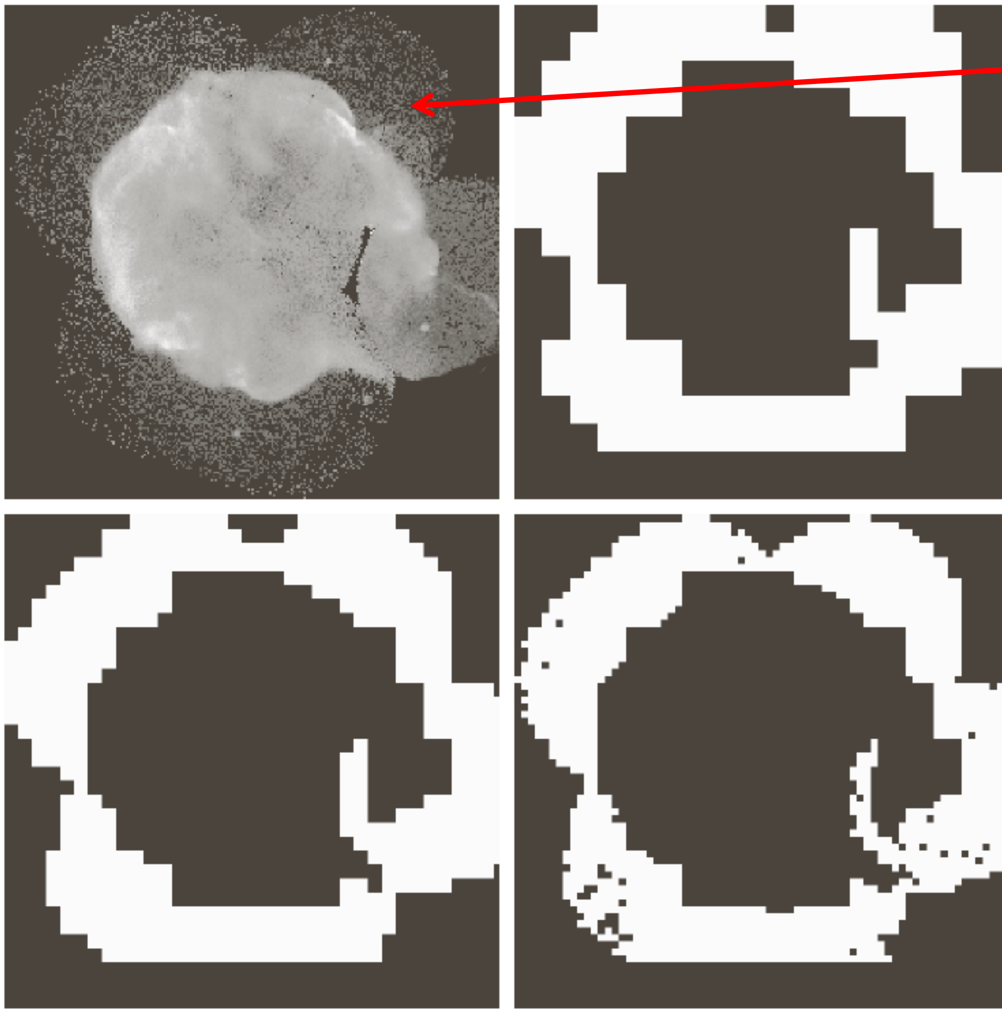


Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

An Example



a b
c d

FIGURE 10.53 (a) Image of the Cygnus Loop supernova, taken in the X-ray band by NASA's Hubble Telescope. (b)–(d) Results of limiting the smallest allowed quadregion to sizes of 32×32, 16×16, and 8×8 pixels, respectively. (Original image courtesy of NASA.)

Extract the outer ring

$$Q = \begin{cases} TRUE & if\,\sigma > a \,\&\, 0 < m < b \\ FALSE & otherwise \end{cases}$$

Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

Morphological Image Processing – Techniques to Improve Image Segmentation

Objective:

- **Extract image components for representation and description of region shape including**
  - Boundaries
  - Skeletons
  - Convex hull

- **Improve segmentation results**
  - Reducing noise
  - Filling small holes and narrow breaks
  - Smoothing the contour
  - etc

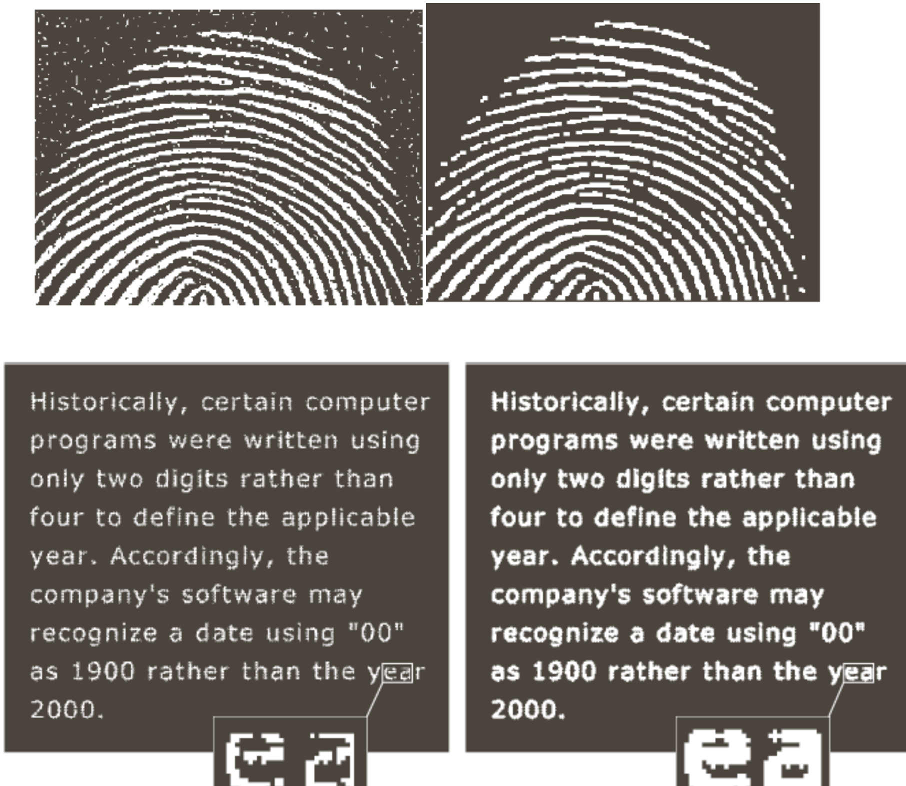


Figure from "Digital Image Processing", 3rd edition, Gonzalez and Woods

More Image Segmentation Methods

Earlier methods

- K-Means
- Watershed
- Active contour (Snake)
- Graph cuts
- Markov random fields (MRF) and Conditional random fields (CRF)

Deep-learning based methods

- Fully convolutional networks
- Encoder-decoder based methods, e.g. U-Net
- etc.

K-Means

Choose a fixed number of clusters

Choose cluster centers and point-cluster allocations to minimize error

Algorithm

- fix cluster centers; allocate points to closest cluster
- fix allocation; compute best cluster centers

$$\sum_{i \in \text{clusters}} \left\{ \sum_{j \in \text{elements of i'th cluster}} \left\| x_j - \mu_i \right\|^2 \right\}$$

x could be any set of features for which we can compute a distance

Image

Clusters on intensity

Clusters on color

K-means clustering using intensity alone and color alone

Graph-based Image Segmentation

From edge-detection to boundary detection

From local clustering (K-means) to global clustering

- Independent on initialization
- No local optima

Combining both image feature and spatial information

- Pixels with same local feature but at different locations play different roles in segmentation

Graph-based Image segmentation is a popular topic in segmentation research

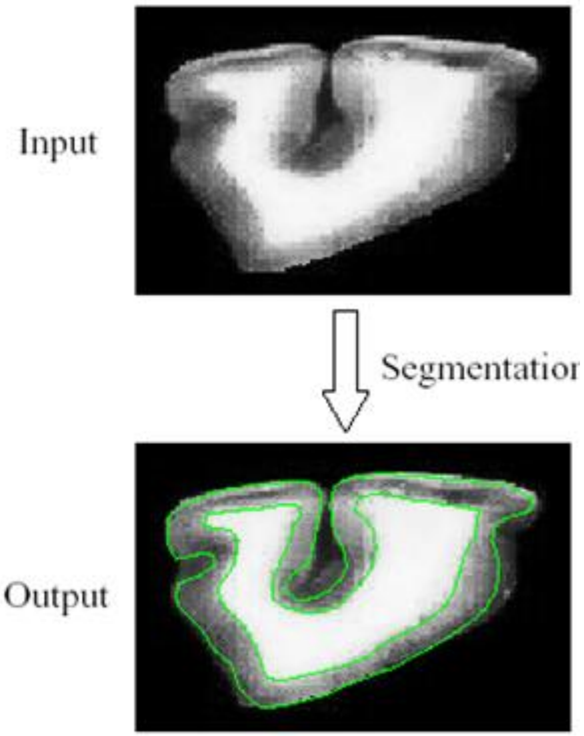
Motivation

Image segmentation:

- Homogeneous regions
- Discontinuity across boundaries

Objective: detect both boundaries and regions

Problems: noise and occlusion



Graph-based segmentation

Graph Models

2D image	→ (undirected) Graph $G = (V, E)$
Pixel	→ vertex $v \in V$
Adjacent pixels	→ edge $e = (u, v) \in E$
Pixel similarity	→ edge-weight $w(u, v)$
(local homogeneity)	

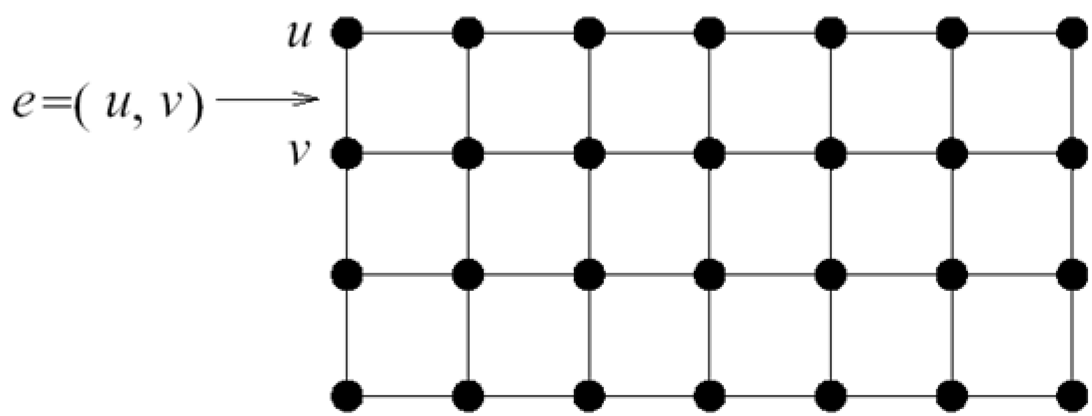
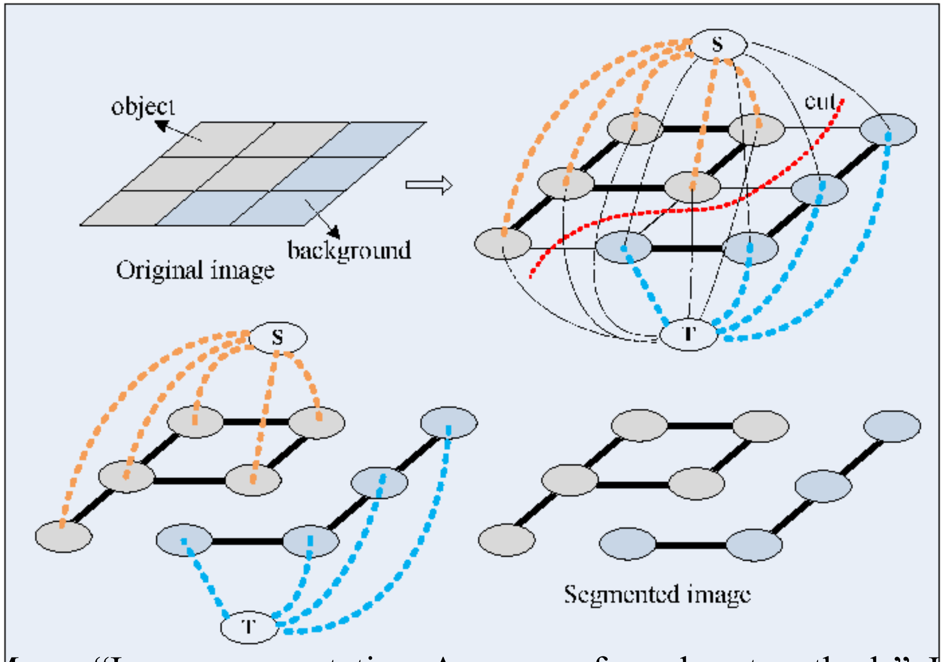


Image Segmentation and Graph Cut

Graph cut:

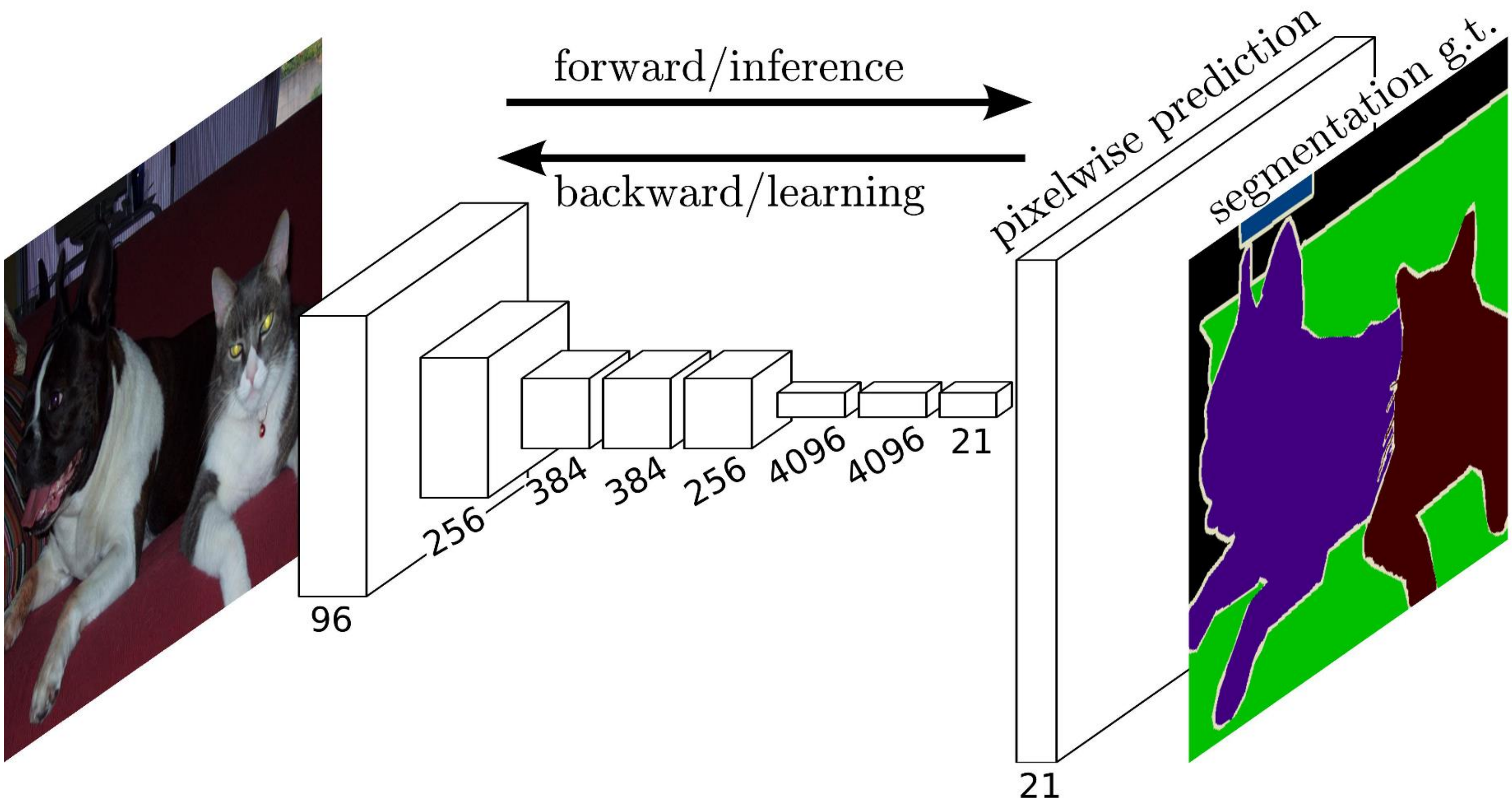
Vertices $V \rightarrow (V_1, V_2)$

Cut boundary: all the edges between (V_1, V_2)



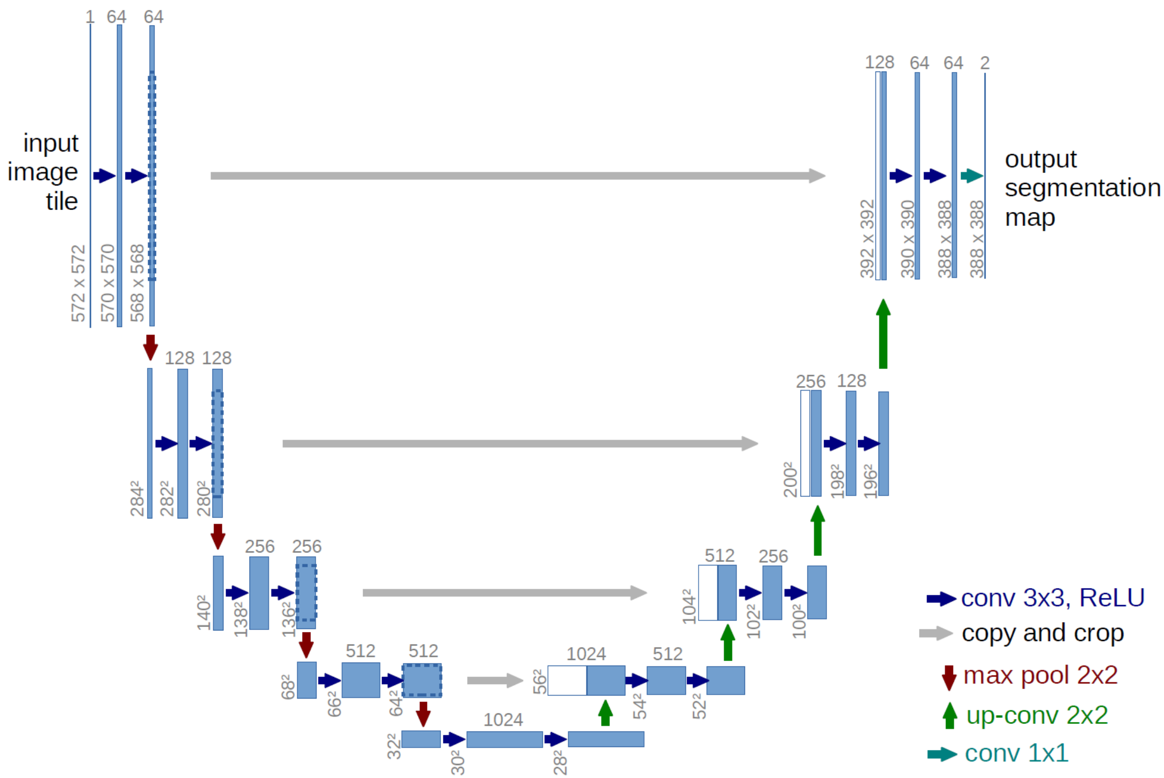
Yi and Moon, "Image segmentation: A survey of graph-cut methods", ICSAI2012

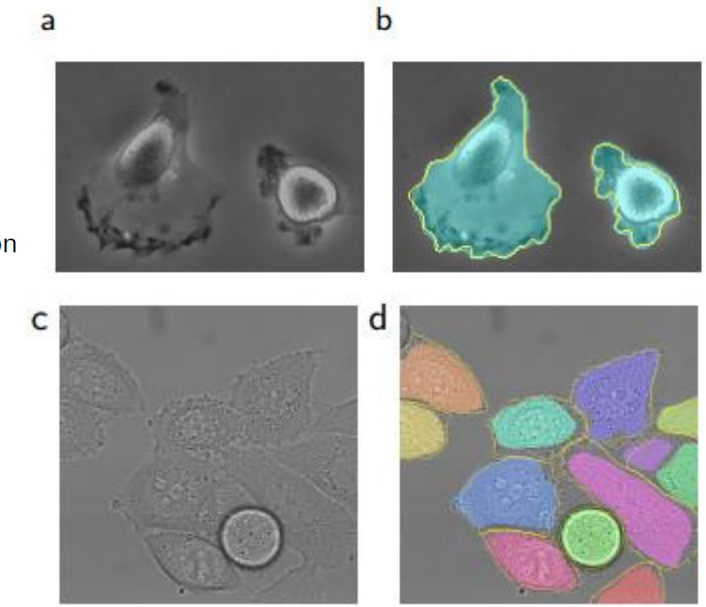
Fully Convolutional Networks for Image Segmentation



Long et al. “Fully Convolutional Networks for Semantic Segmentation”, CVPR 2015

U-Net for Image Segmentation





Ronneberger et al., “U-Net: Convolutional Networks for Biomedical Image Segmentation”, MICCAI 2015
U-Net: Convolutional Networks for Biomedical Image Segmentation (uni-freiburg.de)

Additional Notes

Image segmentation is a fundamental problem in image processing and computer vision

There are huge number of algorithms available for different applications

General-purpose image segmentation is far from well solved

It is still a research problem that is being investigated by many researchers

Readings

Chapter 14 of Forsyth and Ponce

K.S. Fu and J.K. Mui, “A survey on image segmentation”, Pattern Recognition, vol. 13, no. 1, pp. 3-16, 1981.

Minaee S, Boykov YY, Porikli F, Plaza AJ, Kehtarnavaz N, Terzopoulos D. Image Segmentation Using Deep Learning: A Survey. IEEE Trans Pattern Anal Mach Intell. 2021 Feb 17.