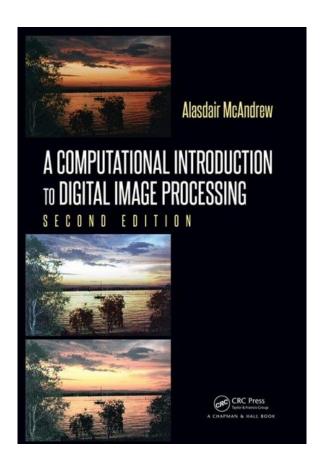
# Chapter 9



#### **Image Segmentation**



#### Contents



- Introduction
- Thresholding
- Applications of Thresholding
- Choosing an Appropriate Threshold Value
- Adaptive Thresholding
- Edge
- Weiner Filtering

### Contents



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- Applications of Thresholding
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### Introduction

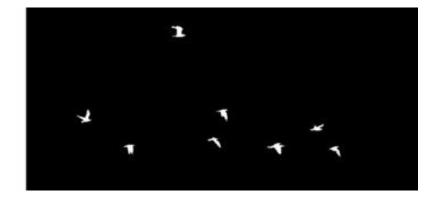
**Segmentation**: the operation of partitioning an image into component parts or into separate objects.

**Thresholding**: A vital part of segmentation where objects are isolated from the background

Important component of robot vision

Figure 9.1: Thresholded image of flying birds







# Thresholding

Thresholding can be done very simply in any of our systems. Suppose we have an 8-bit image, stored as the variable X. Then the command

will perform the thresholding. For example, consider an image of some birds flying across a sky; it can be thresholded to show the birds alone in MATLAB or Octave:

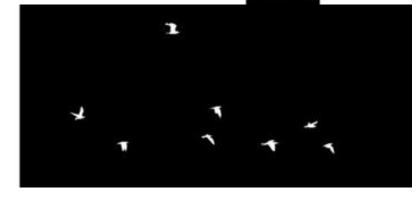
```
>> f = imread('flying.png');
>> imshow(f); figure,imshow(f<50)

MATLAB/Octave

In : f = io.imread('flying.png')
In : io.imshow(f)
In : fig = plt.figure(); fig.show(io.imshow(f<50))

Python</pre>
```

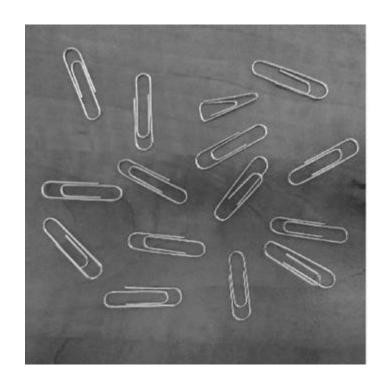


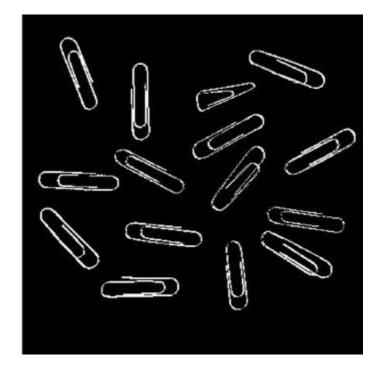


# Thresholding



Figure 9.2: Thresholded image of paperclips







# Thresholding

Thresholding also provides a way of showing hidden aspects of an image

Ex. Handmade paper (Figure 9.3)

Figure 9.3: The paper image and result after thresholding





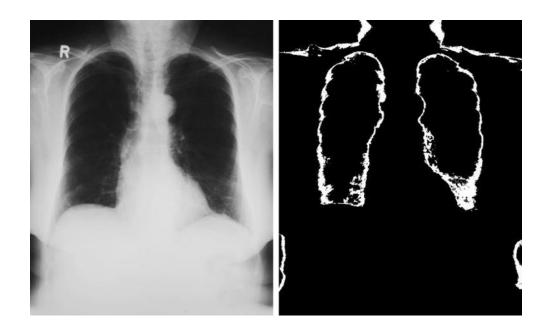
# Double Thresholding

Choose two values  $T_1$  and  $T_2$  and apply a thresholding operation A pixel becomes

White: if gray level is between T<sub>1</sub> and T<sub>2</sub>

Black: gray level is otherwise

Figure 9.4: The image xray.png and the result after double thresholding





# Double Thresholding

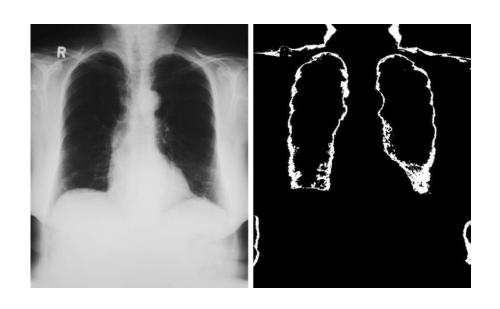
#### Try It:

### MatLab/Octave:

```
x = imread('xray.png');
imshow(x);
dt = (x > 50 & x < 80);
imshow(dt)</pre>
```

#### **Python:**

import skimage.io as io x = io.imread('xray.png') dt = ((x > 50) & (x < 80)) imshow(dt)





# Applications of Thresholding

## When can Thresholding be useful?

Remove unnecessary detail

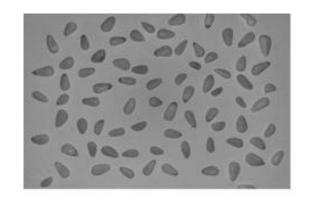
Bring out hidden detail

Remove a varying background

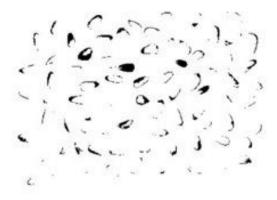
# Choosing an Appropriate Threshold Value



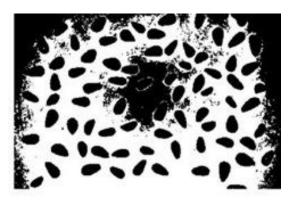
Figure 9.5: Attempts at thresholding



n: Original image



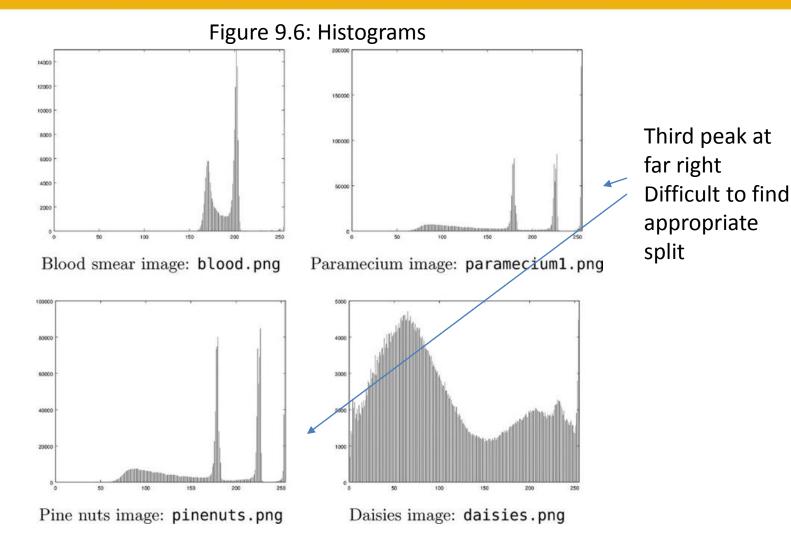
n1: Threshold too low



n2: Threshold too high

# Choosing an Appropriate Threshold Value





Histogram is not the best method for finding a threshold value

# Choosing an Appropriate Threshold Value



Two methods for choosing the best threshold:

- Otsu's Method
  - First described by Nobuyuki Otsu in 1979
  - Maximizes inter-class variance
- The ISODATA Method
  - Iterative Self-Organizing Data Analysis Technique A

Both methods perform statistical analyses on the pixel data to determine the best threshold value.

# Choosing an Appropriate Threshold Value



#### MATLAB and Octave graythresh function:

- Parameter 'otsu' for Otsu's method
- Parameter 'intermeans' for ISODATA method

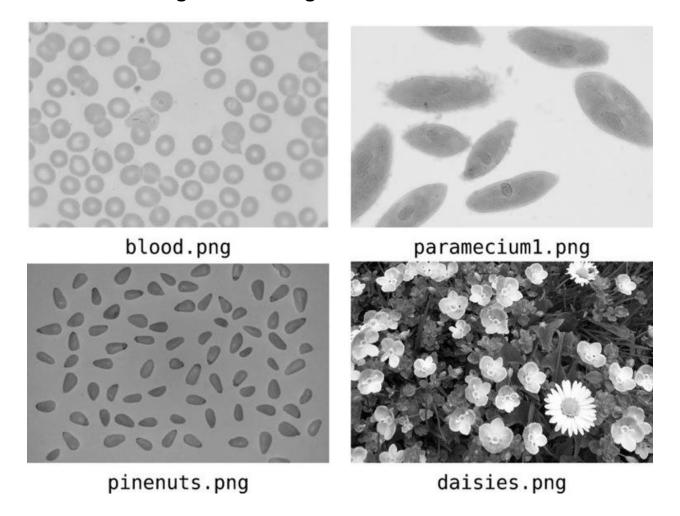
#### Python filter module of skimage:

- Method threshold\_otsu
- Method threshold\_isodata



## Otsu's Method

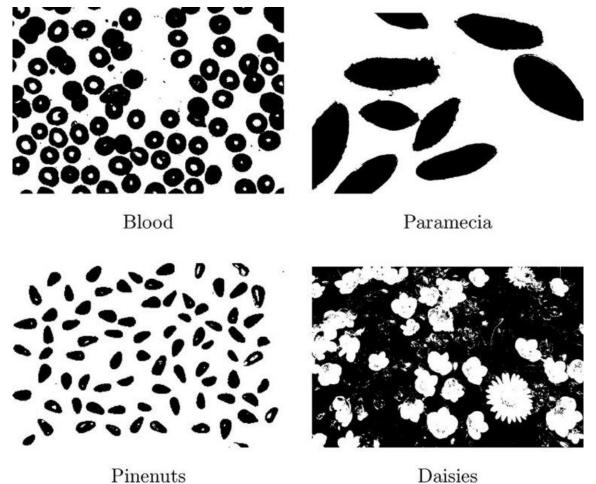
Figure 9.9: Images to be thresholded





## Otsu's Method

Figure 9.10: Thresholding with values obtained with Otsu's method





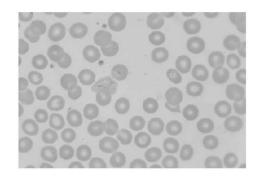
# Otsu's Method – Try It

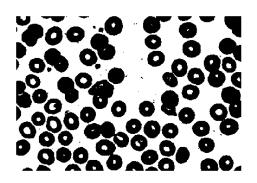
#### MatLab/Octave:

```
b = imread('blood.png');
imshow(b);
t = graythresh(b, 'otsu')
int_t = t * 255
bt = b > t_int;
imshow(bt);
```

#### Python:

```
import skimage.io as io
import skimage.filters as fl
b = io.imread('blood.png')
imshow(b)
t = fl.threshold_otsu(b)
bt = (b > t)
imshow(bt)
```





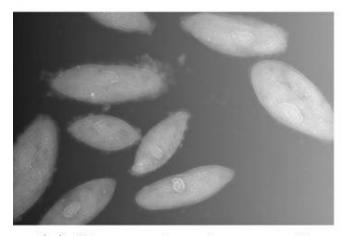


# Adaptive Thresholding

Sometimes it is not possible to obtain a single threshold value that will isolate an object completely

This may happen if both the object and its background vary.

Figure 9.11: An attempt at thresholding



(a) Paramecium image: p2

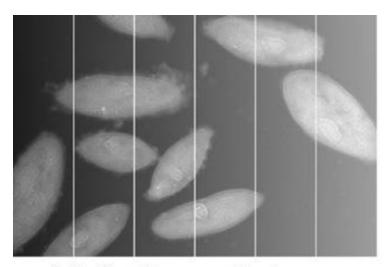


(b) Thresholding attempt



# Adaptive Thresholding

**Adaptive Thresholding:** Cut the image into small pieces, and apply thresholding to each piece individually.



(a) Cutting up the image



(b) Thresholding each part separately



# Edge Detection

- Edges contain some of the most useful information in an image
- Edges can be used to
  - Measure the size of objects in images
  - Isolate particular objects from their backgrounds
  - Reorganize or classify objects
- Edge: a local discontinuity in the pixel values which exceeds a given threshold (an observable difference in pixel values)

Figure 9.14: Blocks of pixels

51	52	53	59
54	52	53	62
50	52	53	68
55	52	53	55

50	53	155	160
51	53	160	170
52	53	167	190
51	53	162	155

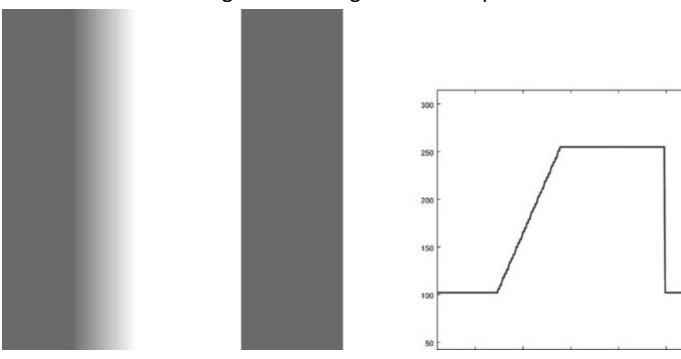


# Derivatives and Edges

#### **Fundamental Definitions**

- Ramp edge: gray values change slowly
- Step (Ideal) edge: gray values change suddenly

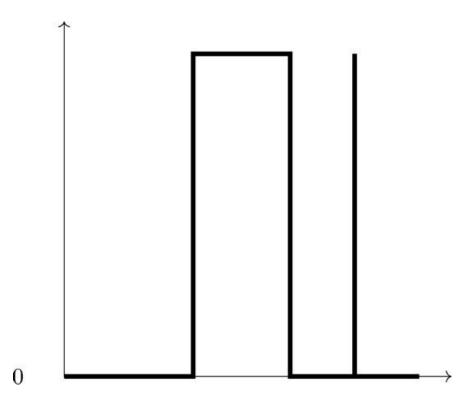
Figure 9.15: Edges and their profiles





# Derivatives and Edges

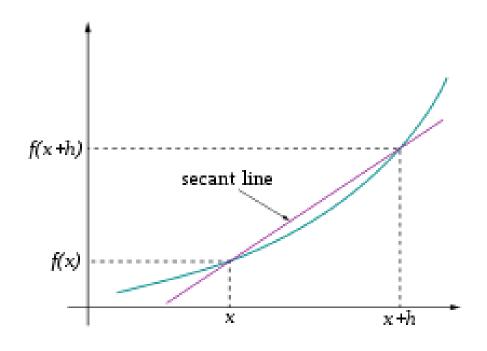
Figure 9.16: The derivative of the edge profile



The derivative, as expected, returns zero for all constant sections of the profile, and is non-zero (in this example) only in those parts of the image in which differences occur

## Return of Calculus!!!!





$$\frac{df}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}.$$

## Return of Calculus!!!!



$$\frac{df}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}.$$

In an image, the smallest possible value of h is 1, the difference between the two adjacent pixels. A discrete version of the derivative expression:

$$f(x+1)-f(x)$$
.

### Return of Calculus!!!!



Other expressions for the derivative:

$$\lim_{h \to 0} \frac{f(x) - f(x - h)}{h}, \qquad \lim_{h \to 0} \frac{f(x + h) - f(x - h)}{2h}$$

Discrete counterparts:

$$f(x) - f(x-1),$$
  $(f(x+1) - f(x-1))/2.$ 

For an image, with two dimensions, we use partial derivatives; an important expression is the **gradient**:

$$egin{bmatrix} rac{\partial f}{\partial x} & rac{\partial f}{\partial y} \end{bmatrix}$$

# Edge Detection Filters



Using the expression f(x + 1) - f(x - 1) for the derivative, leaving the scaling factor out, produces horizontal and vertical filters:

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

Will find vertical and horizontal edges but produce "jerky" edges; use smoothing in the opposite direction

$$\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$$

Combined into one filter each, known as the **Prewitt Filters**:

$$P_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad P_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

Vertical edges

Horizontal edges



# Prewitt Filters

Figure 9.17: A set of steps: A test image for edge detection





# Prewitt Method – Try It

#### MatLab/Octave:

```
s = imread('stairs.png');
imshow(s);
px = [-1 0 1; -1 0 1; -1 0 1];
py = px';
sx = imfilter(s, px);
imshow(sx);
sy = imfilter(s, py);
imshow(sy);
```

#### Python: ????

```
import skimage.io as io
import skimage.filters as fl
s = io.imread('stairs.png')
imshow(s)
sx = fl.prewitt_h(s)
io.imshow(sx)
sy = fl.prewitt_v(s)
io.imshow(sy)
```



# Prewitt Filters

### MatLab/Octave:

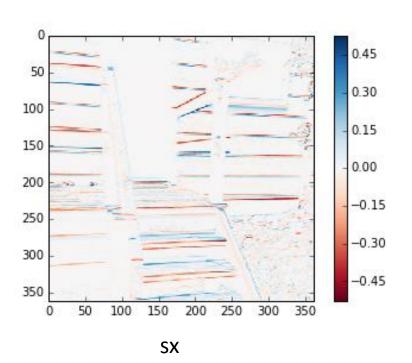


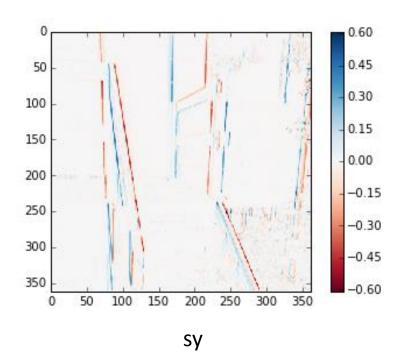






#### **Python:**







## **Prewitt Filters**

#### MatLab/Octave All edges:

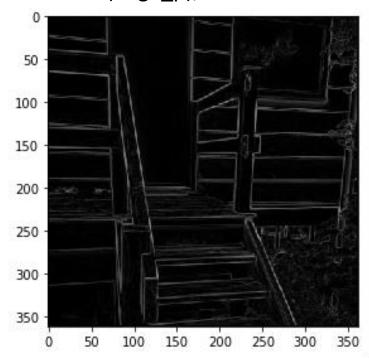
edge\_p = edge(s, 'prewitt');
imshow(edge\_p);



Performs edge detection and thresholding

#### **Python:**

import numpy as np
edge\_p = np.sqrt(sx\*\*2 + sy\*\*2)
io.imshow(edge\_p);





# Roberts and Sobel Filters

Figure 9.21: Results of the Roberts and Sobel filters



(a) Roberts edge detection



(b) Sobel edge detection



## Roberts and Sobel Filters

Figure 9.22: Results of the Roberts and Sobel filters in Python



(a) Roberts edge detection



(b) Sobel edge detection



# Laplacian Filter

#### Laplacian

- The sum of second derivatives in both directions
- Isotropic filter: invariant under rotation
- Extremely sensitive to noise

$$\left[ egin{array}{cccc} 0 & 1 & 0 \ 1 & -4 & 1 \ 0 & 1 & 0 \ \end{array} 
ight]$$

Discrete Laplacian Filter



Figure 9.24: Result after filtering with a discrete Laplacian



# Laplacian Filter

#### Laplacian

- The sum of second derivatives in both directions
- Isotropic filter: invariant under rotation
- Extremely sensitive to noise

$$\left[ egin{array}{cccc} 0 & 1 & 0 \ 1 & -4 & 1 \ 0 & 1 & 0 \ \end{array} 
ight]$$

Discrete Laplacian Filter



Figure 9.24: Result after filtering with a discrete Laplacian



# Laplacian Filter

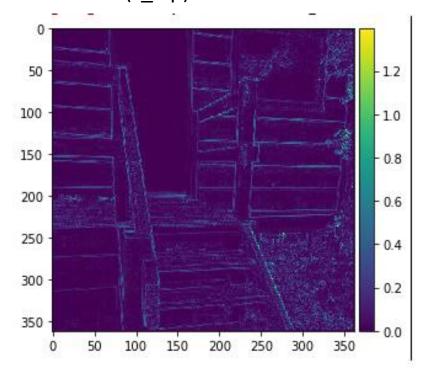
#### MatLab/Octave:

lap = fspecial('laplacian', 0)
s\_lap = imfilter(s, lap);
imshow(s\_lap);



#### Python: ????

import skimage.util as ut
s2 = ut.img\_as\_float(s)imshow(s\_lap)
s\_lap = abs(fl.laplace(s2))
io.imshow(s\_lap)





## The Canny Edge Detector

Canny designed his method to meet 3 criteria for edge detection:

- Low error rate of detection. (It should find ALL edges, and only edges)
- Localization of edges. (Distance between actual edges in the image and edges found by this algorithm should be minimized)
- Single response. (Algorithm should not return multiple edge pixels when only a single edge exists)



# The Canny Edge Detector

#### MatLab/Octave:

sc = edge(s, 'canny');
imshow(sc)



#### **Python:**

import skimage.feature as ft
sc = ft.canny(s)
io.imshow(sc)

