#### Digital Image Processing

**Image Segmentation:** 

Point, Line and Edge Detection

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#### Contents

So far we have been considering image processing techniques used to transform images for **human interpretation** 

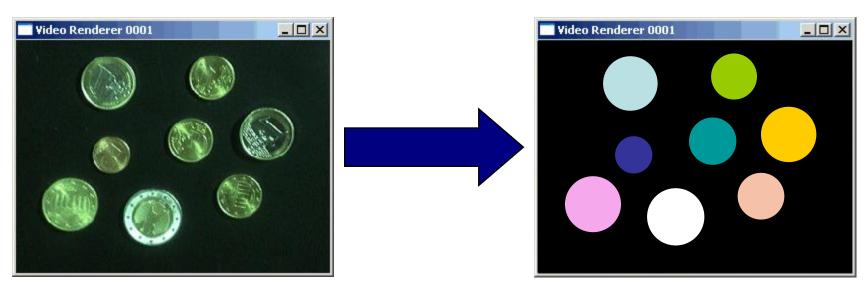
Today we will begin looking at automated image analysis by examining the thorny issue of **image segmentation**:

- The segmentation problem
- Finding points, lines and edges

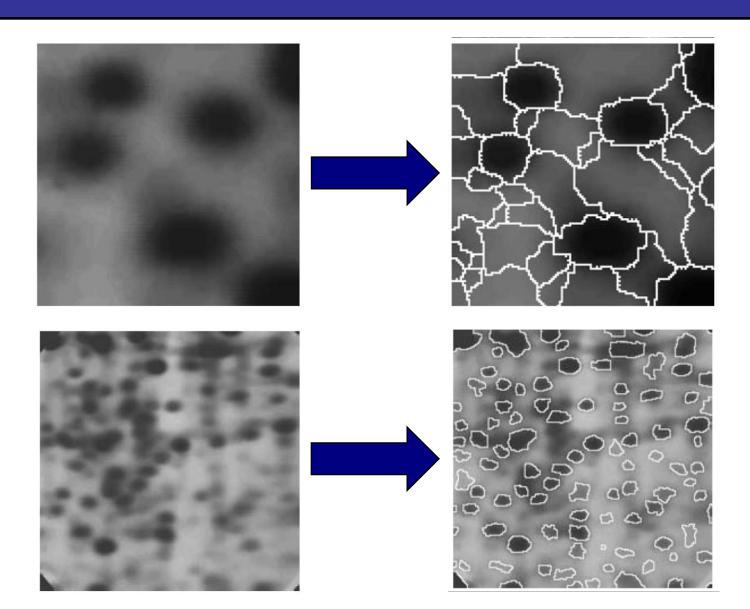
#### The Segmentation Problem

Segmentation attempts to partition the pixels of an image into groups that strongly correlate with the objects in an image

Typically the first step in any automated computer vision application



## Segmentation Examples





#### **Detection Of Discontinuities**

There are three basic types of grey level discontinuities that we tend to look for in digital images:

- Points
- Lines
- Edges

We typically find discontinuities using masks and correlation

#### Point Detection

Point detection can be achieved simply using the mask below:

#### Output 1 if:

$$R = \sum_{i=1}^{9} w_i z_i \qquad |R| \ge T$$

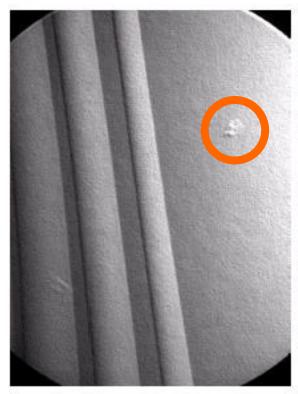
Else output 0.

-1	-1	-1	
-1	8 4-	-1	R is called Response of
-1	-1	-1	the filter.

Points are detected at those pixels in the subsequent filtered image that are above a set threshold



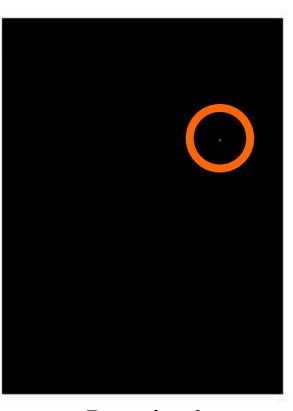
#### Point Detection (cont...)



X-ray image of a turbine blade



Result of point detection



Result of thresholding



#### Line Detection

The next level of complexity is to try to detect lines

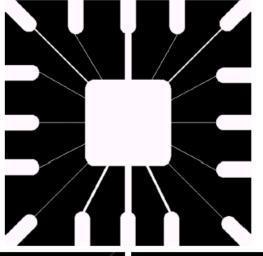
The masks below will extract lines that are one pixel thick and running in a particular direction

-1	-1	-1	-1	-1	2	-1	2	-1	2	-1	-1
2	2	2	-1	2	-1	-1	2	-1	-1	2	-1
-1	-1	-1	2	-1	-1	-1	2	-1	-1	-1	2
Н	orizon	tal		+45°		'	Vertica	1		-45°	

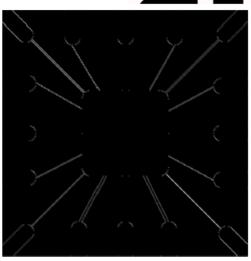


#### Line Detection (cont...)

Binary image of a wire bond mask



After processing with -45° line detector



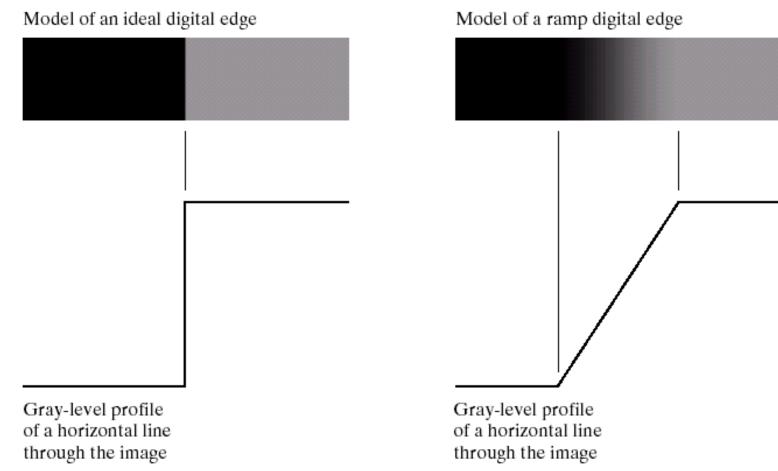


Result of thresholding filtering result



#### **Edge Detection**

# An edge is a set of **connected pixels that lie on the boundary** between two regions





#### Edge Point

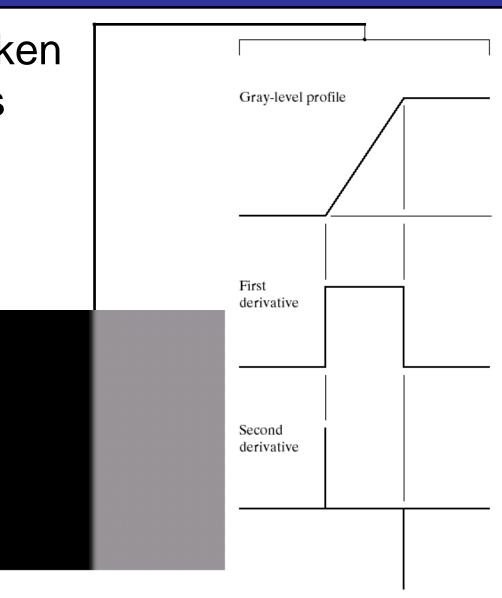
We define a point in an image as being an <u>edge point</u> if its 2-D 1<sup>st</sup> order derivative is greater than a specified threshold.

A **set** of **such points** that are connected according to a <u>predefined</u> <u>criterion</u> of <u>connectedness</u> is by definition an <u>edge</u>.

#### Edges & Derivatives

We have already spoken about how derivatives are used to find discontinuities 1<sup>st</sup> derivative tells us where an edge is 2<sup>nd</sup> derivative

show double response with thin



#### Common Edge Detectors

# Given a 3\*3 region of an image the following edge detection filters can be used

$z_1$	$z_2$	<i>z</i> <sub>3</sub>
$z_4$	$z_5$	$z_6$
Z <sub>7</sub>	$z_8$	Z9

-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

	_			
- 1	$\mathbf{D}_{\sigma D}$	NT.	: 1	-1
	10	w	н	1

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

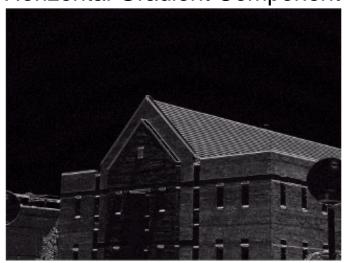
-1	0	1
-2	0	2
-1	0	1



Original Image









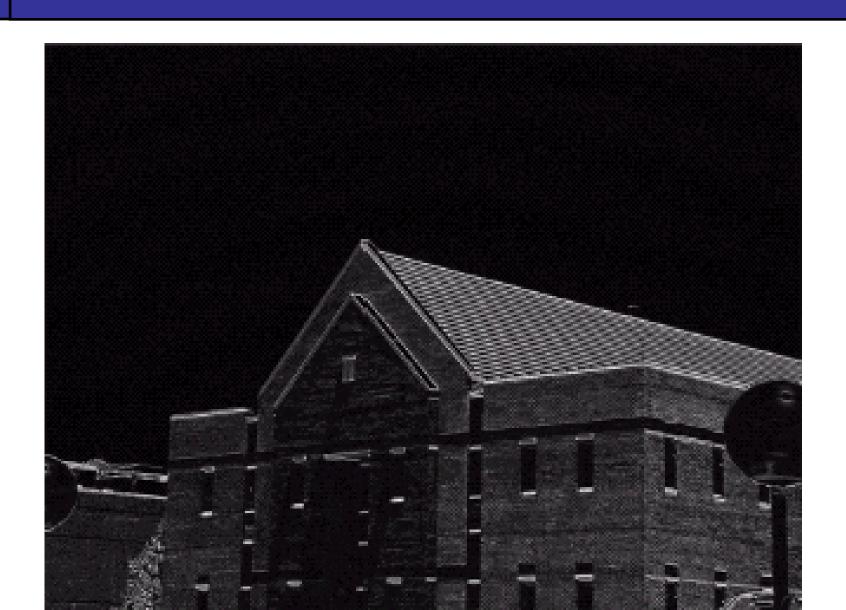
Vertical Gradient Component

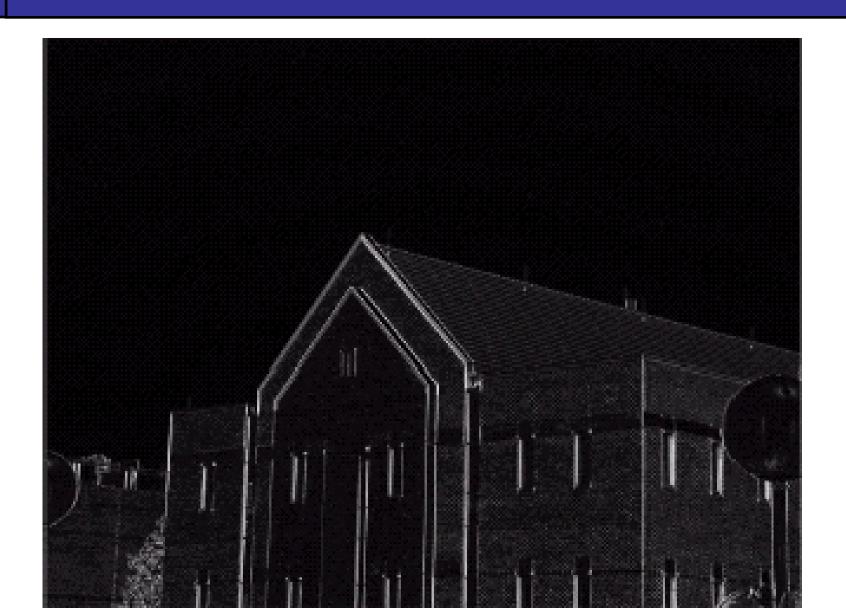


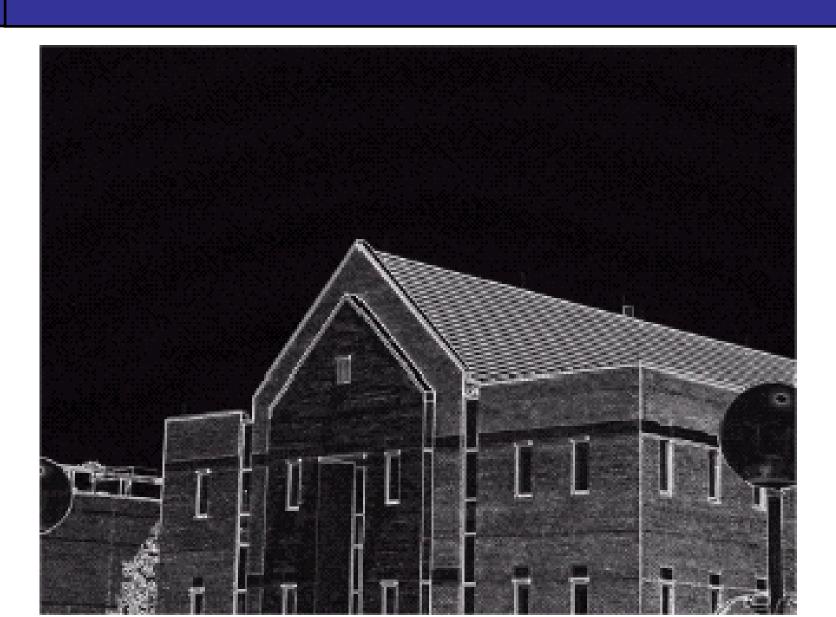
Combined Edge Image







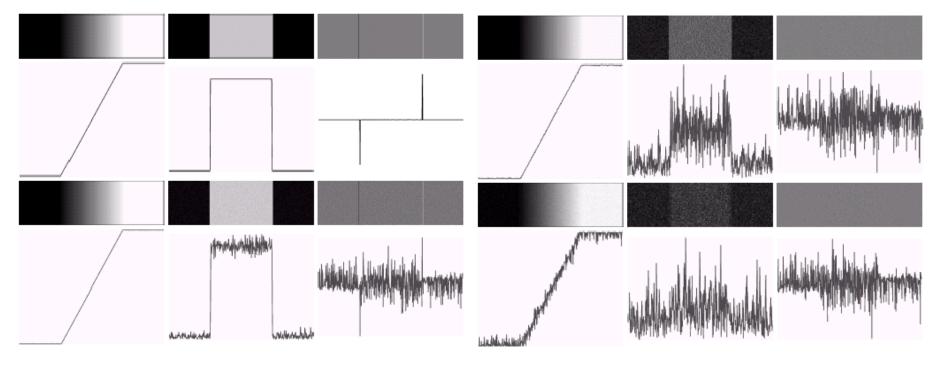




#### Derivatives & Noise

Derivative based edge detectors are extremely sensitive to noise

We need to keep this in mind





#### Edge Detection Problems

Often, problems arise in **edge detection** in that there is **too much detail** 

For example, the brickwork in the previous example

One way to **overcome this** is to **smooth images** prior to edge detection

#### Laplacian Edge Detection

We encountered the 2<sup>nd</sup>-order derivative based Laplacian filter already

0	-1	0	-1	-1	-1
-1	4	-1	-1	8	-1
0	-1	0	-1	-1	-1

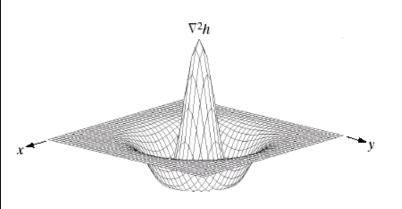
The Laplacian is typically not used by itself as it is too sensitive to noise

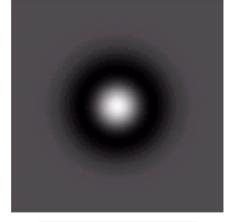
Usually used for edge detection the Laplacian is combined with a smoothing Gaussian filter

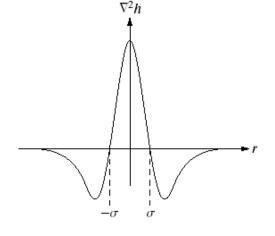


#### Laplacian Of Gaussian

The Laplacian of Gaussian (or Mexican hat) filter uses the Gaussian for noise removal and the Laplacian for edge detection

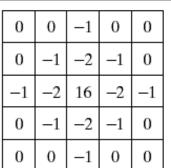




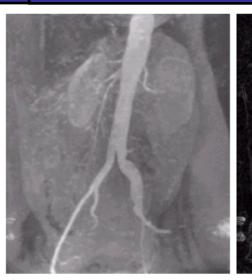


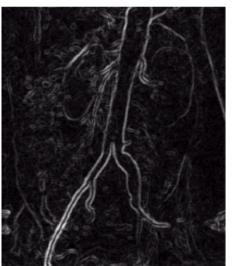
$$h(r) = -\exp(-r^2/2\sigma^2)$$

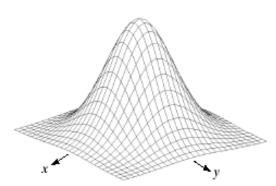
$$\nabla^2 h(r) = -\left[\frac{r^2 - \sigma^2}{\sigma^4}\right] \exp(-r^2/2\sigma^2)$$



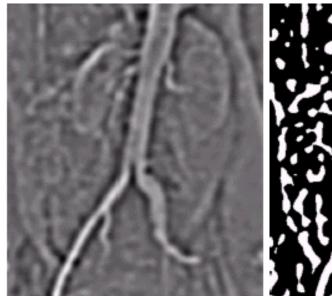
## Laplacian Of Gaussian Example

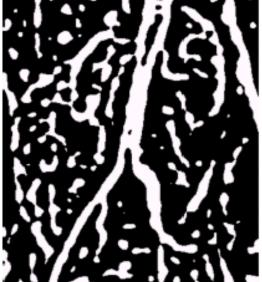






-1	-1	-1
-1	8	-1
-1	-1	-1







#### **Thresholding**

Thresholding is usually the first step in any segmentation approach

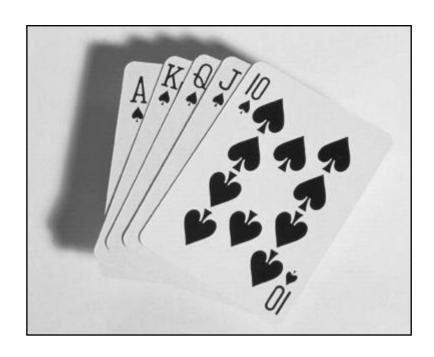
We have talked about simple single value thresholding already

Single value thresholding can be given mathematically as follows:

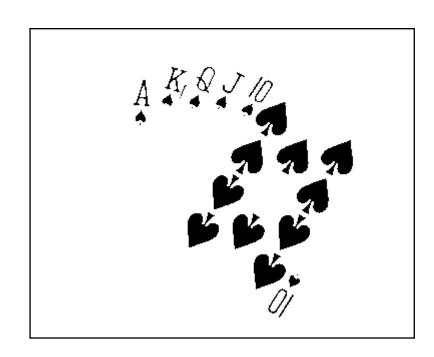
$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \le T \end{cases}$$

#### Thresholding Example

# Imagine a poker playing robot that needs to visually interpret the cards in its hand



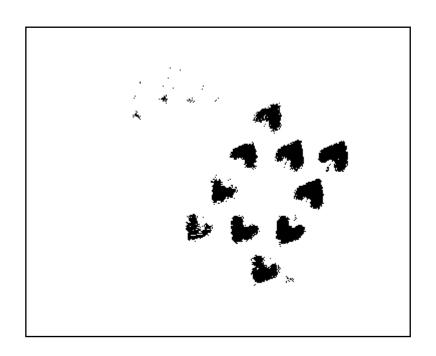
Original Image



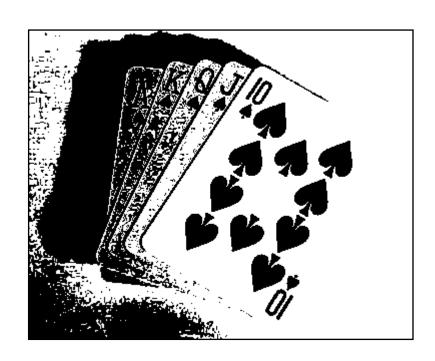
Thresholded Image

#### **But Be Careful**

## If you get the threshold wrong the results can be disastrous



Threshold Too Low



Threshold Too High

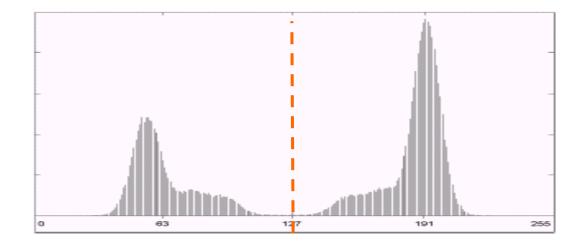
#### Basic Global Thresholding

Based on the histogram of an image

Partition the image histogram using a single **global threshold** 

The success of this technique very strongly depends on how well the histogram can be

<u>partitioned</u>



#### Basic Global Thresholding Algorithm

The basic global threshold, T, is calculated as follows:

- 1. Select an initial estimate for T (typically the average grey level in the image)
- 2. Segment the image using T to produce two groups of pixels: G₁ consisting of pixels with grey levels >T and G₂ consisting pixels with grey levels ≤ T
- 3. Compute the average grey levels of pixels in  $G_1$  to give  $\mu_1$  and  $G_2$  to give  $\mu_2$

#### Basic Global Thresholding Algorithm

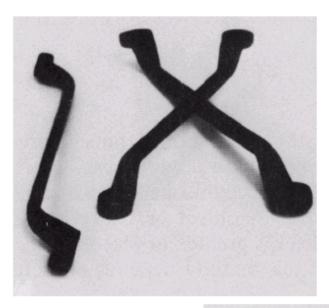
4. Compute a new threshold value:

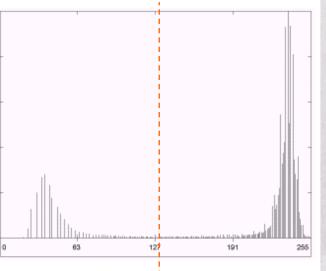
$$T = \frac{\mu_1 + \mu_2}{2}$$

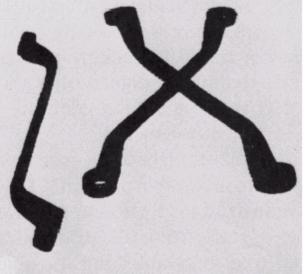
5. Repeat steps 2 – 4 until the difference in T in successive iterations is less than a predefined limit  $\Delta T$ 

This algorithm works very well for finding thresholds when the histogram is suitable

## Thresholding Example 1

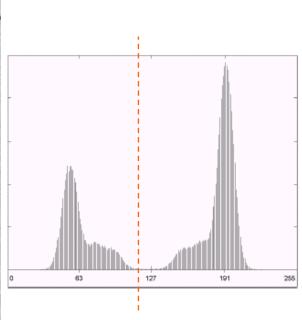






### Thresholding Example 2



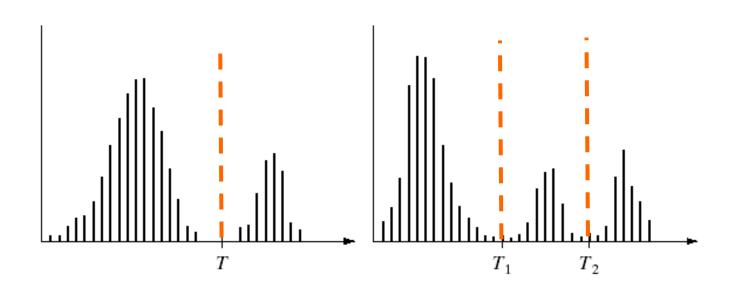




# Problems With Single Value Thresholding

Single value thresholding only works for bimodal histograms

Images with other kinds of histograms need more than a single threshold

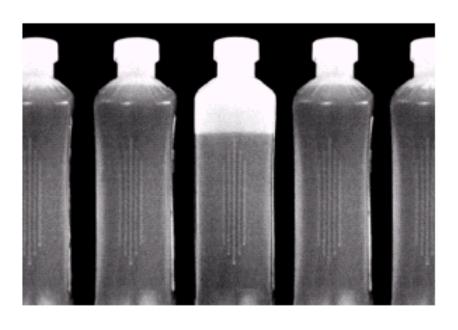




# Problems With Single Value Thresholding (cont...)

Let's say we want to isolate the contents of the bottles

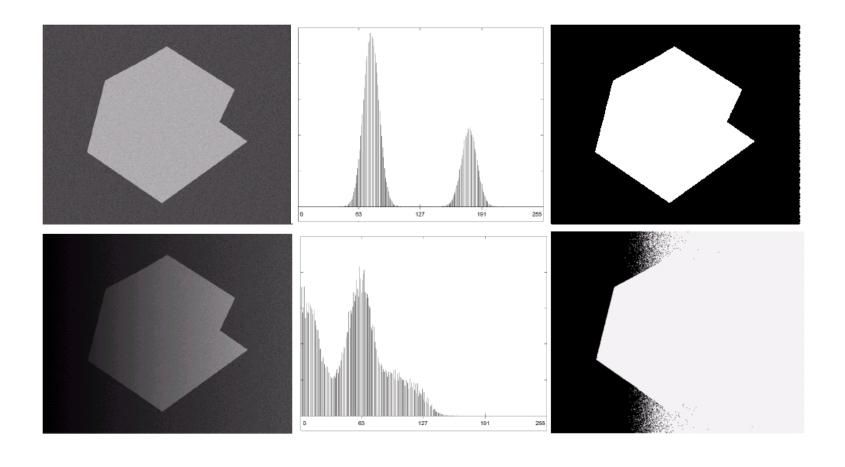
Think about what the histogram for this image would look like



What would happen if we used a single threshold value?



# Single Value Thresholding and Illumination



Uneven illumination can really upset a single valued thresholding scheme

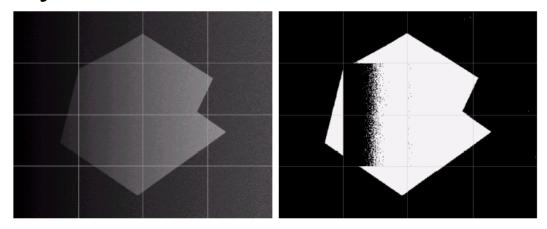
#### Basic Adaptive Thresholding

An approach to handling situations in which single value thresholding will not work is to divide an image into sub images and threshold these individually

Since the threshold for each pixel depends on its location within an image this technique is said to *adaptive* 

#### Basic Adaptive Thresholding Example

The image below shows an example of using adaptive thresholding with the image shown previously



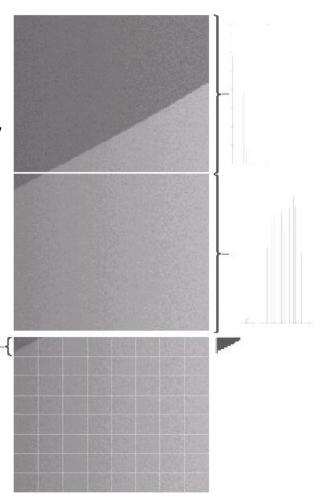
As can be seen success is mixed

But, we can further subdivide the troublesome sub images for more success

# Basic Adaptive Thresholding Example (cont...)

These images show the troublesome parts of the previous problem further subdivided

After this sub division successful thresholding can be achieved



#### Summary

In this lecture we have begun looking at segmentation, and in particular edge detection

Edge detection is massively important as it is in many cases the first step to object recognition

We have also looked at the very basic type of segmentation i.e., Thresholding and what it offers.