

Computer Vision

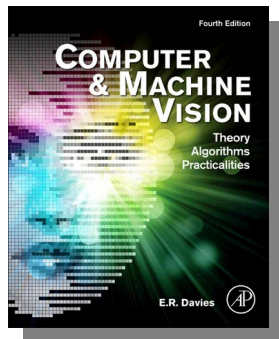
Gustavo Teodoro Laureano

gustavo@inf.ufg.br

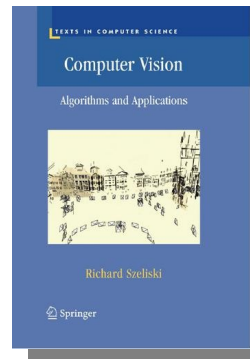
Programa de Pós-Graduação em Ciência da Computação
Instituto de Informática – Universidade Federal de Goiás

- Thresholding
 - Global and Local Methods
- Hough Transform

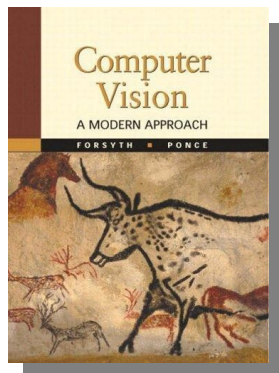
- Many of the words of this course are taken from the books:



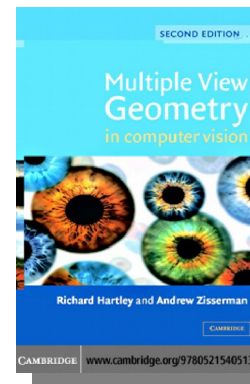
Computer & Machine Vision – Theory, Algorithms, Practicalities.
Fourth Edition, 2012. Elsevier Inc.
E. Roy Davies



Computer Vision – Algorithm and Applications.
2010. Springer.
Richard Szeliski



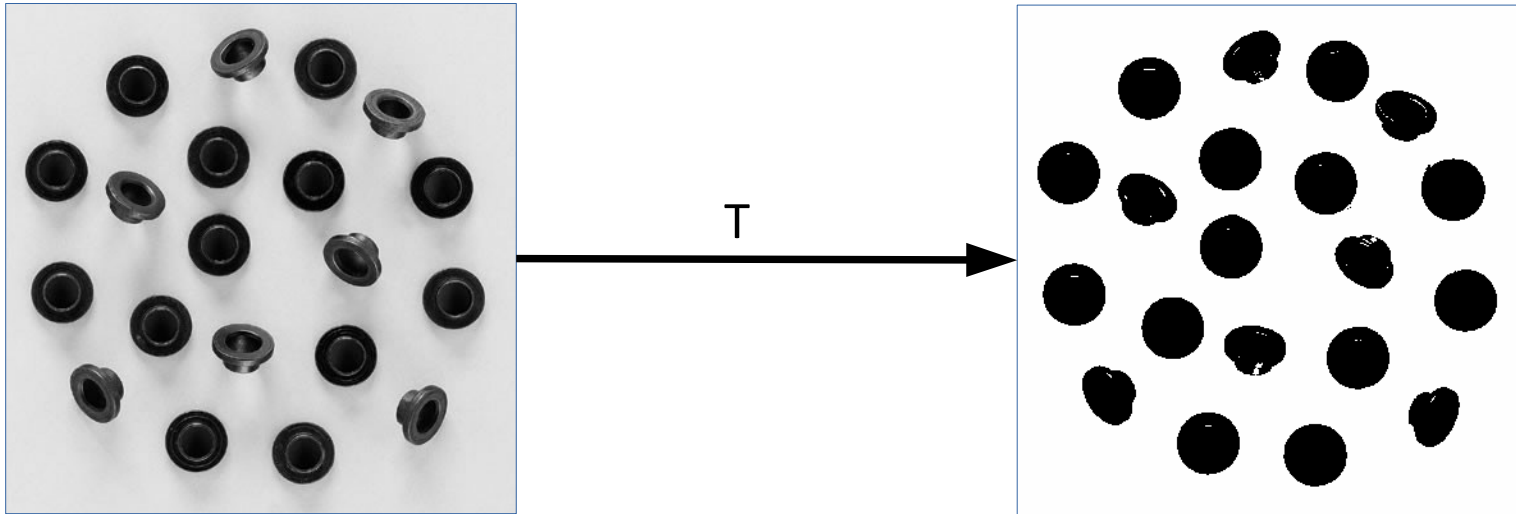
Computer Vision – A modern Approach.
2003. Prentice Hall.
David Forsyth and Jean Ponce



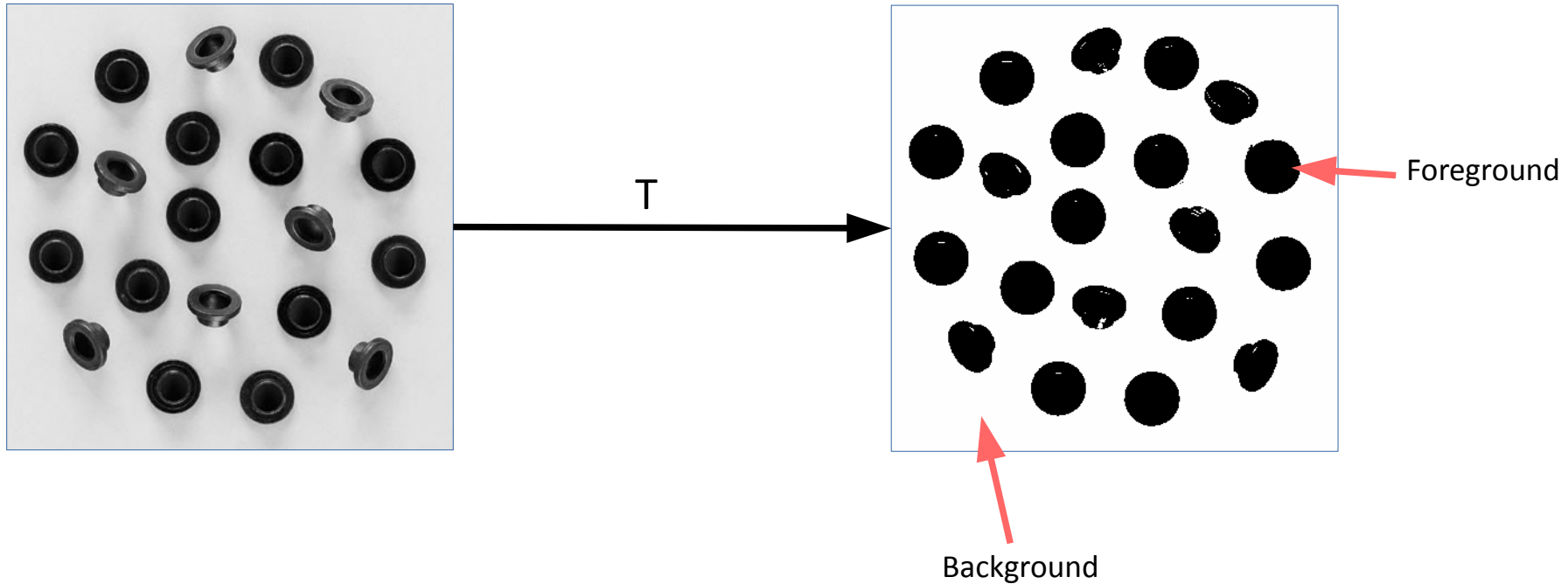
Multiple View Geometry.
Second Edition, 2012. Cambridge.
Richard Hartley & Andrew Zisserman

Image Binarization

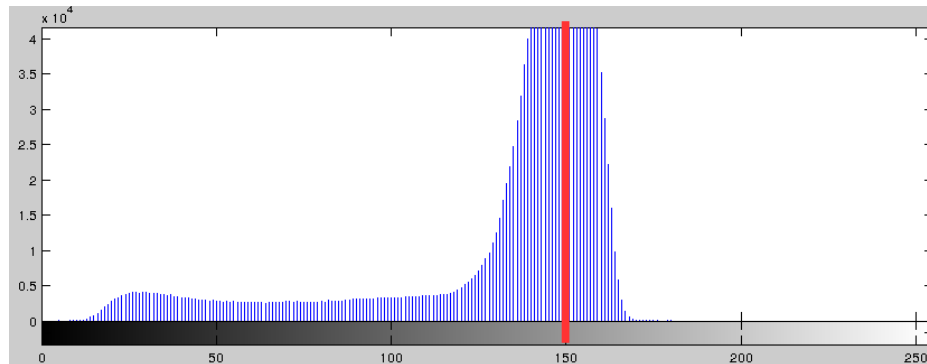
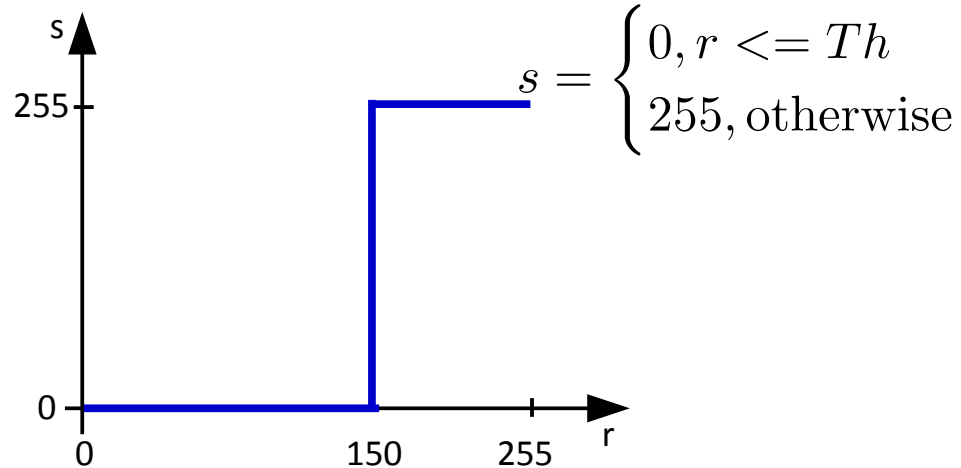
- Image Thresholding ...



- Image Thresholding ...



- Manual Thresholding

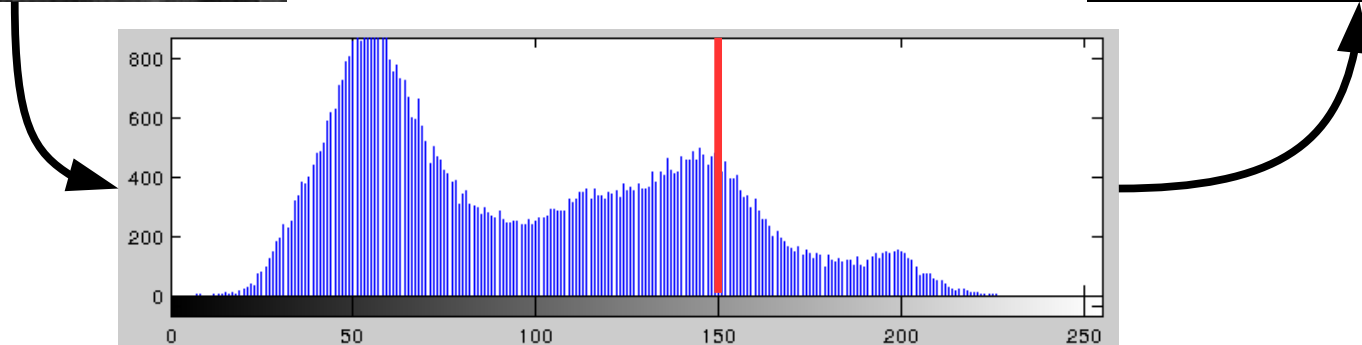
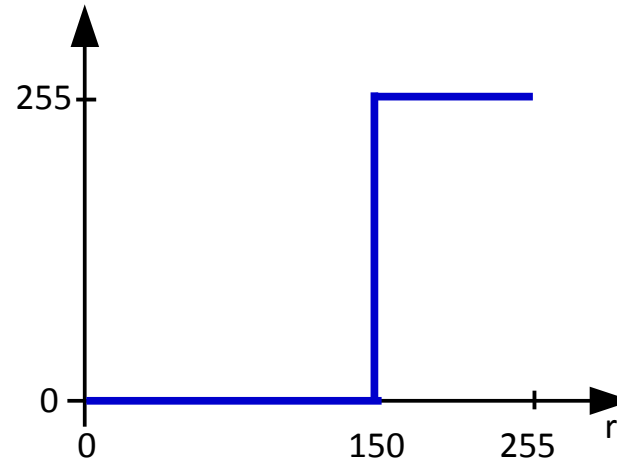


ponents or broken connection paths. There is no position past the level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in computer vision. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, considerable effort must be taken to improve the probability of rugged segmentation. In applications such as industrial inspection applications, at least some degree of ruggedness in the environment is possible at times. The experienced image designer invariably pays considerable attention to such factors.

Segmentation of nontrivial images is one of the most difficult tasks in computer vision. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, considerable effort must be taken to improve the probability of rugged segmentation. In applications such as industrial inspection applications, at least some degree of ruggedness in the environment is possible at times. The experienced image designer invariably pays considerable attention to such factors.

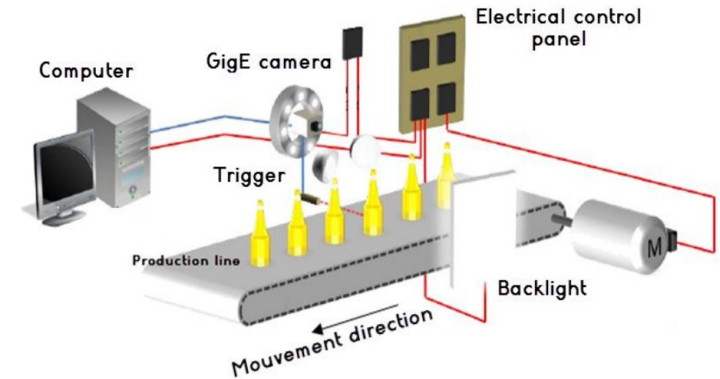
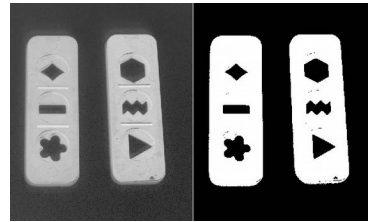
- Manual Thresholding



- When use an empirical threshold value?
 - In controlled conditions, an empirical threshold may be usefully.
 - Illumination, Noise, Background must be known.
 - When the two distributions are reasonably well separated:
 - some overlap between classes but not too much.

- Examples:

- Industry
 - Assembly-line
 - Visual Inspection
- Off-the-shelf products
 - Xerox machines
 - Optical Readers
 - QR Code Readers

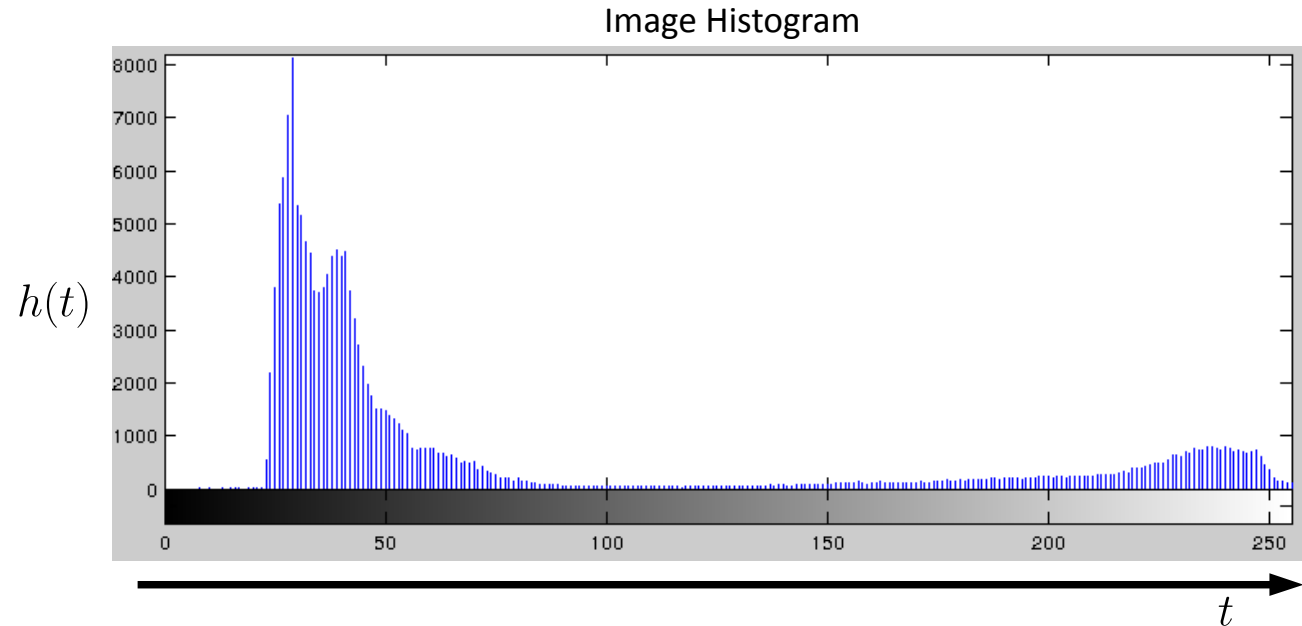


- Adaptive Thresholding:
 - Global Methods
 - Local Methods
- In both there is the question: **What the Best Threshold Value?**

- What the Best Threshold Value for this image?



Grayscale Image

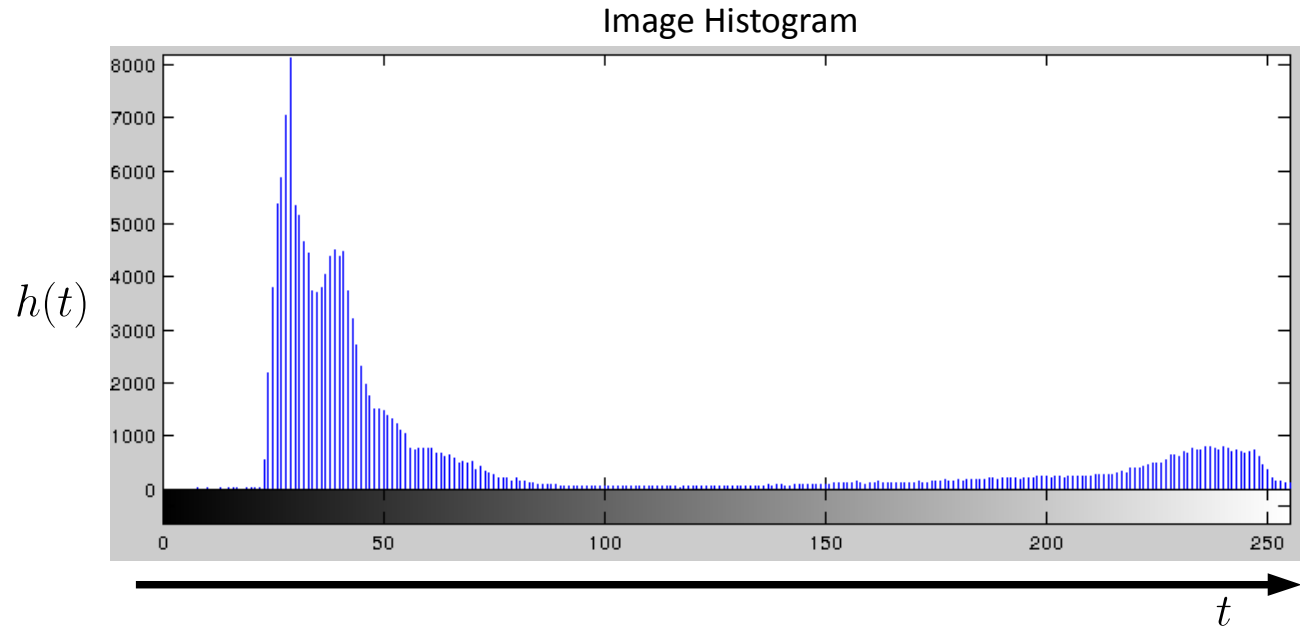


- How to compute histogram?

```
function [ h ] = histogram( I )
    h = zeros(1,256);
    for i = 1 : length( I(:) )
        h( I(i)+1 ) = h( I(i)+1 ) + 1;
    end
end
```

or

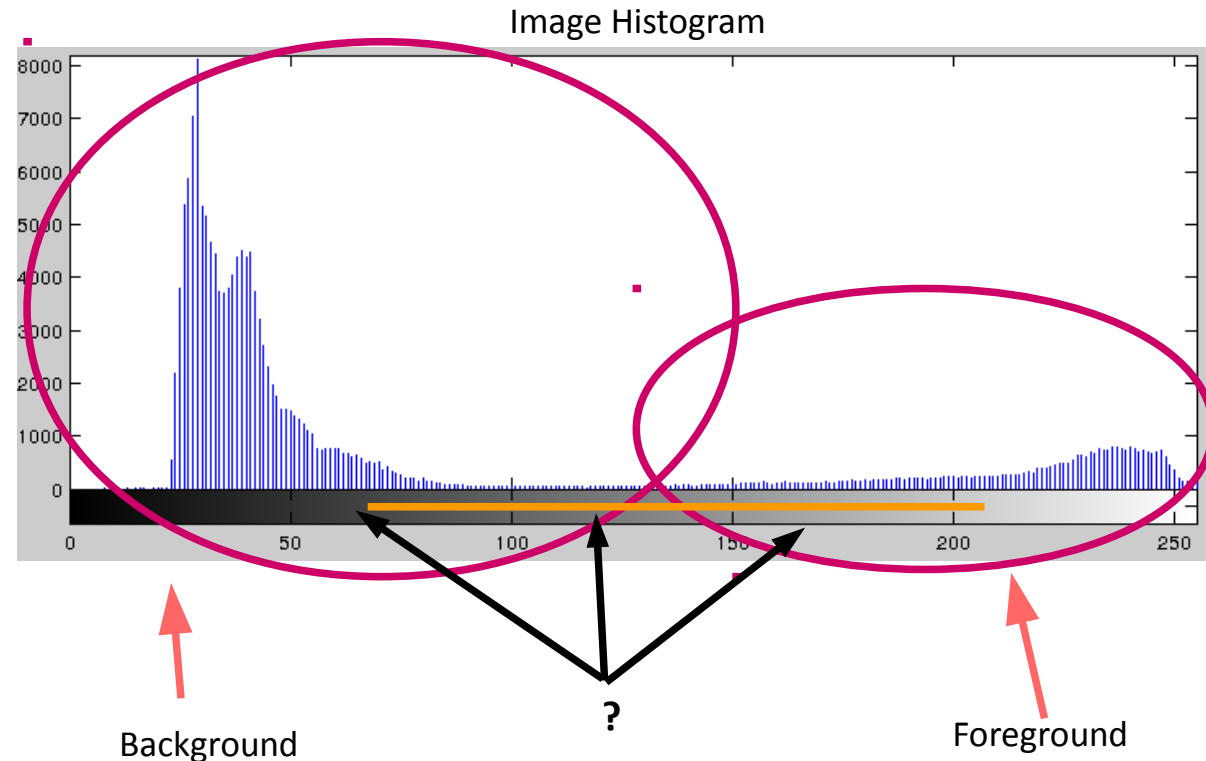
```
h = imhist( I );
```



- What the Best Threshold Value for this image?

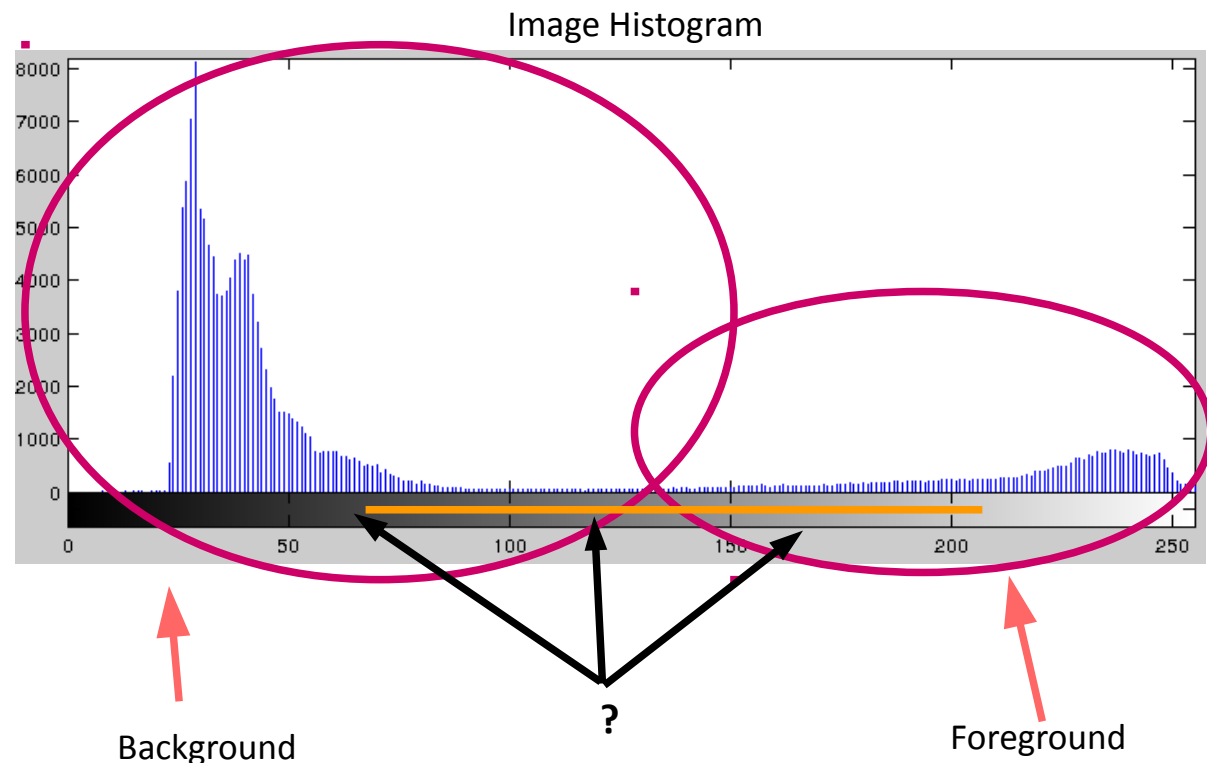
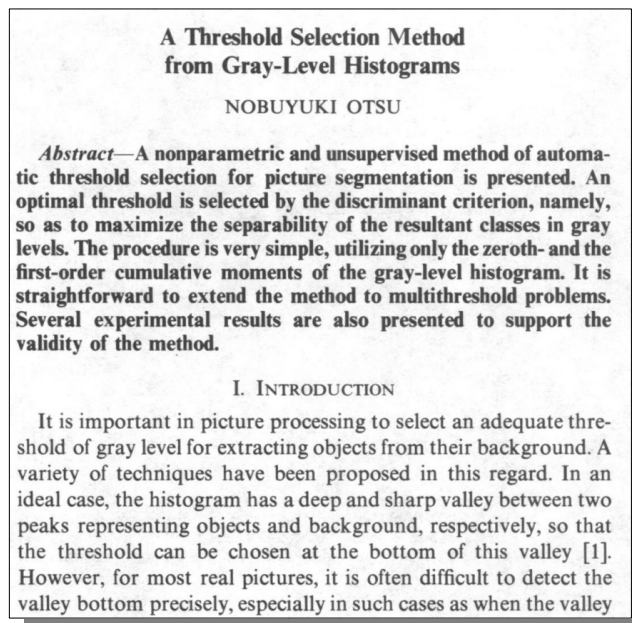


Grayscale Image



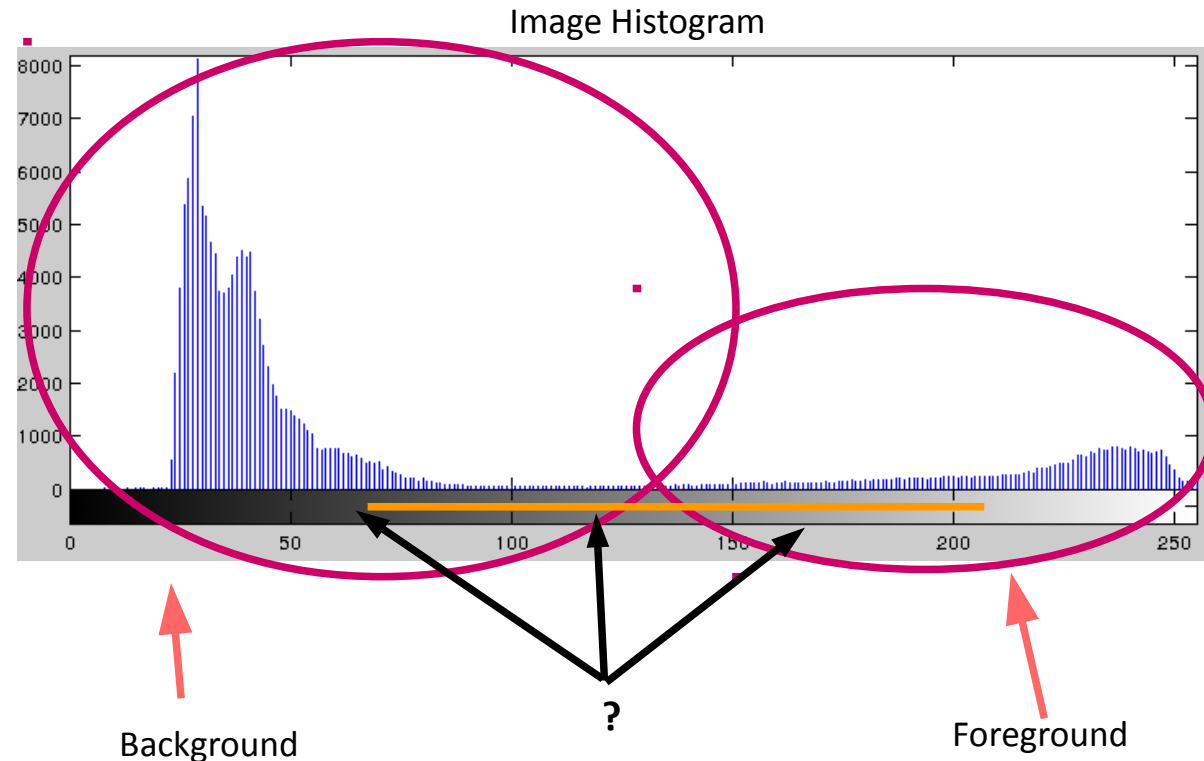
- What the Best Threshold Value for this image?

- Otsu 's Method



OTSU, N. 1979. *A Threshold Selection Method from Gray-Level Histograms*. IEEE Transactions On Systems, MAN, And Cybernetics, Vol. Smc-9, No. 1, January 1979

- What the Best Threshold Value for this image?
 - Otsu 's Method
 - Exhaustive search for Th that:
 - Minimize intra-class variance (within class variance)
 - or
 - Maximize inter-class variance (between class variance)



- What the Best Threshold Value for this image?

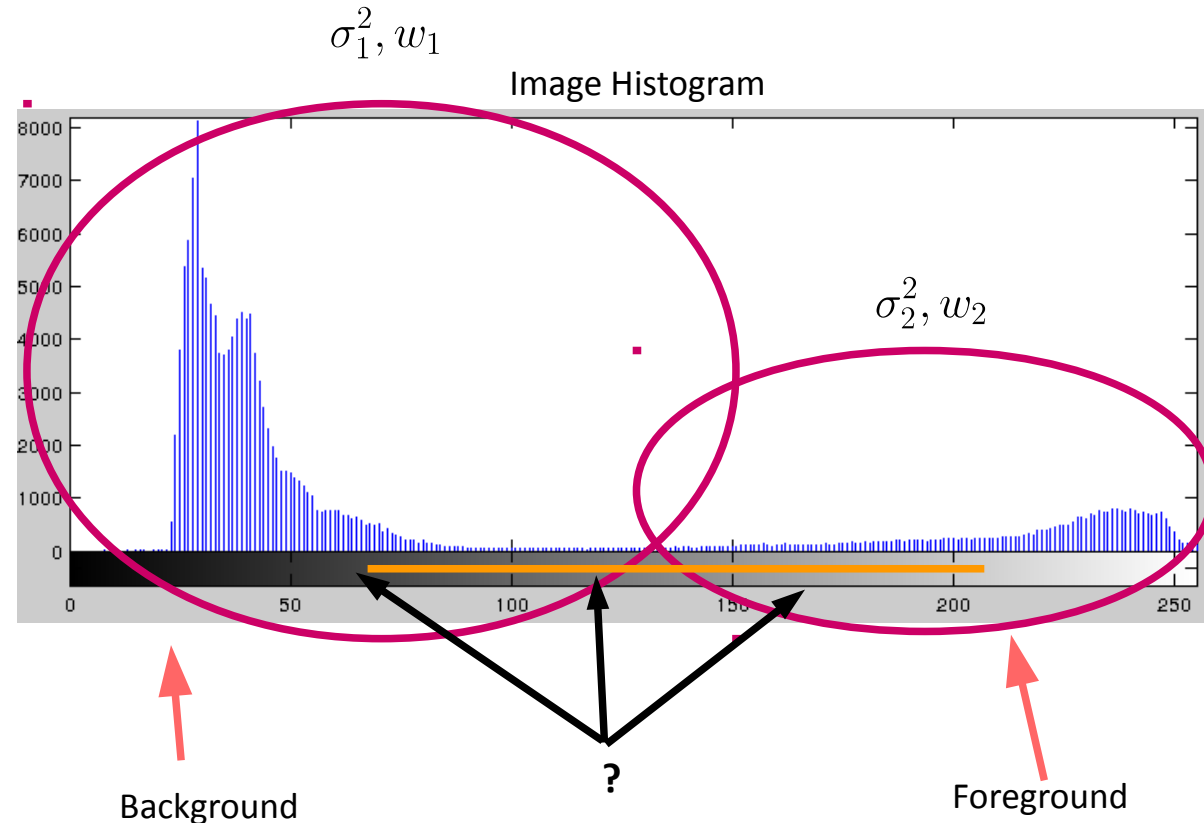
- Otsu 's Method
- Exhaustive search for Th that:
 - Minimize intra-class variance (within class variance)
 - or
 - Maximize inter-class variance (between class variance)

σ_1^2 : background variance

σ_2^2 : foreground variance

w_1 : background weight

w_2 : foreground weight



- What the Best Threshold Value for this image?

- Intra-class variance (within):

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t)$$

where:

$\sigma_1^2(t)$: background variance

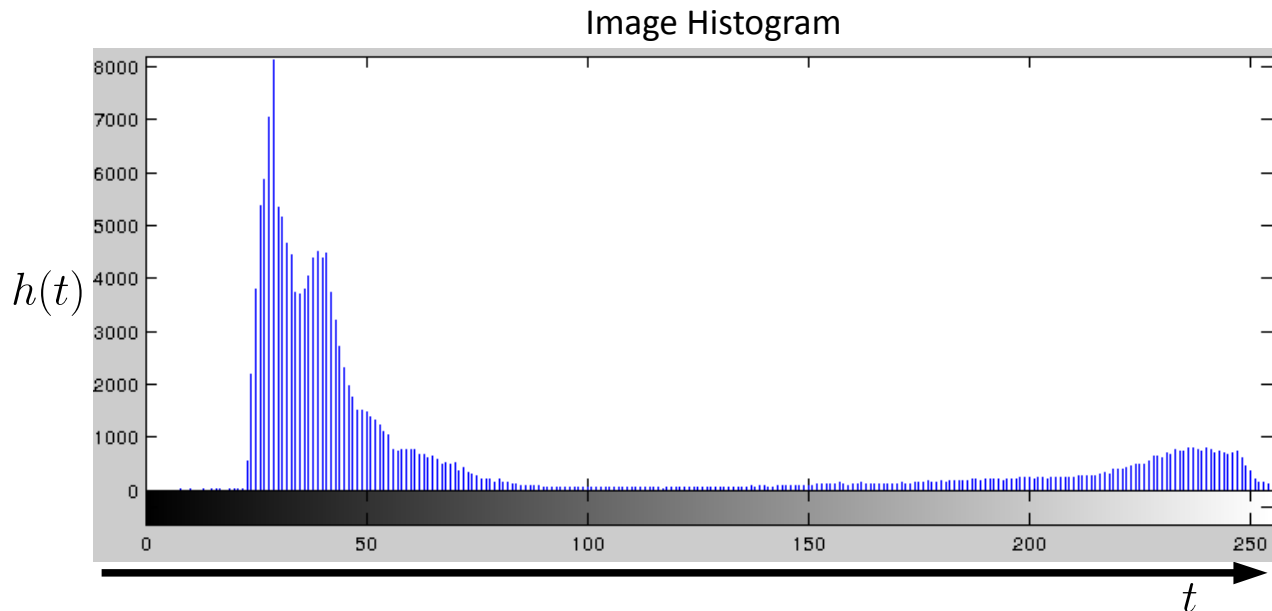
$\sigma_2^2(t)$: foreground variance

$w_1(t)$: background weight

$w_2(t)$: foreground weight

- Otsu 's Method:

$$\arg \min_t \sigma_w^2(t)$$



- What the Best Threshold Value for this image?

- Intra-class variance (within):

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t)$$

- Inter-class variance (between):

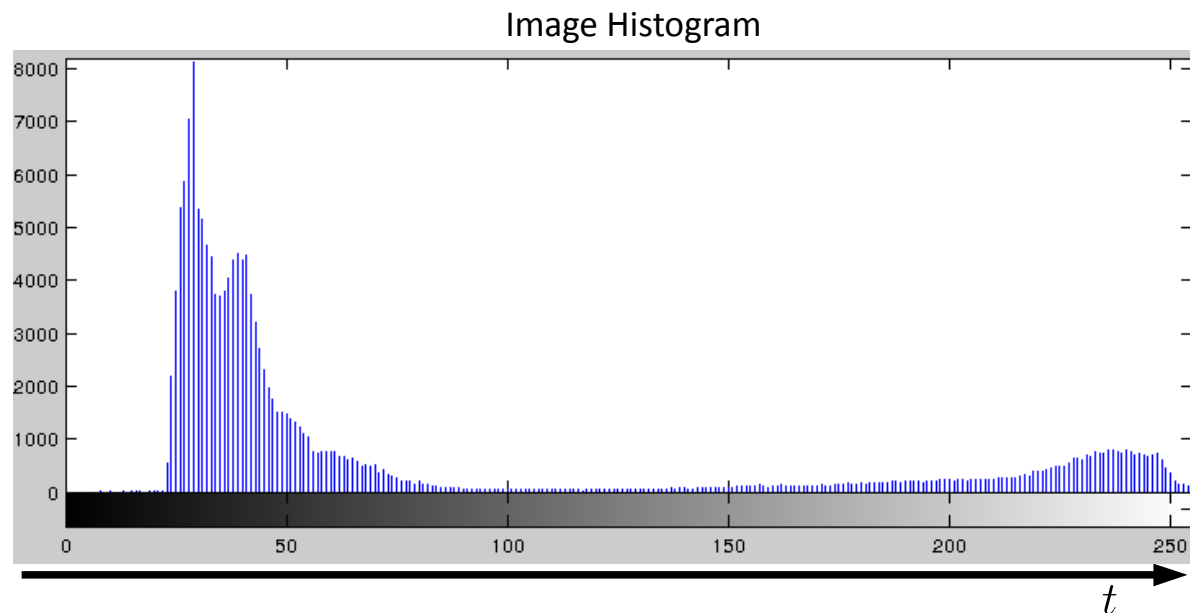
$$\begin{aligned}\sigma_b^2 &= \sigma^2 - \sigma_w^2 \\ &= w_1(\mu_1 - \mu) + w_2(\mu_2 - \mu)\end{aligned}$$

$$= w_1w_2(\mu_1 - \mu_2)^2$$

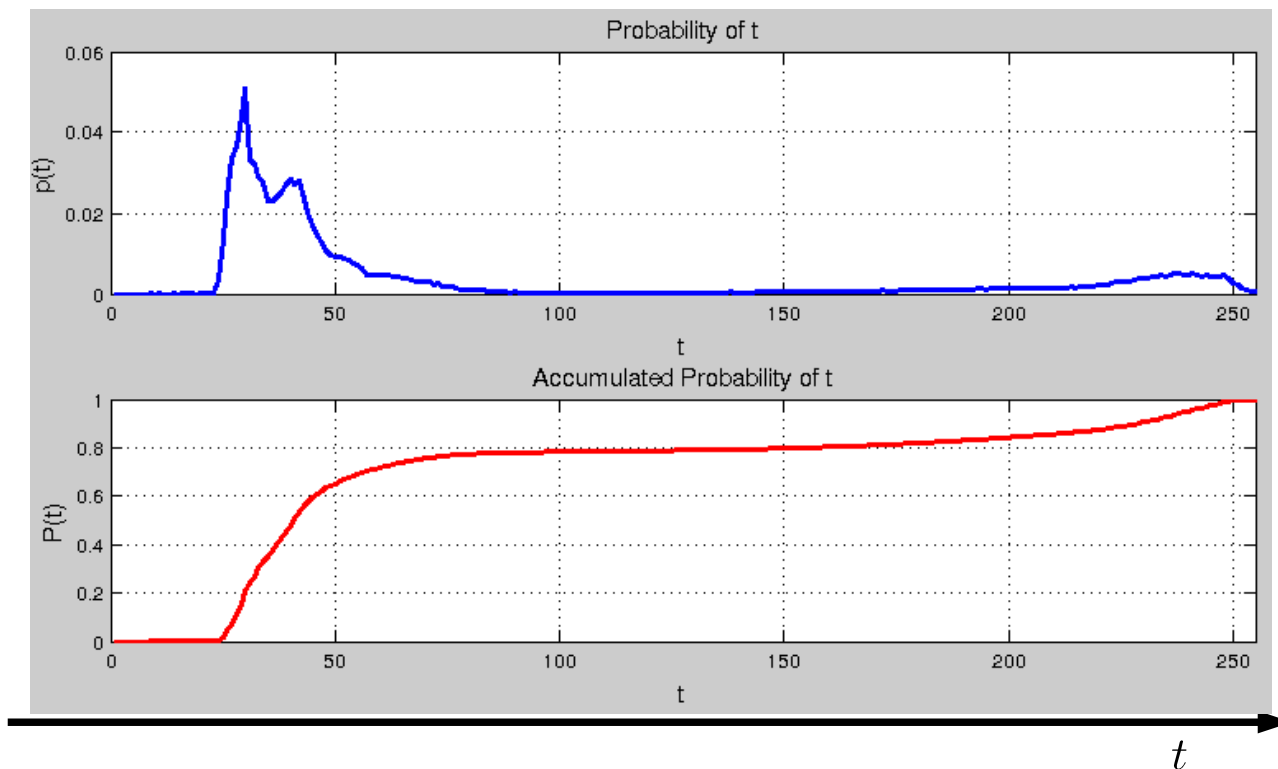
$$\text{where } \mu = w_1\mu_1 + w_2\mu_2$$

- Otsu 's Method:

$$\arg \min_t \sigma_w^2(t) \Leftrightarrow \arg \max_t \sigma_b^2(t)$$



- Otsu 's Method:



- What the Best Threshold Value for this image?

- Otsu's Algorithm $\arg \min_t \sigma_w^2(t) \Leftrightarrow \arg \max_t \sigma_b^2(t)$

$$\begin{aligned}\sigma_b^2 &= \sigma^2 - \sigma_w^2 \\ &= w_1(\mu_1 - \mu)^2 + w_2(\mu_2 - \mu)^2 \\ &= w_1 w_2 (\mu_1 - \mu_2)^2\end{aligned}$$

where $\mu = w_1 \mu_1 + w_2 \mu_2$

- Probability of t: $p(t) = \frac{h(t)}{WH}$

- Weights:

$$w_1(t) = \sum_{i=0}^t p(i) = P(t)$$

- Accumulated Probability $w_2(t) = \sum_{i=t+1}^{L-1} p(i) = P(L-1) - P(t)$

$$P(t) = \sum_{i=0}^t p(i)$$

- Otsu 's Method:

// Total number of pixels

```
int total = W*H;
```

// Calculate histogram

```
for (int t=0 ; t< 256 ; t++) hist[t]=0;
```

```
for (int i=0 ; i< total ; i++) hist[ data[i] ]++;
```

// Calculate total sum

```
float sum = 0;
```

```
for (int t=0 ; t<256 ; t++) sum += t * hist[t];
```

```
float sumB = 0;
```

```
int w1 = 0;
```

```
int w2 = 0;
```

```
float varMax = 0;
```

```
char threshold = 0;
```

```
for (int t=0 ; t<256 ; t++) {
```

```
    w1 += histData[t];           // Weight Background
```

```
    if (w1 == 0) continue;
```

```
    w2 = total - w1;           // Weight Foreground
```

```
    if (w2 == 0) break;
```

```
    sum1 += (float) (t * histData[t]);
```

```
    float m1 = sum1 / w1;       // Mean Background
```

```
    float m2 = (sum - sum1) / w2; // Mean Foreground
```

// Calculate Between Class Variance

```
float varBetween = (float)w1 * (float)w2 * (m1 - m2) * (m1 - m2);
```

// Check if new maximum found

```
if (varBetween > varMax) {
```

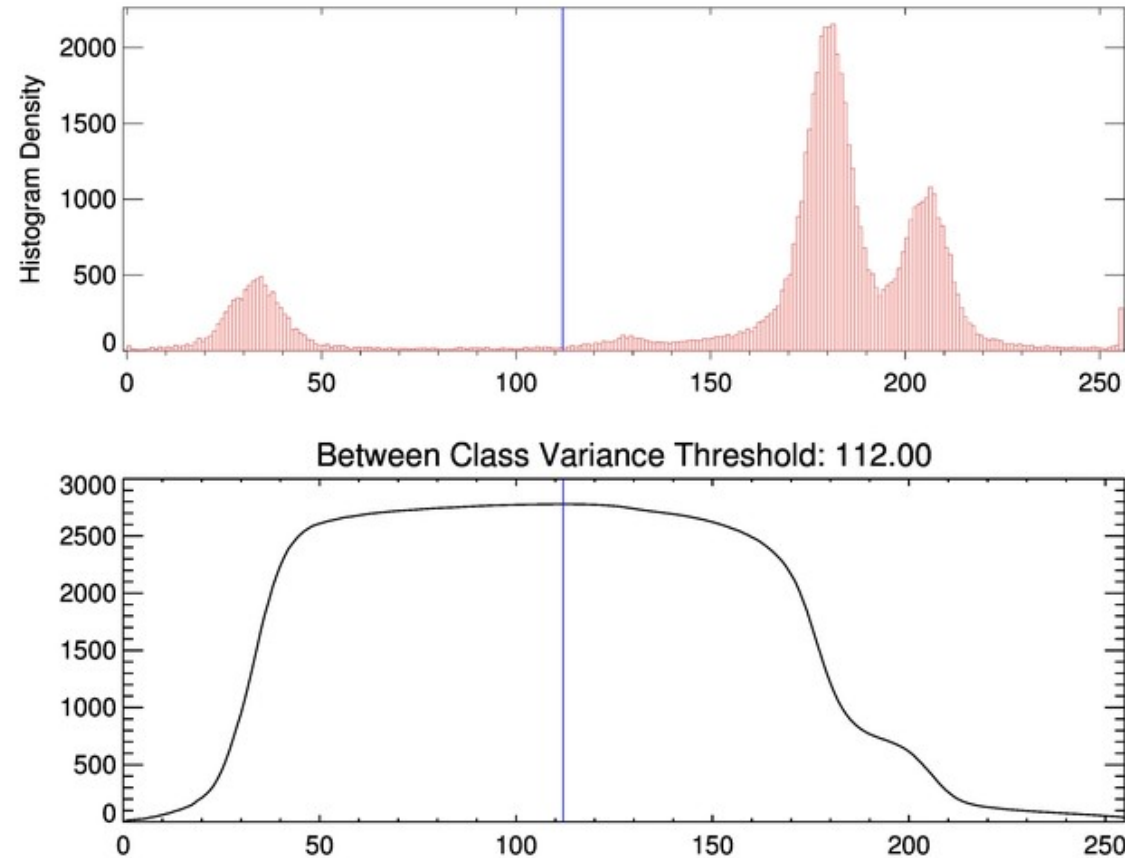
```
    varMax = varBetween;
```

```
    threshold = t;
```

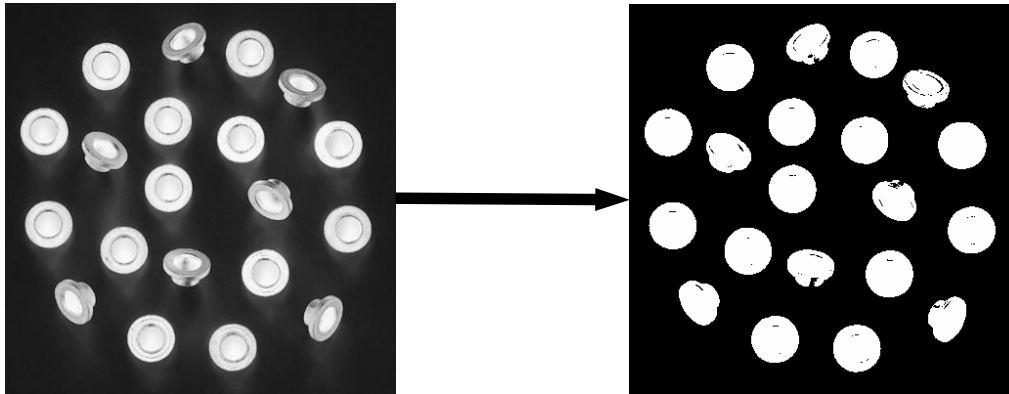
```
}
```

```
}
```

- Otsu 's Method:



- Otsu's Method:



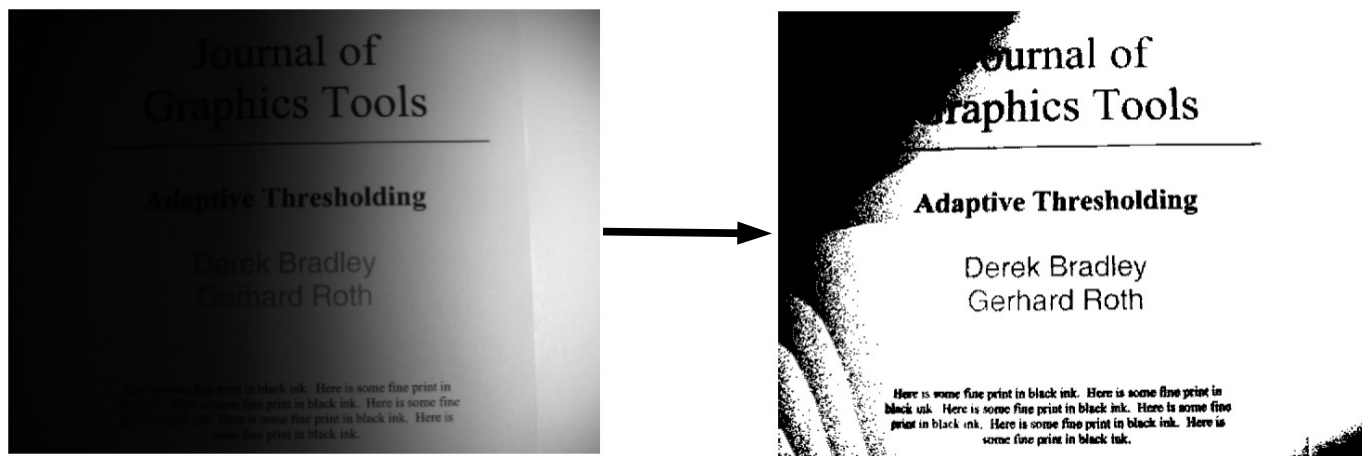
ponents or broken connection paths. There is no point in going past the level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, considerable effort can be taken to improve the probability of rugged segmentation, especially in applications such as industrial inspection applications, at least some of the time. The experienced designer invariably pays considerable attention to such

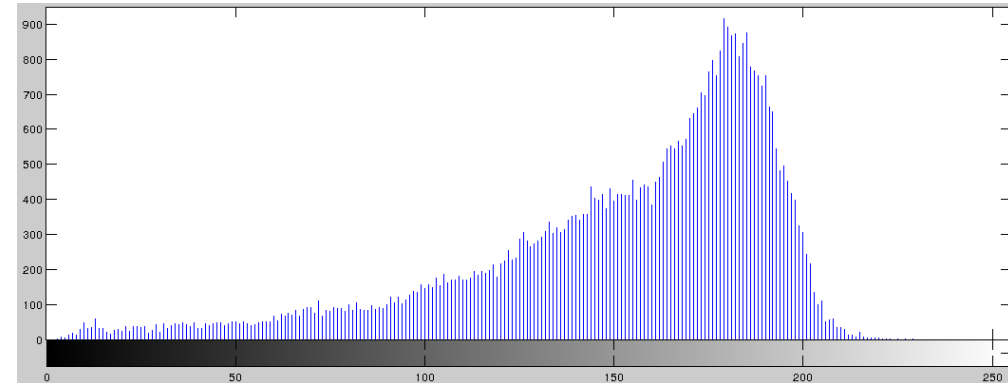
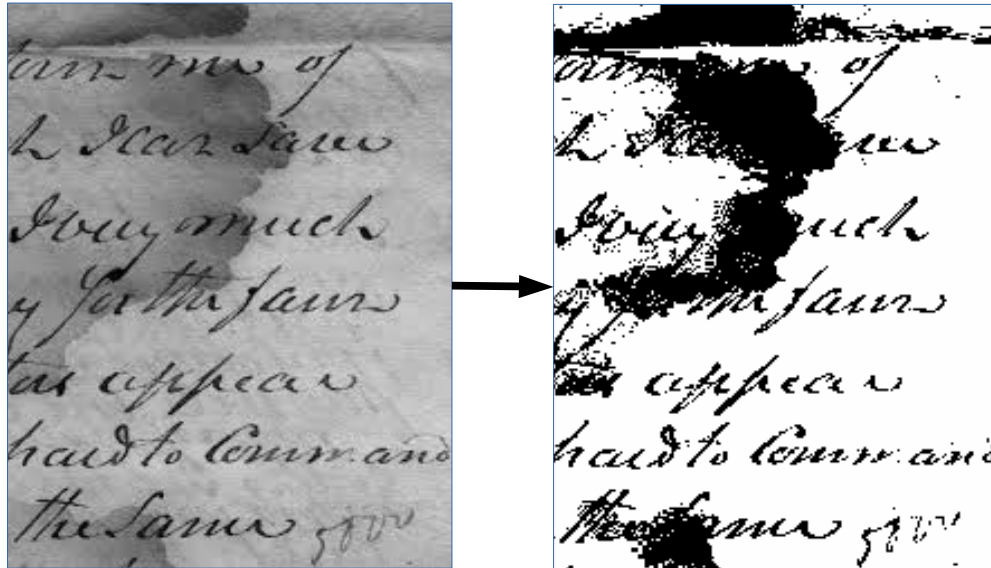
ponents or broken connection paths. There is no point in going past the level of detail required to identify those components.

Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the effectiveness of computerized analysis procedures. For this reason, considerable effort can be taken to improve the probability of rugged segmentation, especially in applications such as industrial inspection applications, at least some of the time. The experienced designer invariably pays considerable attention to such

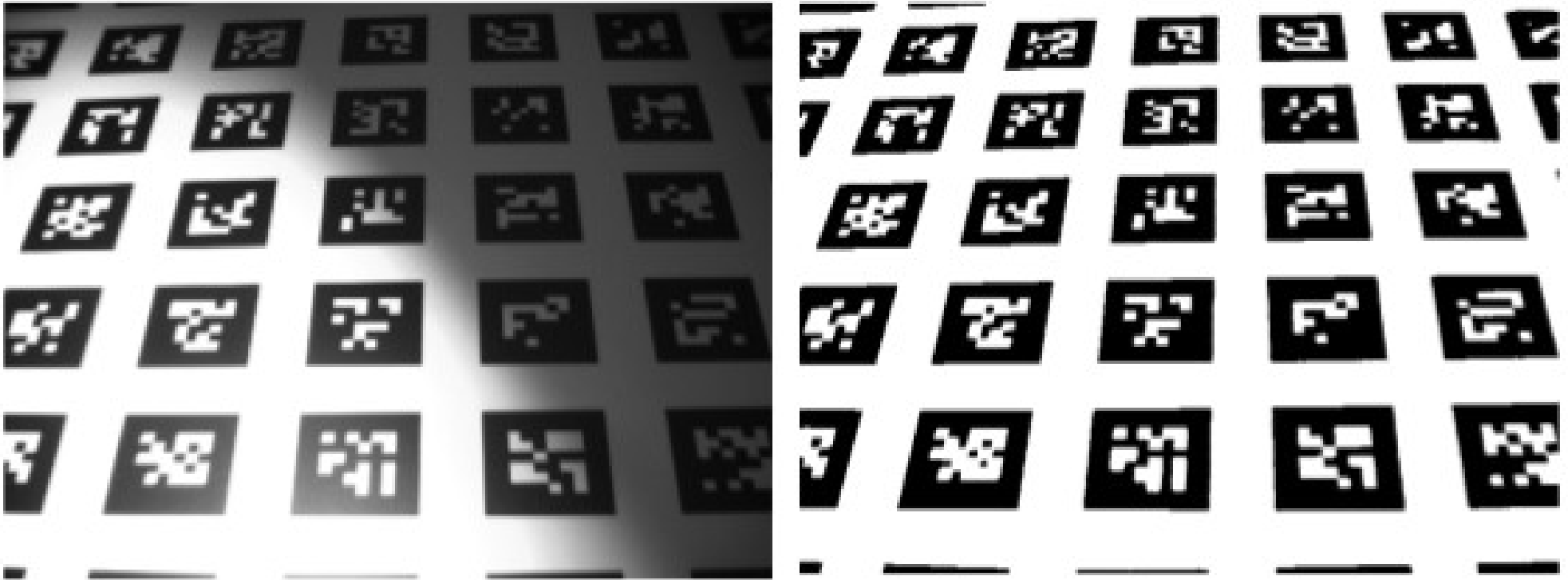
- Otsu's Method:



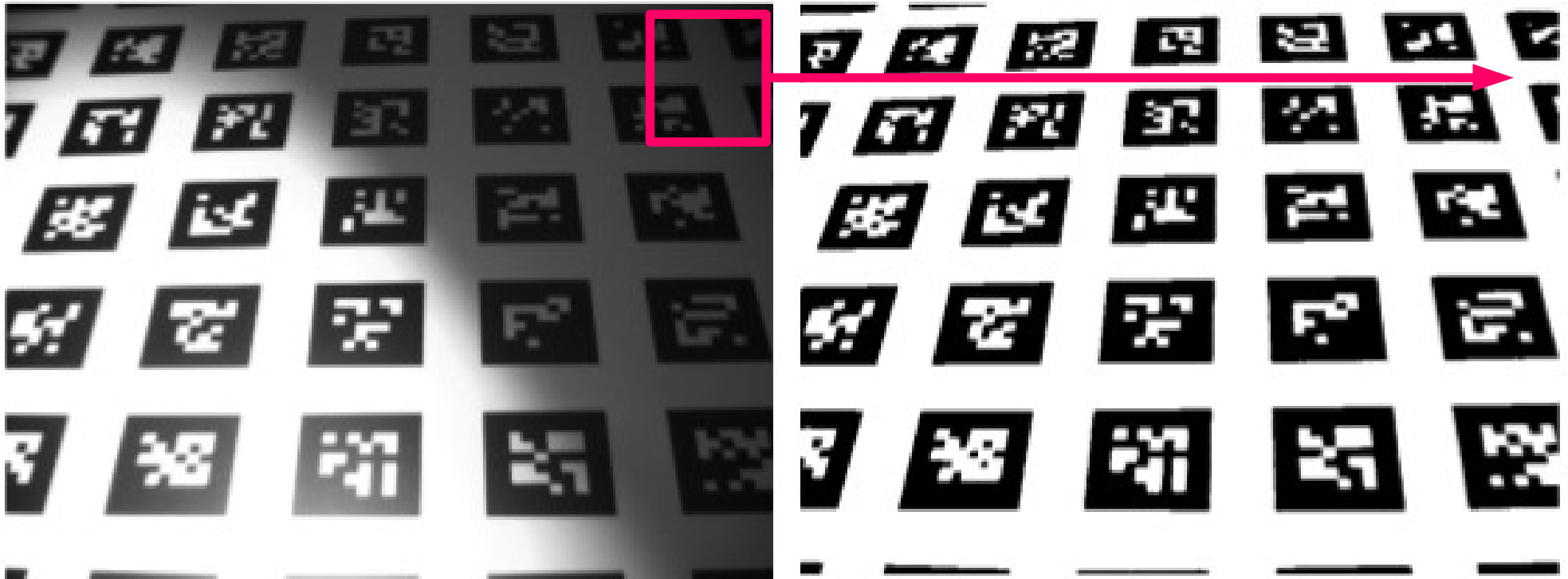
- Otsu's Method:



- Local Methods



- Local Methods



- Local Methods




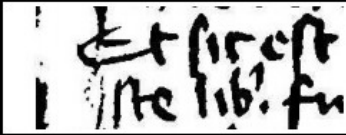


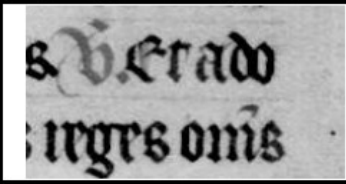
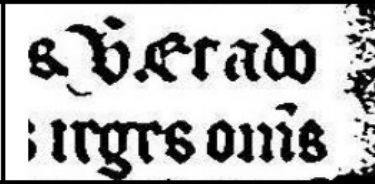
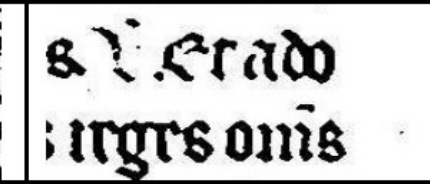




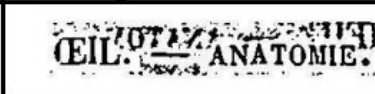

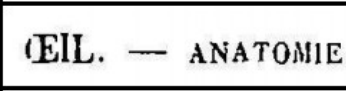
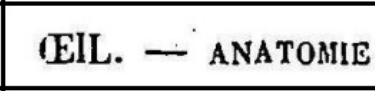
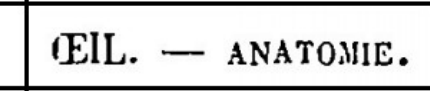
- Local Otsu

- Niblack's Algorithm $T_{Niblack} = \mu + k\sigma$

- Sauvola's Algorithm $T_{Sauvola} = \mu(1 - k(1 - \frac{\sigma}{R}))$

- How to measure accuracy of thresholding methods?

- How to measure accuracy of thresholding methods?
 - Visual

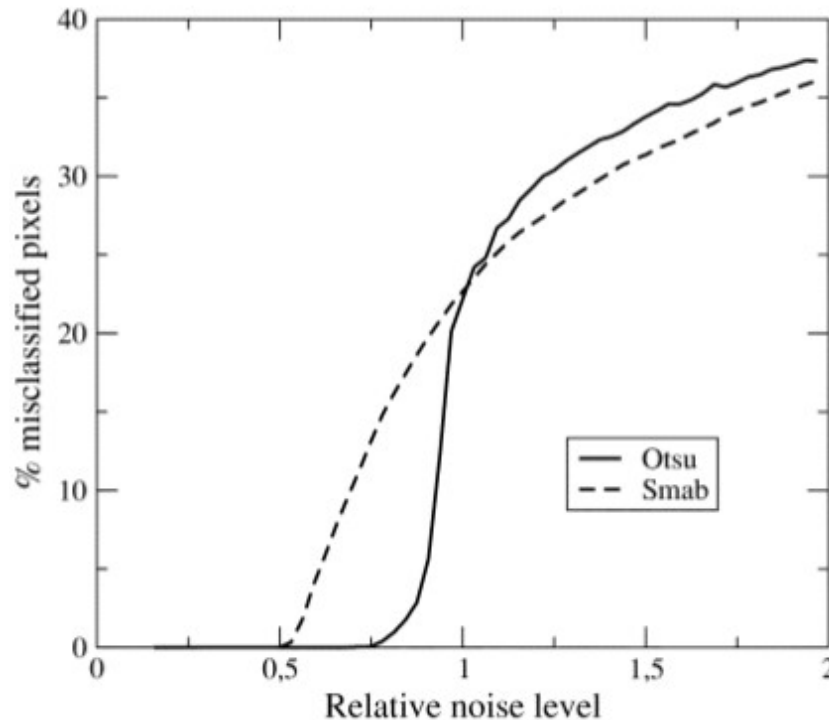
		
		
		
		
		
		

- How to measure accuracy of thresholding methods?
 - Influence in final results

Image	Total Characters	Number of characters correctly recognized				
		Niblack	Sauvola	Wolf	Feng	NICK
Image 1	2012	0	1907	2003	1932	2002
Image 2	944	887	0	821	938	940
Image 3	241	239	233	233	230	238
Image 4	364	0	356	354	344	363
Other 21 images	5446	2687	3783	4828	5364	5411
Total	9007	3813	6279	8239	8808	8954
RECG RATE		42.33	69.71	91.47	97.79	99.41

- How to measure accuracy of thresholding methods?
 - Using a ground truth image

- How to measure accuracy of thresholding methods?
 - Counting misclassified points after inject noise



Torbjørn Sund and Karsten Eilertsen (2003).
*An Algorithm for Fast Adaptive Image Binarization
With Applications in Radiotherapy Imaging*

Hough Transform

