

# Segmentation

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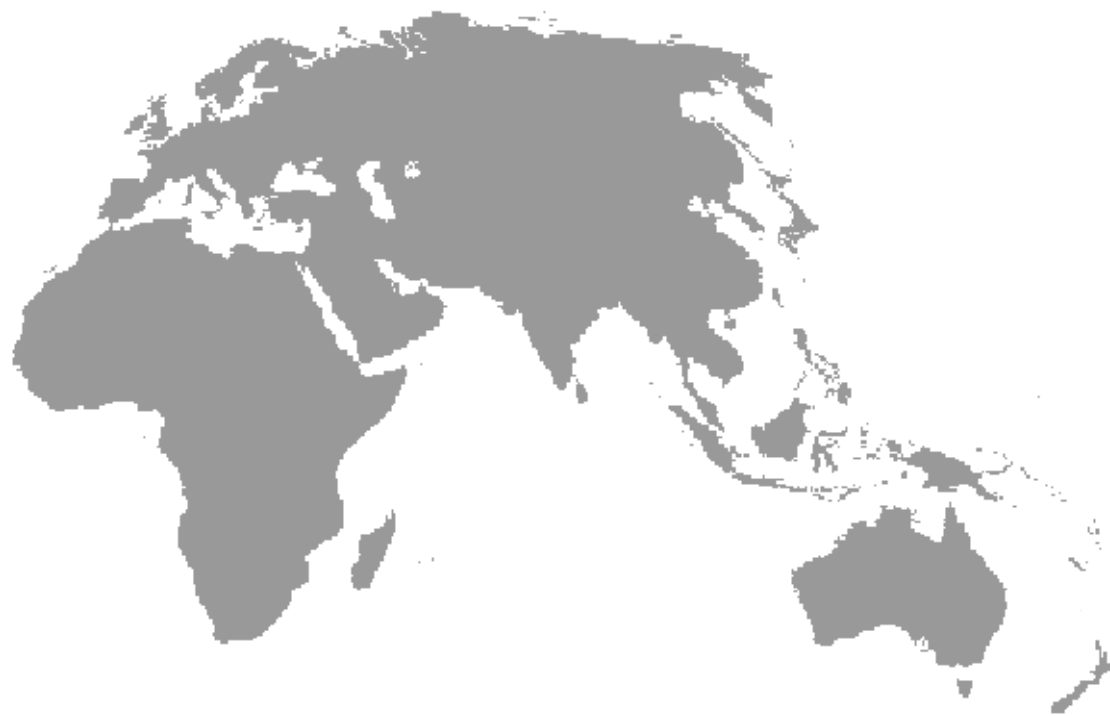
Segmentation is the task of isolating the objects of interest in an image.

Typically, given an image  $R$ , the segmented image consists of regions  $R_1, R_2, \dots, R_n$  such that,

1.  $R_i$ 's are disjoint (i.e.  $R_i \cap R_j = \emptyset$  if  $i \neq j$ ),
2.  $R_i$ 's are connected,
3.  $R_i$ 's partition the image (i.e.  $\cup R_i = R$ ).

# Segmentation

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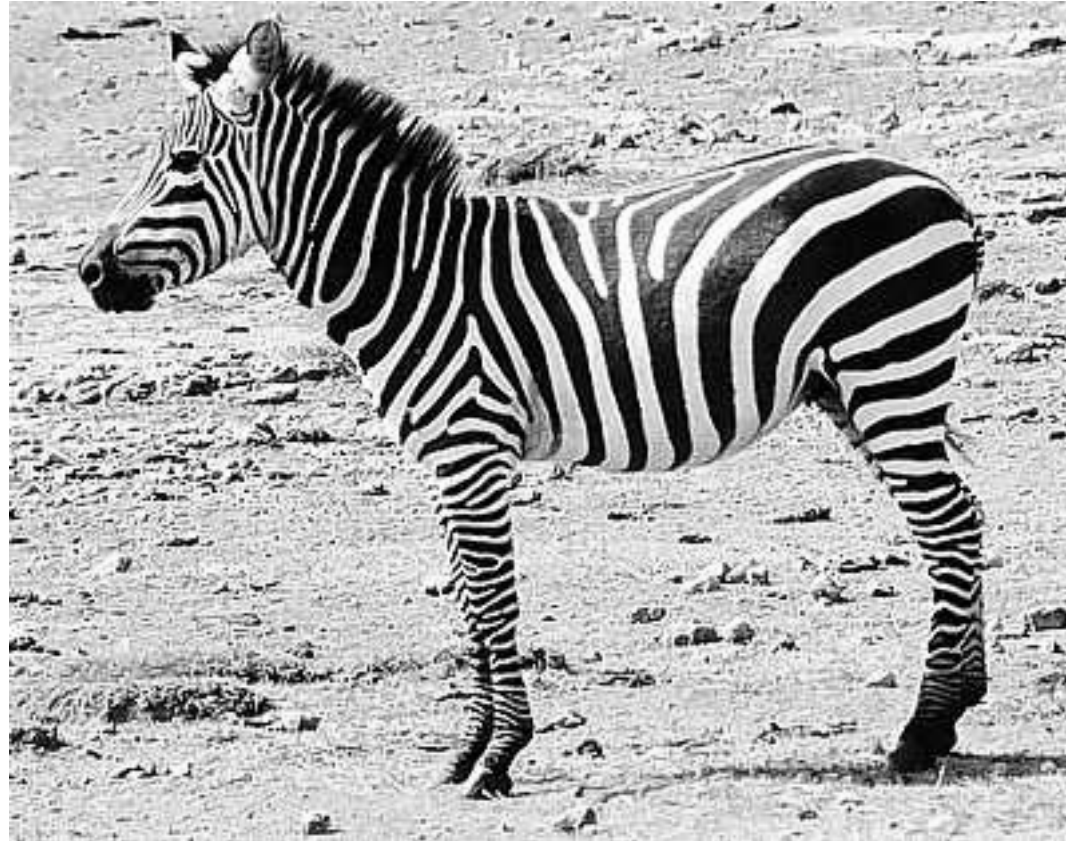
# Segmentation

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# Segmentation

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# What is an Edge?

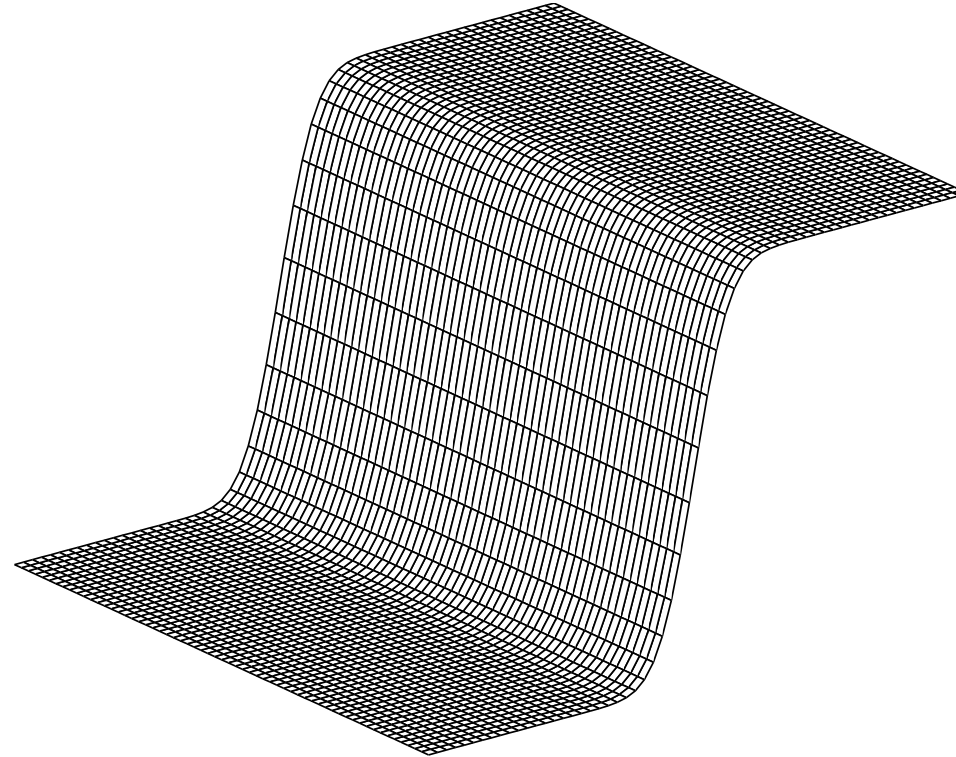
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An edge involves a transition from an intensity level to another intensity level.



# Edge Detection

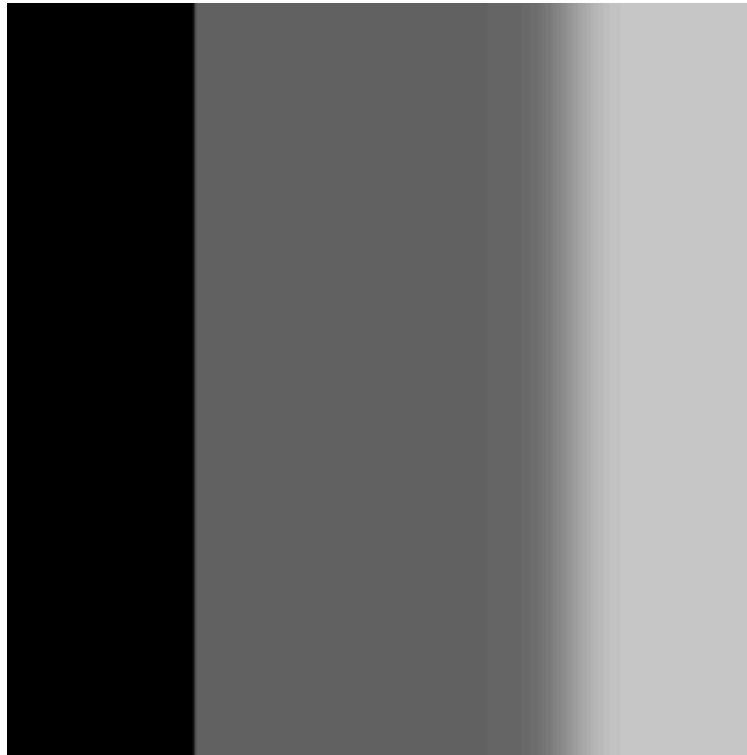
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# Edge Models

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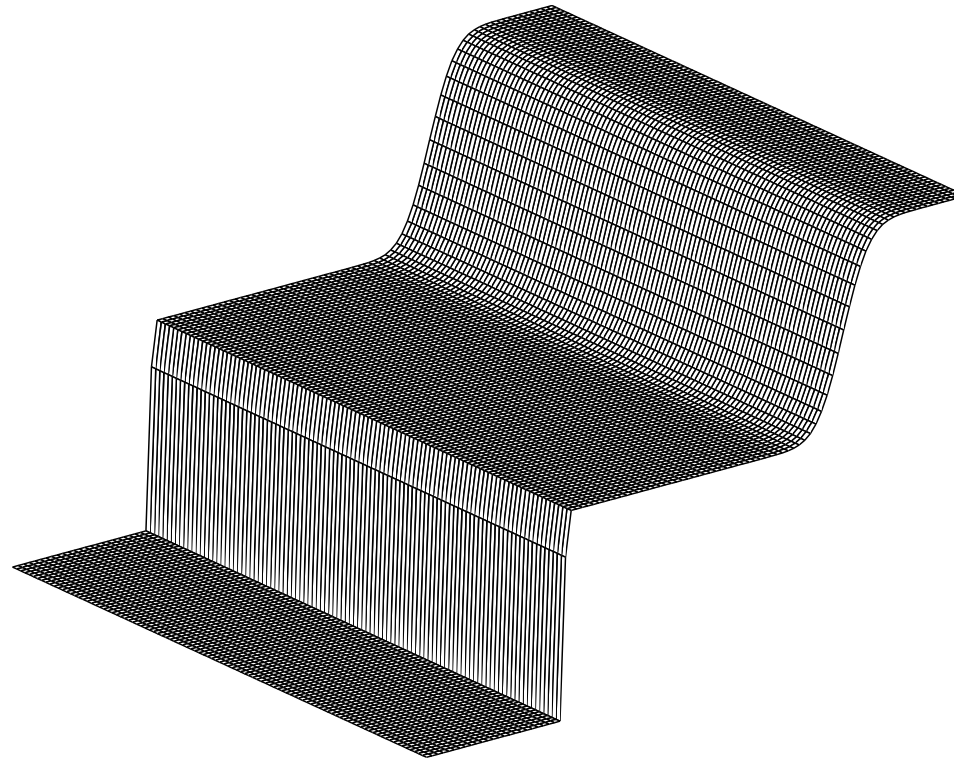
Edges may be sharp (step edge) or diffuse (ramp edge).



# Edge Models

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Edges may be sharp (step edge) or diffuse (ramp edge).





# Edge Models

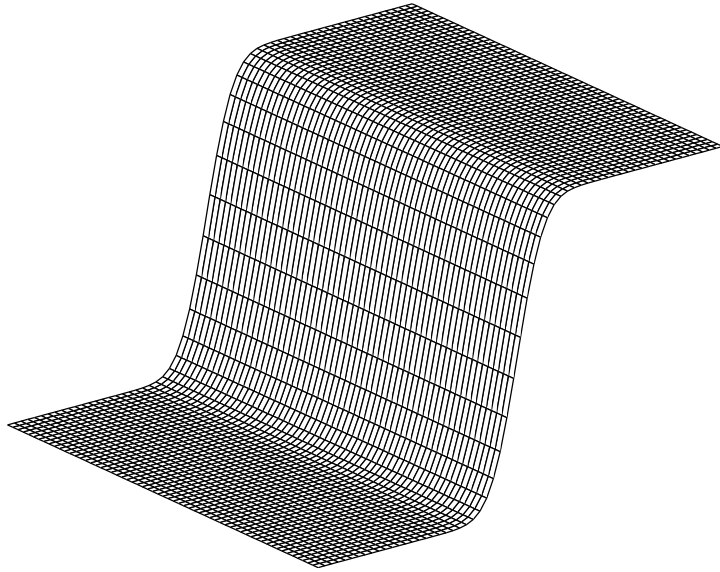
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Edges may be sharp (step edge) or diffuse (ramp edge).

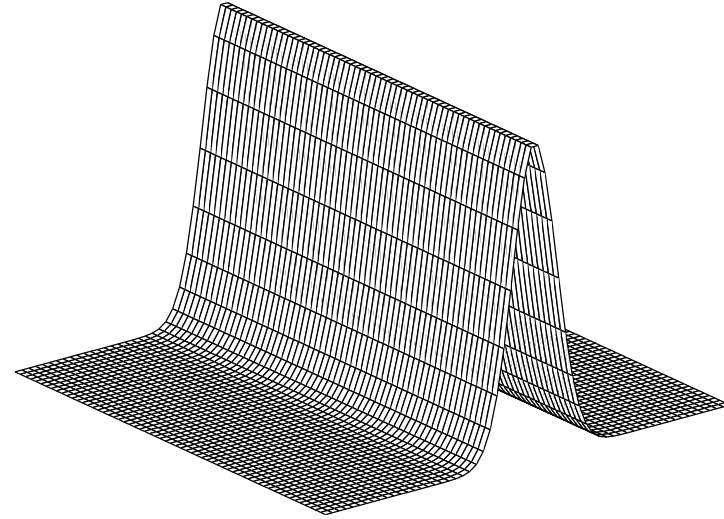


# Edge Detection

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(a)



(b)

$Q$  : How do we go from (a) to (b)?

# Derivative Images

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$\mathcal{Q}$  : How do we go from (a) to (b)?

$\mathcal{A}$  : Compute the derivative in the horizontal direction.

In practice, we can convolve with

1	0	-1
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or

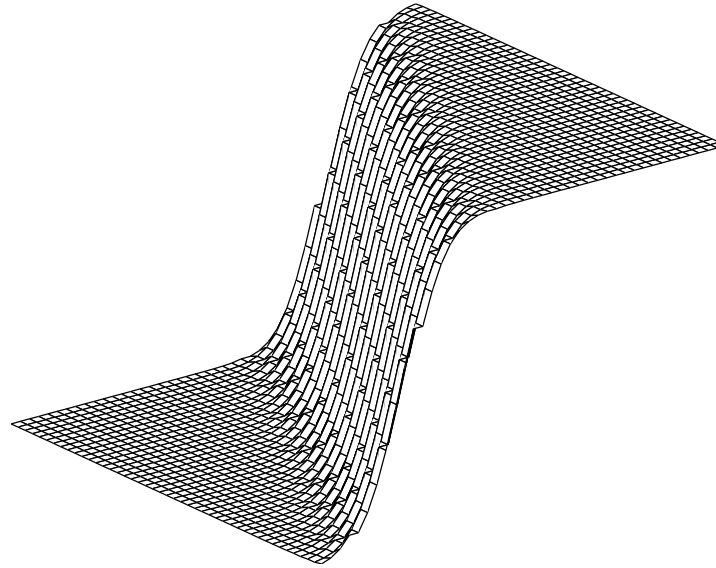
1	0	-1
1	0	-1
1	0	-1

or

1	0	-1
2	0	-2
1	0	-1

# Directional Derivative

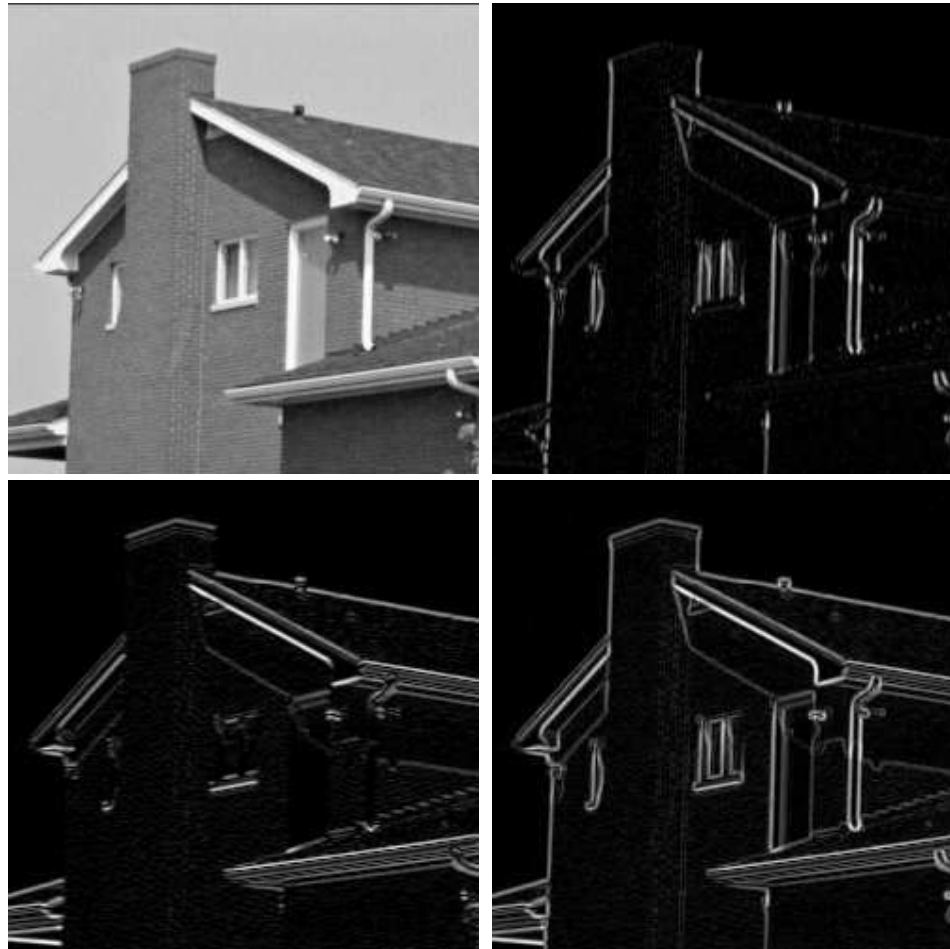
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$Q$  : What if the edge is not vertical?

# Gradient Magnitude

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$$\frac{f}{f_y} \left| \frac{f_x}{\sqrt{f_x^2 + f_y^2}} \right|$$

# Gradient Magnitude

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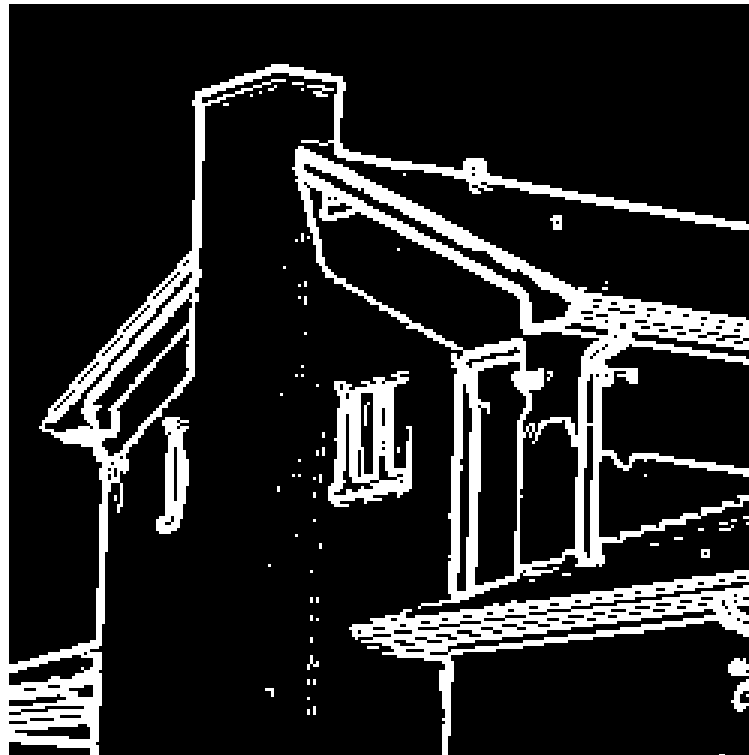
Given the gradient magnitude, how do we determine the edges?

- (i) Set the pixels below a threshold to zero.
- (ii) Determine the local maxima – ( how? )

# Gradient Magnitude

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Set the pixels below a threshold to zero.



# Laplacian Operator

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Determine the local maxima by looking at the zero crossings of second order derivatives.

The Laplacian operator is frequently used for this purpose.

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

The discrete approximation is :

0	1	0
1	-4	1
0	1	0



# Laplacian Operator

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Zero crossings of the discrete Laplacian.



# Noisy Images

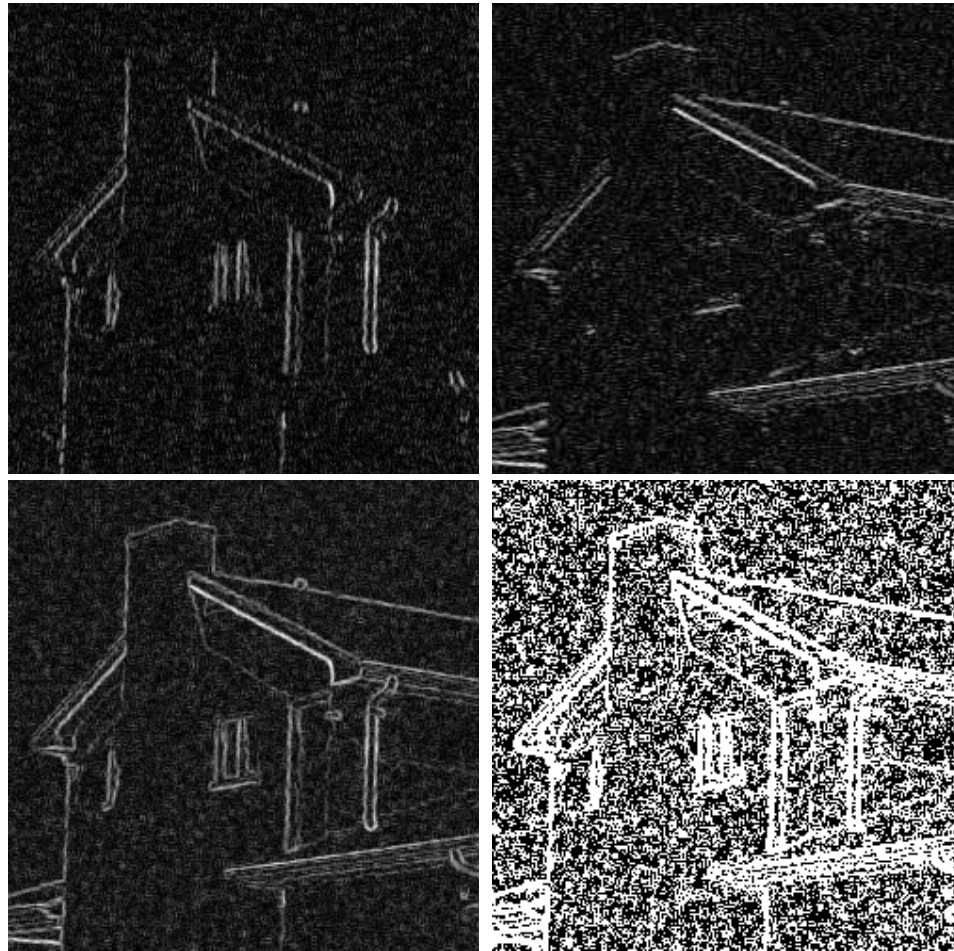
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What if there is noise ?



# Noisy Images

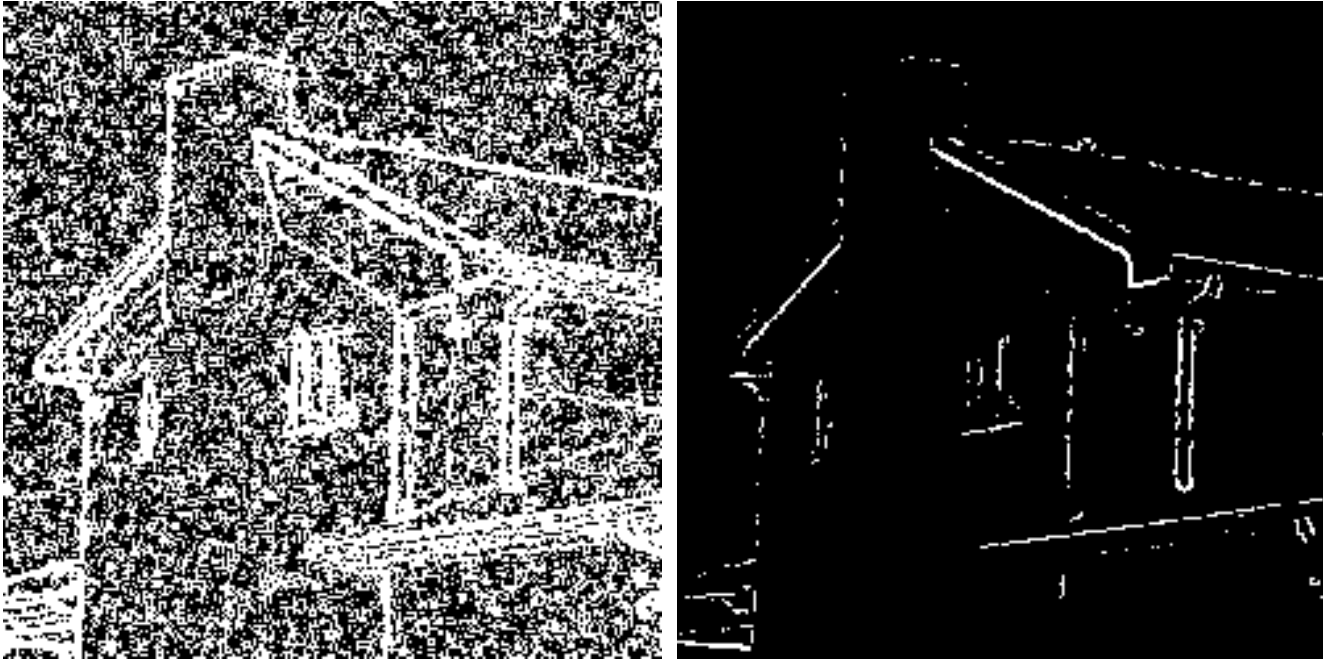
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We end up with a very dirty edge map.

# Noisy Images

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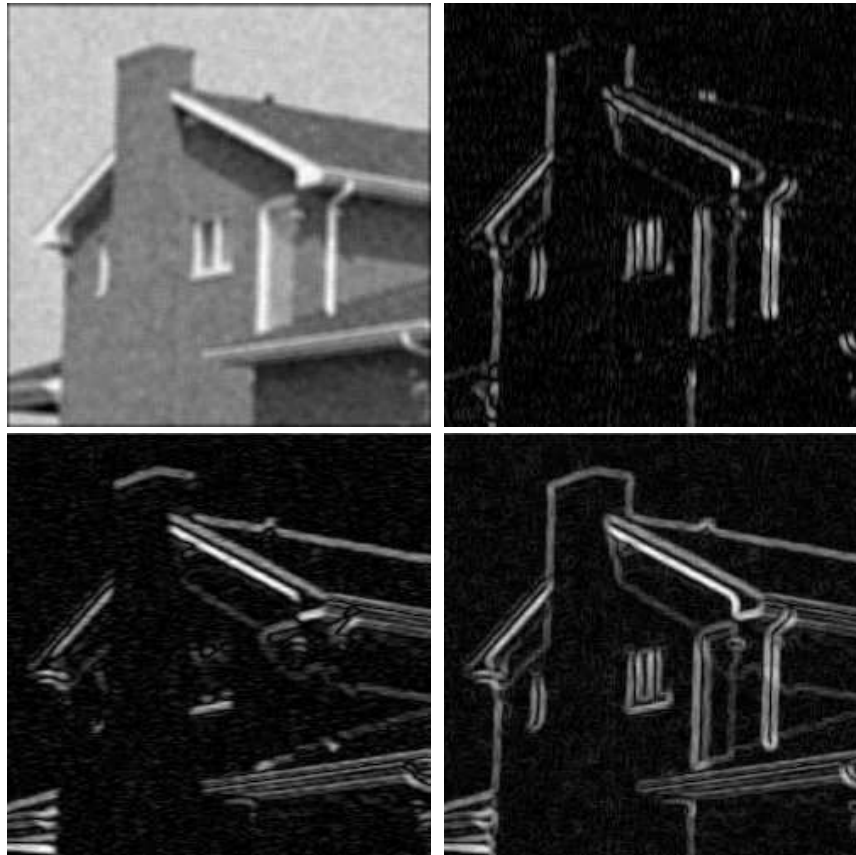
Effects of using different thresholds.

# Noisy Images

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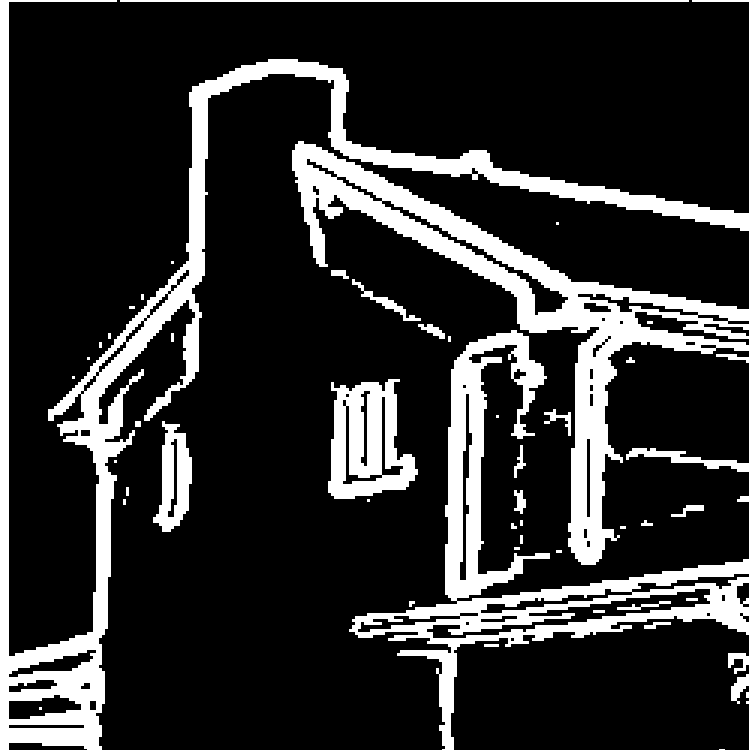
Apply a lowpass filter in order to suppress noise.

Following the lowpass filter, perform edge detection.



# Noisy Images

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Lowpass filter followed by gradient magnitude thresholding.

# Laplacian of Gaussian (LoG)

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The lowpass filter and the laplacian operator may be combined.

The Marr-Hildreth edge detector considers the zero crossings of the image after applying a Laplacian of a Gaussian.

In this case, the idea is to

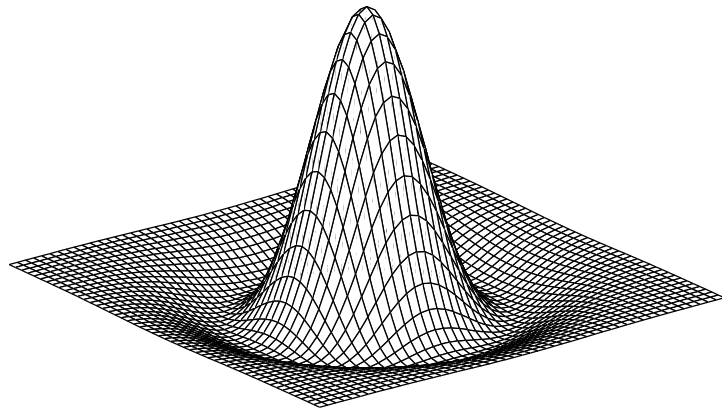
- (i) Filter with  $\nabla^2 \left( e^{-(x^2+y^2)/2\sigma^2} \right)$
- (ii) Determine the zero crossings of the resulting image.

By modifying  $\sigma$ , one selects the right scale for detecting edges.

# Laplacian of Gaussian (LoG)

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The Laplacian of Gaussian and its  $5 \times 5$  approximation.



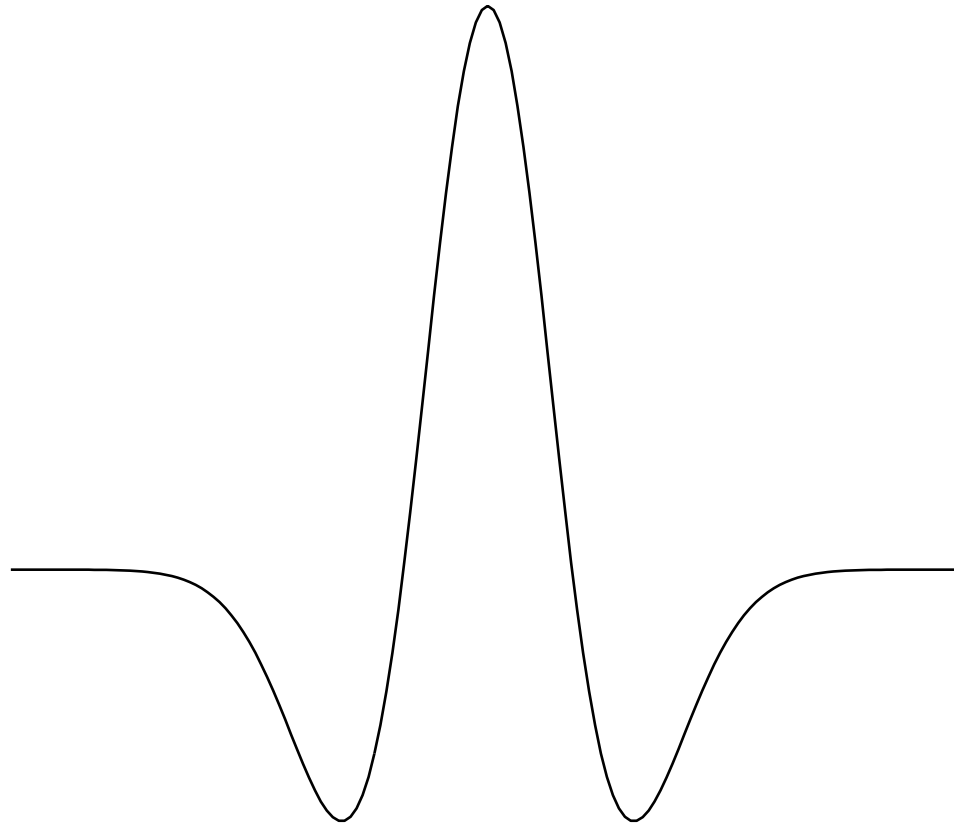
0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0



# Laplacian of Gaussian (LoG)

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Cross section from  $y = 0$ .



‘Mexican Hat’

# Difference of Gaussians (DoG)

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The Laplacian of Gaussian can be approximated by a difference of Gaussians :

$$\text{DoG} = \frac{1}{2\pi\sigma_1^2} \exp\left(-\frac{x^2 + y^2}{2\sigma_1^2}\right) - \frac{1}{2\pi\sigma_2^2} \exp\left(-\frac{x^2 + y^2}{2\sigma_2^2}\right)$$

with  $\sigma_1 > \sigma_2$ .

# Canny Edge Detector

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The edges obtained by thresholding the gradient magnitude are usually too thick.

If the threshold is selected too high, the edges that have relatively low gradient magnitudes are eliminated – also, gaps may form.

Canny edge detector produces thin edges that are connected.

How can we overcome these problems?

# Canny Edge Detector

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To thin the edges, apply 'non-maxima suppression' :

- (i) For each putative edge pixel, determine whether the magnitude of the gradient is a local maximum in the gradient direction.
- (ii) Remove the pixel if it is not a local maximum.

# Canny Edge Detector

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Suppose  $g_N(x, y)$  is thresholded gradient magnitude image with the non-maxima suppressed.

To connect the edges,

(i) Determine two edge maps

$$g_{NH}(x, y) = (g_N(x, y) > T_H)$$

$$g_{NL}(x, y) = (T_H > g_N(x, y) > T_L)$$

(ii) For each non-zero pixel of  $g_{NH}$ , add a neighbor if it is non-zero in  $g_{NL}$ .

# Canny Edge Detector

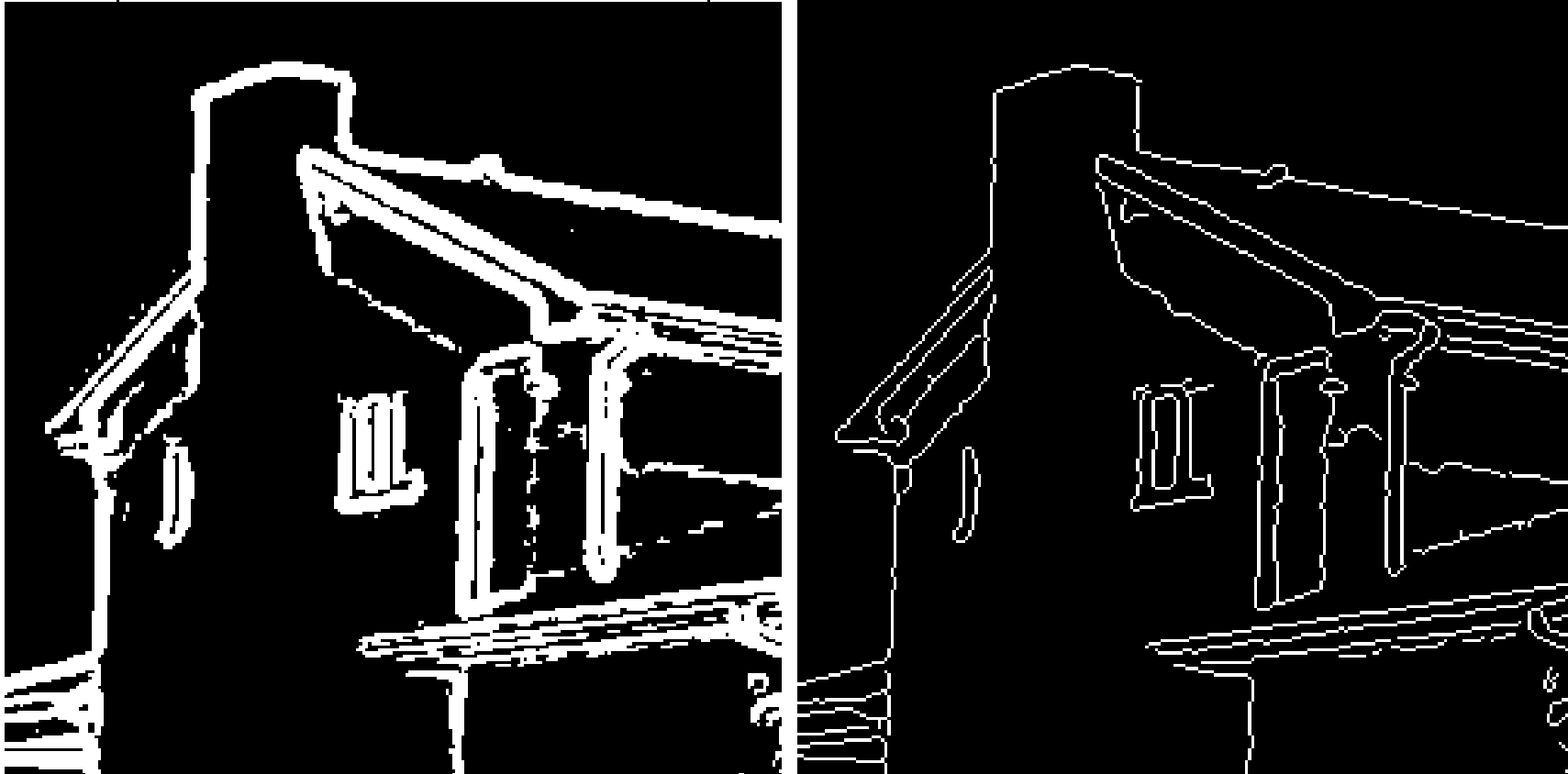
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In summary, the Canny Edge Detector consists of

- (i) Smooth the image with a Gaussian filter.
- (ii) Compute the gradient magnitude image.
- (iii) Suppress the non-maxima from the gradient magnitude image.
- (iv) Link the edges.

# Canny Edge Detector

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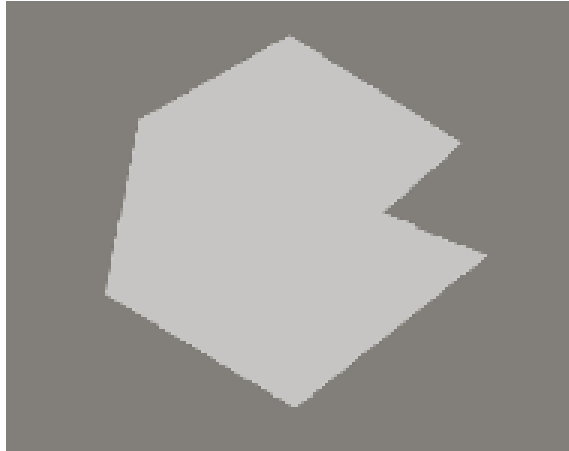


Left : Threshold applied to the gradient magnitude of the lowpass filtered image.

Right : Output of Canny edge detector with manually chosen parameters.

# Segmentation<sup>1</sup>

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*Q*: How can we separate the object from the background?

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<sup>1</sup>The images in the rest of the slides are from Gonzalez & Woods' book.



# Thresholding

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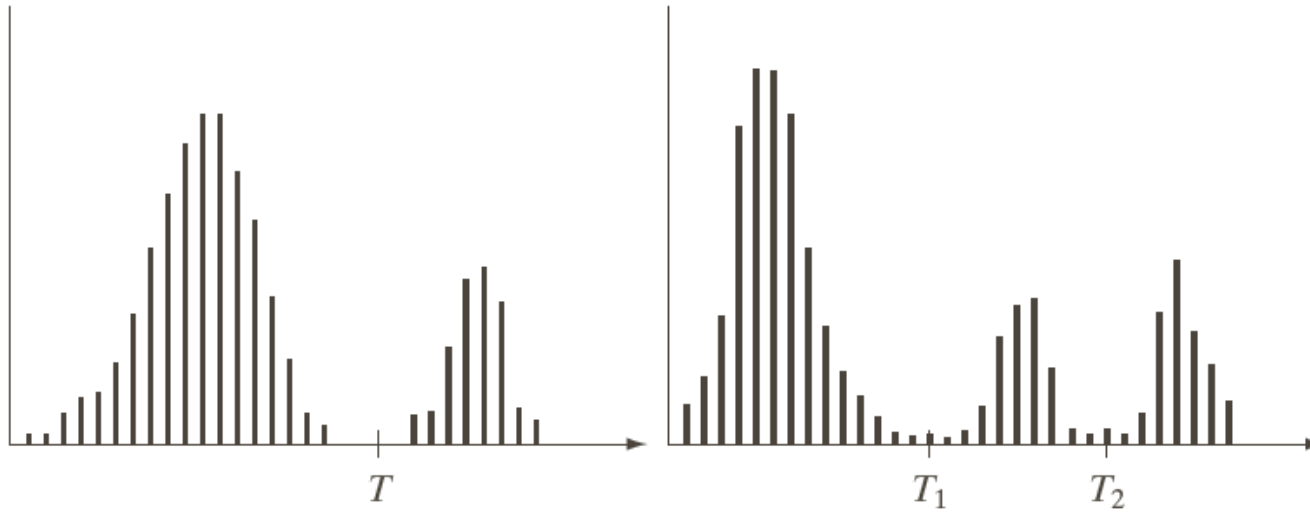


*Q*: How can we separate the object from the background?

*A*: Threshold the image.

# Thresholding with Histograms

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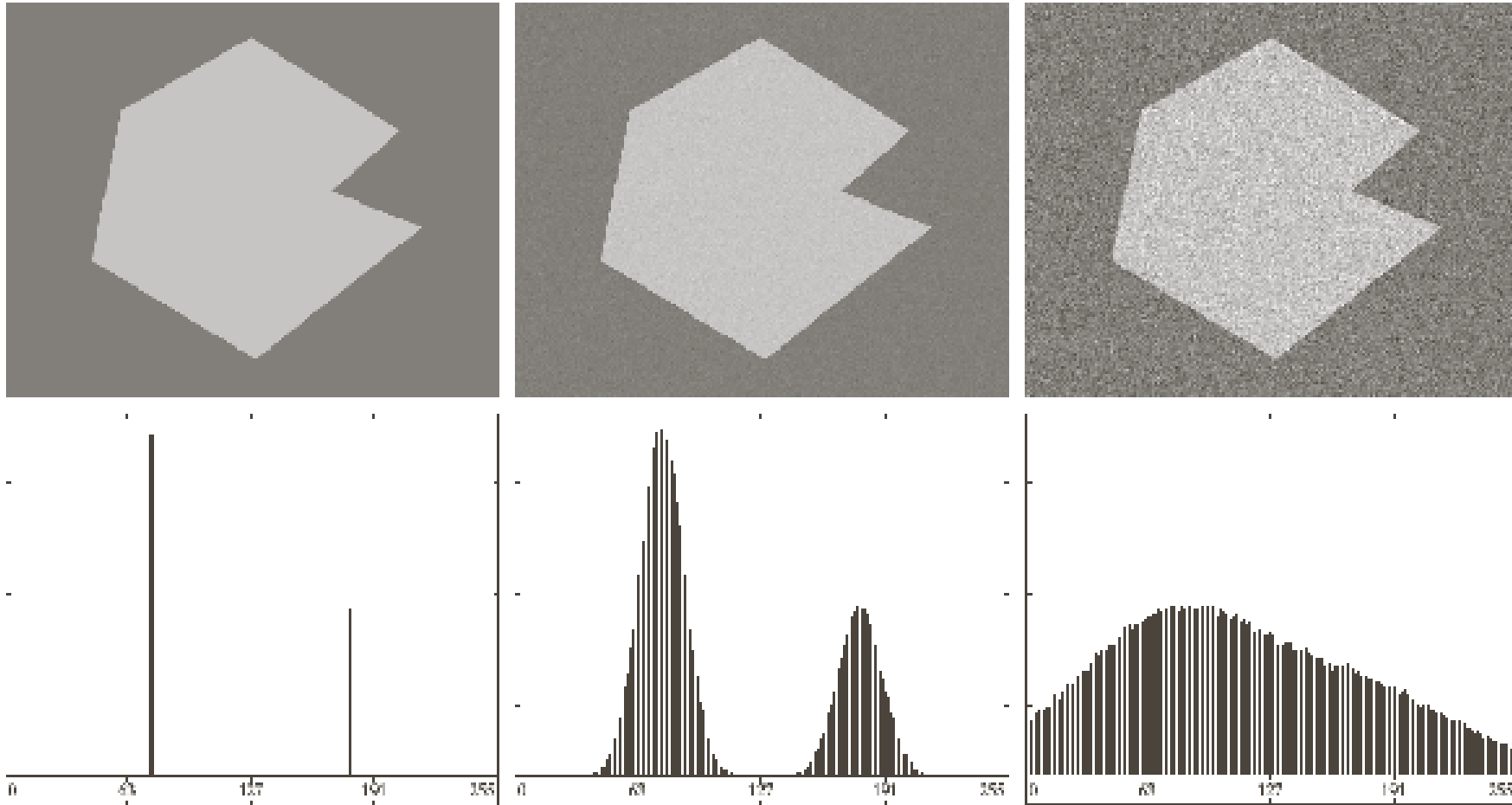


(a) Object and background

(b) ?

# Effects of Noise

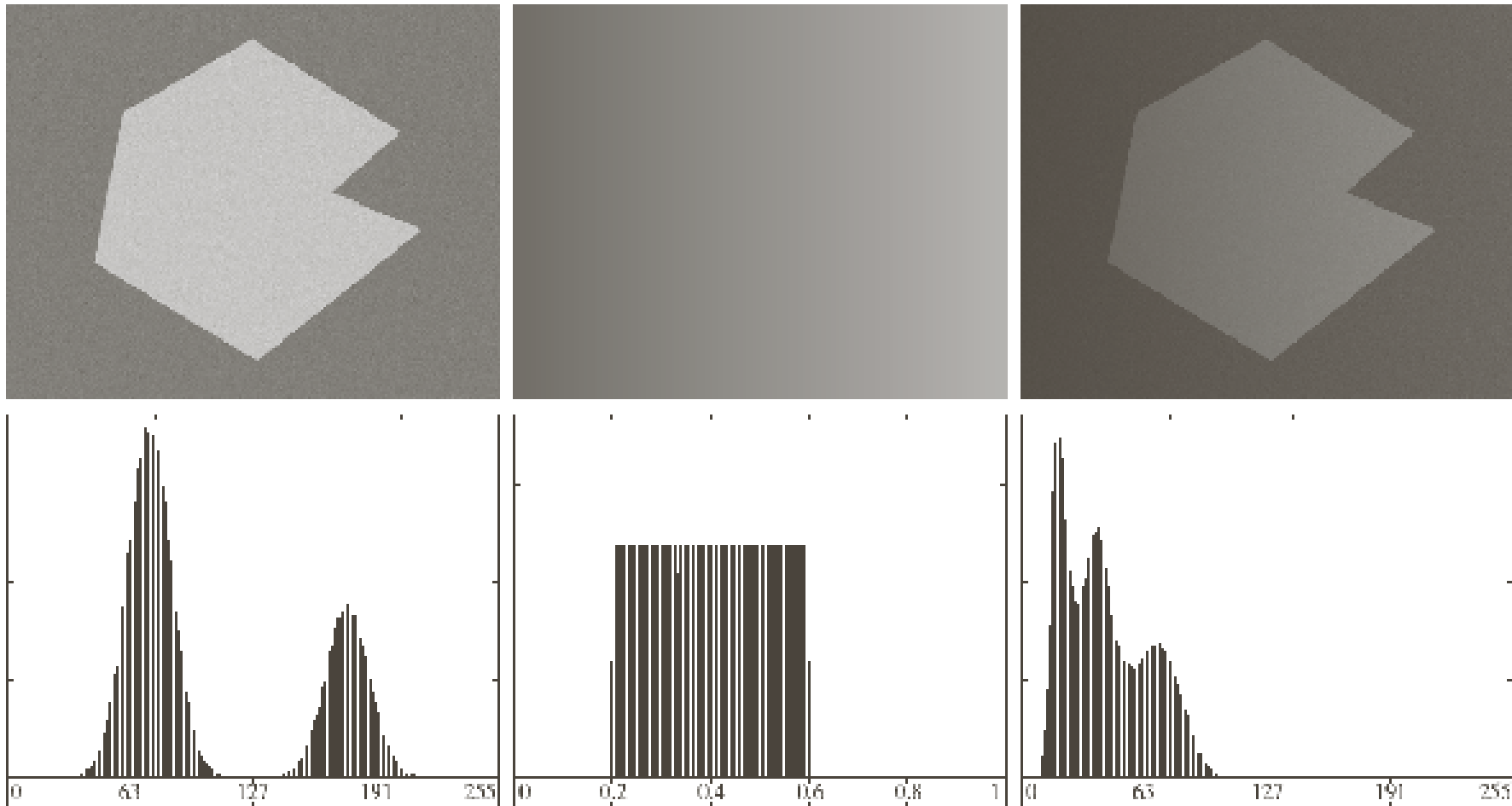
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Additive noise smooths the histogram. (Why?)

# The Role of Illumination and Reflectance

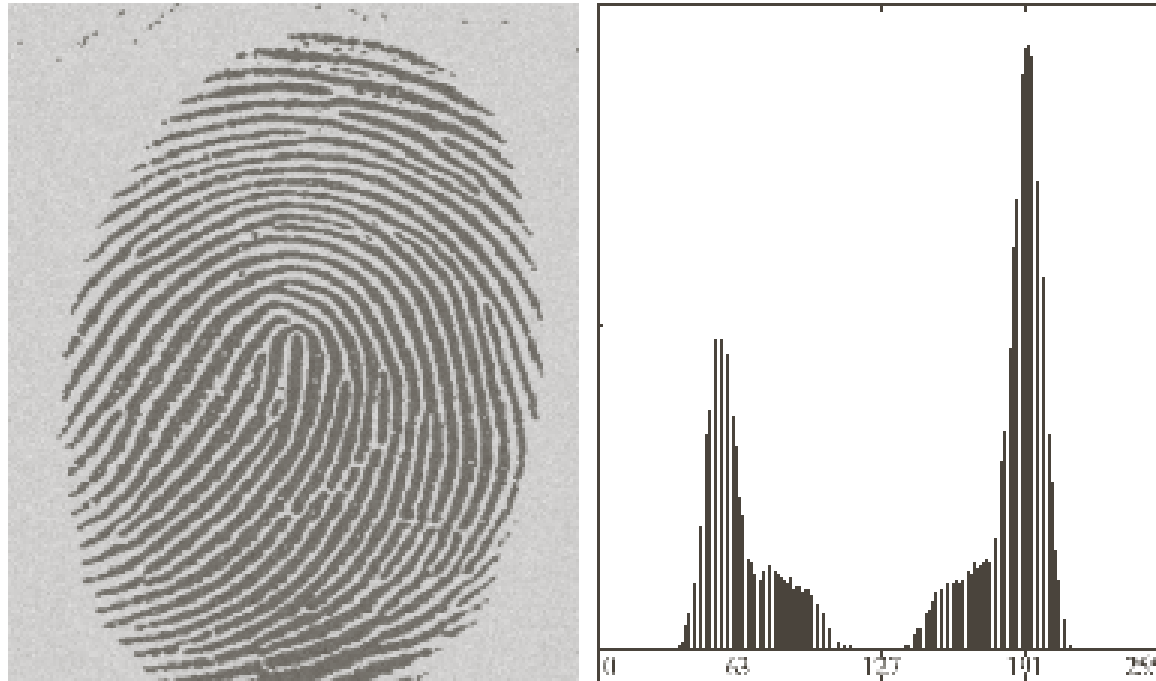
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Suppose we have the image in the third column, which is obtained by imaging the source in the first column with a spatially varying illumination source.

# Global Thresholding

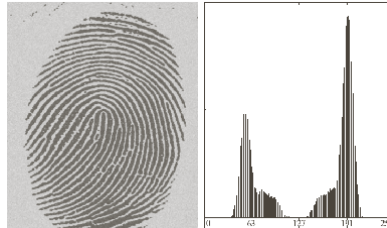
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Given the histogram of the image, how do we select the threshold automatically?

# Global Thresholding

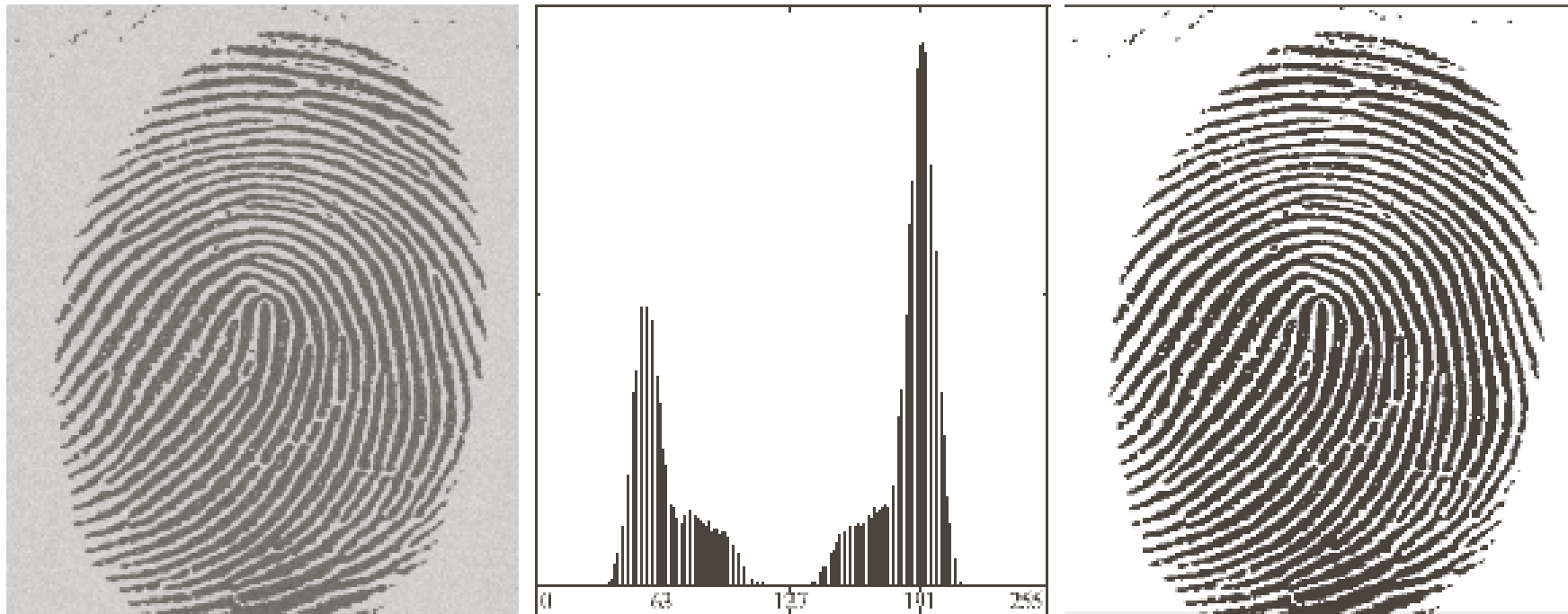
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- (1) Select an initial estimate,  $T$ .
- (2) Segment the image using  $T$  to create two images  $G_1(x, y) = (g(x, y) > T)$ ,  $G_2(x, y) = (g(x, y) \leq T)$ .
- (3) Compute the average intensity values  $m_1, m_2$  for the pixels in  $G_1, G_2$  respectively.
- (4) Update  $T = (m_1 + m_2)/2$ .
- (5) Repeat steps (2)–(4) until convergence.

# Global Thresholding

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Result of thresholding with the described algorithm.

# Selection of the Threshold Using Otsu's Method

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The method proposed by Otsu for threshold selection consists of finding the threshold that maximizes a certain metric, the so-called between-class variance, defined as,

$$\sigma_B^2(T) = P_1(T) (m_1(T) - m)^2 + P_2(T) (m_2(T) - m)^2$$

where

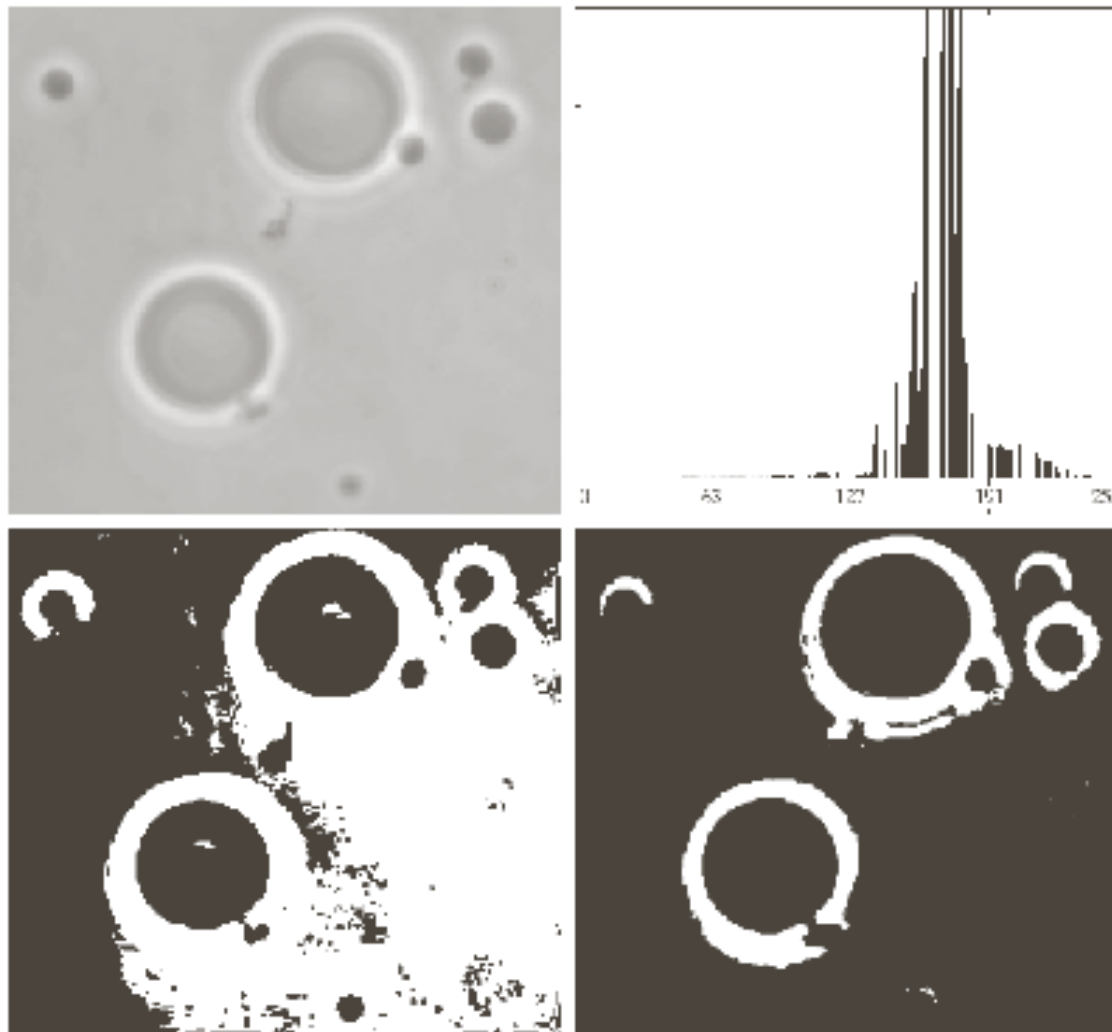
- $P_1(T)$  is the probability that a pixel lies in  $G_1$ , using  $T$  as the threshold.
- $P_2(T)$  is the probability that a pixel lies in  $G_2$ , using  $T$  as the threshold.
- $m_1(T)$  is the mean value of the pixels from  $G_1$ , using  $T$  as the threshold.
- $m_2(T)$  is the mean value of the pixels from  $G_2$ , using  $T$  as the threshold.
- $m$  is the mean of the whole image.

$T$  is selected by computing  $\sigma_B^2(T)$  for all possible thresholds (there are 256 of them for an 8-bit intensity resolution) and determining the maximizer.



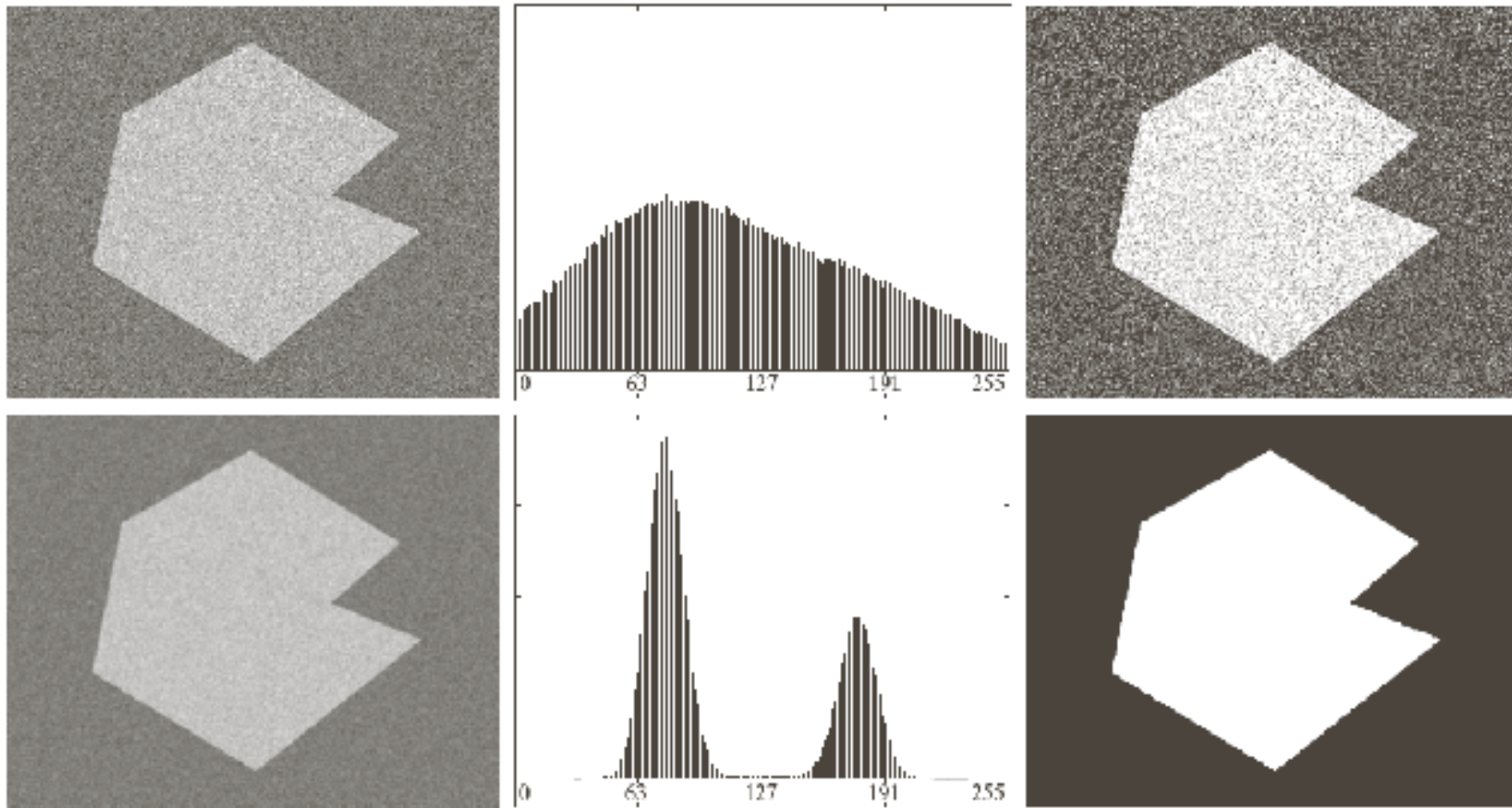
# Global Thresholding

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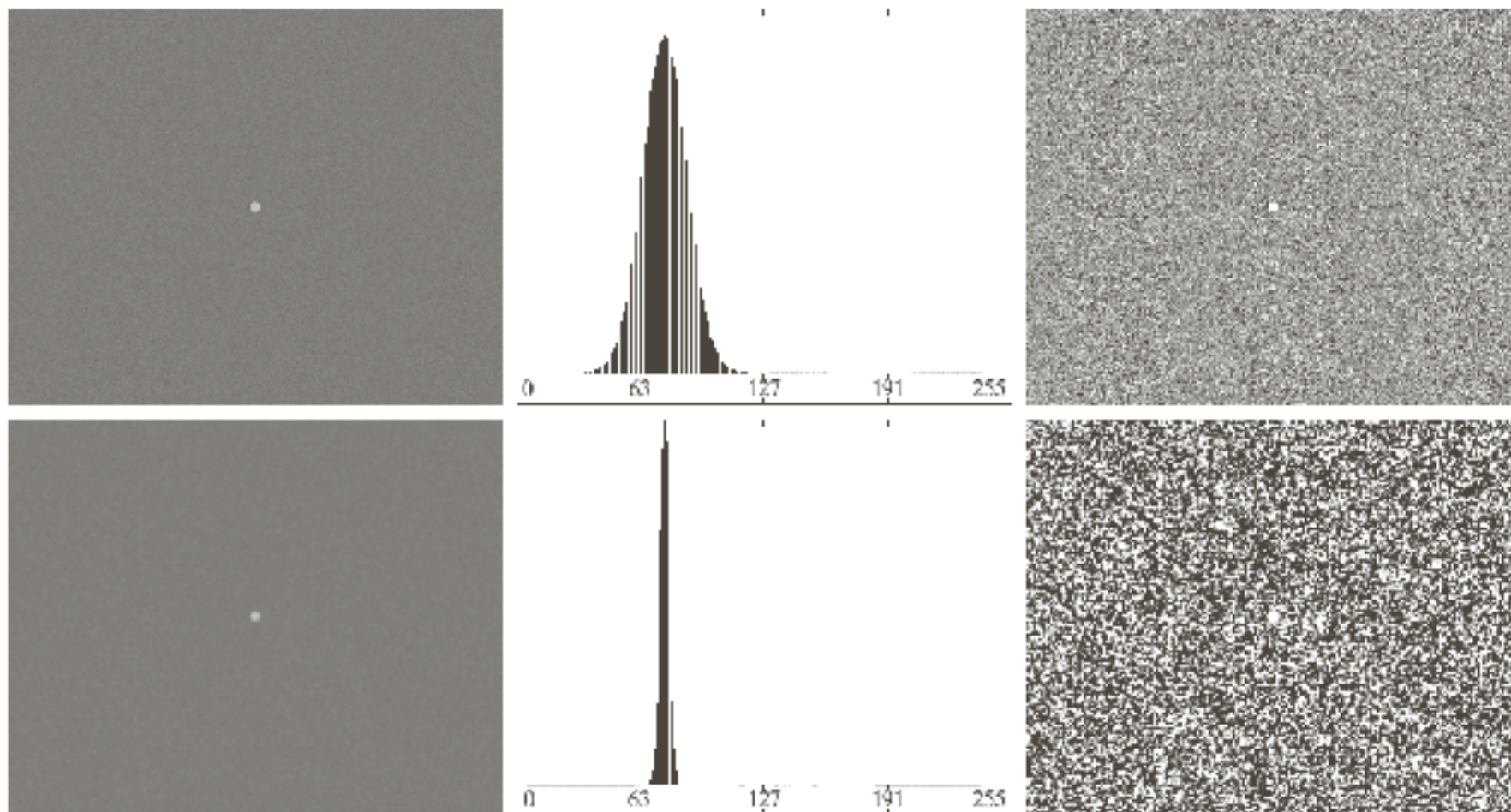
Result of thresholding with the two different threshold selection algorithms (right : Otsu's method).

# Dealing with Noise – Smoothing



Threshold, selected with Otsu's method, applied with and without lowpass filtering the noisy image.

# Dealing with Noise

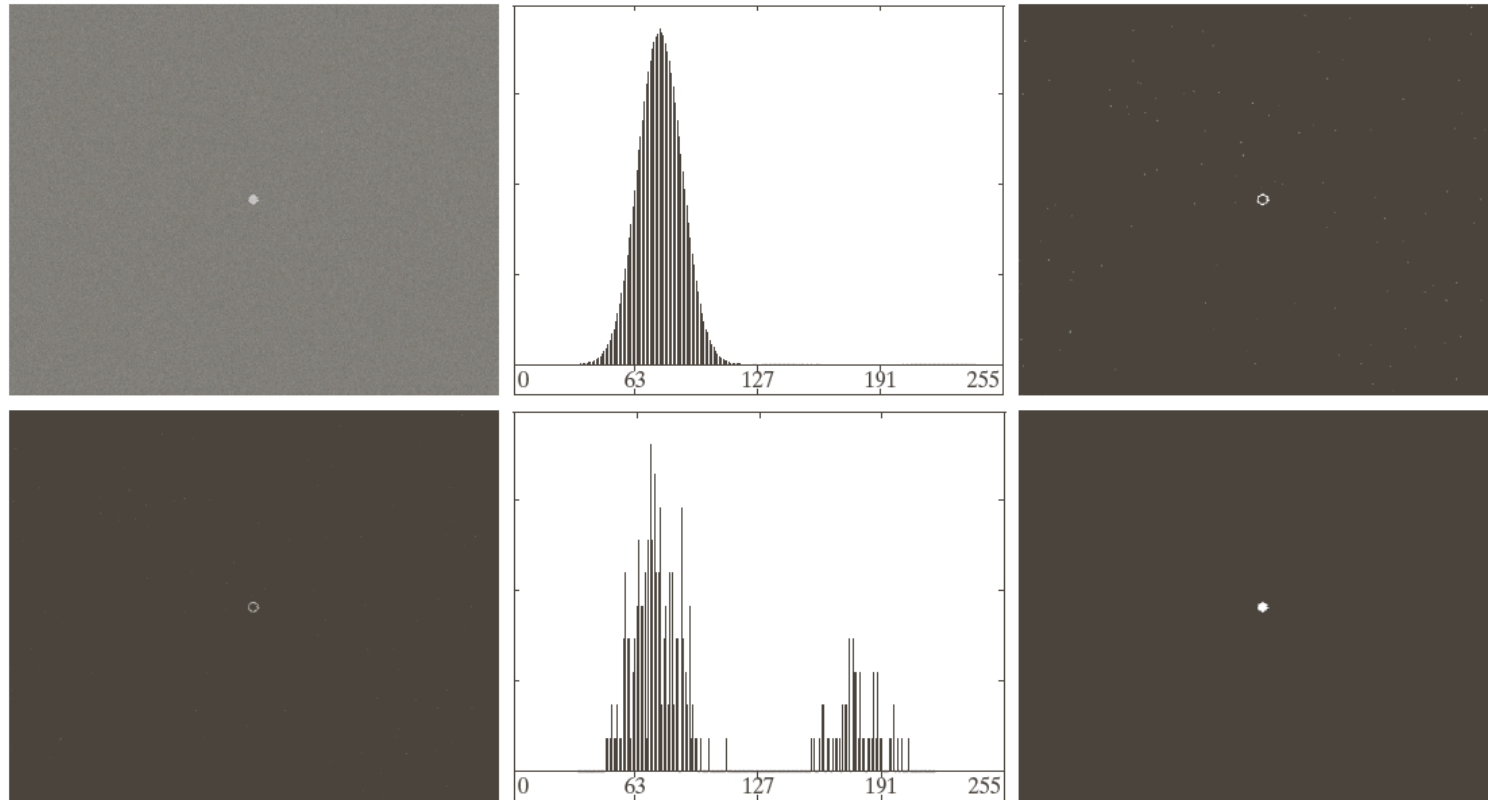


Threshold selection based on the histogram of the whole image (lowpass filtered or not) is doomed to failure in this example. Why?

# Dealing with Noise – Making use of Edges

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Idea : Form the histogram based on the pixels that lie on a neighborhood of the edges.

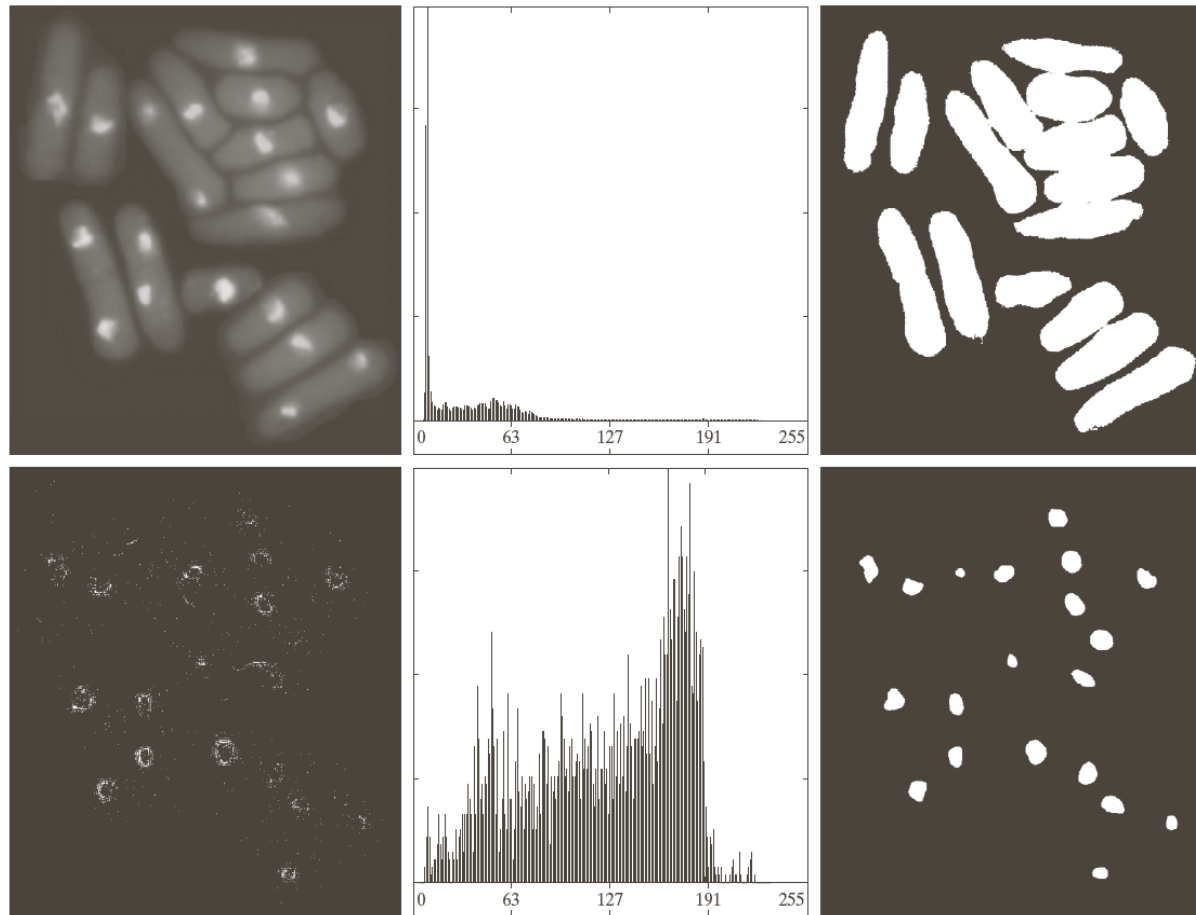


The histogram obtained by restricting attention to a neighborhood of the edge has two clearly distinguishable peaks.

# Thresholding – Making use of Edges

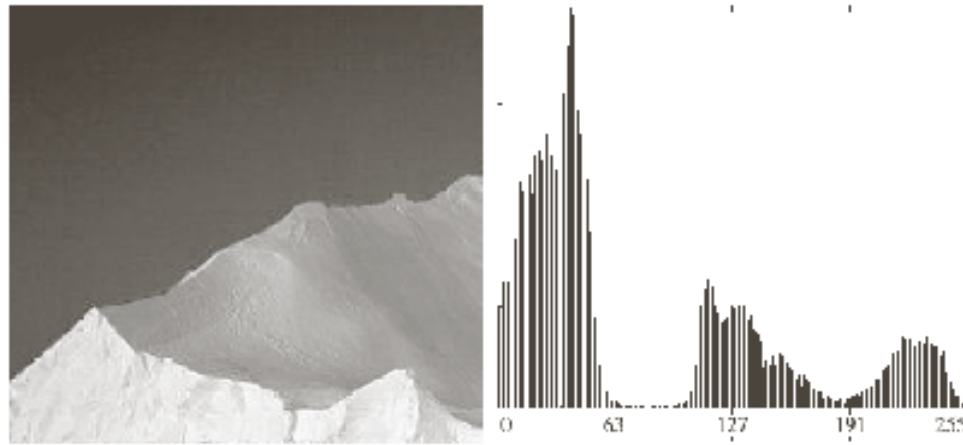
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Edge information can be useful in other scenarios as well. Here the goal is to segment the bright spots in the yeast cells.



# Multiple Objects of Interest

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How to segment in this case?

# Multiple Thresholds

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Otsu's threshold selection method can be generalized to  $K$  classes.

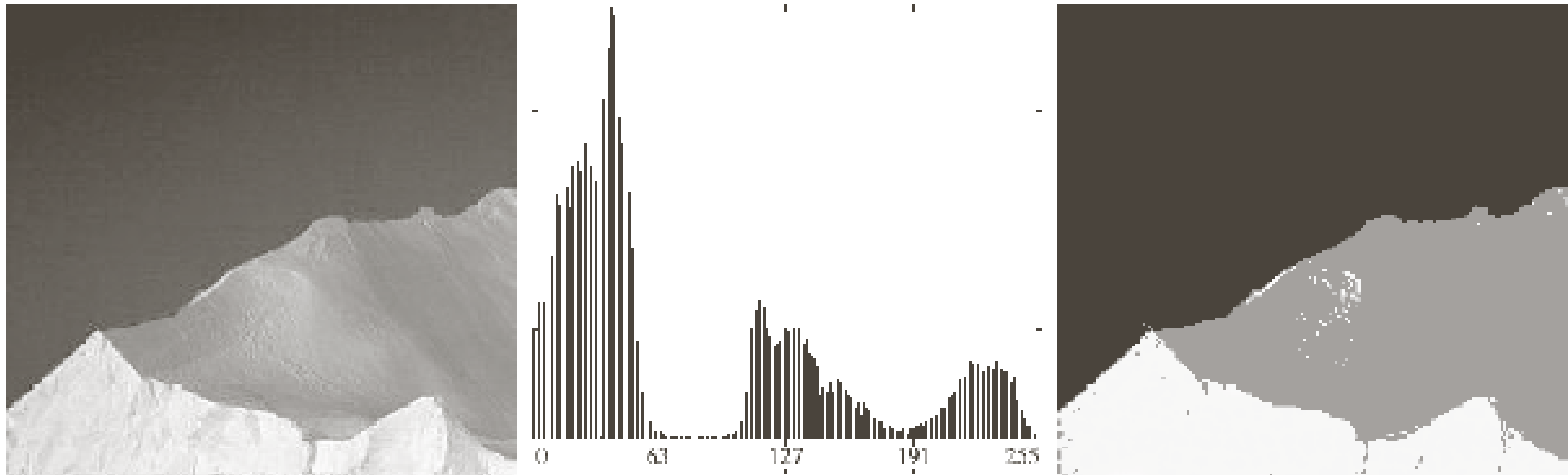
In this case, the metric to maximize is

$$\sigma_B^2(T_1, T_2, \dots, T_K) = \sum_{k=1}^K P_k (m_k - m)^2$$

Determine the set  $(T_1, \dots, T_K)$  that maximizes  $\sigma_B^2$ .

# Multiple Thresholds

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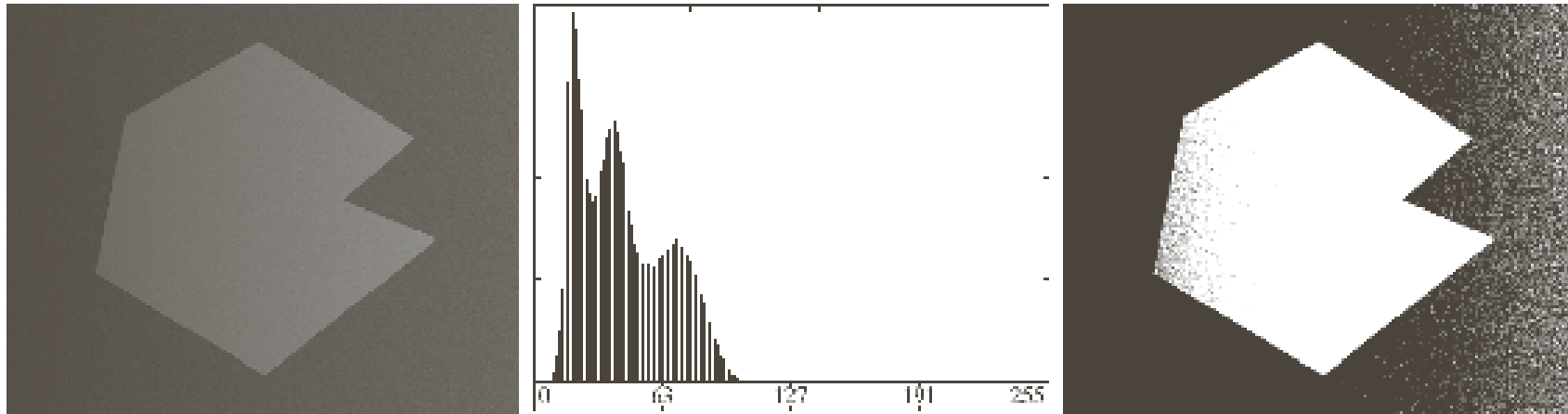


What can go wrong?



# Image Partitioning

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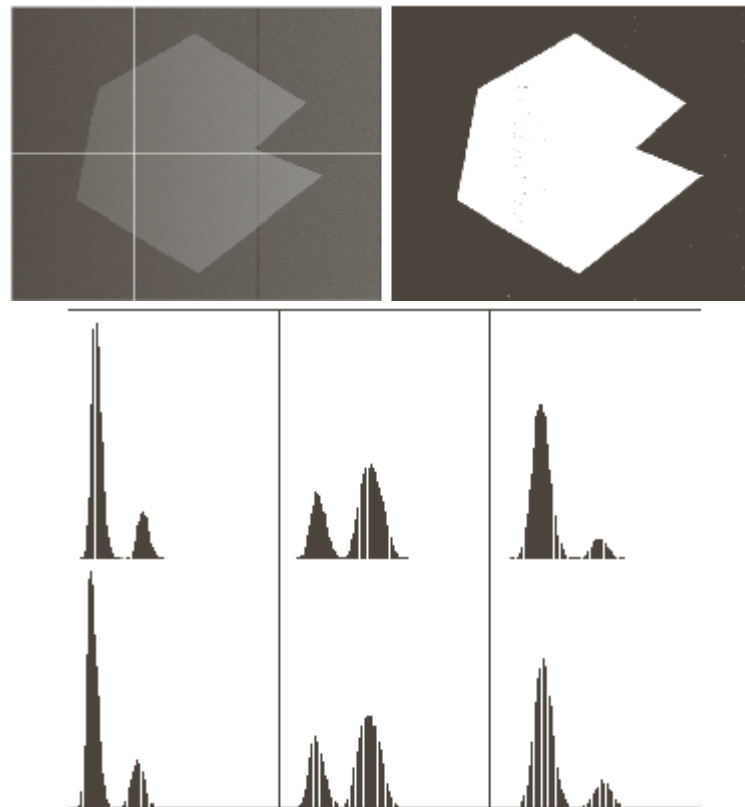
Noisy, shaded images with different characteristics in different regions do not allow the use of a single threshold.

What can we do?

# Image Partitioning

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Idea : Partition the image and apply a single threshold in each part independently.



# Segmenting Images with Changing Characteristics

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Indemnity Six between Stockley  
of Knox And State of Tennessee  
Andrew Jackson of the County  
State of Tennessee of the other part  
said Stockley Donelson for A  
of the Sum of two thousand  
hand paid the receipt where  
hath And by these presents  
self alien enfeof And confer  
Jackson his heirs And A  
certain traits or parcels of La  
and acres one thousand five

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