

Procesamiento de Imágenes II



Jorge Jara, Dante Castagnini, Nicole C. Huerta

www.scian.cl / www.cimt.cl / <https://bni.cl/biomat.php>

Laboratory for Scientific Image Analysis (SCIAN-Lab)
Centro de Informática Médica y Telemedicina (CIMT)
Biomedical Neuroscience Institute (BNI)
Programa de Biología Integrativa
Instituto de Ciencias Biomédicas (ICBM)
Facultad de Medicina, U. de Chile

0. Concepts

- Signal & noise
 - Signal amplitude
 - Signal frequency/frequencies
 - Signal amplitude
 - Fluorescence intensity
- ~~Pixel / Voxel~~
 - ~~Bit~~
 - ~~(Sample) Bit depth~~
 - Sampling frequency/interval
 - Filter

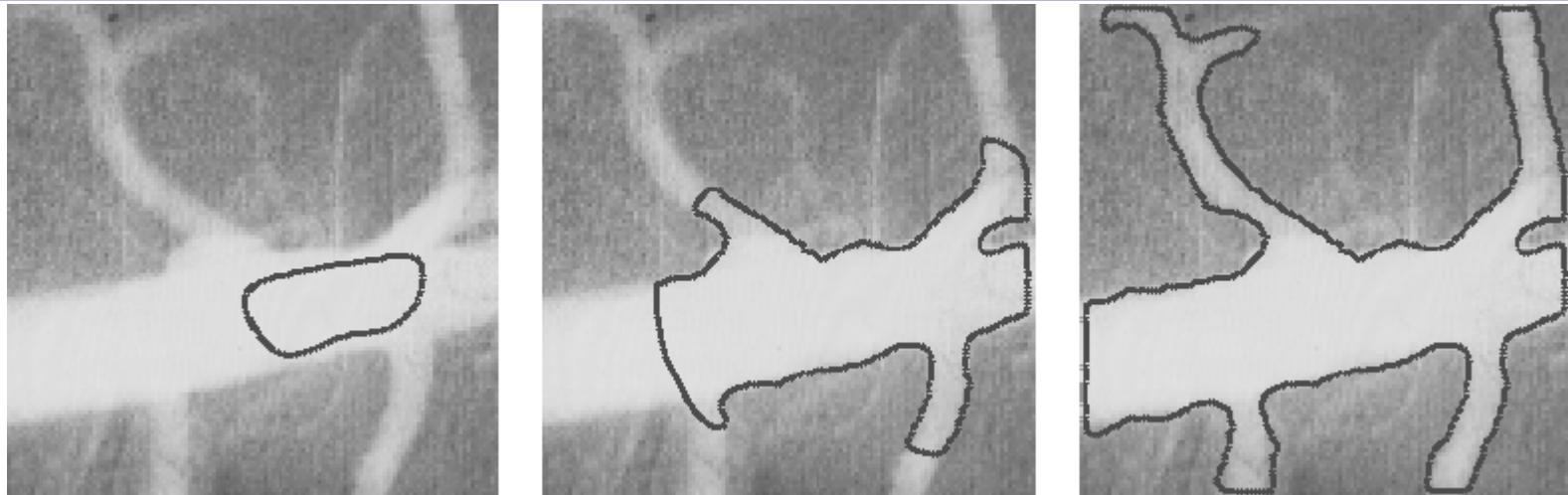
Problems

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

[1] Jason D. Hipp et all. Tryggo: Old nurse 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

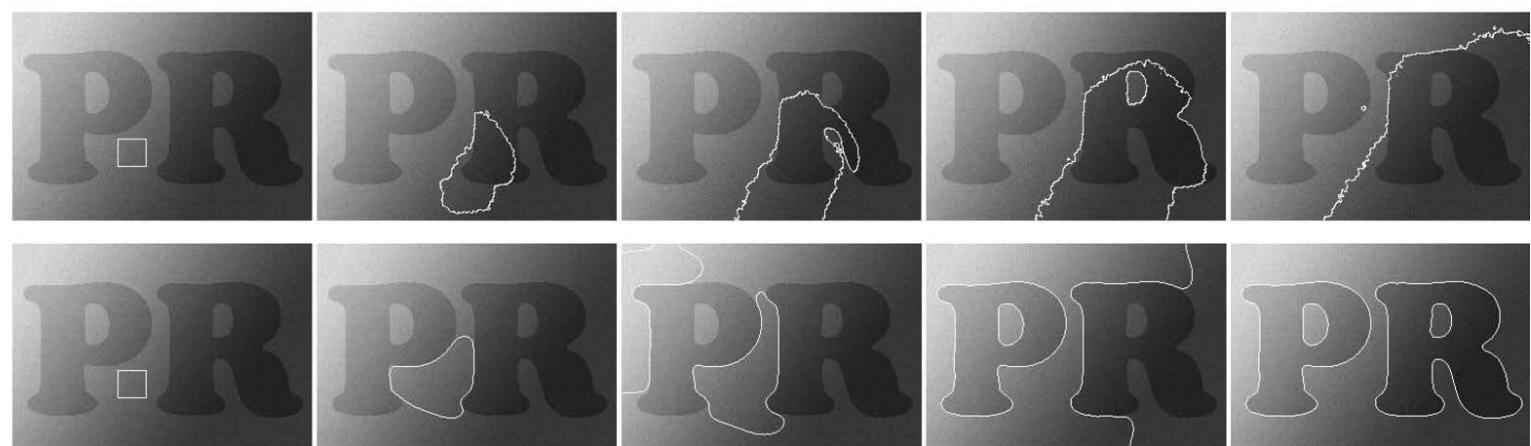
[2] Luc Bidaut, Pierre Jannin. Biomedical multimodality imaging for clinical and research applications: principles, techniques and validation. In *Molecular Imaging:Computer Reconstruction and Practice (NATO Science for Peace and Security Series B: Physics and Biophysics)*, Springer, 2008, ISBN-13: 978-1402087516.

Segmentation models
regarded as “good”
for a given case can
be “bad” for other



J A Sethian – Fast marching and level set methods

http://math.berkeley.edu/~sethian/2006/Applications/Medical_Imaging/artery.html

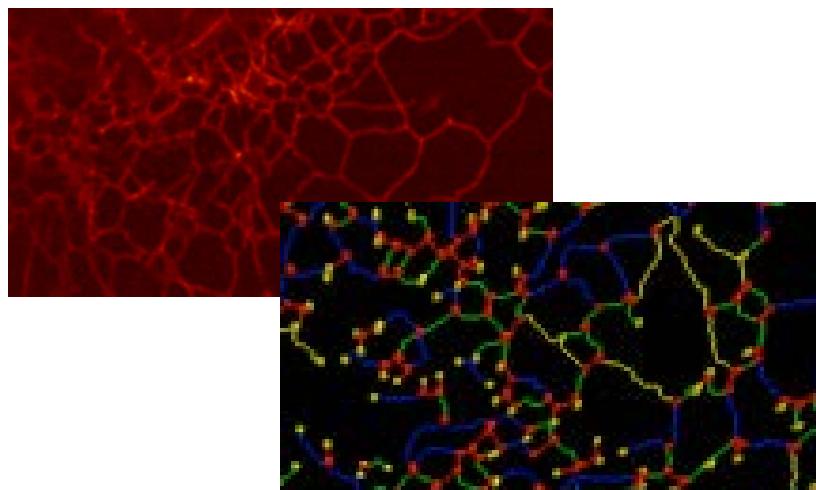


X Xie (2010) Magnetostatic Active Contours

- Segmentation is the first step toward further quantifications

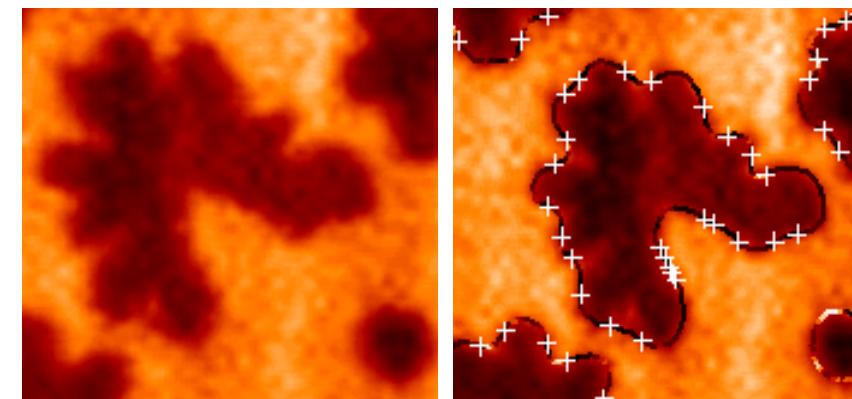
- In addition to images, ROI models and data structures can suit for different types of descriptions

Parameter estimation...



Endoplasmic reticulum in a COS-7 cell
O Ramírez, L Alcayaga (2012)

- Size: area, perimeter
- Boundary: inflections, shape
- Topology: connectivity, endpoints



Lipid monolayers
J Jara (2006), Fanani et al (2010)

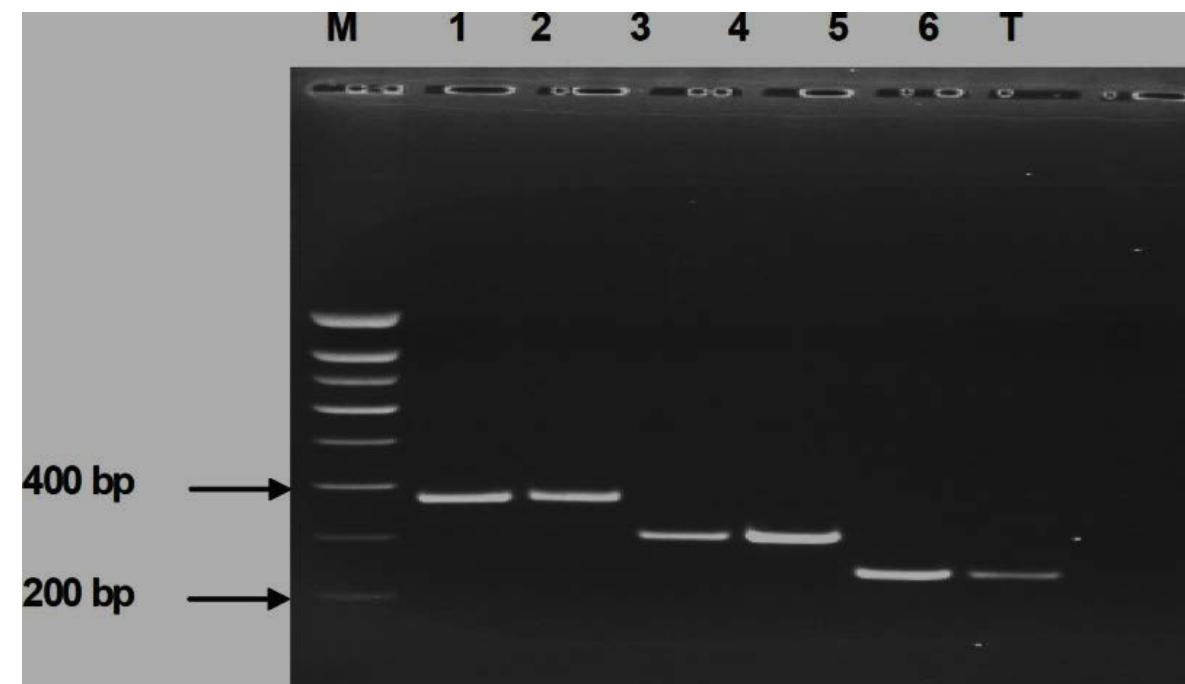
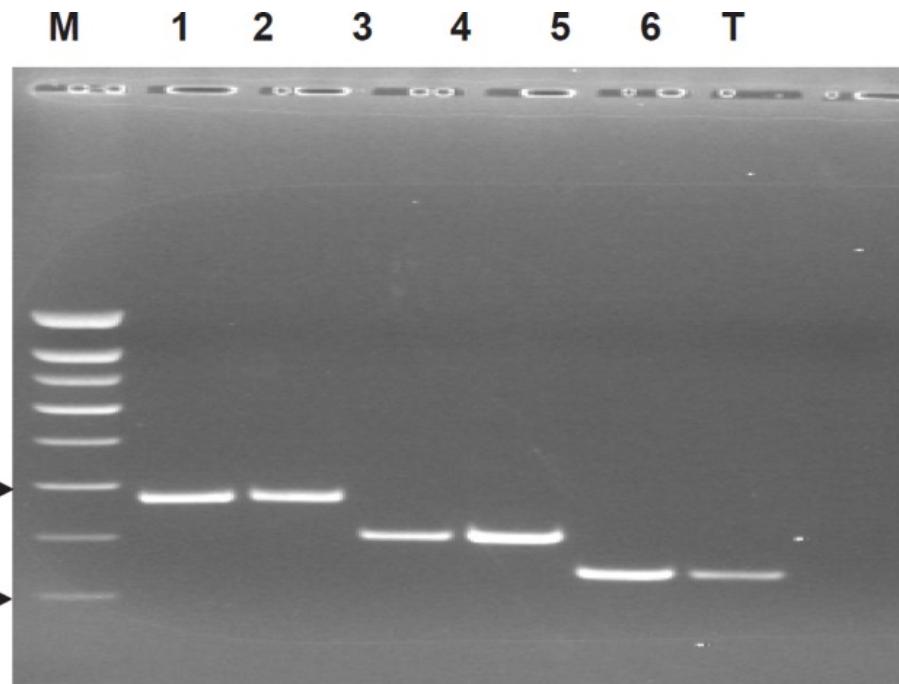
Segmentation approaches

(One possible categorization)

1. Classic approaches (filters)
 - Thresholding
 - Matrix convolution filters
 - Mathematical morphology
 - Fourier
 - ...
2. Advanced approaches
 - Shape priors (*pattern matching*)
 - Clustering methods (k-means, region growing, graph cuts, entropy)
 - Deformable models (active contours)
 - parametric
 - Implicit
 - ...
- 3. Trainable approaches (*machine learning*)
 - SVM
 - Random forest
 - Deep learning
 - ...

- Filters... for what?

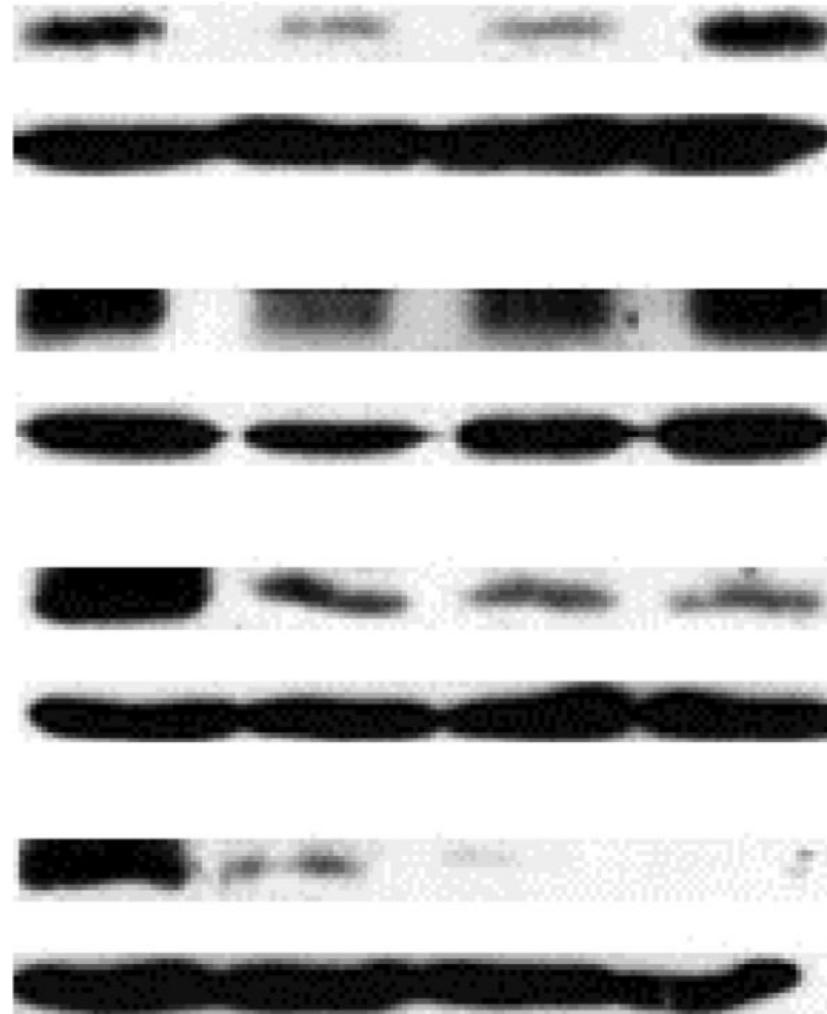
Example 1: PCR



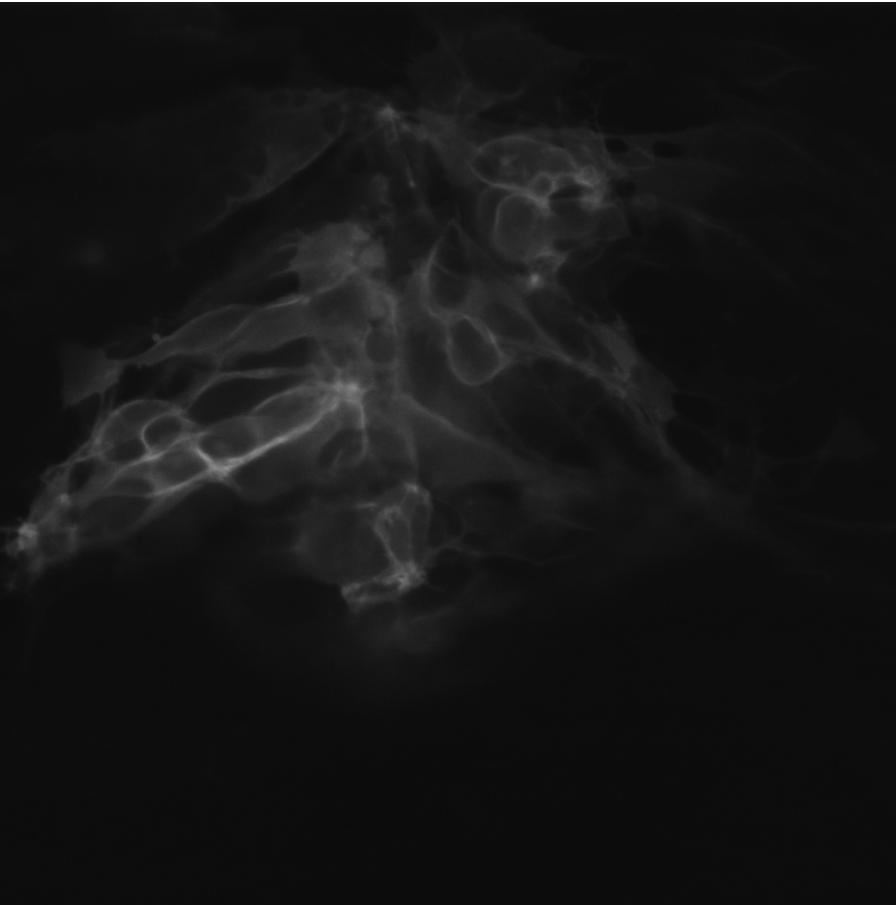
https://www.ncbi.nlm.nih.gov/books/NBK402331/figure/wt_manguin1_ch8.F6/

Filters... for what?

- Example 2: Western blots



Filters... for what?

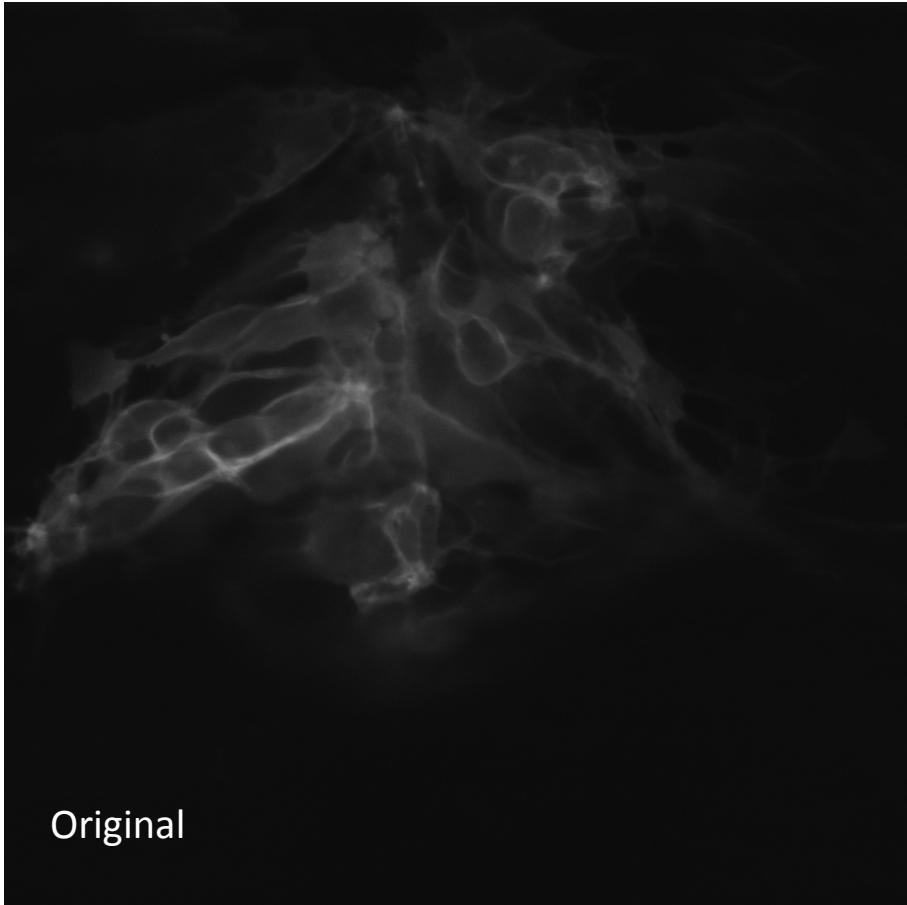


Fluorescent zebrafish embryo parapineal complex
Transgenic *f/h*::gap43-EGFP zebrafish embryo , 38 hpf
(hours post-fertilization). Spinning disk microscopy
C.G. Lemus (LEO/SCIAN)

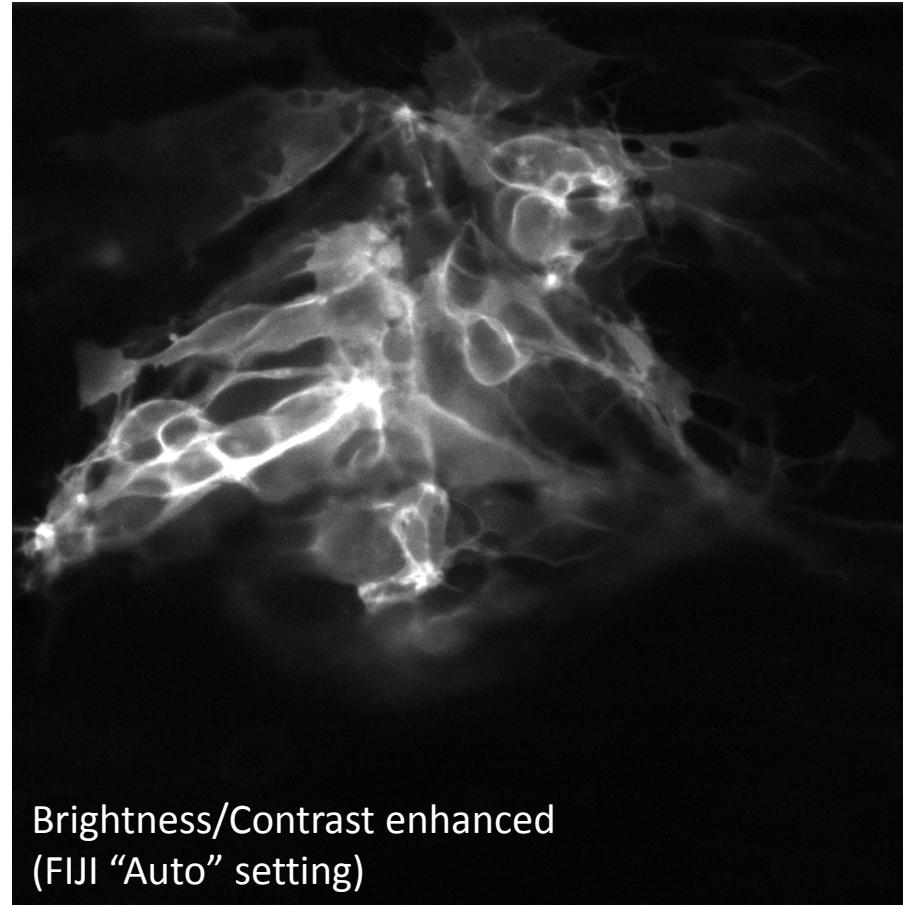
8 bits per pixel, 768x768x69 voxels
166x166x500 nm³ voxel size

Filters... for what?

Visualization (screen)



Original



Brightness/Contrast enhanced
(FIJI "Auto" setting)

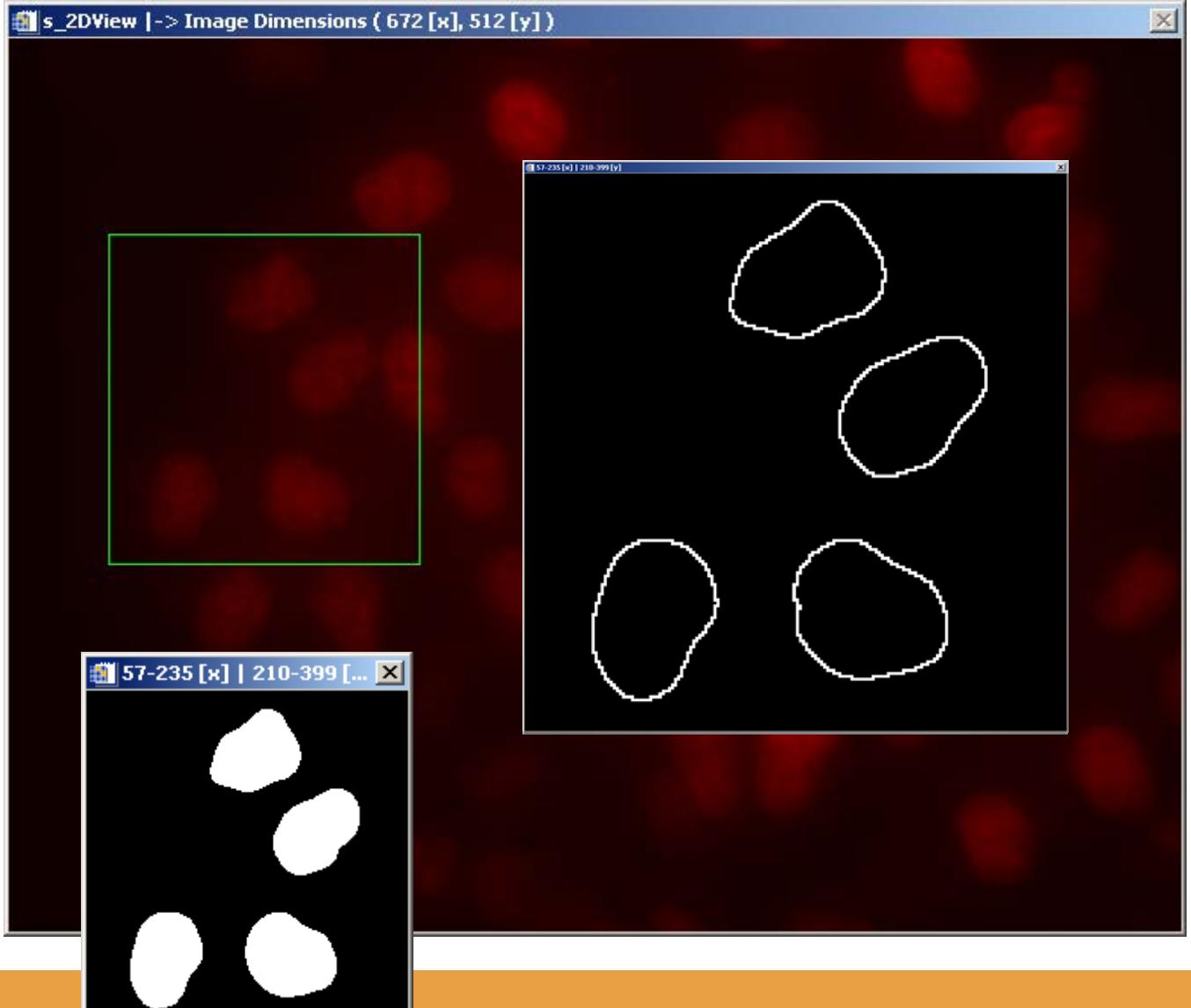
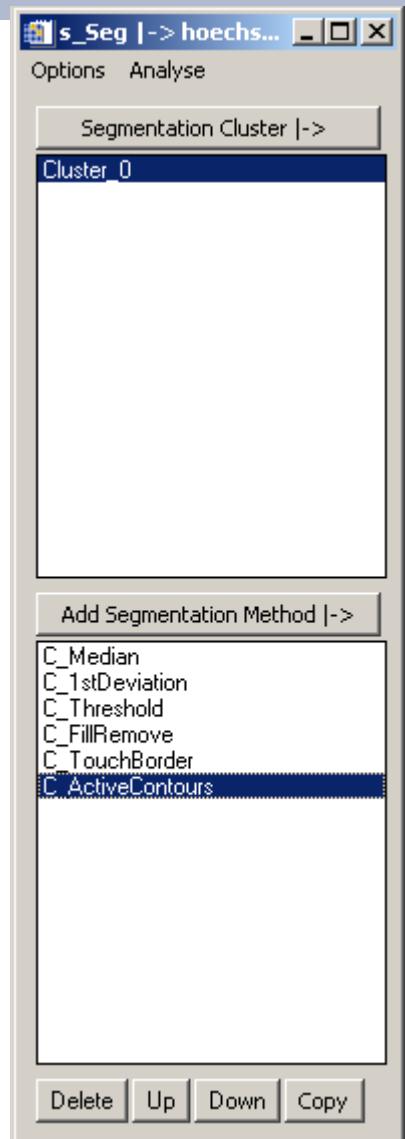
- Filters... for what?

Visualization
(screen + print)

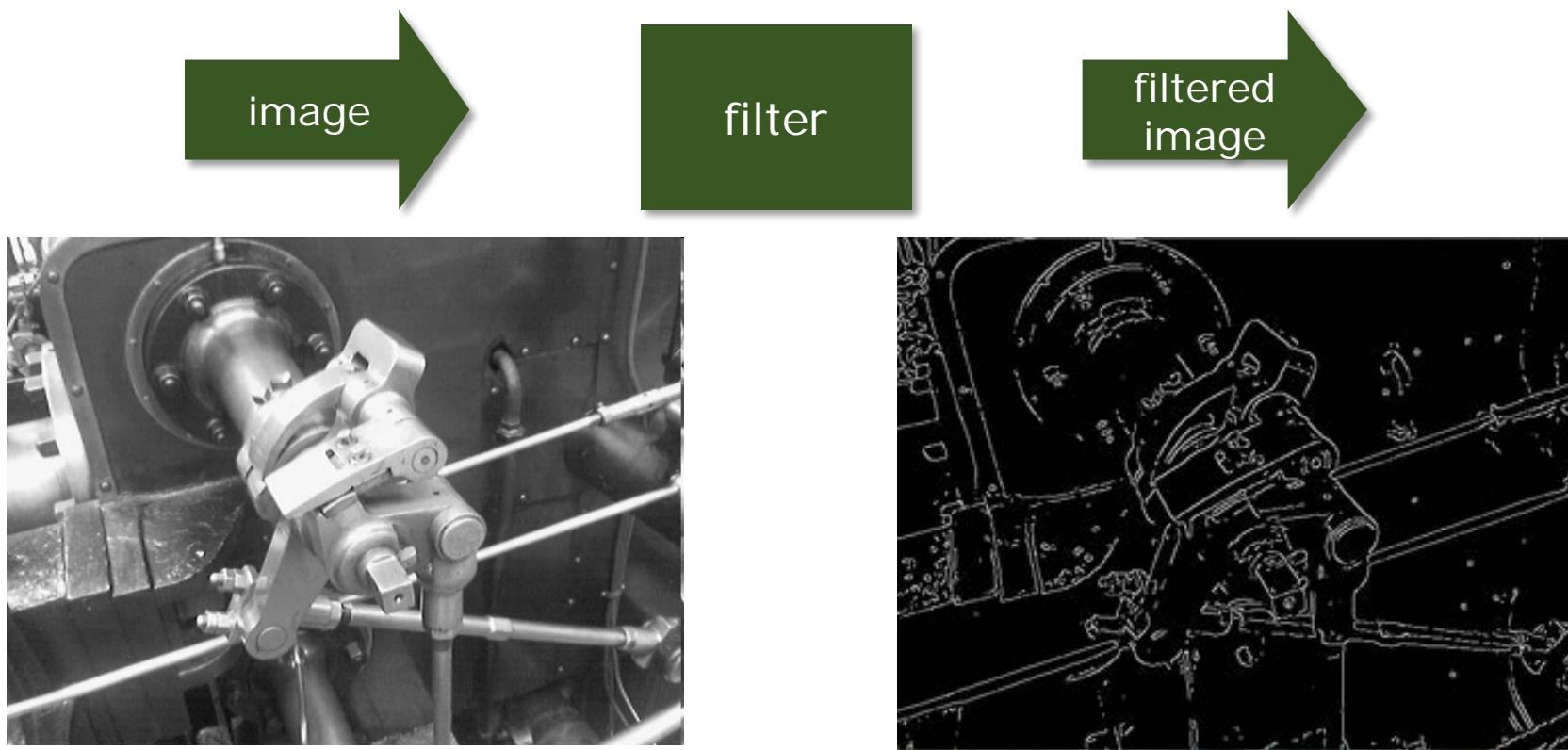
Inverted greyscale LUT + contrast enhancement for publication. Scale bars: 10 µm
Jara-Wilde et al. (2020) Journal of Microscopy

Filters... for what?

Easier segmentation

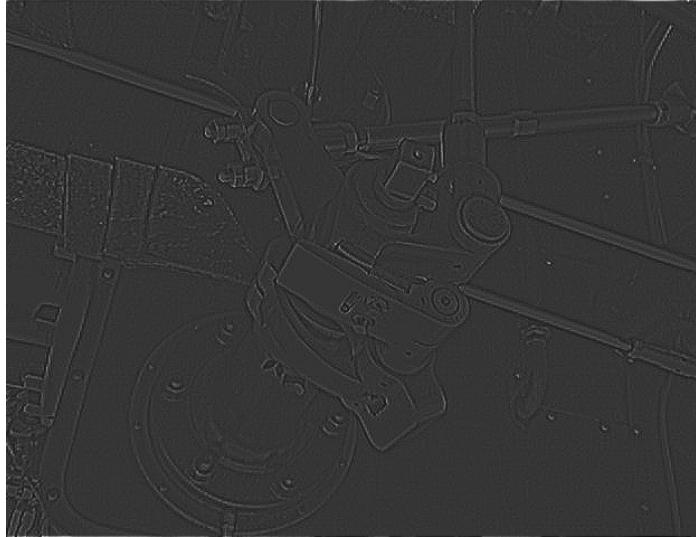
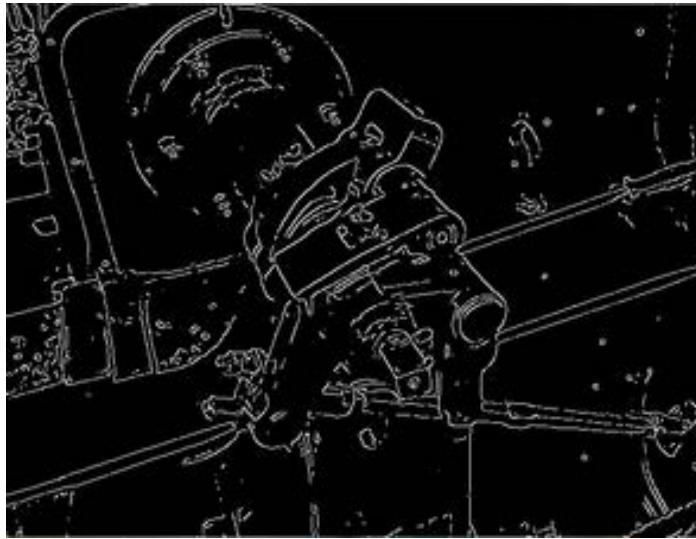
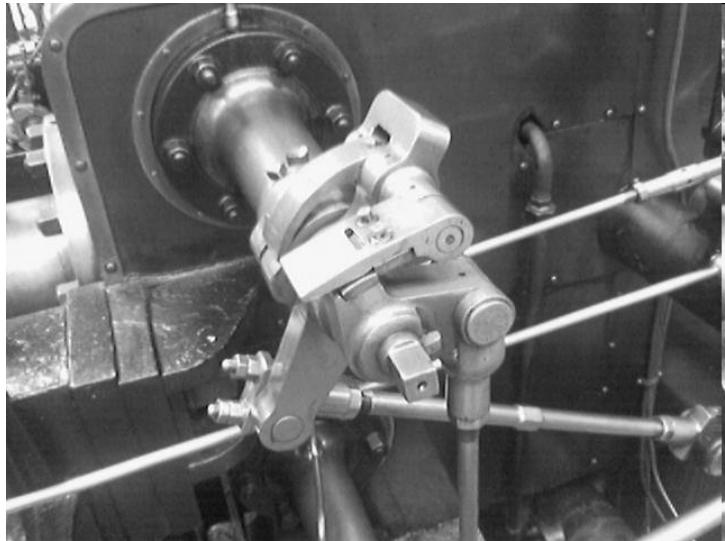


- “Filter” approach



Images from Wikipedia

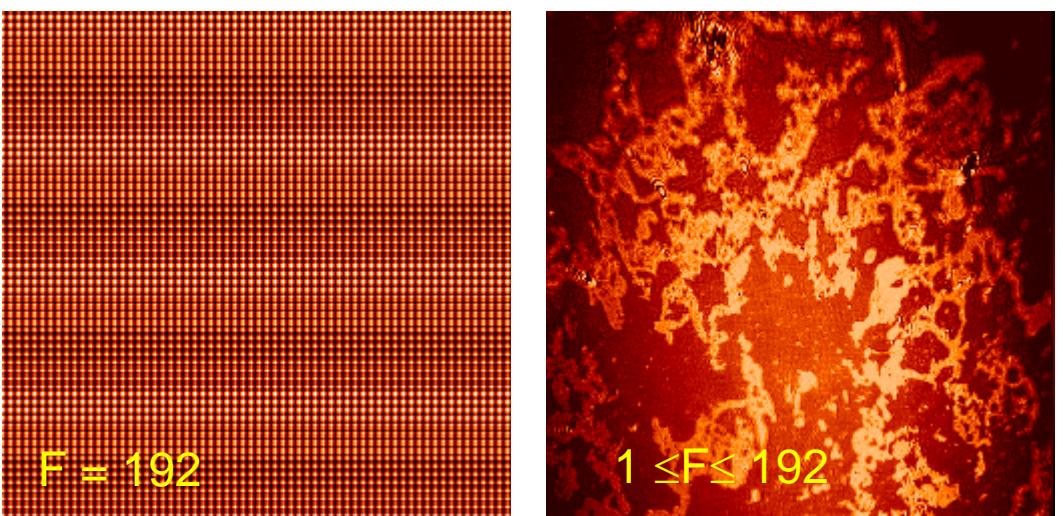
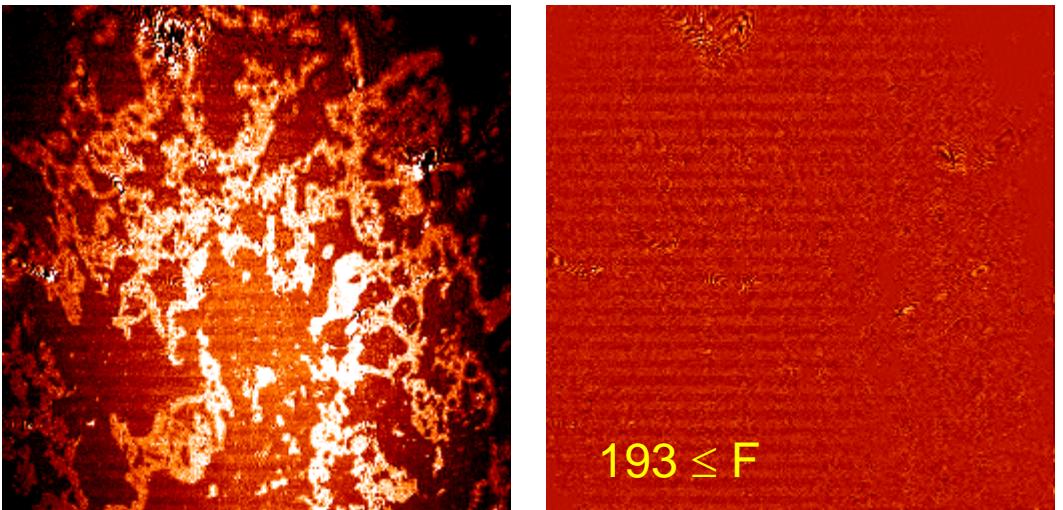
- A sample filter...



- Fourier filtering
- Think of a different base (e.g. polynomials)

https://imagejdocu.tudor.lu/plugin/filter/fit_polynomial/start

<https://imagej.nih.gov/ij/plugins/inserm514/>



Thresholding

example: Otsu

Convolution based

Convolution operation

Examples: gradient, Laplace, Sobel, Gaussian

Morphological

Morphological operators

Size

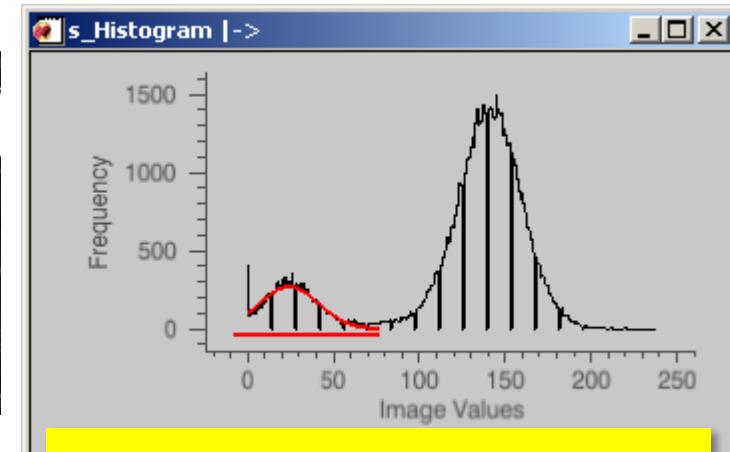
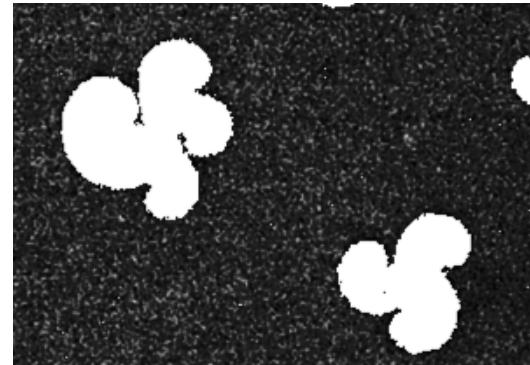
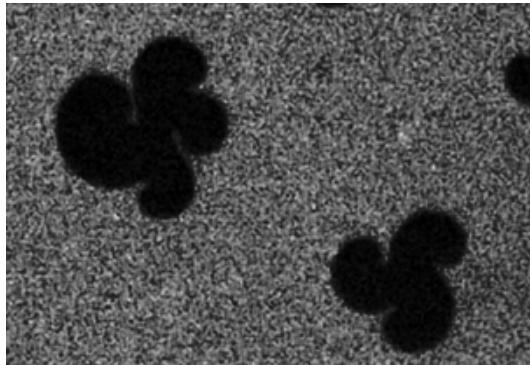
Thinning / skeletonization

Arithmetic-logic

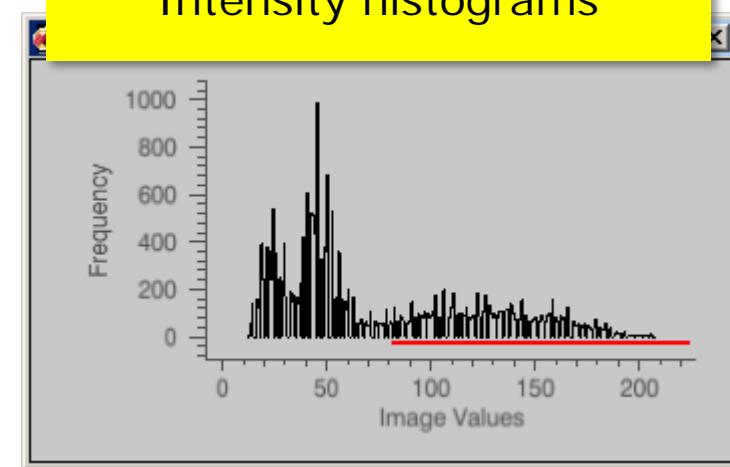
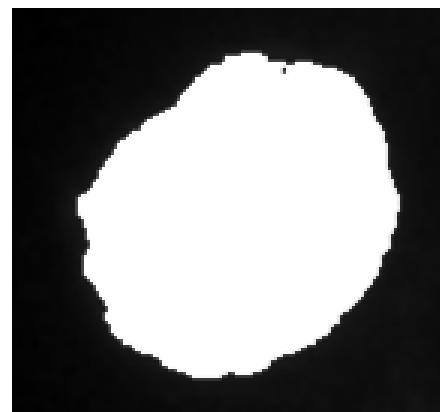
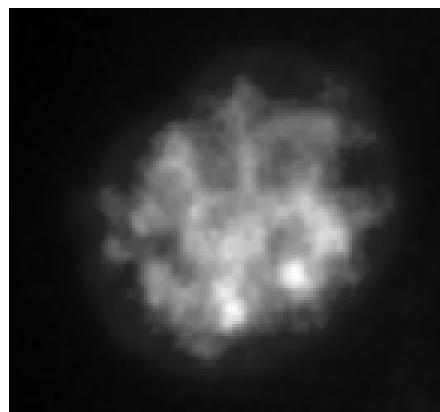
AND, OR, XOR

And a long etc.

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

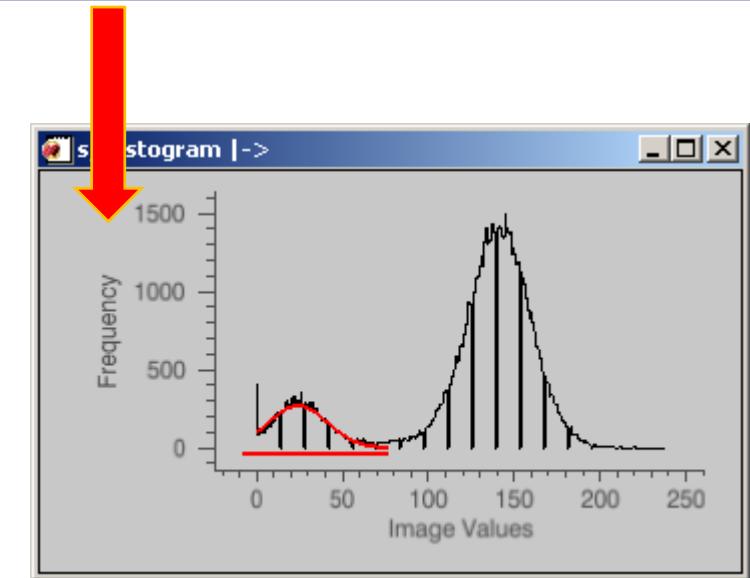
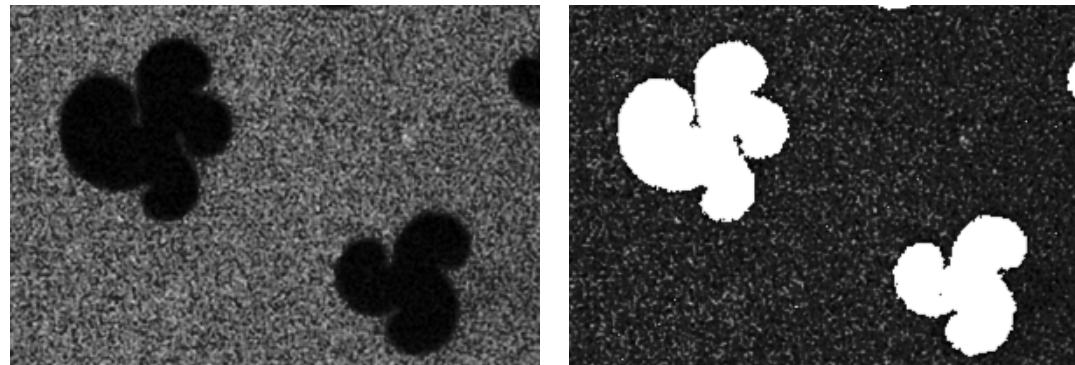


Intensity histograms



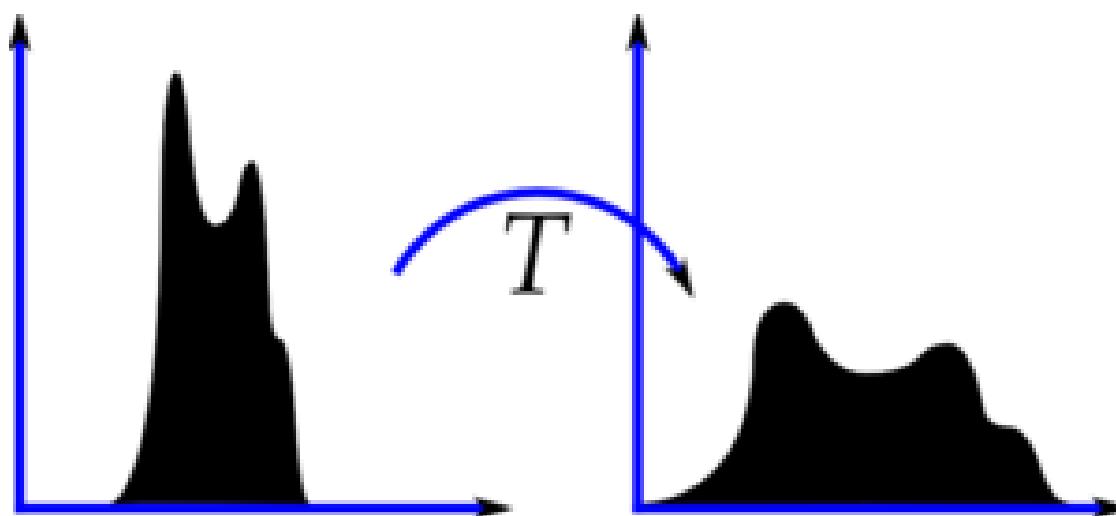
Let's call this "statistical frequency" to avoid confusions with the Nyquist/time/space domain frequency

- Here comes the Intensity Histogram



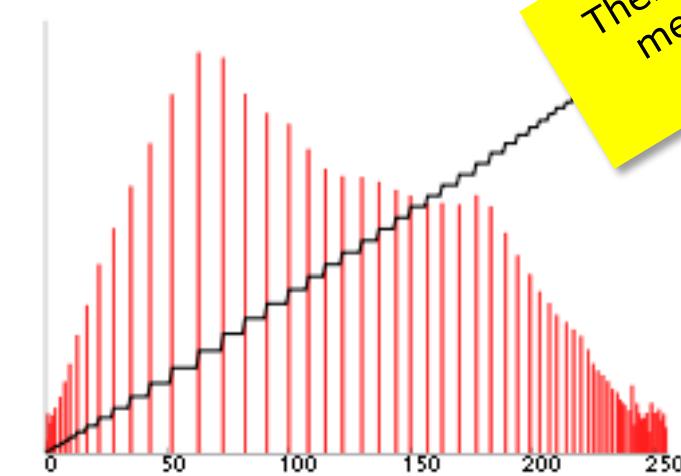
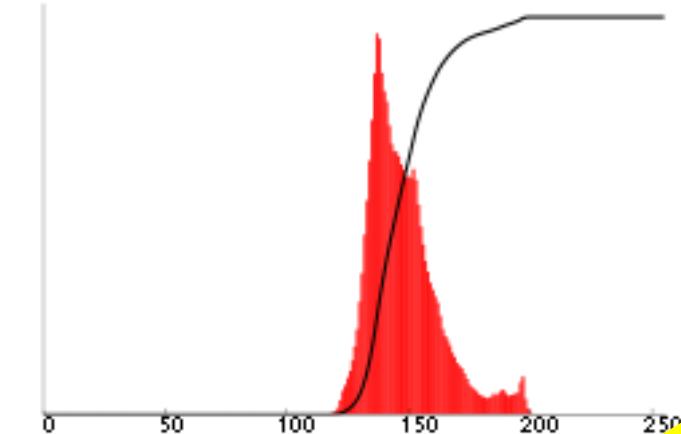
- Throwback to the acquisition...
 - Offset
 - Clipping (sometimes "Saturation"...try not to confuse with the HSV Saturation)

- Histogram equalization



http://en.wikipedia.org/wiki/Histogram_equalization

- Histogram equalization



There are (many) more methods... adaptive, contrast-limited...

- Otsu threshold

- Idea: to separate the image pixel in two classes (sets), minimizing the sum of variances from both classes



$$\min \sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

t : threshold, ω_i : probability of class i

Algorithm

1. Compute histogram and probabilities of each intensity level
2. Set up initial $\omega_i(0)$ and $\mu_i(0)$
3. Step through all possible thresholds $t = 1 \dots$ maximum intensity
 1. Update ω_i and μ_i
 2. Compute $\sigma_b^2(t)$
4. Desired threshold corresponds to the maximum $\sigma_b^2(t)$
5. You can compute two maximums (and two corresponding thresholds). $\sigma_{b1}^2(t)$ is the greater max and $\sigma_{b2}^2(t)$ is the greater or equal maximum
6. Desired threshold = $\frac{\text{threshold}_1 + \text{threshold}_2}{2}$

A Couple More “Concepts”

- Dynamic Range
- Clipping (in photography can be referred to as “color saturation”)

Some examples with music (“Loudness war”)

<https://www.youtube.com/watch?v=dcKDMBuGodU>

<https://www.youtube.com/watch?v=u9Fb3rWNWDA>

- 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

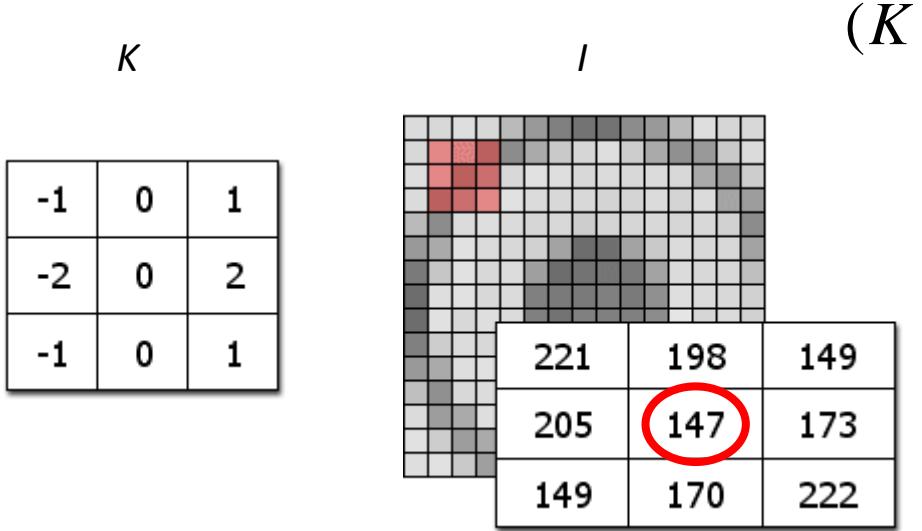
-1	0	1
-2	0	2
-1	0	1



$$\begin{aligned} &= (-1 \cdot 221) \\ &+ (0 \cdot 198) \\ &+ (1 \cdot 149) \\ &+ (-2 \cdot 205) \\ &+ (0 \cdot \mathbf{147}) \\ &+ (2 \cdot 173) \\ &+ (-1 \cdot 149) \\ &+ (0 \cdot 170) \\ &+ (1 \cdot 222) = -63 \end{aligned}$$

Adapted from James Matthews, 2002

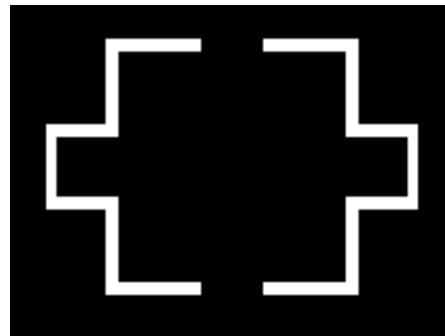
<http://www.generation5.org/content/2002/convolution.asp>



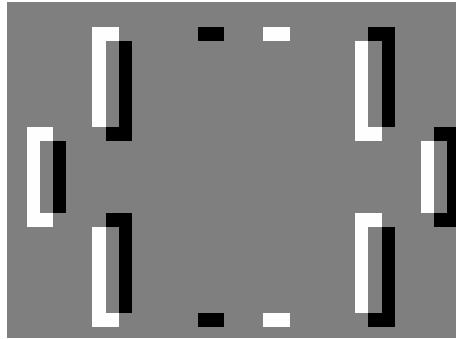
$$\begin{aligned}
 (K \otimes I)_{i,j} = & (-1 * 222) \\
 & + (0 * 170) \\
 & + (1 * 149) \\
 & + (-2 * 173) \\
 & + (0 * \mathbf{147}) \\
 & + (2 * 205) \\
 & + (-1 * 149) \\
 & + (0 * 198) \\
 & + (1 * 221) = +63
 \end{aligned}$$

Matrix convolution can be implemented in different ways... beware of the algorithm!

- Intensity gradients
(discrete approximation)

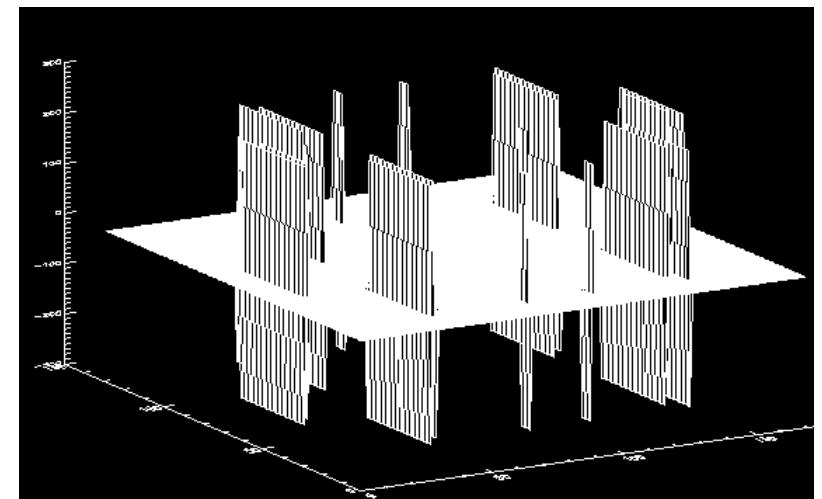
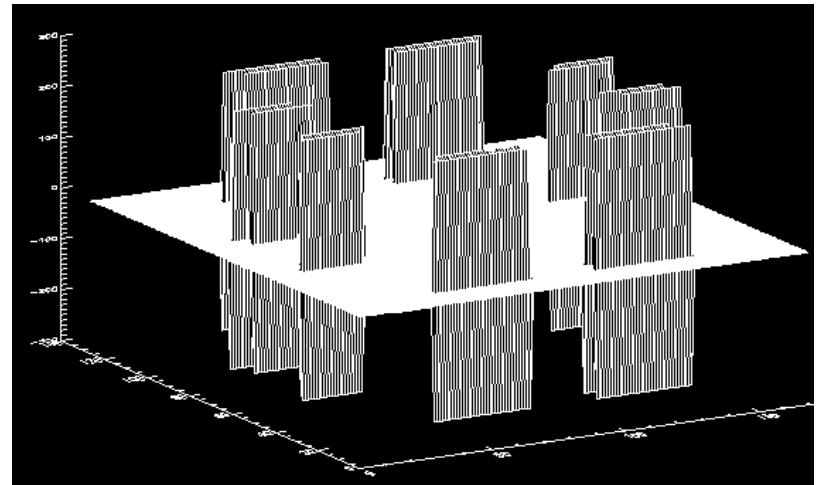
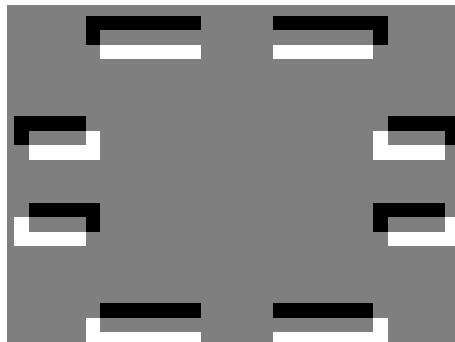


$$\frac{\partial I}{\partial x} \approx$$

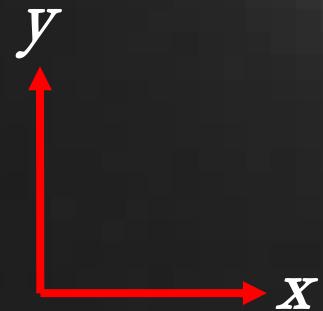


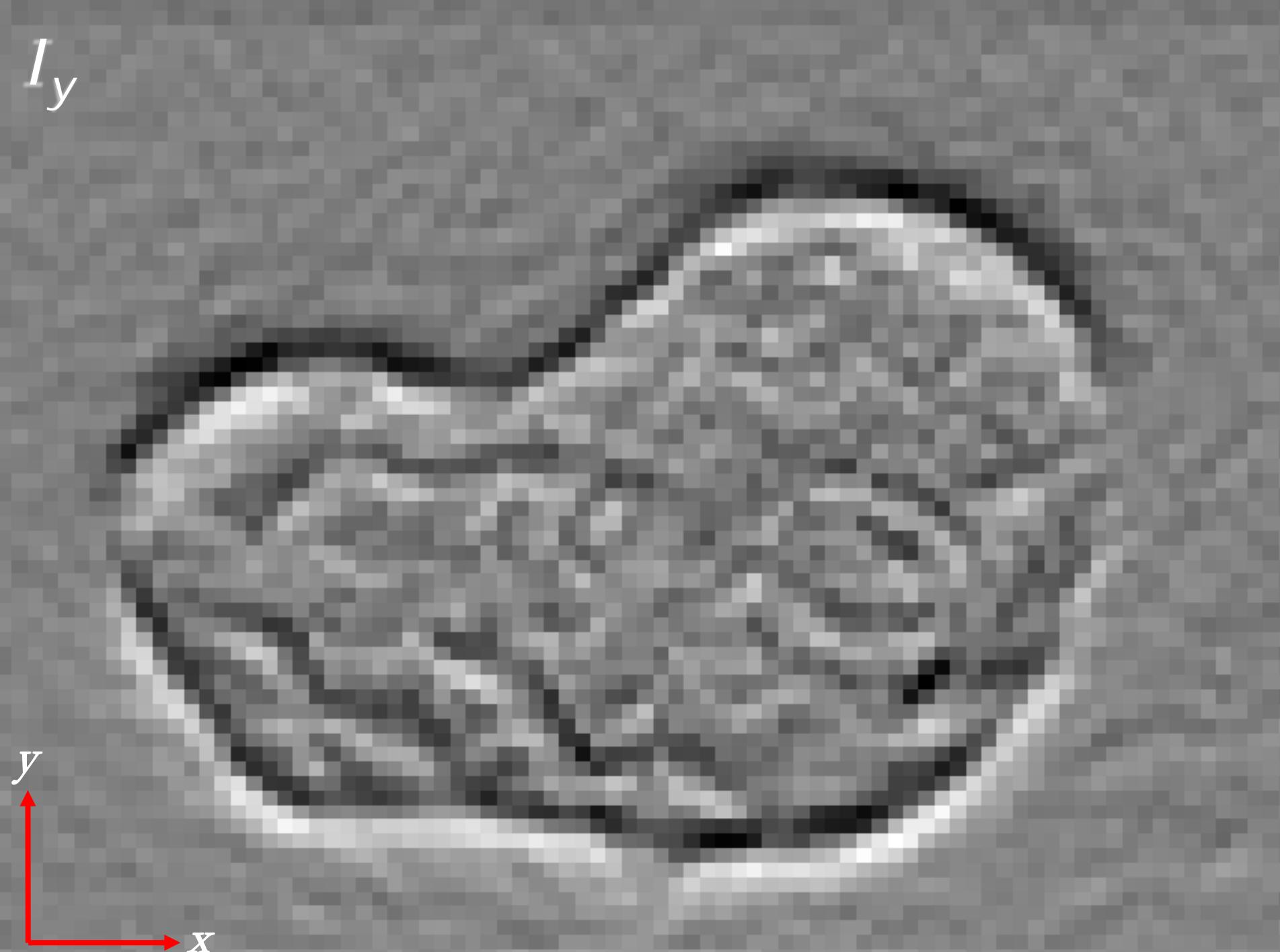
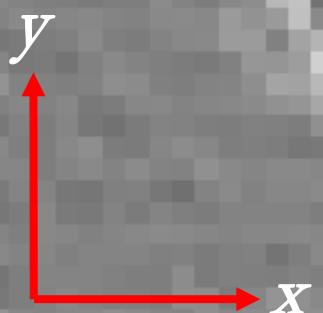
flat + -

$$\frac{\partial I}{\partial y} \approx$$



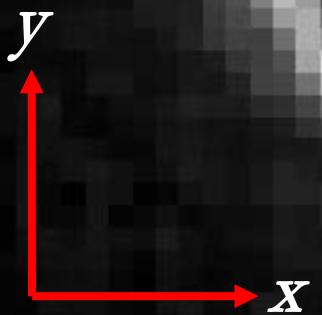
$$I = I(x, y)$$



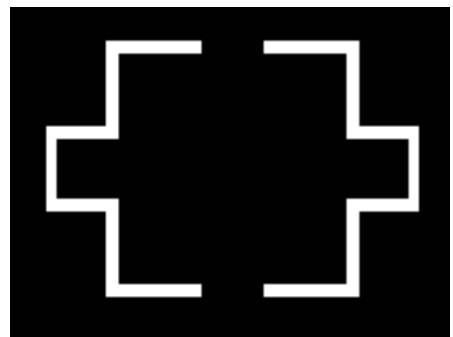
I_y 

“Edgemap”

$$|\nabla I| = |I_x| + |I_y|$$



- Intensity gradients (discrete approximation)

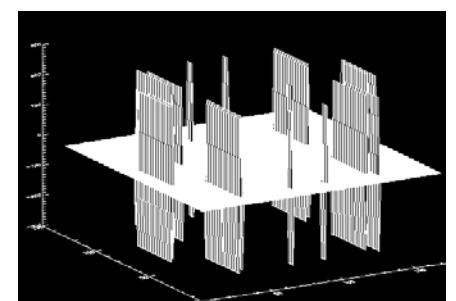


$$I = I(x, y)$$

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

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

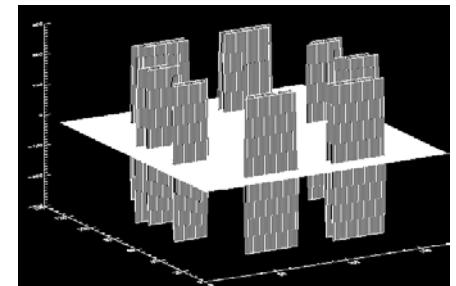
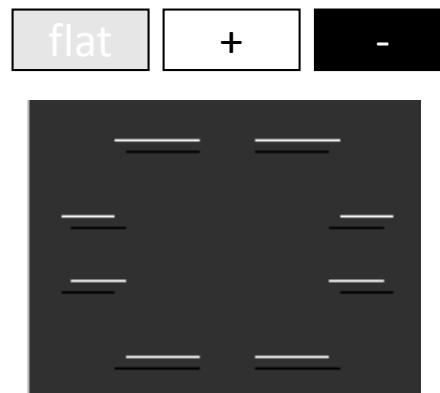
$$K_x = \begin{Bmatrix} 0 & 0 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{Bmatrix}$$



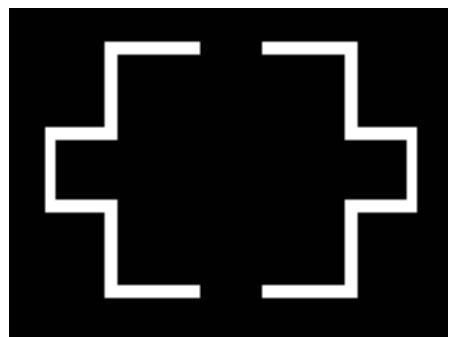
$$\frac{\partial I}{\partial y} \approx \frac{I(x, y + \Delta y) - I(x, y)}{\Delta y} = K_y \otimes I$$

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

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



Kernels...



$I = I(x, y)$

Laplace

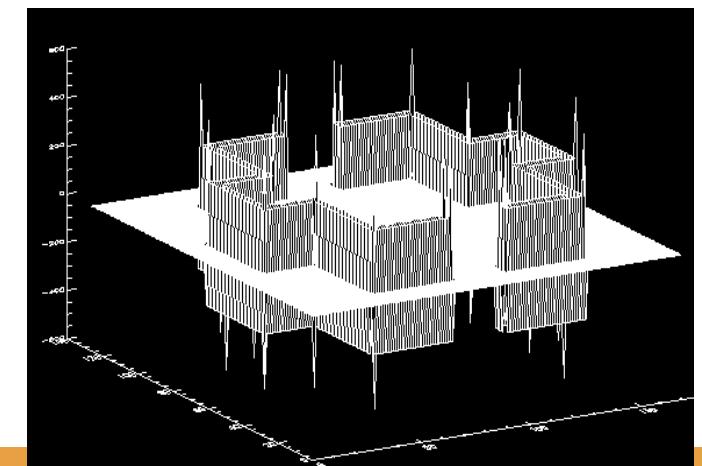
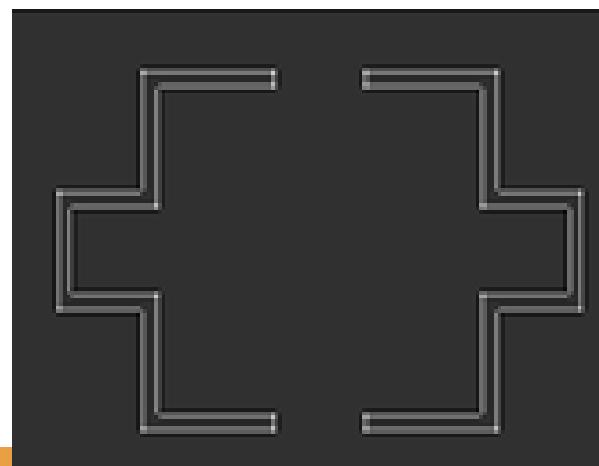
$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

$$\nabla^2 I \approx \frac{f(x + \Delta x, y) - 2f(x, y) + f(x - \Delta x, y)}{(\Delta x)^2} + \frac{f(x, y + \Delta y) - 2f(x, y) + f(x, y - \Delta y)}{(\Delta y)^2}$$

$$\nabla^2 I \approx \frac{f(x + \Delta x, y) + f(x, y + \Delta y) - 4f(x, y) + f(x - \Delta x, y) + f(x, y - \Delta y)}{(\Delta x)^2} = K_L \otimes I$$

$\Delta x = \Delta y = 1$ pixel

$$K_L = \begin{Bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{Bmatrix}$$



Edgemaps

An **edgemap** filter takes intensity changes as ROI boundaries or “edges”

$$f = \sqrt{(Kx \otimes I)^2 + (Ky \otimes I)^2}$$

Example:Sobel filter

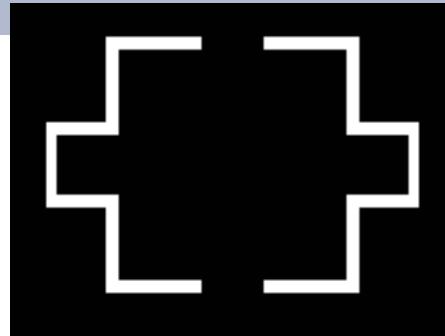
(notice the thick ROI edges)

$$\begin{array}{c} \left\{ \begin{array}{ccc} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{array} \right\} \quad \left\{ \begin{array}{ccc} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{array} \right\} \\ Sx \qquad \qquad \qquad Sy \end{array}$$

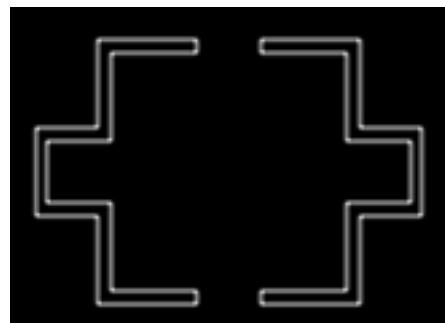
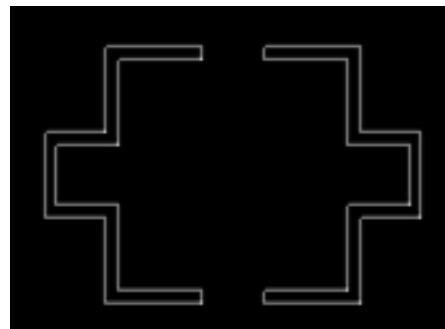
$Sx \otimes I$?

$Sy \otimes I$?

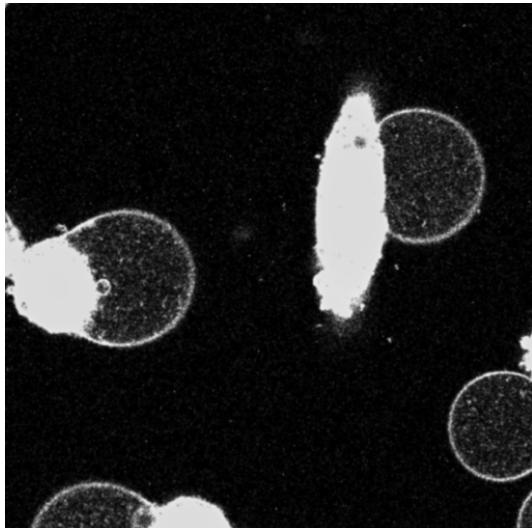
$$f_{Sobel} = \sqrt{(Sx \otimes I)^2 + (Sy \otimes I)^2}$$



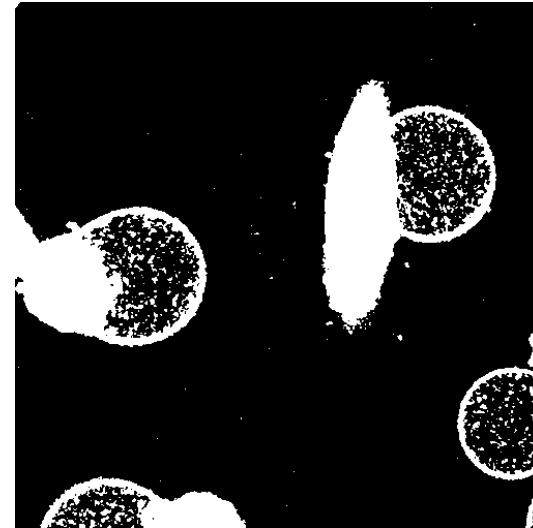
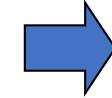
$I = I(x, y)$



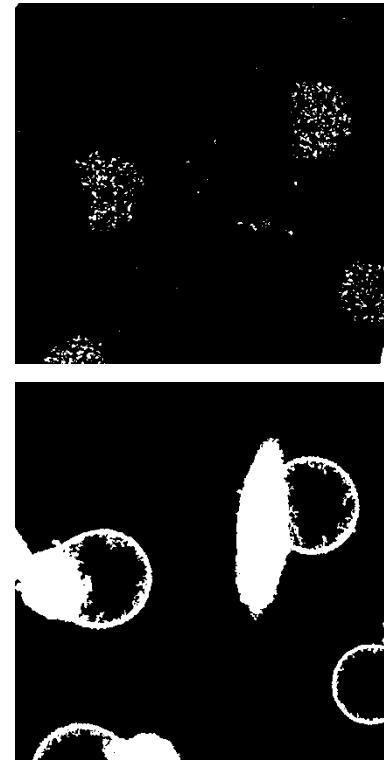
- Morphology based filters
 - Example: size selection



Input greyscale image



After thresholding...



Size selection

How to define a size-select algorithm?

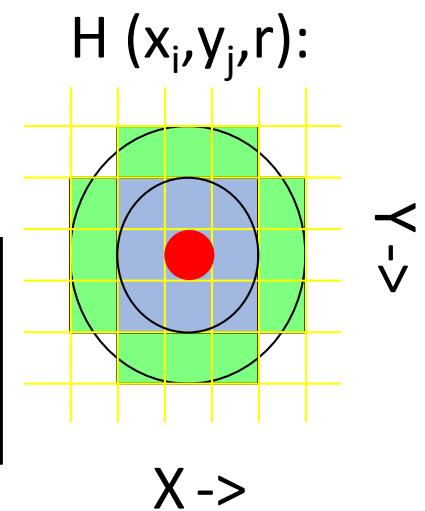
- Filtering with morphological operators:

Filtering with morphological operators:

- Structuring element, template or mask H ...

- Additional rules...

$$H = \begin{array}{c} \text{Filtermaske} \\ \cdot \end{array}$$



Polynomial filters $y(m, n) = \bar{h}_1[x(m, n)] + \bar{h}_2[x(m, n)],$

$$\bar{h}_1[x(m, n)] = \sum_{\substack{p=0 \\ (p,q) \neq (0,0)}}^{P-1} \sum_{q=0}^{Q-1} a(p, q) \cdot x(m - p, n - q)$$

$$\bar{h}_2[x(m, n)] = \sum_{\substack{p=0 \\ (p,q) \neq (0,0)}}^{P-1} \sum_{q=0}^{Q-1} \sum_{k=0}^{P-1} \sum_{l=0}^{Q-1} b(p, q, k, l) \cdot x(m - p, n - q) \cdot x(m - k, n - l)$$

- Mathematical morphology

Minkowski Operations

Addition... dilation: $A \oplus S = \{(m, n) | [S + (m, n)] \cap A \neq \emptyset\}$.

Subtraction ... erosion: $A \ominus S = \{(m, n) | [S + (m, n)] \subseteq A \neq \emptyset\}$

...opening : $A \circ S = (A \ominus S) \oplus S,$

...closing : $A \bullet S = (A \oplus S) \ominus S,$

- A: image
- S: structuring element

- Mathematical morphology

$$A \oplus S = \{(m, n) | [S + (m, n)] \cap A \neq \emptyset\}.$$

$$A \ominus S = \{(m, n) | [S + (m, n)] \subseteq A \neq \emptyset\}$$

$$A \circ S = (A \ominus S) \oplus S,$$

$$A \bullet S = (A \oplus S) \ominus S,$$

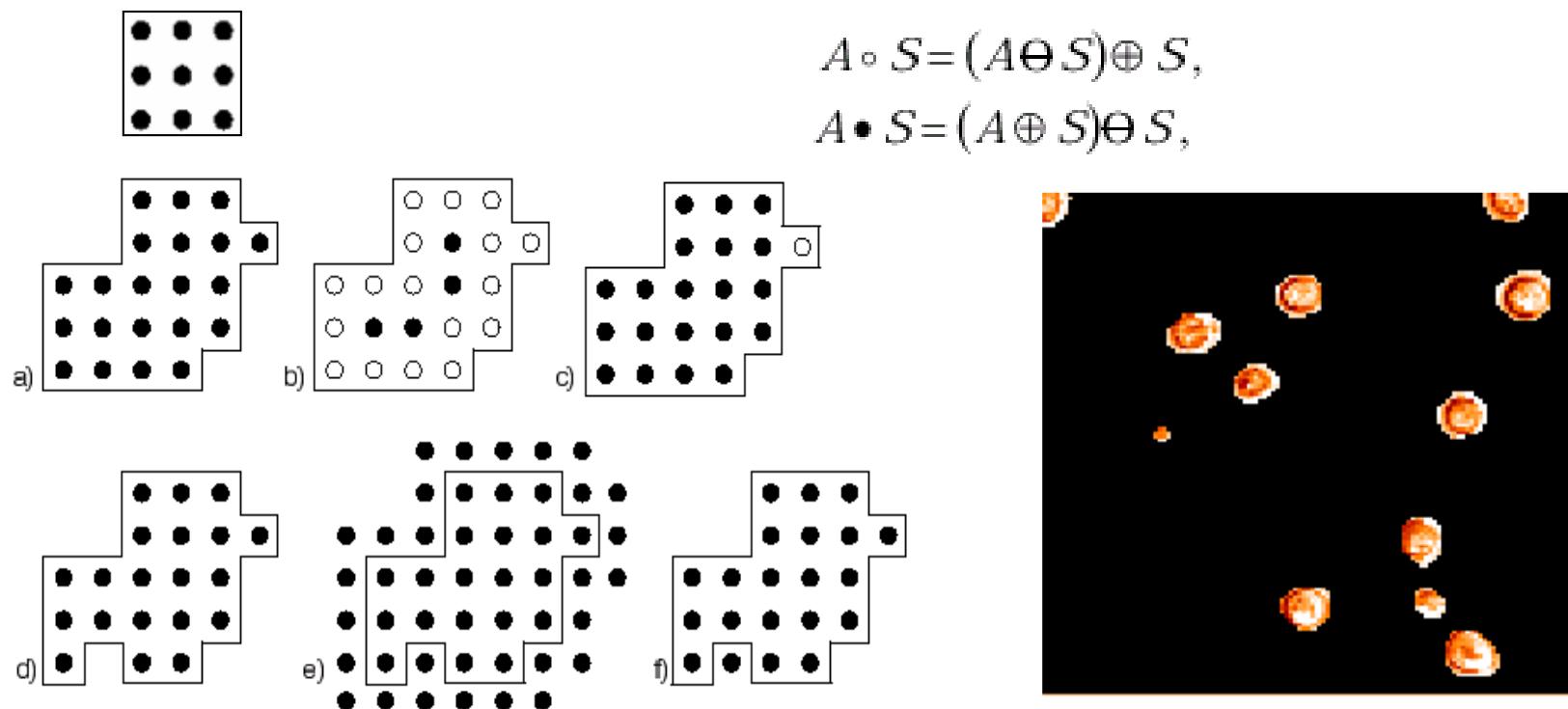


Abb. 2.5. a Originalform b erodiert c opening (Dilatation von b)
d Originalform e dilatiert f closing (Erosion von e)

- Watershed
(Distance transform +
Watershed)

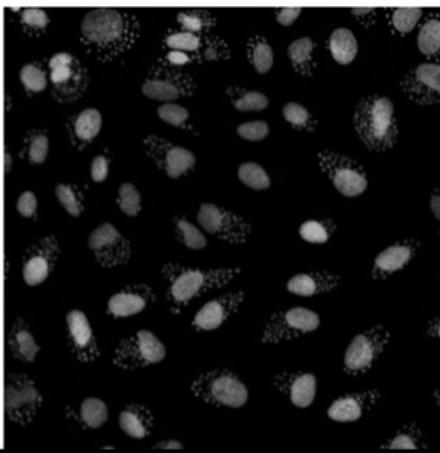


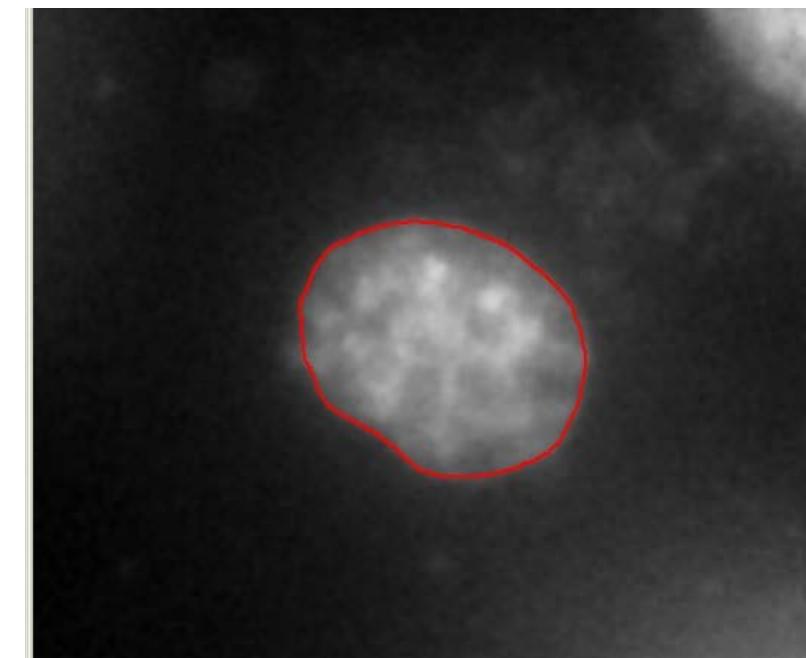
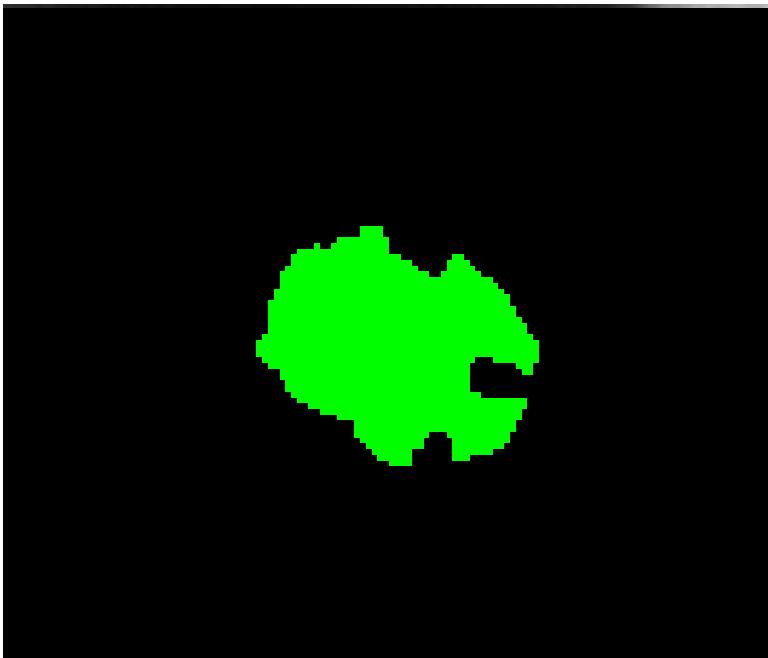
Figura 1. Imágenes de línea de osteoblastos humanos infectados con *Trypanosoma cruzi* (Nature 2010).

Dato útil: el comando <Ctrl> + <Shift> + D permite duplicar la imagen activa en FIJI/ImageJ. Resulta útil para conservar el resultado del último filtro aplicado.

El objetivo de este práctico es realizar una segmentación de imágenes 2D usando FIJI para obtener datos básicos, responder las preguntas indicadas en esta misma hoja y entregarla al final del práctico.

1. **Segmentación 2D.** Sobre la imagen de entrada, similar a la de la Figura 1, se aplicarán distintos filtros para generar imágenes blanco/negro que representen a las regiones de interés (blanco) sobre el fondo (negro). Comience por segmentar los núcleos de osteoblastos. Algunas indicaciones para utilizar FIJI:
 - a. Para binarizar una imagen en (escala de grises) use la opción del menú "Image / Adjust / Threshold"
 - b. Los filtros binarios: erosión, dilatación, apertura están en el menú "Process / Binary", y en el menú "Binary / Options" puede indicar cuantas veces realizar la operación.
- c. Una vez obtenida una primera segmentación, puede utilizar el filtro Watershed para separar núcleos muy cercanos, disponibles desde el menú "Process / Binary / Watershed".

- Sometimes more information is needed in order to achieve a good segmentation



- David Marr. Vision
MIT press, 1982
- John Russ. The image processing handbook, 4th ed.
CRC Press, 2002
- Nixon, Aguado. Feature extraction & image processing, 1st | 2nd | 3rd ed.
Academic Press, 2002 | 2008 | 2012
- Aubert & Kornprobst. Mathematical Problems In Image Processing
Springer, 2006

Some free and open source software tools

- Java based (Java runtime required)
 - ImageJ (<http://rsbweb.nih.gov/ij/>, public domain)
 - FIJI (<http://fiji.sc>; GPL license)
 - Icy (<http://icy.bioimageanalysis.org>; GPLv3 license)
- Others
 - CellProfiler (<http://cellprofiler.org>; GPL, BSD licenses)
 - Slicer (www.slicer.org; BSD license)
 - IPOL (Image Processing Online): open access electronic journal with peer reviewed articles + code (languages: C/Python) + examples (www.ipol.im; BSD / GPL / LGPL licenses or similar)

Literature, Links & Software

- The Good, the Bad and the Ugly. Helen Pearson. 2007 Nature 447:138-140
- Seeing is believing? A beginners' guide to practical pitfalls in image acquisition. Alison J. North. 2006 The Journal of Cell Biology, 172(1):9-18
- V Castañeda, M Cerdá, F Santibáñez, J Jara, E Pulgar, K Palma, ... Computational methods for analysis of dynamic events in cell migration, Current molecular medicine 14 (2), 291-307
- Fluorescence Microscopy, From Principles to Biological Applications, Ulrich Kubitscheck (Editor), 2nd Edition, June 2017, Hardcover, ISBN: 978-3-527-33837-5
- <https://www.zeiss.com/microscopy/int/cmp/edr/21/microscopy-for-dummies.html>
- <https://www.microscopyu.com/tutorials>
- <http://zeiss-campus.magnet.fsu.edu/tutorials/index.html>
- <https://www.leica-microsystems.com/science-lab/topics/basics-in-microscopy>
- https://www.youtube.com/playlist?list=PLG8B8Uyfh7-Azddns5nv_kZU1YQGD4bBg
- Principles of Fluorescence Spectroscopy, Joseph R. Lakowicz 4.1 Introduction to Fluorescence
- A global view of standards for open image data formats and repositories JR Swedlow, P Kankaanpää, U Sarkans, W Goscinski, G Galloway, ..., Nature Methods, 1-7
- Jonkman, J., Brown, C.M., Wright, G.D. et al. Tutorial: guidance for quantitative confocal microscopy. Nat Protoc 15, 1585–1611 (2020), <https://doi.org/10.1038/s41596-020-0313-9>