Characterization and modeling of the spatial distribution of local signatures in images: Application to classification of seabed's sonar image.

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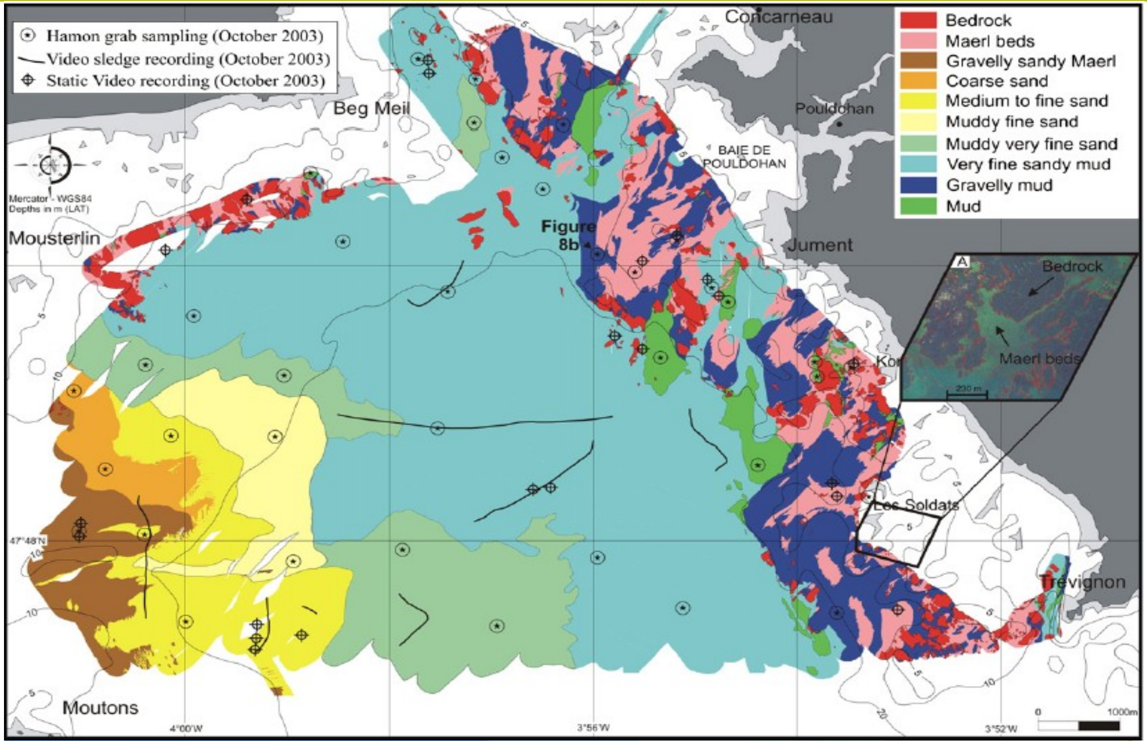
14/11/11

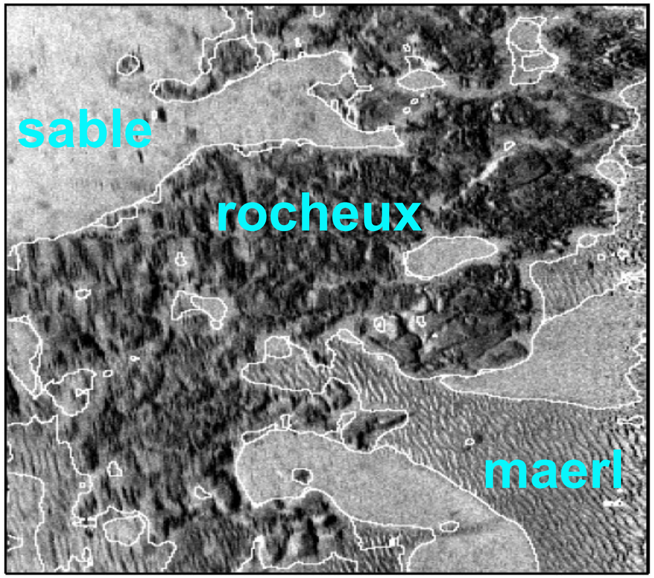
Introduction

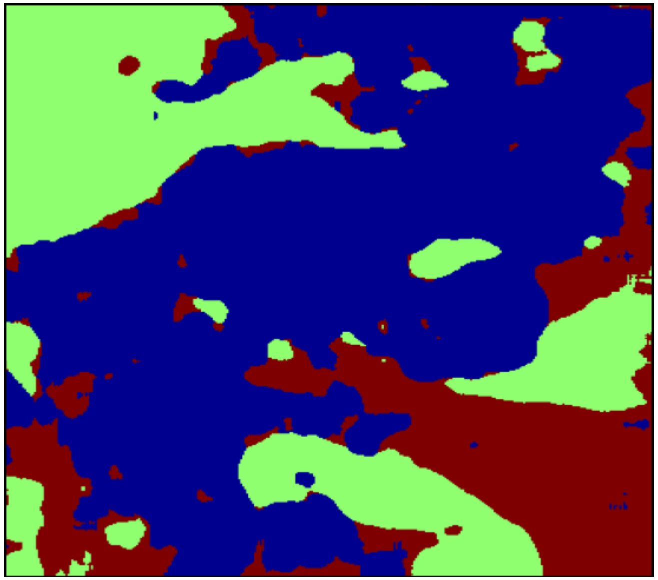


• Collaboration between Telecom Bretagne and IFREMER for sonar image analysis of seabed.

• Project REBENT (Ifremer) on benthic habitats in a coastal area of 200km2 in Concarneau Bay in 2003.

Introduction

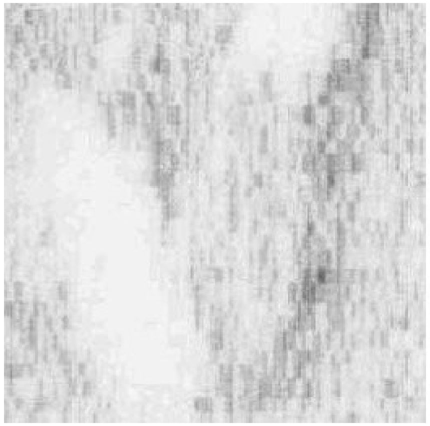


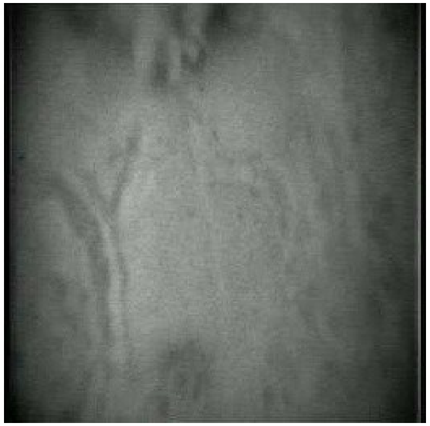
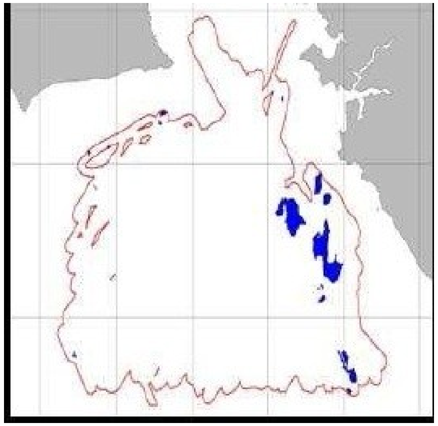


L. Hellequin 1998 & G. Le Chenadec 2004 & I.Karoui 2007

Introduction
Sonar texture database

- 6 classes of sonar images
- Each class comprises 40 256 x 256 images



Mud

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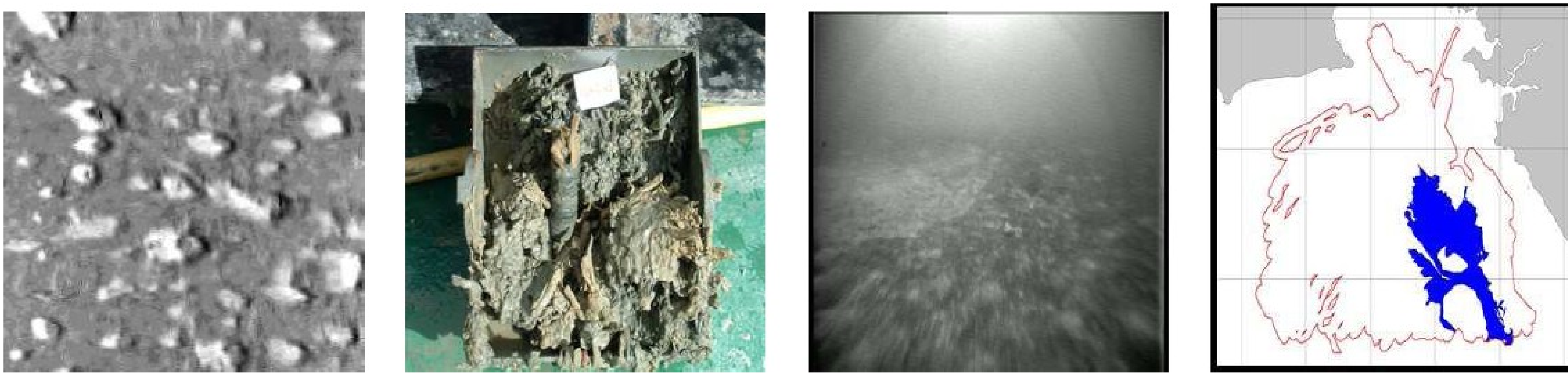

Sandy mud

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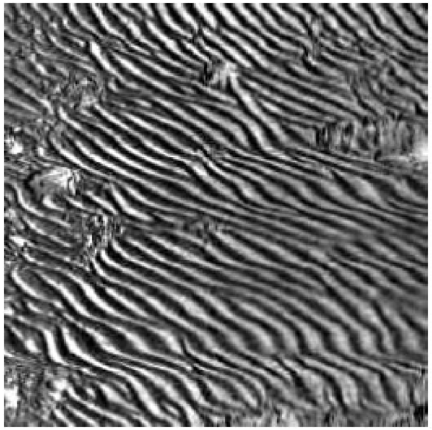



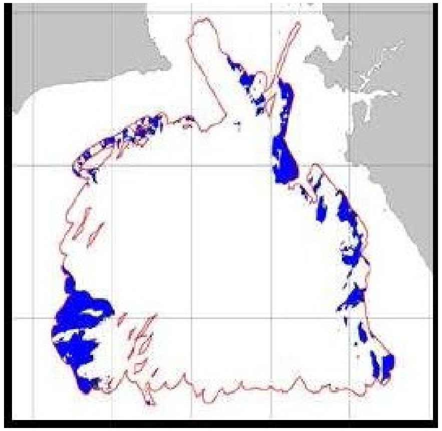

Maerly and gravelly sand

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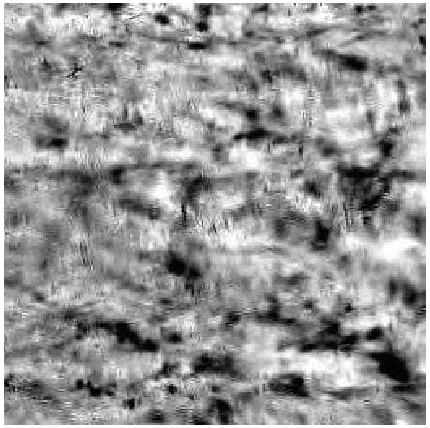

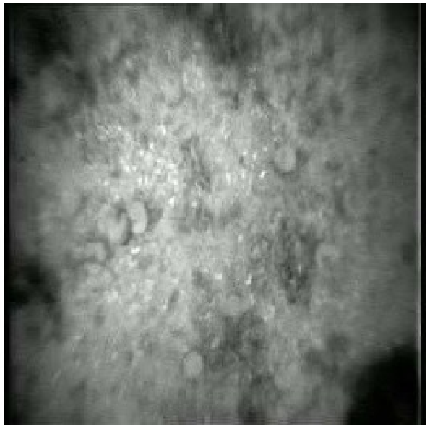
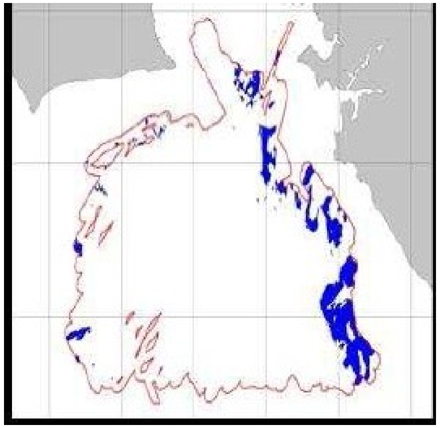

Mixed Sediment

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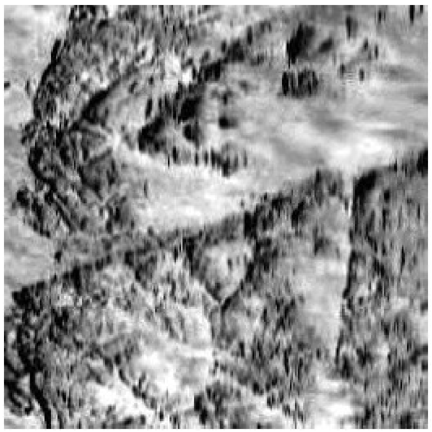
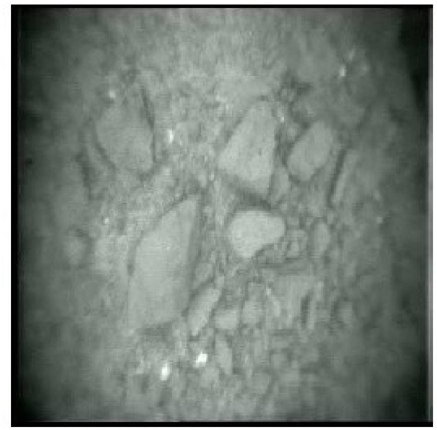
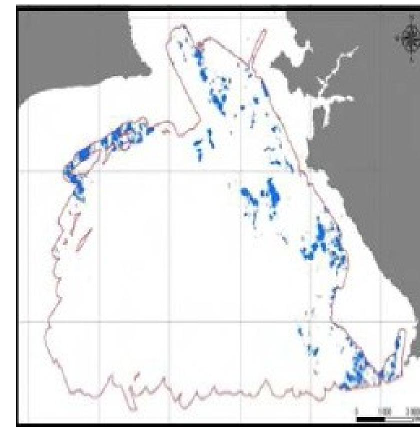

Rock

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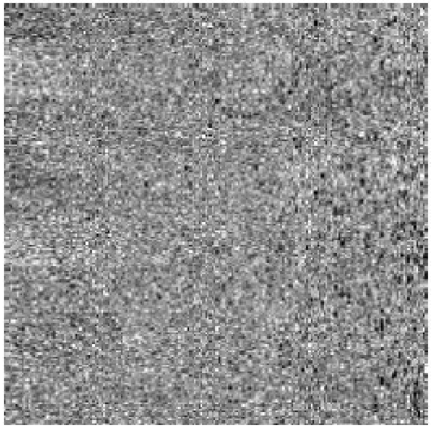
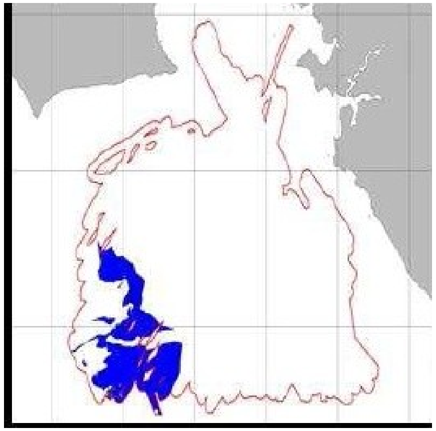






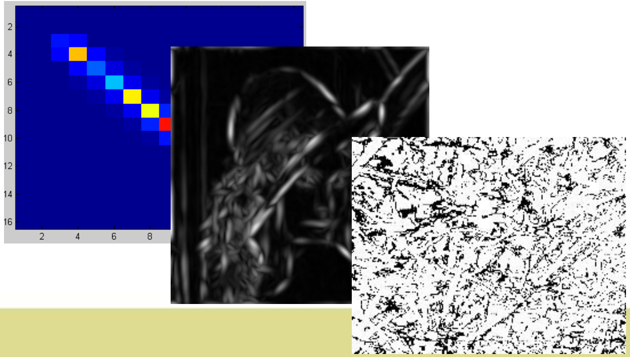
Clearly sand

How to distinguish the different classes of sonar images?

Cooccurrence matrix [Haralick 73]

Gabor and wavelet [Daugman 88]

Multifractal [Kaplan 99]



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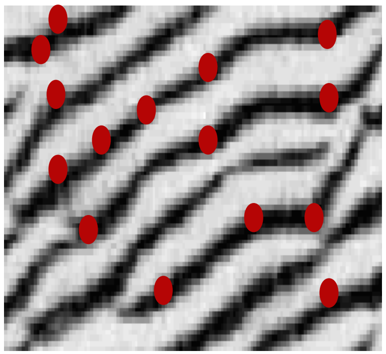
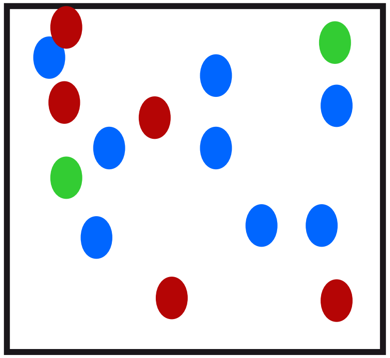
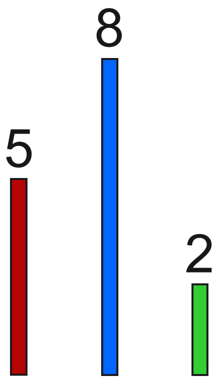


Detection

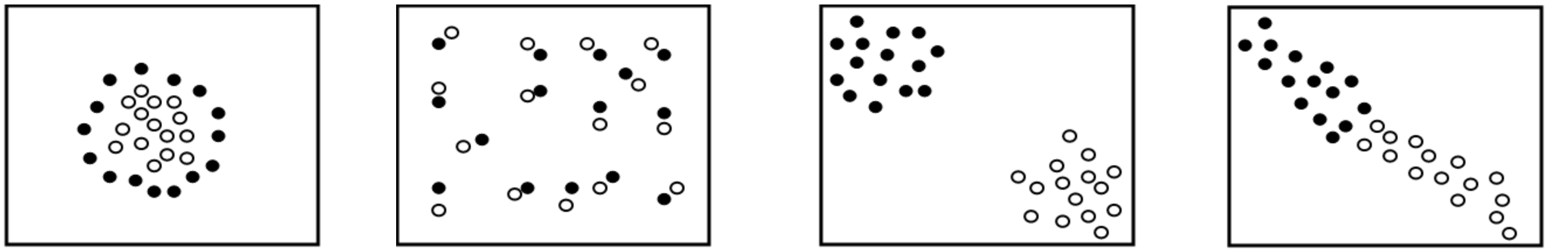


Codebook construction



Descriptor vector calculation

[Bag of keypoints - Sivic 2003]



Examples of different spatial distributions of two marked-points

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Outline

1. Spatial point statistics
    - Multi-marked point process and associated descriptive statistic
    - Log-Gaussian Cox model
2. Local signature detection and characterization in images
    - Keypoints
    - Shapes
3. Experimental evaluation

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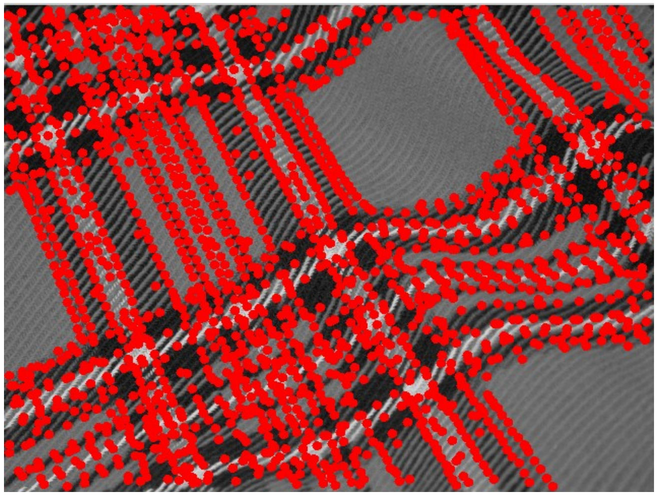
Spatial pattern of local signatures in images



Set of local signatures in image I

Set of points $\{s_i\}$ **in region** B

Each point $\{s_i\}$ **:**

- **Spatial position** $s_i(x,y)$
- **Visual information** $V_{si}(u_1, \ldots, u_n)$

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Spatial point process

A spatial point process S is defined as a locally finite random subset of a given bounded region $B \subset R^2$. A realization of such a process is a spatial point pattern $\{s_i\} \subset S$ of n points contained in B. [Diggle83,Stoyan87]

$$\mu^{(p)}(B_1 \times \ldots \times B_p) = E\left[N(B_1)\ldots N(B_p)\right]$$

- **First-order moment(p=1):** $$\mu(B) = E\left[\sum_{s \in S} I_B(s)\right]$$

- **Second-order moment(p=2):** $$\mu^{(2)}(B_1 \times B_2) = E\left[\sum_{s_1 \in S}\sum_{s_2 \in S} I_{B_1}(s_1) I_{B_2}(s_2)\right]$$

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Marked point process

A *marked point process* is defined as a spatial point process for which a mark m_i is associated to each point s_i in B.

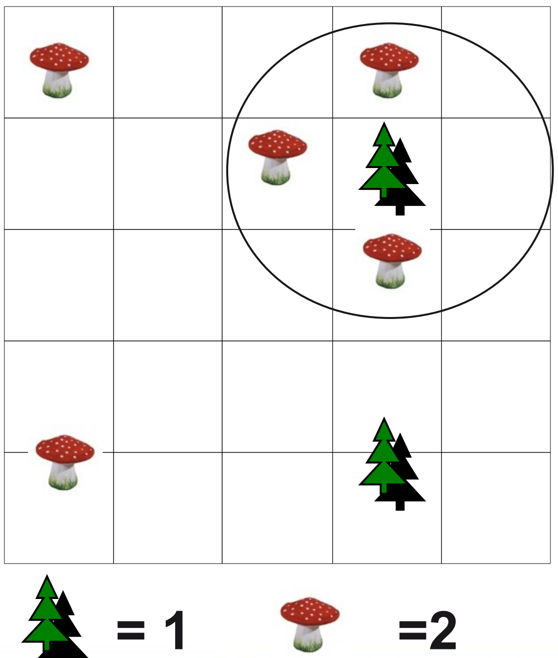
- **First-order moment:**

  (Bag of keypoints)

$$\mu_i(B) = E\left[\sum \delta_i(m_t) I_B(s_t)\right]$$

- **Second-order moment:**

$$\alpha_{ij}^{(2)}(r) = E\left[\sum_h \sum_{l \neq h} \delta_i(m_h)\delta_j(m_l) I(\|s_h - s_l\| \leq r)\right]$$



$$\boxed{\begin{array}{l} \mu_1 = 2 \quad ; \quad \mu_2 = 5 \\ \alpha_{11}^{(2)} = 0 \quad ; \quad \alpha_{12}^{(2)}(3) = 3 \quad ; \quad \alpha_{22}^{(2)}(3) = 4 \end{array}}$$

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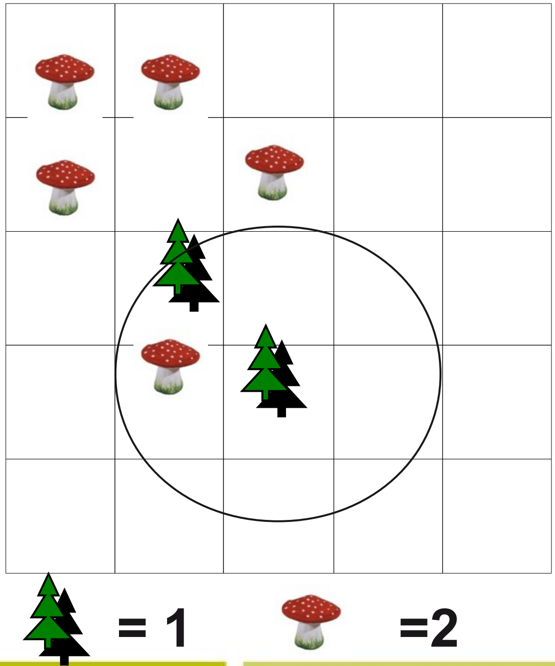


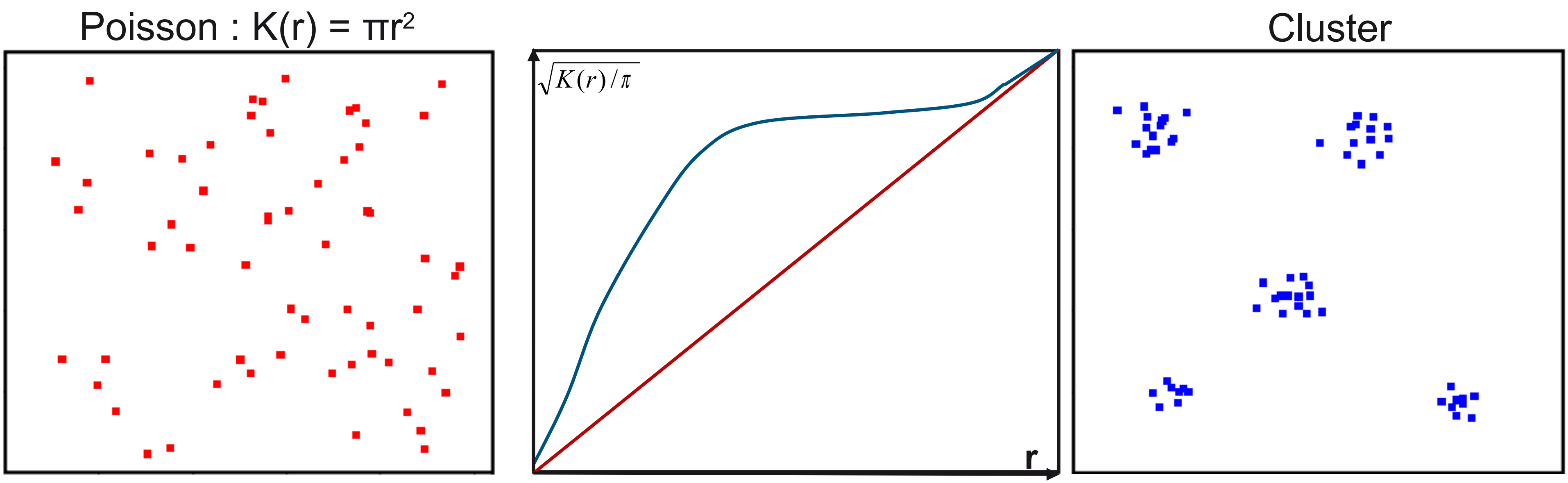
$$\mu_1 = 2 \quad ; \quad \mu_2 = 5$$

$$\alpha_{11}^{(2)} = 2 \quad ; \quad \alpha_{12}^{(2)}(3) = 4 \quad ; \quad \alpha_{22}^{(2)}(3) = 8$$

Second-order descriptive statistics

- *Ripley's K function :* (Ripley81) $K_{ij}(r) = (\lambda_i \lambda_j)^{-1} \alpha_{ij}^{(2)}(r)$

Where the mean density $\lambda = \mu(B) / |B|$



Proposed descriptor vector : the second-order spatial cooccurrence statistics are used to measure the mean number of points of type j located in a study region of radius r centered at the points of type i (which itself is excluded).

$$\Gamma_{ij}(r) = \lambda_j K_{ij}(r)$$

Statistical model

Measure on random observations

Describe relationships between variables

Empirical description

Λ = f(Y(s))

Statistical model

$$\begin{cases} \text{Order1}: \mu(B) \\ \text{Order2}: \alpha_{ij}^{(2)}(r), K_{ij}(r) \end{cases}$$

log-Gaussian Cox model

(Moller98)

<u>Definition</u> : A multivariate Cox process $X=\{X_i\}$ is conditionally independent w.r.t. a multivariate intensity field $\Lambda=\{\Lambda_i(s):s\in R^2\}$ such that $X_i|\Lambda_i$ is a Poisson process with intensity measure Λ_i.

$\Lambda_i(s)=\exp(Y_i(s))$: log-Gaussian Cox process (LGCP)

where $Y_i(s)$ a multivariate Gaussian field.

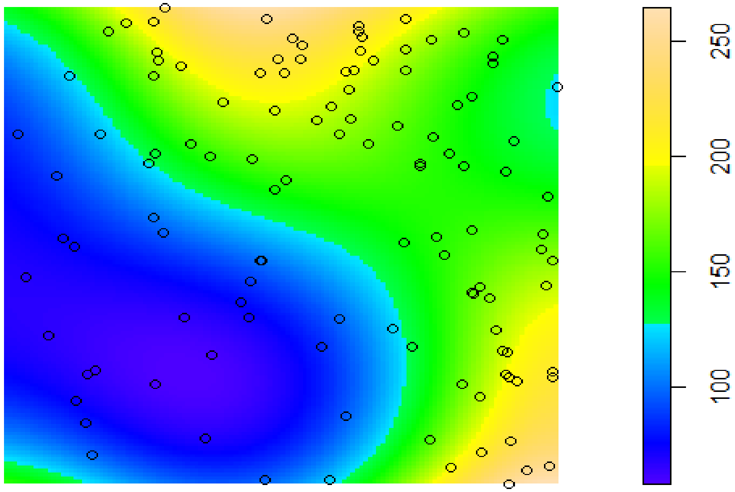
Estimation & simulation of log-Gaussian Cox model

- Order1 : $\lambda_i = \exp(\mu_i + \frac{\sigma_i^2}{2})$
- Order2 : $K_{ij}(R) = 2\pi \int_0^R r \exp\left(c_{ij}(r)\right) dr$

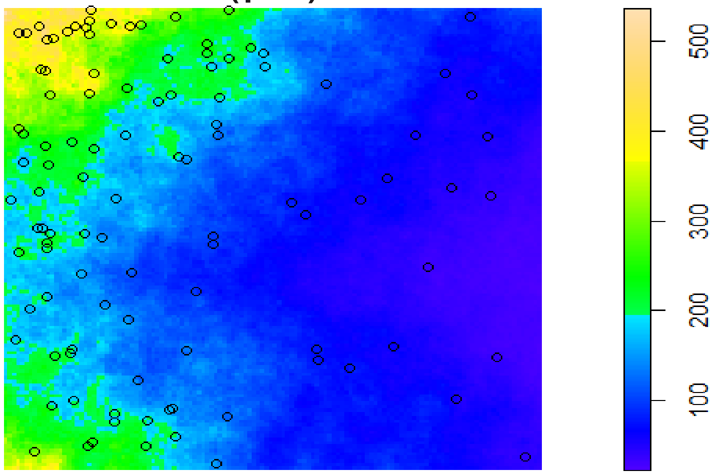
$$\int_0^R \left\{\sigma_{ij}^2 \mathbb{L}(\beta, r) - c_{ij}(r)\right\}^2 dr$$

Proposed descriptor vector: ***(λ_i , σ_{ij}, β_{ij})***

- Simulation of LGCP with the different covariance model L(β,r) :



Gaussian : *exp(-(r/β)²)*



Hyperbolic : $(1+r/\beta)^{-1}$

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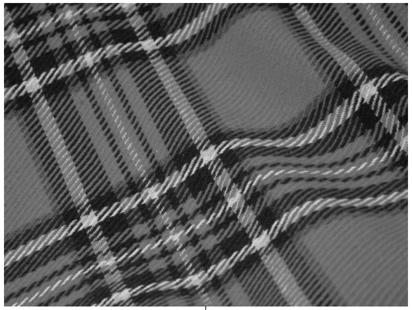
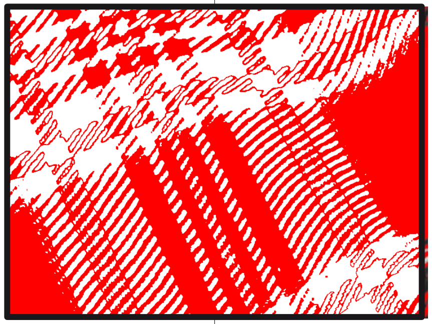
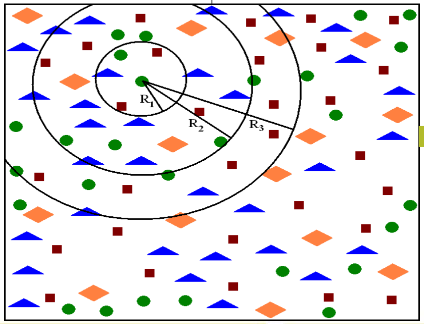
Proposed approach



Keypoint

Shapes





Statistical calculation of descriptor

$$\Gamma_{ij}(r)\,;(\lambda_j,\sigma_{ij},\beta_{ij})$$

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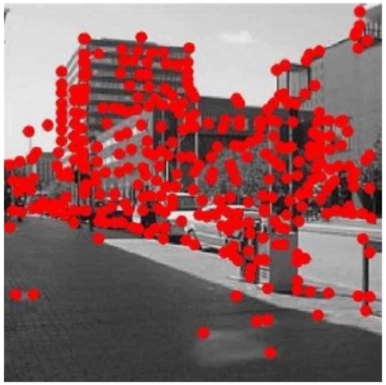
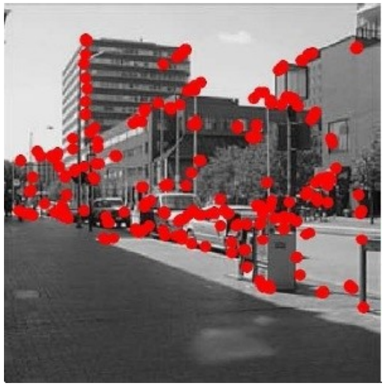
Keypoint detection



Harris



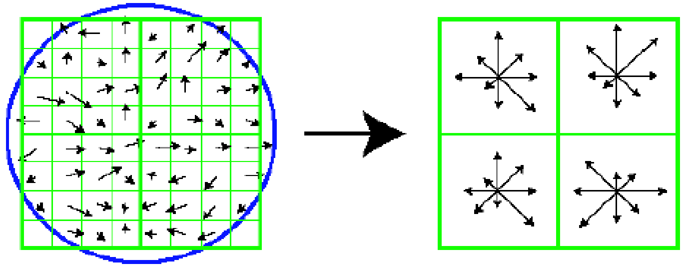
Harris-Laplacian

Harris-Affine

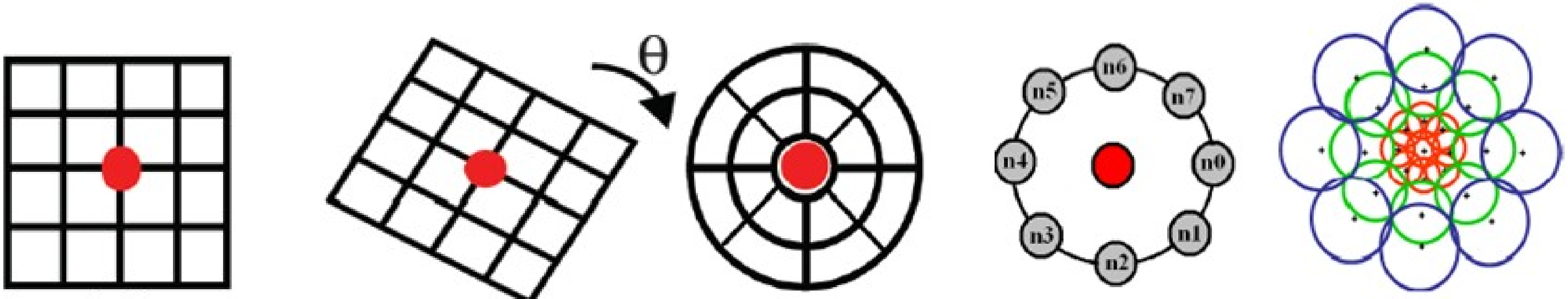
DoG

Detector	Coin	Region	Rotation	Scale	Affine	Ref.
Harris	x		x			Harris88
Harris-Laplacian	x	(x)	x	x		Mikolajczyk01
Hessian-Laplacian	(x)	x	x	x		
Harris-Affine	x	(x)	x	x	x	Mikolajczyk05
Fast Hessian	(x)	x	x	x		Bay06
DoG	(x)	x	x	x		Lowe04

Keypoint's description

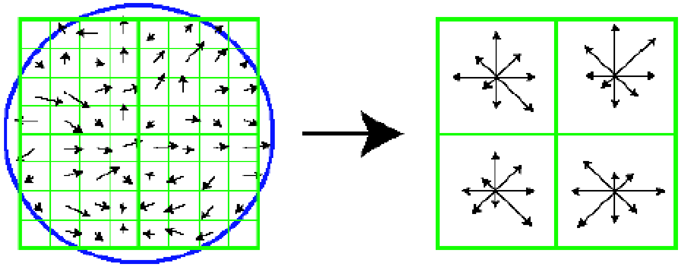


Scale-invariant feature transform-
DoG+SIFT (Lowe 04)



SIFT Lowe04 | SURF Bay06 | GLOH Mikolajczyk05 | CS-LBP Heikkilä09 | DAISY Tola10

Keypoint's description



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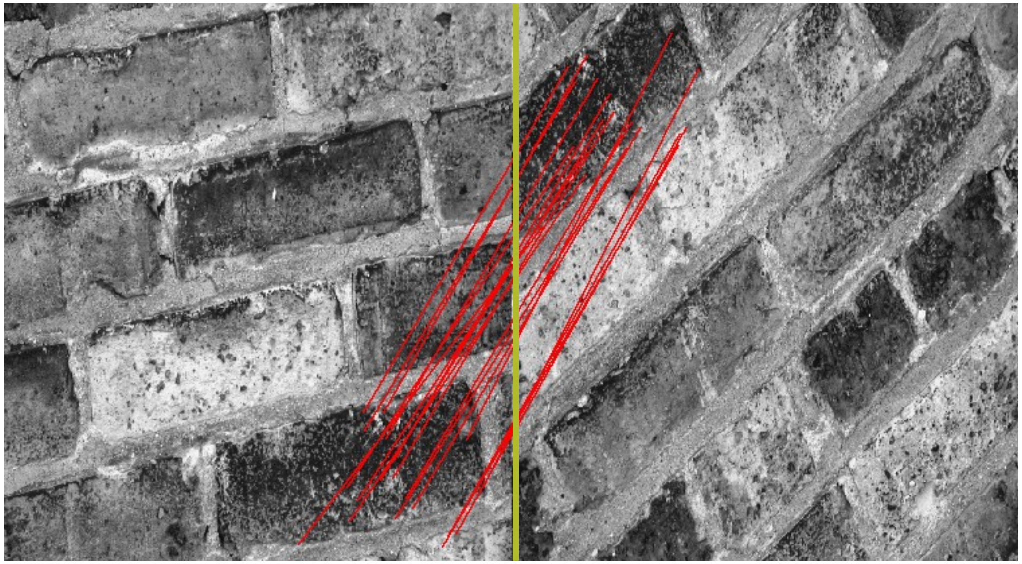
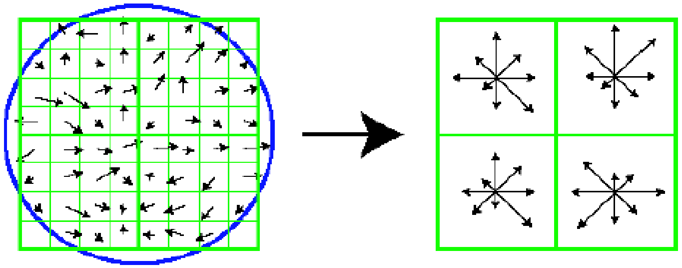


Rotation

Keypoint's description



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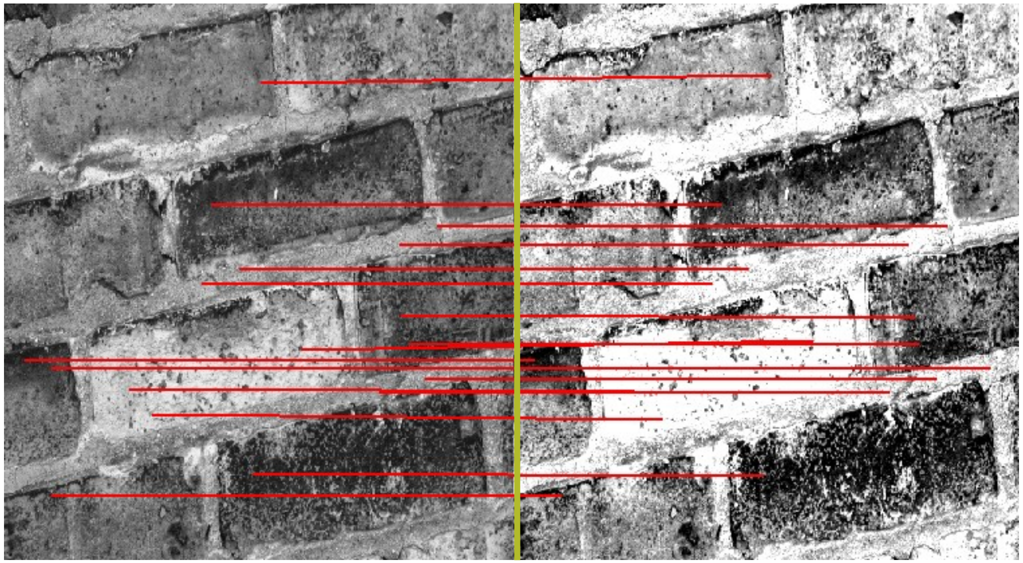
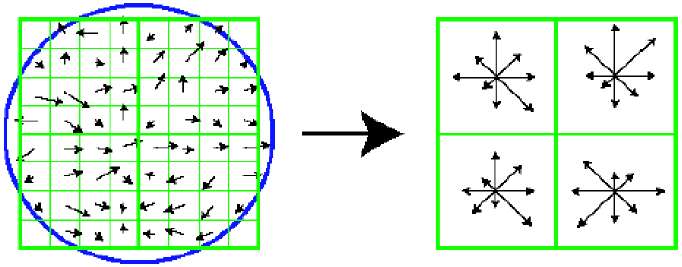


Contrast

Keypoint's description



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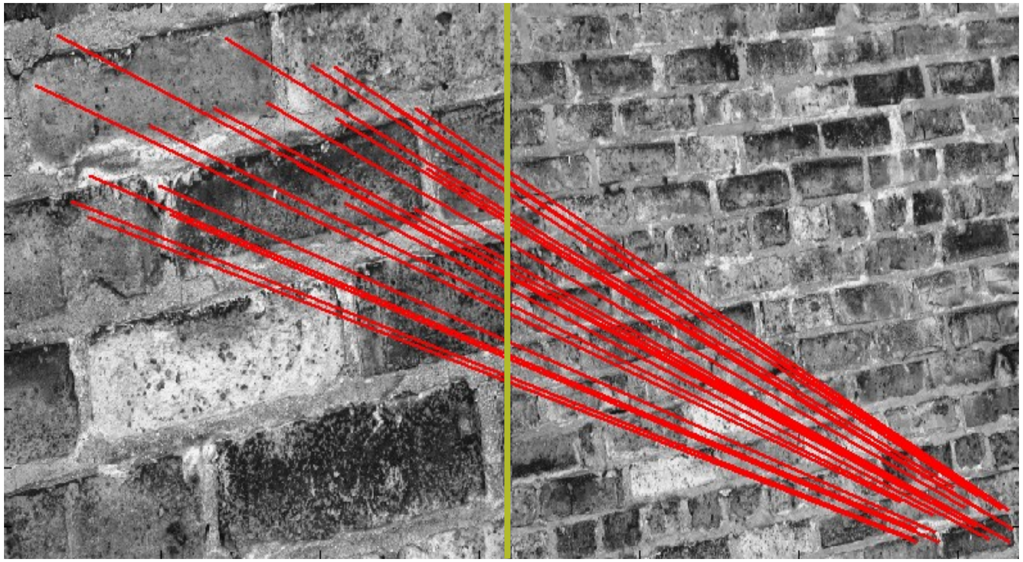
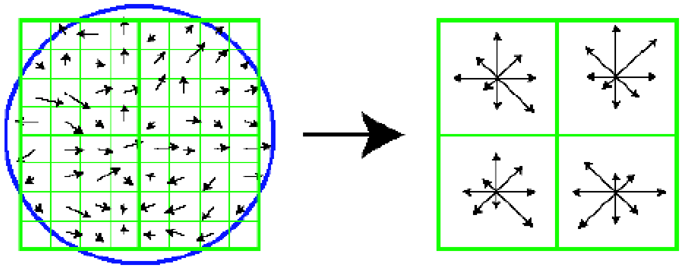


Scale

Keypoint's description



Scale-invariant feature transform-
DoG+SIFT (Lowe 04)

Detector	DoG	Fast-Hes	Fast-Hes	Hes-Lap	Har-Lap
Descriptor	Sift	Surf	Brief	Daisy	Sift-Spin
Ref.	Lowe04	Bay 06	Calonder10	Tola10	Zhang07

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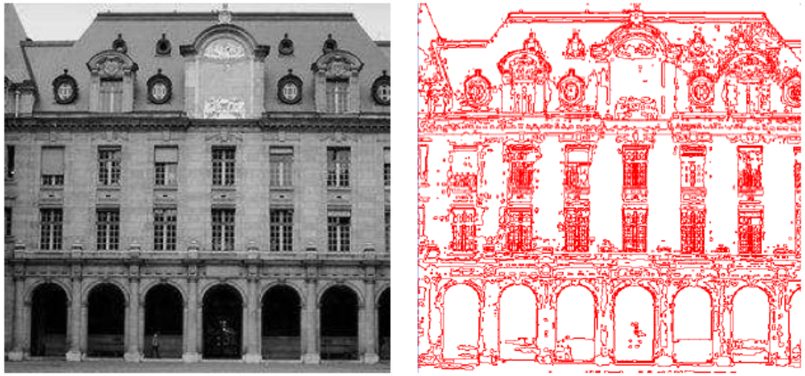
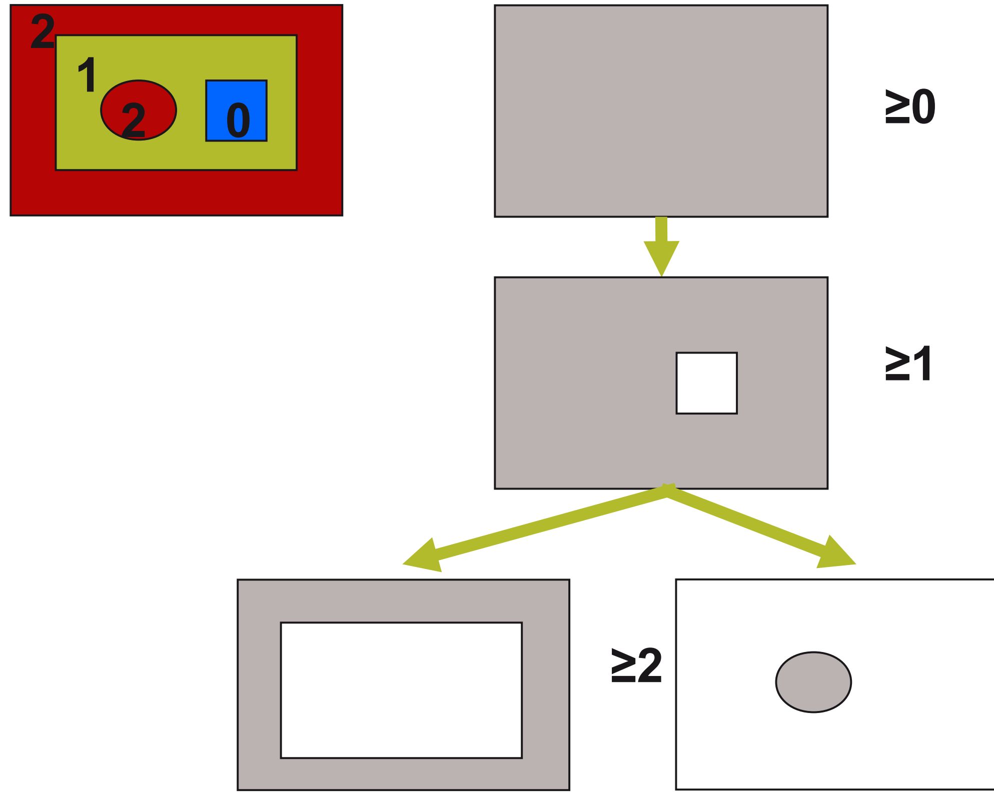
Shape detector



Level-line representation

$$\begin{cases} \chi^{\geq\lambda}(u) = \{x \in X, u(x) \geq \lambda\} \\ \chi_{\leq\mu}(u) = \{x \in X, u(x) \leq \mu\} \end{cases}$$

Upper and lower level set

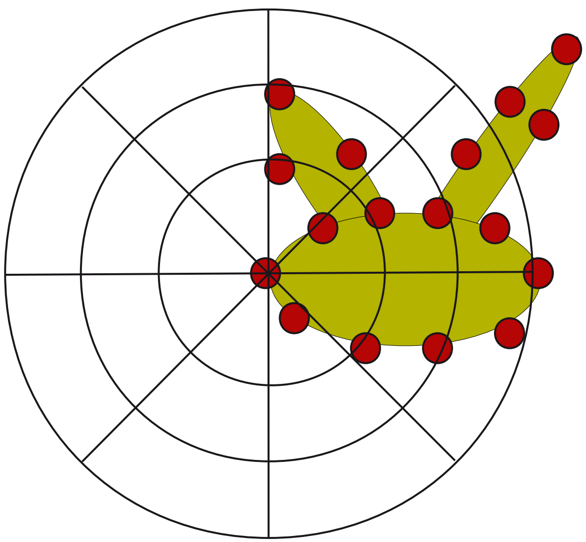


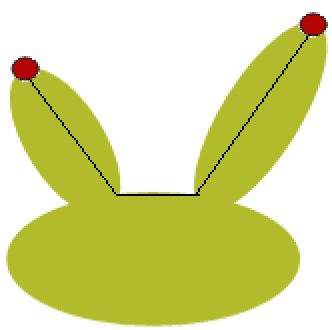
Upper level set tree
Fast Level-Set Transform -FLST (Caselles99)

Shape's description

Inner-distance shape context descriptor (Ling05):

$$h_i(k) = E_{j \neq i}\left\{x_j : \left\langle d(x_j, x_i), \theta(x_j, x_i) \right\rangle \in bin(k)\right\}$$





inner-distance $d(x_j, x_i)$

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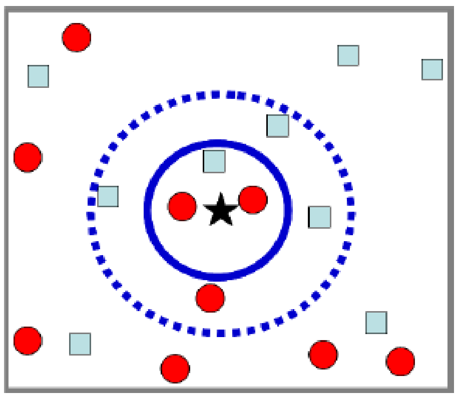
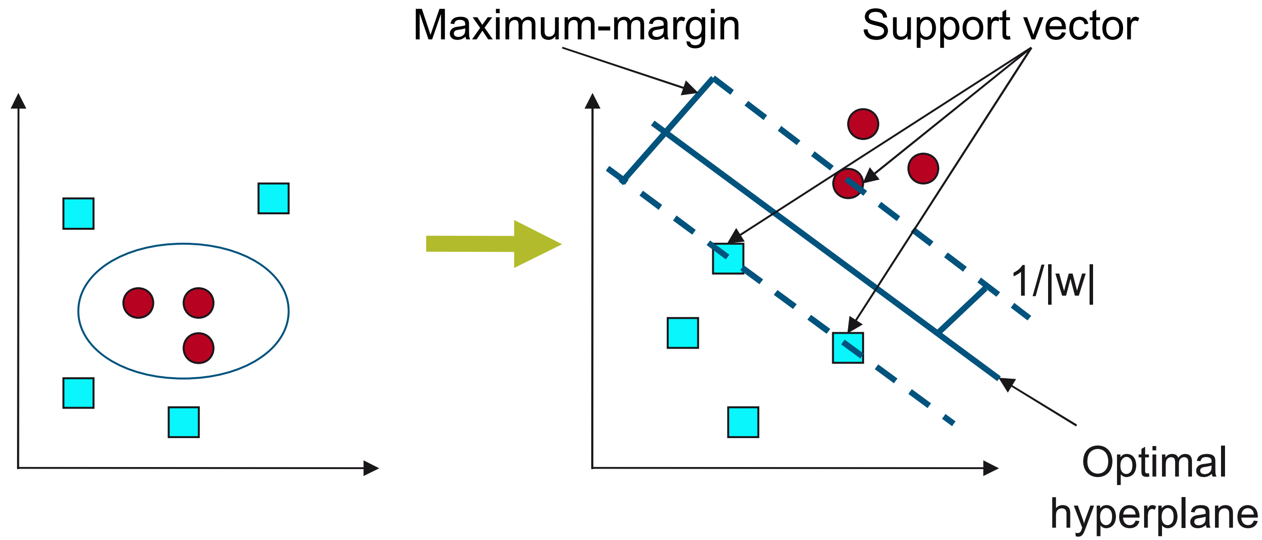
Supervisor classification

k-NN



SVM



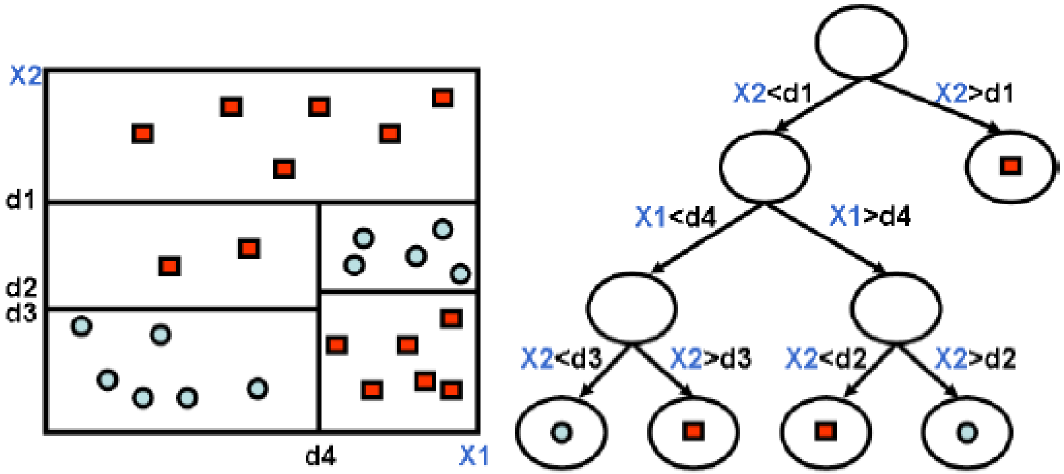
Distance : Euclidiean, χ^2 and Jensen-Shannon divergence

Supervisor classification

Random forest (RF):

- Choose a training set with n samples of N training cases, and m variables from *M variables of sample* to determine the decision at a node of the tree.

The class of new sample is the major vote of all trees.



Binary Decision Tree

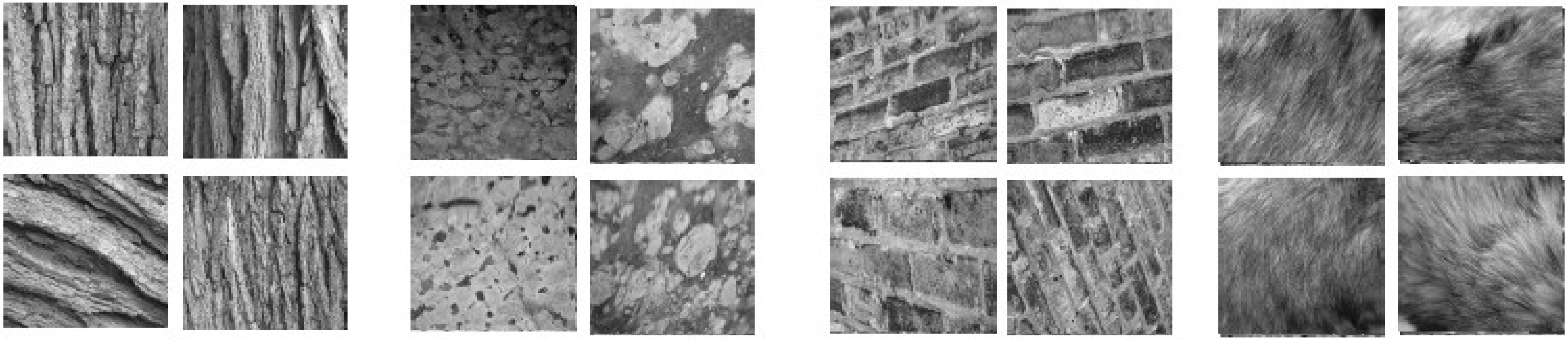
Sonar texture classification

N_t	1	5	10
Filtre de Gabor [7]	51.71±3.24	59.27±1.97	69.81±1.48
Matrice de Cooc. [8]	62.13±3.17	72.15±1.53	81.21±1.27
SDM[9]	67.15±2.55	85.42±1.56	92.03±1.21
Ling[10]	66.83±2.33	85.27±1.83	91.92±1.24
Xu[11]	67.54±2.49	87.12±1.91	91.85±1.12
Zhang[12]	73.33±2.17	90.67±1.15	94.25±0.73
SSC[104]	**74.57±1.69**	91.17±1.08	96.67±0.35
LGCM	73.85±1.75	**91.34±0.72**	**97.14±0.37**

Classification rates and standard deviations over 50 random selections

Natural texture classification

25 classes of UIUC textures [Lazebnik05]; 40 640x480 images/class.



N_t	1	10	20
Filtre de Gabor [7]	31.22±3.14	57.37±1.93	67.78±1.28
Matrice de Cooc. [8]	45.33±3.03	70.67±1.72	80.12±1.30
SDM[9]	67.25±2.75	81.12±1.45	91.28±1.15
Ling[10]	67.62±2.93	84.14±1.72	91.87±1.38
Zhang[12]	72.53±2.45	93.17±1.15	96.67±0.93
SSC[104]	**75.66±1.65**	94.33±0.78	97.34±0.25
LGCM	75.21±1.75	**95.42±0.71**	**97.84±0.32**

Classification rates and standard deviations over 50 random selections

Natural scene classification

- 15 classes of natural scene




[Lazebnik06]

Bayesian hierarchical model (Fei-Fei 05)	74,8%
Spatial pyramid of keypoint (Lazebnik06)	81,4%
Spatial concept correlogram (Liu 07)	81,72%
log-Gaussian Cox model	82,9%

Publications

- H-G Nguyen et al. "Keypoint-based analysis of sonar images : application to seabed recognition." IEEE Transaction on Geoscience and Remote Sensing **TGRS’2011**.
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- H-G Nguyen et al." Log Gaussian Cox Processes of visual keypoints for sonar texture recognition." IEEE Conf. on Acoustics, Speech and Signal Processing, pp.1005-1008, **ICASSP’2011**.
- H-G Nguyen et al." Spatial statistics of visual keypoints for texture recognition." European Conference on Computer Vision, Vol.6314, pp.764-777, **ECCV’2010**.
- H-G Nguyen et al." Invariant descriptors of sonar textures from spatial statistics of local features." IEEE Conf. on Acoustics, Speech and Signal Processing, pp. 1674-1677, **ICASSP’2010**.
- H-G Nguyen et al." Statistiques spatiales de points d’intérêt pour la reconnaissance invariante de textures.", 5ème Congrès Francophone AFRIF-AFIA de Reconnaissance des Formes et Intelligence Artificielle, **RFIA’2010**.