Lecture 04

Morphology and Segmention

2024-02-29

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Introduction

Previous lecture:

convolution: $f(x, y)$, $g(x, y)$, **w**: $\mathbb{N} \to \mathbb{R}$

where w = filter kernel

$\to$ (mostly) linear operators

Today:

morphology: $f(x, y)$, $g(x, y)$, **b**: $\mathbb{N} \to \{0, 1\}$

where b = structuring element

$\to$ non-linear operators

$\to$ concerned with connectivity and shape (close to set theory)

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$\to$ labeling image pixels to partition an image into regions

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2.1. Basic concepts

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Morphological filtering mechanics are similar to spatial filtering using convolutions:

1) a kernel called a **structuring element** is used to determine filtering operation:

- the size is determined by the matrix dimensions
- the shape is determined by the pattern of 1 and 0 in the matrix
- the origin is usually the matrix center, although it can also off-centered or even outside it

NB: like convolution kernels, it is common to have structuring elements of odd dimensions with the center as the origin.
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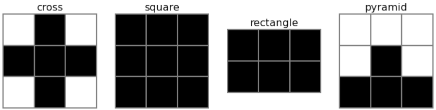

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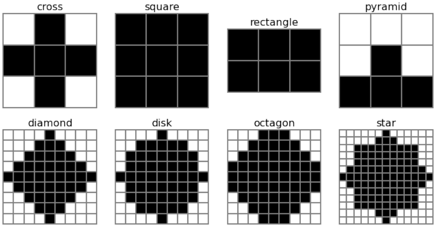

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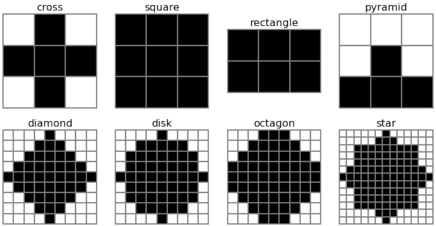
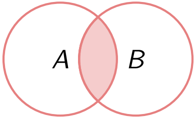


2) the image is first **padded**, and the structuring element than **slides** across it

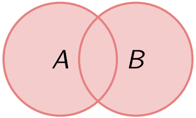
Morphological filters are essentially set operations

Intersection (AND)



$A \cap B = \{x : x \in A \textit{ and } x \in B\}$

Union (OR)



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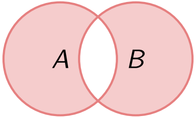
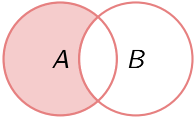
Symmetric difference (XOR)



$\overline{A \cap B}$

Difference



$A - B$

2.2. Primitive Morphological Operations

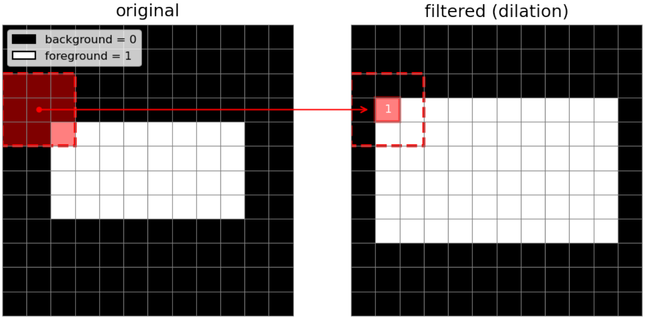
$\rightarrow$ Primary Morphological Operations are: **dilation** and **erosion**

$\rightarrow$ Concatenation of dilation and erosion result in higher level operations

$\Rightarrow$ Composite Morphological Operations: **closing** and **opening**

1. **Dilation**: the dilation of a set F with a structuring element b is defined as:

$$G = F \oplus b = \{x : \left(\hat{b}\right)_x \cap F \neq \emptyset\}$$



if >= 1 pixel within the mask = "1", the result is "1", otherwise "0"

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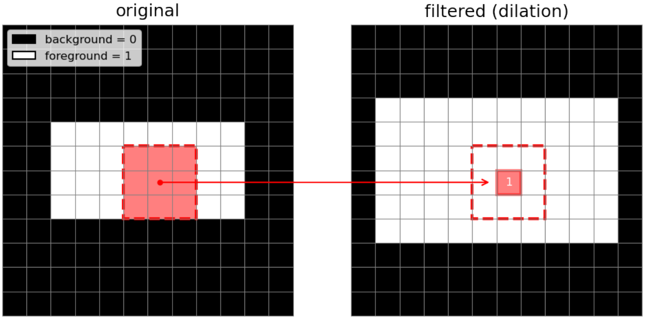

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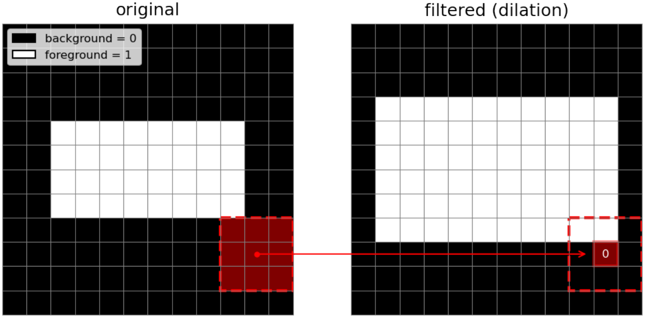

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1. **Dilation**: the dilation of a set F with a structuring element b is defined as:

⇒ Foreground objects get larger
⇒ Background objects get smaller
⇒ Small gaps are closed

original

dilation (b=**3x3**)

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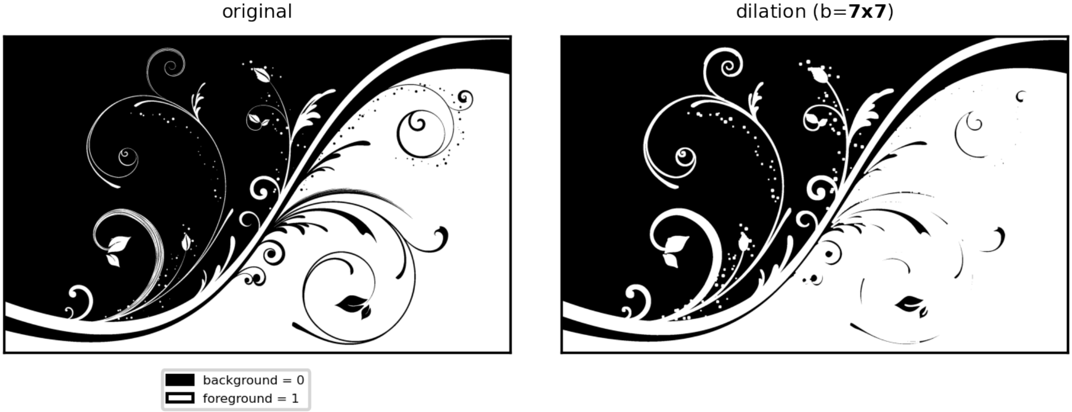

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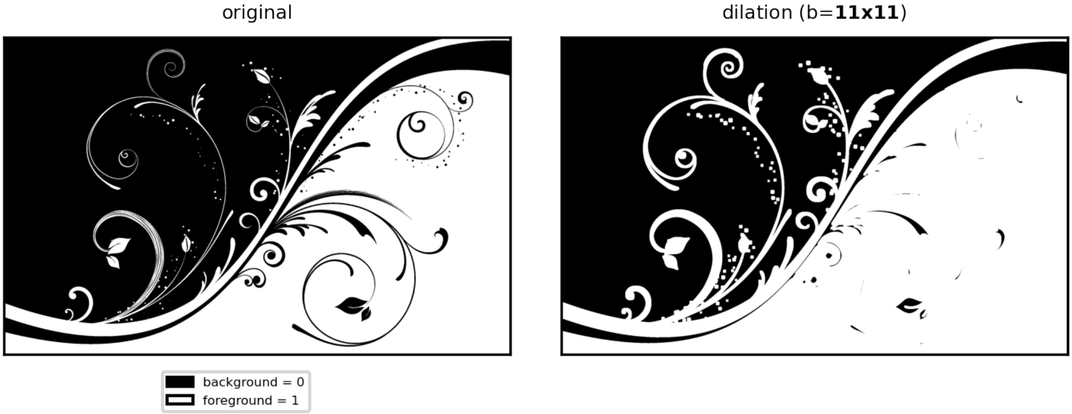

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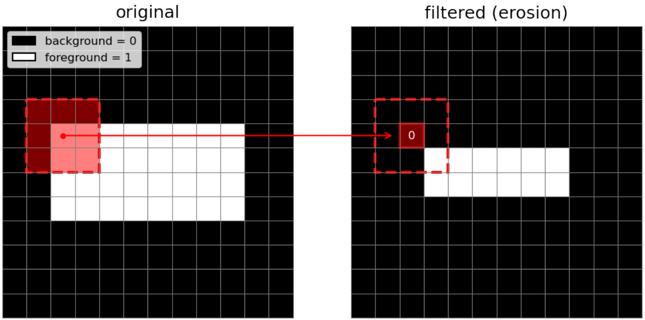

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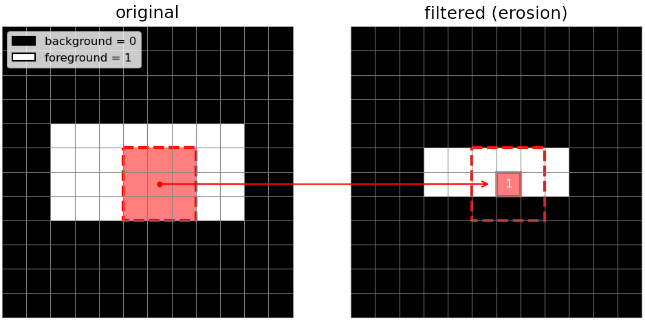

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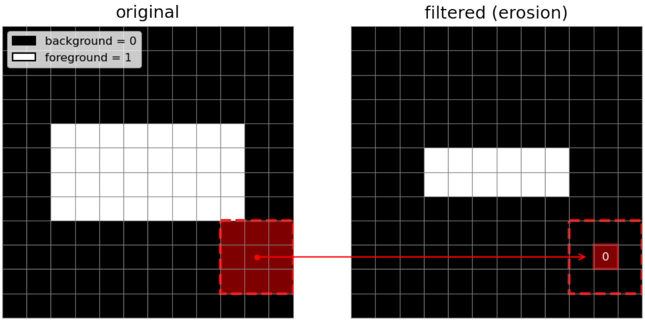

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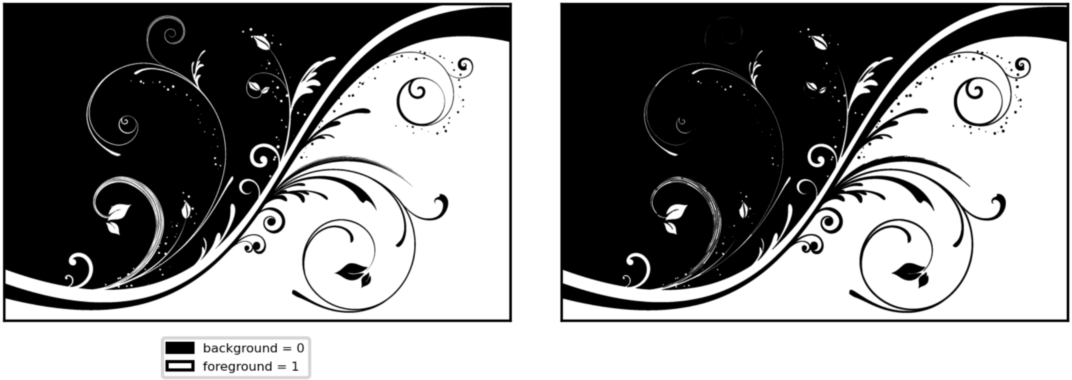

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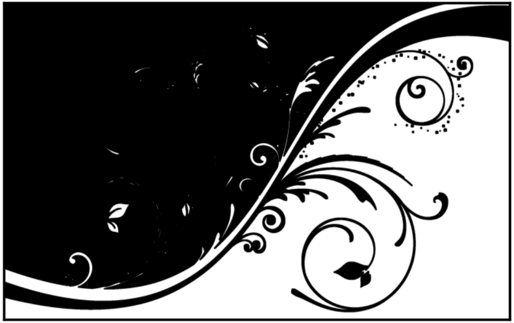
erosion (b=**7x7**)



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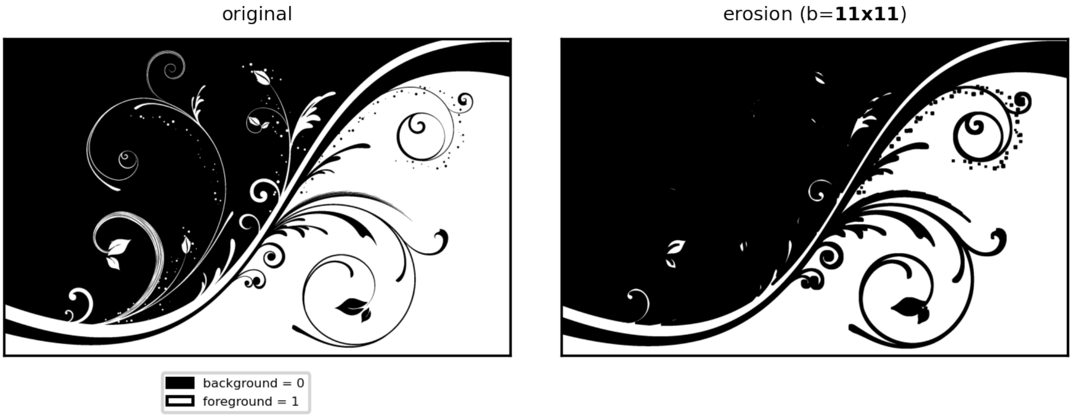

Concatenation of **dilation** and **erosion** result in higher level operations: **closing**, **opening**

1. **Opening**:

   Problem: erosion causes deletion of small objects, BUT other objects shrink
   Solution: after *erosion*, apply *dilation* with the same structuring element ⇒ **opening**

$$G = F \circ b = (F \ominus b) \oplus b$$

   Usage example: removing small isolated "bright spots" *(EX: volcanic SO_2 detection from Sentinel-5P as foreground (mask=1))*

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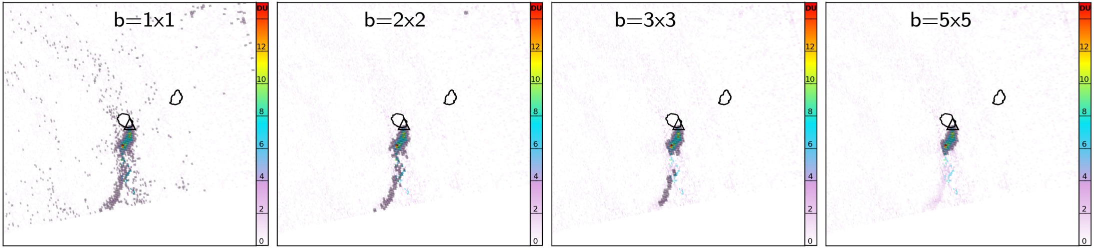

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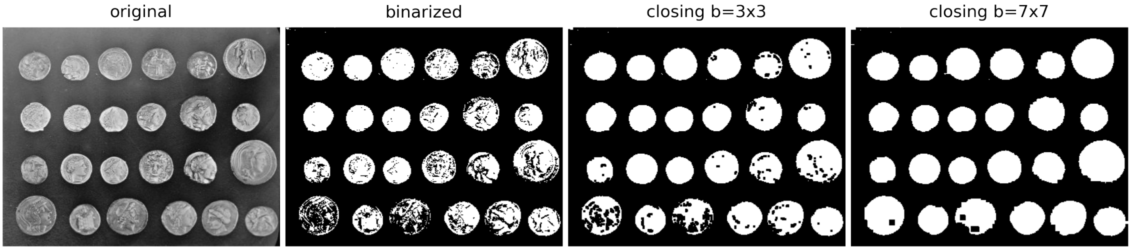

Image segmentation = labeling image pixels to partition an image into regions

- Histogram-based segmentation
  $\Rightarrow$ based on thresholding of pixel values
  - ex: manual thresholding
  - ex: automatic thresholding (e.g., Otsu)
  - ex: k-means clustering
- Edge-based segmentation
  $\Rightarrow$ based on local contrast $\rightarrow$ uses gradients rather than the grey values
- Region-based segmentation
  $\Rightarrow$ based on image gradients and region properties
  - ex: Watershed transform
  - ex: Random Walker
  - ex: Flood Fill
- Many other!
  - ex: Graph-cuts
  - ex: Active Contours, Region Growing, Weighted Pyramid Linking, Mean-Shift, etc.

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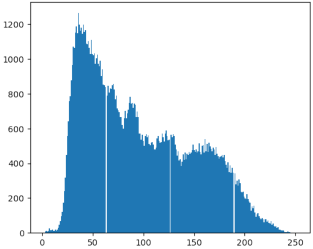

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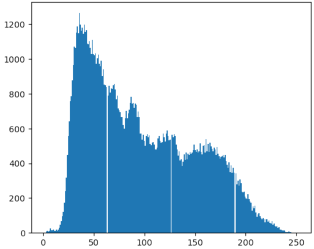
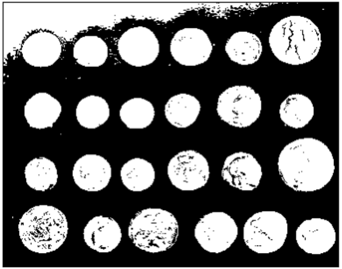


automatic threshold (Otsu thresh=107)



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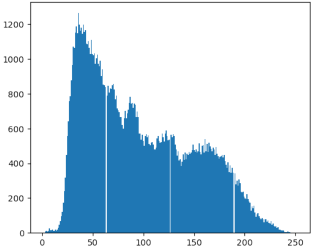

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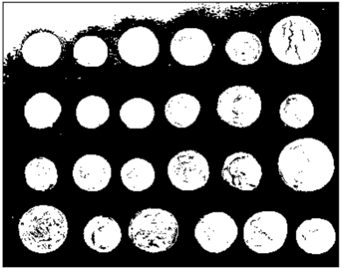
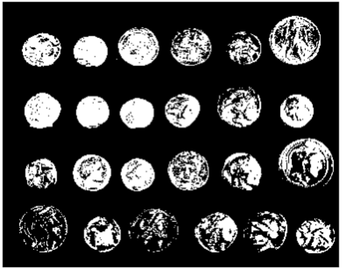


manual threshold (thresh=150)



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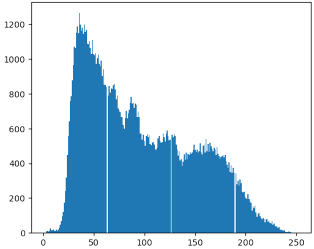

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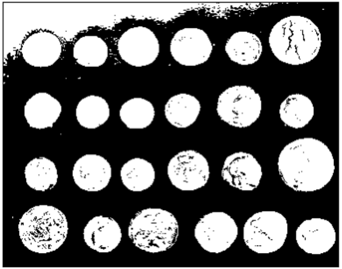
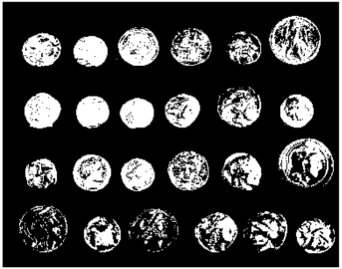
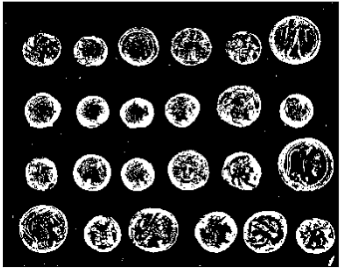


manual threshold (thresh=150)



local thresholds (blocksize=41, offset=-20)



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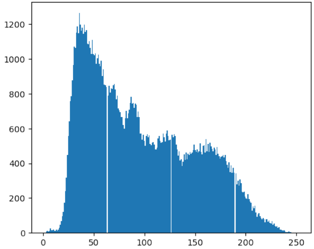

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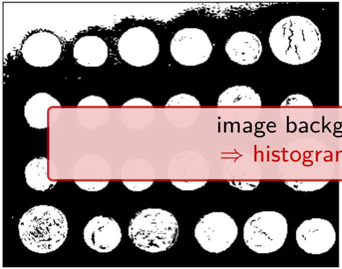

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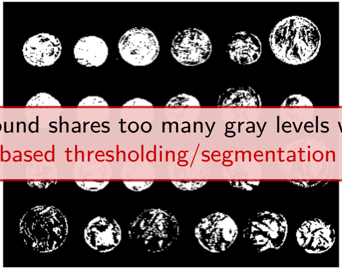
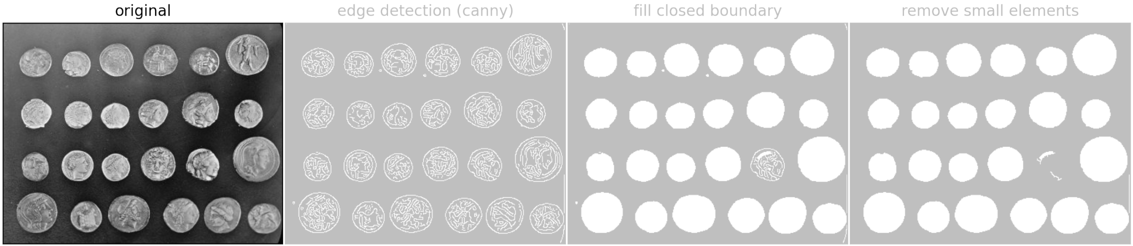


local thresholds (blocksize=41, offset=-20)

image background shares too many gray levels with the coins
⇒ histogram-based thresholding/segmentation is insufficient

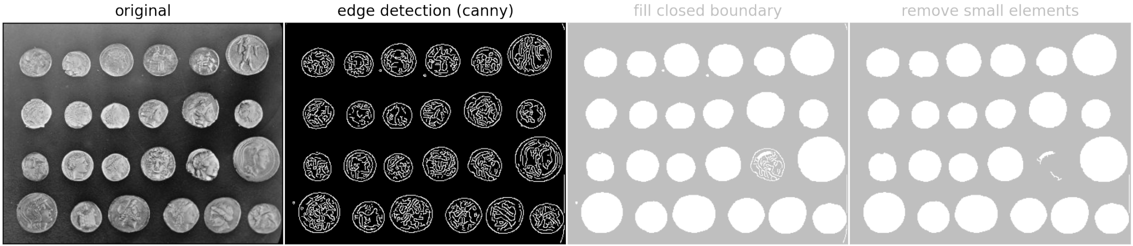
Edge-based segmentation

$\Rightarrow$ based on image gradients



Edge-based segmentation

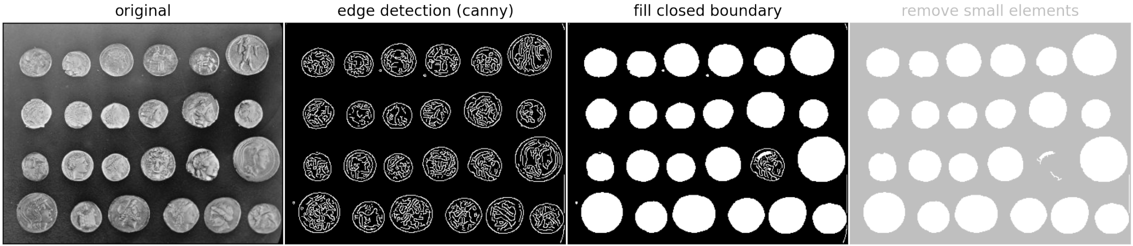
$\Rightarrow$ based on image gradients



1. apply Canny edge detection algorithm (involves gradient detection using e.g. Sobel operator)

Edge-based segmentation

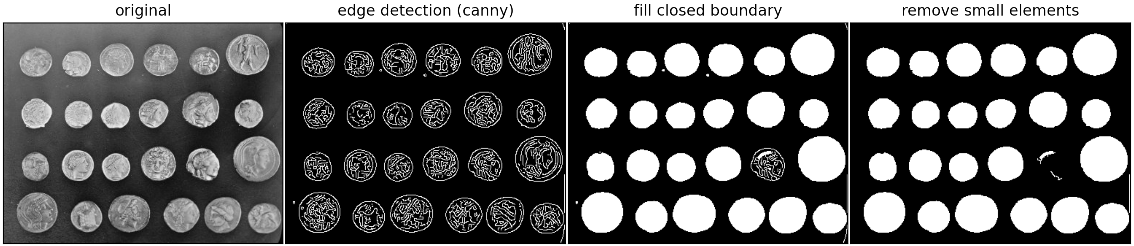
$\Rightarrow$ based on image gradients



1. apply Canny edge detection algorithm (involves gradient detection using e.g. Sobel operator)
2. apply mathematical morphology to fill inner part of the coins

Edge-based segmentation

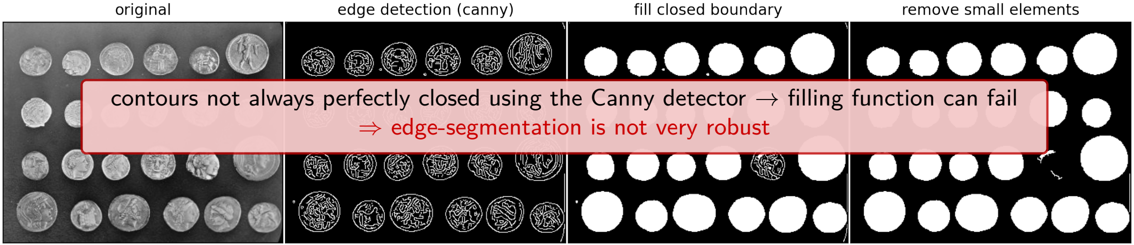
⇒ based on image gradients



1. apply Canny edge detection algorithm (involves gradient detection using e.g. Sobel operator)
2. apply mathematical morphology to fill inner part of the coins
3. remove objects smaller than a threshold

Edge-based segmentation

$\Rightarrow$ based on image gradients



contours not always perfectly closed using the Canny detector $\rightarrow$ filling function can fail
$\Rightarrow$ edge-segmentation is not very robust

1. apply Canny edge detection algorithm (involves gradient detection using e.g. Sobel operator)
2. apply mathematical morphology to fill inner part of the coins
3. remove objects smaller than a threshold

Region-based segmentation: *watershed transform*

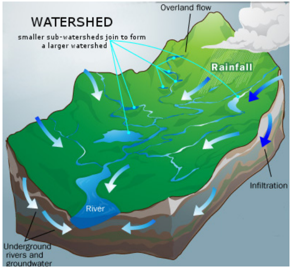
$\Rightarrow$ region-growing approach that fills “basins” in the image

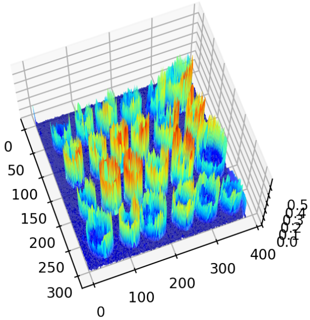
Region-based segmentation: *watershed transform*

⇒ region-growing approach that fills "basins" in the image

⇒ the name "watershed" comes from an analogy with hydrology:

- → the *watershed transform* "floods" a "topographic" representation of the image
- → flooding starts from "markers", in order to determine the catchment basins of these markers





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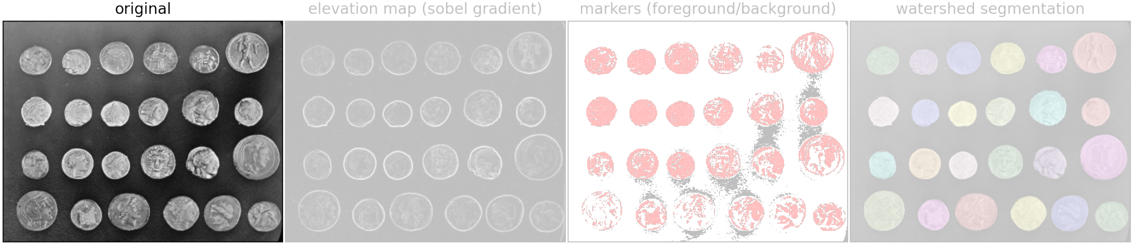

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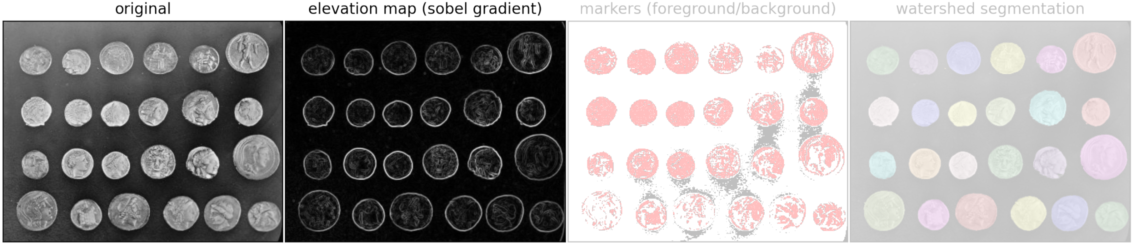

1. build "elevation map" from image gradient amplitude (using the Sobel operator)

Region-based segmentation: *watershed transform*

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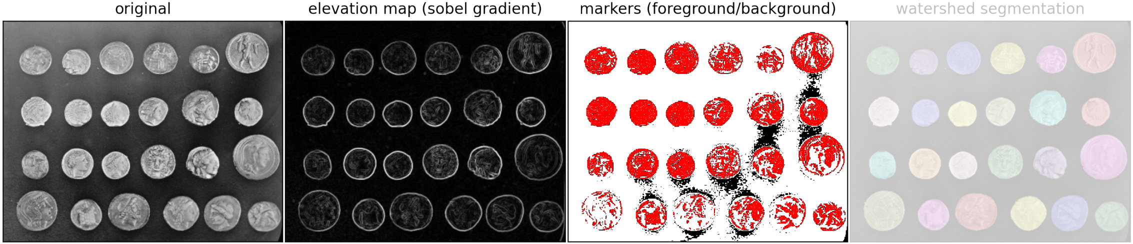

1. build “elevation map” from image gradient amplitude (using the Sobel operator)
2. define markers for background / foreground (here based on the extreme parts of the histogram)

Region-based segmentation: *watershed transform*

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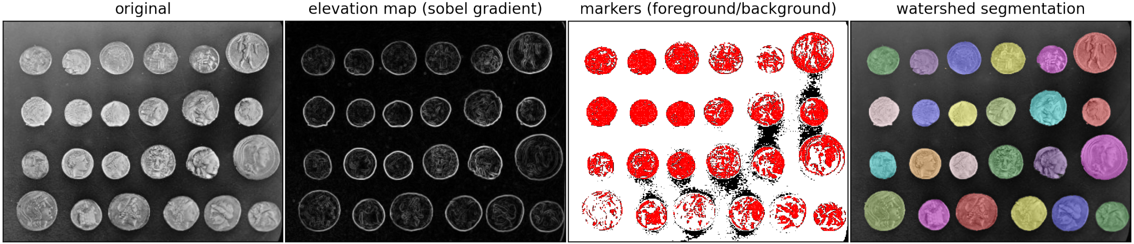

1. build “elevation map” from image gradient amplitude (using the Sobel operator)
2. define markers for background / foreground (here based on the extreme parts of the histogram)
3. apply watershed transform (and colorize segmented elements)

Region-based segmentation: *watershed transform*

⇒ region-growing approach that fills "basins" in the image

⇒ the name "watershed" comes from an analogy with hydrology:

- → the *watershed transform* "floods" a "topographic" representation of the image
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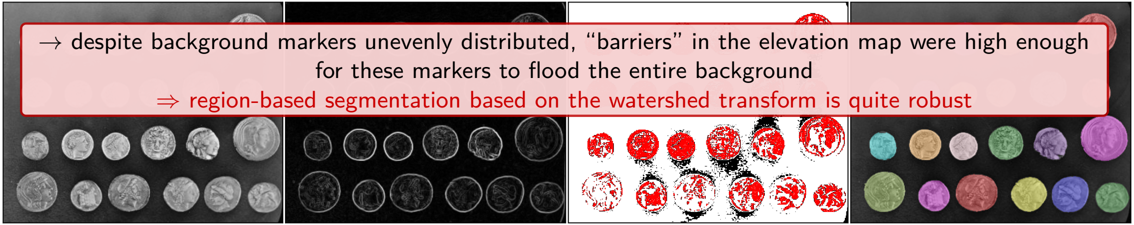
original | elevation map (sobel gradient) | markers (foreground/background) | watershed segmentation

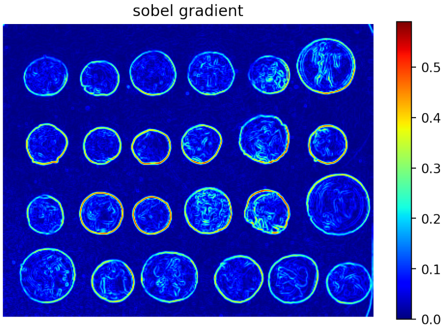


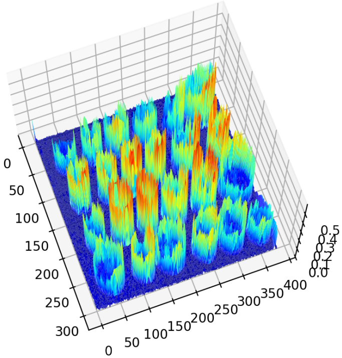
→ despite background markers unevenly distributed, "barriers" in the elevation map were high enough for these markers to flood the entire background

⇒ region-based segmentation based on the watershed transform is quite robust

1. build "elevation map" from image gradient amplitude (using the Sobel operator)
2. define markers for background / foreground (here based on the extreme parts of the histogram)
3. apply watershed transform (and colorize segmented elements)

Region-based segmentation: *watershed transform*





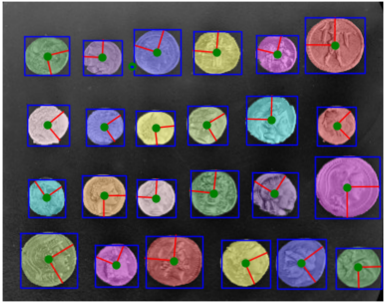
1. Start with lowest "altitude" (Gradient amplitude)
2. Increase the "water level" each time by 1
3. Merge all connected pixel with same/less level

Analyze segmented image

The segmented elements can be analysed indidually to:

→ provide statistics on their shape, distribution, orientation, etc.

(e.g. fields in a satellite image, crystal/bubble shape distribution in a rock sample, etc.)



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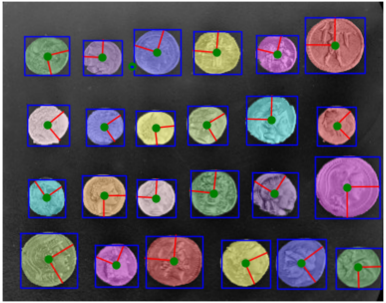

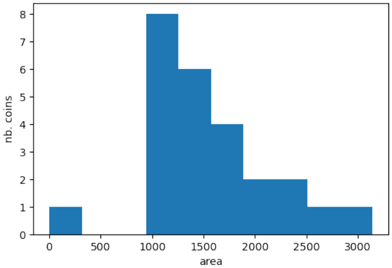

Analyze segmented image

Exercises:

1. Exercise 1:
   $\Rightarrow$ histogram-based segmentation of Popocatépetl
2. Exercise 2:
   $\Rightarrow$ analyze a thermal infrared image of a lava lake
   $\rightarrow$ segment the crustal plates from the incandescent cracks and analyze