

Image segmentation

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FAIIA

Outline

Intensity thresholding

Clustering

Region growing

Frequency decomposition methods

Supervised machine learning

Morphological operations

Intensity thresholding

- **Estimate** an **intensity threshold** such that all pixels with an intensity **superior** (*resp.* **inferior**) to the threshold are part of the **object** component (*resp.* **background** component)

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Intensity thresholding

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- **Global** and **local** thresholding methods
- First example: the **global mean thresholding method**:

$$T = \frac{\sum_{i \in \Omega} I_i}{|\Omega|}, \quad (1)$$

where Ω is the set of pixels in the image and I_i is the intensity observed at pixel $i \in \Omega$

Intensity thresholding

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- Second example: the **local mean thresholding method**:

$$T_s = \frac{\sum_{i \in \Omega_s} I_i}{|\Omega_s|}, \quad (2)$$

where T_s is the local threshold estimated at pixel s , Ω_s is a local neighborhood defined around pixel s and I_i is the intensity observed at pixel $i \in \Omega_s$

Intensity thresholding

Advantages:

- **No parameters** for global thresholding (but at least **local neighborhood size** for local thresholding)
- **Many global and local thresholding methods** exist in Fiji

Drawbacks:

- Sensitivity to **noise**
- Sensitivity to **intensity variations**

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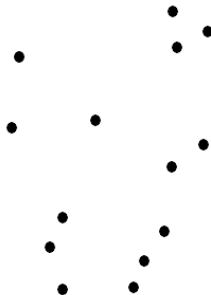
Morphological operations

Image clustering

Image clustering: **classifying** or **grouping** objects based on intensity

Image clustering

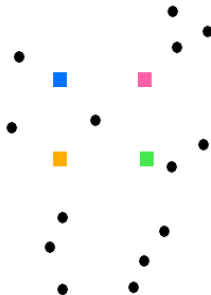
k-means clustering algorithm:



- $K = 4$ clusters
- **Euclidean** distance

Image clustering

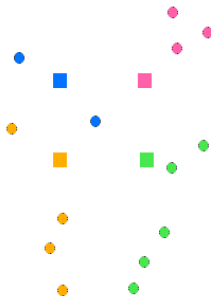
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Image clustering

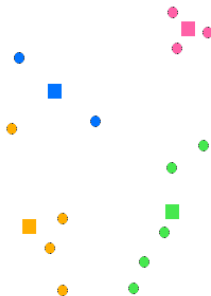
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Image clustering

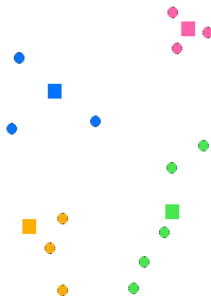
k-means clustering algorithm:



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Image clustering

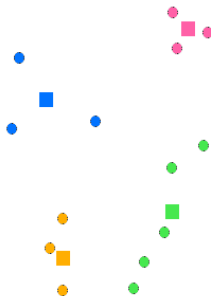
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Image clustering

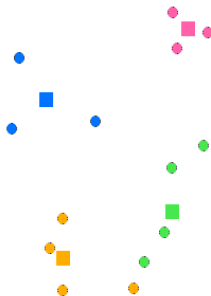
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Image clustering

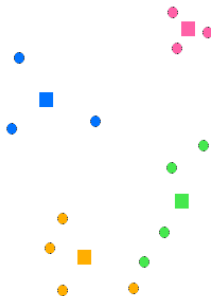
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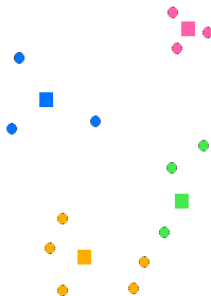
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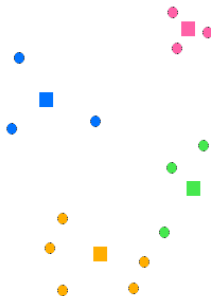
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Image clustering

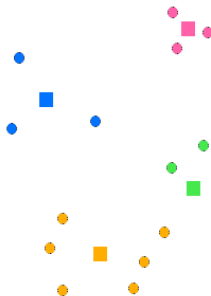
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Image clustering

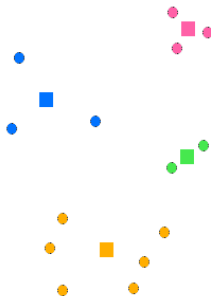
k-means clustering algorithm:



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Image clustering

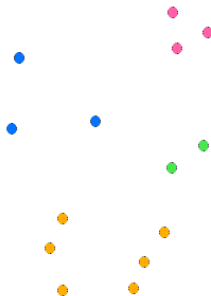
k-means clustering algorithm:



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Image clustering

k-means clustering algorithm:



- **$K = 4$ clusters**
- **Euclidean distance**

Image clustering

Advantages:

- Any **number** of **categories** (not limited to object/background)
- **Gray level** and **color** images (or any number of channels)

Drawbacks:

- Need to define a **number** of categories
- Sensitivity to **initialization**
- Sensitivity to **local minima**

Outline

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Region growing

Frequency decomposition methods

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Morphological operations

Region growing

Region growing algorithms have **two** main steps:

- **Seed** initialization
- **Expansion** through **similarity** criteria (average intensity, variance, texture, ...)

Region growing

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Example: **Active contours** approach

Energy based on **partial differential equations**:

$$E(C) = \sum_0^1 (E_{\text{int}}(C(q)) + (E_{\text{ext}}(C(q))))dq \quad (3)$$

where E_{int} controls the **smoothness** of the contours
 E_{ext} is responsible for **attracting** the contours towards **objects**

Region growing

Advantages:

- **Flexibility** of criteria (possibility to have several criteria)

Drawbacks:

- **Parameterization**
- Need for **seed initialization**
- **Slow**

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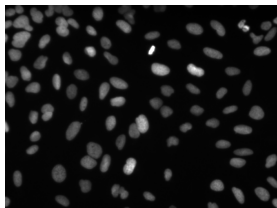
Frequency decomposition methods

Frequency decomposition methods methods (DoG, Fourier transform, ...) identify a specific **scale** in the image

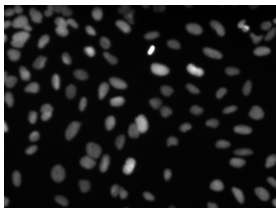
Frequency decomposition methods

DoG (Difference of Gaussians):

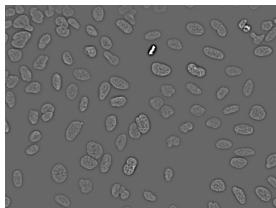
Gaussian kernel = 1



Gaussian kernel = 2



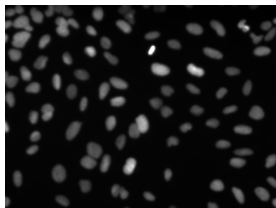
Difference



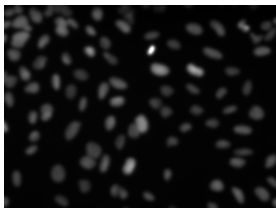
Frequency decomposition methods

DoG (Difference of Gaussians):

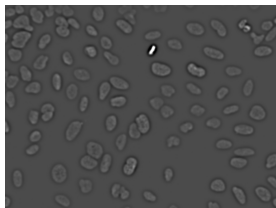
Gaussian kernel = 2



Gaussian kernel = 4



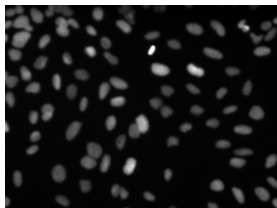
Difference



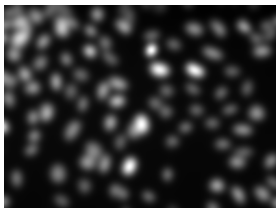
Frequency decomposition methods

DoG (Difference of Gaussians):

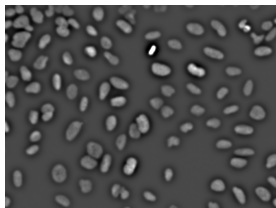
Gaussian kernel = 2



Gaussian kernel = 10



Difference



Frequency decomposition methods

Advantages:

- **Accurate** when objects are the **same size**
- **Robust** to noise

Drawbacks:

- Need for **specific scale** that is **different enough** from the rest of the image

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Supervised machine learning

Contrary to **traditional approaches** where each **single step** is fully **determined** by the developer, supervised machine learning algorithms are **trained to "learn"**:

- A **training dataset** is defined such that input images and outputs (detection, classification, decision, ...) are **known**
- The **training process** for the algorithm consists in finding how to estimate the outputs given the input images
- Once the **algorithm** is **trained**, other images can be processed

Supervised machine learning

Advantages:

- Potentially solves **complex problems**

Drawbacks:

- Need for **large training datasets** if using deep learning
- Need to define **image features** if using traditional machine learning algorithms
- Need for **optimization** (complex for non specialists)

Practice

<https://youtu.be/5YLf0RZukA8>

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Morphological operations

Morphological operations correspond to **image filtering** applied to **binary images**

Morphological operations

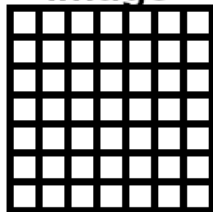
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0	0	0	0	0	0	0
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Dilation

1	1	1
1	1	1
1	1	1

Filtered
image

Morphological operations

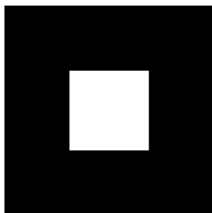
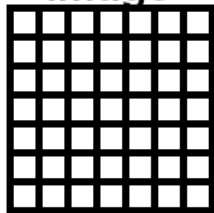
Image



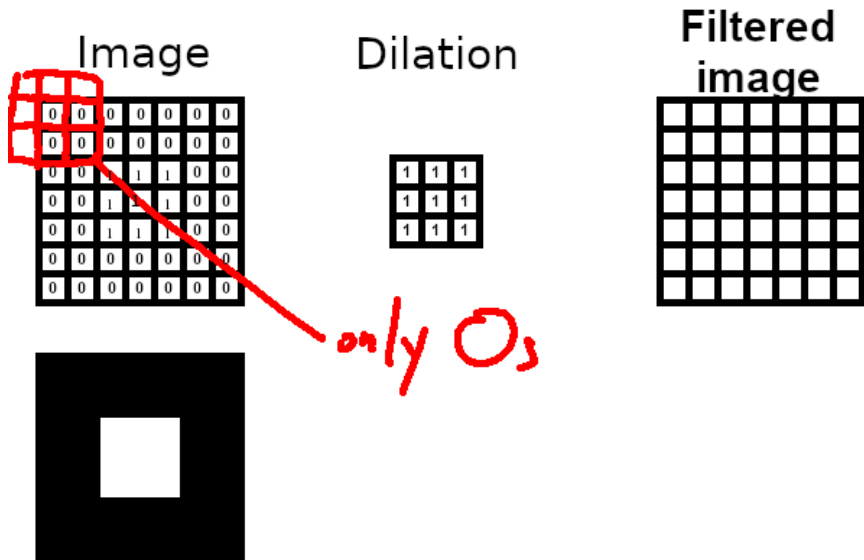
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Dilation

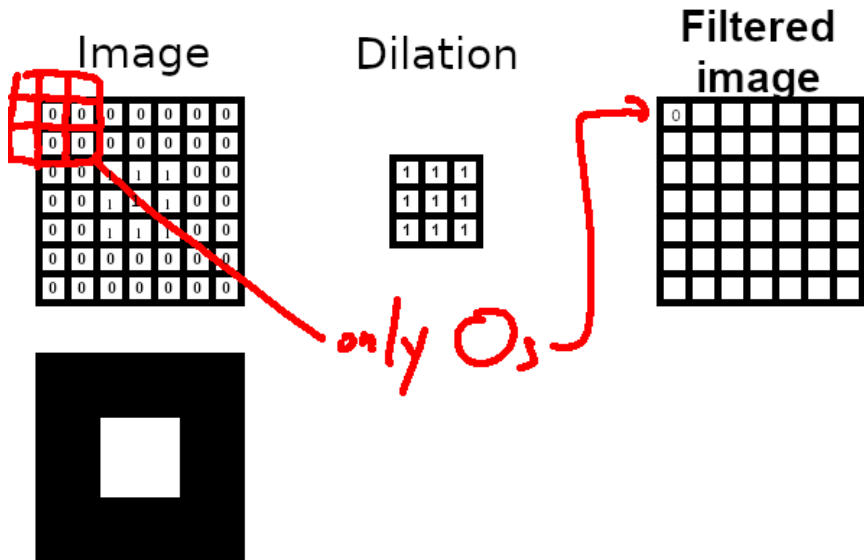
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1	1	1
1	1	1

Filtered
image

Morphological operations



Morphological operations



Morphological operations

Image

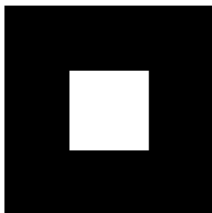
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Dilation

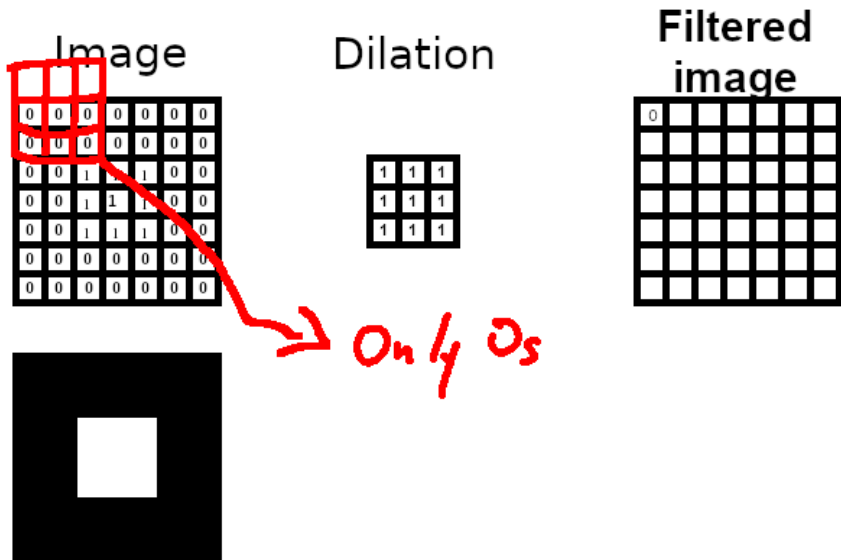
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Filtered
image

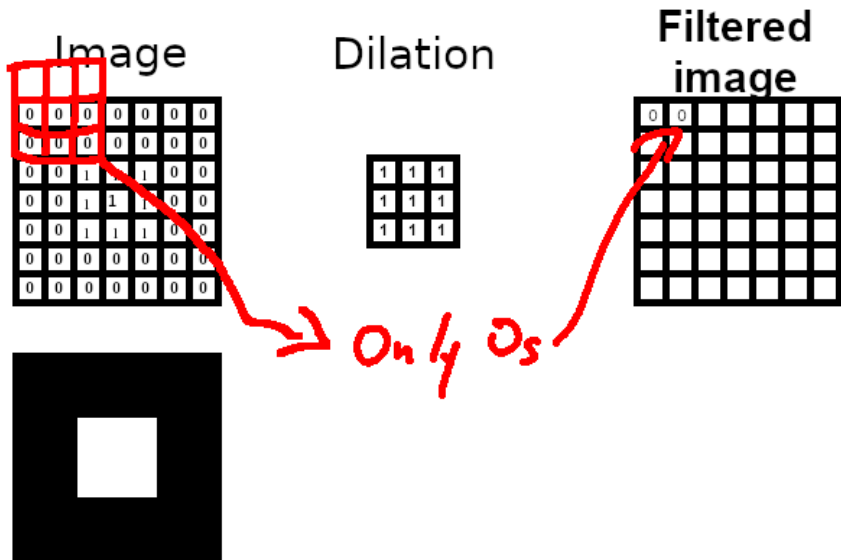
0							



Morphological operations



Morphological operations



Morphological operations

Image

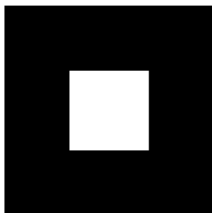
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0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Dilation

1	1	1
1	1	1
1	1	1

Filtered
image

0	0	0	0	0	0	0	0
0							



Morphological operations

Image

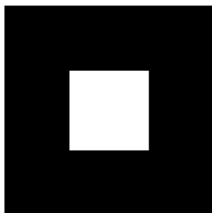
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Dilation

1	1	1
1	1	1
1	1	1

Filtered
image

0	0	0	0	0	0	0	0
0							



Morphological operations

Image

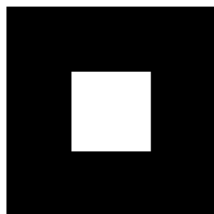
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Dilation

1	1	1
1	1	1
1	1	1

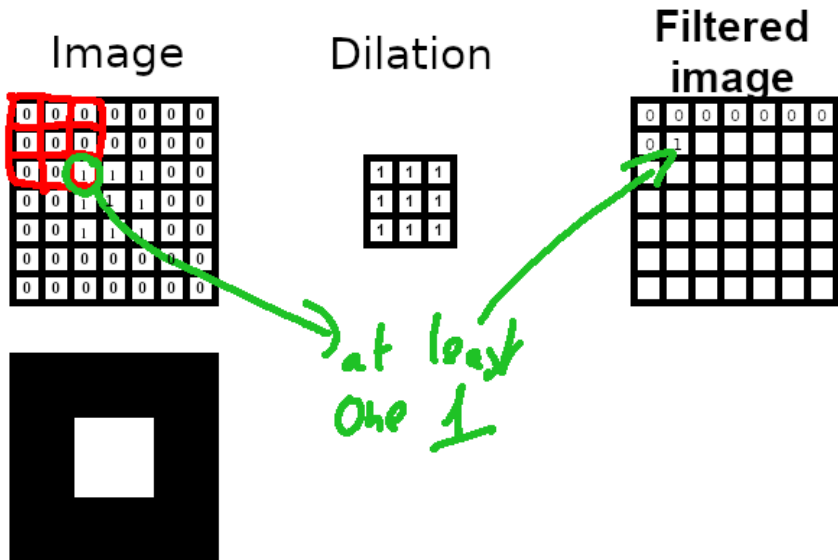
Filtered image

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0							



at least
one 1

Morphological operations



Morphological operations

Image

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Dilation

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1	1	1
1	1	1

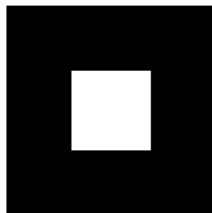
Filtered
image

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0	1	1	1	1	1	0
0	0	0	0	0	0	0

Morphological operations

Image

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0	0	0	0	0	0	0
0	0	1	1	1	0	0
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Dilation

1	1	1
1	1	1
1	1	1

Filtered image

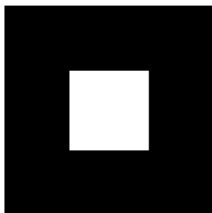
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Morphological operations

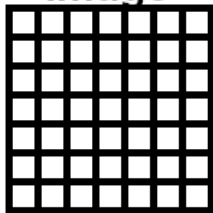
Image

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Erosion

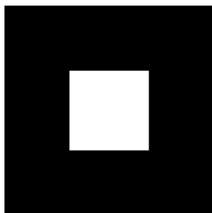
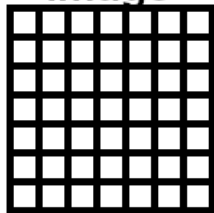
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Filtered
image

Morphological operations



Erosion

Filtered
image

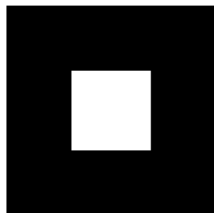
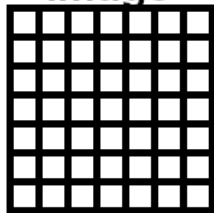
Morphological operations

Image

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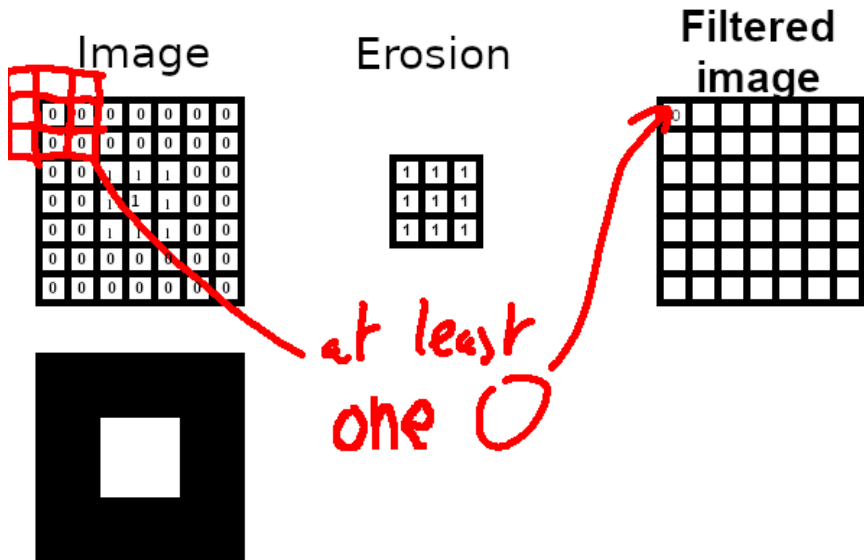
Erosion

1	1	1
1	1	1
1	1	1

Filtered
image

at least
one 0

Morphological operations



Morphological operations

Image

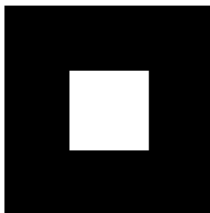
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0	0	0	0	0	0	0

Erosion

1	1	1
1	1	1
1	1	1

Filtered
image

0	0	0	0	0	0	0
0	0	0	0	0	0	0
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0	0	0				



Morphological operations

Image

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0	0	1	1	1	0	0	0
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0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Erosion

1	1	1
1	1	1
1	1	1

Filtered
image

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
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0	0	0					



Only 1s

Morphological operations

Image

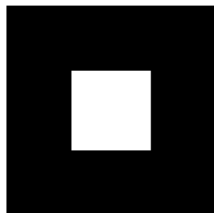
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0	0	0	0	0	0	0	0

Erosion

1	1	1
1	1	1
1	1	1

Filtered image

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	1				

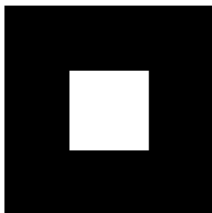


Only 1s

Morphological operations

Image

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0



Erosion

1	1	1
1	1	1
1	1	1

Filtered
image

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Morphological operations

Image

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

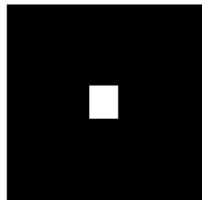


Erosion

1	1	1
1	1	1
1	1	1

Filtered
image

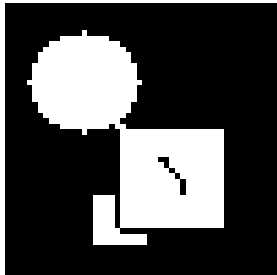
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0



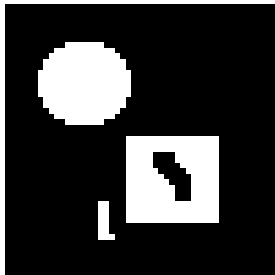
Opening

Opening: first **erosion** then **dilation**

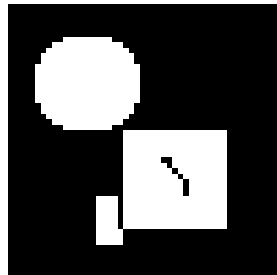
Binary image



1.Erosion



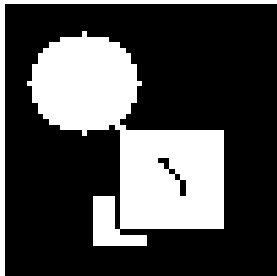
2.Dilation



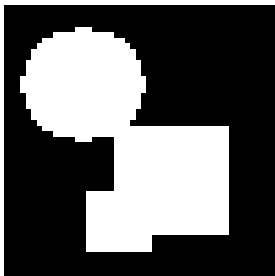
Closing

Closing: first **dilation** then **erosion**

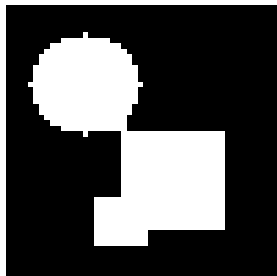
Binary image



1.Dilation



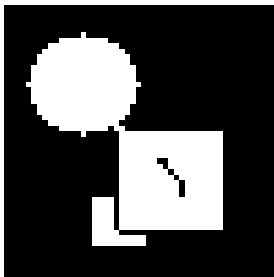
2.Erosion



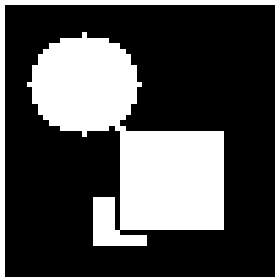
Fill holes

Fill holes: swap regions in the **background** component **to the object** component when **completely surrounded** by pixels belonging to the object component

Binary image

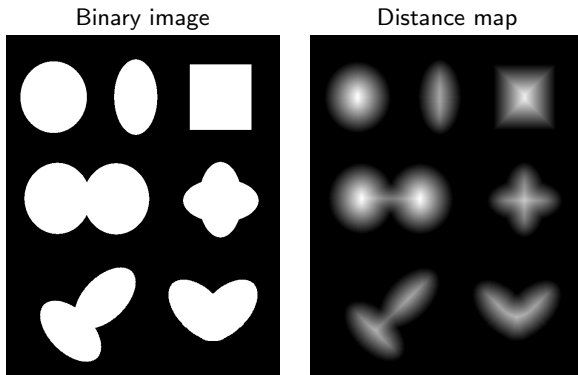


Fill holes



Distance map

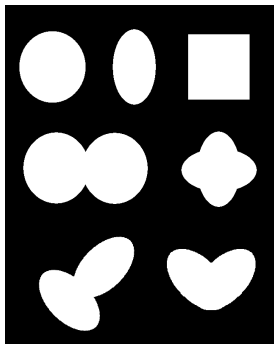
Distance map: distance to the **closest** pixel in the **background** component for each pixel in the object component



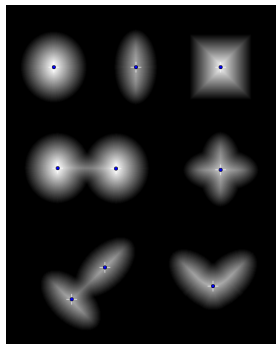
Watershed

Watershed: object separation based on the **local maxima** in the **distance map**

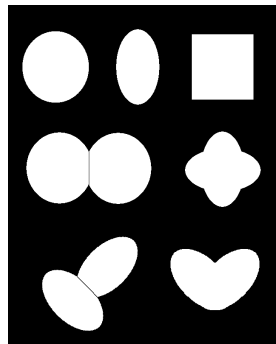
Binary image



Distance map with maxima



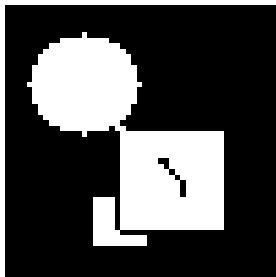
Watershed



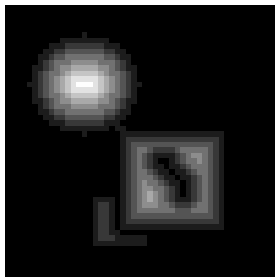
Watershed

Watershed: object separation based on the **local maxima** in the distance map

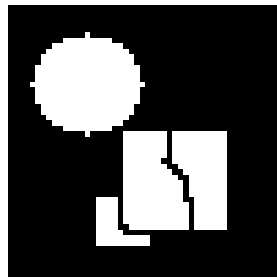
Binary image



Distance map



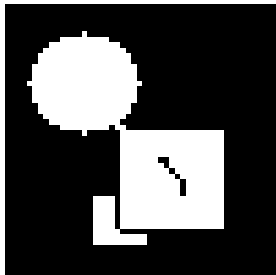
Watershed



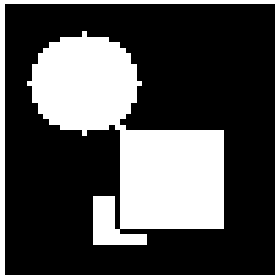
Watershed

Watershed: object separation based on the **local maxima** in the distance map

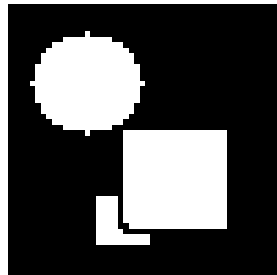
Binary image



1.Fill holes



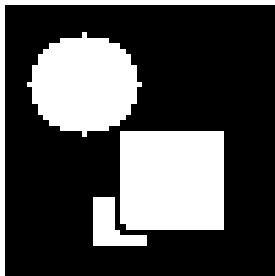
2.Watershed



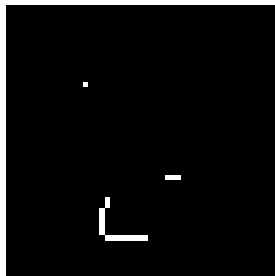
Skeletonization

Skeletonization: single pixel wide **skeletons** obtained by **iteratively removing** pixels located at the object **edge**

Binary image



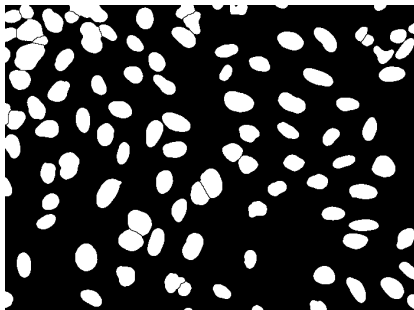
Skeletons



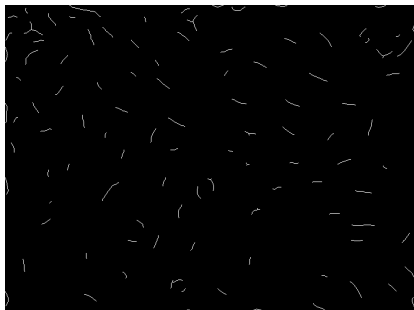
Skeletonization

Skeletonization: single pixel wide **skeletons** obtained by **iteratively removing** pixels located at the object **edge**

Binary image



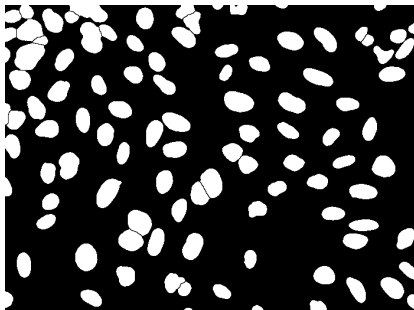
Skeletons



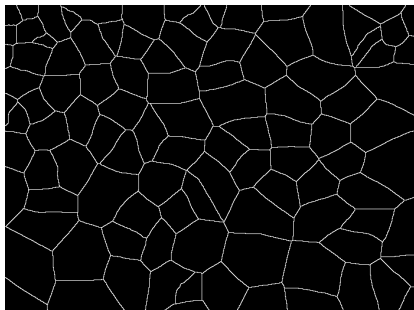
Voronoi

Voronoi tessellation: identification of points that are **equidistant** from at least two **separated objects**

Binary image



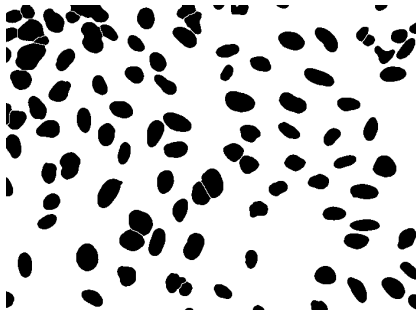
Voronoi



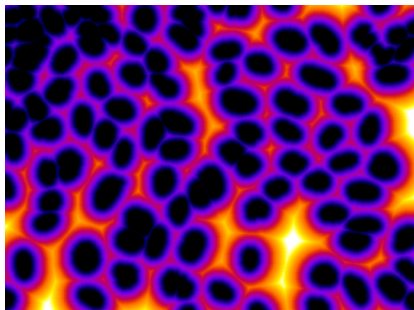
Distance map

Distance map applied to background gives the **closest distance** from each pixel in the background **to objects**

Binary image



Distance map



Practice

<https://youtu.be/OfDEtmyztNE>