Image Processing 1

images, segmentation, shape

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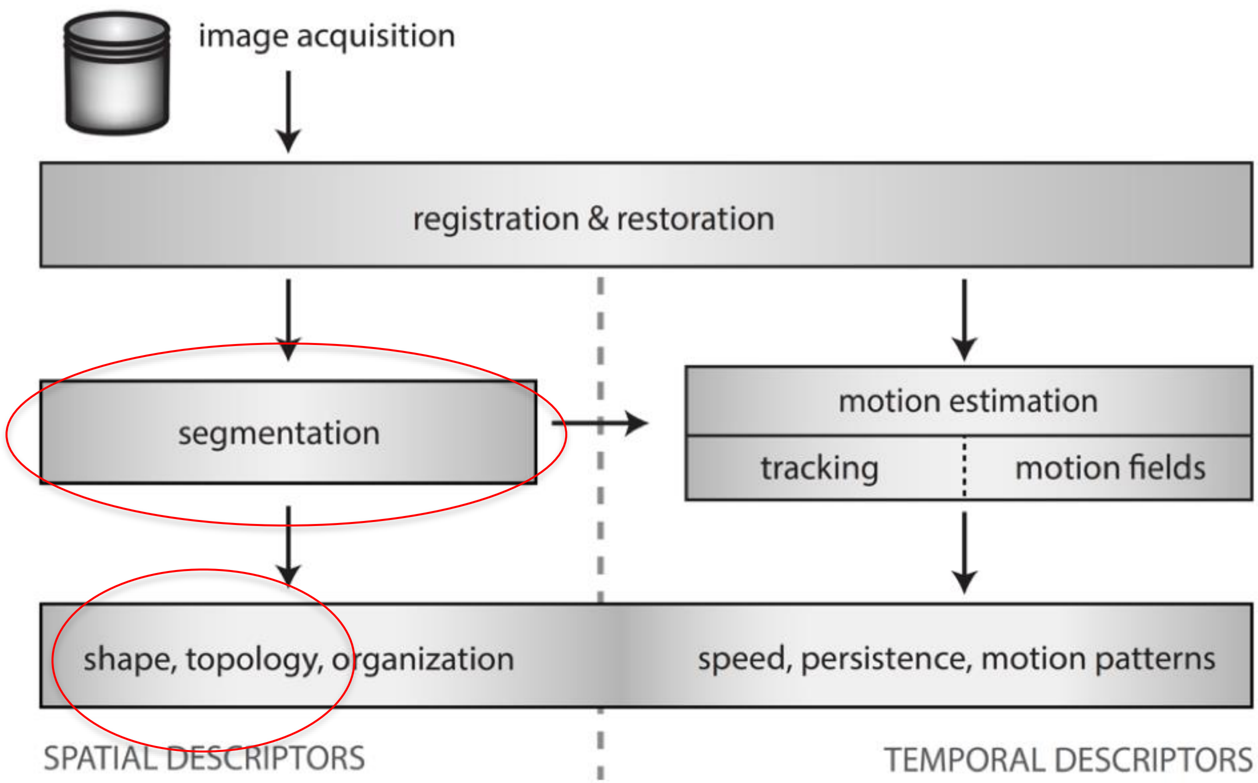
Outline

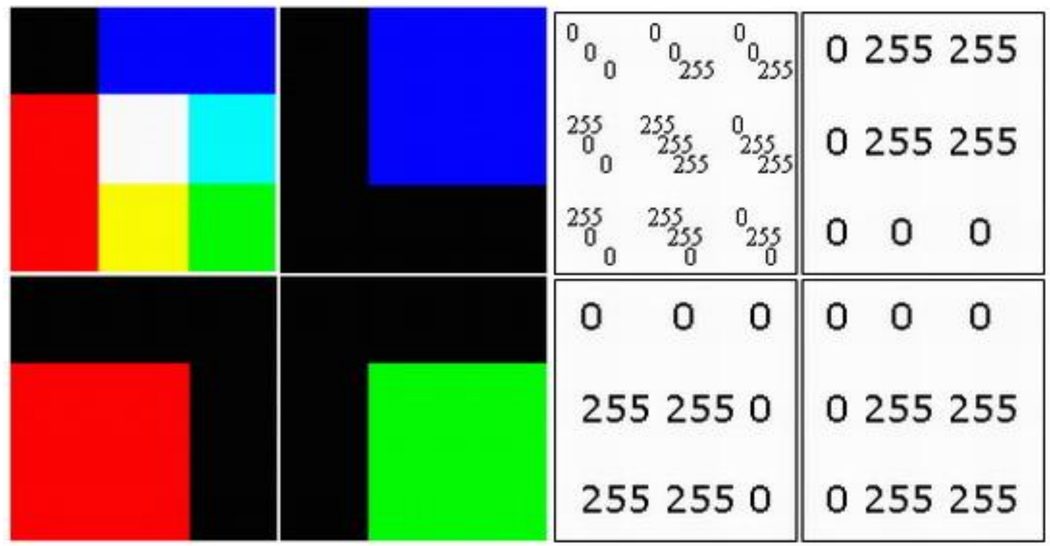


Computational methods for analysis of dynamic events in cell migration

Castañeda V, Cerda M, 2014

Digital Images

- A digital image can be defined as a function over a discrete space
  - A typical 2D image model is the raster image: array (matrix) of pixeles in cartesian coordinates (*x, y*)
  - A numeric value for brightness (intensity) or color is associated to each pixel



$$I = f(x, y)$$

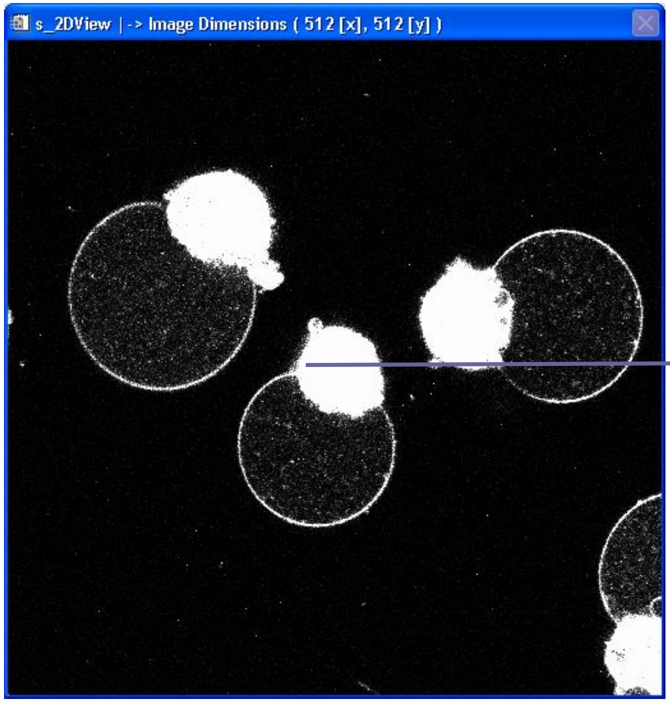
$$(x, y) \in [0, \dim_x - 1] \times [0, \dim_y - 1]$$

$$I\,[x_i, y_j] = f\,[x_i, y_j]$$

Aubert & Kornprobst (2006)
Mathematical Problems In Image Processing

Digital Images

Binary value	Decimal value
0000 0000	0 (black)
0000 0001	1
0000 0010	2
0000 0011	3
0000 0100	4
0000 0101	5
0000 0110	6
0000 0111	7
0000 1000	8
…	…
1111 1011	251
1111 1100	252
1111 1101	253
1111 1110	254
1111 1111	255 (blanco)



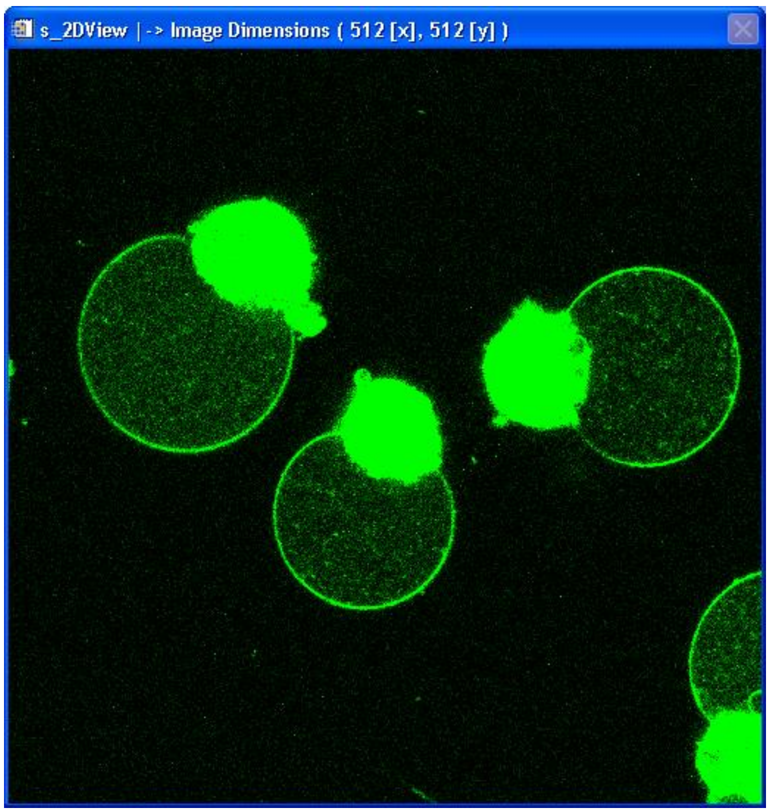
$I(290,267) = 255$

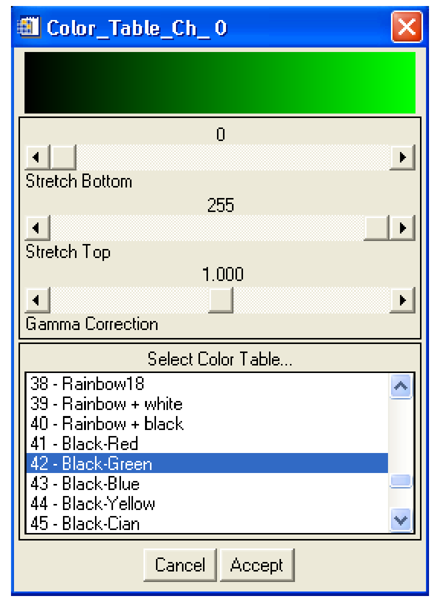
8 bit greyscale image

A *n* bit greyscale image encodes up to 2^n intensity values

Digital Images

- It is possible to define color tables (or lookup tables, LUTs) for visualization purposes. A grayscale image can be displayed using a green scale.



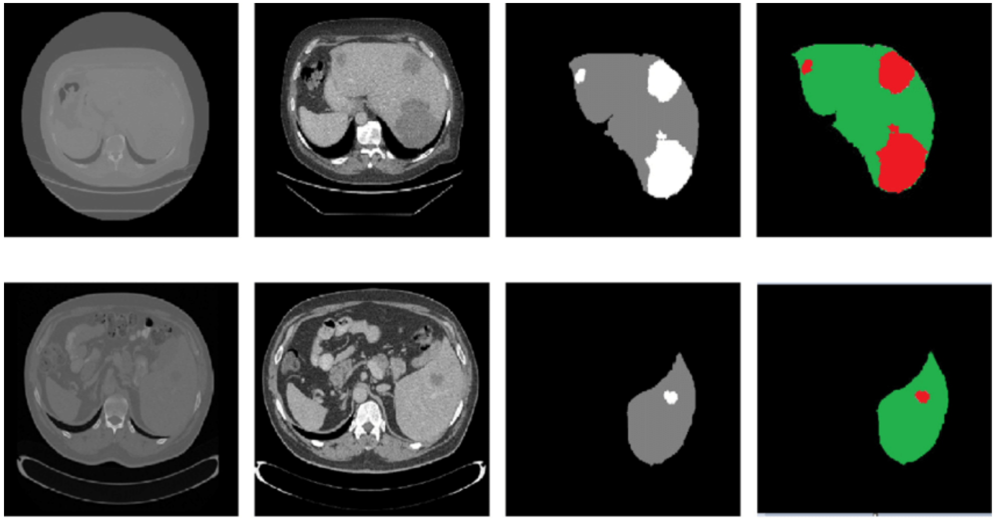


r	g	b
0	0	0
0	1	0
0	2	0
:	:	:
:	:	:
:	:	:
:	:	:
0	200	0
:	:	:
:	:	:
0	255	0

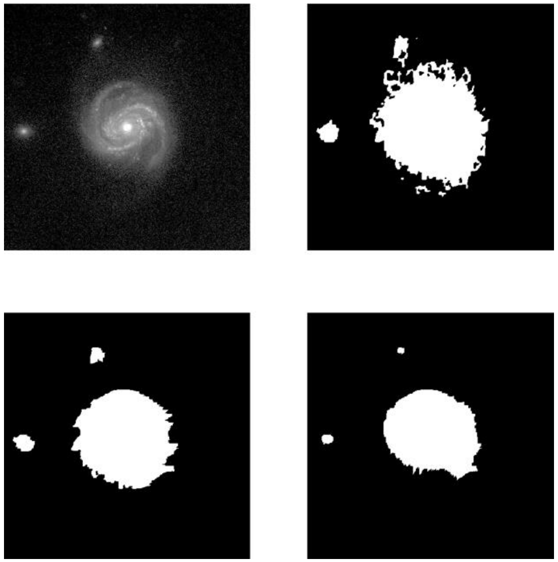
- Segmentation
  - The partitioning of a given image into Regions Of Interest (ROIs) according to given criteria (e.g. color).
  - After segmentation, further characterizations can be performed upon the resulting ROIs.

Shapiro LG and Stockman GC (2001):
“Computer Vision”, pp 279-325
New Jersey, Prentice-Hall

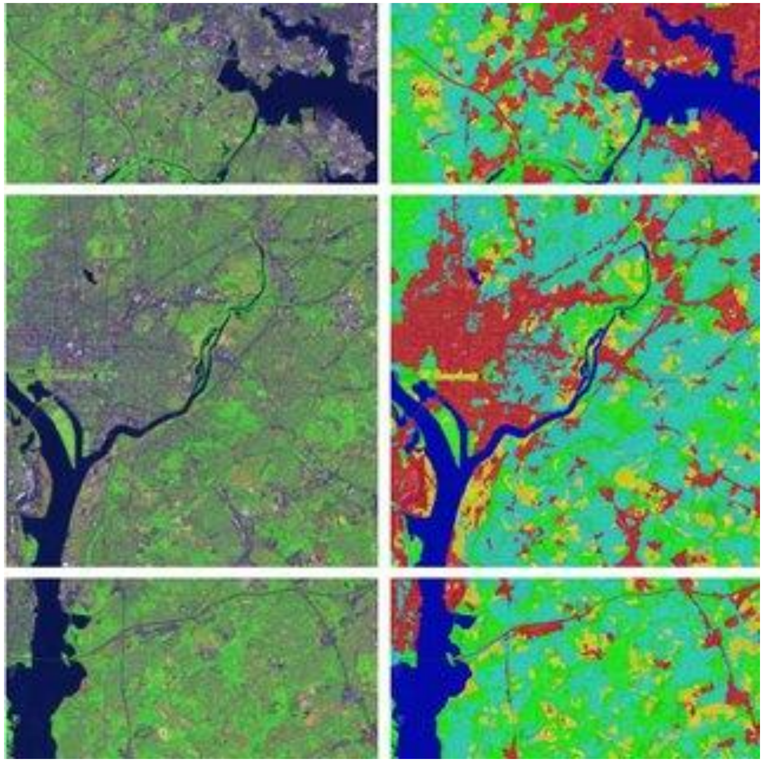
Segmentation examples



Medical



Astronomy



NASA (satellite)

Problems

- Lack of absolute criteria or standards (Ground Truth, Gold Standard [1,2])
- Missing or erroneus information (e.g. non-specific markers in samples)
- What to do? A “good” (i.e. carefully performed and controlled) acquisition ease this process

[1] Jason D. Hipp et all. Tryggo: Old norse for truth: The real truth about ground truth. New insights into the challenges of generating ground truth maps for WSI CAD algorithm evaluation. Pathol. Inform 2012, 3:8

[2] Luc Bidaut, Pierre Jannin. Biomedical multimodality imaging for clinical and research applications: principles, techniques and validation. In Molecular Imaging:Computer Reconstruction and Practice (NATO Science for Peace and Security Series B: Physics and Biophysics), Springer, 2008, ISBN-13: 978-1402087516.

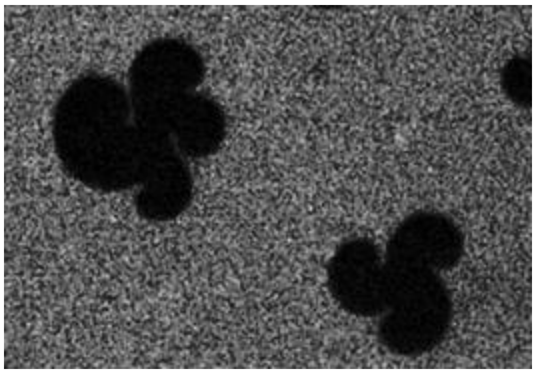
Segmentation

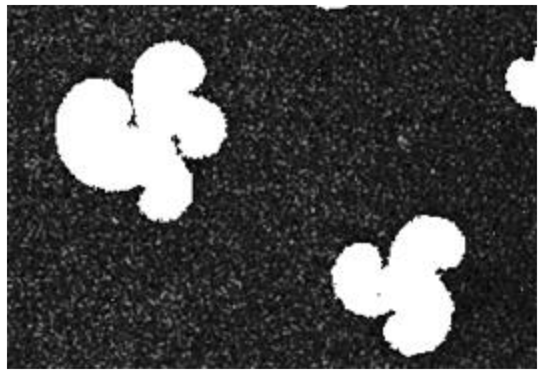
Classic segmentation approaches (“filters”)

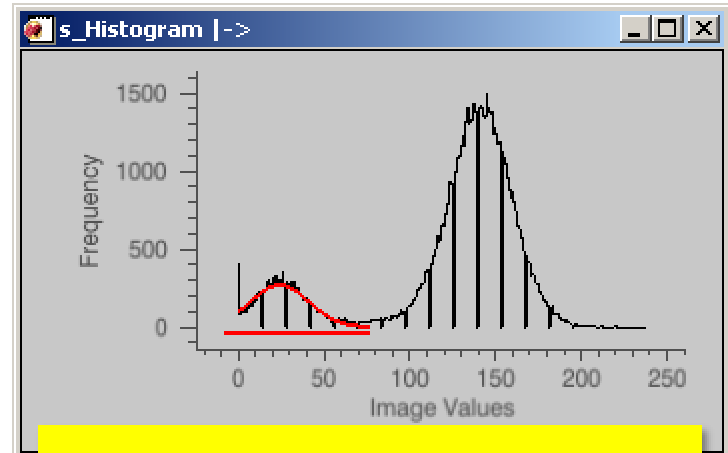
- Thresholding
- Matrix convolution filters + threshold
- Mathematical morphology

Segmentation – basics

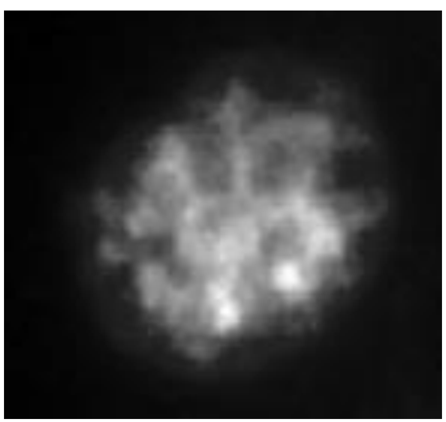
- Threshold filter
  segmentation: ROIs (white) / background (black)

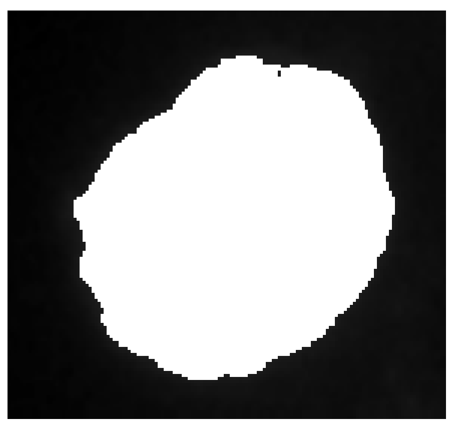


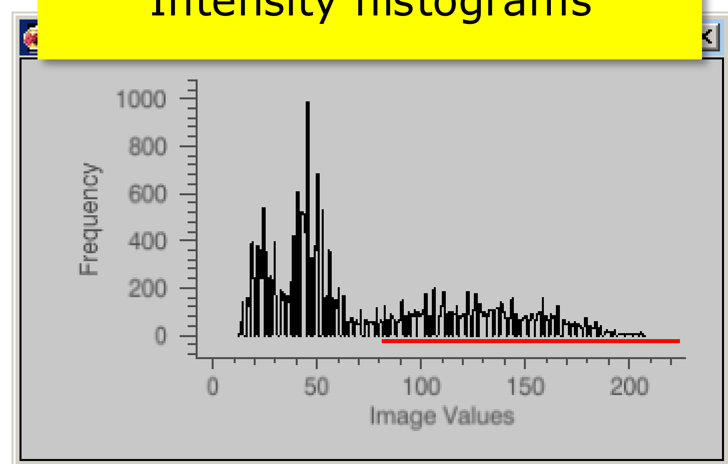




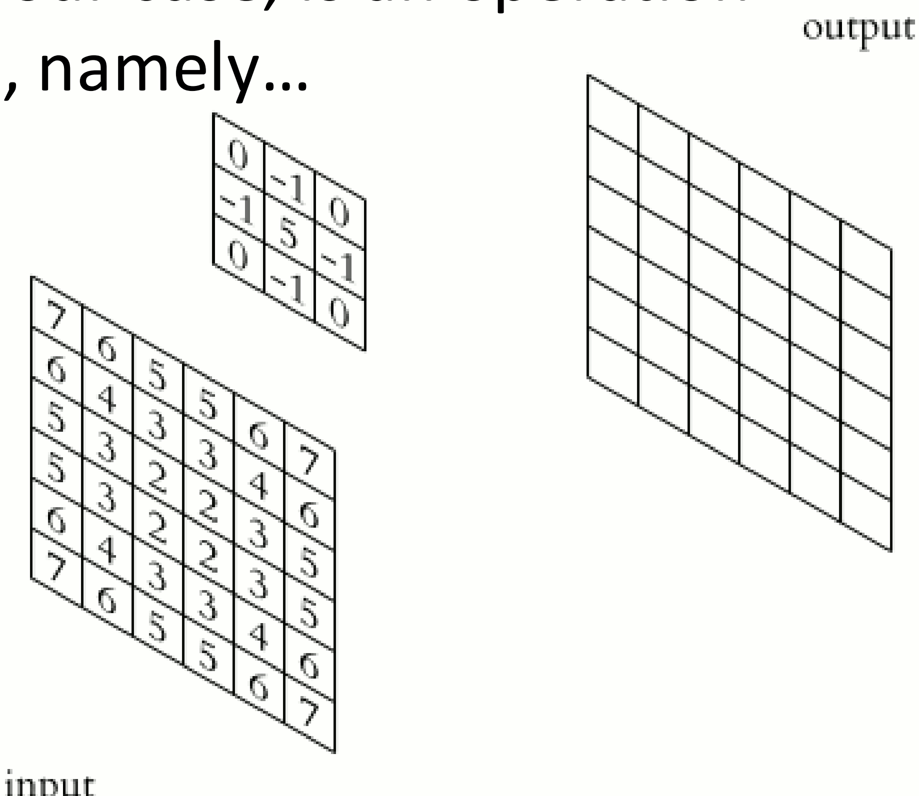
Intensity histograms







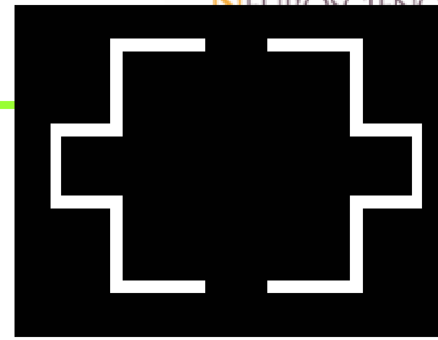
- Convolution
  - Lots of filters based on this principle
    http://en.wikipedia.org/wiki/Convolution
- Matrix convolution, in our case, is an operation between two matrices, namely…
  - the input image, *I*
  - a *kernel*, *K*



Adapted from James Matthews, 2002
http://www.generation5.org/content/2002/convolution.asp

Segmentation – basics

- Intensity gradients (discrete approximation)

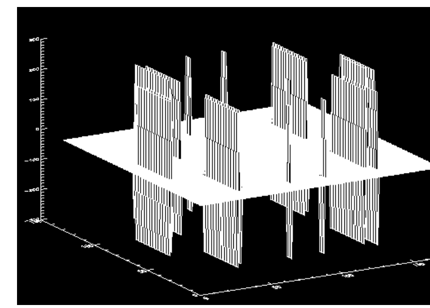


$$I = I(x, y)$$

$$\frac{\partial I}{\partial x} \approx \frac{I(x+\Delta x, y) - I(x, y)}{\Delta x} = Kx \otimes I$$

$\Delta x = 1\,\text{pixel}$

$$Kx = \begin{Bmatrix} 0 & 0 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{Bmatrix}$$

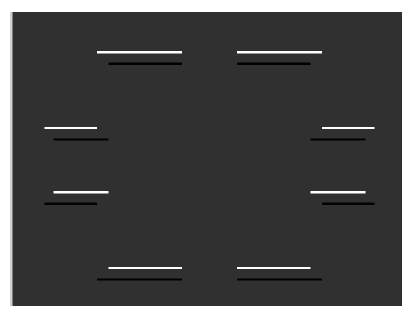


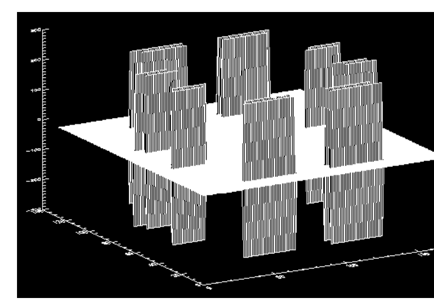
flat + -

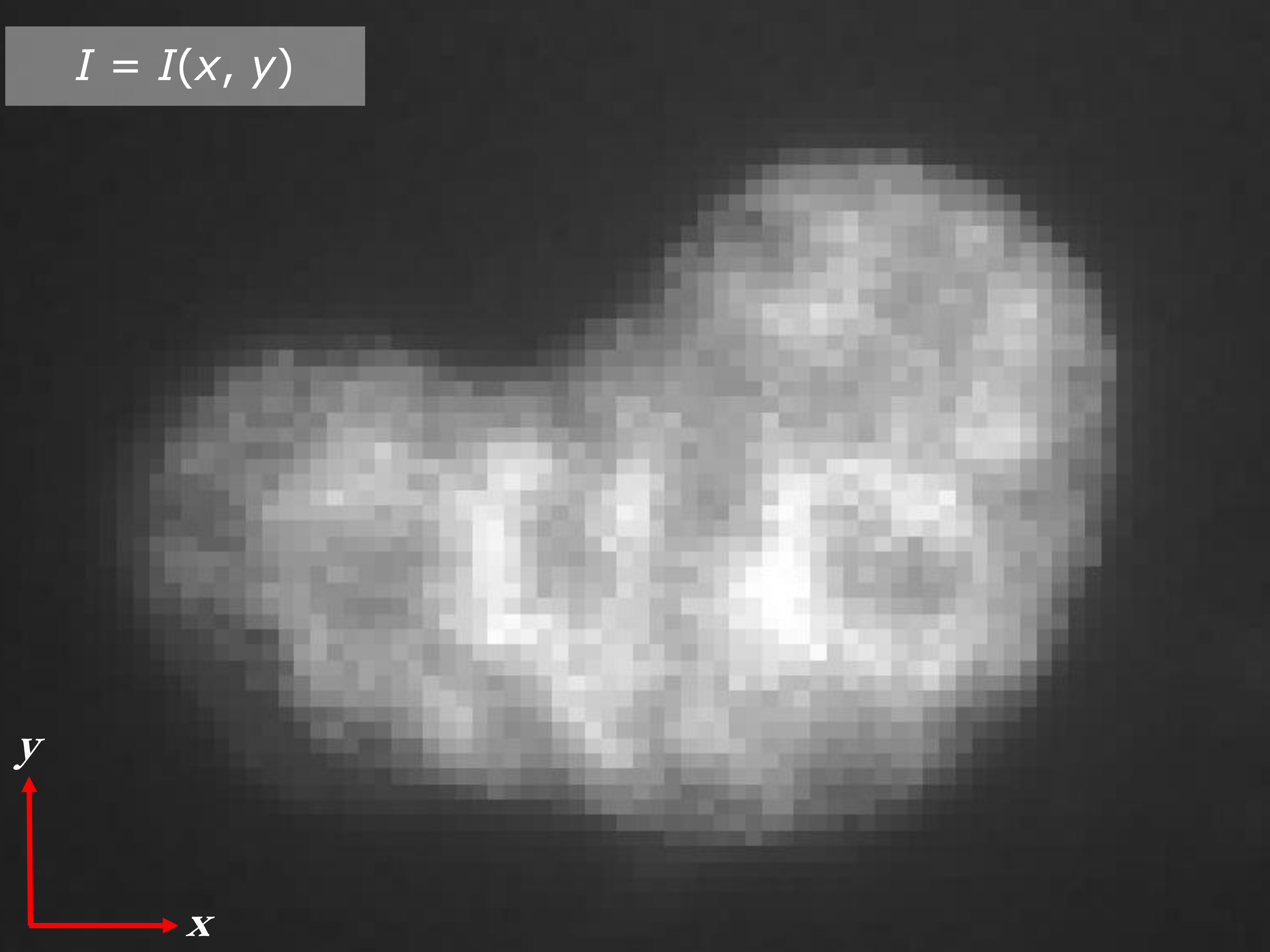
$$\frac{\partial I}{\partial y} \approx \frac{I(x, y+\Delta y) - I(x, y)}{\Delta y} = Ky \otimes I$$

$\Delta y = 1\,\text{pixel}$

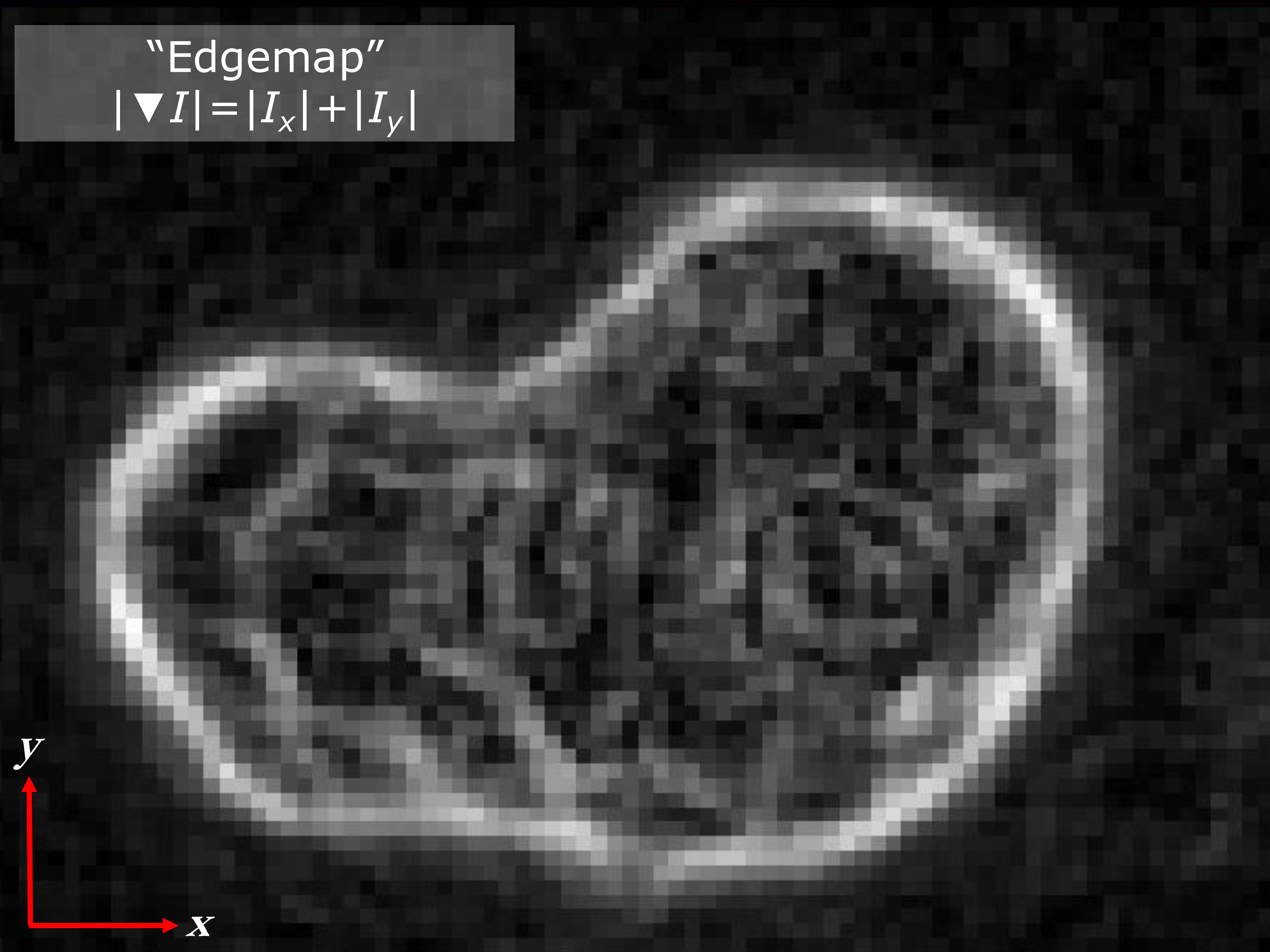
$$Ky = \begin{Bmatrix} 0 & 1 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{Bmatrix}$$





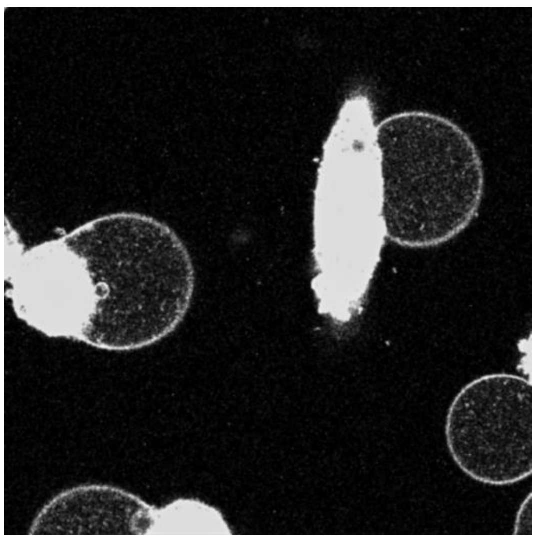

$I = I(x, y)$
y
x


$I_y = K_y \otimes I$
y
x

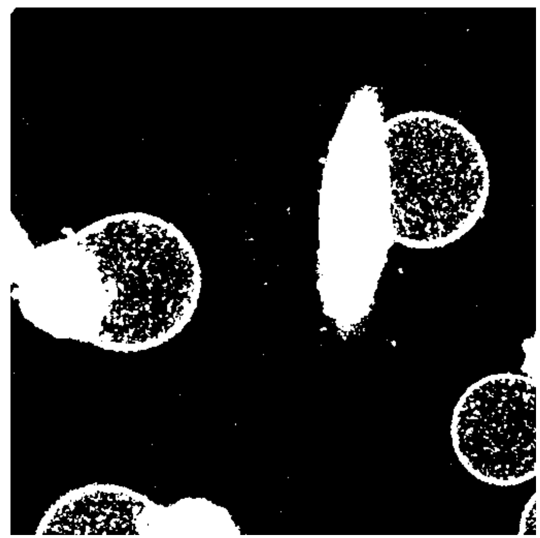

"Edgemap"
$|\nabla I| = |I_x| + |I_y|$
y
x

Segmentation – basics

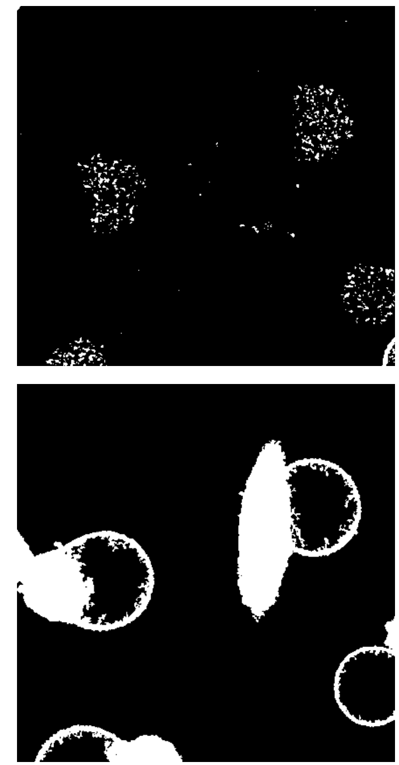
- Morphology based filters
  - Example: size selection



Input greyscale image



After thresholding…



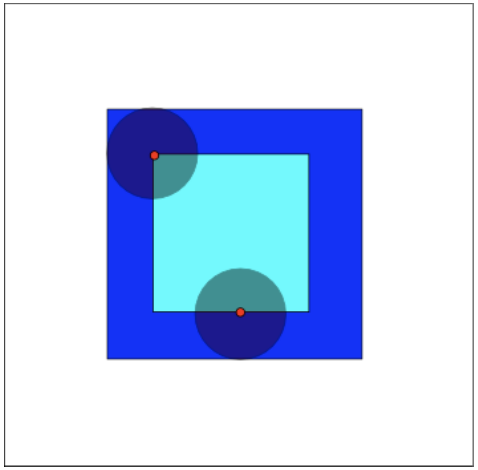
Size selection

How to define a size-select algorithm?

- Mathematical morphology

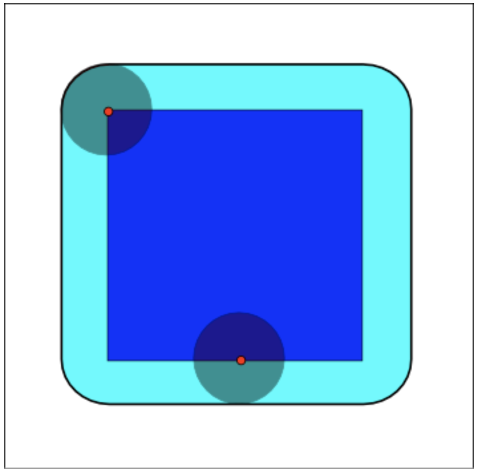
Erode

$$A \ominus B = \{z \in \mathbb{R}^2 | B_z \subseteq A \}$$



Dilate

$$A \oplus B = \bigcup_{b \in B} A_b$$



What is B?

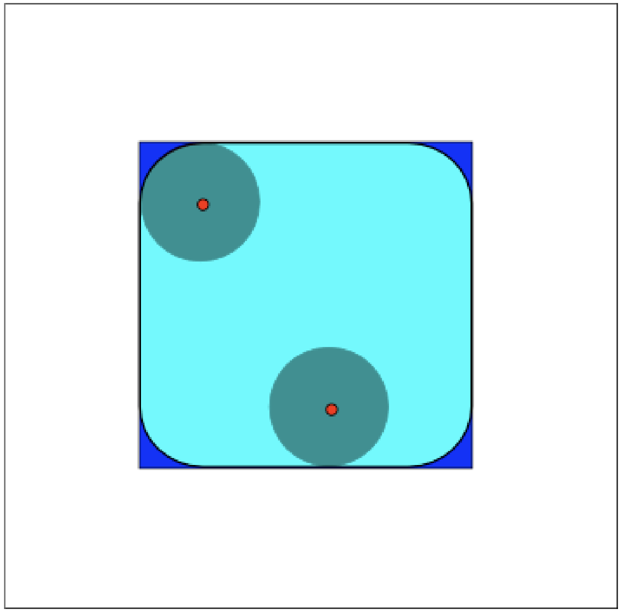
- Mathematical morphology

To open:

$$A \circ B = (A \ominus B) \oplus B$$

To close:

$$A \bullet B = (A \oplus B) \ominus B$$



Outline

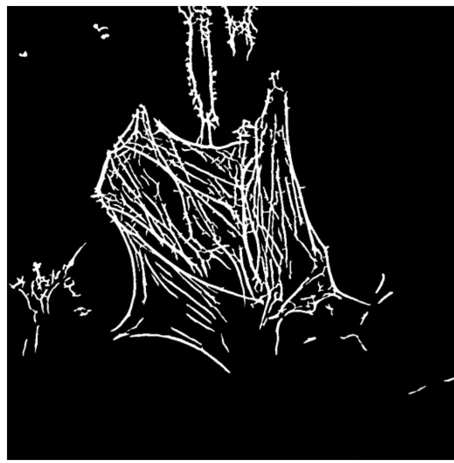
2. Descriptors

- Shape

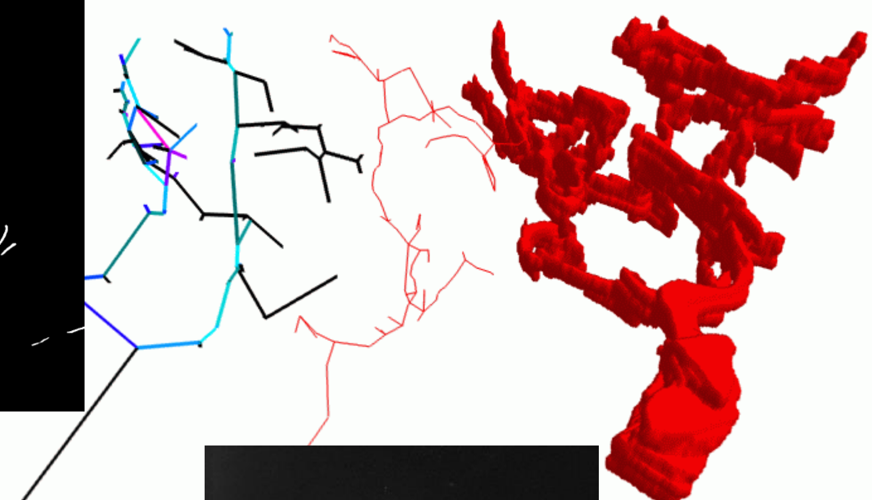
Motivation

Shape descriptors

Ex. 1
Shape and structure analysis of fibroblast actin fibers (astrocytes)



Ex. 2
Zebrafish parapineal organ neuron

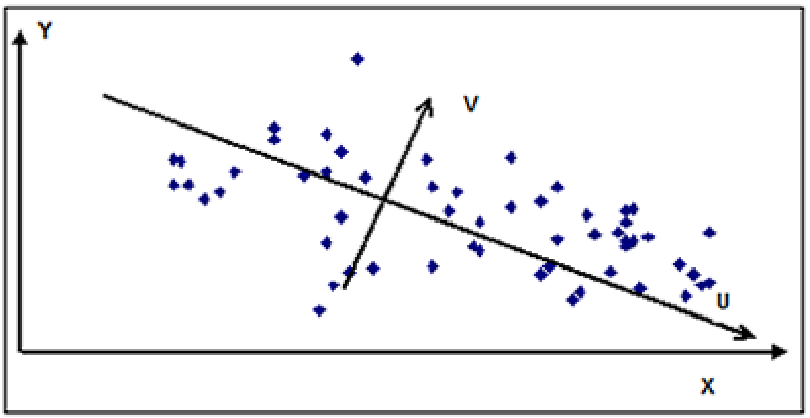


2D image and segmentations, Lisette Leyton's Lab (BNI)

Original image and 3D segmentation , Karina Palma (LEO, BNI).

Moments of morphology

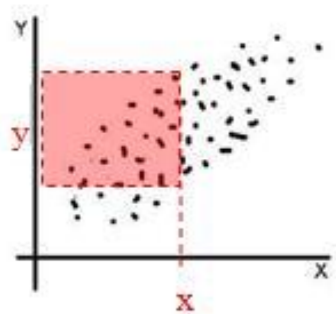
Variance



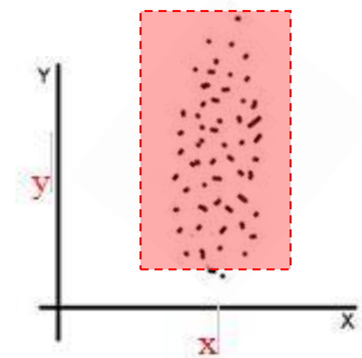
Axes U and V maximize **the variance in U**

$$\sigma_x^2 = \frac{\sum (x-\overline{x})^2}{N}$$

Covariance



Positive covariance

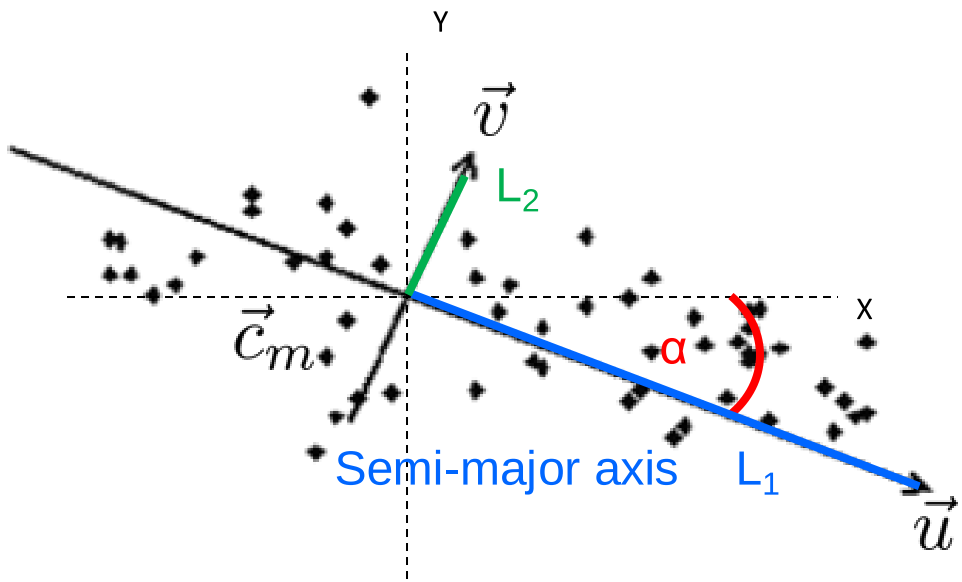


Zero covariance

$$\sigma_{xy}^2 = \frac{\sum (x-\overline{x})(y-\overline{y})}{N}$$

Moments of morphology

We look for two parameters to characterize the binary ROI…



Moments of morphology

- If the variance/covariance matrix is diagonal for a certain rotation α,

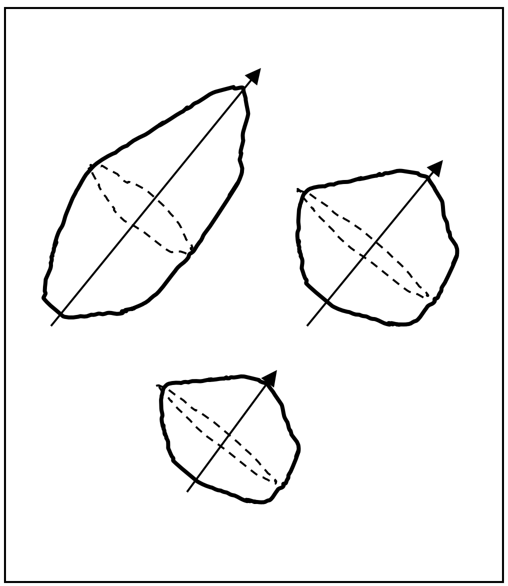
- Semi-major axis length *l* is a function of second-order moments

$$L_1^2 = \frac{1}{2}\left(\sigma_{xx}^2 + \sigma_{yy}^2 + \sqrt{(\sigma_{xx}^2 - \sigma_{yy}^2)^2 + 4(\sigma_{xy}^2)^2}\right)$$

$$L_2^2 = \frac{1}{2}\left(\sigma_{xx}^2 + \sigma_{yy}^2 - \sqrt{(\sigma_{xx}^2 - \sigma_{yy}^2)^2 + 4(\sigma_{xy}^2)^2}\right)$$

Moments of morphology

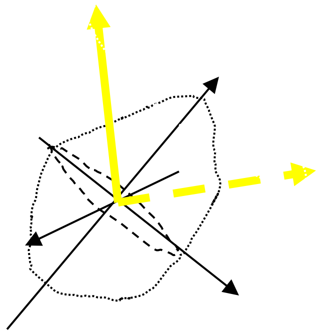
Second order moments of morphology describe a ROI main axis (principal components)



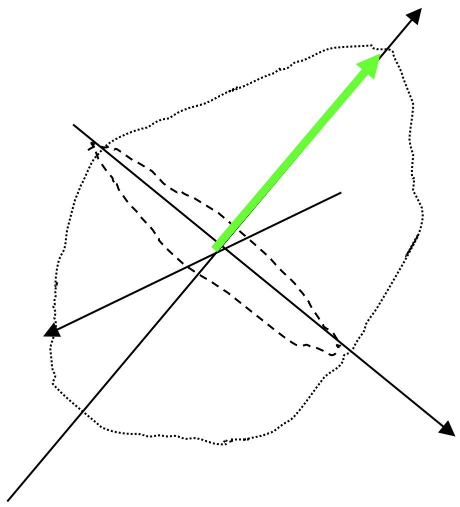
- The **major axis** corresponds to the direction with the biggest variance.
- The **secondary axis (minor in 2D)** is orthogonal to the major axis, giving in 3D the direction of the second biggest variance.
- The **third axis** (3D) is orthogonal to the major and secondary axes.

Moments of morphology

Principal axes are useful object descriptors because…



- they directly define the object *length*, *height*, and *width*

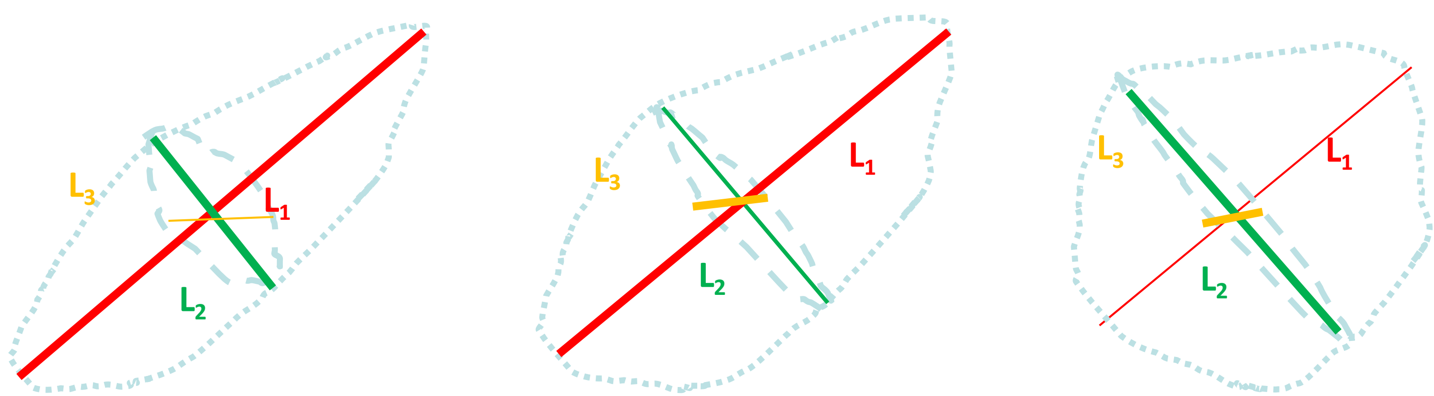


- using principal axes, similarities between objects can be found

Moments of morphology

By combining the principal axes, we can define *Elongation*, *Relative Elongation*, and *Flatness*.

$$Elong = 1 - \frac{L_2}{L_1} \qquad R.\ Elong = 1 - \frac{L_3}{L_1} \qquad Flatness = 1 - \frac{L_3}{L_2}$$



$L_1 >> L_2$
Elong. ~ 1

$L_1 >> L_3$
R. Elong. ~ 1

$L_2 >> L_3$
Flatn. ~ 1

Moments of morphology - remarks

- The variance allows to computer principal axes (eigenvectors) and to quantify dispersion for each principal axis direction (eigenvalues)
- Higher order moments describe more detailed information like asymmetry or kurtosis
- Composed parameters between eigenvalues deliver morphological parameters like elongation or flatness