Marked point processes for object detection in high resolution images : Application to Earth observation and cartography.

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Ariana research group, http://www.inria.fr/ariana/

Bayesian Approach

$$\boxed{P(X \mid Y) = \frac{P(X)P(Y \mid X)}{P(Y)} \propto P(X)P(Y \mid X)}$$

$P(Y \mid X)$: likelihood

$P(X)$: prior

$P(X \mid Y)$: posterior

Example : Classification

Prior : Markov Random Field

Likelihood : conditional independence assumption

$$P(Y \mid X) = \prod_{s \in S} P(y_s \mid x_s)$$

No contextual information in the likelihood:

1 - uncorrelated noise

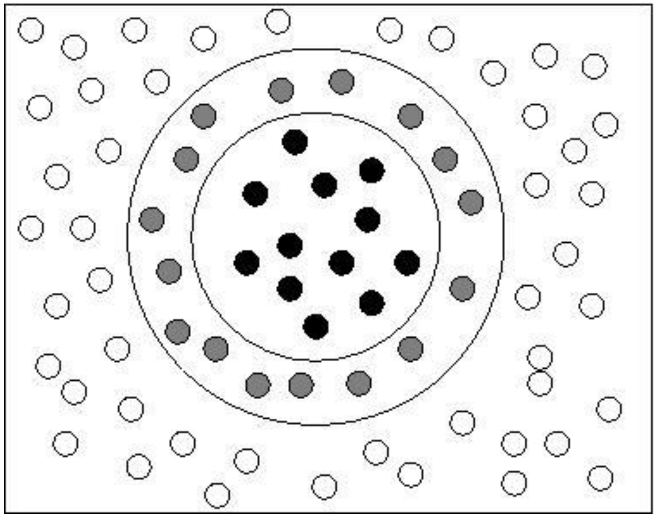
2 - no texture

Markov Random Field Approach

Markov Random Field :

$$P(x_s \mid x_t, t \neq s) = P(x_s \mid x_t, t \in v_s)$$

v_s being the neighborhood of s



- Contextual Information Modeling
- Link with Statistical Physics : Gibbs Fields

Hammersley-Clifford Theorem

A MRF verifying a positivity constraint can be written as a Gibbs field:

$$P(X) = \frac{1}{Z} \exp - \left[\sum_{c \in C} V_c(x_s, s \in S) \right]$$

$S = \text{all the pixels}$

$C = \text{all the cliques associated to the neighborhood } v$

Potts Model

$$C = \{((i,j),(i,j+1));((i,j),(i+1,j)), s=(i,j)\in S\}$$

$$V_c(x_s,x_t) = \begin{cases} 0 & if\ x_s = x_t \\ \beta > 0 & if\ x_s \neq x_t \end{cases}$$

$$P(X) = \frac{1}{Z}\exp -\#_c$$

$\#_c$: Number of heterogeneous cliques

Simple modeling

Prior : Potts model

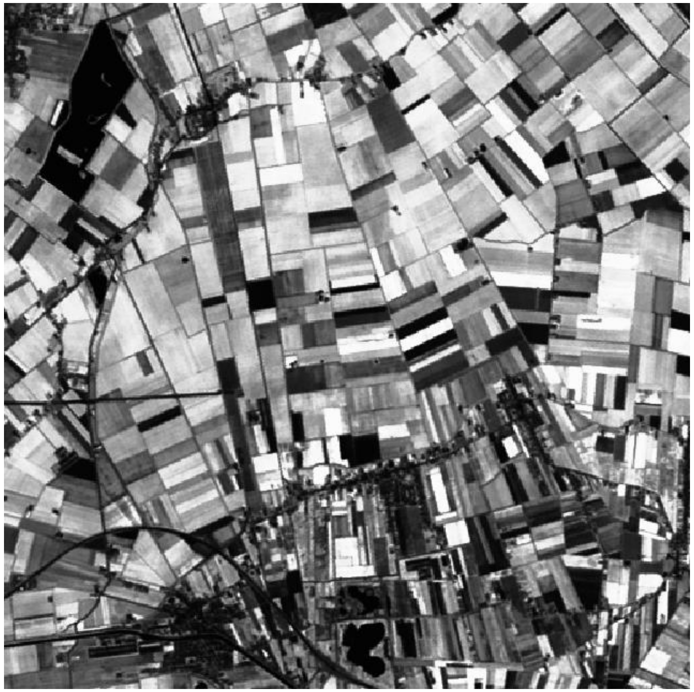
Likelihood : Gaussian model

$$P(X \mid Y) \propto \exp -\left[U(X) + U(Y \mid X)\right]$$

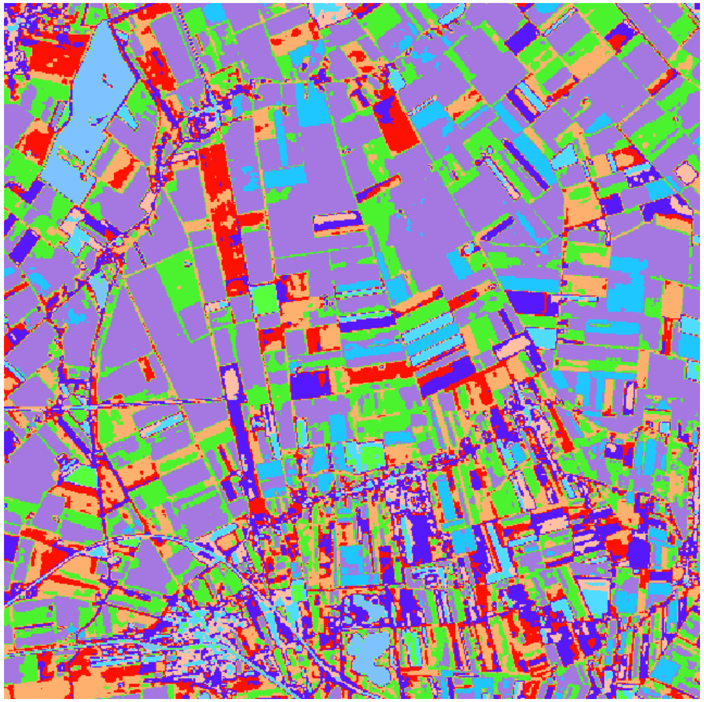
$$U(X) = \beta \sum_{c=\{s,t\}\in C} \delta_{x_s \neq x_t}$$

$$U(Y \mid X) = \sum_{s\in S} \sum_{i} \left((y_s - \mu_i)^2 + \frac{1}{2}\log(\sigma_i^2) \right) \delta_{x_s = i}$$

Example : Classification



SPOT image © CNES / Airbus D & S



Classification result © Ariana / INRIA

From context to geometry

SPOT image © CNES

IKONOS image © Satellite imaging Corporation

IKONOS image © Satellite image Corporation

From context to geometry

SPOT image © CNES

aerial image © IGN

From pixels to objects

- Goals :
  - To take into account data at a macroscopic scale.
  - To take into account the geometry of objects.
  - To take into account relations between objects (macro-texture).
- But we do not know the number of objects (Markov random fields on graphs are excluded).

→ Solution : Marked point processes

Marked Point process defined by a density w.r.t. the Poisson process

- A **marked point process** X on $\chi = \mathcal{P} \times \mathcal{M}$ is a point process on χ for which the point location is in $\mathcal{P}$ and the marks in $\mathcal{M}$.

- We define X by its probability density f w.r.t. the law $\pi_\nu(.)$ of a Poisson process known as the reference process ($\nu(.)$ is the intensity measure) :

$$\boldsymbol{f} : \boldsymbol{N}^{\boldsymbol{f}} \rightarrow [0, \infty[: \int_{\boldsymbol{N}^{\boldsymbol{f}}} \boldsymbol{f}(\boldsymbol{x}) \boldsymbol{d}\pi_\nu(\boldsymbol{x}) = 1$$

Markov process

- A point process density $\boldsymbol{f} : \boldsymbol{N}^f \to [0, \infty[$

  is Markovian under the neighborhood relation ~ if and only if there exists a measurable function $\phi : \boldsymbol{N}^f \to [0, \infty[$ such that :

$$\boldsymbol{f}(\boldsymbol{x}) = \alpha \prod_{\text{cliques } \boldsymbol{y} \subseteq \boldsymbol{x}} \phi(\boldsymbol{y})$$

for all $\boldsymbol{x} \in \boldsymbol{N}^f$

Stability

• Condition required for proving the convergence of MCMC sampling methods.

• A point process defined by its f(.) w.r.t. a reference measure π_ν(.) is locally stable if there exists a real number M such that :

$$\boldsymbol{f}\left(\boldsymbol{x} \cup \{\boldsymbol{u}\}\right) \leq \boldsymbol{M}\boldsymbol{f}\left(\boldsymbol{x}\right), \forall \boldsymbol{x} \in \boldsymbol{N}^{\boldsymbol{f}}, \forall \boldsymbol{u} \in \chi$$

Sampling : Birth and death algorithm (Geyer/Moller-94)

- Birth : with probability ½, propose to add a new point u in χ following some density $\mu(.)$ to the current configuration x.

  Let y = x U {u}, compute the ratio :

$$R_1(x,y) = \frac{f(y)}{f(x)}\frac{\nu(\chi)}{n(y)}$$

- Death : with probability ½, propose to remove a point v uniformly chosen in x. Let y = x / {v}, compute the ratio :

$$R_2(x,y) = \frac{f(y)}{f(x)}\frac{n(x)}{\nu(\chi)}$$

- With probability $\alpha_i = \min(1, R_i)$ $i = 1,2$ accept the proposition x_{t+1} = y, otherwise accept the proposition x_{t+1}=x.

Sampling : RJMCMC (Green-95)

- Mixture of several proposition kernels :

$$\boldsymbol{Q}(\boldsymbol{x},.) = \sum_{\boldsymbol{m}} \boldsymbol{p}_{\boldsymbol{m}}(\boldsymbol{x})\boldsymbol{Q}_{\boldsymbol{m}}(\boldsymbol{x},.) \quad \text{with} \quad \boldsymbol{Q}(\boldsymbol{x}, \boldsymbol{N}^{\boldsymbol{f}}) \leq 1$$

- Convergence condition exists.

RJMCMC

- **Algorithm**:

At time ***t****:*

1) Select randomly a kernel $\mathbf{q_m}$ *using the discrete law* $(\mathbf{p_m}(\mathbf{x}))$

2) *Generate a new configuration* ***y*** *with respect to the selected kernel :* $\mathbf{y} \sim \mathbf{q_m}(\mathbf{x},.)$

3) Compute the acceptance ratio : $\mathbf{R_m}(\mathbf{x},\mathbf{y})$

4) Compute the acceptance rate $\boldsymbol{\alpha}$ *:* $\alpha = \min(\mathbf{1},\mathbf{R_m}(\mathbf{x},\mathbf{y}))$

5) With probability
- $\boldsymbol{\alpha}$ *set:* $\mathbf{X_{t+1}} = \mathbf{y}$
- $\boldsymbol{(1-\alpha)}$ *set:* $\mathbf{X_{t+1}} = \mathbf{x}$

Optimization

- **Goal** : Estimate a configuration maximizing **f(.)**

- **Simulated annealing** :

> *Successive simulations of* $\mathbf{f_t(x)}$ $\mathbf{n(dx)}$ *using an RJMCMC algorithm with :*
>
> $$\mathbf{f_t(x) = f(x)^{\frac{1}{T_t}}}$$
>
> *where* $\mathbf{(T_t)}$ *(≡ temperature) decreases toward zero.*

- Logarithmic decrease ⇒ global maximum.

- **In practice** : geometric decrease.

  At each step, $\mathbf{T_{t+1} = T_t \times c}$, where **c** is a constant close to 1.

  (c=0.99999 or c=0.999999 depending on the difficulty of the detection)

Summary

Goal :

To model the observed scene as a configuration of objects (roads, rivers, buildings, trees, flamingos).

- **Stochastic modeling**:

  Set of objects in the scene $\equiv$ realization of a marked point process, **X**.

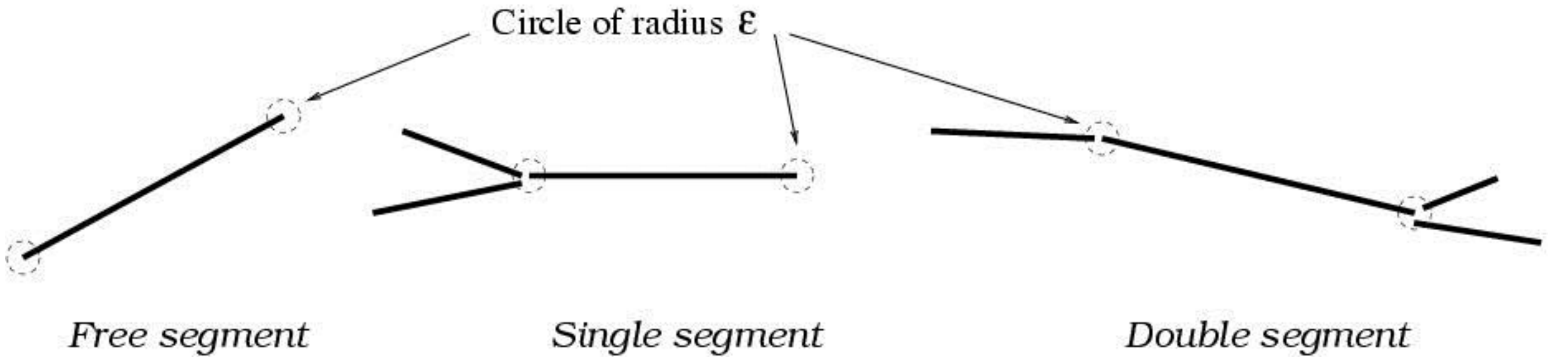
- **Density**:

$$\mathbf{f}(\mathbf{x}) = \frac{\mathbf{1}}{\mathbf{Z}} \underbrace{\mathbf{h_d}(\mathbf{x})}_{\textit{data term}} \underbrace{\mathbf{h_p}(\mathbf{x})}_{\textit{prior}}$$

- **Algorithm :** Monte Carlo sampler (e.g. RJMCMC) + simulated annealing

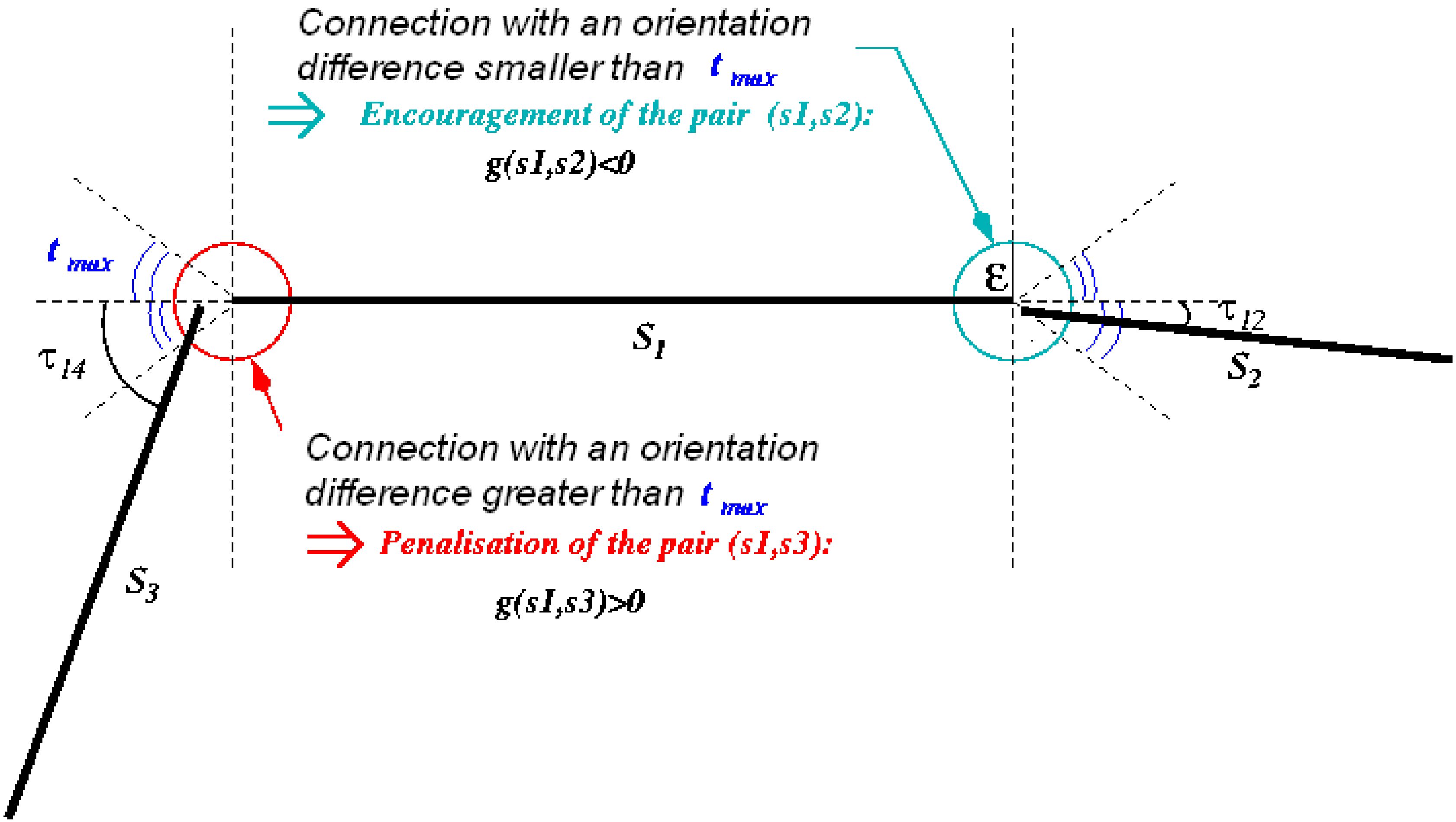
First example : Quality Candy Model for road network extraction

- Objects : Segments
- Prior : models the connectivity and the curvature
- Data term



PhDs : R. Stoïca, C. Lacoste in collaboration with IGN and BRGM

First example : Quality Candy Model for road network extraction



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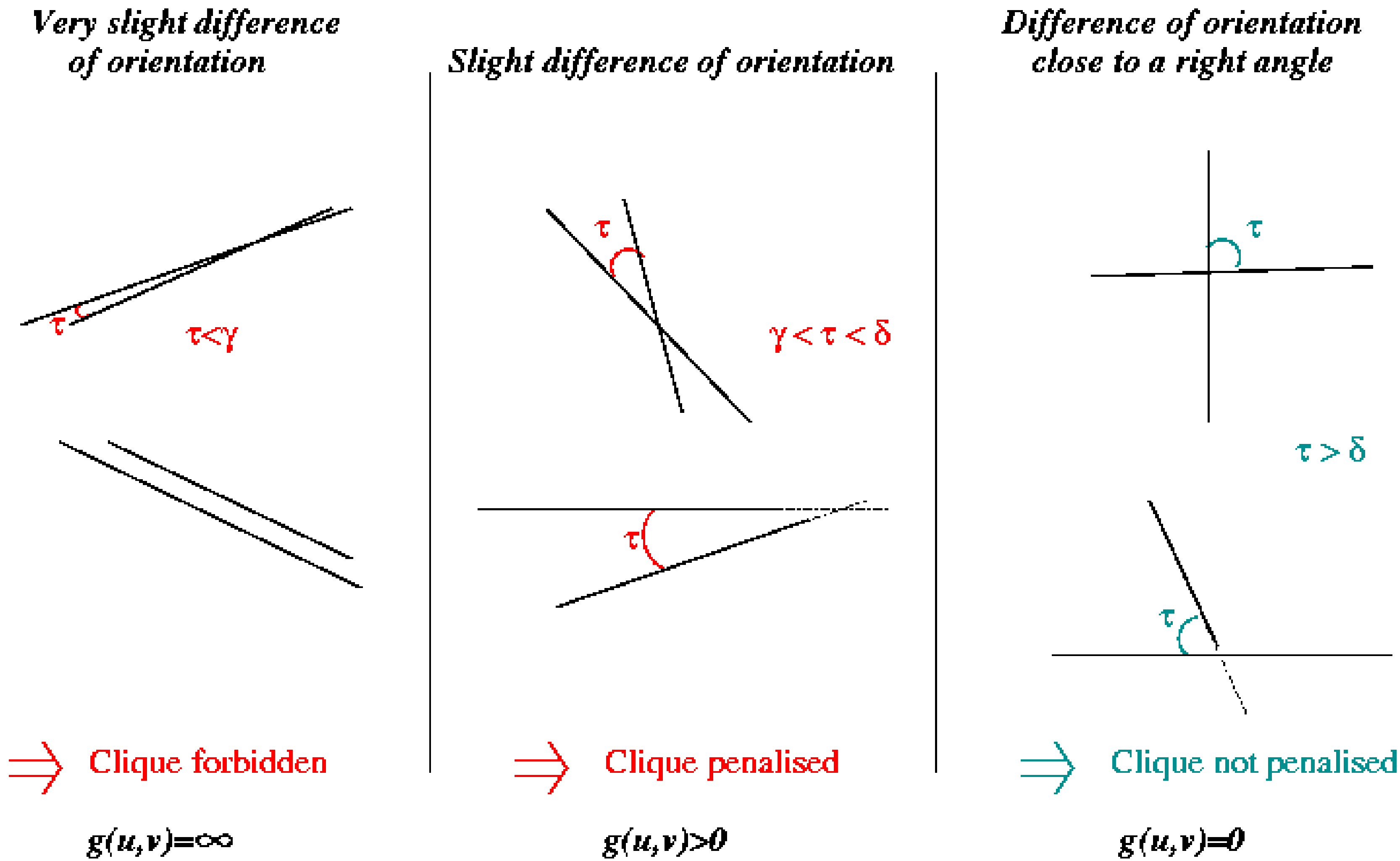
First example : Quality Candy Model for road network extraction



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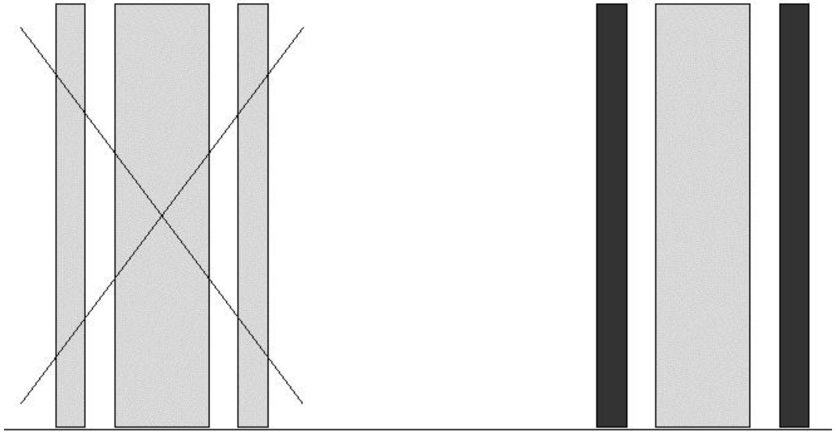
First example : Quality Candy Model for road network extraction

- Objects : Segments
- Prior : models the connectivity and the curvature
- First data term : t-test



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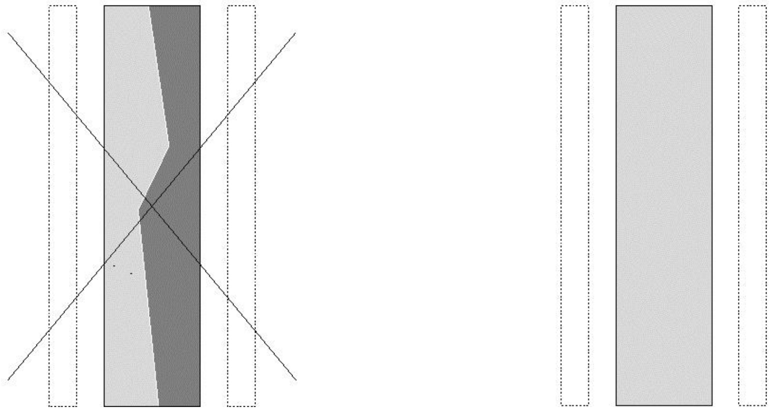
First example : Quality Candy Model for road network extraction

- Objects : Segments
- Prior : models the connectivity and the curvature
- Second data term : t-test



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Kernels of the RJMCMC algorithm

- Uniform birth and death
- Birth and death in a neighborhood
- Extension/contraction of a segment
- Translation of a segment
- Rotation of a segment

Results

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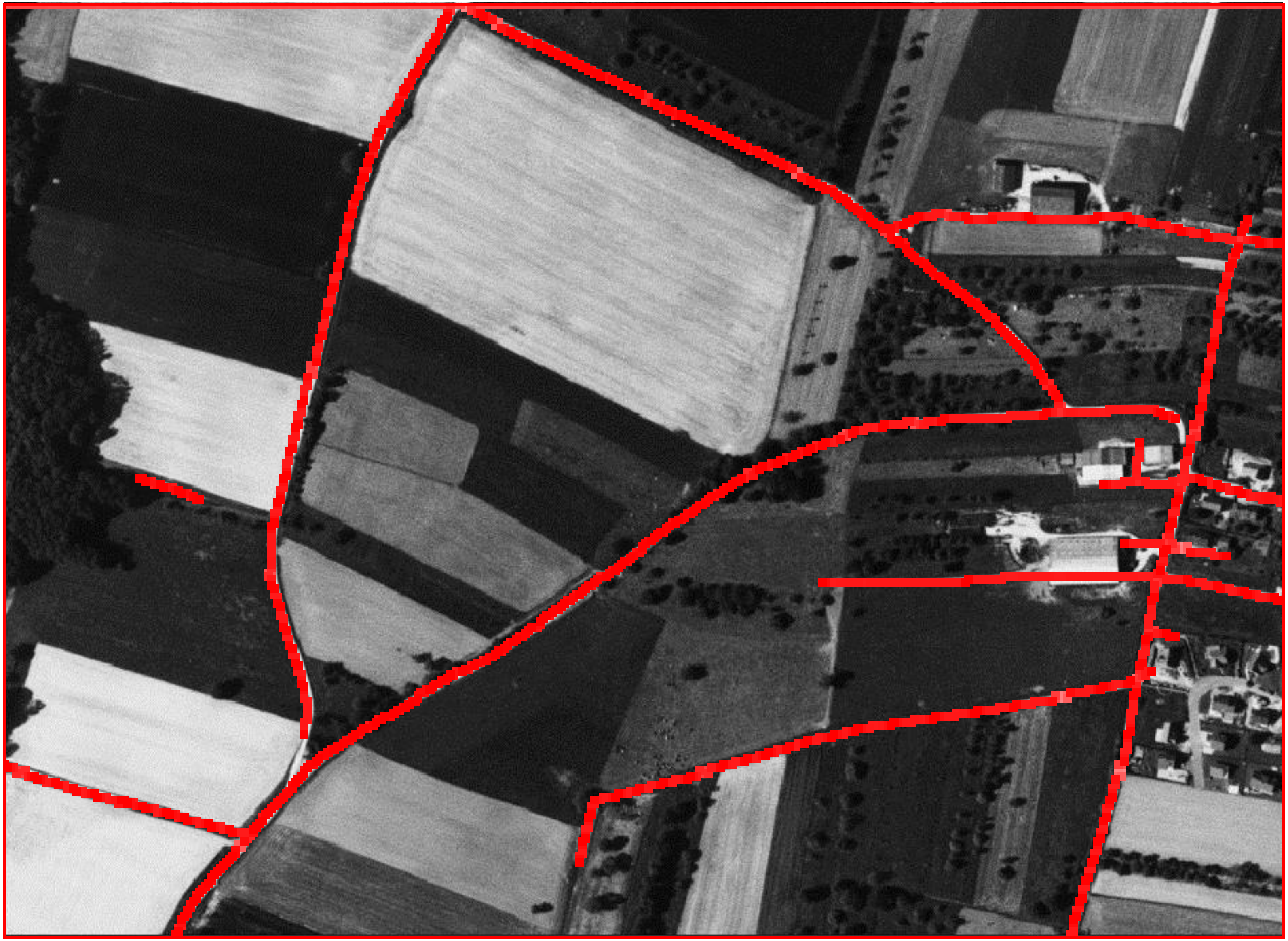
Results



Results

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Results

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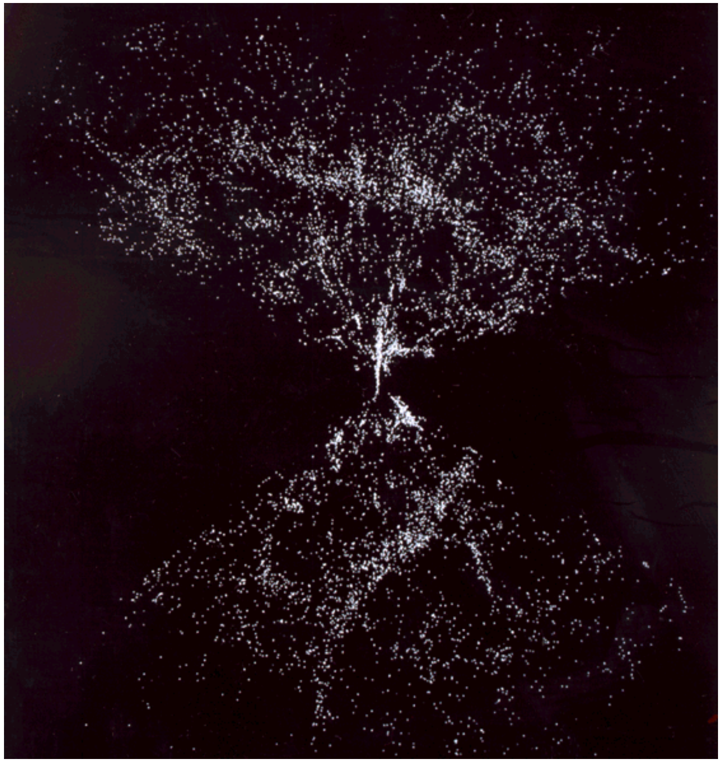
Galaxy Filament Detection



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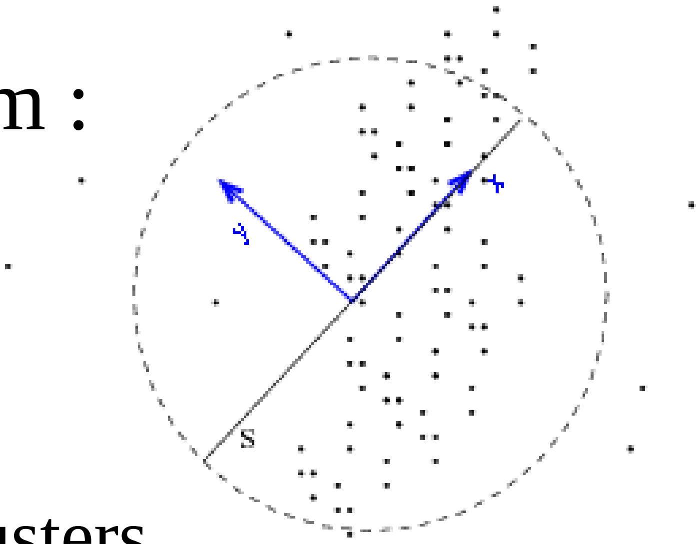
Masters : P.Gernez in collaboration with OCA

Galaxy Filament Detection

- Prior : Quality Candy model
- Assumptions for the data term :
  - Segments live in dense areas
  - Segments live in the center of clouds
  - Segments live in elongated clusters



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Results

Masters : P.Gernez

Second example : tree crown extraction

- Object : disk $r \in [r_{\min}, r_{\max}]$
- Prior : non-overlapping $d_i \propto_\rho d_j \Leftrightarrow \|c_i c_j\| < r_i + r_j$

$$N_{\propto_\rho}(d_i) = \{d_j \neq d_i : d_i \propto_\rho d_j\}$$

$$t_\rho(d_i) = \gamma^{A\left(S(d_i) \cap S\left(N_{\propto_\rho}(d_i)\right)\right)}$$

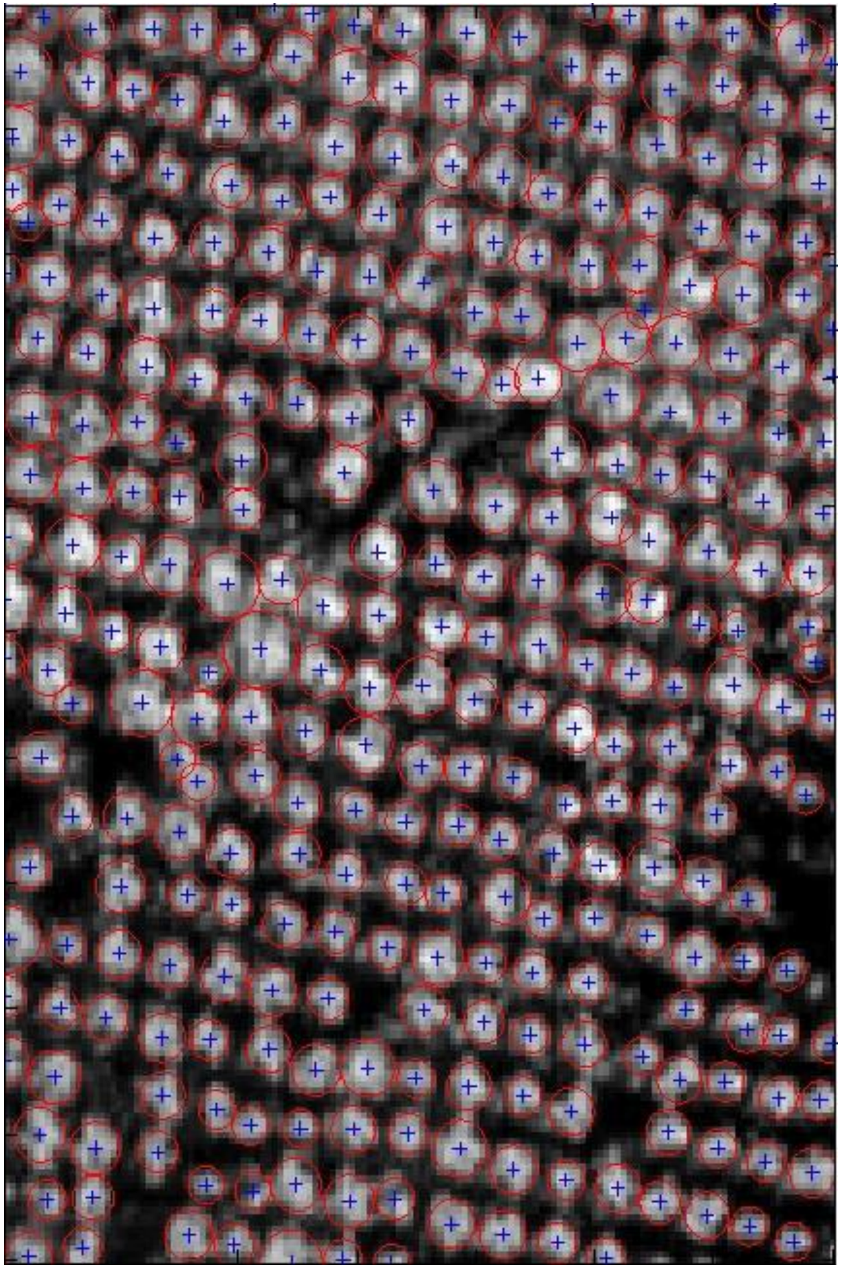
A : area

- Data : Gaussian likelihood

$$A_y(S(x)) = \prod_{p \in S(x)} p_{tree}(y_p) \prod_{p \notin S(x)} p_{notree}(y_p)$$

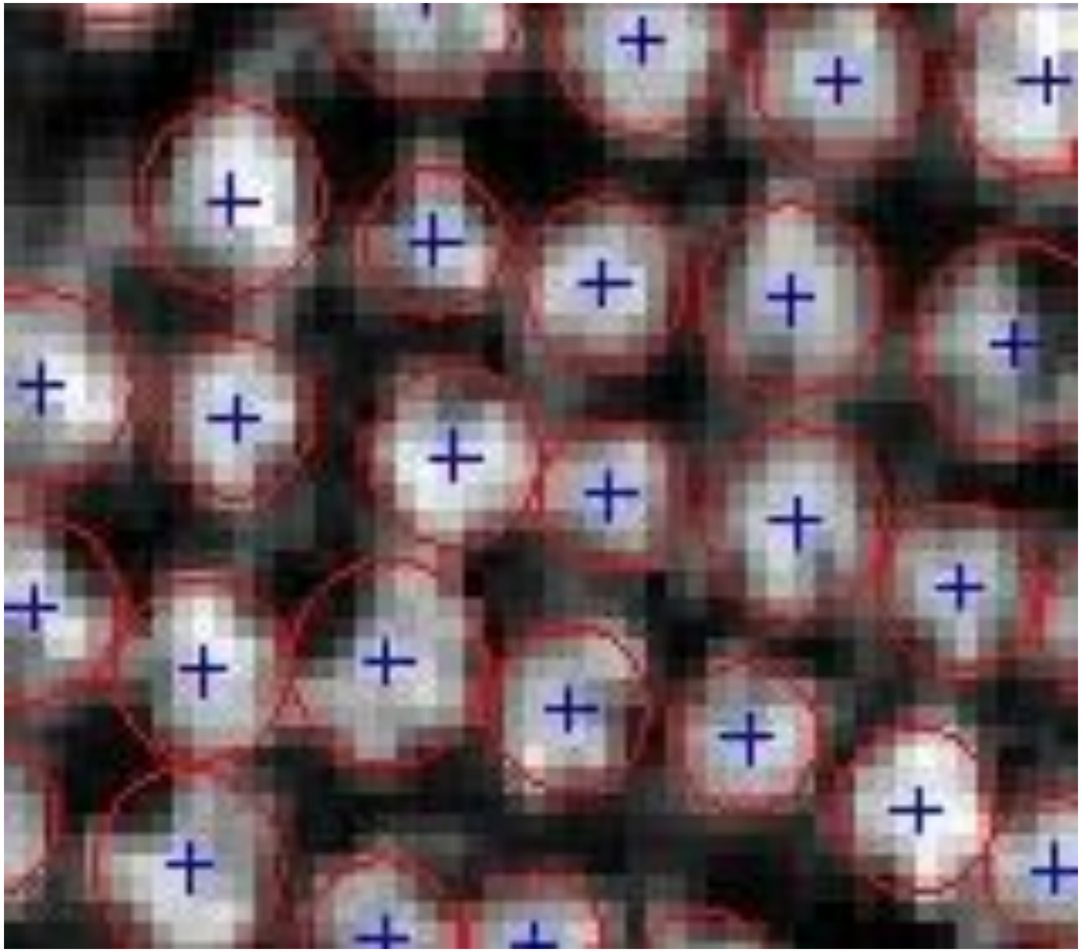
PhD : G. Perrin in collaboration with ECP

Result



PhD : G. Perrin in collaboration with ECP

Result



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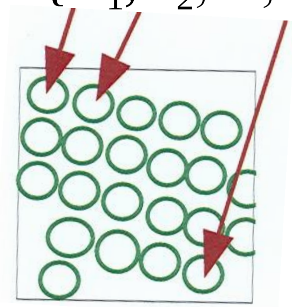
Proposed method

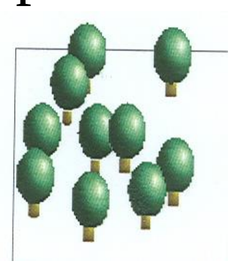
- Marked point processes : find an unknown number of geometric objects (ellipses or ellipsoids) whose positions and sizes are unknown.
- Find the best configuration of objects :

$$X = \{X_1, X_2, \ldots, X_n\}$$



ELLIPSES : 2D model

Dense area : plantation (merged shadows)



ELLIPSOIDS : 3D model

Sparse vegetation (drop shadows)

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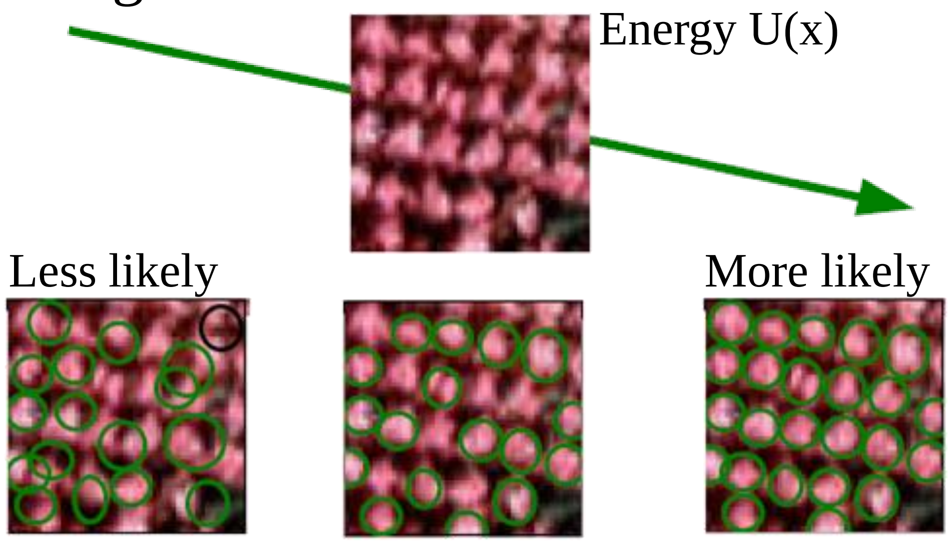
Density of the process

- Goal : design the density of the mpp in order to make tree configurations be the most likely configurations.
- Minimise the energy : $U(x) : \mathrm{f}(x) = \frac{1}{Z}\exp\left(-U(x)\right)$
- Mathematical tools : Markov Chain Monte Carlo algorithms + simulated annealing.



Poplars to be extracted with ellipses

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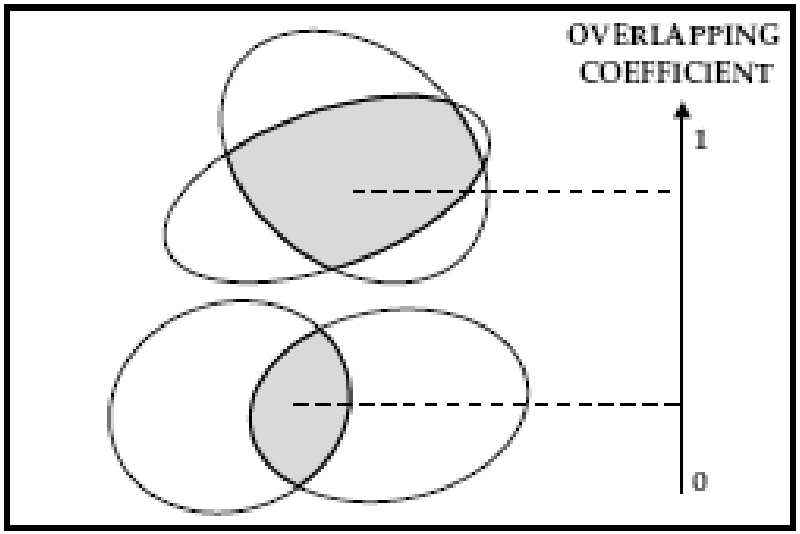
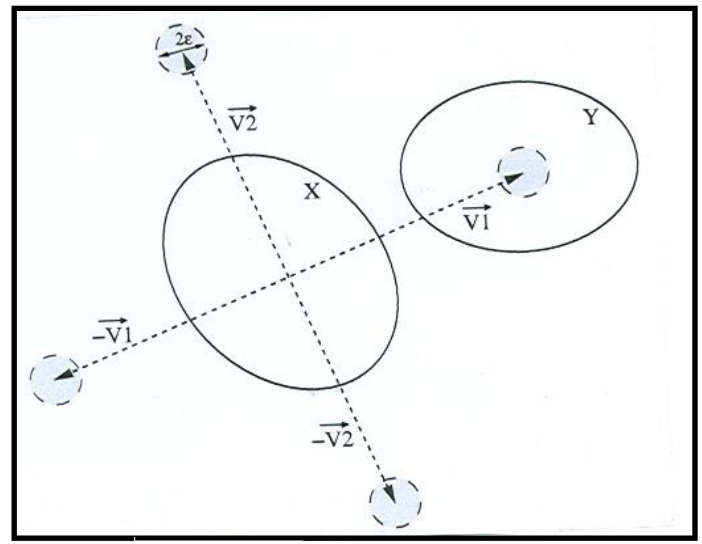
Energy of the model

- Regularizing term + Data term :

$$U(x) = U_r(x) + U_d(x)$$

- $U_r(x)$: prior term = interactions btw objects.



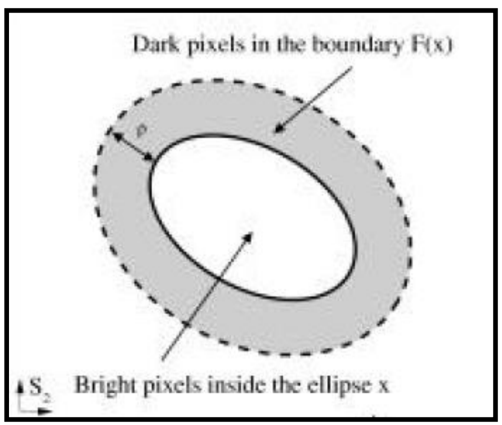


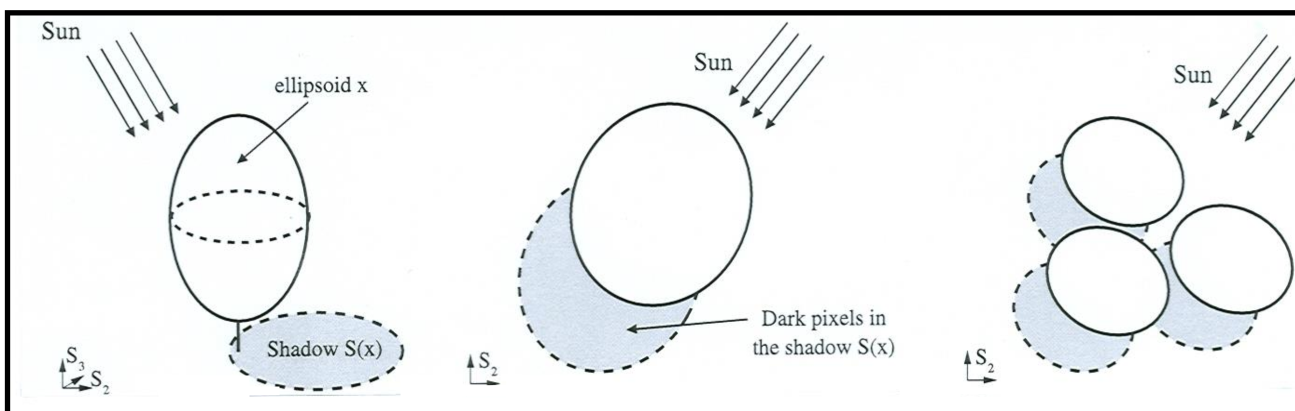
- $U_d(x)$: data term = fitting the object into the image.

$$U_d(x) = \gamma_d \sum_{xi \in x} U_d(xi)$$

Data energy term $U_d(x)$

- What is typical of the presence of a tree ?
  - high reflectance in the near infrared.
  - shadow.
  - neighbourhood.
- In dense vegetation : merged shadows, shadow area = all around the tree.
- In sparse vegetation : drop shadows, shadow area = in the direction of the sun light.





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Results with the 2D model (1)

Poplar plantation. 1 ha ©IFN (now IGN).

2D model extraction. © Ariana / INRIA

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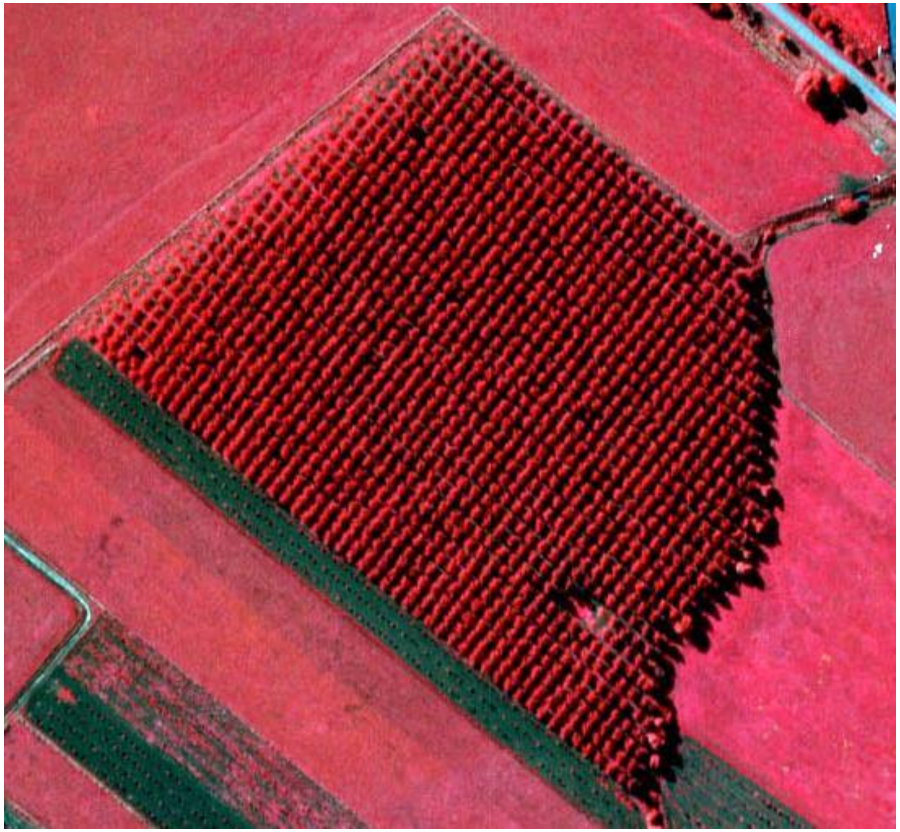
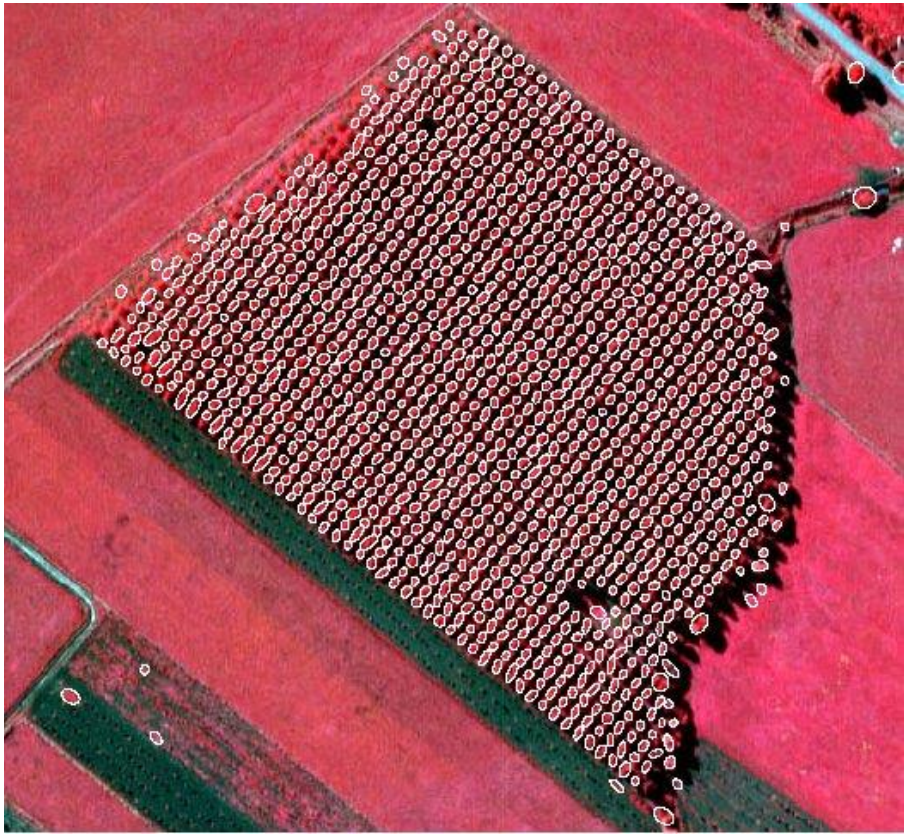
Results with the 2D model (2)



Poplar plantation. 7 ha ©IFN (now IGN)



2D model : more than 1300 objects. © Ariana / INRIA

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Results with the 3D model (1)

• Application : sparse vegetation, trees on the borders of plantations, mixed height stands.

• Hypotheses : the position of the sun is given, trees close to the Nadir and at ground level (no deformation).

• Results : position, crown diameter, approximate height of the tree.

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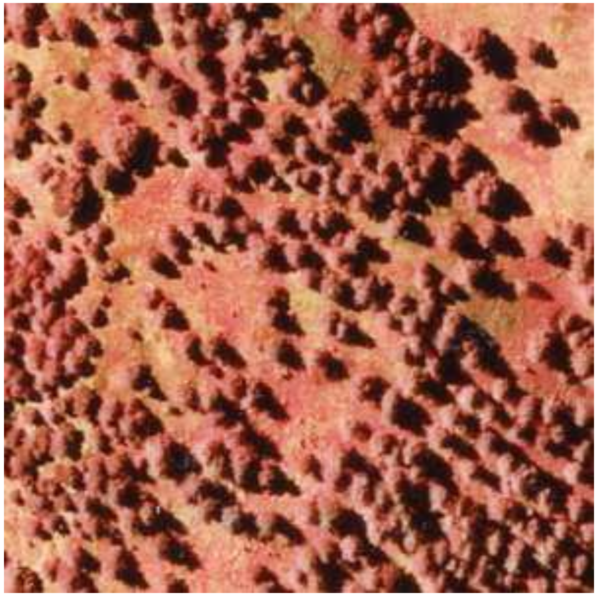
Results with the 3D model (2)

- 3D model extraction in sparse vegetation.



2.5 ha (Alpes Maritimes)
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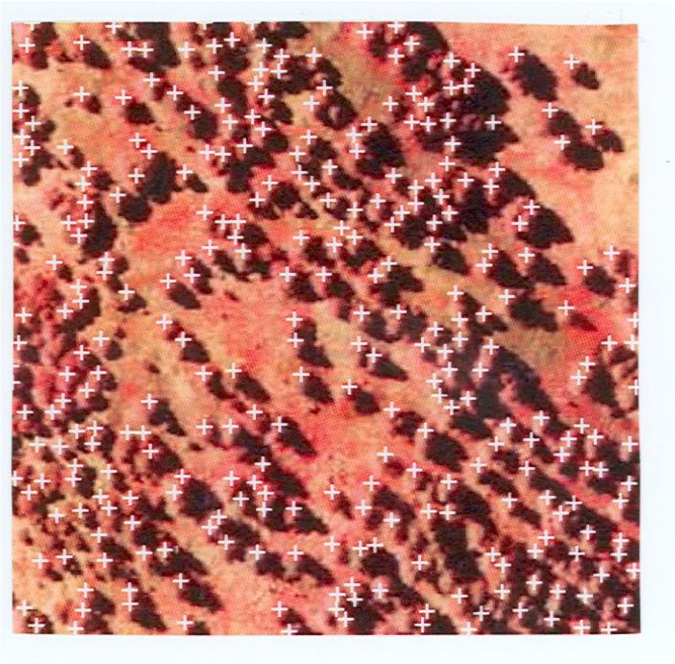

3D model extraction © Ariana / INRIA

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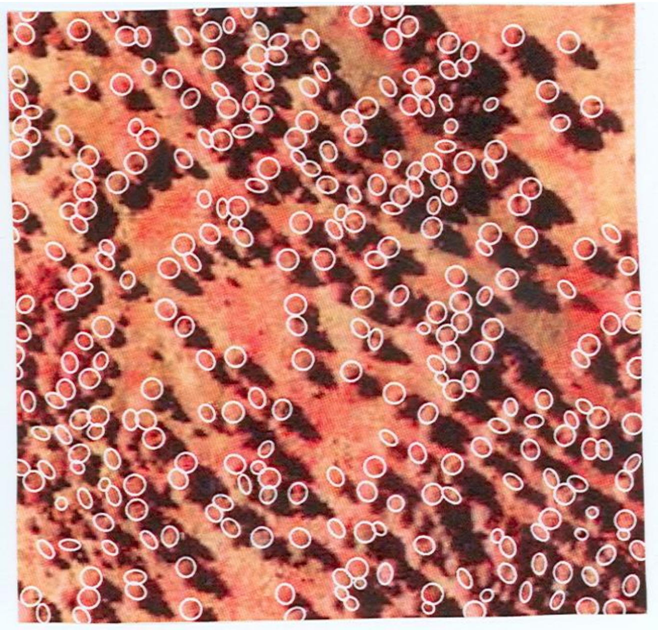
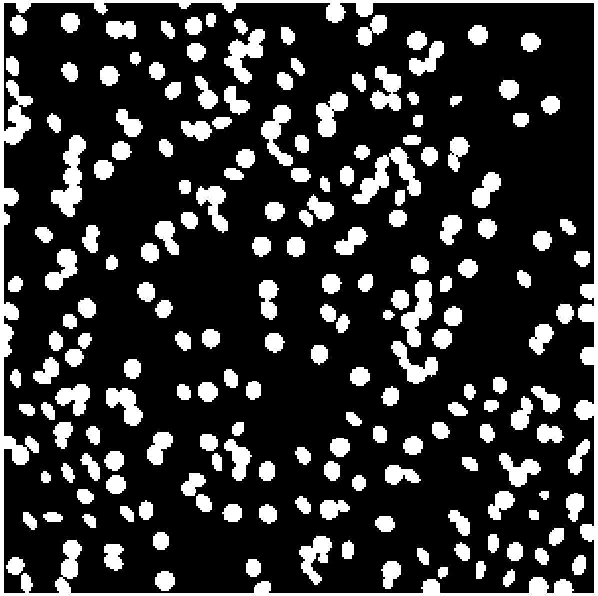
Results with the 3D model (3)

- Application : density of the sparse vegetation $\approx$ 19%.



3D model extraction. © Ariana / INRIA



Binary image of the vegetation.

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Results with the 3D model (4)

- Too many objects.
- Information on the timber forest density $\approx 15\%$.

Mixed height stand (3 ha) © IFN (now IGN).

3D model extraction © Ariana / INRIA

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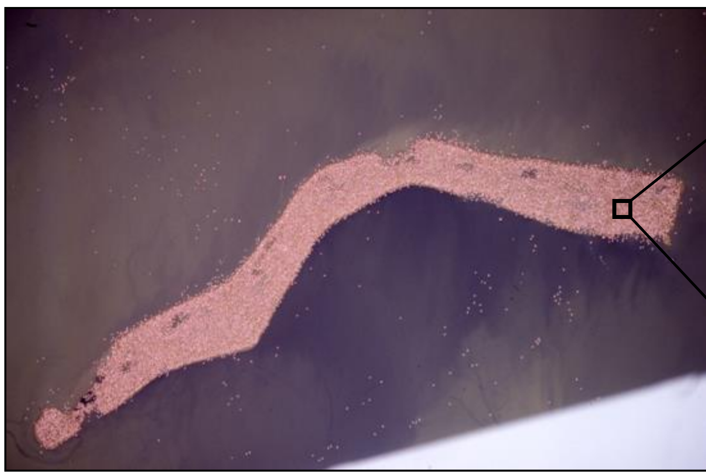
Third example : Counting Flamingos

<u>Previous techniques for counting flamingos</u> :

- ✓ Manually, by sampling, counting then extrapolating
- ✓ Tricky because of the low quality of the aerial images
- ✓ Time consuming and in the end not accurate



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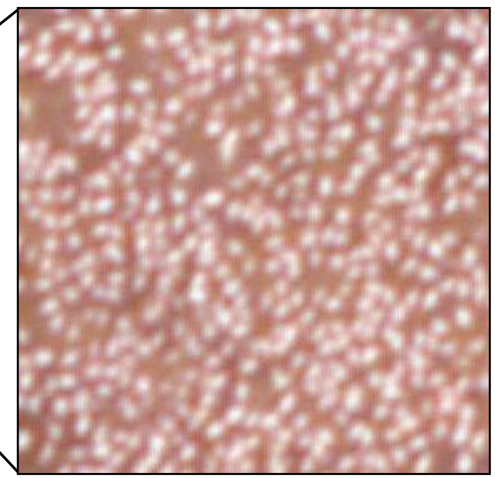

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➡ **Need to develop a method to count flamingos automatically**

(free software available with CeCILL C licence at http://www.flamingoatlas.org/dwld_flamingo.php)

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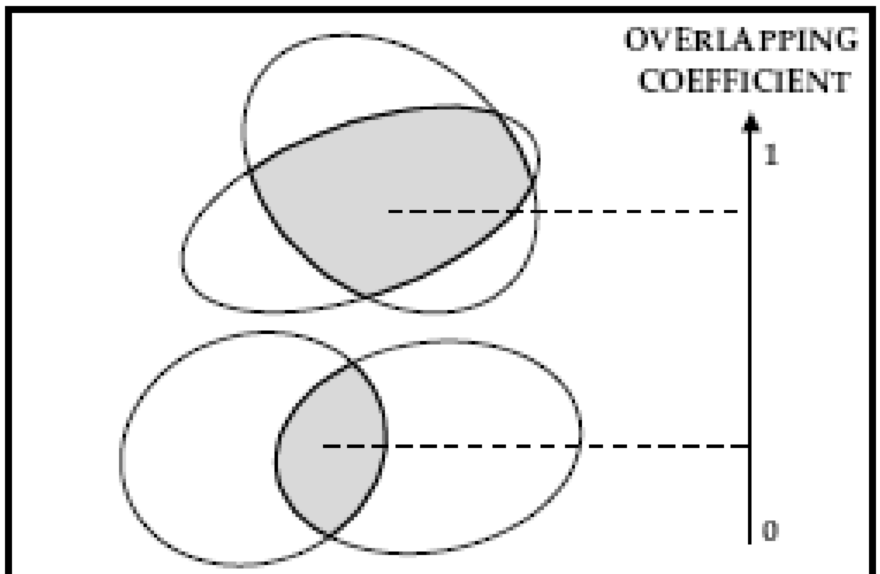
Model for the extraction of flamingos

A priori model : Interaction between objects *[G.Perrin et al., 06]*

➡ Penalization of overlapped objects



Top: high energy, Bottom: low energy

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Model for the extraction of flamingos

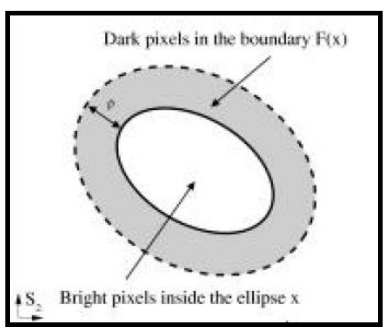
***Data* model** **: to adapt objects to flamingos**

Flamingos considered as bright ellipses making a contrast with their crowns.

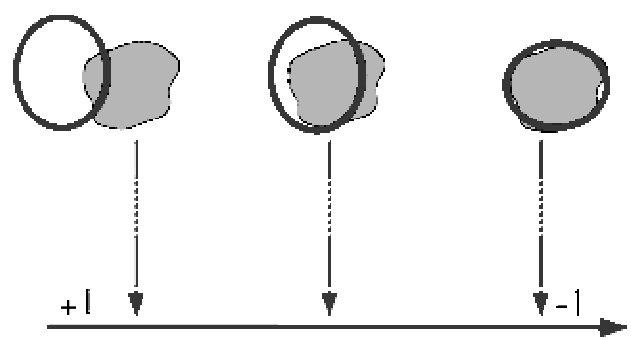
✓ Bhattacharya distance computation from the pixel distributions in the ellipse and in its crown *[G.Perrin et al., 06]*.

✓ Comparison of the center of the ellipse with the mean value of a flamingo in the image. *[S. Descamps et al., 08]*

We favor good objects, we penalize bad ones (automatic computation of the limit ***L***):



Ellipse and its crown



Different levels of energy

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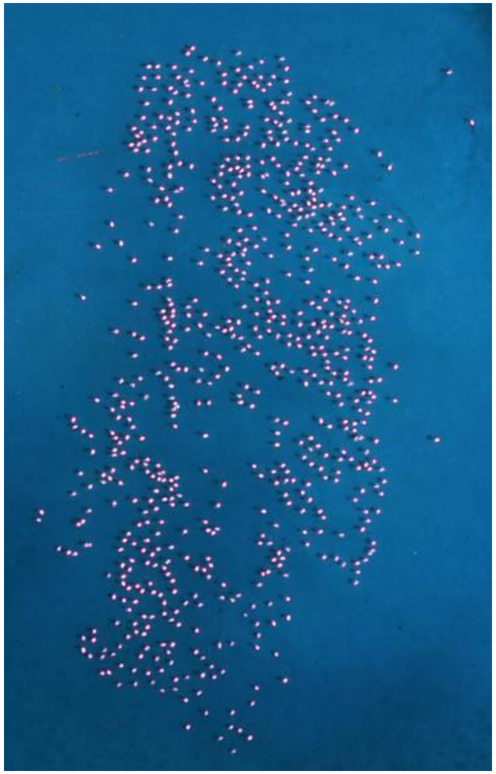
Results

Estimation of size of a French colony:

✓ 560 flamingos detected



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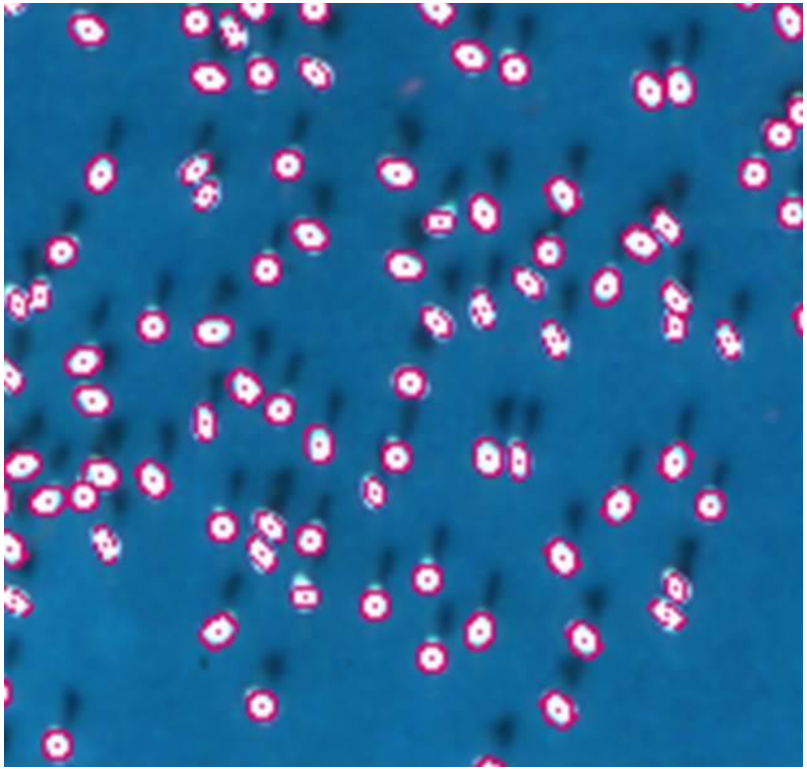

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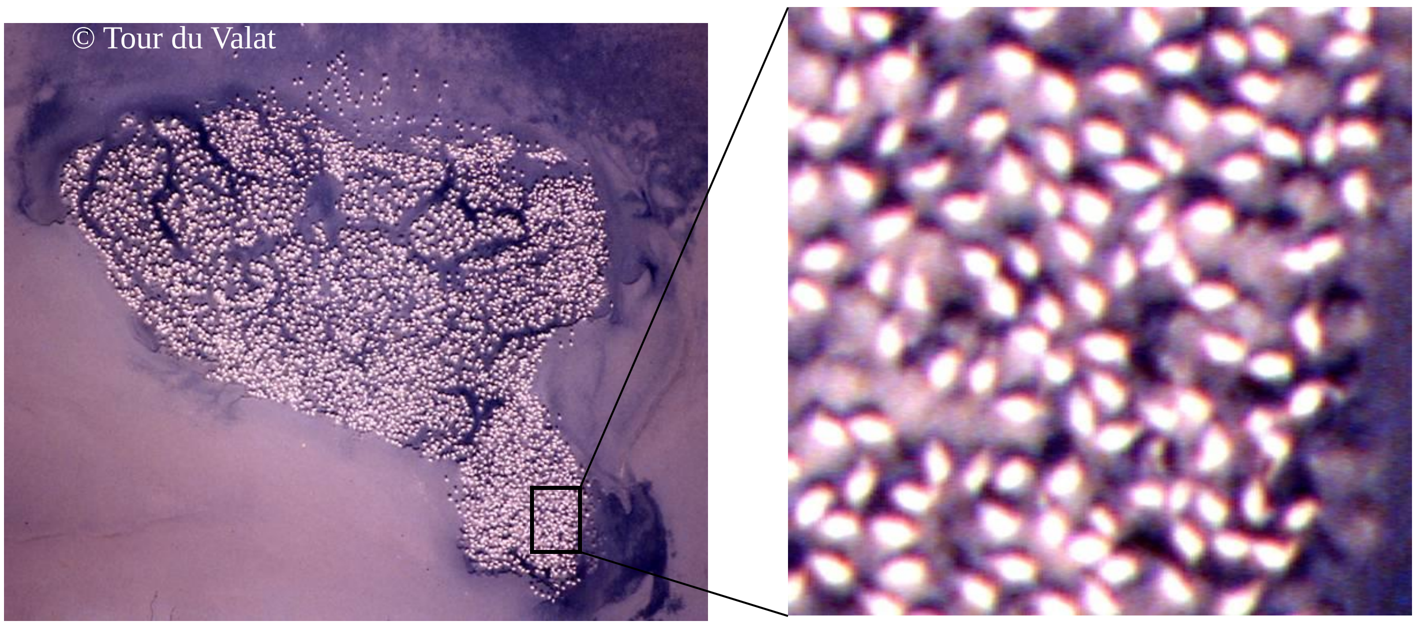
Results

<u>Estimation of size of a Turkish colony (2005):</u>

✓ Low density



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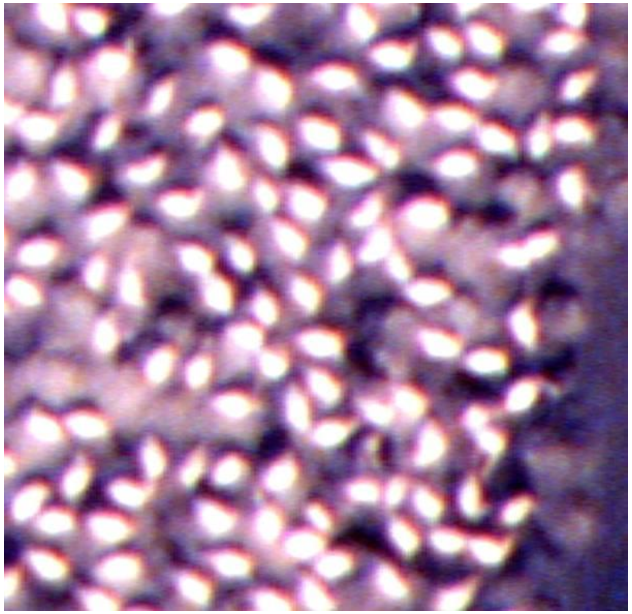
Results

Estimation of size of a Turkish colony (2005):

- ✓ Automatic: 3680 flamingos; Manually: 3682 flamingos
- ✓ Computation time: 80 minutes
- ✓ Image size: 6080 x 4128



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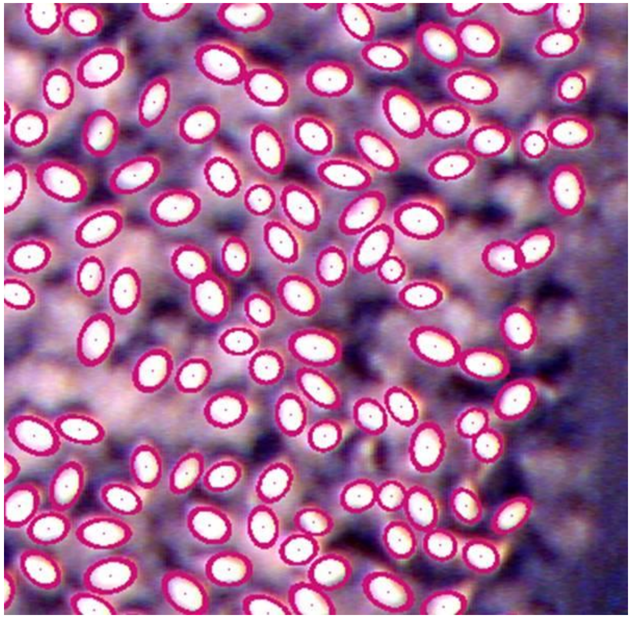

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Masters : S. Descamps in collaboration with Tour du Valat

Results

<u>Estimation of size of an African colony (2004):</u>

✓ High density

© Tour du Valat

Results

Estimation of size of an African colony (2004):

- ✓Automatic: 14300 flamingos
- ✓ Manually: 13650 flamingos
- ✓ Computation time: 15 minutes
- ✓ Image size: 3008 x 2000

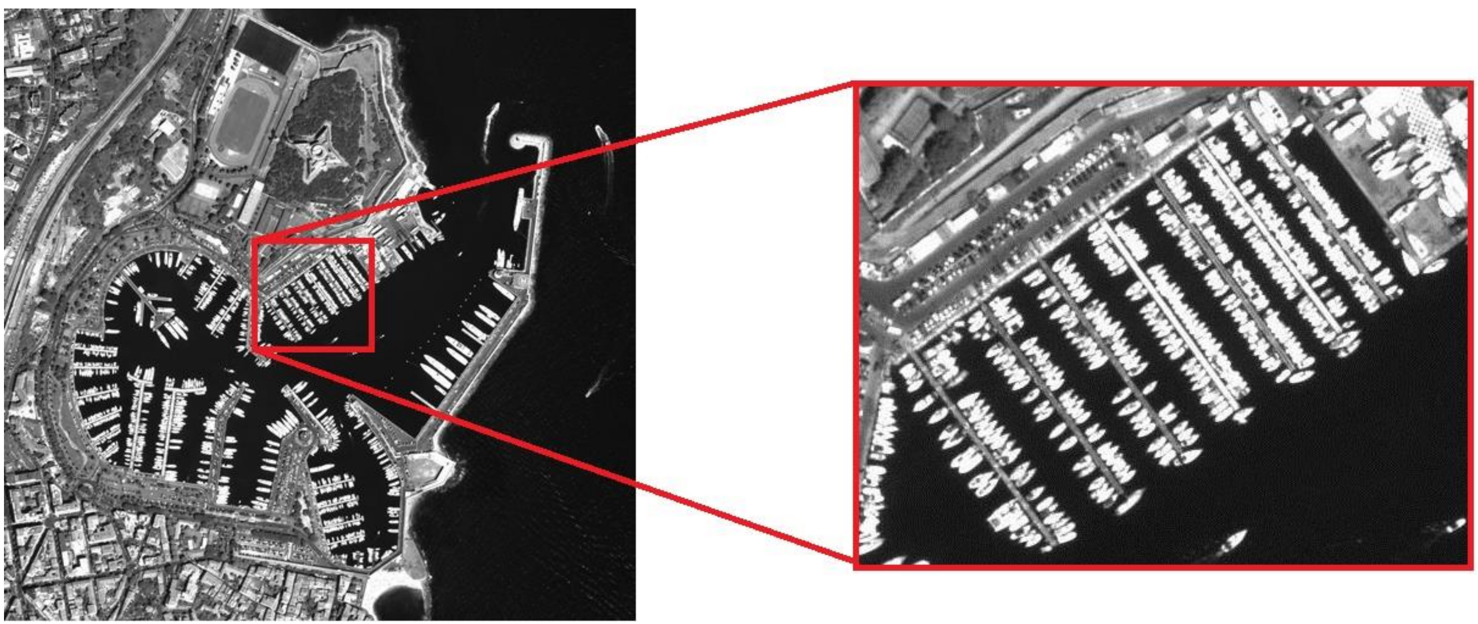
Masters : S. Descamps in collaboration with Tour du Valat

Fourth example : boat detection

<u>Harbor management is a difficult problem due to</u> :

✓ Big increase in the recreational fleet

✓ Reduced anchoring space

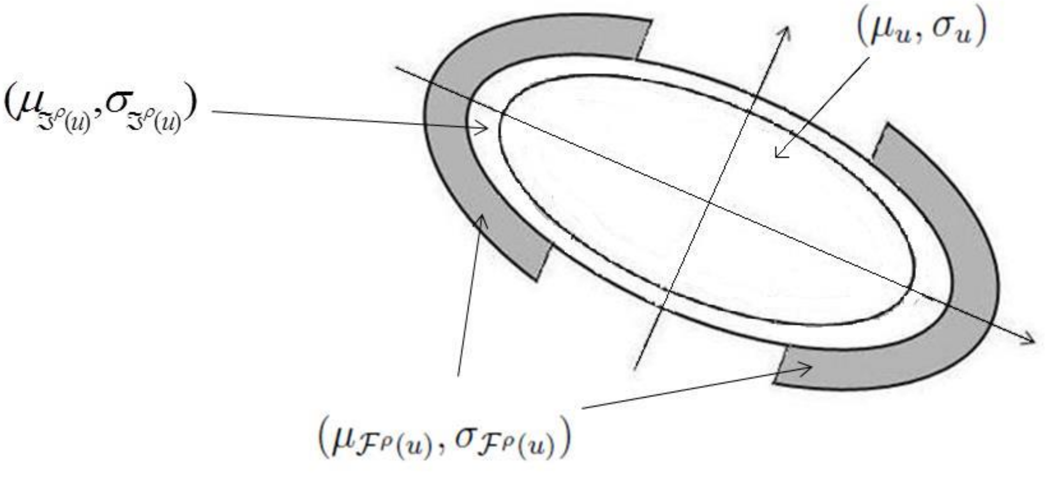


Model for the detection of boats

A new data term : to adapt the objects to boats

Boats tend to have a small dark area in the middle

- ✓ Distance similar to Bhattacharyya distance between interior of the object and the surrounding border *[G. Perrin et al. 06]*
- ✓ Distance similar to Bhattacharyya distance between inner border of the object and the surrounding border *[P. Craciun et al. 13]*

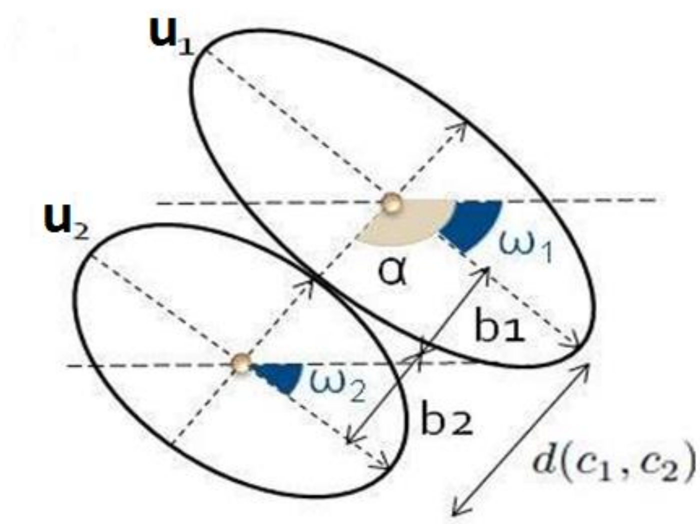


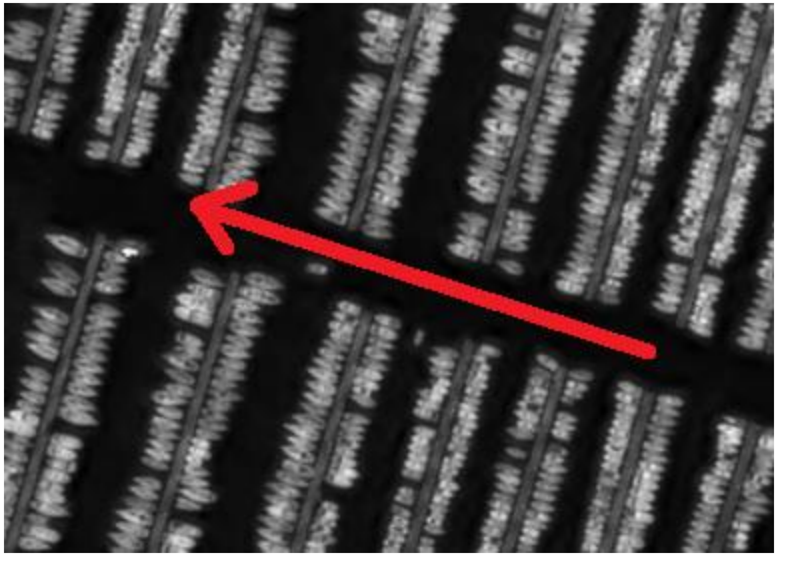
Model for the detection of boats

<u>**A first prior model**</u> : to adapt the interactions between objects

Boats in harbors are aligned and close to each other

- ✓ Favor close and aligned objects which have the same global orientation *[S. Ben Hadj et al. 10]*





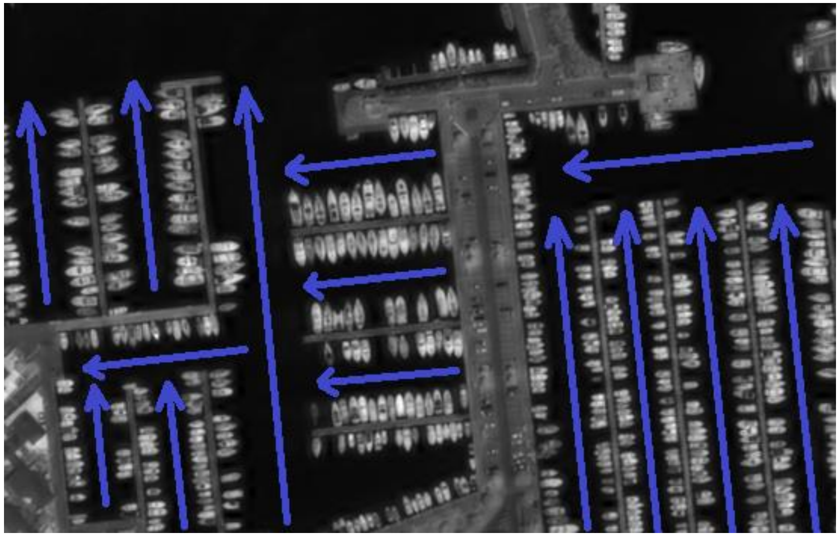
Model for the detection of boats

A second prior model : to handle multiple orientations of objects

Docks in harbor can have multiple orientations and thus, boats too

- ✓ Favor close and aligned objects
- ✓ Pre-compute orientation of water area *[P. Craciun et al. 13]*

Boats are perpendicular to the local orientation of the water

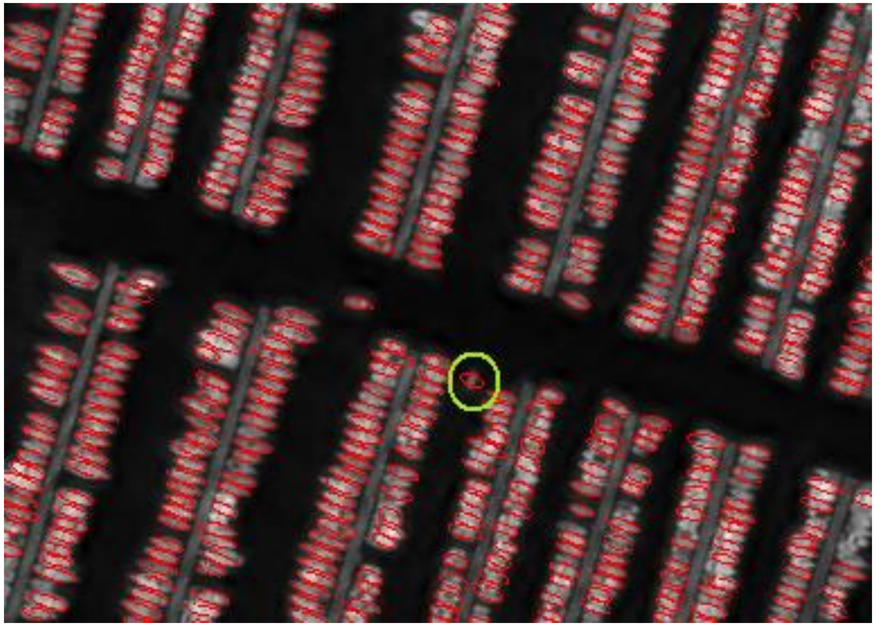


Local orientation of the water © Ayin / INRIA

Results

<u>Estimation of recreational fleet in harbor (Ben Hadj's model):</u>

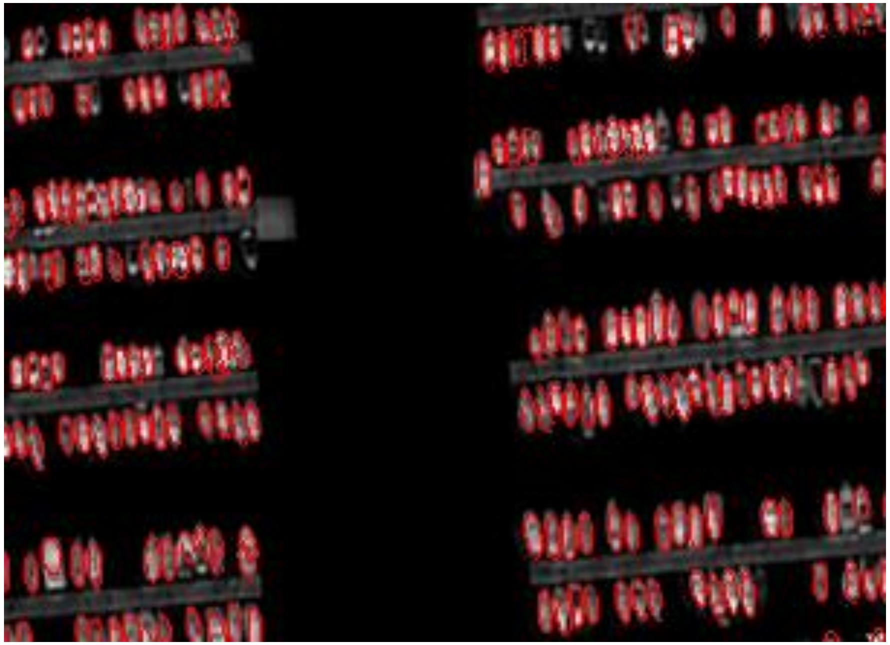
- ✓Automatic: 518 boats
- ✓ Manually: 523 boats
- ✓ Computation time: 55 minutes
- ✓ Image size: 375 x 285



Results

Estimation of recreational fleet in harbor (Ben Hadj's model):

- ✓Automatic: 233 boats
- ✓ Manually: 234 boats
- ✓ Computation time: 32 minutes
- ✓ Image size: 304 x 220



© Ayin / INRIA

Results

Estimation of recreational fleet in harbor (Craciun's model):

- ✓Automatic: 168 boats
- ✓ Manually: 190 boats
- ✓ Computation time: 36 minutes
- ✓ Image size: 326 x 226

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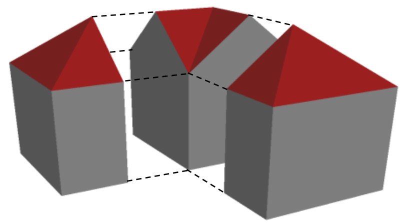
Fifth example : building extraction

Context

- spatial data (PLEIADES simulations)
- single type of data : a DEM
- automatic (without cadastral maps, without focalisation process)
- dense urban areas

Toward structural modeling

- adapted to data (object approach)
- good compromise generality / robustness
- modular and developable



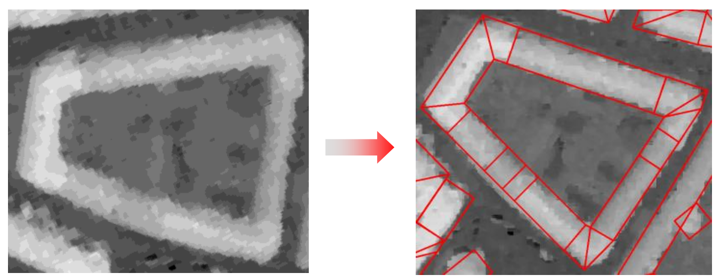
A building = an assembly of simple urban structures

2 stages : 2D extraction, then 3D reconstruction

- computation is greatly reduced

PhDs : M. Ortner, F. Lafarge in collaboration with IGN/CNES/DGA

Stage 1:
2D extraction of buildings



PhDs : M. Ortner, F. Lafarge in collaboration with IGN/CNES/DGA

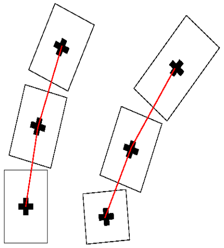
2D extraction of buildings

Outlines of buildings by marked point processes [Ortner04]

- Energy minimization : $U = \rho U_{ext} + U_{int}$

  - U_{ext} data term
    - coherence between the location of a rectangle and discontinuities in the DEM

  - U_{int} regularizing term
    - introduction of prior knowledge about the object layout (alignment, paving, completion)



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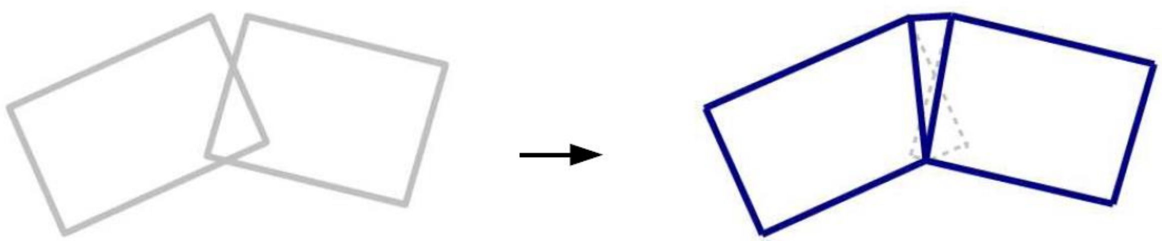
2D extraction of buildings

Transformation of rectangles into structural supports

- transformation of rectangles into unspecified quadrilaterals which are ideally connected (without overlapping, with a common edge)



- partitioning of rectangles that represent different urban structures

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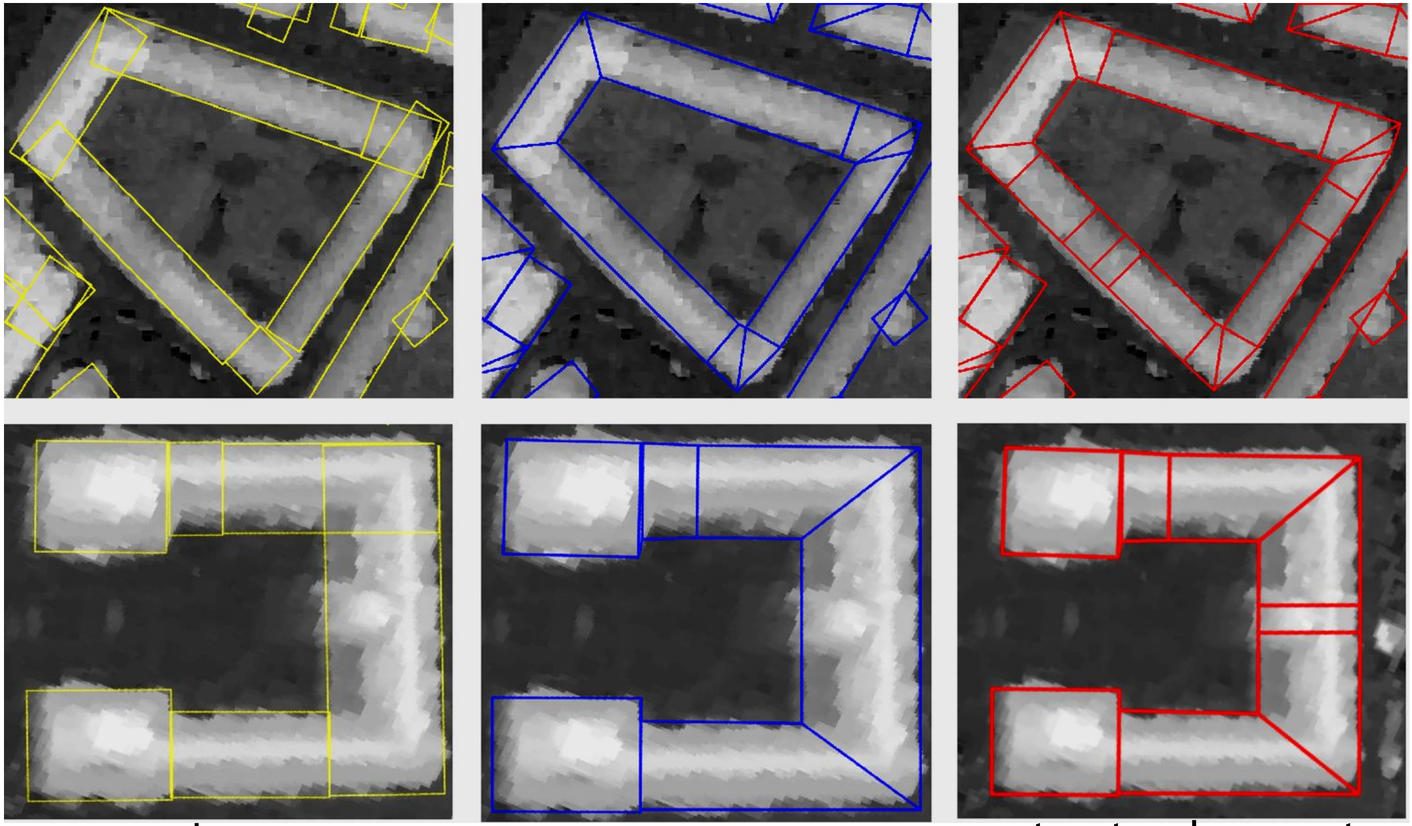
2D extraction of buildings

Examples © Ariana / INRIA



rectangular supports by [Ortner04]

"connected" supports by [Lafarge07]

structural supports by [Lafarge07]

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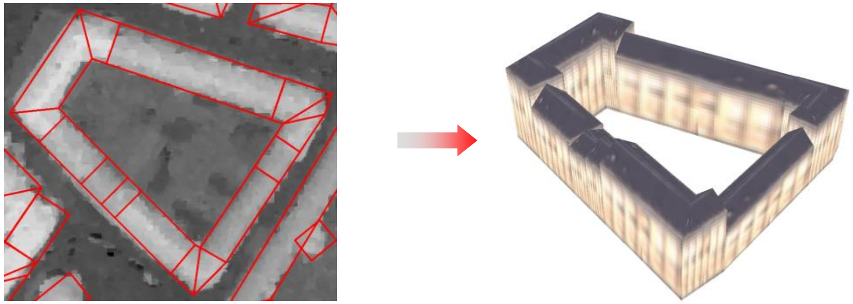
Stage 2:
3D reconstruction of buildings



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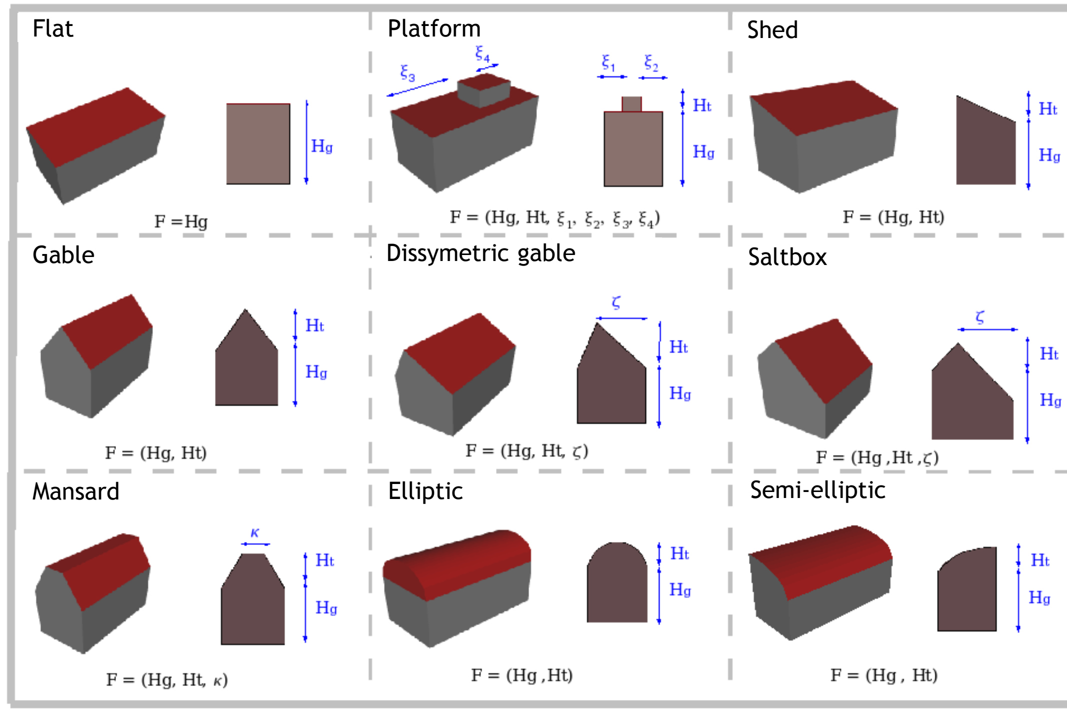
3D reconstruction of buildings

Library of 3D models

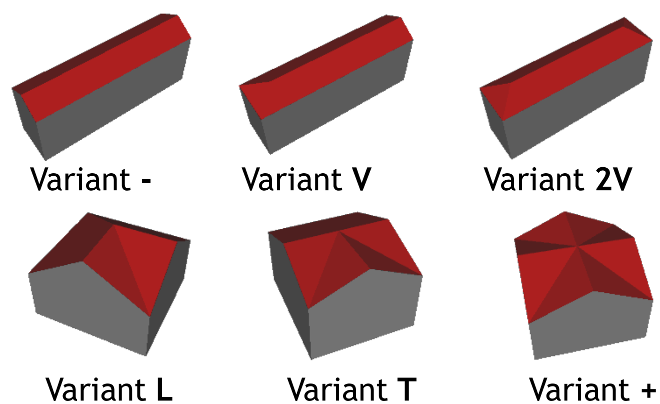
The roof shapes :

- 9 forms
- 1 to 6 parameters
- includes curved roofs



The variants :

- ends and junctions
- orientation of the object



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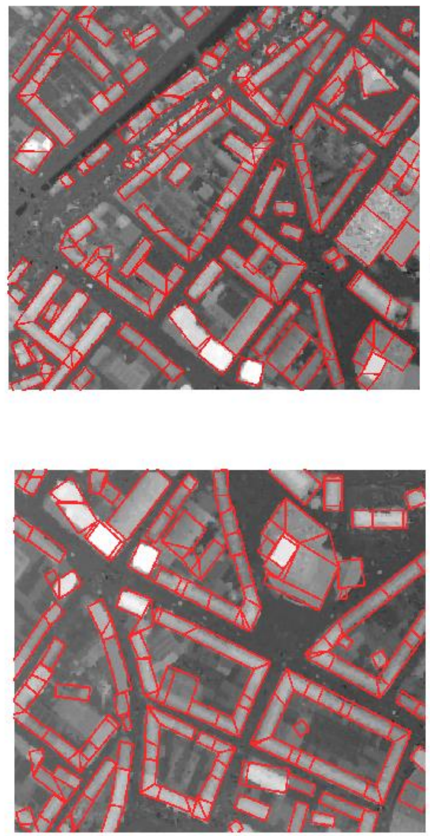
Results

PLEIADES simulations
©CNES



Building Extraction
© Ariana / INRIA

3D Reconstruction
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PhDs : M. Ortner, F. Lafarge in collaboration with IGN/CNES/DGA

Conclusion

- The marked point process framework extends the application domain of Markov approaches :
  - Data taken into account at the object level
  - Geometrical information taken into account
- Markov random fields are still an efficient tool (depending on the image resolution)

Current extensions

- Point process with marks living in a shape space
  - Multiple object detection [F. Lafarge et al.]
  - Computational issues [Y. Verdie et al., P. Craciun et al.]
- New optimization dynamics
  - Diffusion processes [X. Descombes et al.]
  - Multiple Birth and Cut [A. Gamal et al.]
- Different applications
  - Vascular network detection in the brain in 3D [X. Descombes et al.]
  - Cell counting [X. Descombes et al.]
  - Pimple detection in dermatology [J. Zerubia et al.]

Future work

- Point process with marks living in a shape space
  - More accurate definition of the geometry
- Parameter estimation
  - Quasi-MCMC techniques
  - Genetic algorithms
- New applications
  - Object tracking in image sequences

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For more information :

- Previous team:

http://www.inria.fr/ariana

- Current teams:

http://team.inria.fr/ayin

http://www-sop.inria.fr/morpheme/

http://team.inria.fr/titane

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