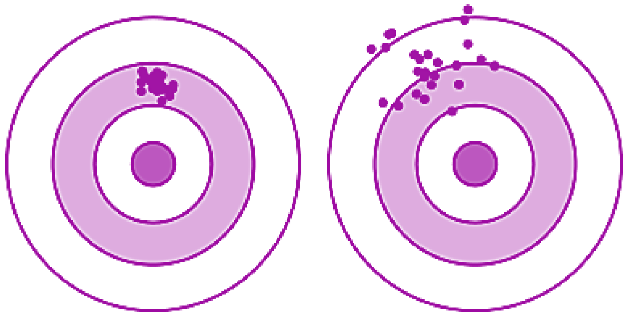
Segmentation:
Otsu’s method

Dr. Tushar Sandhan

Introduction

- Variance
  - intraclass
  - interclass



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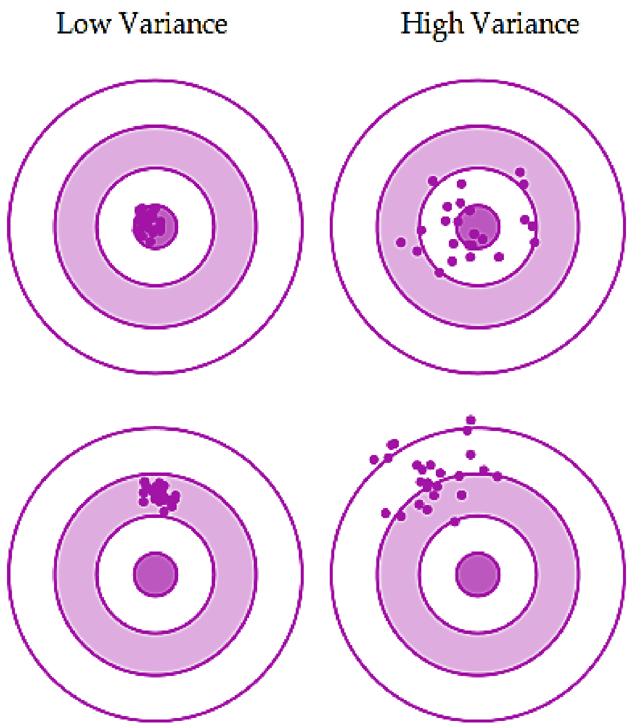

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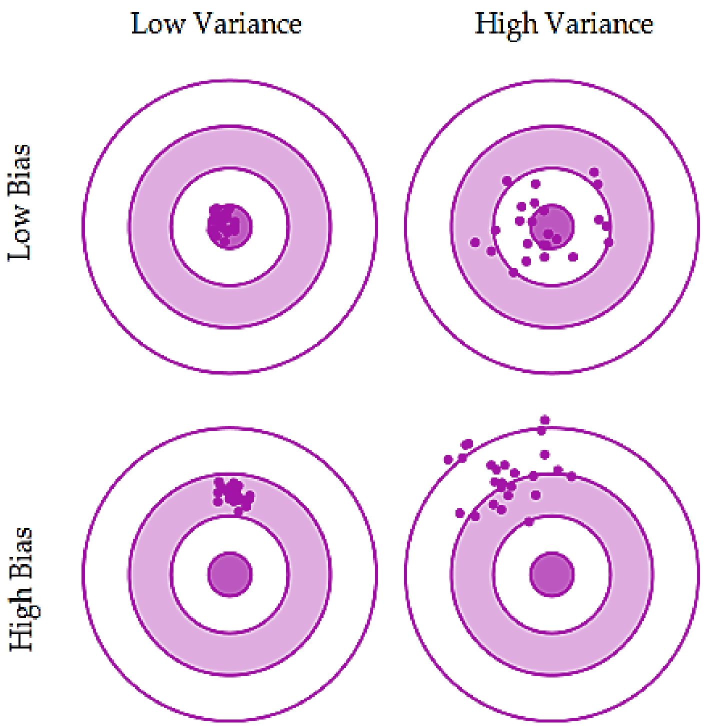

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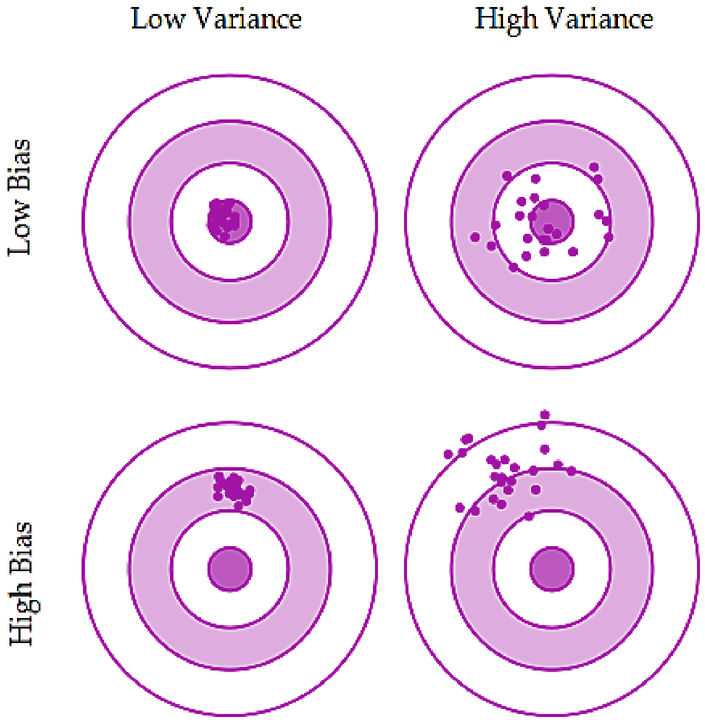

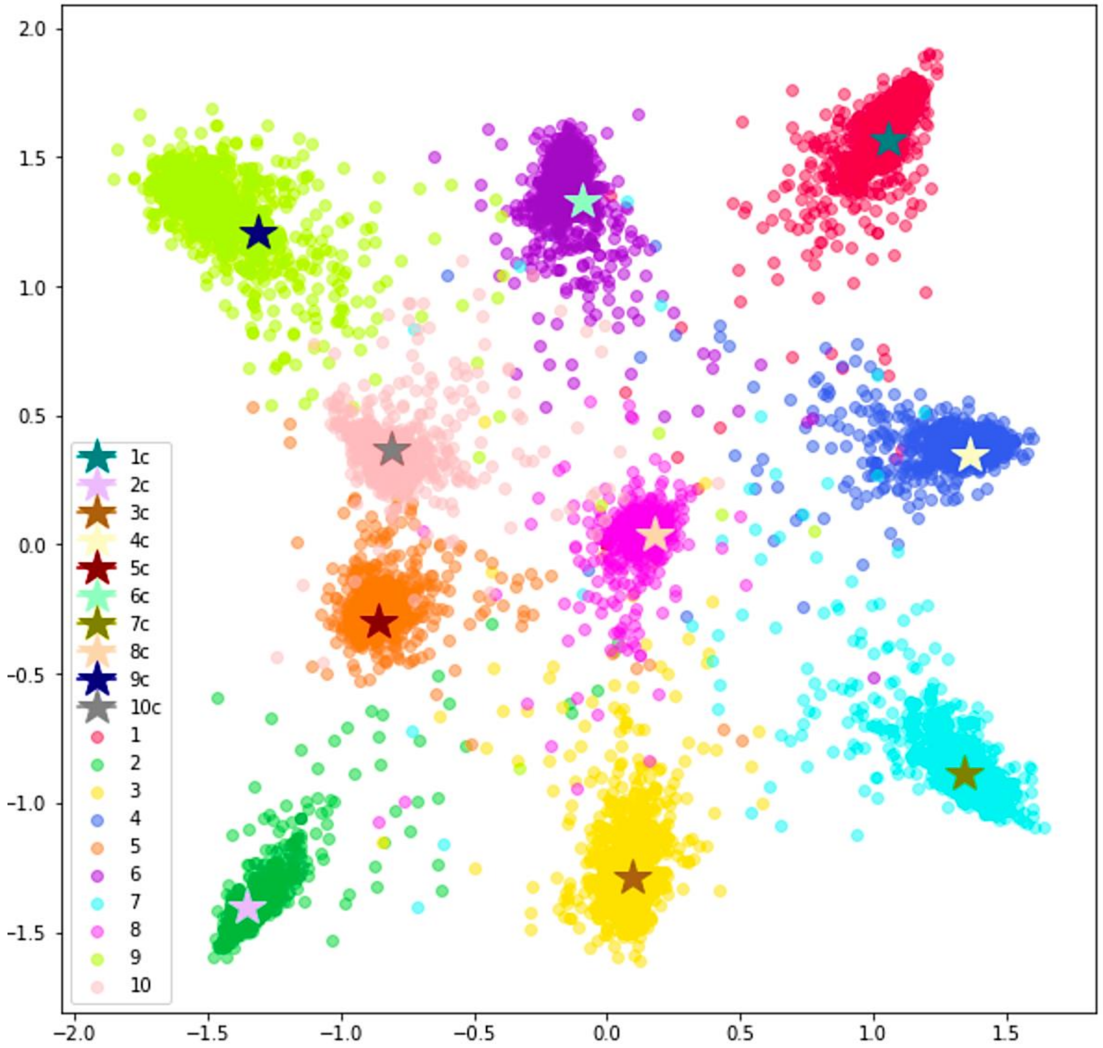

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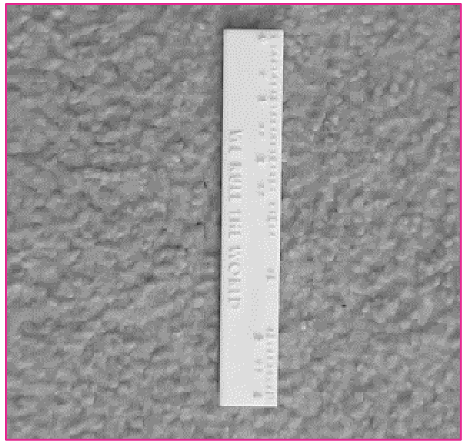

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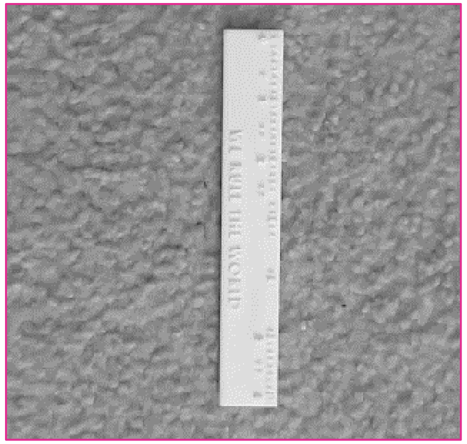

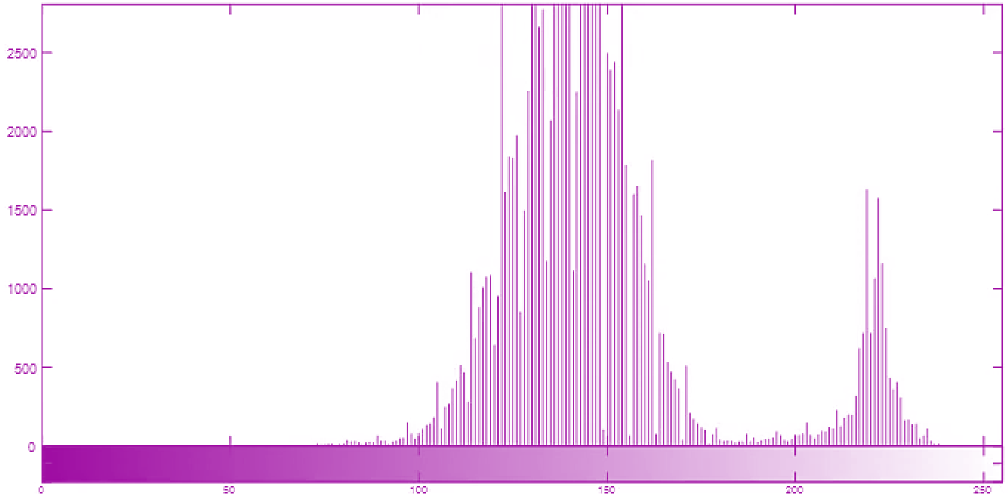

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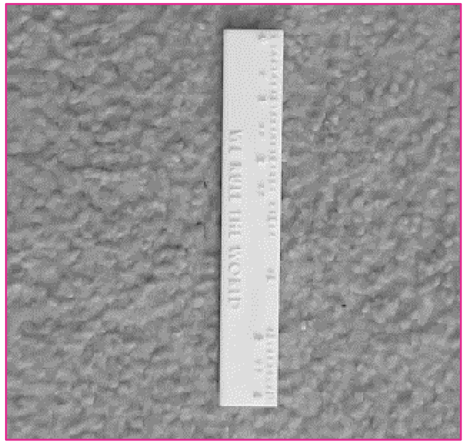

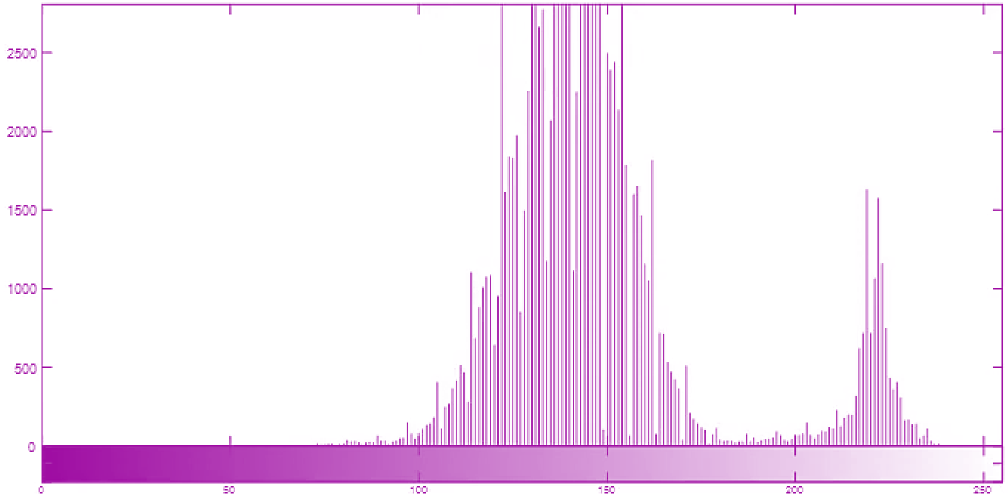

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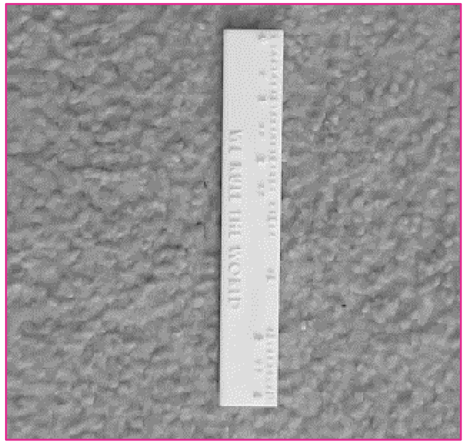
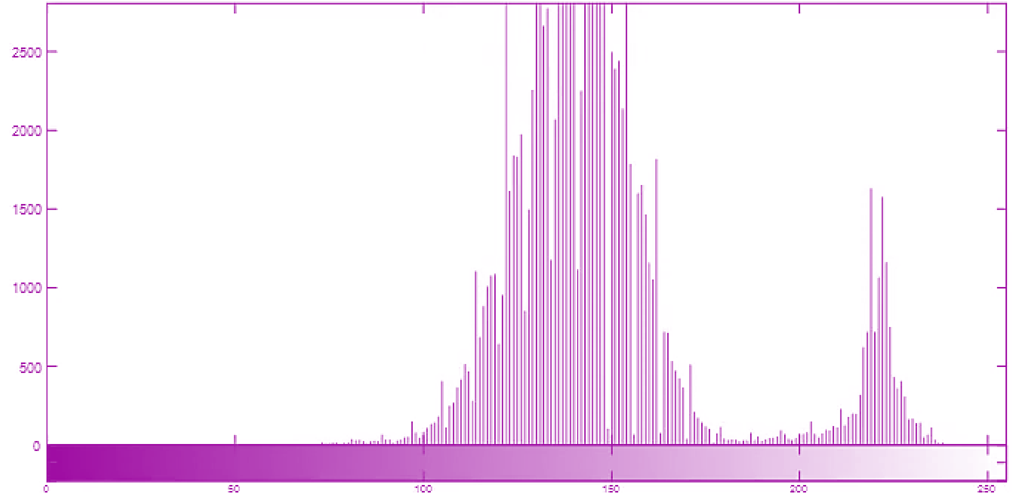
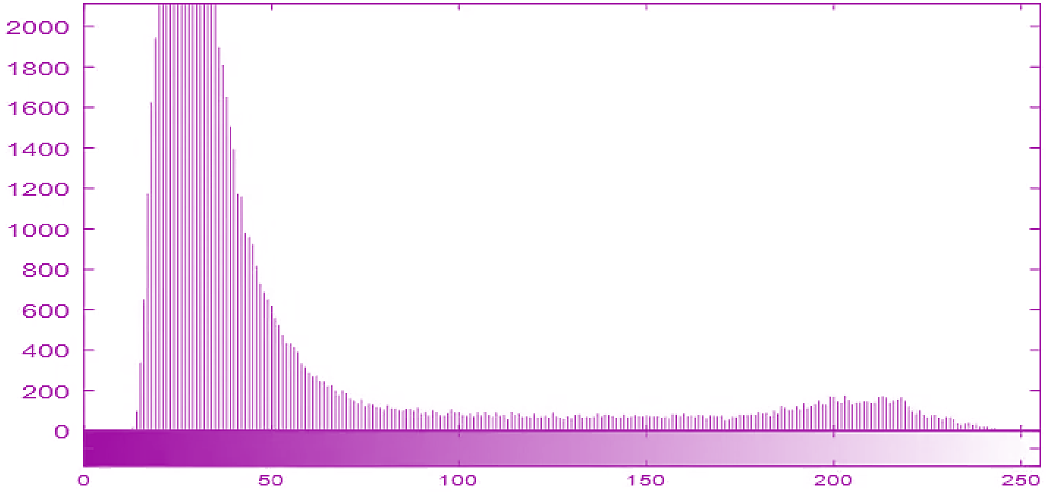
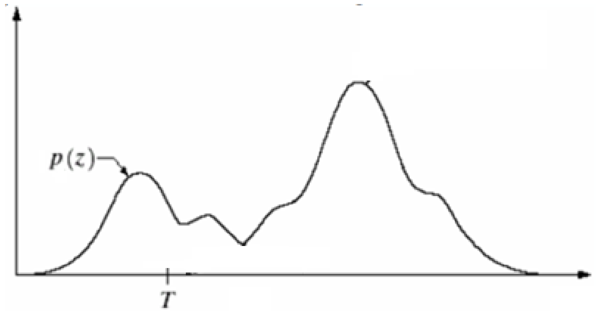






Otsu's thresholding

- Global: adaptive Otsu's threshold
  - exhaustively searches $\forall\, T$ that minimizes intra-class variance
  - min. intra-class var. is equivalent to max. inter-class var.



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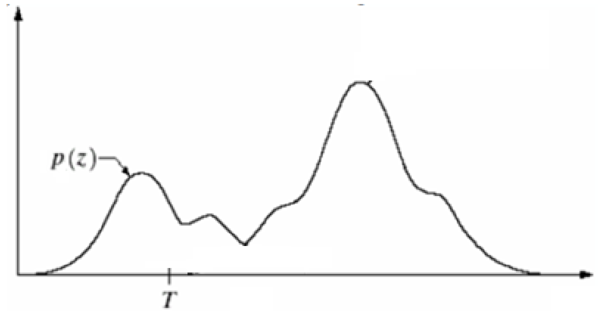

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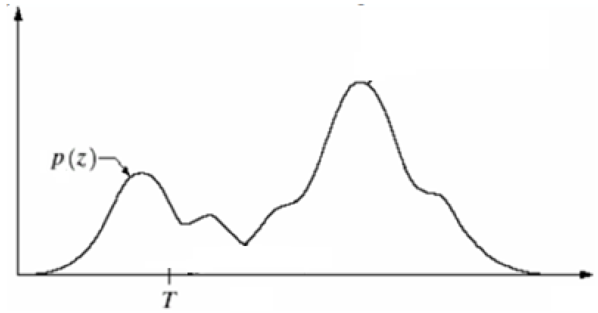

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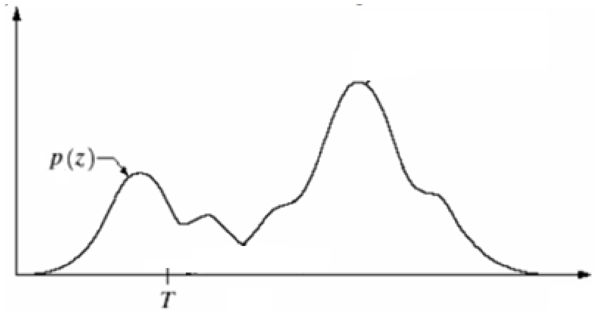

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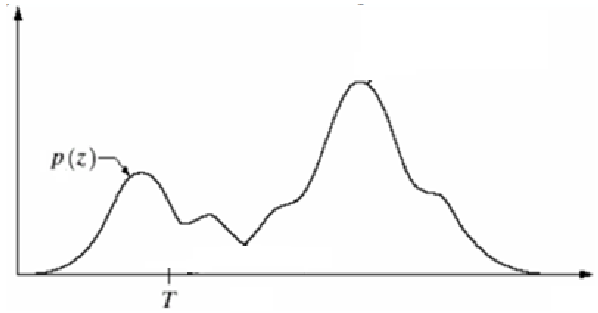

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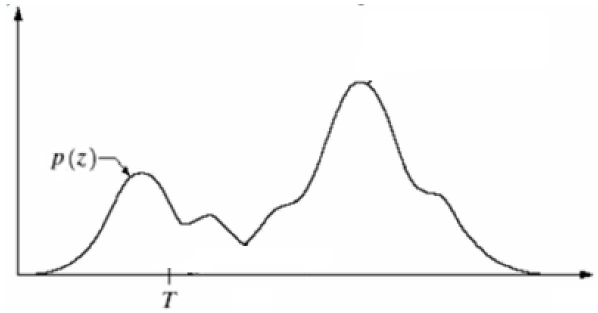

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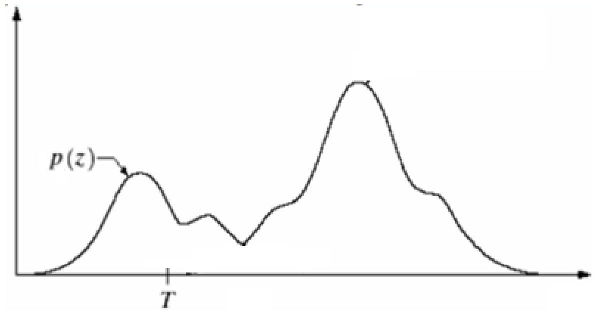

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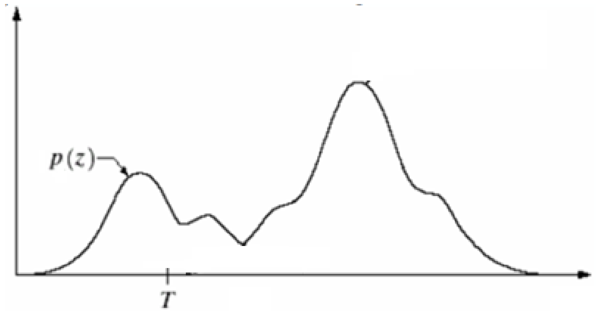

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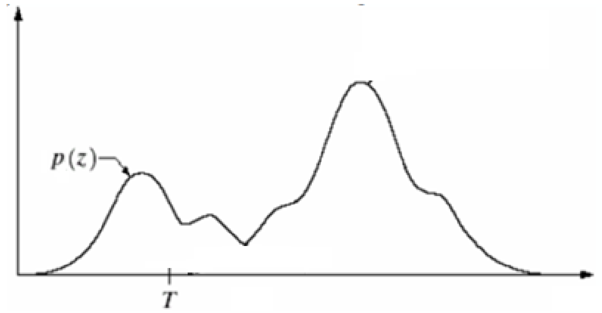

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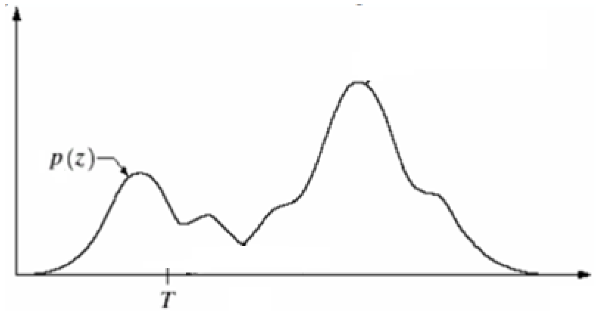

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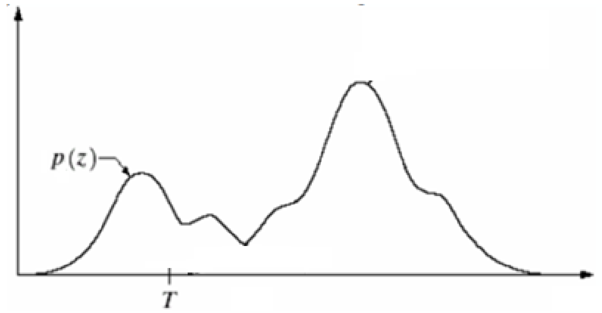

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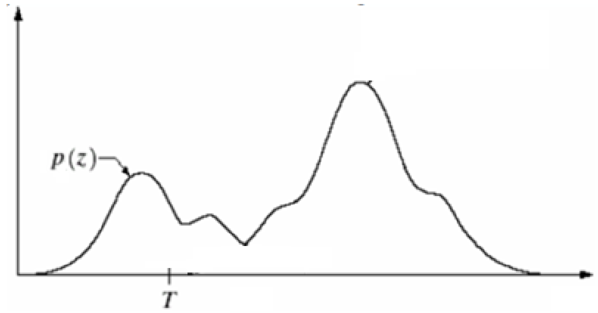

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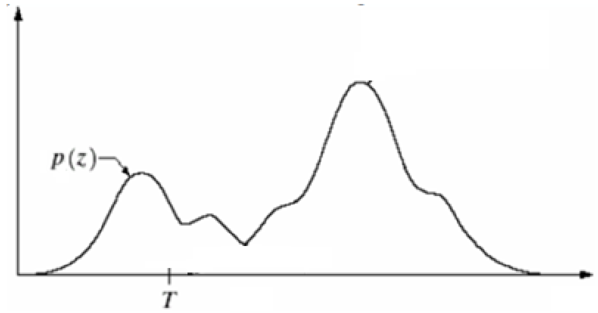

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$$\boxed{\sigma_e^2(T) = P_1(T)P_2(T)\left(\mu_1(T) - \mu_2(T)\right)^2}$$

Otsu's thresholding

- Global: adaptive Otsu's threshold

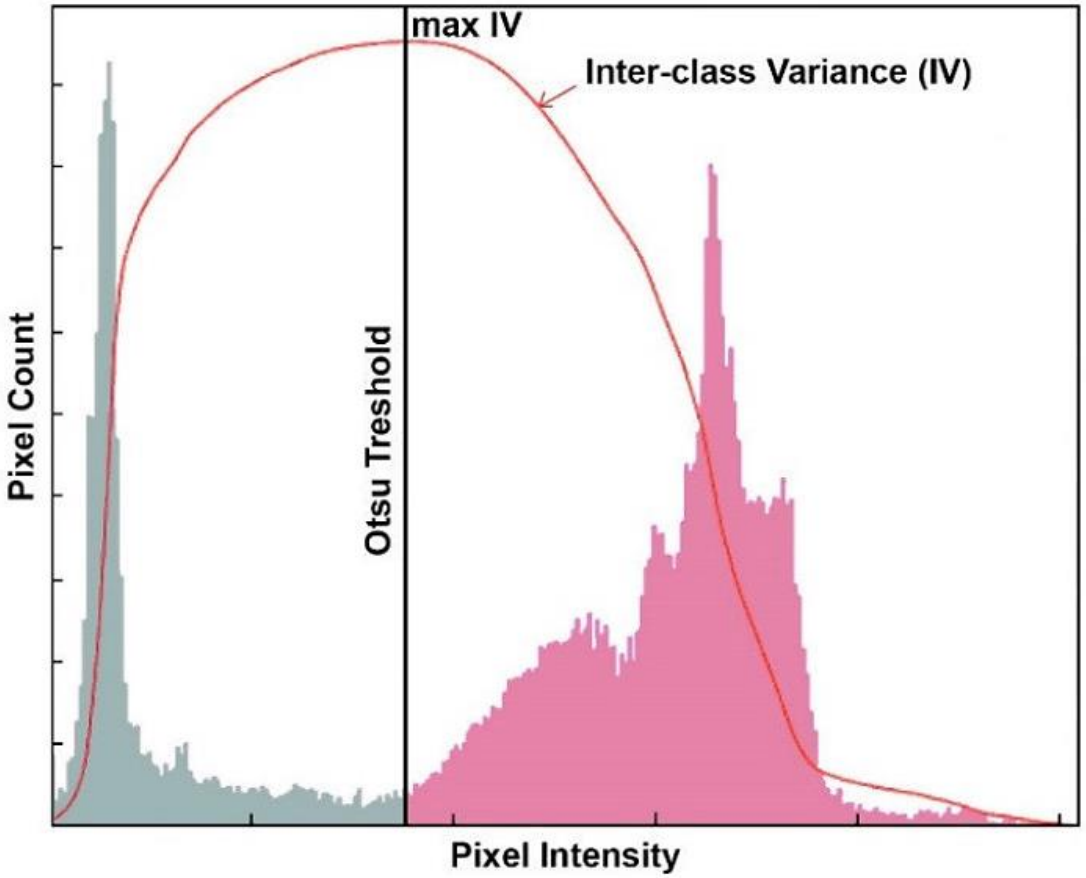
$$\sigma_e^2(T) = P_1(T)P_2(T)\big(\mu_1(T) - \mu_2(T)\big)^2$$

1. Compute histogram and probabilities of each intensity level t
2. Set up initial $P_i(0)$ and $\mu_i(0)$
3. Step through all possible thresholds $T = 1, \ldots, L$
    1. Update $P_i(T)$ and $\mu_i(T)$
    2. Compute $\sigma_e^2(T)$
4. Desired threshold T^* corresponds to the maximum $\sigma_e^2(T)$

Otsu's thresholding

- Variance variation
  - inter-class var maximization

$$\sigma_e^2(T) = P_1(T)P_2(T)\big(\mu_1(T) - \mu_2(T)\big)^2$$



Otsu's thresholding

- Global: iterative adapting threshold: TH = 125
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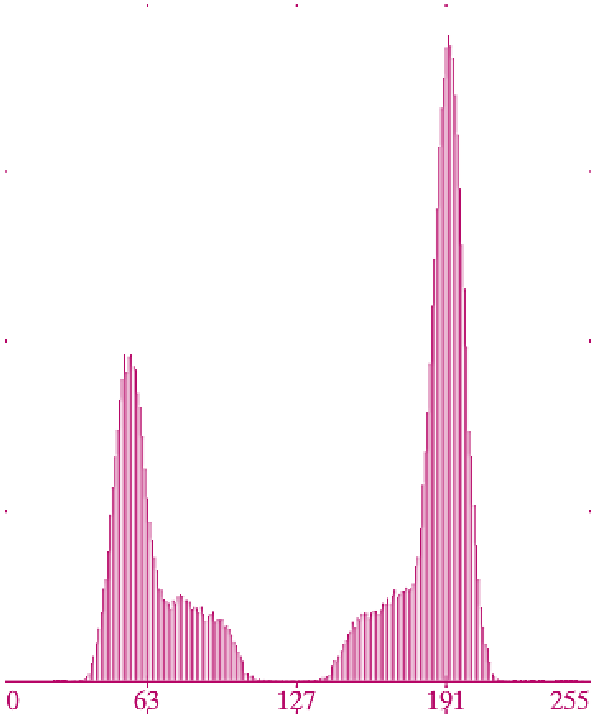

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Otsu's thresholding

- Example
  - microscopic image (polymer cells)

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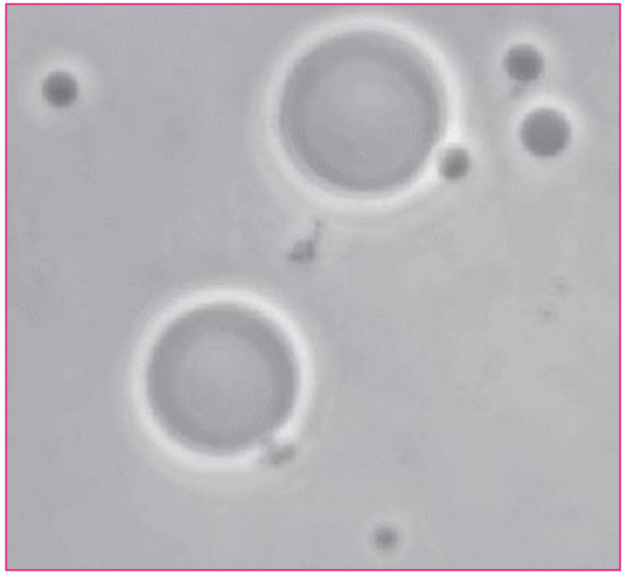

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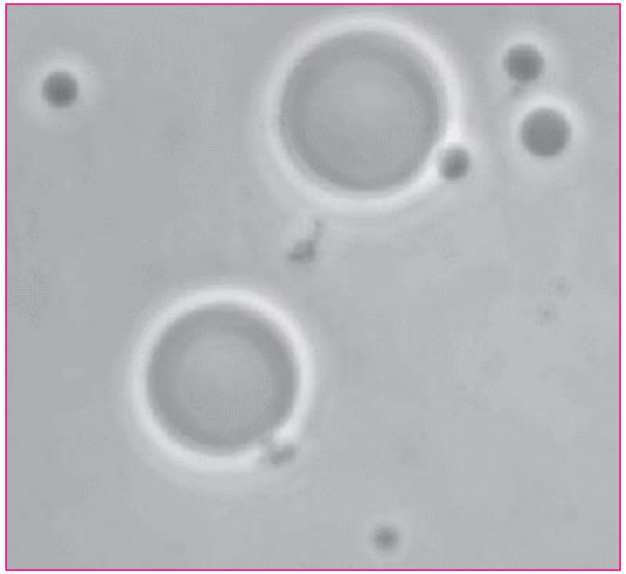

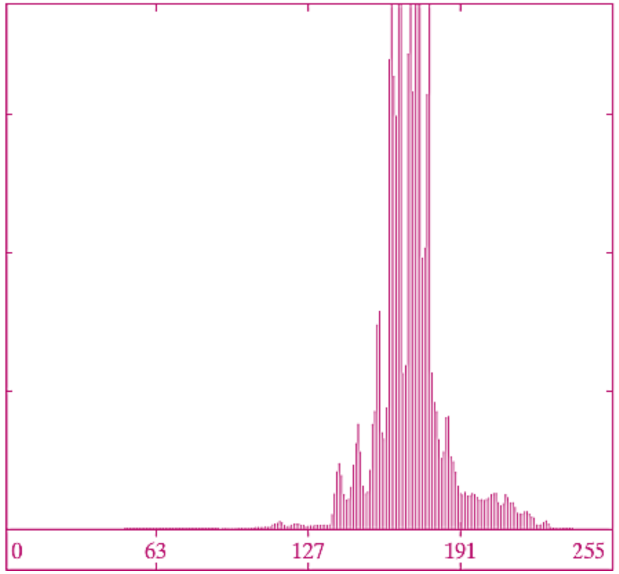

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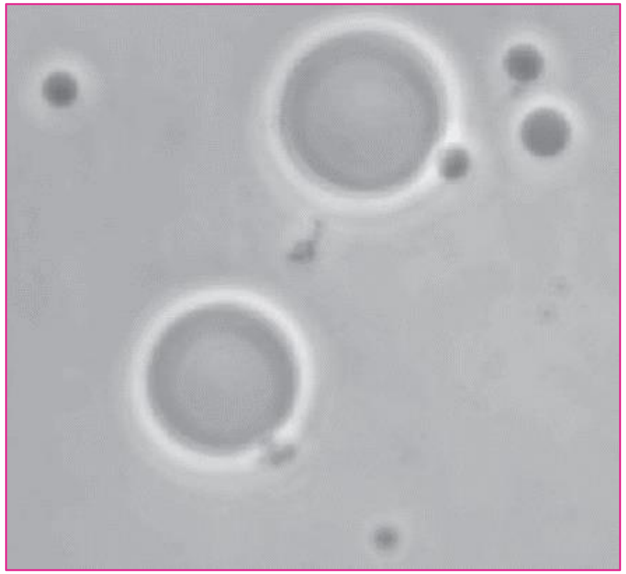

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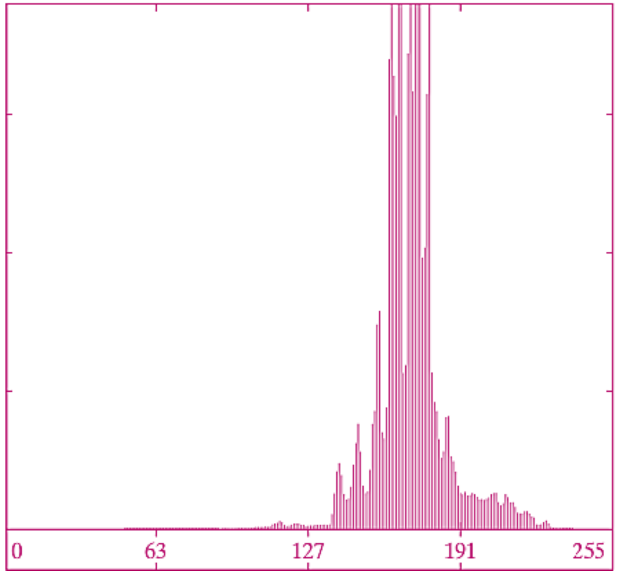

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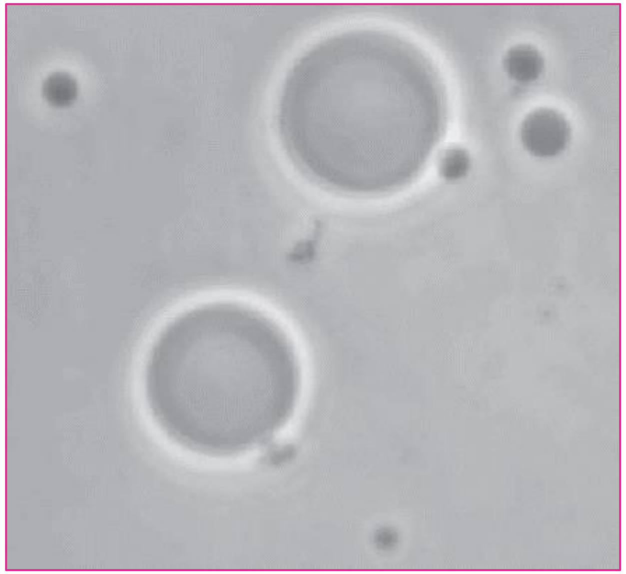

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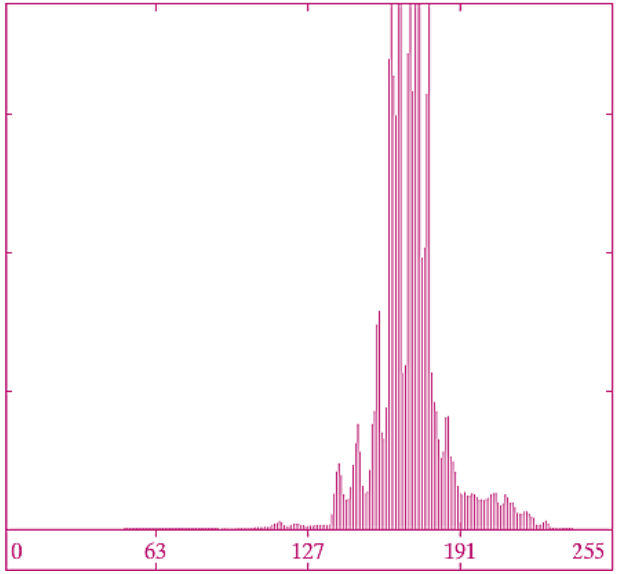

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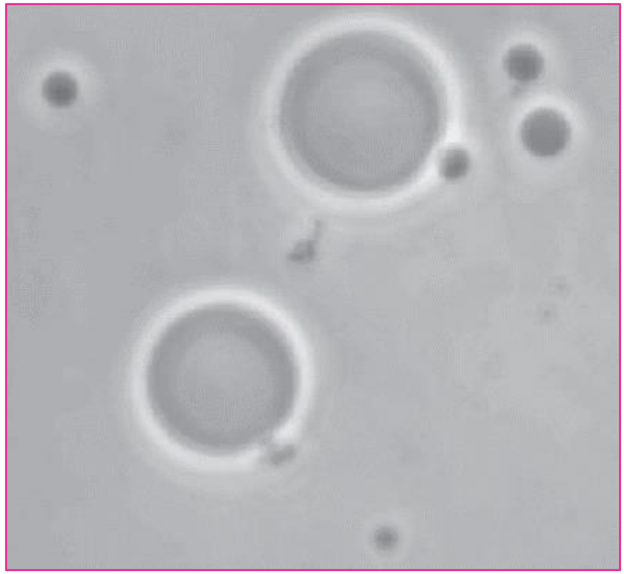

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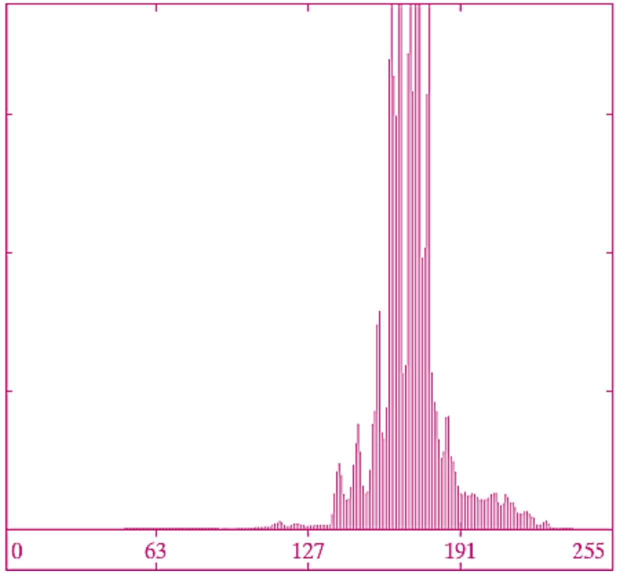

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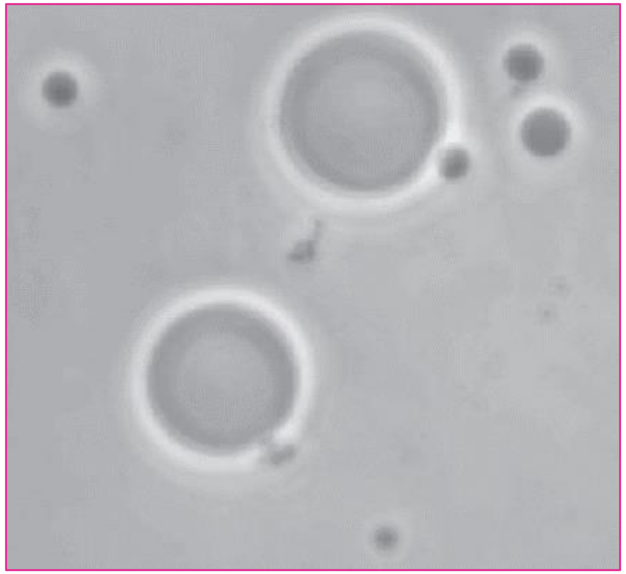

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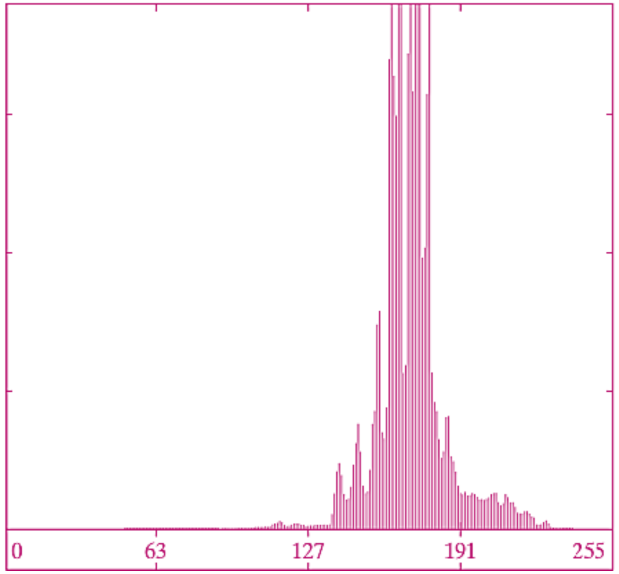

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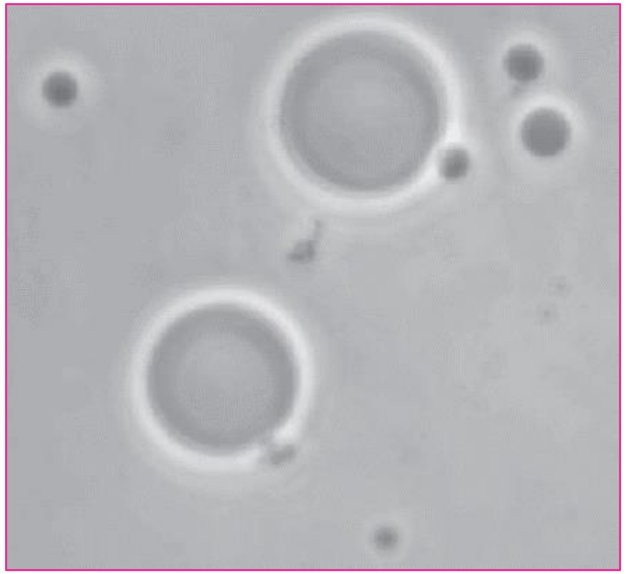

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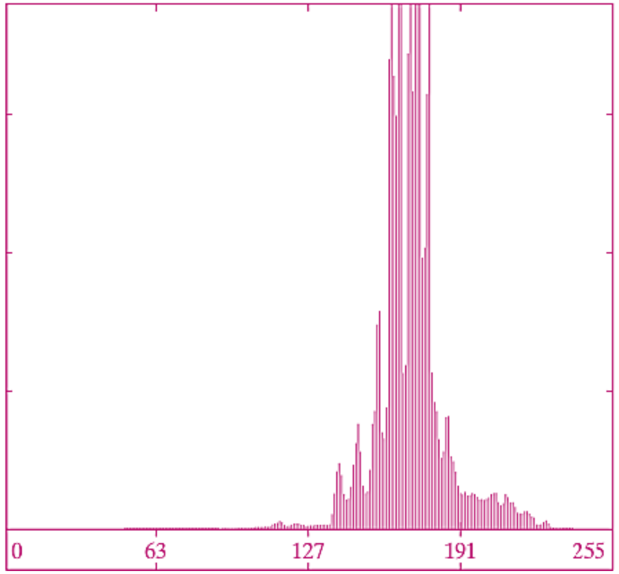


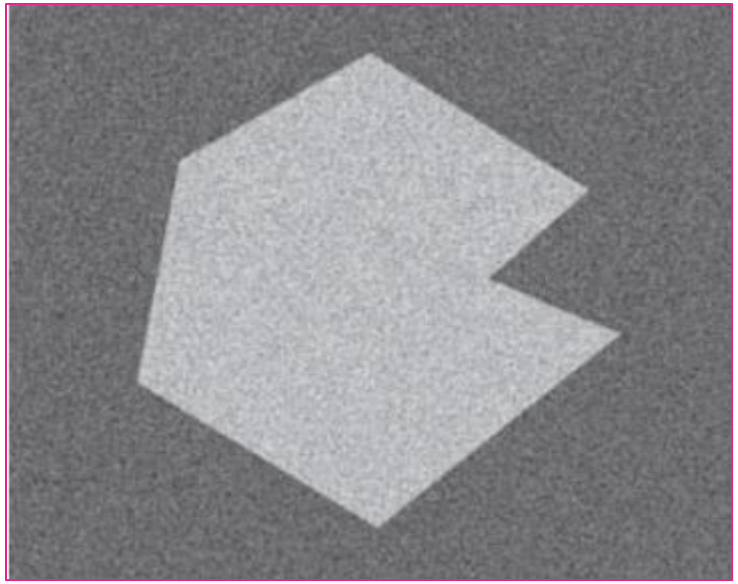
Global: iterative adaptive TH

Global: Otsu's TH

Otsu's thresholding

- Example
  - noisy input as it is

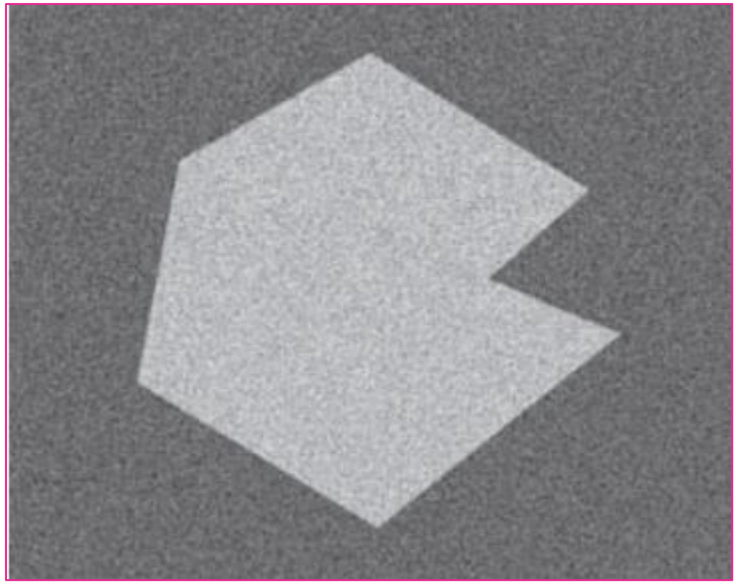
Input

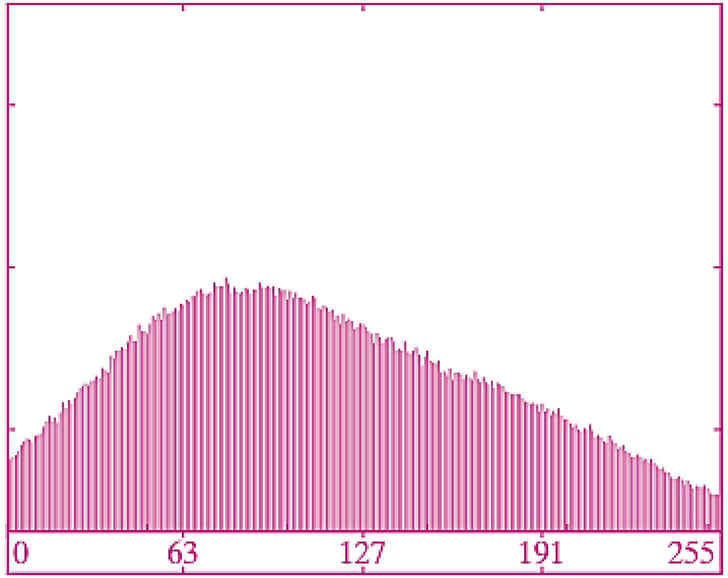


Otsu's thresholding

- Example
  - noisy input as it is

Input

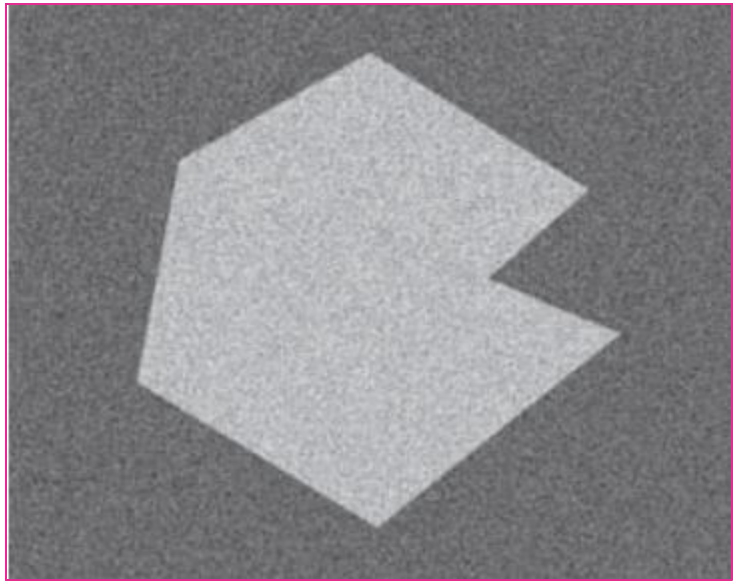




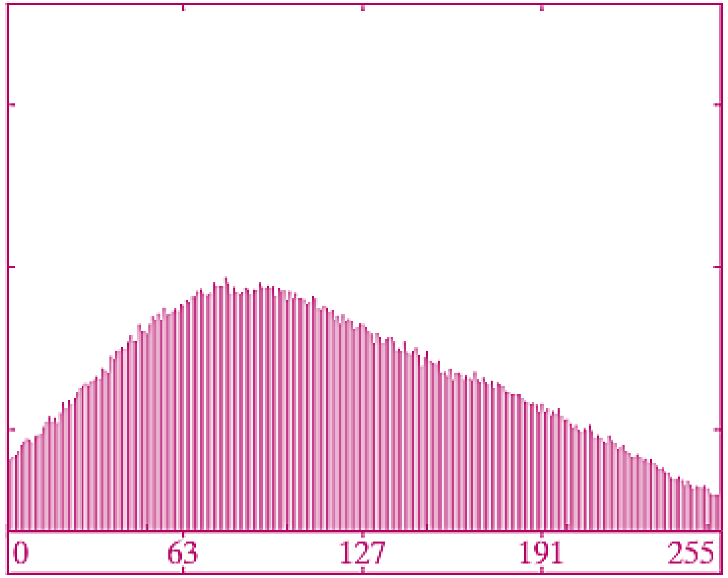
Otsu’s thresholding

- Example
  - noisy input as it is

Input



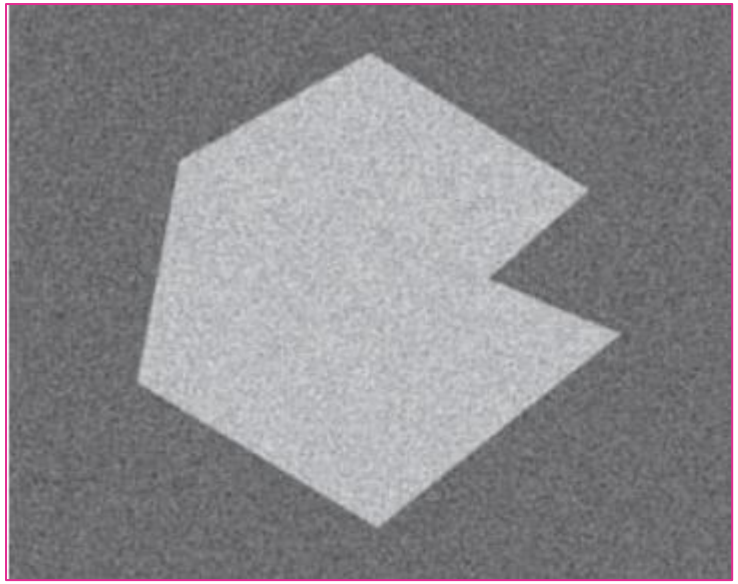
Hist



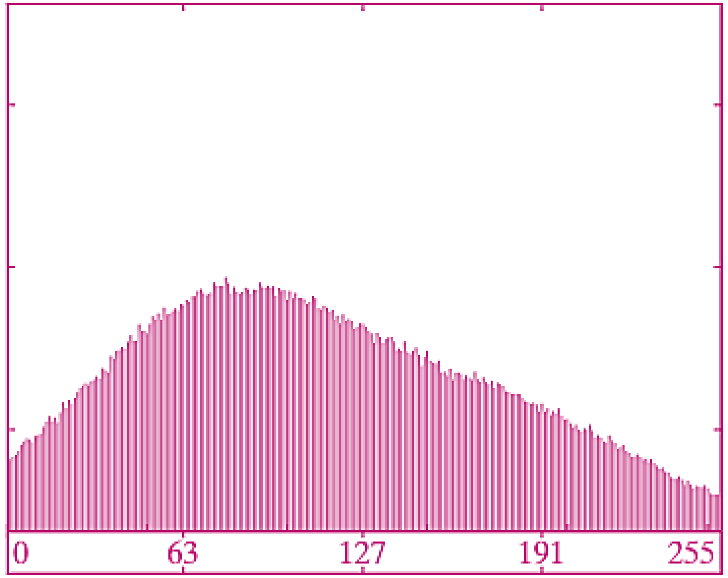
Otsu's thresholding

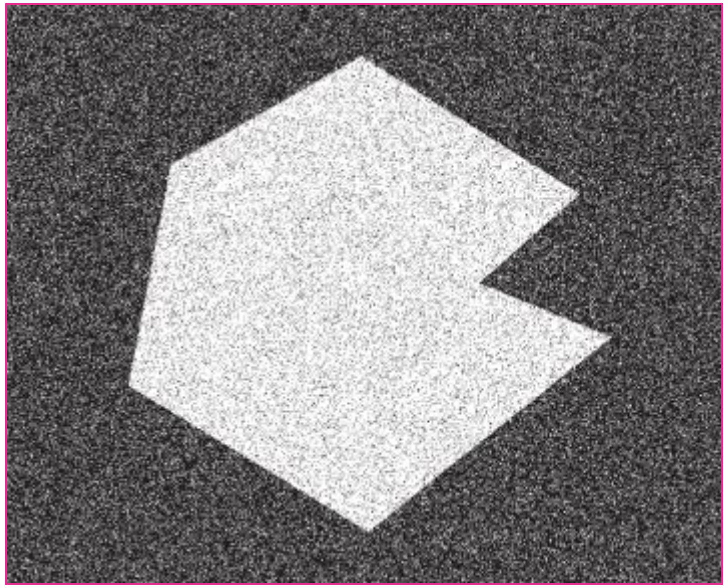
- Example
  - noisy input as it is

Input



Hist

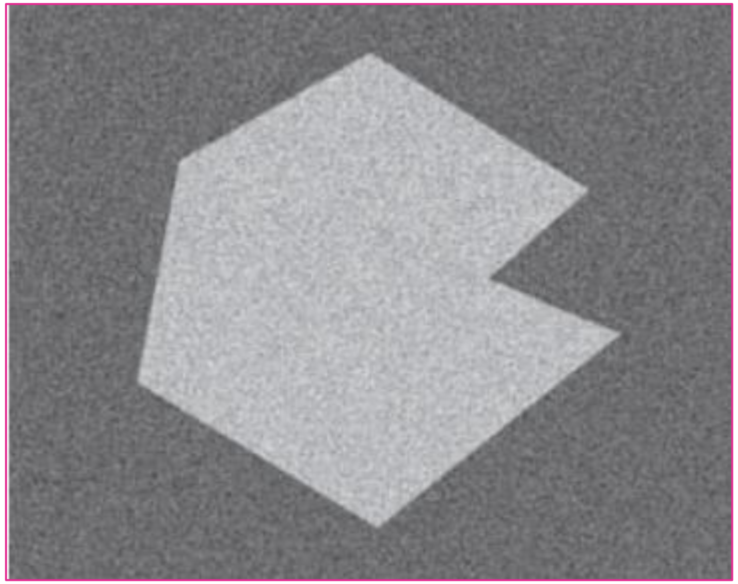




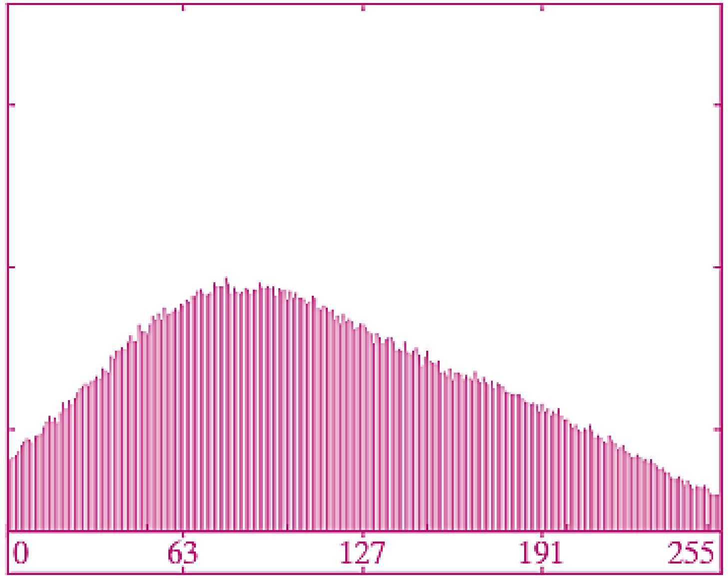
Otsu's thresholding

- Example
  - noisy input as it is

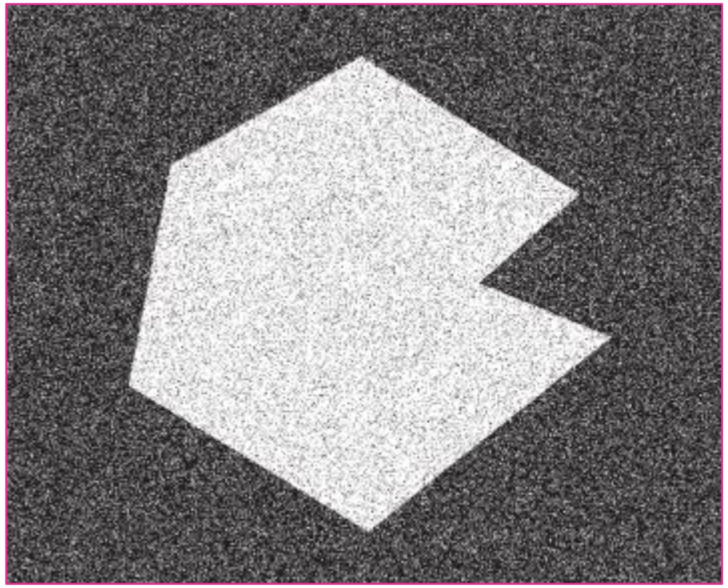
Input



Hist



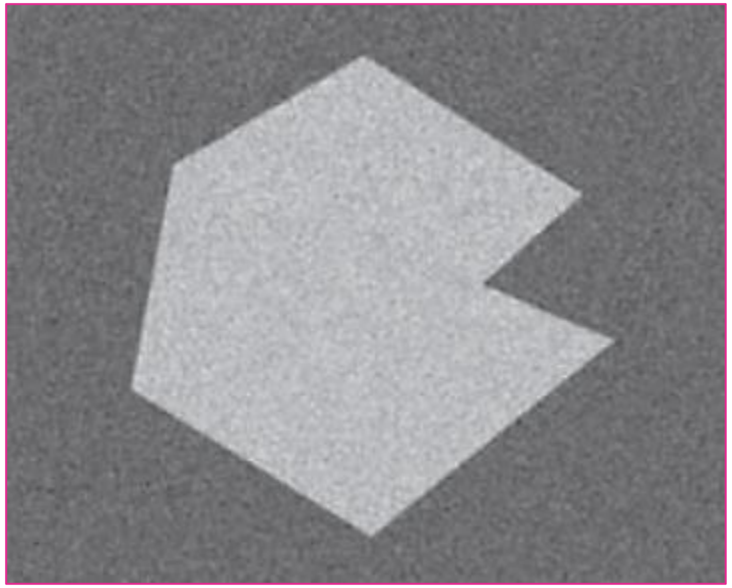
Global: Otsu's TH



Otsu’s thresholding

- Example
  - noisy input after minor smoothing

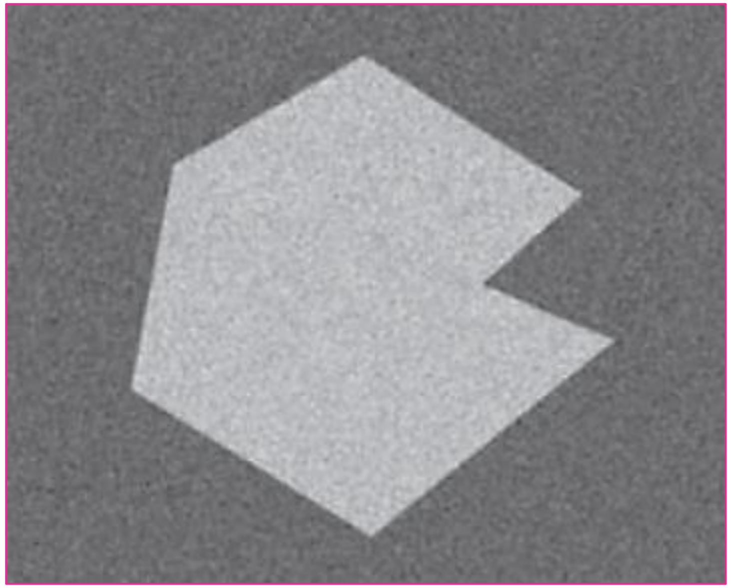
Input

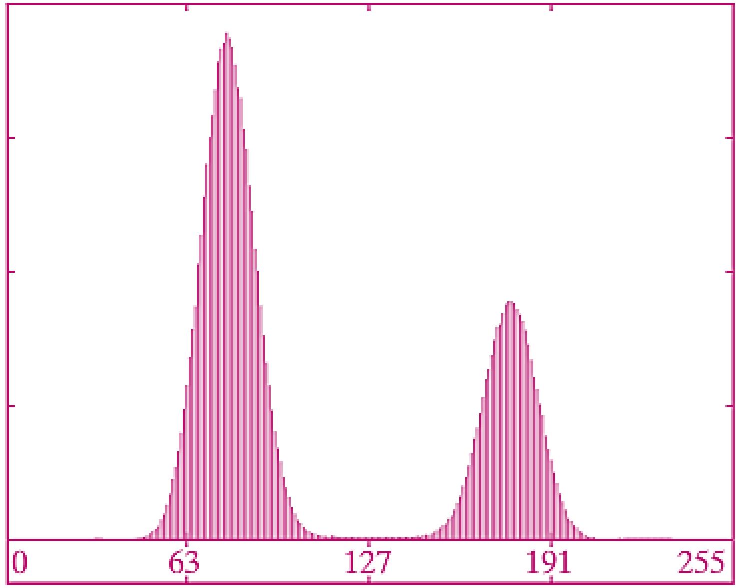


Otsu's thresholding

- Example
  - noisy input after minor smoothing

Input

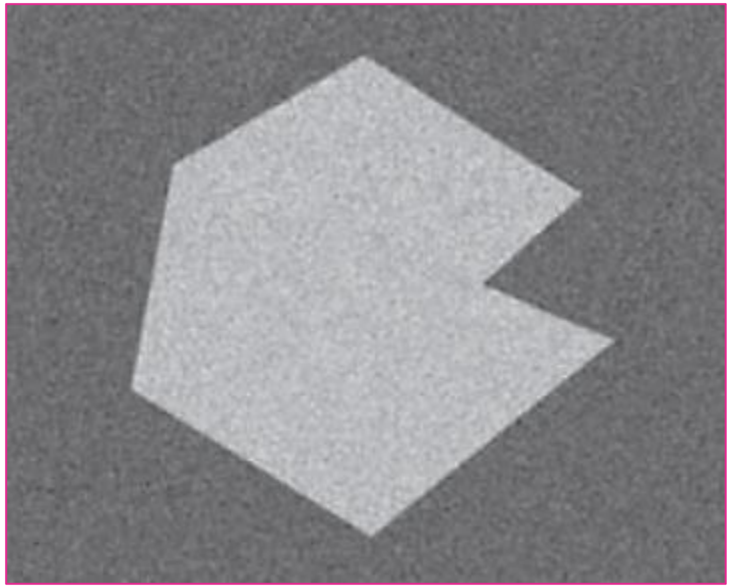




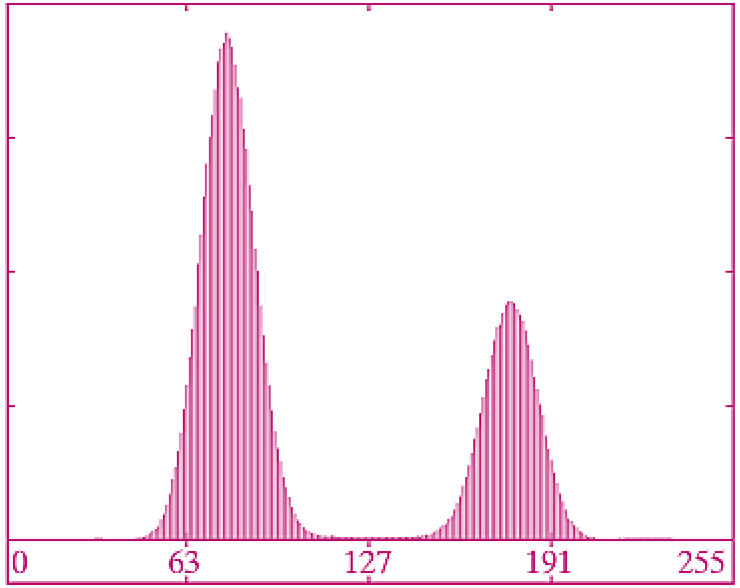
Otsu's thresholding

- Example
  - noisy input after minor smoothing

Input



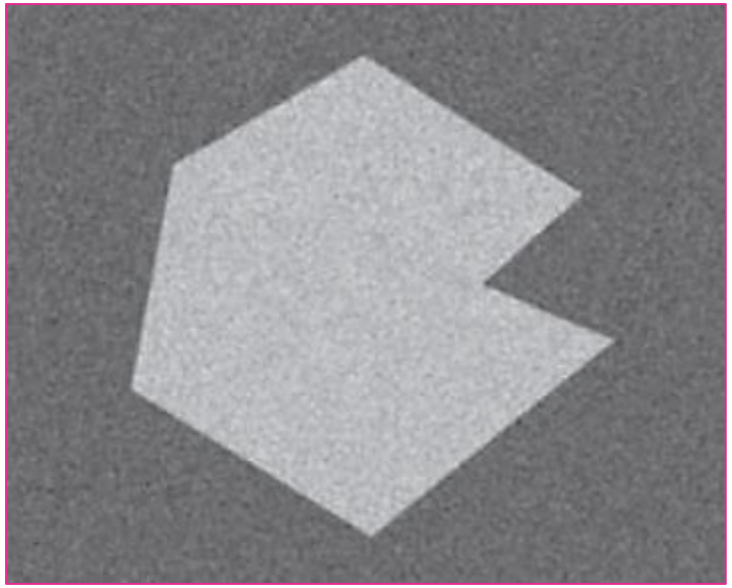
Hist



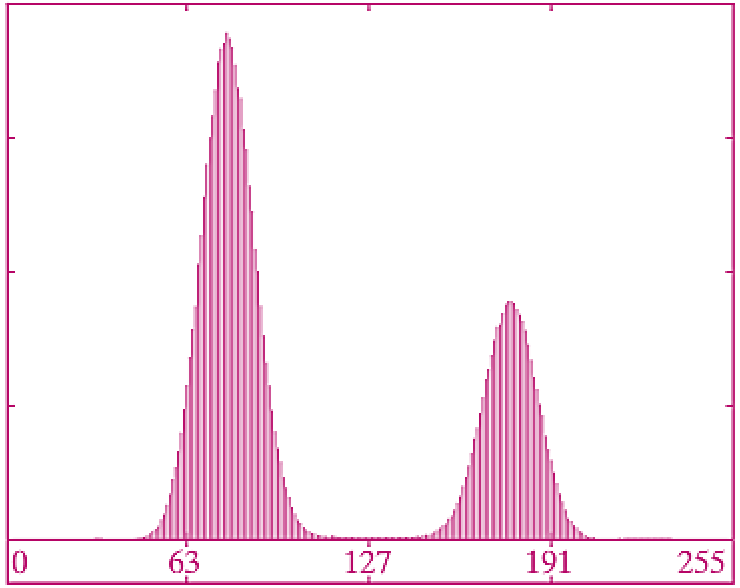
Otsu's thresholding

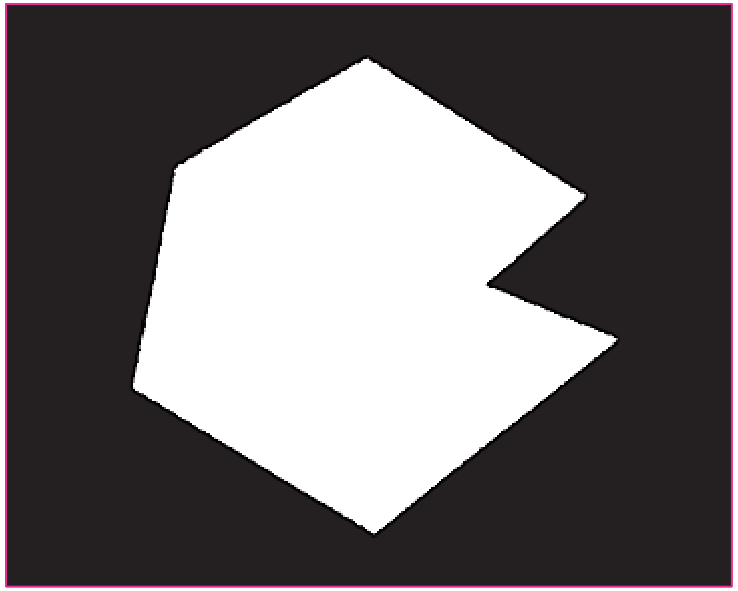
- Example
  - noisy input after minor smoothing

Input



Hist

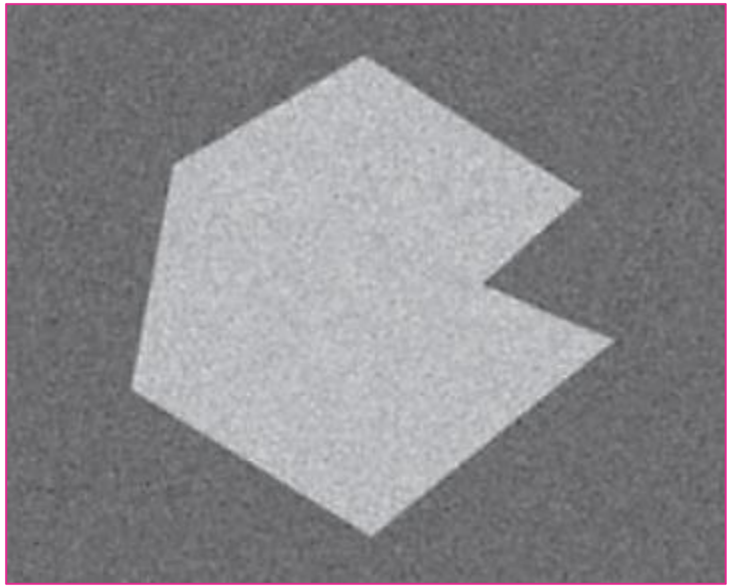




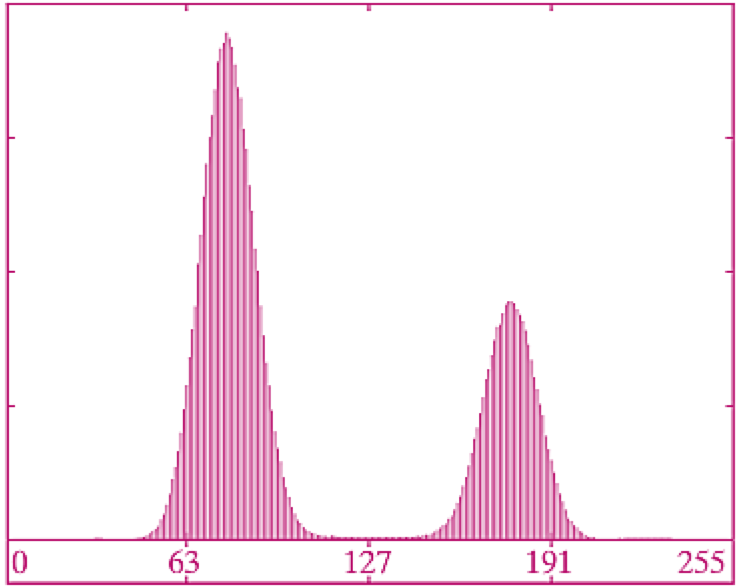
Otsu’s thresholding

- Example
  - noisy input after minor smoothing

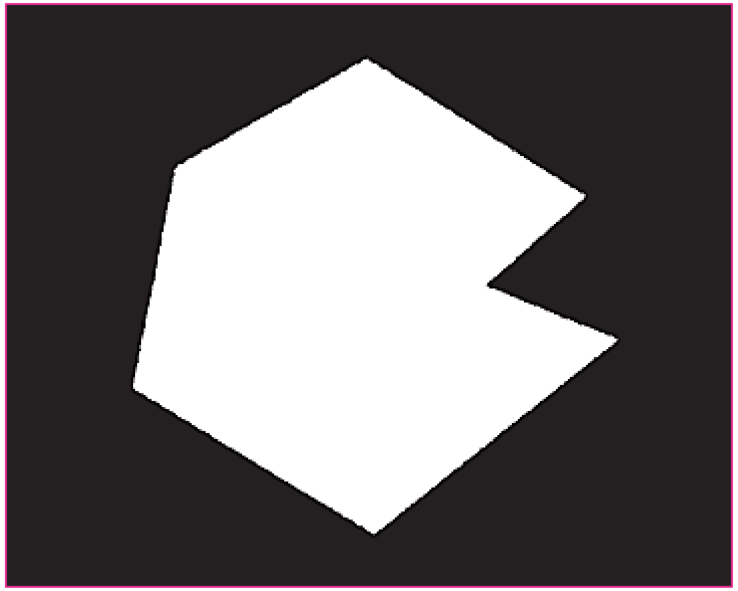
Input



Hist



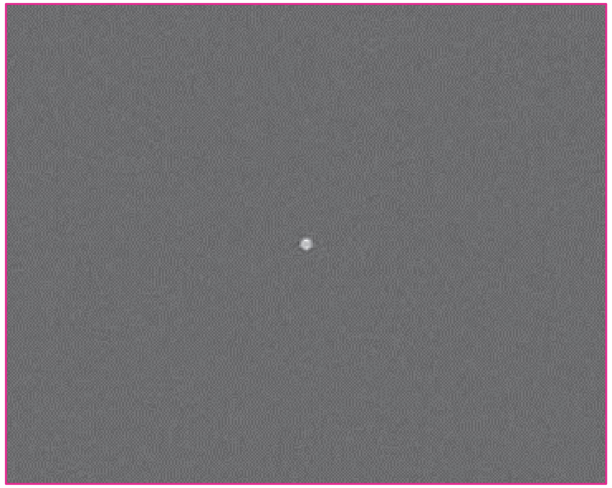
Global: Otsu’s TH



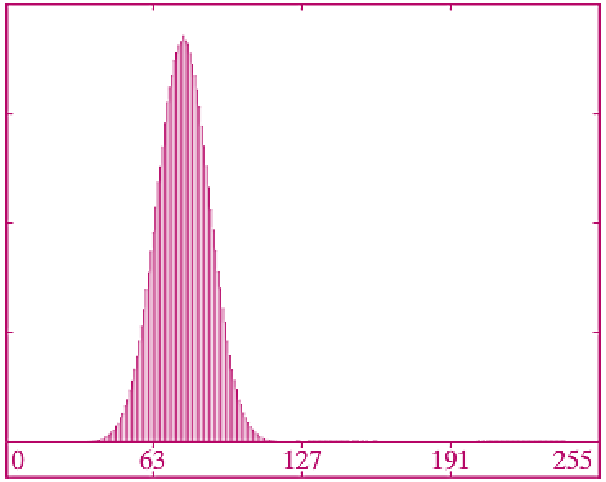
Otsu’s thresholding

- Example
  - small object’s noisy image

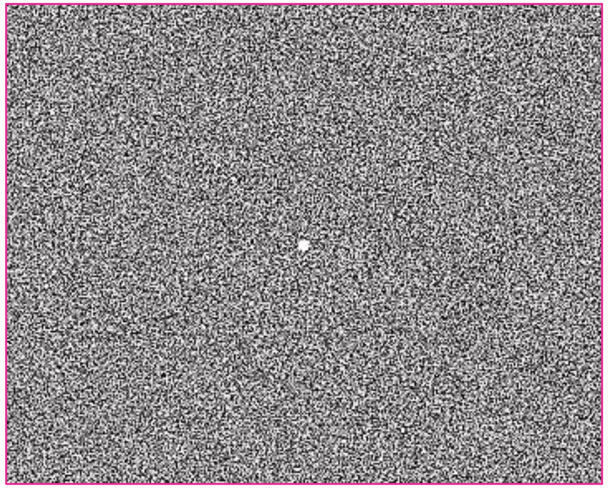
Input



Hist



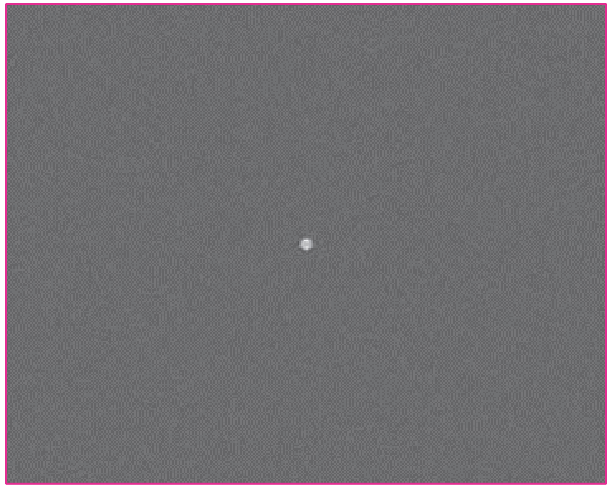
Global: Otsu’s TH



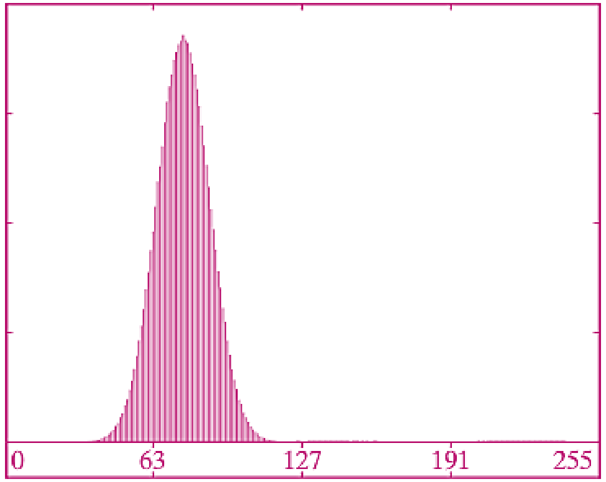
Otsu’s thresholding

- Example
  - small object’s noisy image

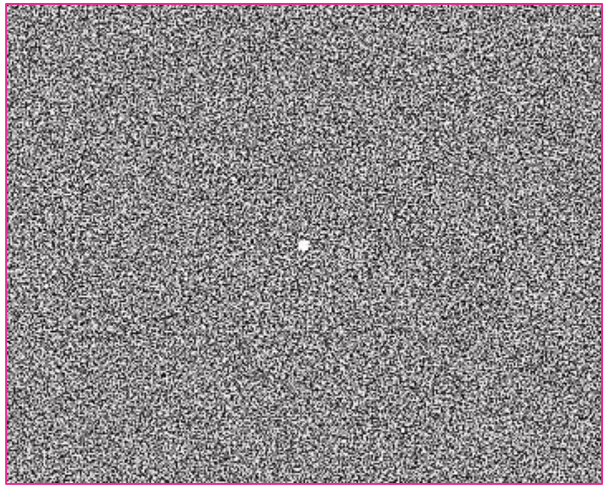
Input

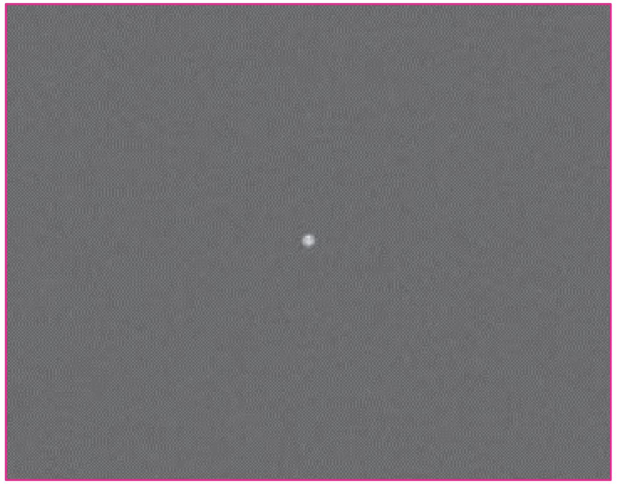


Hist



Global: Otsu’s TH

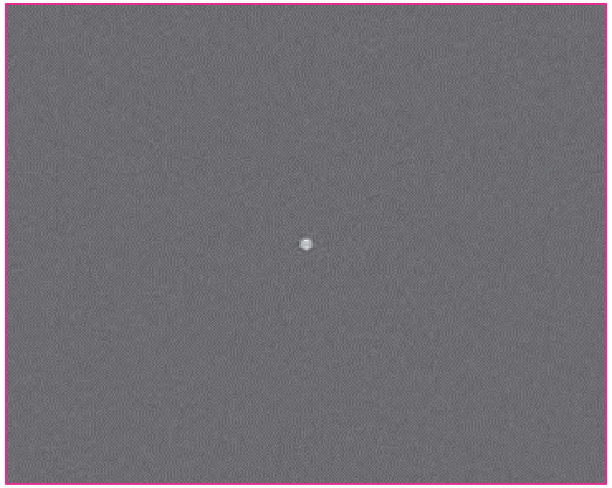




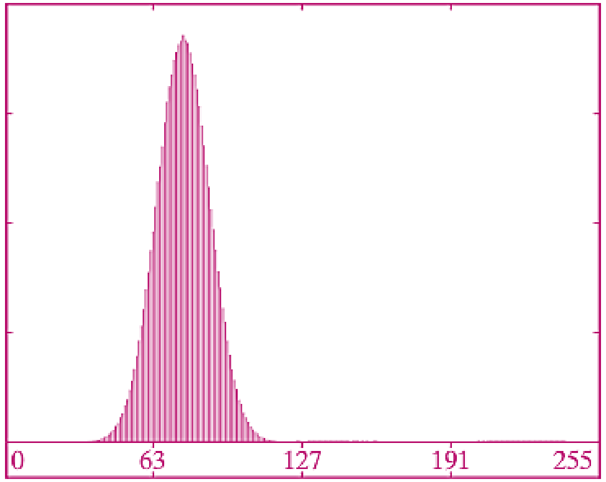
Otsu’s thresholding

- Example
  - small object’s noisy image

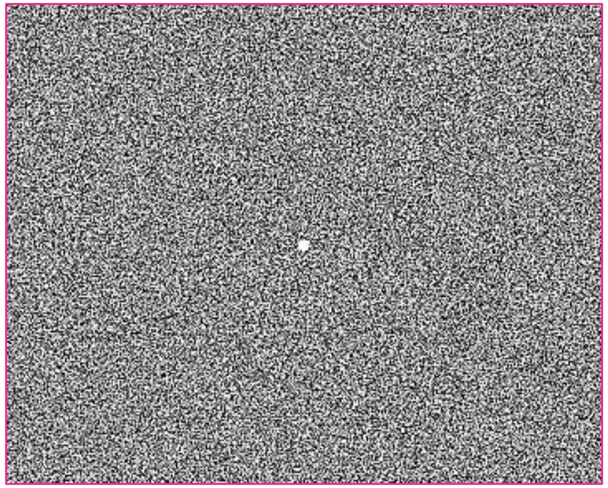
Input

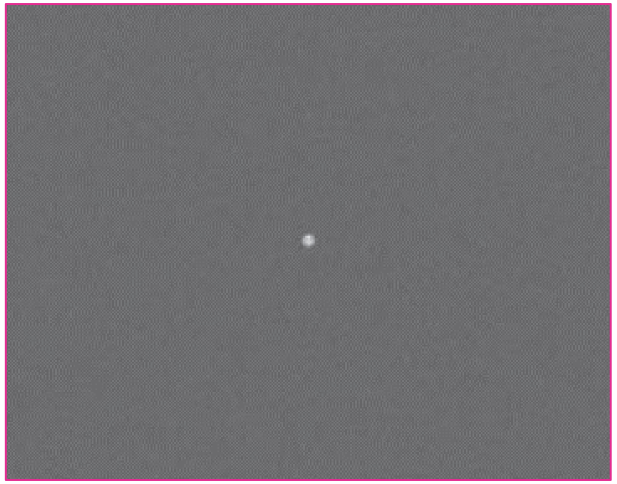


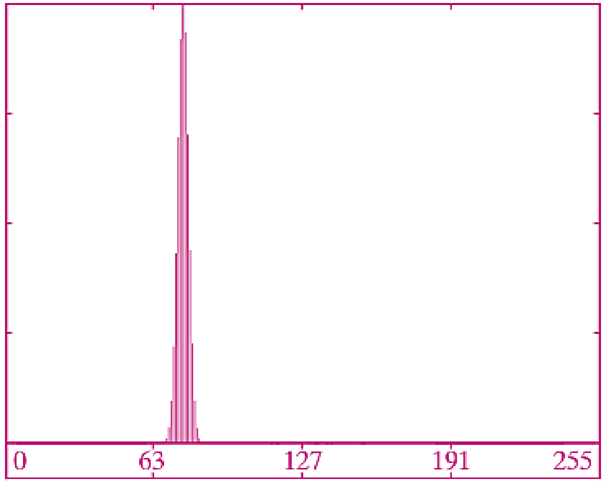
Hist



Global: Otsu’s TH



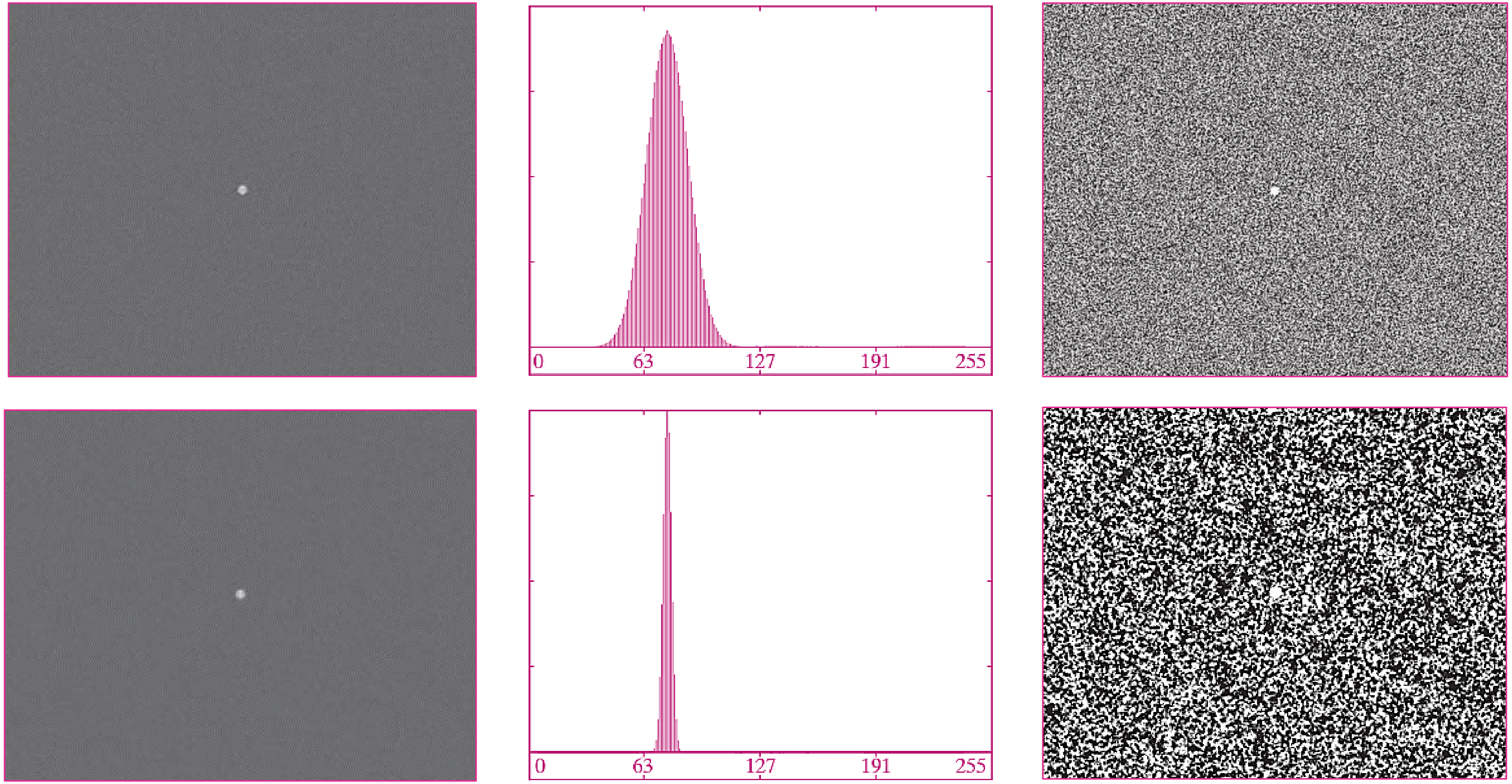




Otsu’s thresholding

- Example
  - small object’s noisy image

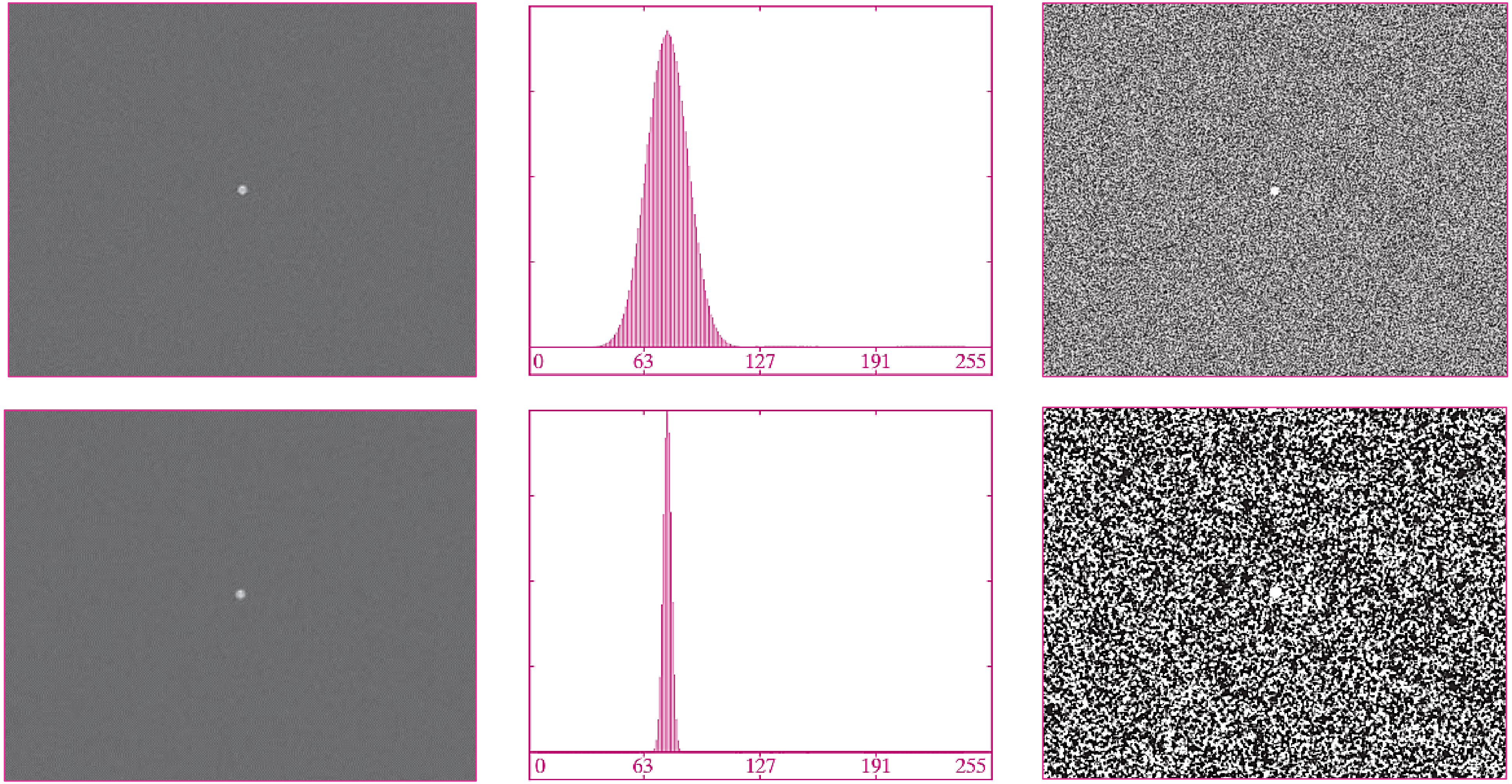
Input | Hist | Global: Otsu’s TH



Otsu's thresholding

- Example
  - small object's noisy image
  - smoothing degrades the performance

Input | Hist | Global: Otsu's TH



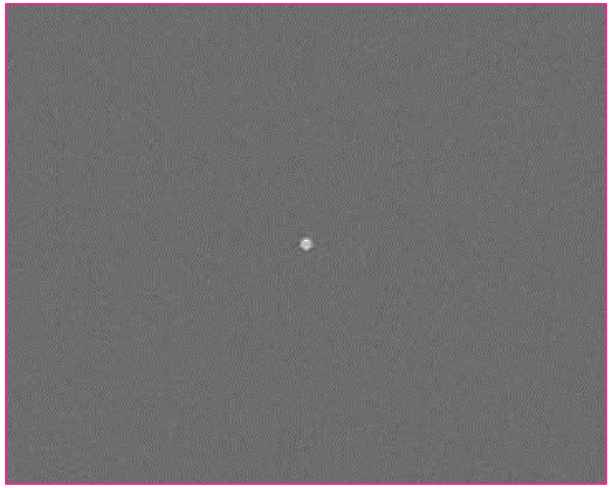
Otsu's thresholding

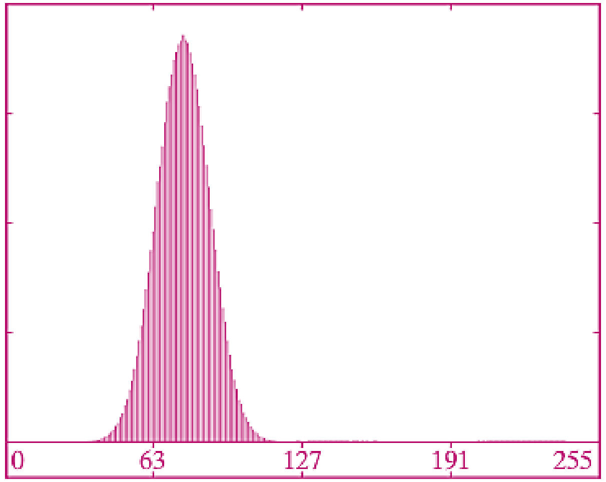
- Example
  - small object's noisy image
  - smoothing degrades the performance
  - what caused the problem?
  - how to solve the problem?

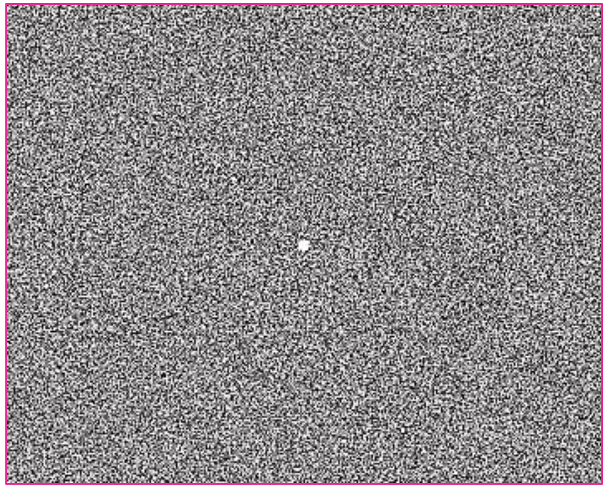
Input

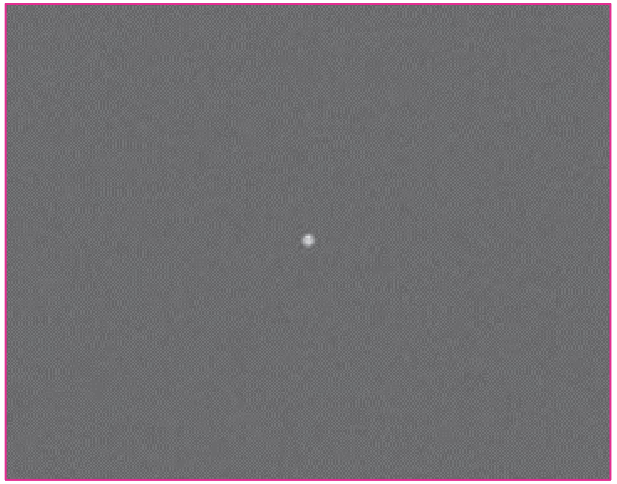
Hist

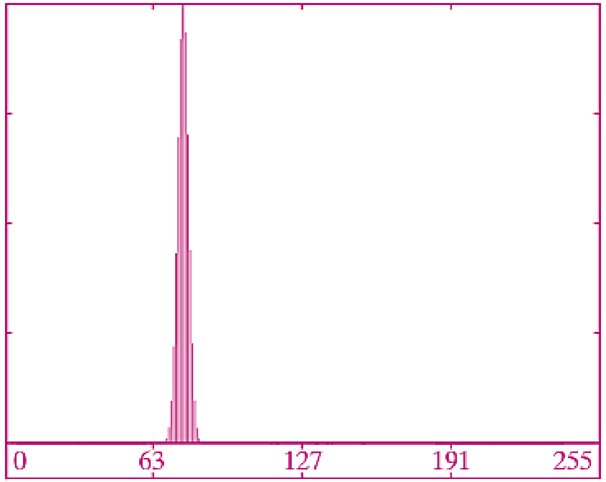
Global: Otsu's TH

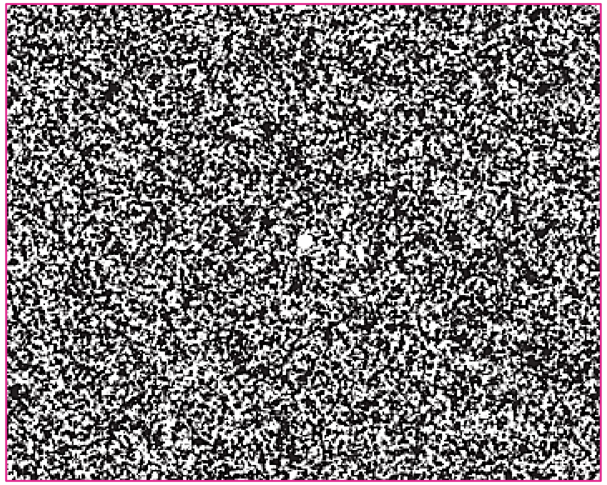








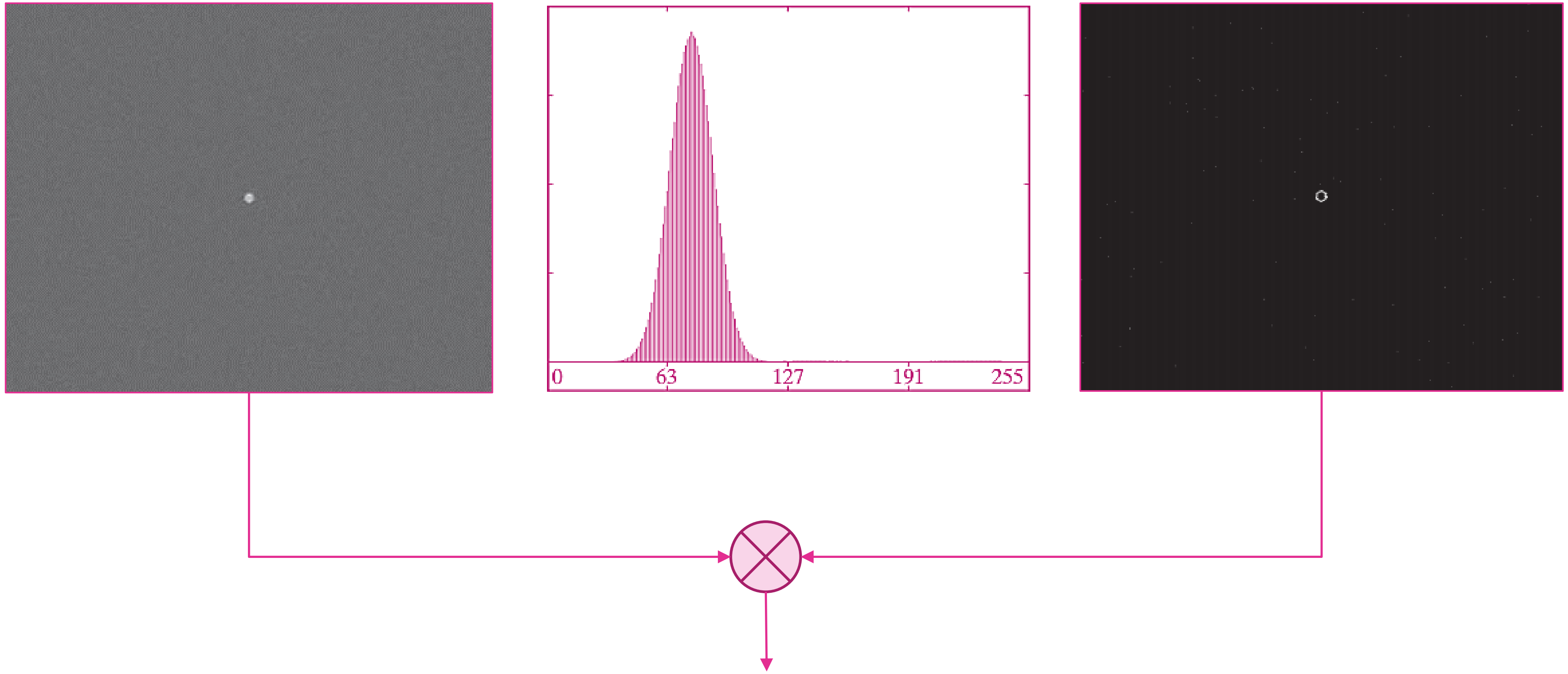




Otsu’s thresholding

- Example
  - small object’s noisy image
  - edge masks

Input | Hist | Edge gradients with TH

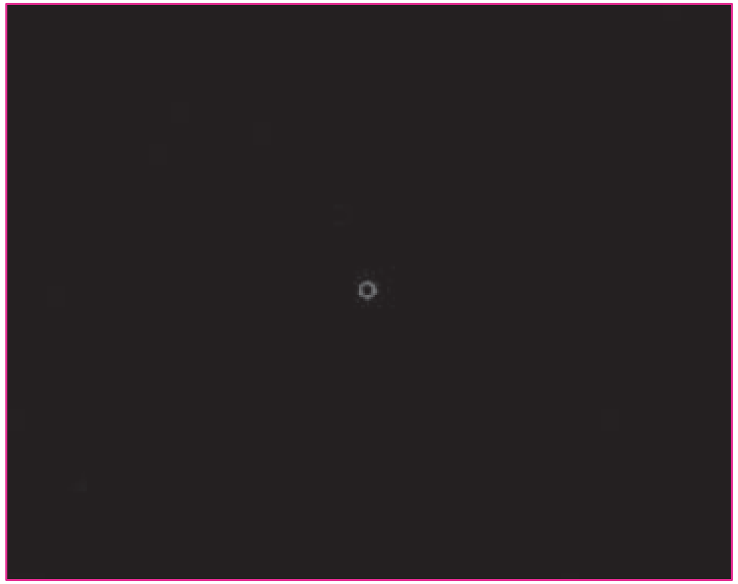


Edge masked input image

Otsu’s thresholding

- Example
  - small object’s noisy image
  - Otsu’s TH obtained via edge masked image but that TH is applied on the original input image

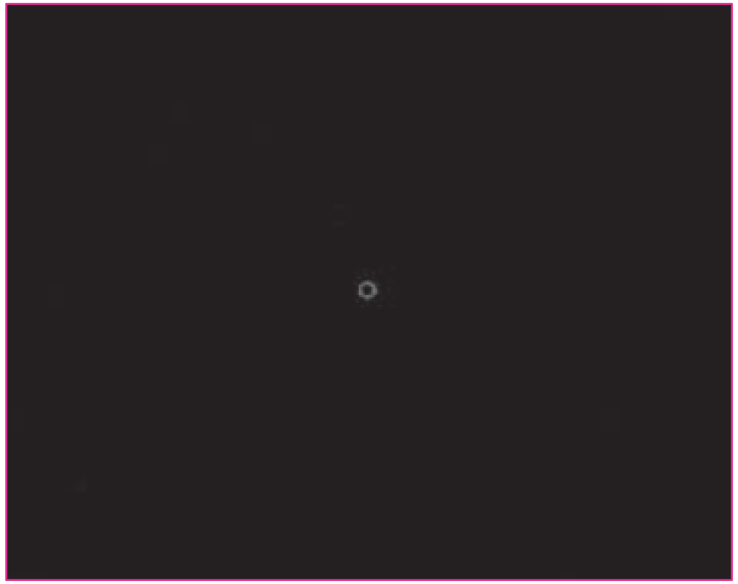
Edge masked input image

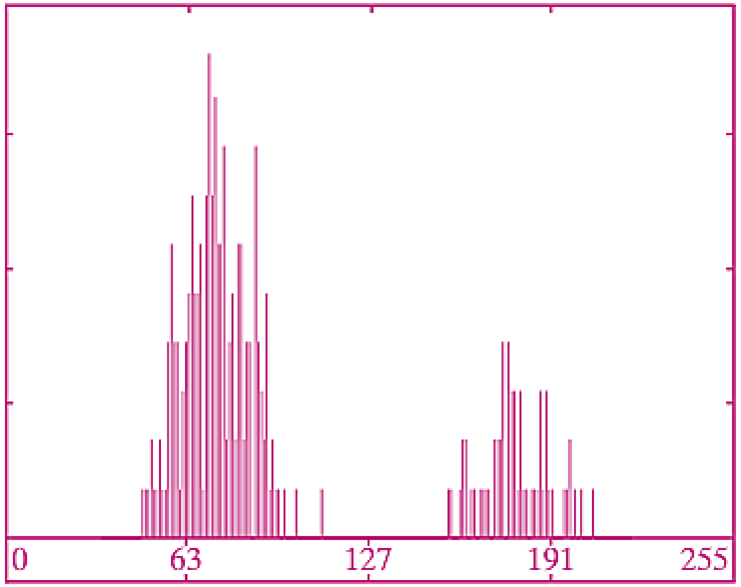


Otsu's thresholding

- Example
  - small object's noisy image
  - Otsu's TH obtained via edge masked image but that TH is applied on the original input image

Edge masked input image

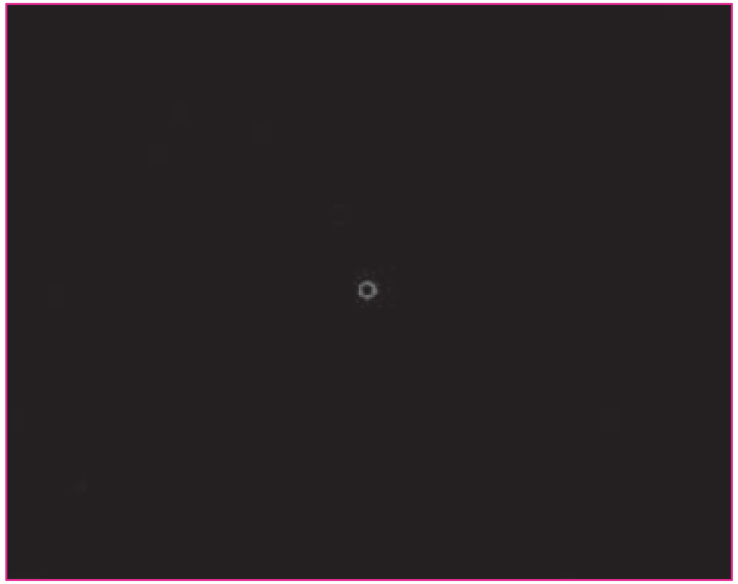




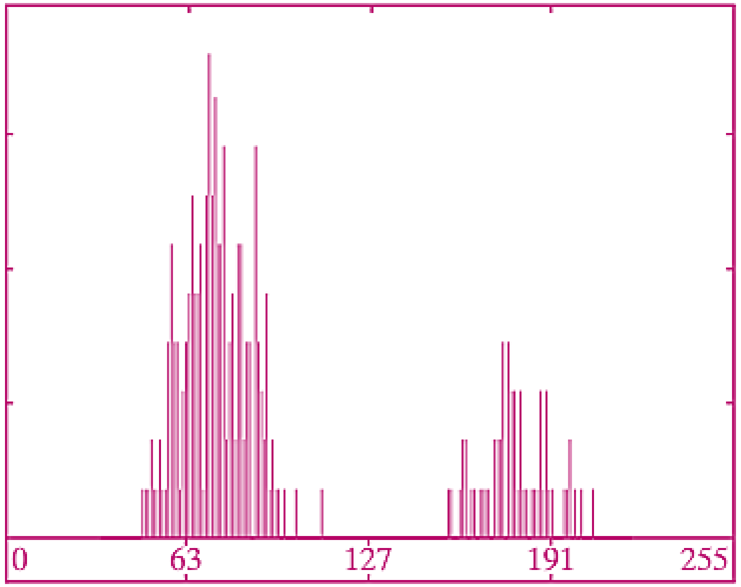
Otsu’s thresholding

- Example
  - small object’s noisy image
  - Otsu’s TH obtained via edge masked image but that TH is applied on the original input image

Edge masked input image



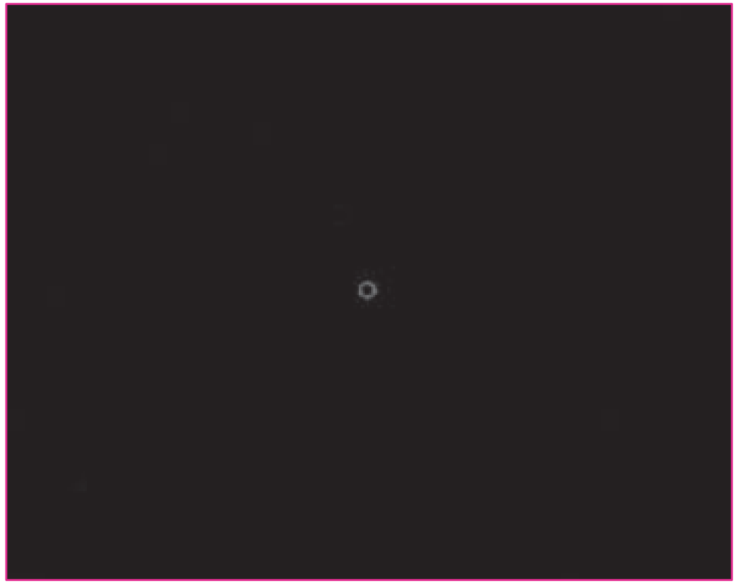
Hist



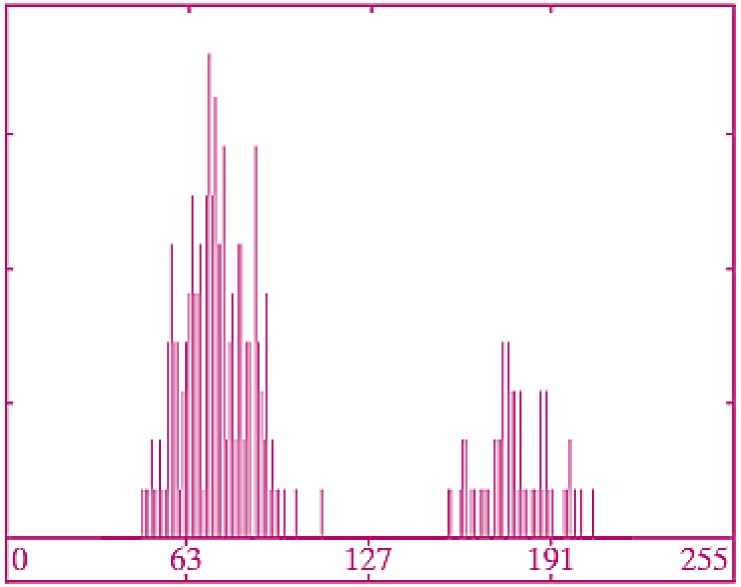
Otsu's thresholding

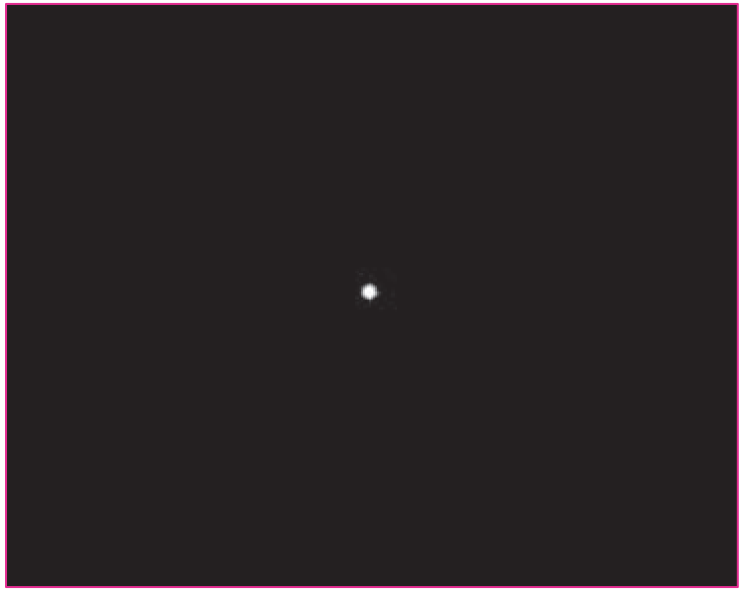
- Example
  - small object's noisy image
  - Otsu's TH obtained via edge masked image but that TH is applied on the original input image

Edge masked input image



Hist

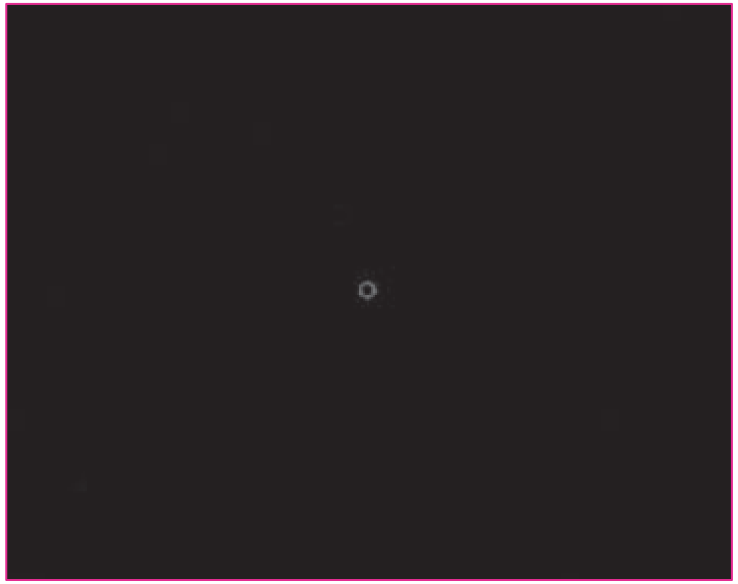




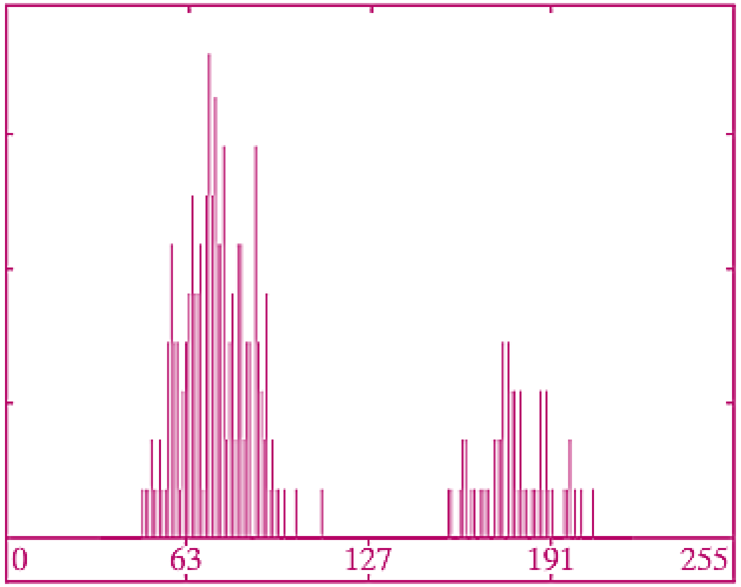
Otsu's thresholding

- Example
  - small object's noisy image
  - Otsu's TH obtained via edge masked image but that TH is applied on the original input image

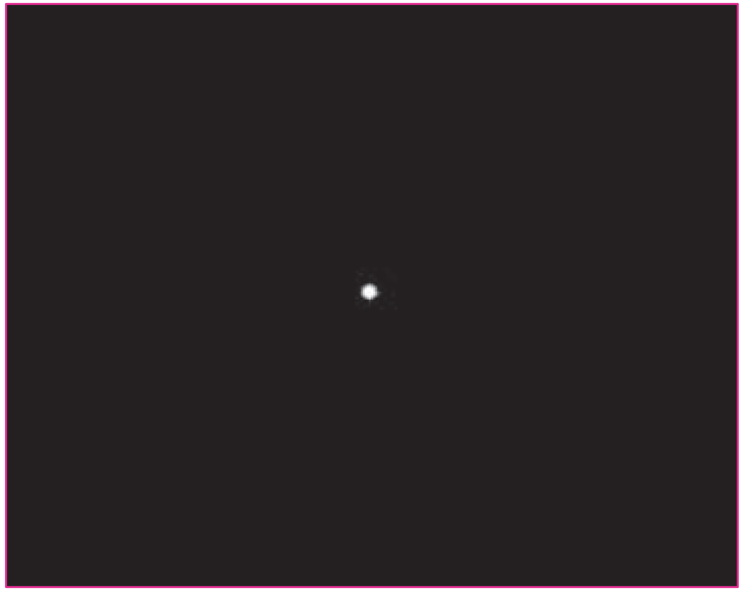
Edge masked input image



Hist



Global: Otsu's TH



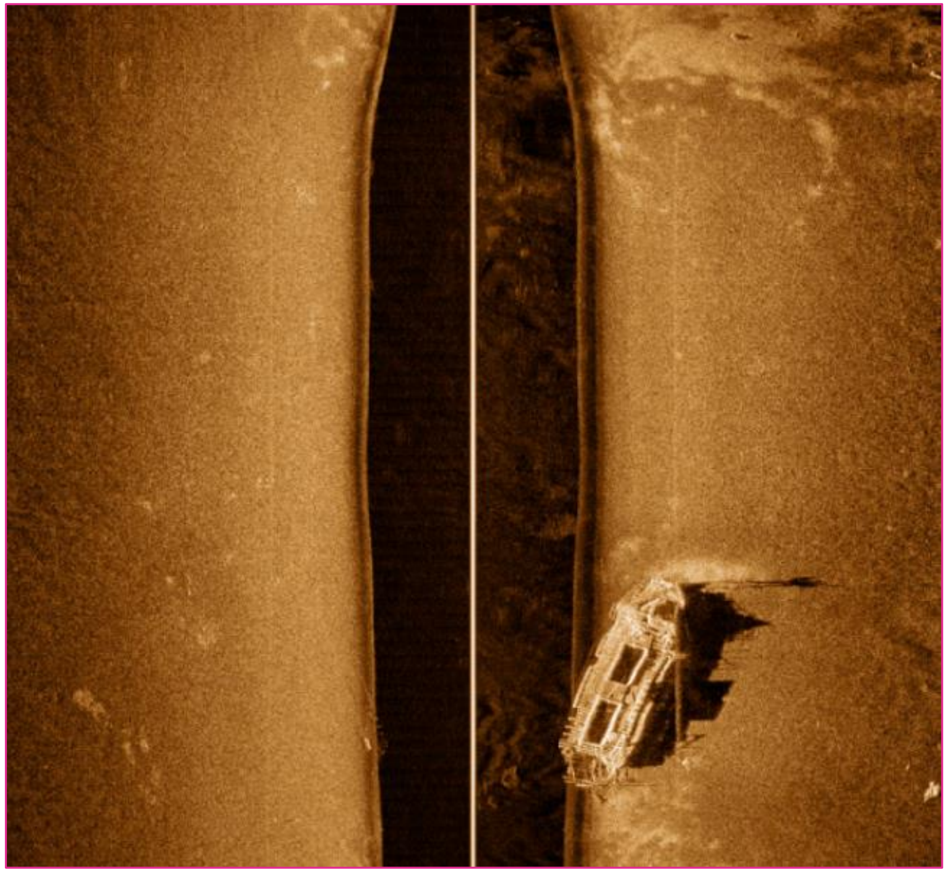
Improving Otsu for underwater imaging

Improving Otsu for underwater imaging

- SONAR
    - Sound Navigation And Ranging

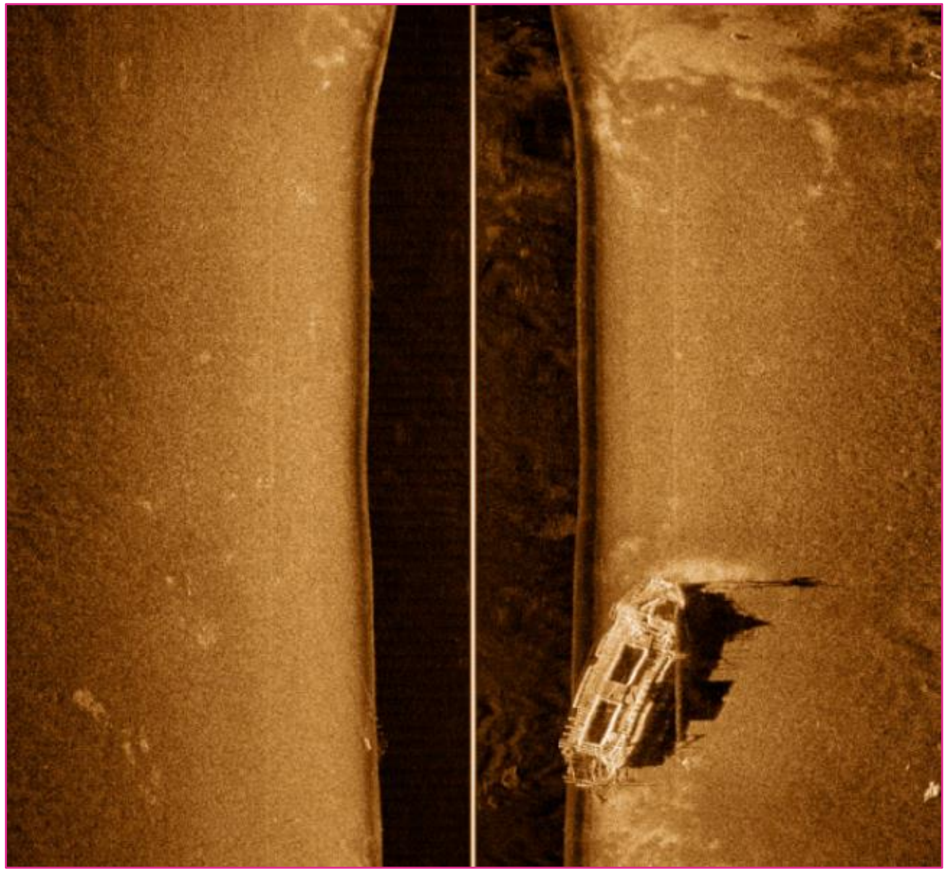
Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging



Improving Otsu for underwater imaging

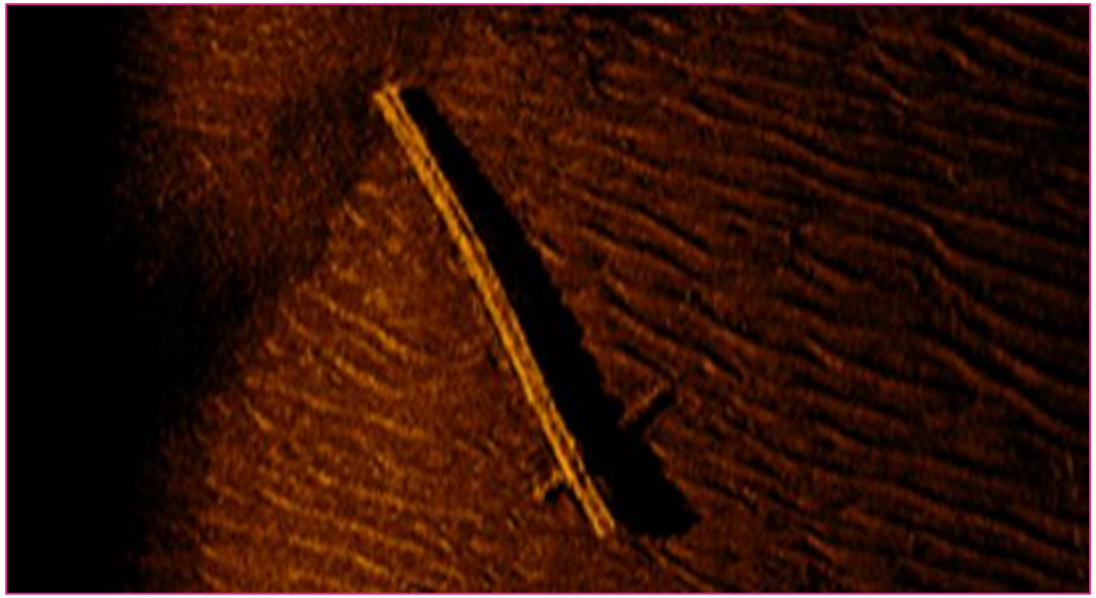
- SONAR
  - Sound Navigation And Ranging

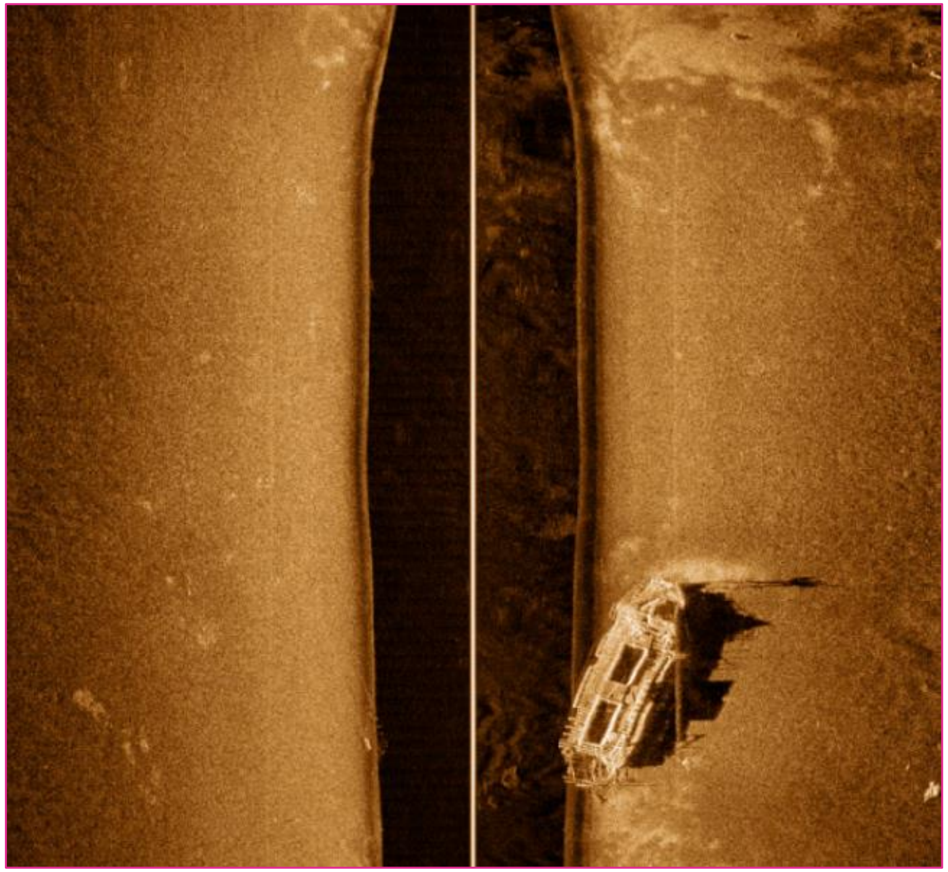


Stockholm sea image

Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging

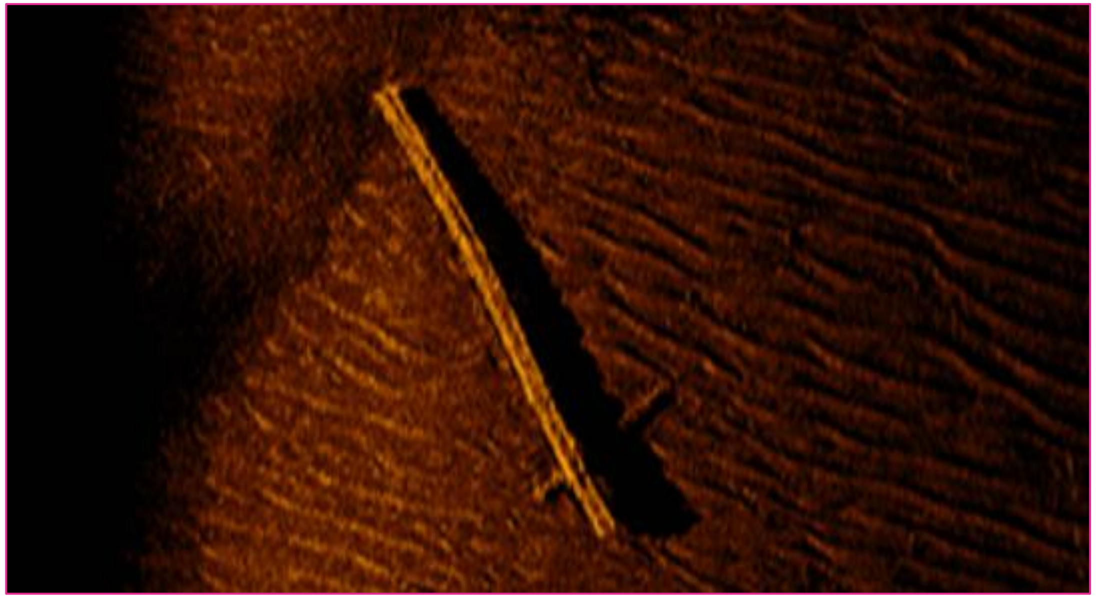




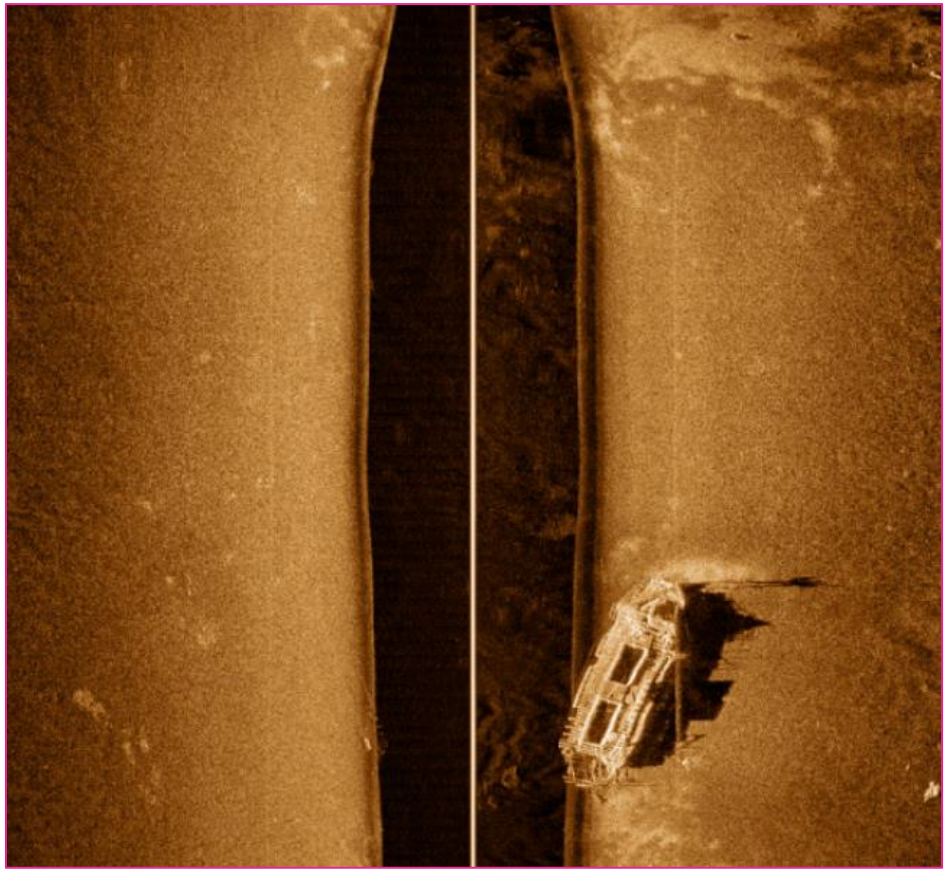
Stockholm sea image

Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging



Underwater plank (by ECA group company)



Stockholm sea image

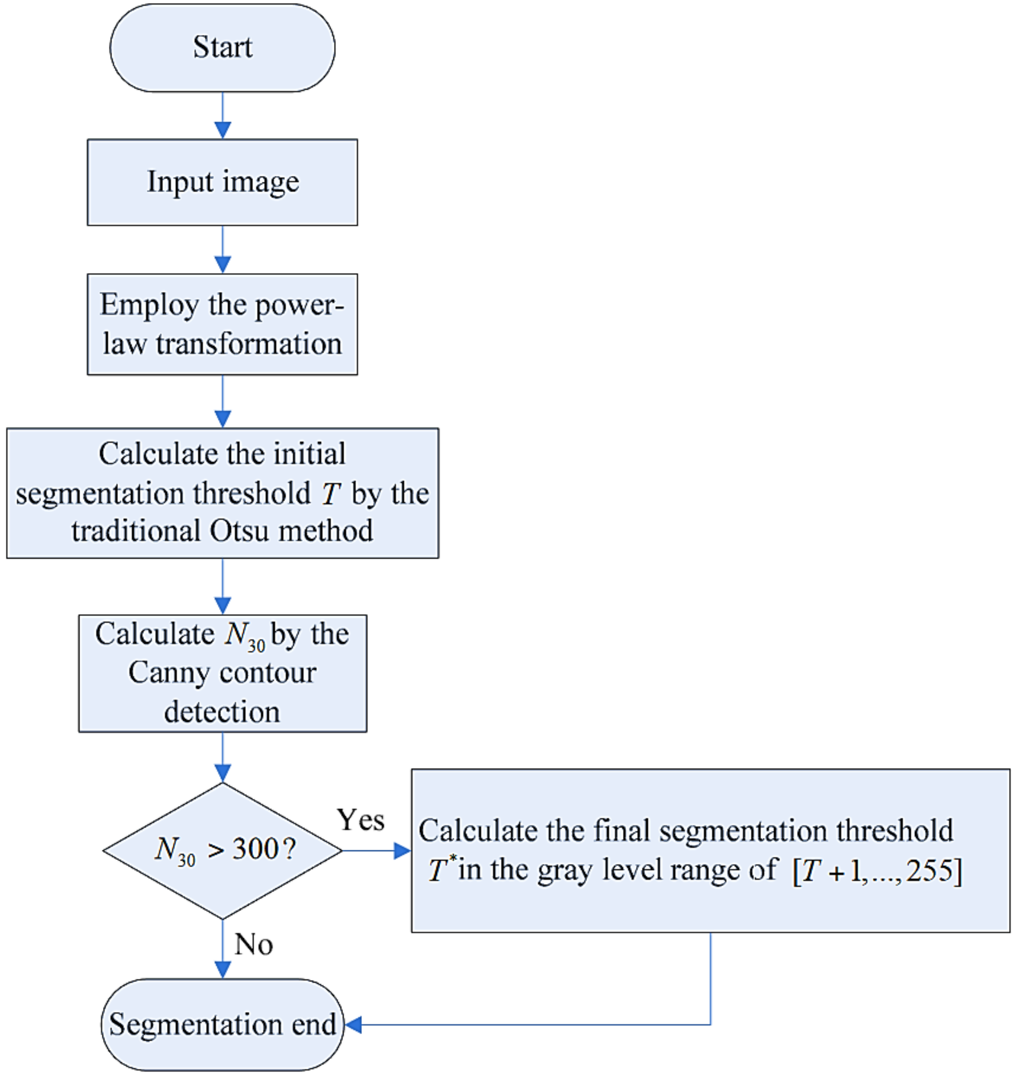
Improving Otsu for underwater imaging

Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging

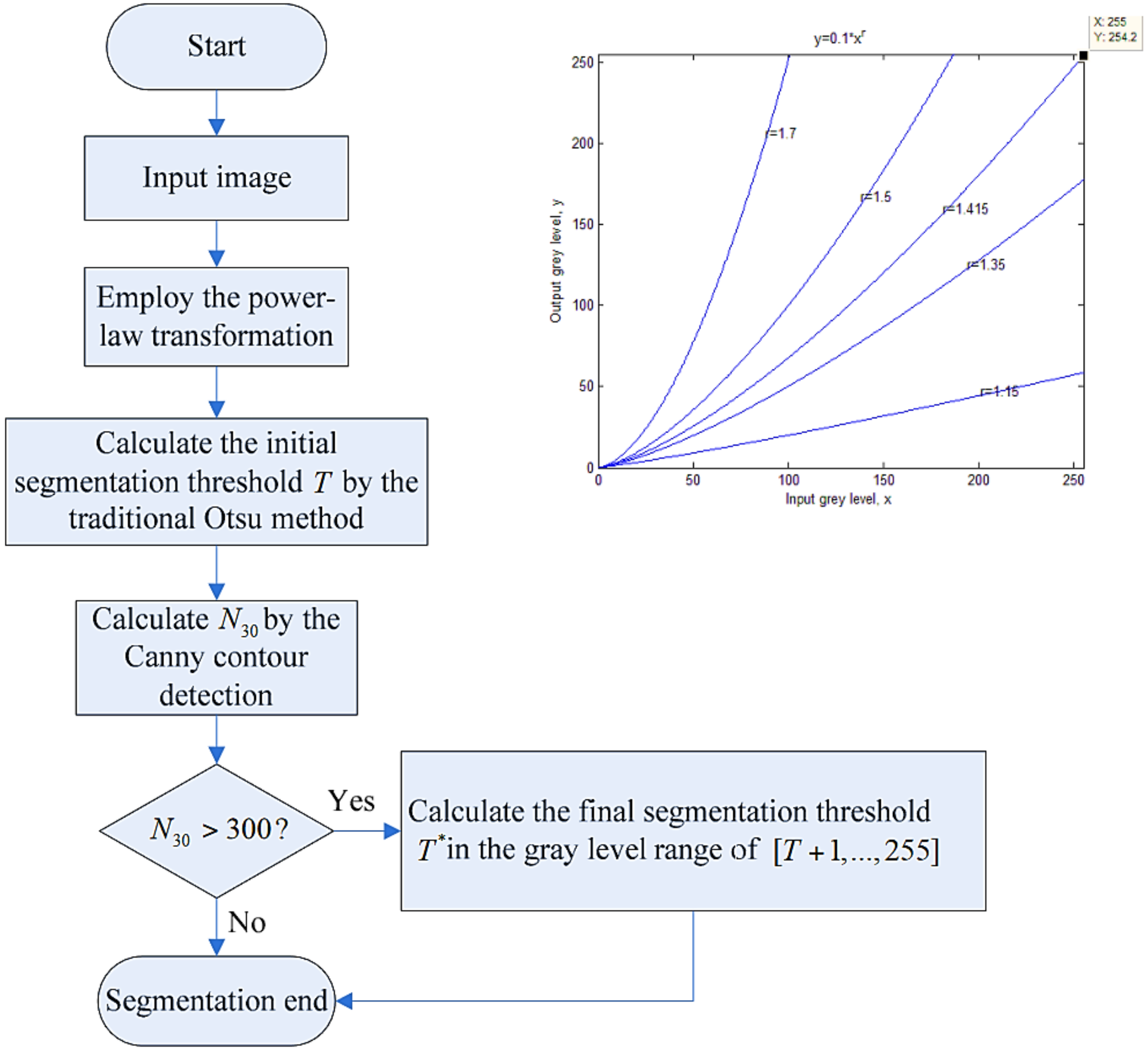
Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging



Improving Otsu for underwater imaging

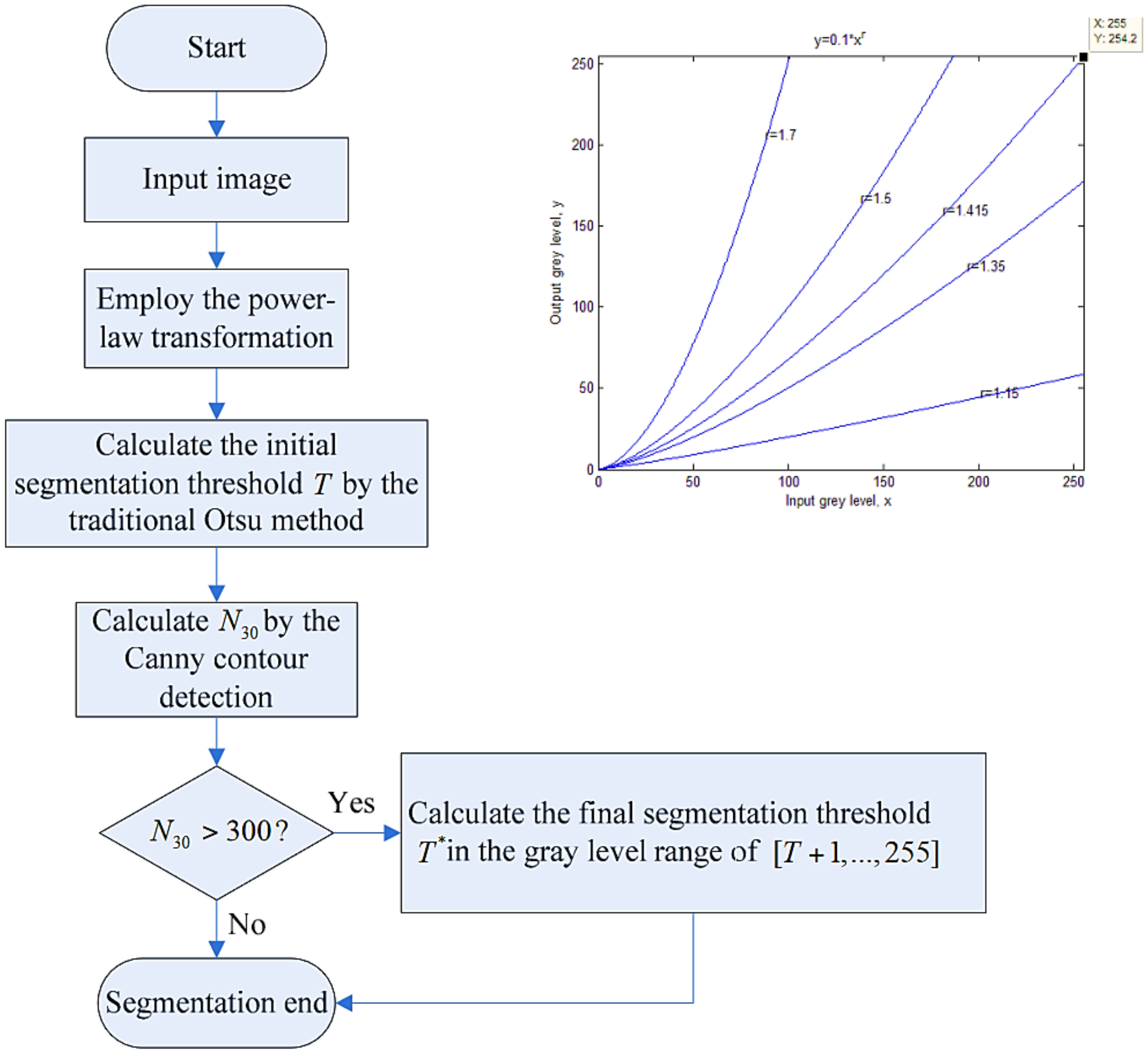
- SONAR
  - Sound Navigation And Ranging



Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging

$$T^* = \arg\left\{\max_{T+1\leqslant i\leqslant 255}\left\{\sigma_B^2(i)\right\}\right\} = \arg\left\{\min_{T+1\leqslant i\leqslant 255}\left\{\sigma_W^2(i)\right\}\right\}$$



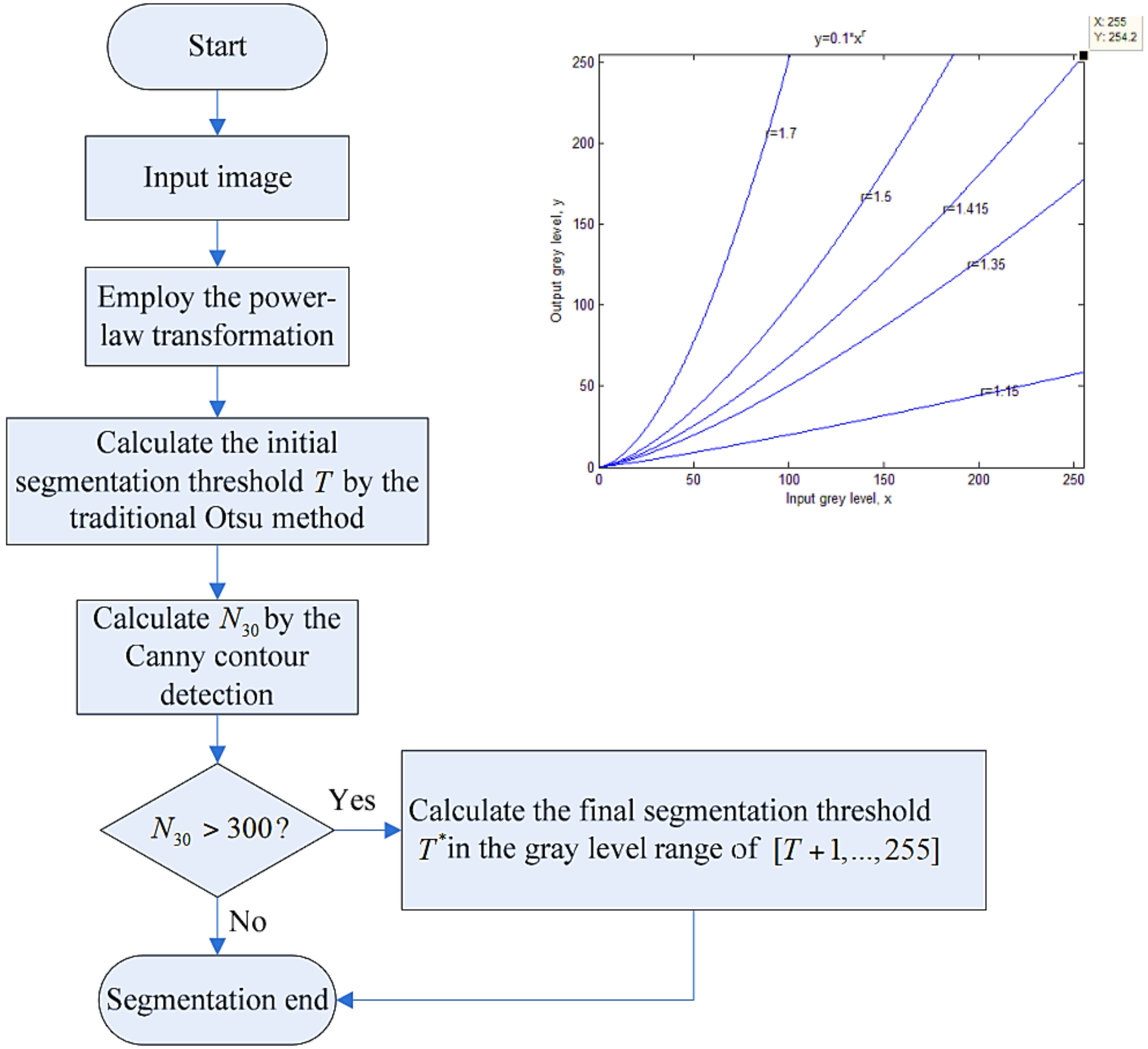
Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging

$$T^* = \arg\left\{\max_{T+1\leqslant i\leqslant 255}\left\{\sigma_B^2(i)\right\}\right\} = \arg\left\{\min_{T+1\leqslant i\leqslant 255}\left\{\sigma_W^2(i)\right\}\right\}$$

between-class variance σ_B^2

within-class variance σ_W^2



Improving Otsu for underwater imaging

- SONAR
  - Sound Navigation And Ranging

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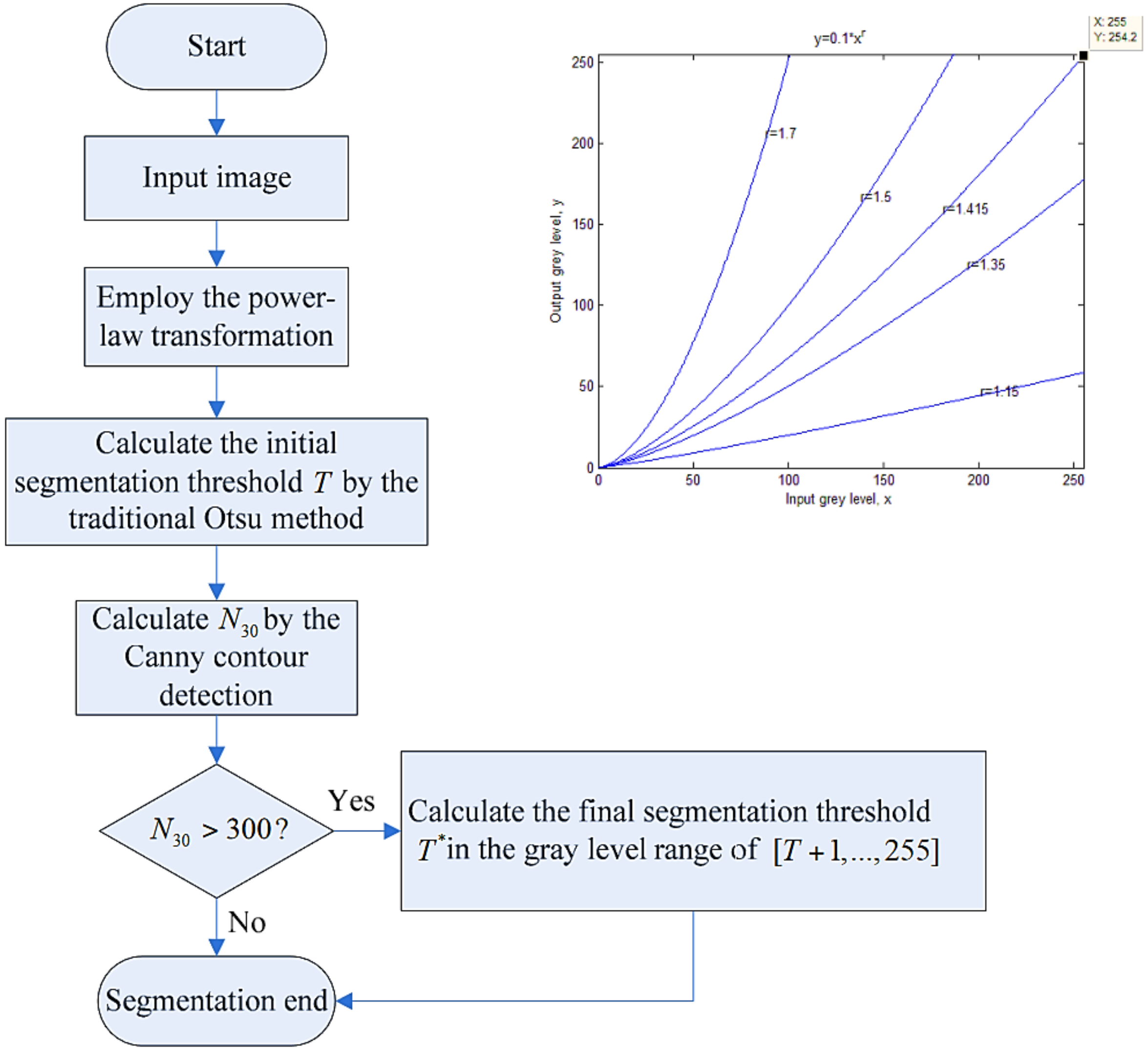
between-class variance σ_B^2

within-class variance σ_W^2

- area size of the background spots is < 30 pixels
- N_{30}: # contours to be found with an area of 30 pixels



Improving Otsu for underwater imaging

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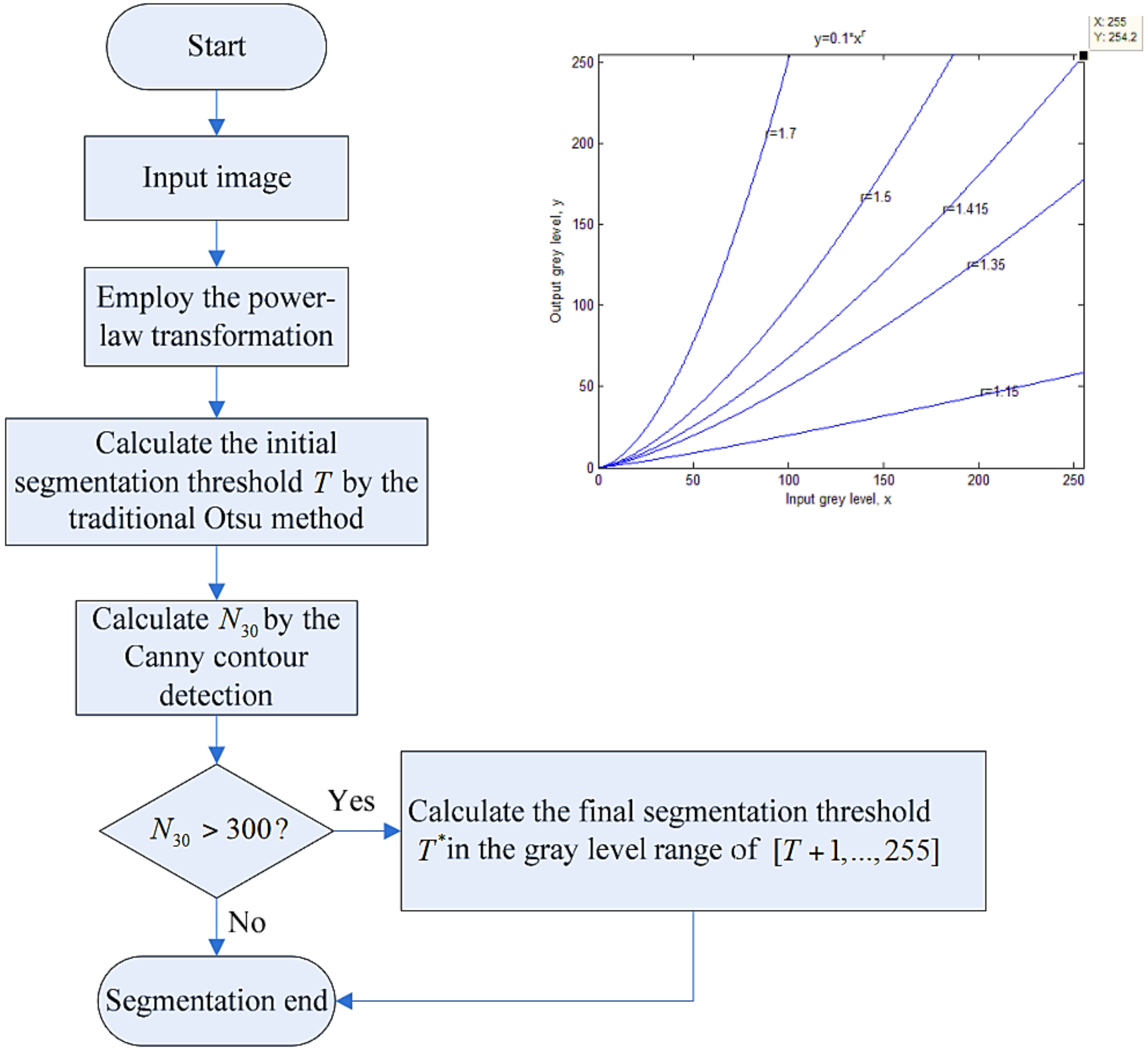

X. Yuan et al. “An Improved Otsu Threshold Segmentation Method for Underwater SLAM Navigation”, Sensors, 2016

Improving Otsu for underwater imaging

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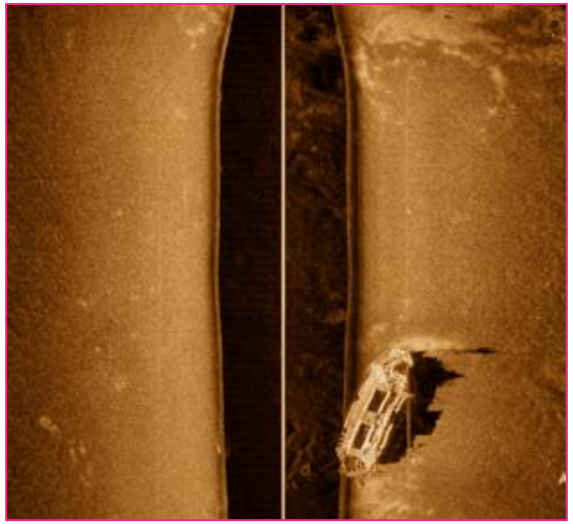

Improving Otsu for underwater imaging

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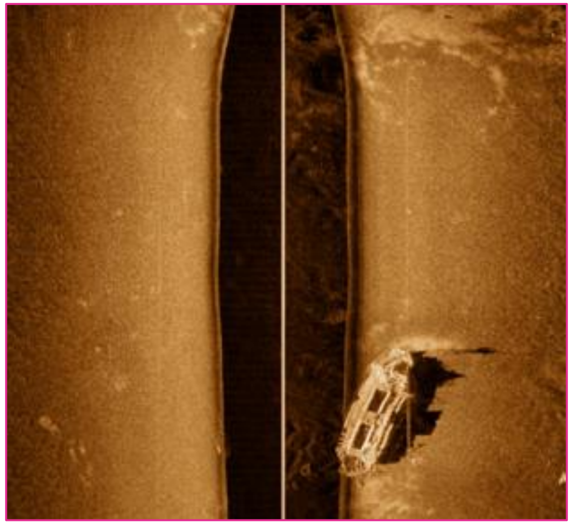

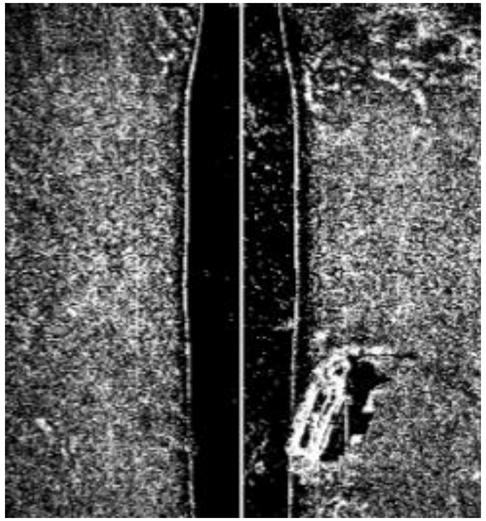

Improving Otsu for underwater imaging

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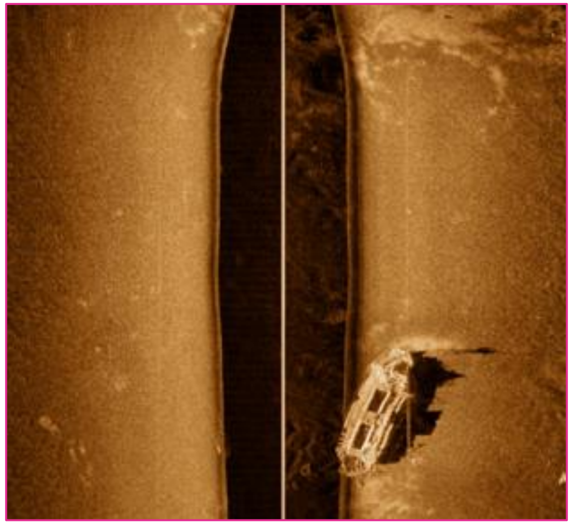
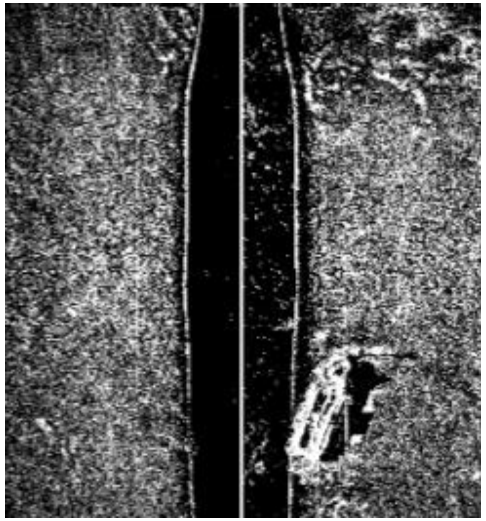


Local TH



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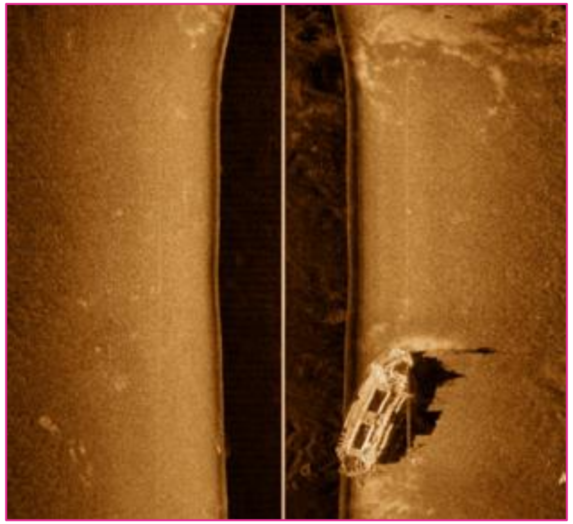

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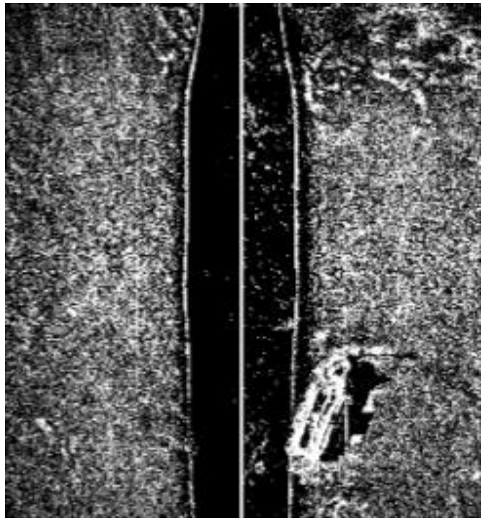

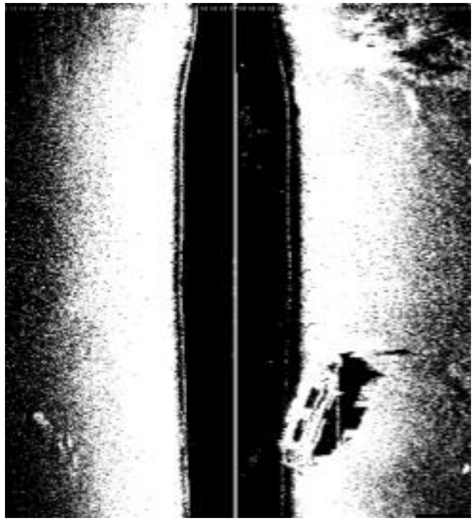

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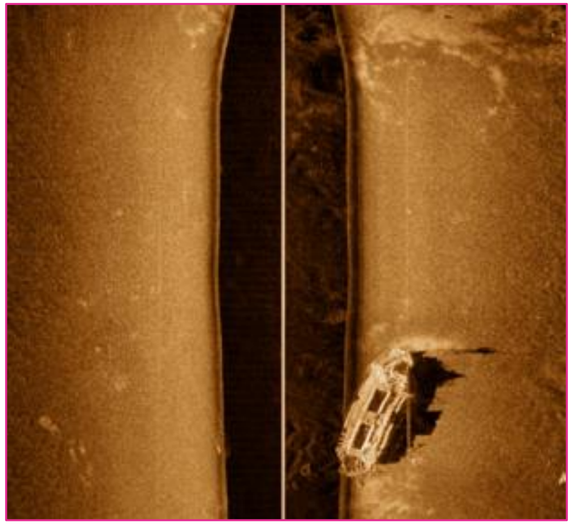

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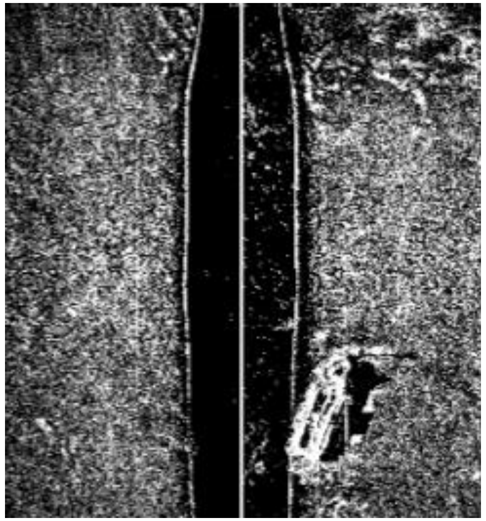

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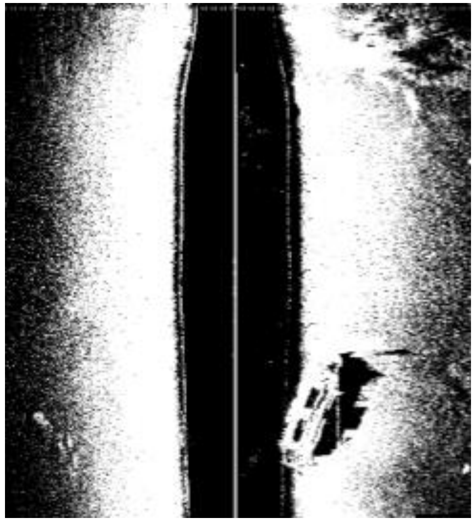

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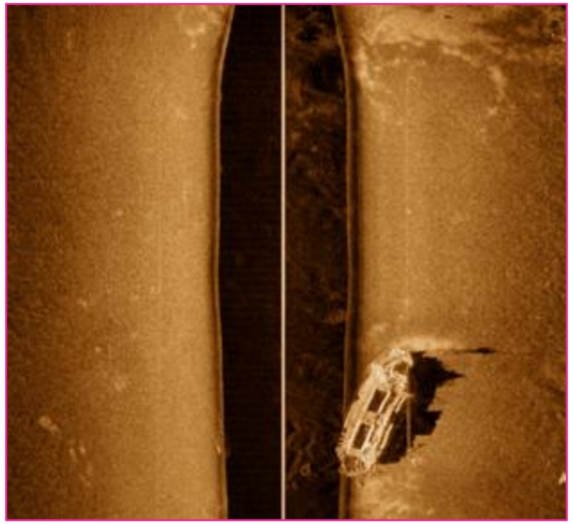

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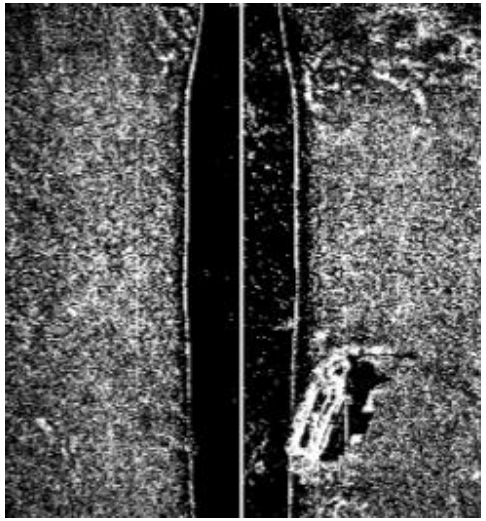

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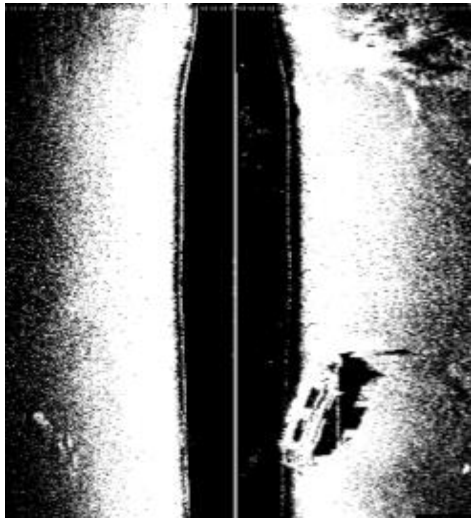

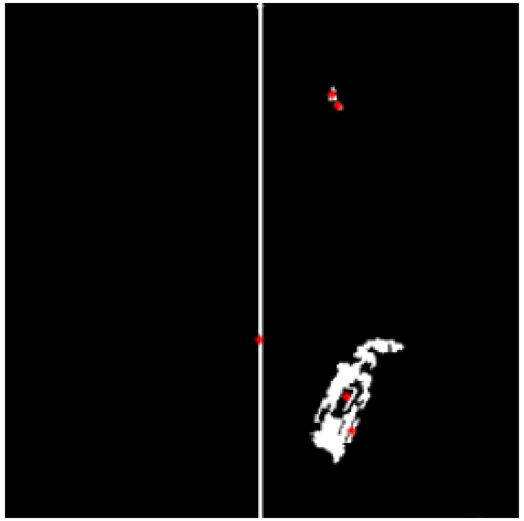

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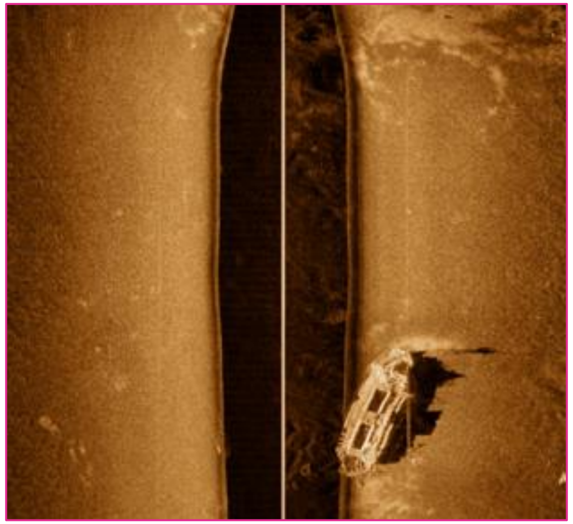

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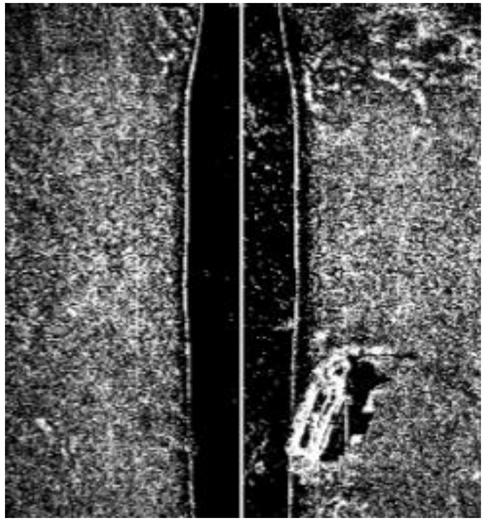

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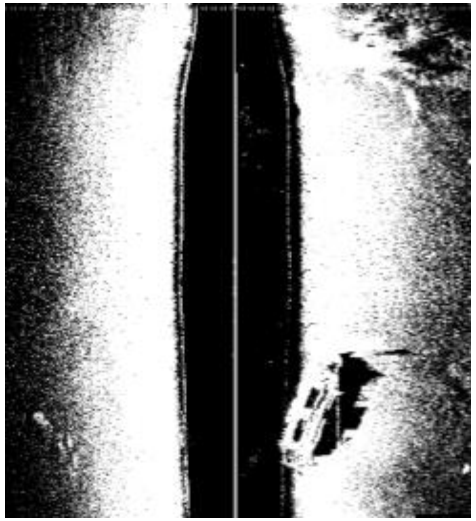
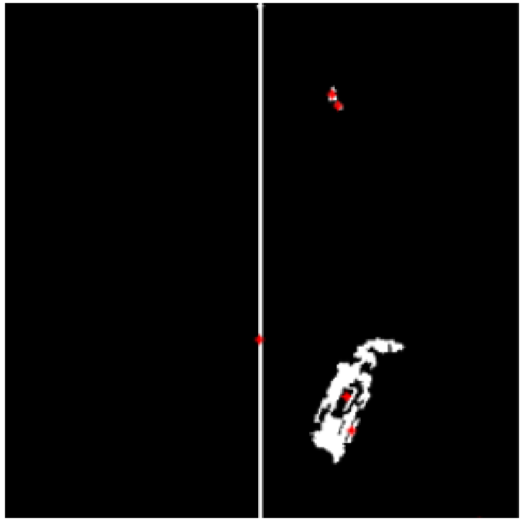


Underwater Otsu



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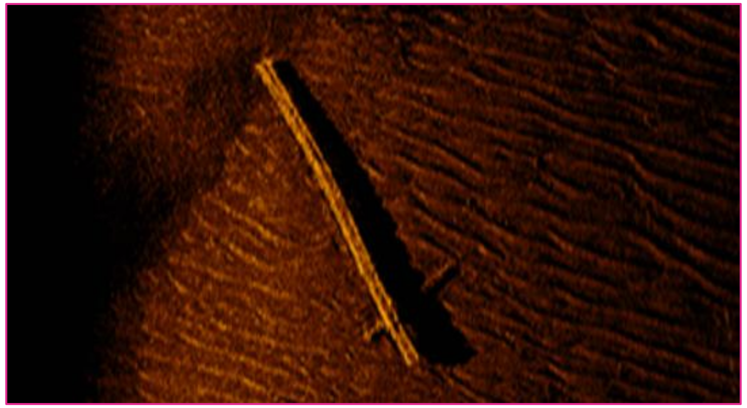

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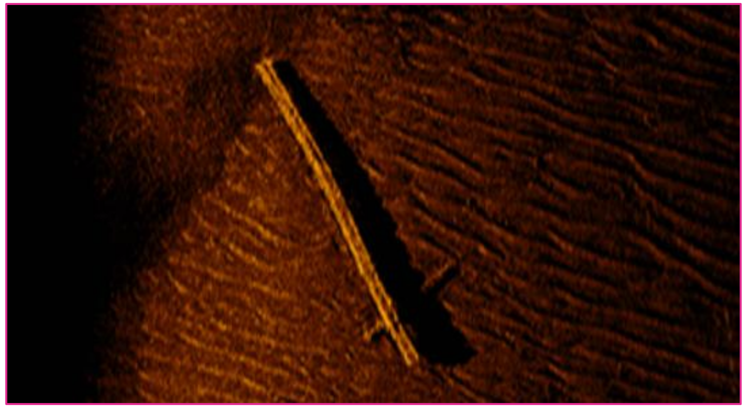

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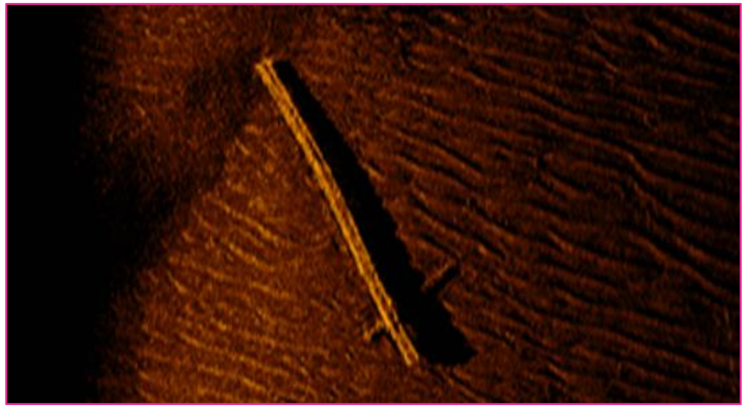

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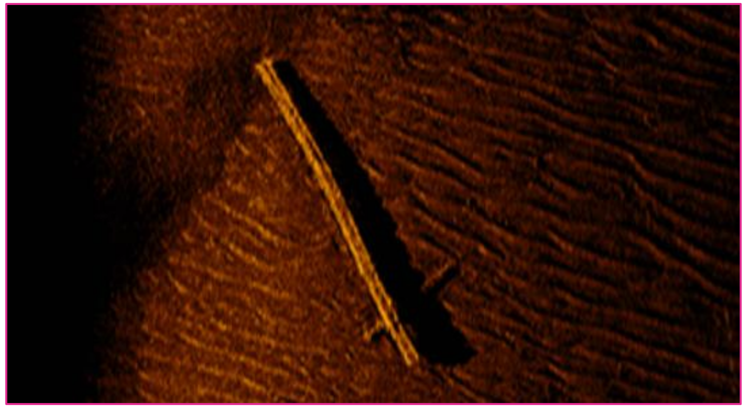

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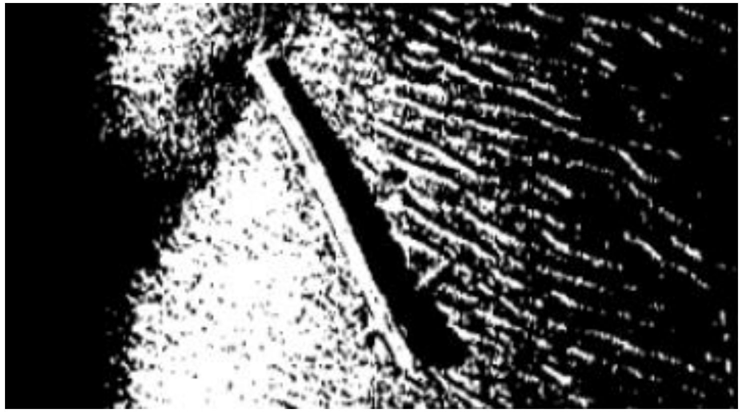

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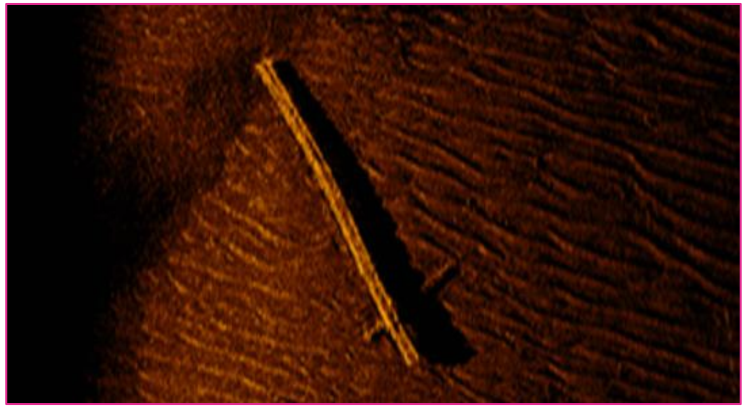

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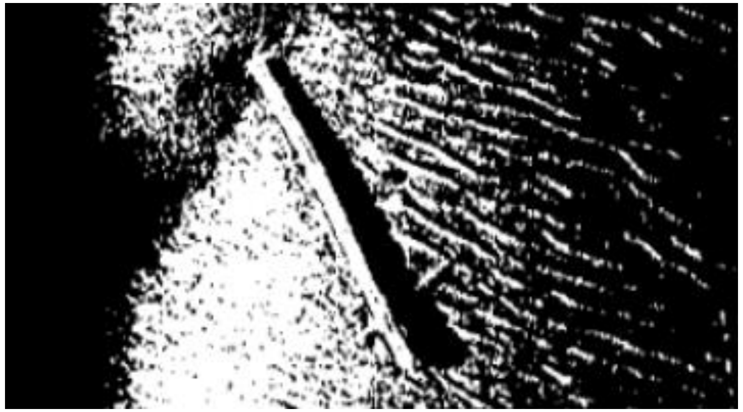

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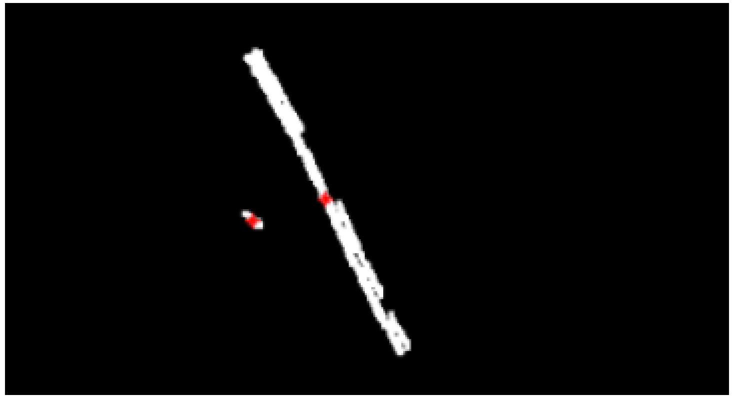

Conclusion

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- Global Otsu's method
  - Input image histogram processing
  - Noise handled via smoothing
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NOBUYUKI OTSU

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I. INTRODUCTION

It is important in picture processing to select an adequate threshold of gray level for extracting objects from their background. A

Conclusion

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❑ Global optimal

❑ Global Otsu's method
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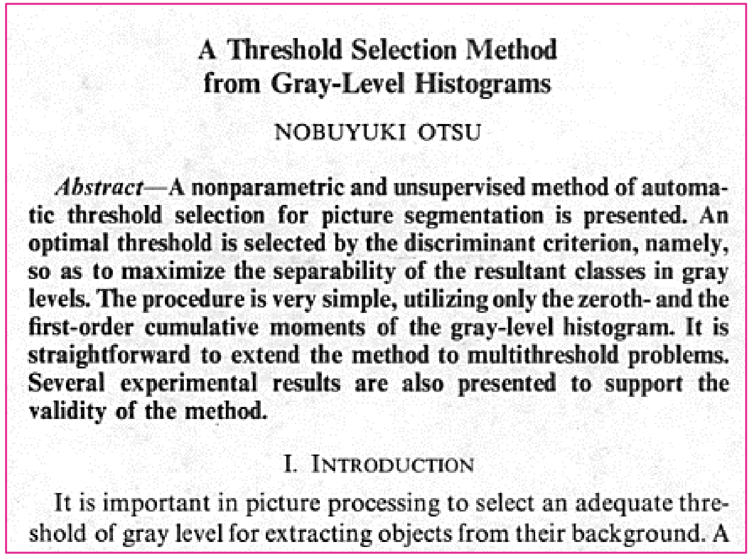
Threshold the Otsu's paper via Otsu's method:



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