

# Object Detection in Microscopic Images

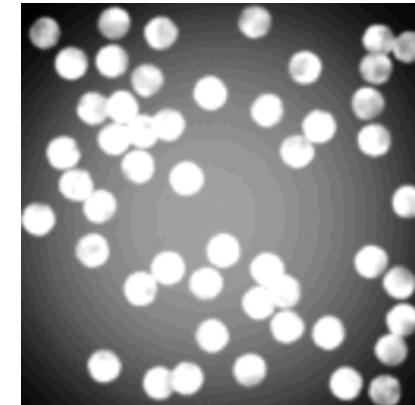
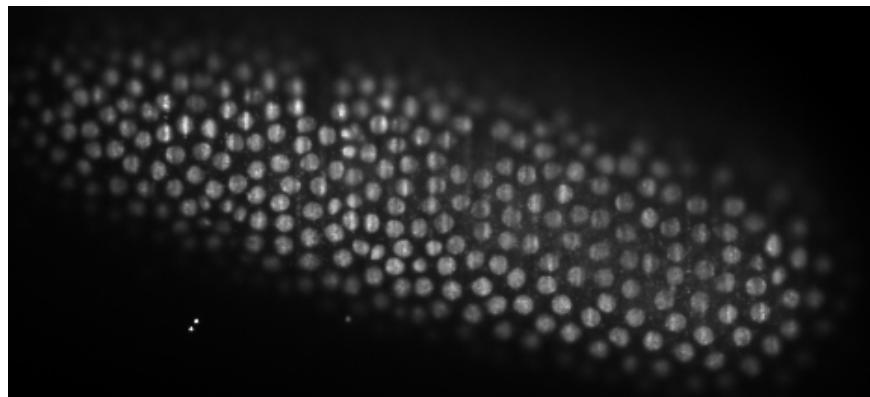
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Morpheme team  
INRIA/I3S/iBV

# Multiple objects detection

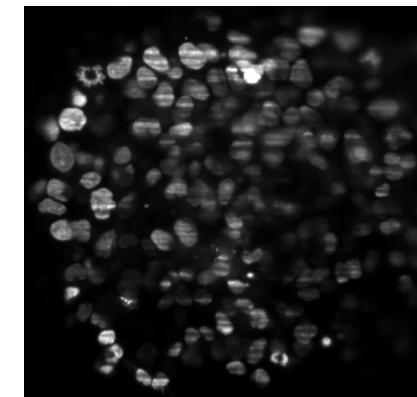
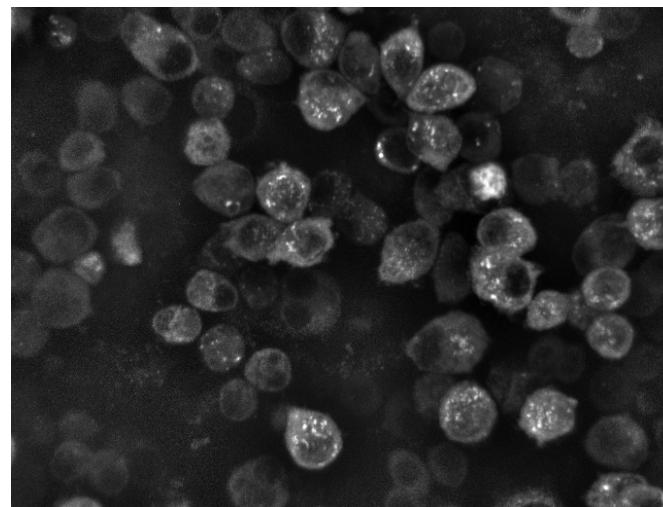
- Goal : evaluate a population, classification, shape statistics, initialize a tracking algorithm,  
...
- Automaticity : large sets of data, high throughput, expert independent
- Requirements: robustness, efficiency, ergonomic

# Examples

- Cells :



- Vesicles :



# The ImageJ (Fiji) approach

- [https://imagej.net/Particle Analysis](https://imagej.net/Particle_Analysis)

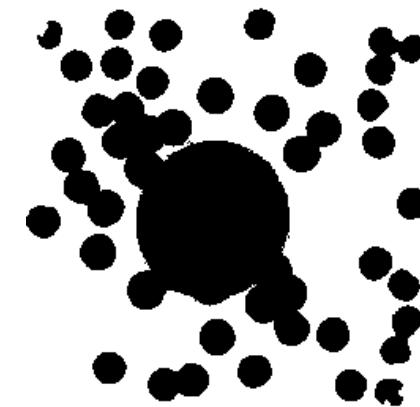
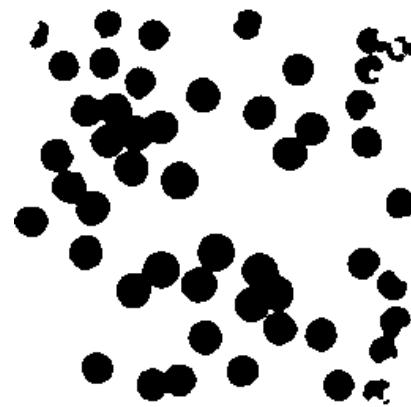
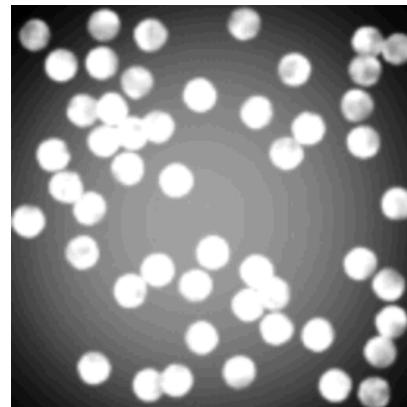
1 – Threshold : manual or automatic

2 – Separation using watershed

3 – Particles selection (« particle analyzer »)

# 1 - Threshold

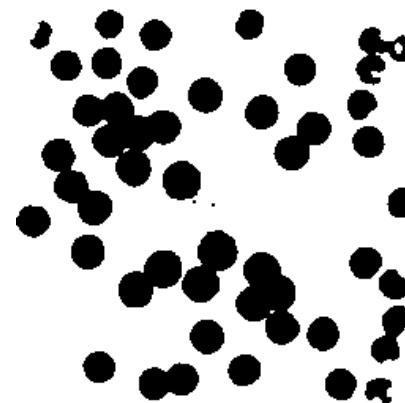
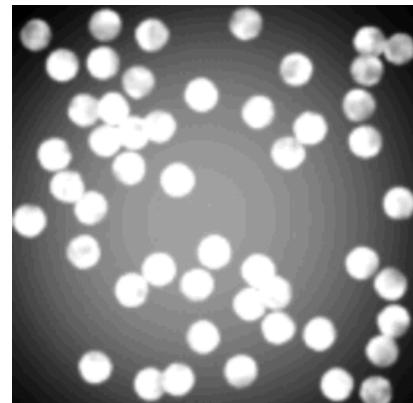
$$T(x, y) = \begin{cases} 1 & \text{if } I(x, y) \geq t \\ 0 & \text{otherwise} \end{cases}$$



# 1 - Threshold (Automatic)

- Numerous techniques
- Otsu : minimum of intra-class variance

$$\operatorname{argmin} \left\{ \omega_1(t) \sigma_1^2(t) + \omega_2(t) \sigma_2^2(t) \right\}$$



## 2 - Watershed

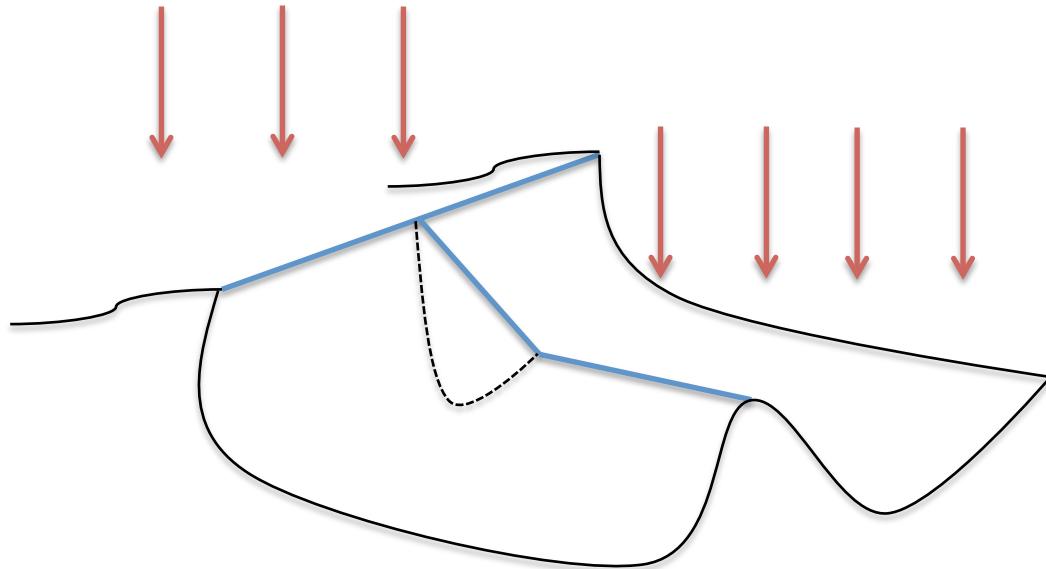
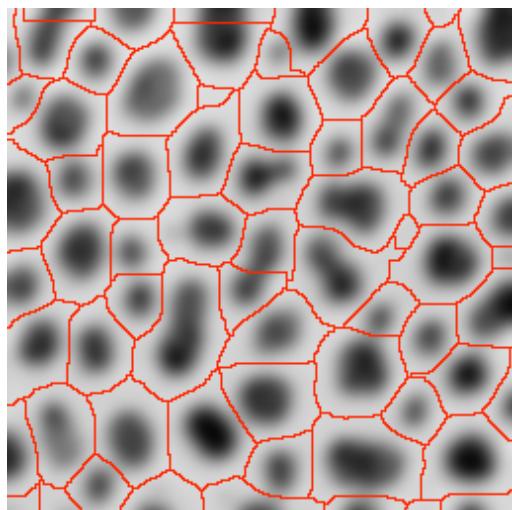
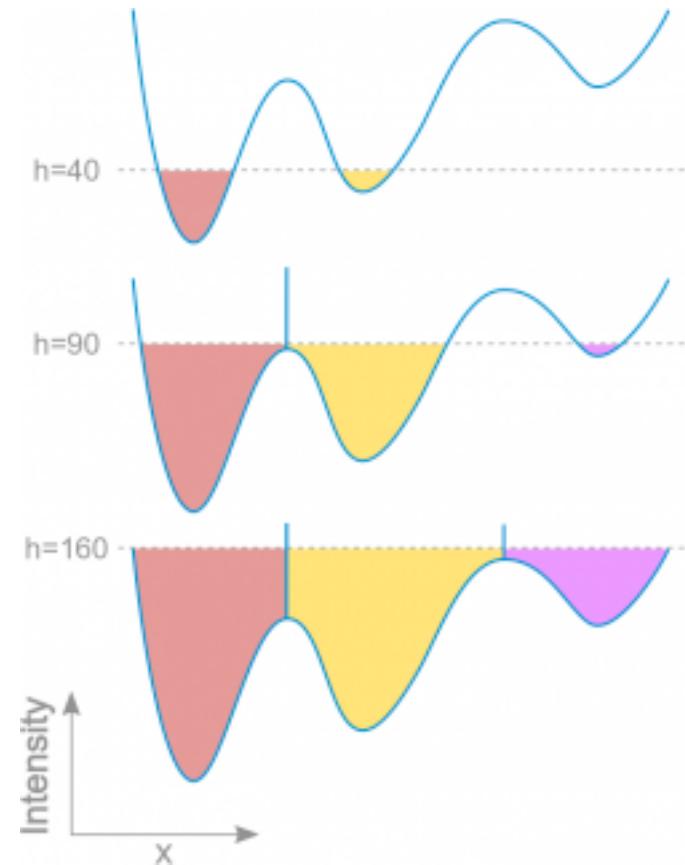


Image : topographical surface

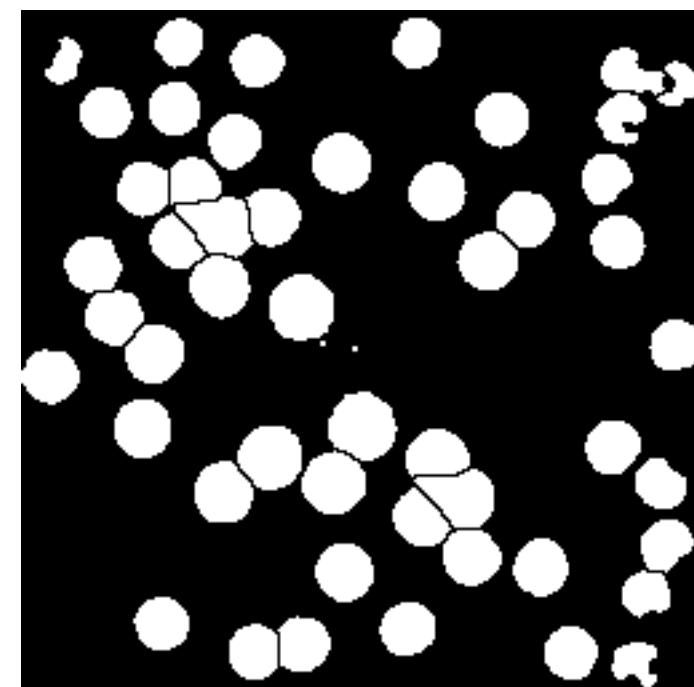


Algorithm : flooding simulation



[https://imagej.net/Classic\\_Watershed](https://imagej.net/Classic_Watershed)

## 2 - Watershed



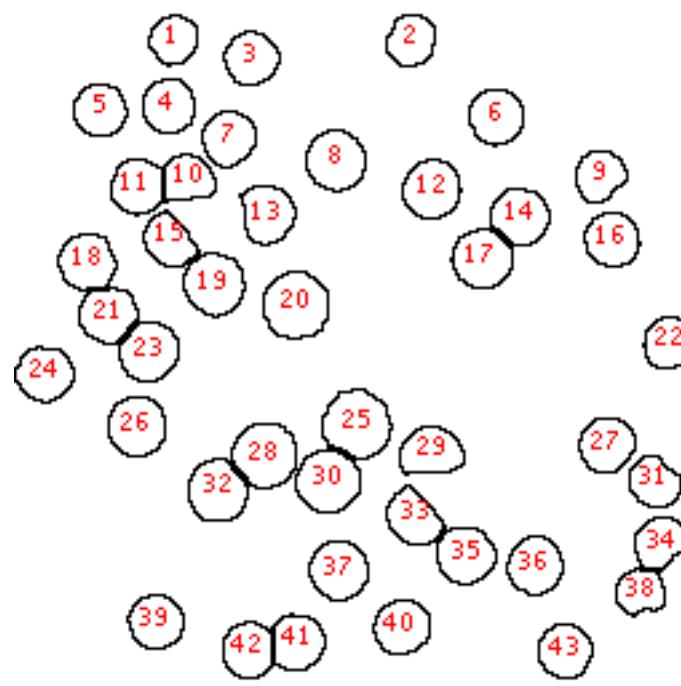
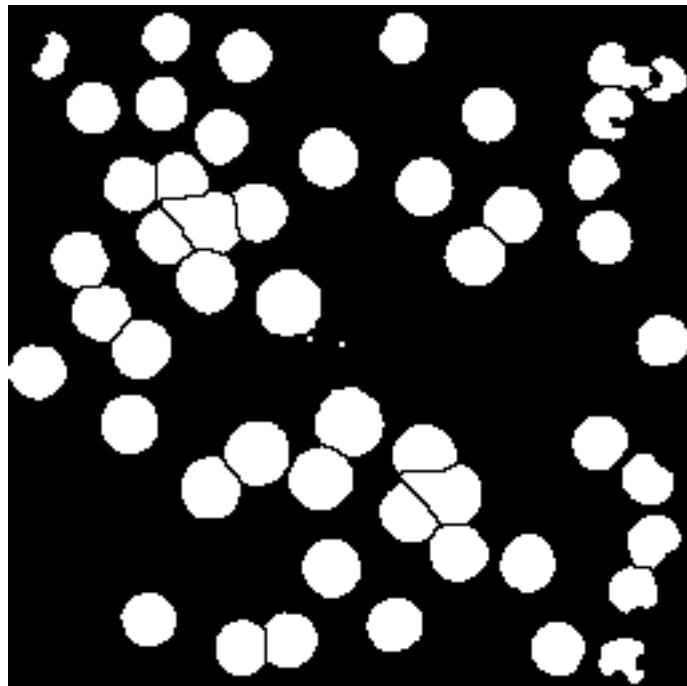
# 3 – Particle Analyzes

Size bounding:  $S_{\min} \leq S(P) \leq S_{\max}$

Circularity bounding:  $C_{\min} \leq C(P) \leq C_{\max}$ ,  $C(P) = \frac{S(P)}{2\pi E(P)}$

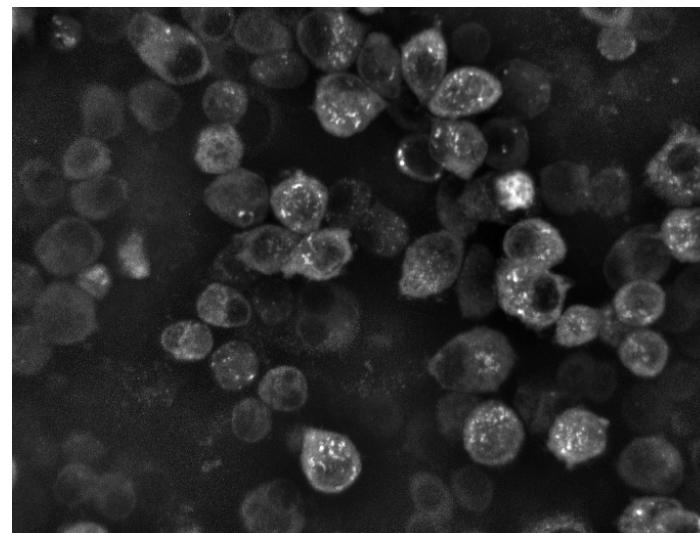
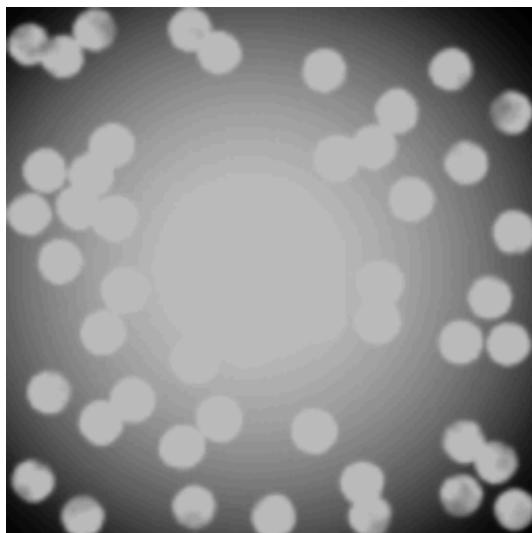
$S(P)$ : Number of pixels in particle P

$E(P)$ : Number of pixels in edge of particle P



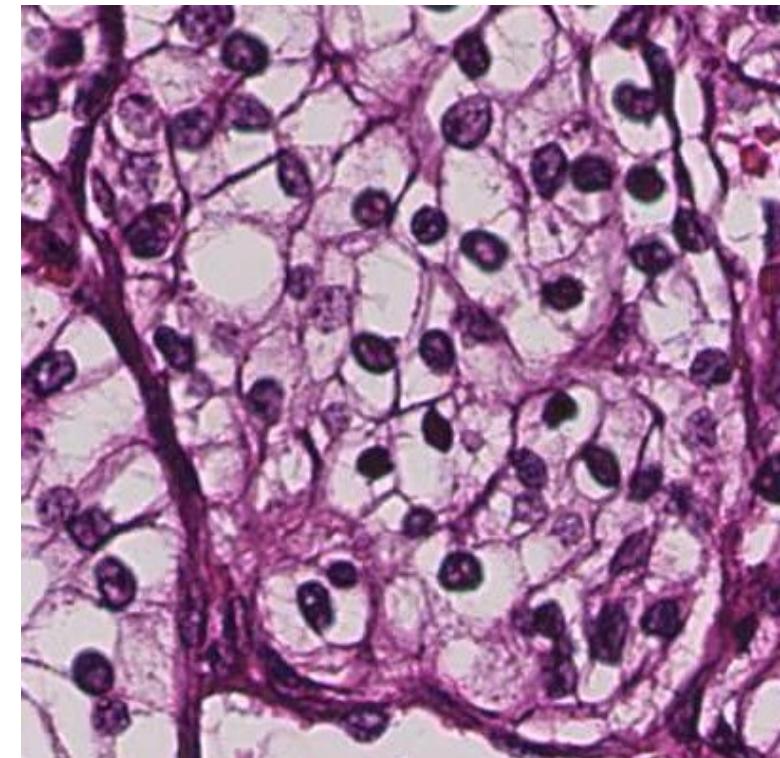
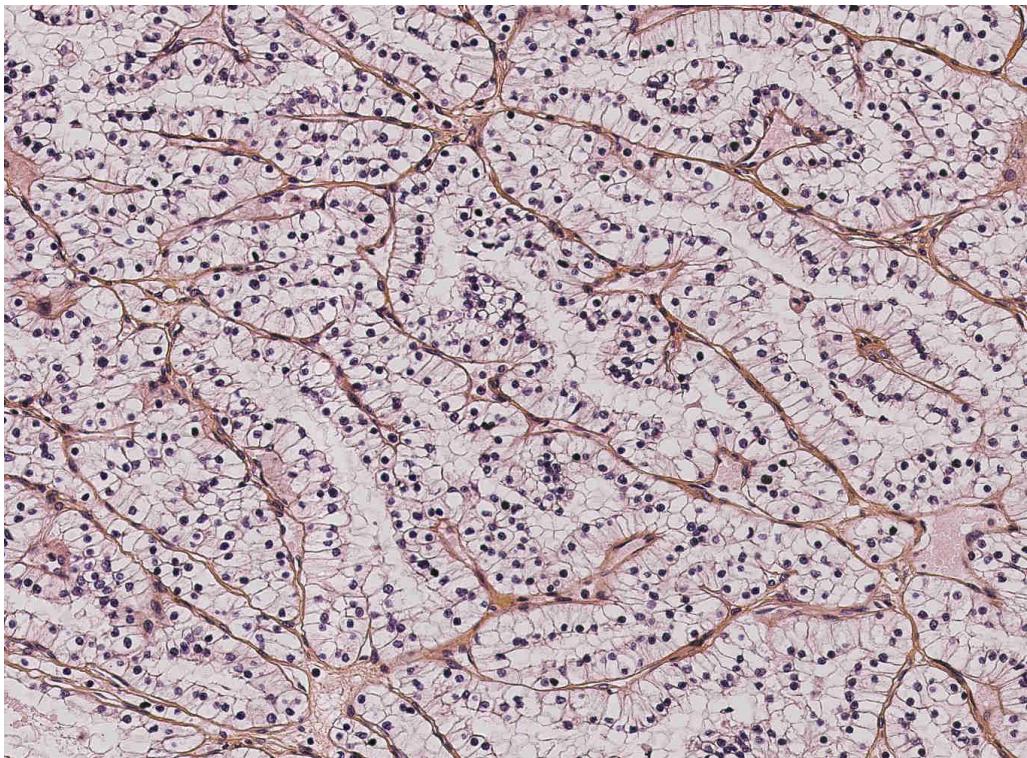
# The challenges

- Issue 1: How to address the intensity heterogeneity that prevents from considering a global threshold on the intensity in order to separate objects from background ?



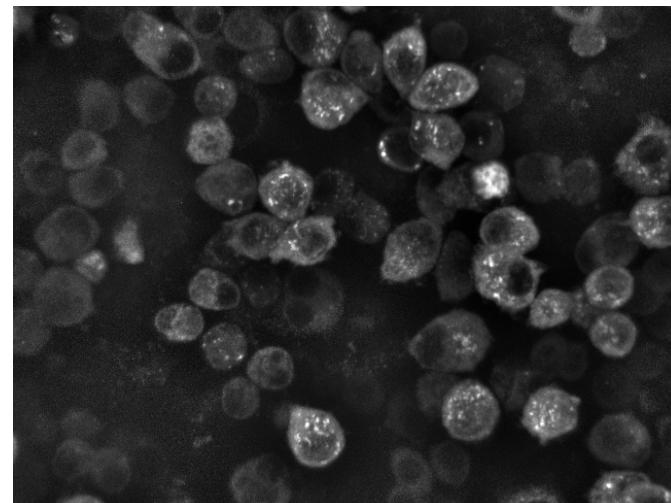
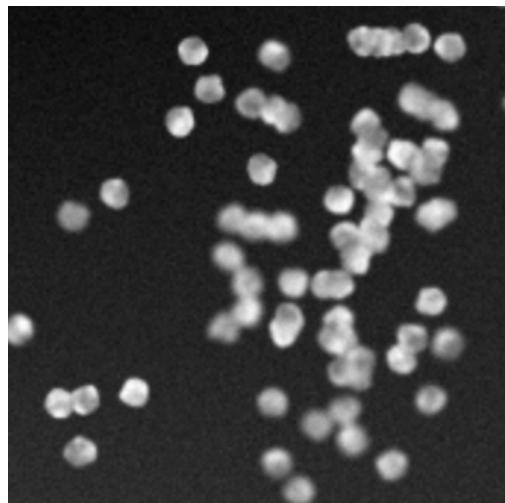
# The challenges

- Issue 2: How to deal with nuisance objects that do not belong to the targeted class of objects but cannot be considered as background neither ?



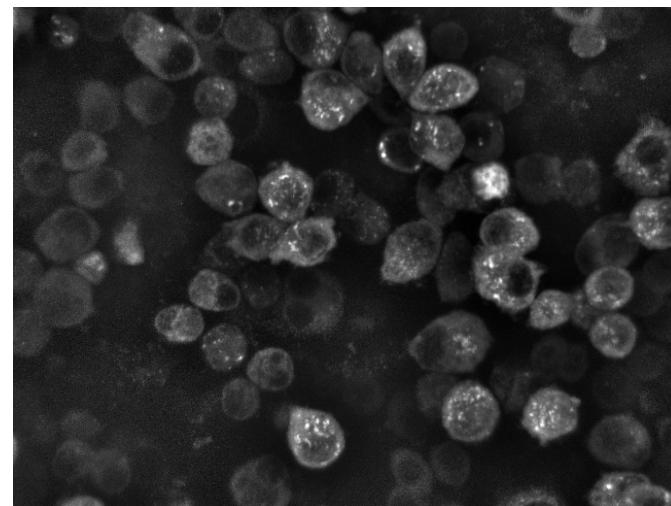
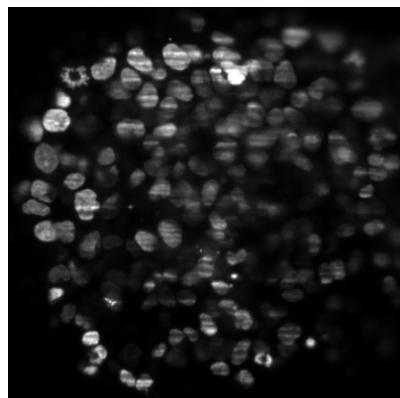
# The challenges

- Issue 3: How to deal with a high density of objects that generates clusters of possibly overlapping objects ?



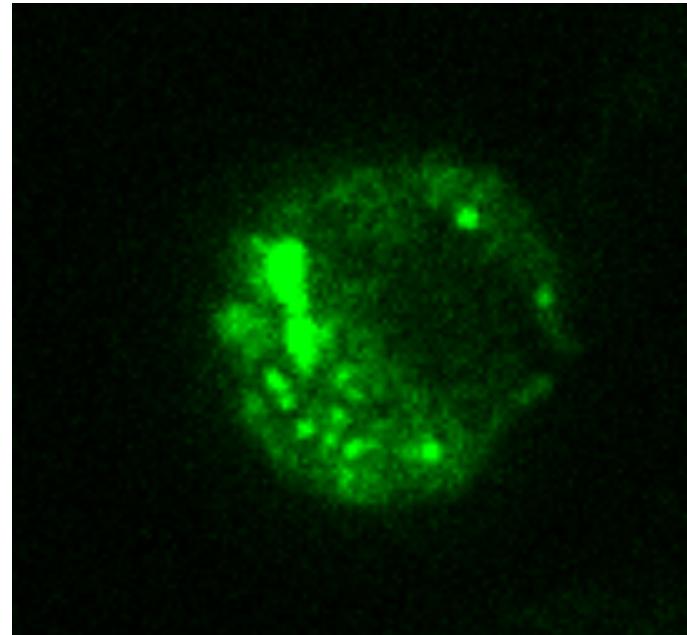
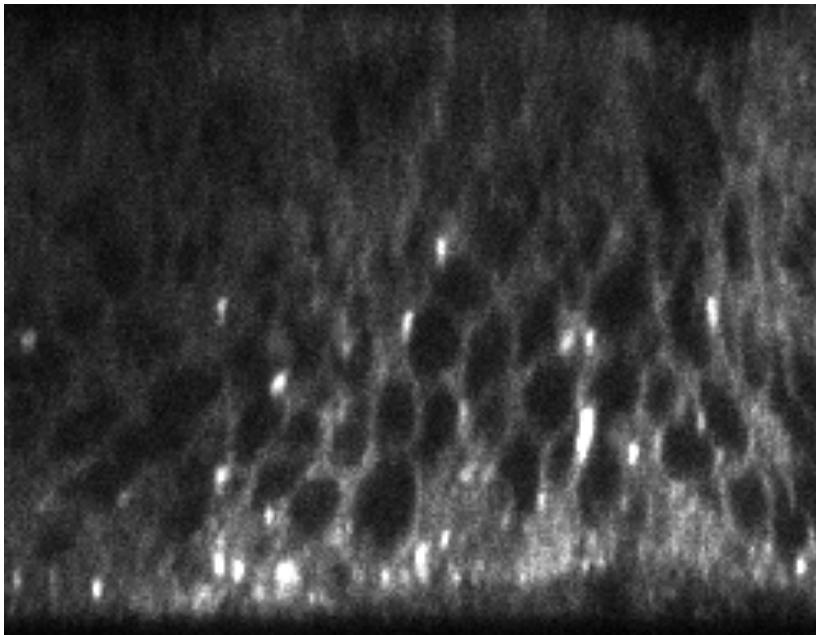
# The challenges

- Issue 4: How to handle the shape variability between objects ?



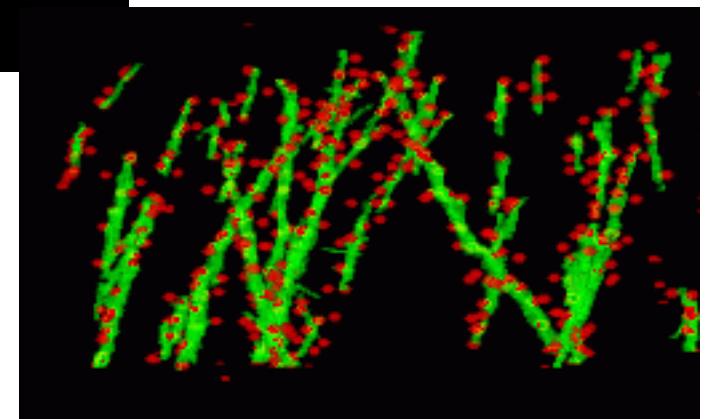
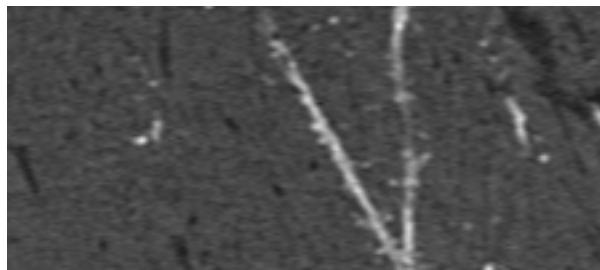
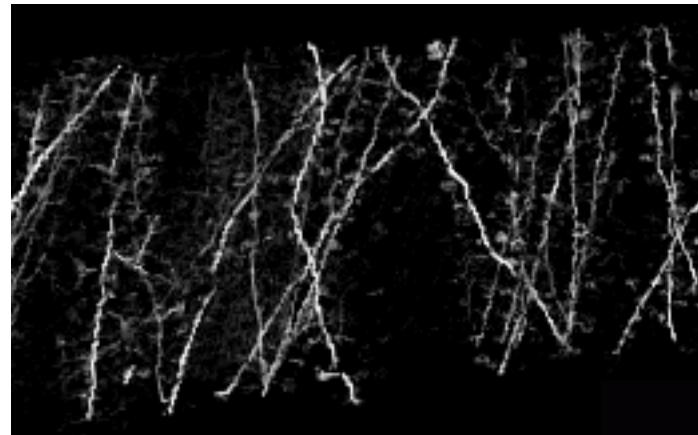
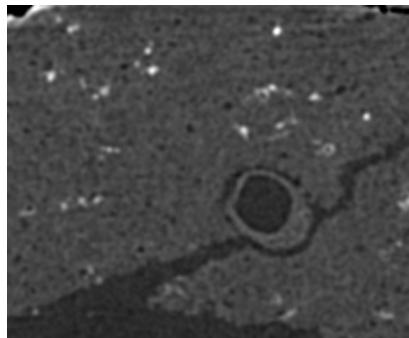
# The challenges

- Issue 5: How to detect objects that consist of a few pixels ?



# The challenges

- Issue 6: How to deal with 3D datasets ?



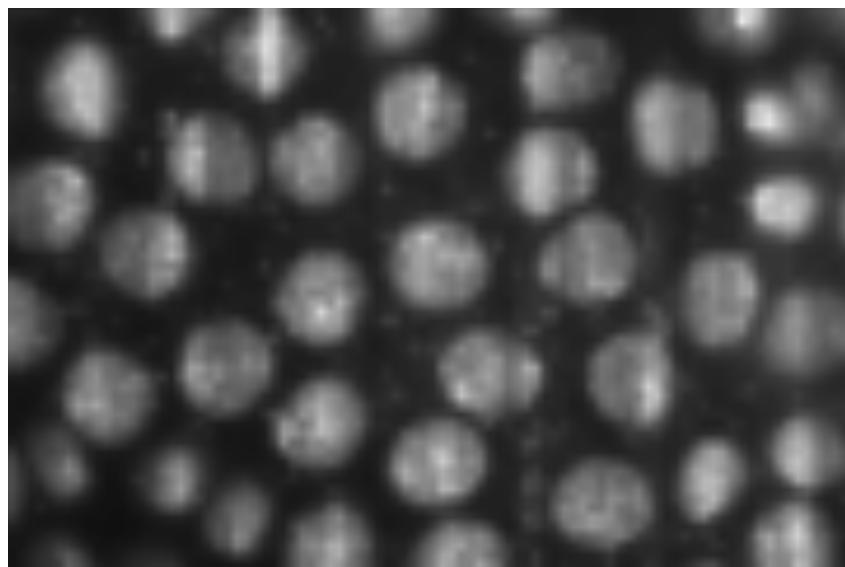
# Main steps

- Improve image quality :
  - Denoising : Gaussian filter, Image restoration (MRF, Variational approaches,...)
  - Spatial normalization
  - Objects enhancement : Edge enhancement, Top Hat
- Detect object location :
  - Threshold + Local maxima, template matching
- Reconstruct object shape :
  - Watershed, Active contour
- Post-processing :
  - Cleaning (opening, closing), Shape parameters
- All in One : Marked Point Processes

# Denoising

- Gaussian Filter :  $O = G * I$

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp - \left[ \frac{x^2 + y^2}{2\sigma^2} \right]$$

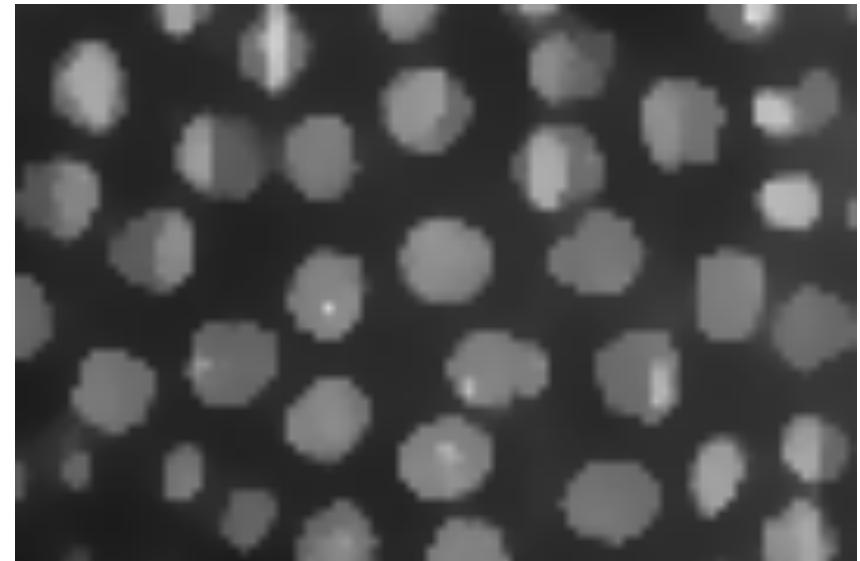
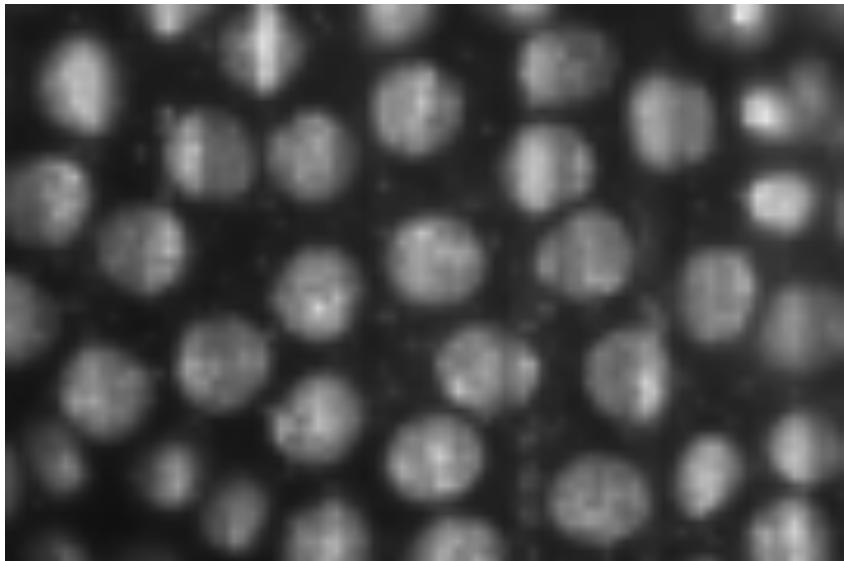


-> Remove noise but **blur** objects

# Denoising

- Restoration :  $\operatorname{argmin} (||O - I||_{L^n} + \Phi(O))$

Example: 
$$U = \sum_s \frac{(o_s - i_s)^2}{2\sigma^2} - \beta \sum_{s \sim s'} \frac{1}{1 + \frac{(o_s - o_{s'})^2}{\delta^2}}$$



-> Higher algorithmic complexity, embed prior information on the solution (cf Bayesian approach).

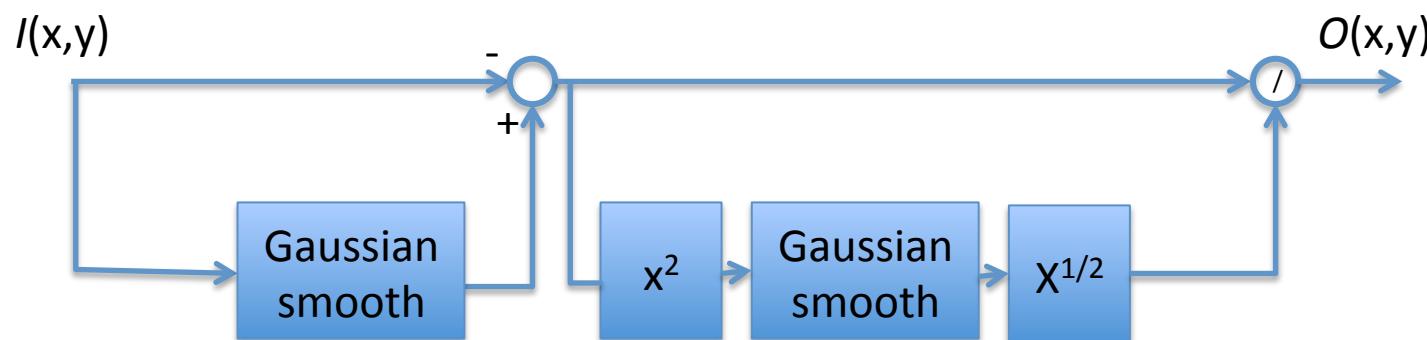
# Spatial normalisation

- Goal : impose locally the same mean and variance

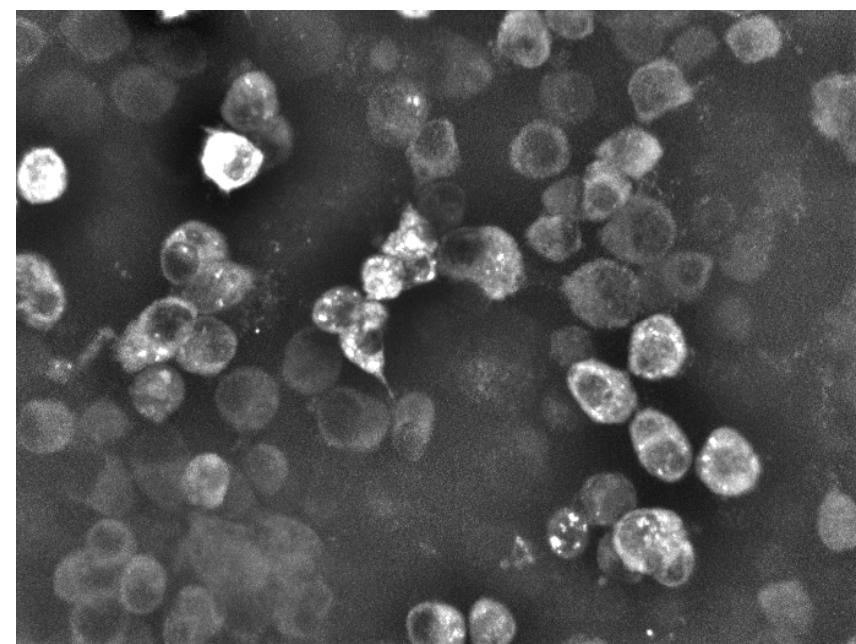
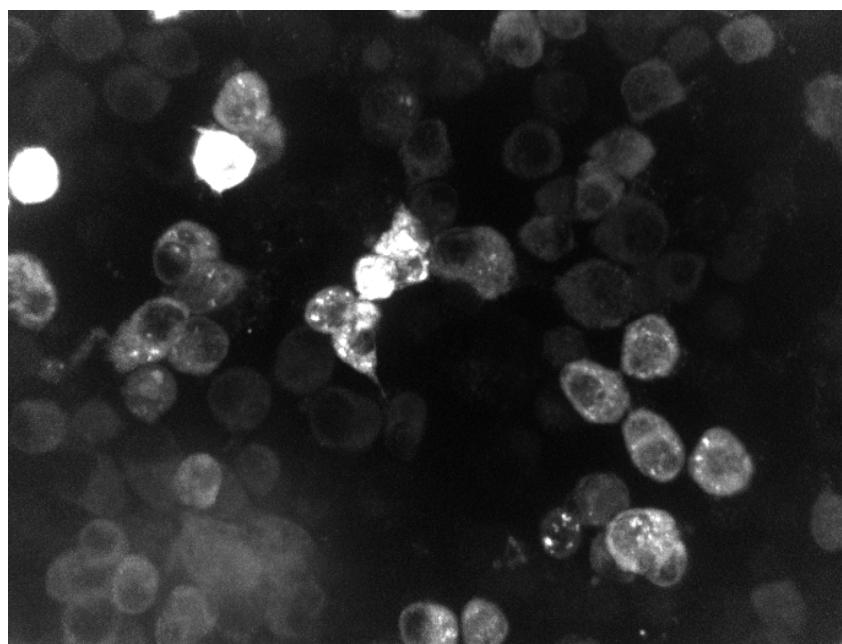
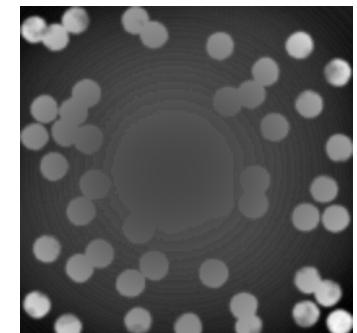
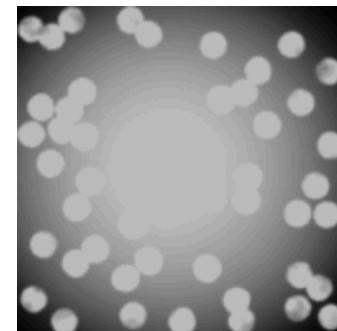
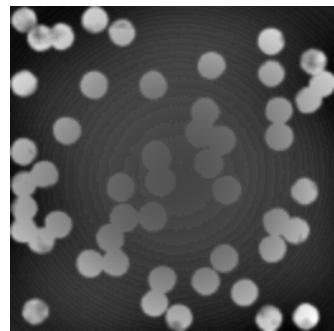
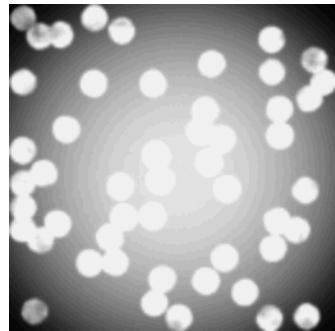
$$O(x, y) = \frac{I(x, y) - m_I(x, y)}{\sigma_I(x, y)}$$

$m_I(x, y)$  : estimation of local mean

$\sigma_I(x, y)$  : estimation of local standard deviation



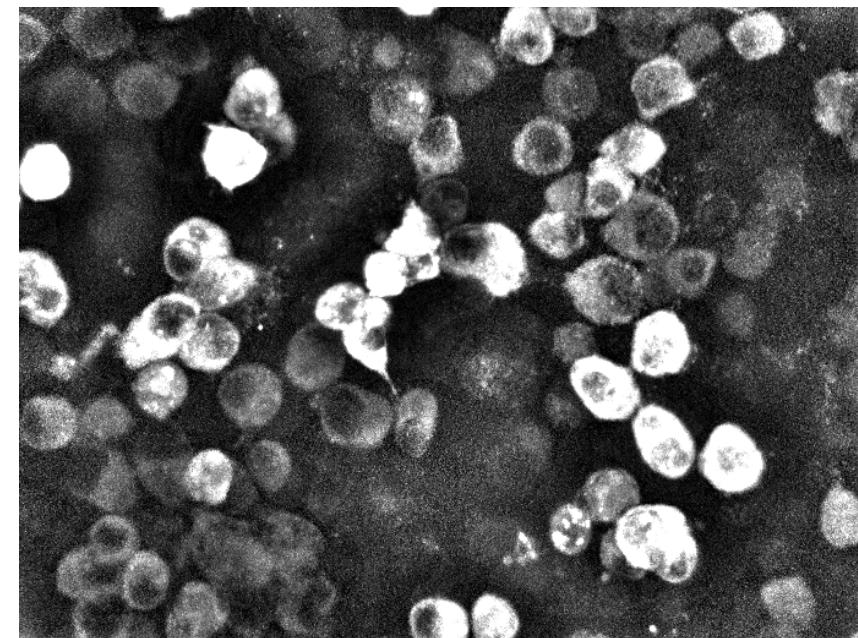
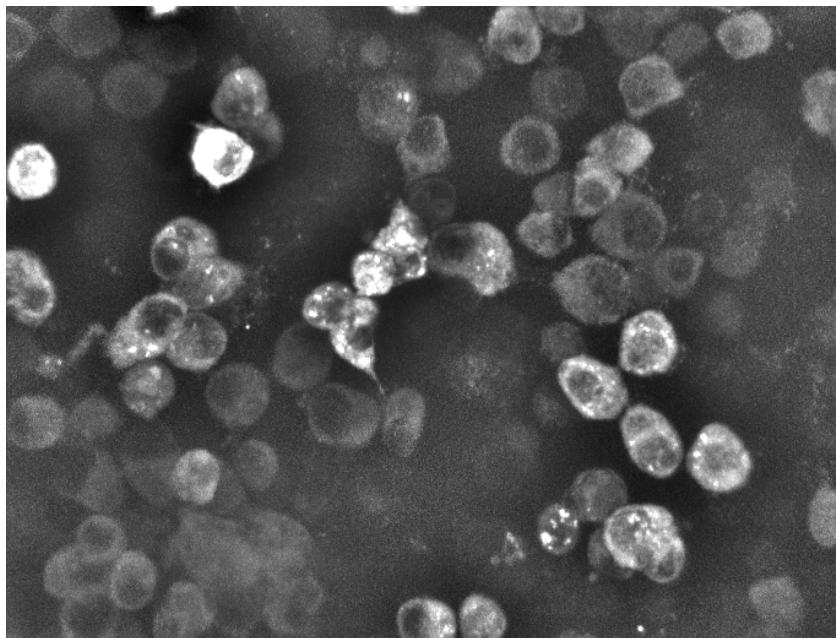
# Spatial normalisation



# Top Hat

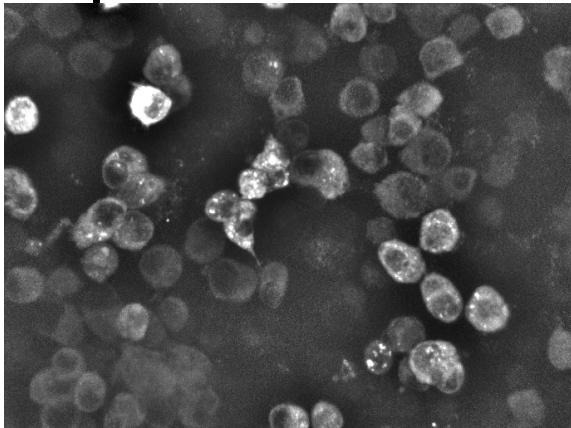
$$O = I - E(I, B)$$

B : Object silhouette

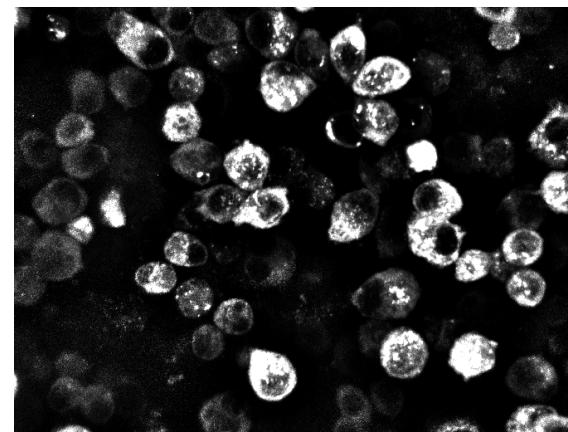
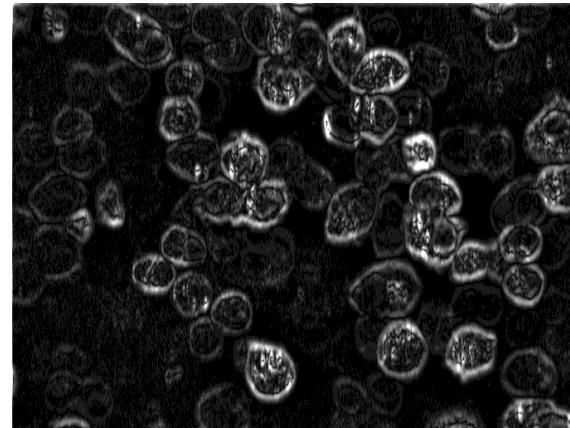


# Edge enhancement

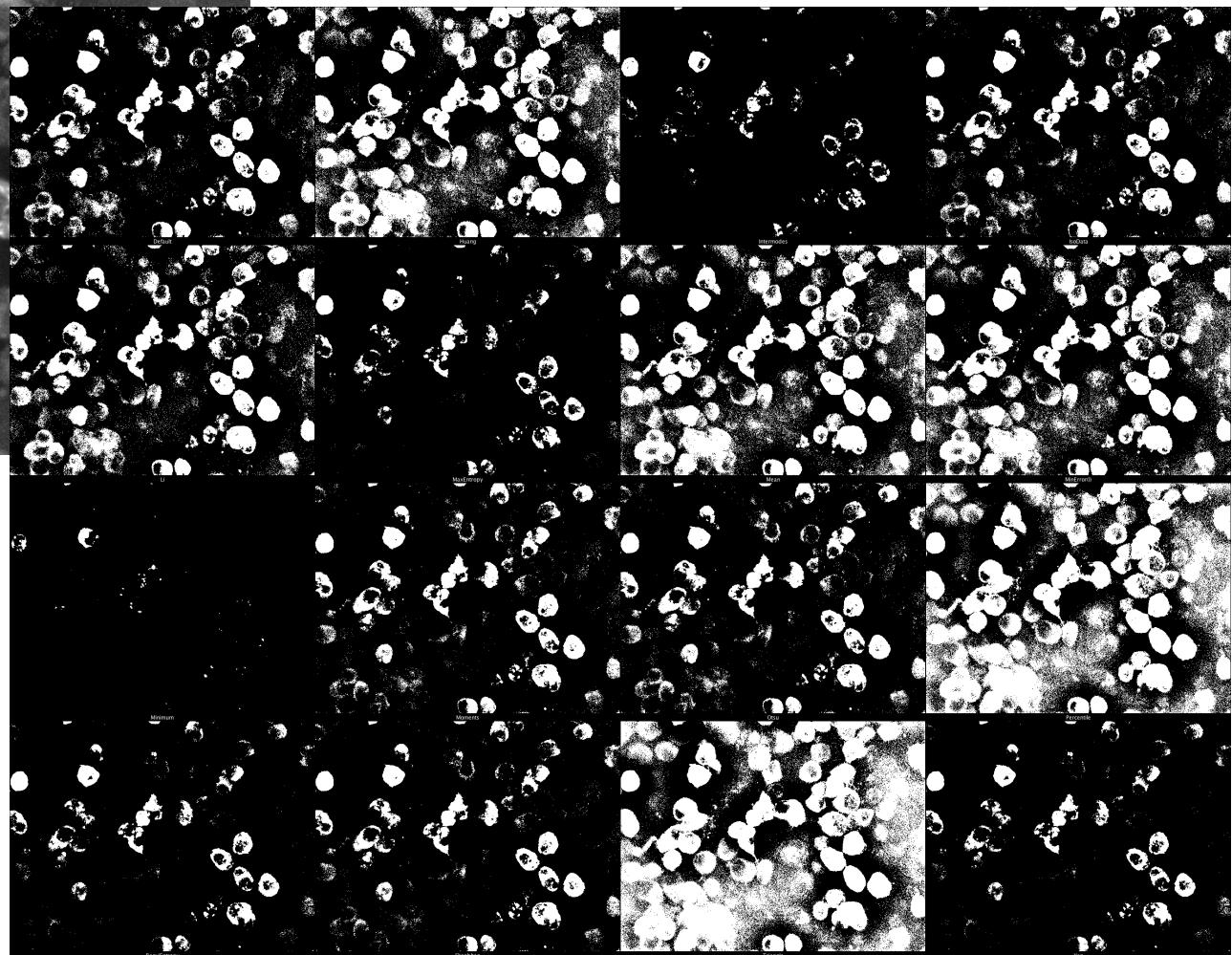
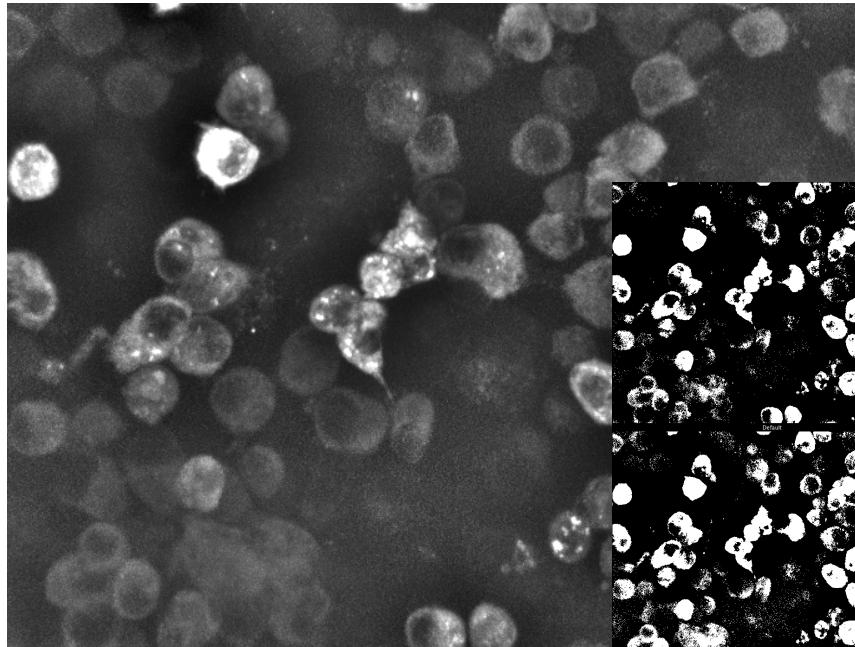
- Edge detection followed by image addition or multiplication



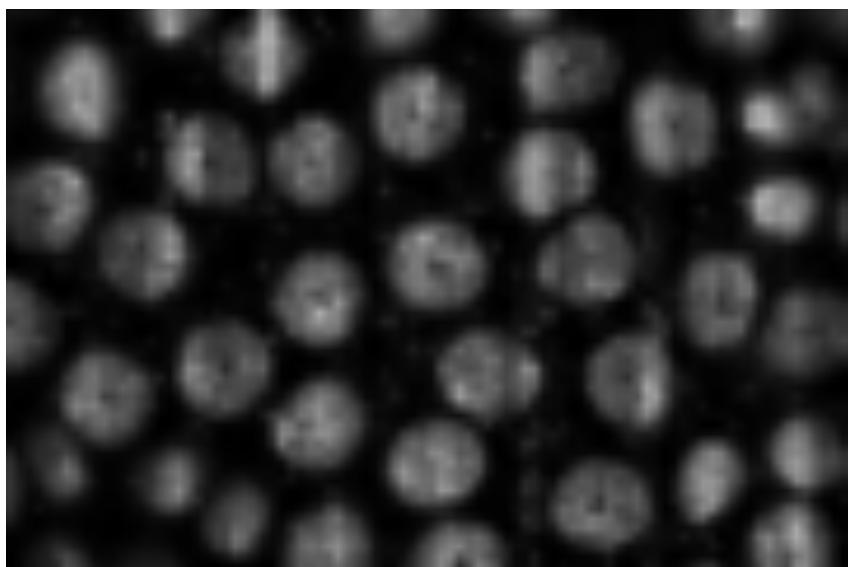
X



# Binarization : threshold

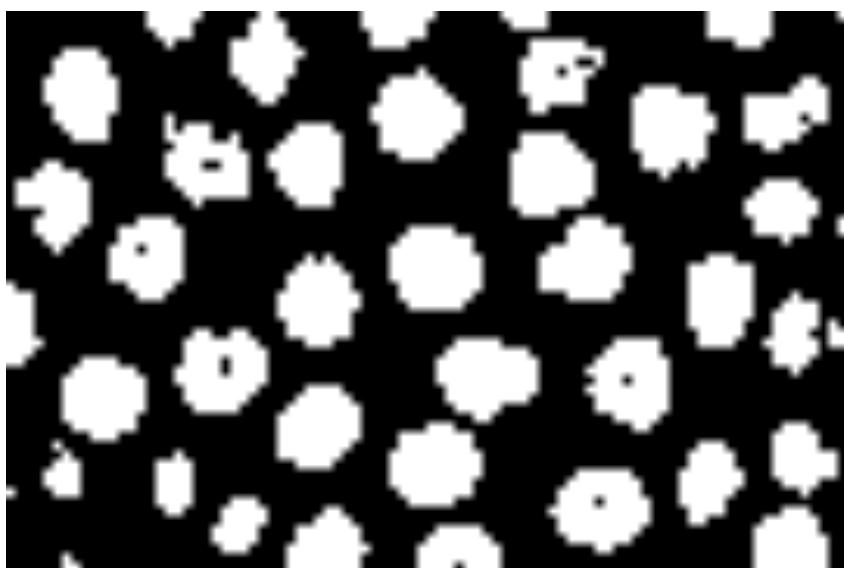


# Binarization : threshold

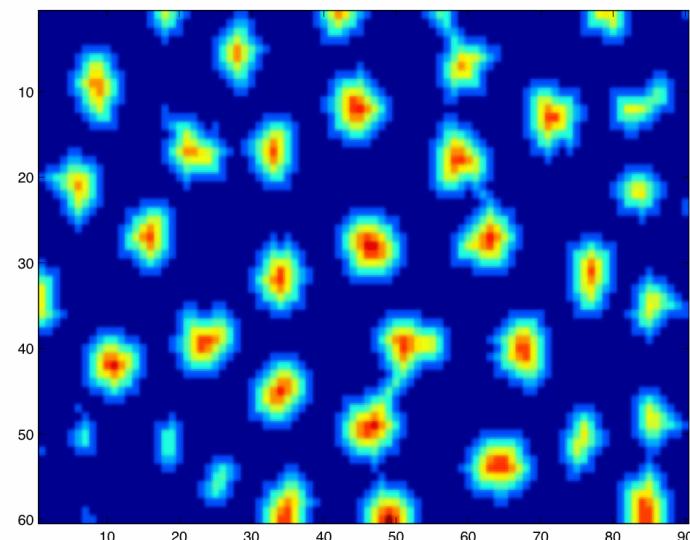


# Closing

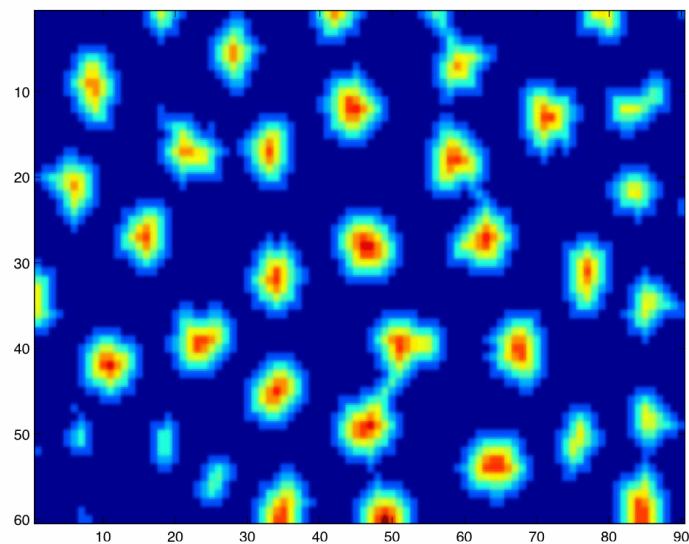
Small structuring element



# Distance map



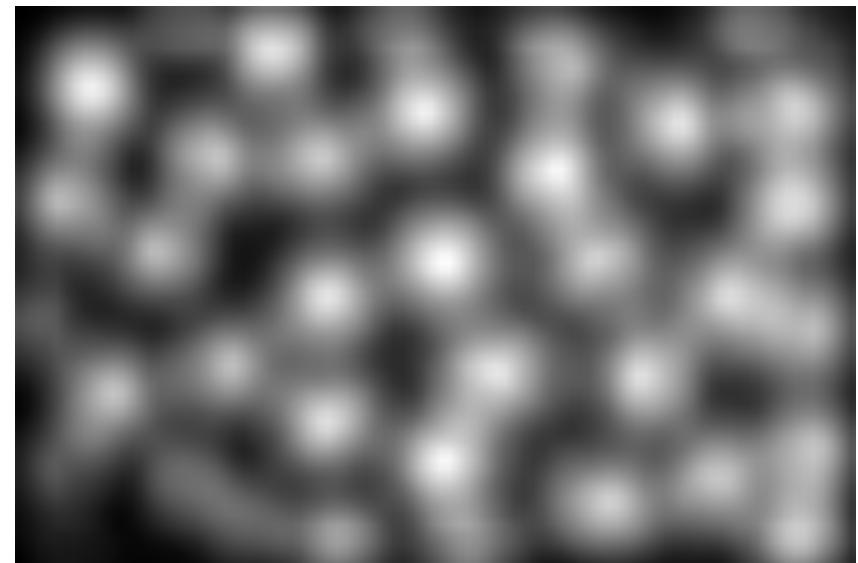
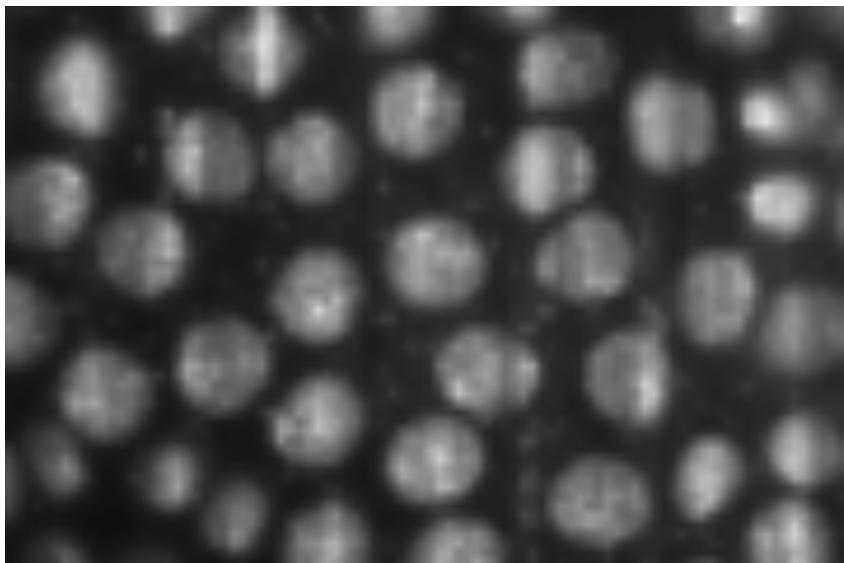
# Local maxima



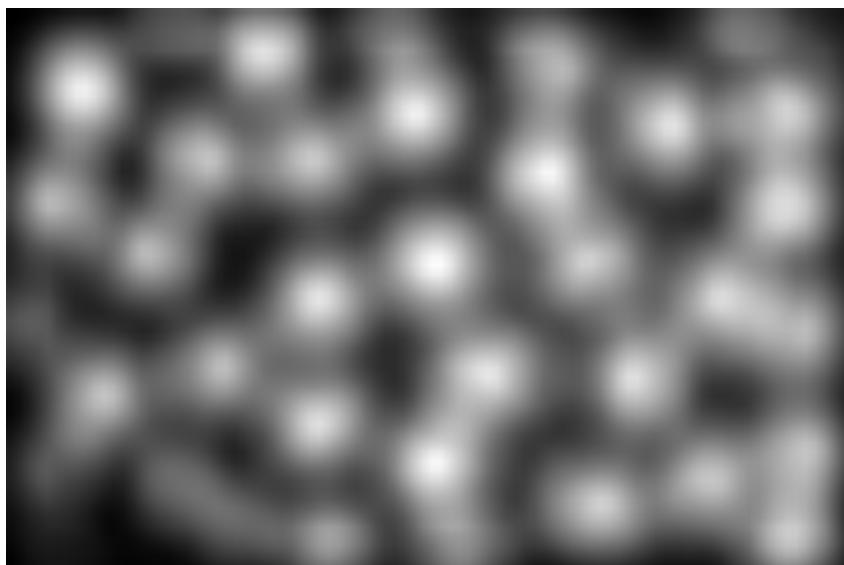
# Template matching

$$O = I * T$$

T : Template



# Local maxima



# All in One: Marked point processes

For more complex case :

- High level of noise
- Objects overlap

Idea : fit a set of objects on the data

Pros :

- Embed constraint on shapes
- Embed structural constraint on the configuration

Cons :

- Low dimensionnal parametric shapes
- Complex algorithms

# Marked point processes : construction

- 1) Define a « shape » space : set of disks, ellipses,...
- 2) Consider the set of object configurations :
- 3) Define an energy function on the configuration set :
- 4) Minimize the energy function

# Marked point processes : construction

- 1) Define a « shape » space : set of disks, ellipses,...

$M$  : Space of marks

$$M = \{r, r \in [r_{\min}, r_{\max}]\}$$

Example : Disks

- 2) Consider the set of object configurations :

$$\Omega_0 = \emptyset, \quad \Omega_n = \{\{(x_1, m_1), \dots, (x_n, m_n)\}, x_i \in X, m_i \in M\}$$

$$\Omega = \bigcup_n \Omega_n$$

# Marked point processes : construction

3) Define an energy function on the configuration set :

$$h(O) = \frac{1}{Z} \exp [-U(O)] d\pi(O)$$

$\pi$  : measure of the Poisson process

$$U(O) = U_p(O) + U_d(O|I)$$

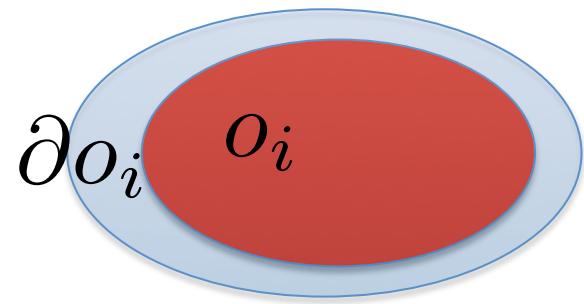
$U_p$  : prior       $U_d$  : data term

4) Minimize the energy function

- Birth and death
- RJMCMC
- Multiple births and Deaths
- Multiple births and cut

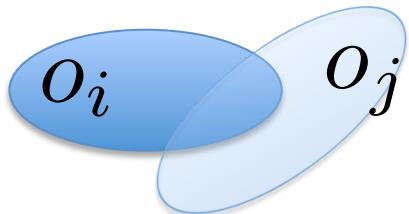
$$\hat{O} = \arg \min U(O)$$

# Marked point processes : example



$$U_d(O|I) = \sum_i u_d(o_i)$$

$$u_d(o_i) = T - \frac{\mu(o_i) - \mu(\partial o_i)}{\sqrt{\sigma^2(o_i) + \sigma^2(\partial o_i)}}$$



$$U_p(O) = \sum_{i \sim j} u_p(o_i, o_j)$$

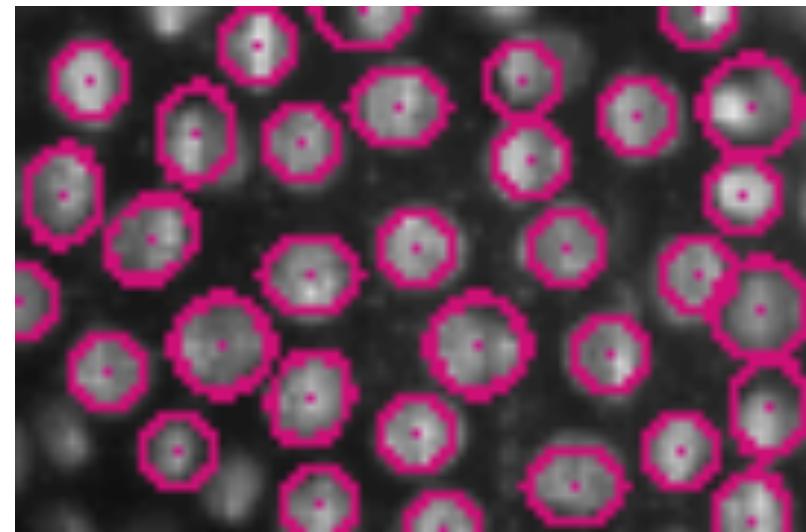
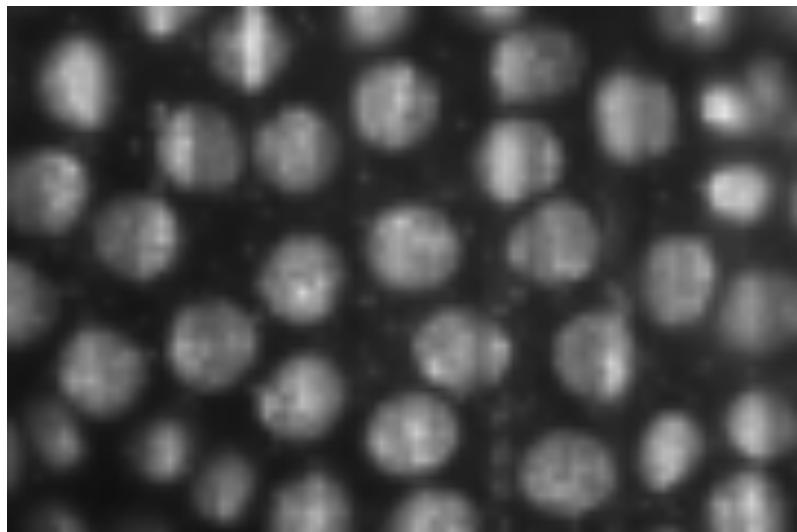
$$u_p(o_i, o_j) = \begin{cases} 0 & \text{if } \frac{|o_i \cap o_j|}{\min(|o_i|, |o_j|)} < p \\ P & \text{otherwise} \end{cases}$$

# Marked point processes

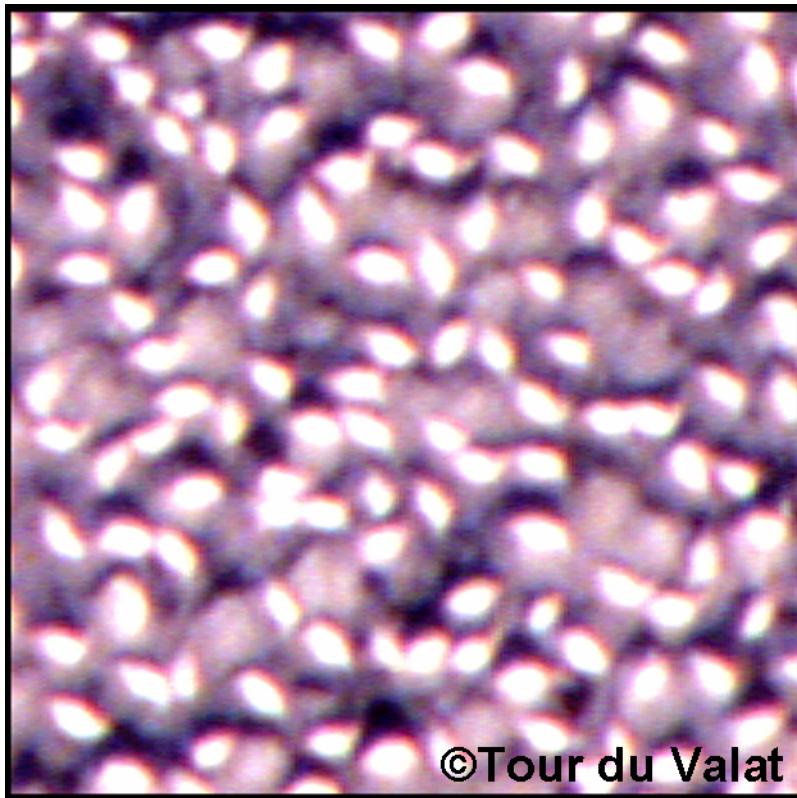
Data term : Battacharrya distance

Priori : non overlap

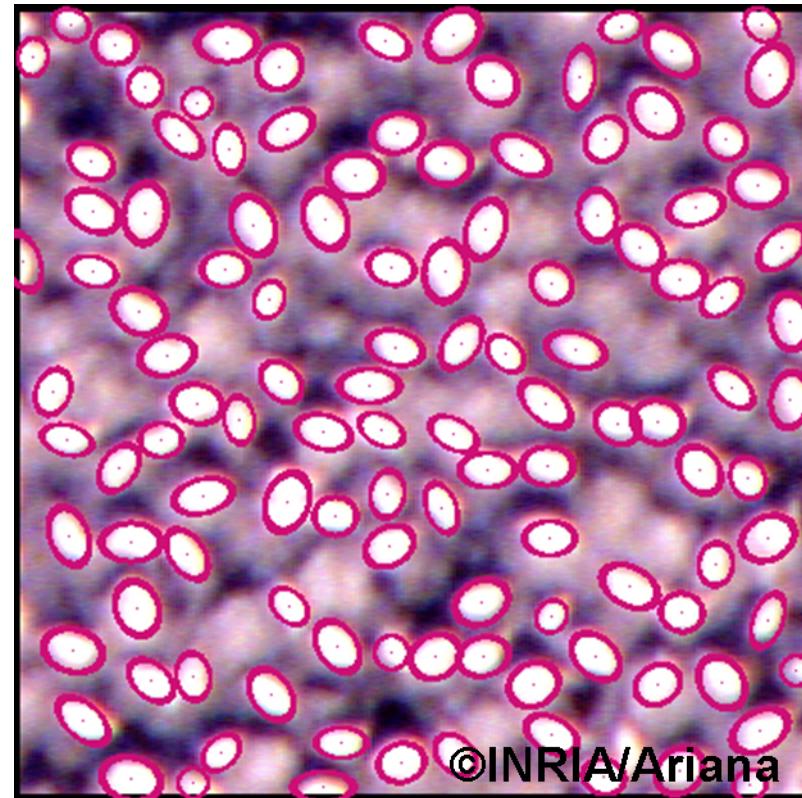
Optimization : Mutiple Births and Deaths



# Flamingos detection



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