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Thesis dissertation on

Advanced methods for the analysis of multispectral and multitemporal remote sensing images

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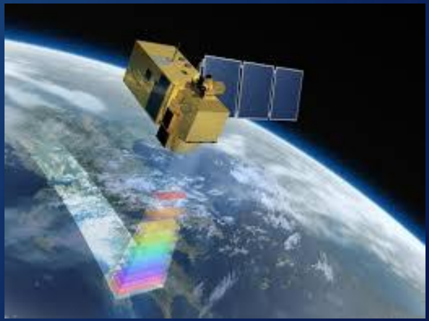
Outline of the thesis

1. Introduction
   - Motivations
   - Contributions
2. Part I: Variational methods for image approximation
3. Part II: Statistical models for change detection in multispectral images
4. Conclusions and future activities

Motivations

- Earth Observation (EO) missions provide huge amount of data.
- Important missions provide open-access to multispectral (MS) imagery (e.g., Landsat-8, Sentinel-2).
- Information needs to be extracted from images automatically and efficiently.
- Processing capability of modern machines is significantly increased w.r.t. the past.
- More chances for mathematical methods for image analysis to be applied on real images (not only remote sensing images).



Contributions

Variational methods for image approximation.

- We propose efficient minimization techniques for variational functionals such as Mumford-Shah (MSh) and Blake-Zisserman (BZ).
- We extend their functional formulation to vector-valued inputs allowing the analysis of multi-band images and also curves in N-dimensional space.
- We develop a parallelizable domain-decomposition technique to address the minimization for large size images.

Statistical models for change detection in multispectral images.

- We present a novel change detection thresholding approach based on the Rayleigh-Rice mixture.
- We introduce a novel compound multi-class model for the statistical description of the so-called difference image.
- We propose a statistical simplification approach for the estimation of class parameters based on a variational formulation.

Variational methods for image approximation

Variational methods: strengths and challenges

Strengths

- Retrieve/extract useful information (smooth representations, edges and other geometrical features).
- Handle a large diversity of data:
  - images at different geometrical resolutions,
  - spectral bands,
  - digital surface models (DSMs),
  - curves.

Challenges

- SoA techniques require high computational time.
- Vector-valued inputs require specific models.
- Image size is a bottleneck for standard algorithms.

Functional model

Input

- Rectangular domain $\Omega \subset \mathbb{R}^2$.
- Image $g: \Omega \to \mathbb{R}^+$ with $||g||_\infty < \infty$.

Unknowns

- A *smooth* function $u: \Omega \to \mathbb{R}^+$
- Two indicator functions $s, z: \Omega \to [0,1]$.

Minimize (see [1])

$$F_\epsilon(s,z,u) = \delta \int_\Omega z^2 |\mathrm{H}u|^2 \, dx + \xi_\epsilon \int_\Omega (s^2 + o_\epsilon)|\nabla u|^2 \, dx$$
$$+ (\alpha - \beta) \int_\Omega \epsilon |\nabla s|^2 + \frac{(s-1)^2}{4\epsilon} dx$$
$$+\beta \int_\Omega \epsilon |\nabla z|^2 + \frac{(z-1)^2}{4\epsilon} dx$$
$$+\mu \int_\Omega |u - g|^2 \, dx$$

[1] L. Ambrosio, L. Faina, and R. March. “Variational approximation of a second order free discontinuity problem in computer vision, ” SIAM Journal on Mathematical Analysis, 32(6):1171{1197, 2001.

This functional is a generalization of both the Mumford-Shah [2] and the Blake-Zisserman [3] models.

[2] D. Mumford and J. Shah. Optimal approximations by piecewise smooth functions and associated variational problems. Communications on pure and applied mathematics, 42(5):577{685, 1989.

[3] A. Blake and A. Zisserman. Visual reconstruction. MIT Press Series in Articial Intelligence. MIT Press, Cambridge, MA, 1987.

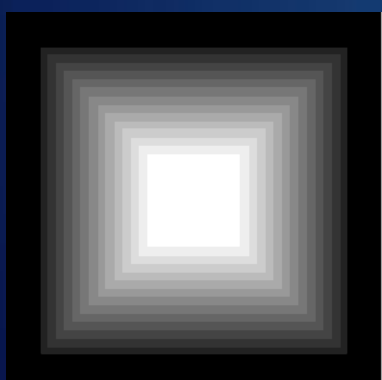
Functional model

$$
\begin{aligned}
F_\epsilon(s,z,u) = {} & \delta \int_\Omega z^2 |Hu|^2 \, dx + \xi_\epsilon \int_\Omega (s^2 + o_\epsilon) |\nabla u|^2 \, dx \\
& + (\alpha - \beta) \int_\Omega \epsilon |\nabla s|^2 + \frac{(s-1)^2}{4\epsilon} \, dx \\
& + \beta \int_\Omega \epsilon |\nabla z|^2 + \frac{(z-1)^2}{4\epsilon} \, dx \\
& + \mu \int_\Omega |u - g|^2 \, dx
\end{aligned}
$$

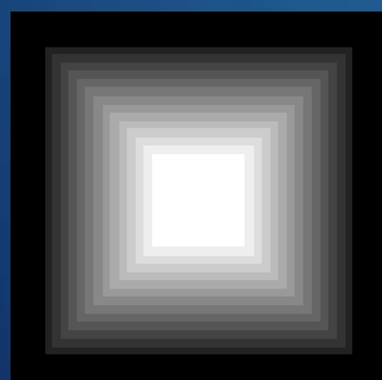
u is close to g and piecewise smooth

$s = 1$ almost everywhere
$s = 0$ for high norm $|\nabla u|^2$
$|\nabla s|^2$ avoids big oscill. of s

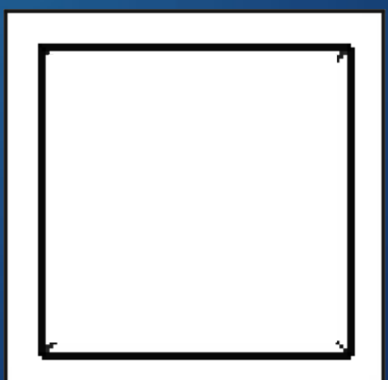
z= 1 almost everywhere
z= 0 for high norm $|Hu|^2$
$|\nabla z|^2$ avoids big oscill. of z



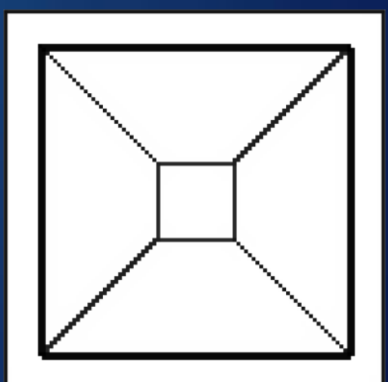
g
noisy grayscale image with 1st and 2nd order geometrical features



u
piecewise linear approximation of g



s
edge map (function discontinuity)



z
edge+crease map (gradient discontinuity)

Proposed algorithm for minimization

- Gauss-Seidel approach to minimization is inefficient

$$\begin{cases} s^{k+1} \leftarrow A_s^k s = b_s \\ z^{k+1} \leftarrow A_z^k z = b_z \\ u^{k+1} \leftarrow A_u^k u = b_u \end{cases}$$

- We proposed an inexact approach based on block coordinate descent algorithm (BCDA). For any iteration k and for any $\mathrm{v} = s, z, \mathrm{u}$ do:
  - Compute search directions: d_v^k (shallow sol. of linear system);
  - Compute optimal step-length: $\alpha_v^k = \frac{-(A_v^k v^k - b_v)\, d_v^k}{{d_v^k}^T A_v^k d_v^k}$;
  - Update value: $v^{k+1} = v^k + \alpha_v^k d_v^k$; $k = k + 1$.

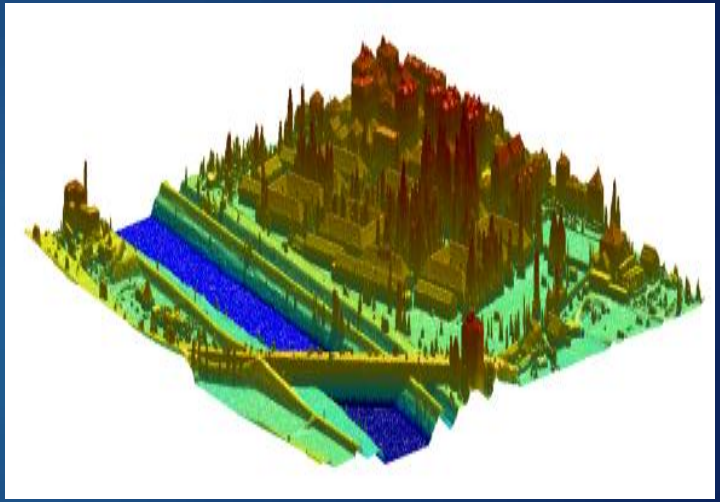
until a convergence condition is satisfied.

M. Zanetti, V. Ruggiero, M. Miranda Jr., "Numerical minimization of a second-order functional for image segmentation," *Communications in Nonlinear Science and Numerical Simulation,* Vol. 36, pp. 528-548, 2016.

Experimental results: computational performance

Datasets:

airport
aerial image
1024 x 1024 pixels



barracks
digital surface model (sp. res. 1mt)
600 x 600 pixels

publicly available at: http://sipi.usc.edu/database/database.php?volume=misc#top .

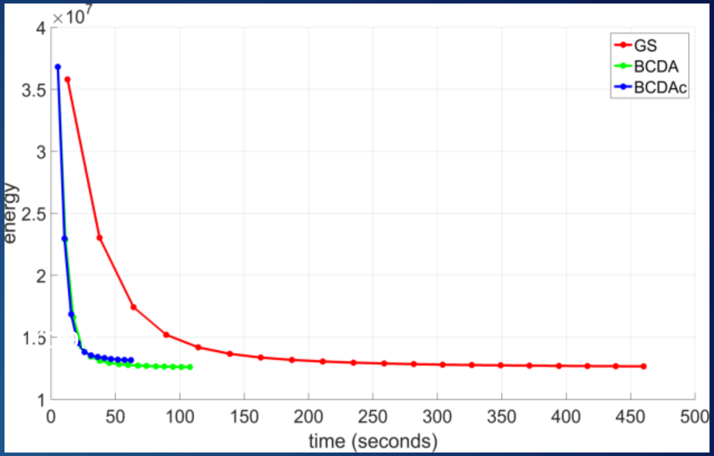
downloadable at http://www.territorio.provincia.tn.it/portal/server.pt/community/lidar/847/lidar/23954.

Experimental results: computational performance

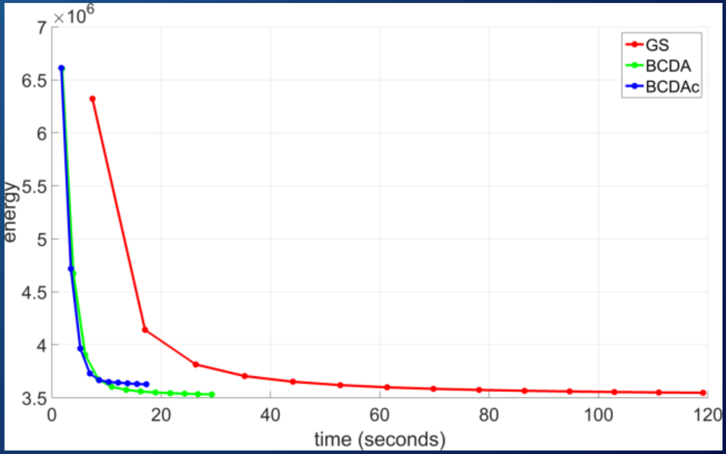
Test:

The proposed BCDA method is compared to GS in terms of computational performance.

dataset	method	k	inner iter. (d_s, d_z, d_u)	time (s)
airport	GS	20	51-55-4937	460.1
	BCDA	16	16-16-493	107.9
	BCDAc	12	12-12-72	62.1
barracks	GS	14	31-39-3906	119.1
	BCDA	12	12-12-463	29.3
	BCDAc	10	10-10-69	17.3



Execution time vs energy value: **airport** dataset



Execution time vs energy value: **barracks** dataset

Experimental results: image restoration

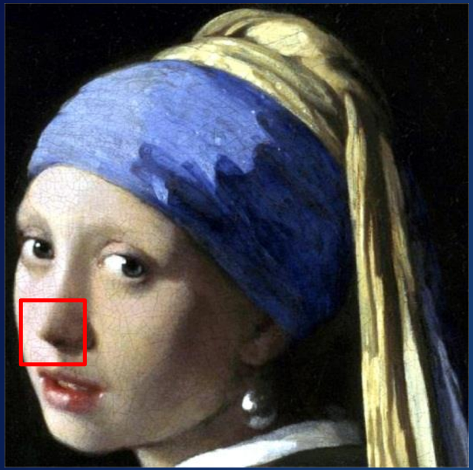
Task:
Restoration of old painting degraded by the *craquelure* ageing effect.

Dataset:
The “Girl with a pearl earring” by Johannes Vermeer.

Color image at 8-bits per band.
Size: 600 x 600.

M. Zanetti, L. Bruzzone, “Piecewise linear approximation of vector-valued images and curves via 2nd-order variational model,” *IEEE Transactions on Image Processing*, to appear, 2017

Experimental results: image restoration



Original image

Approx. via 1st order model (Mumford-Shah)

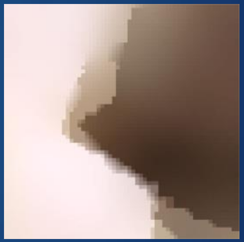
Approx. via mixed model

Proposed approx. via 2nd order model (Blake-Zisserman)

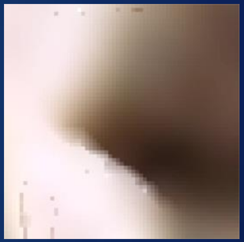
Particulars of the red squared area

Original

Mumford-Shah



Mixed

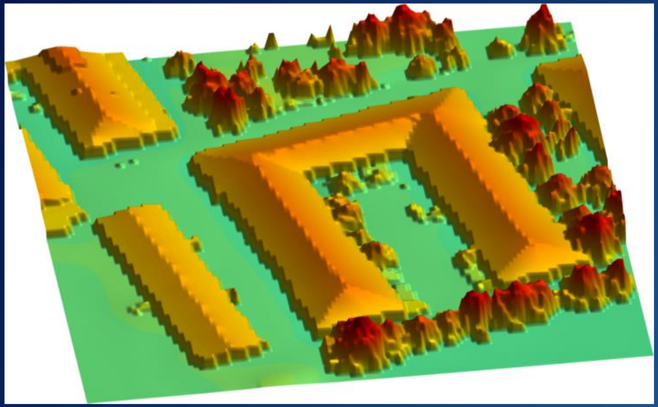


Blake-Zisseramn

The 1st –order penalization introduces over-segmentation.

The pure 2nd -order penalization returns a more natural solution.

Experimental results: curve approximation



Digital surface model
at spatial resolution 1m.

The subject is a polygonal
building (a barrack).

Discrete curve representing
the building shape.

Obtained by proper
processing of the DSM.

Task:
Recovering polygonal shapes from discrete points.

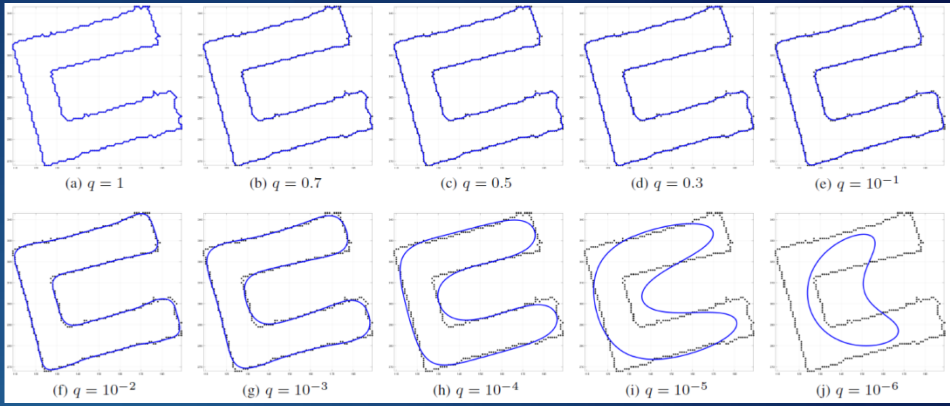
Data:
Discrete building boundaries extracted from DSMs.

Objective:
Emphasize the capability of the BZ model of providing discontinuous solutions.

Experimental results: curve approximation

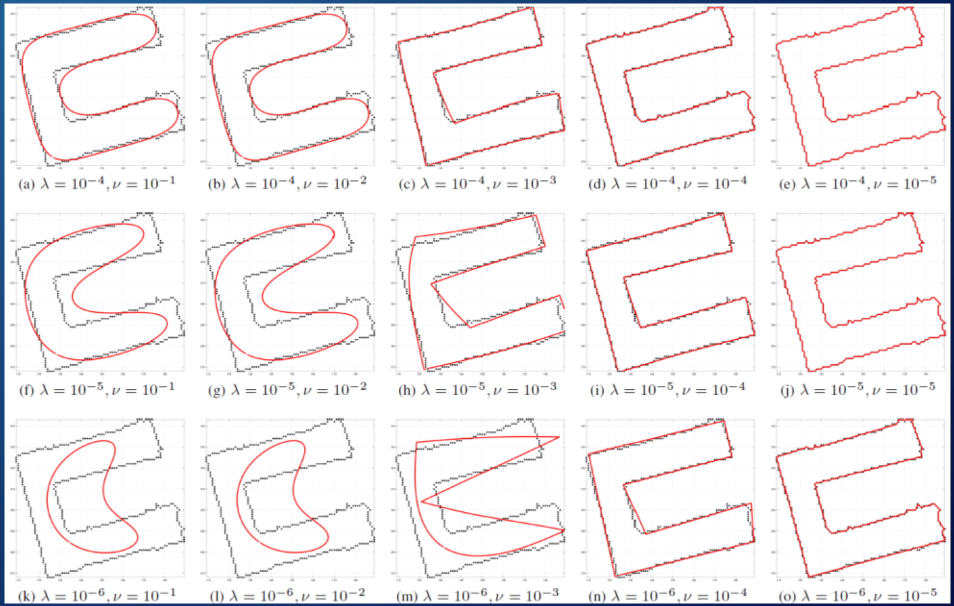
Smoothing cubic splines

$$G(u) = (1-q)\int_T u''^2 dt + q\int_T |u-g|^2 dt$$



1-D Blake-Zisserman model

$$F(u) = \int_T u''^2 dt + \lambda \int_T |u-g|^2 dt + \nu\#(S_{u'})$$



Statistical methods for change detection in multispectral images

Motivations and challenges

Motivations

- Many open-access databases of data (e.g., Landsat, Sentinel).
- Multitemporal multispectral images: study of the global change, environmental monitoring, etc.

Challenges

- Automatic, robust/effective procedures needed to handle such amount of data.
- Mathematical models are needed to explain how to extract information.
- Standard approaches to change detection (effective on previous generation of images) do not show the same accuracy on last generation images .

Multispectral images

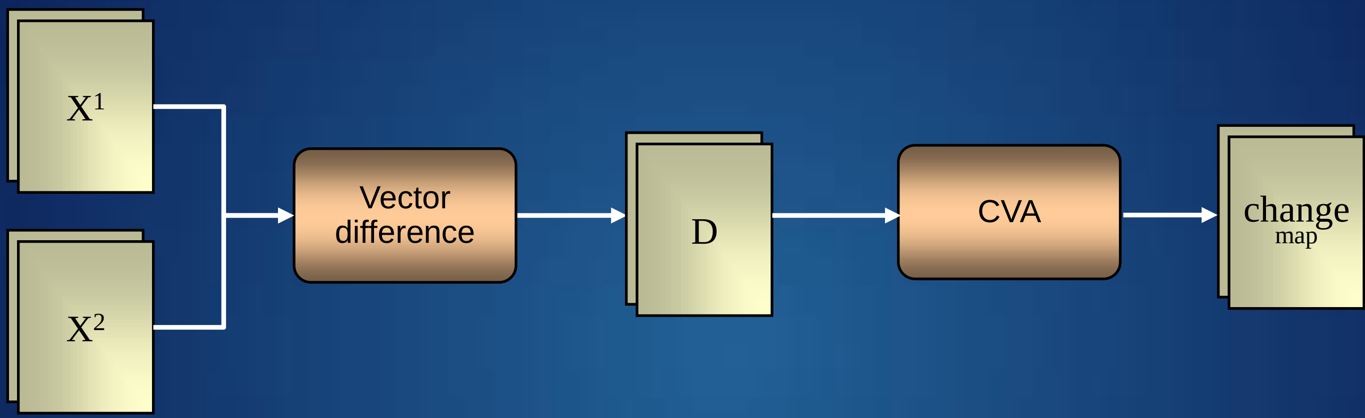
- Multispectral (MS) images are characterized by many spectral bands (from 5 to 13).
- Pixel value is a N-dimensional vector containing information about the spectral signature of the reflecting object.
- Multitemporal analysis of MS images allows to identify changes in the measured spectral signature.

Table: Relevant spaceborne multispectral sensors operating nowadays.

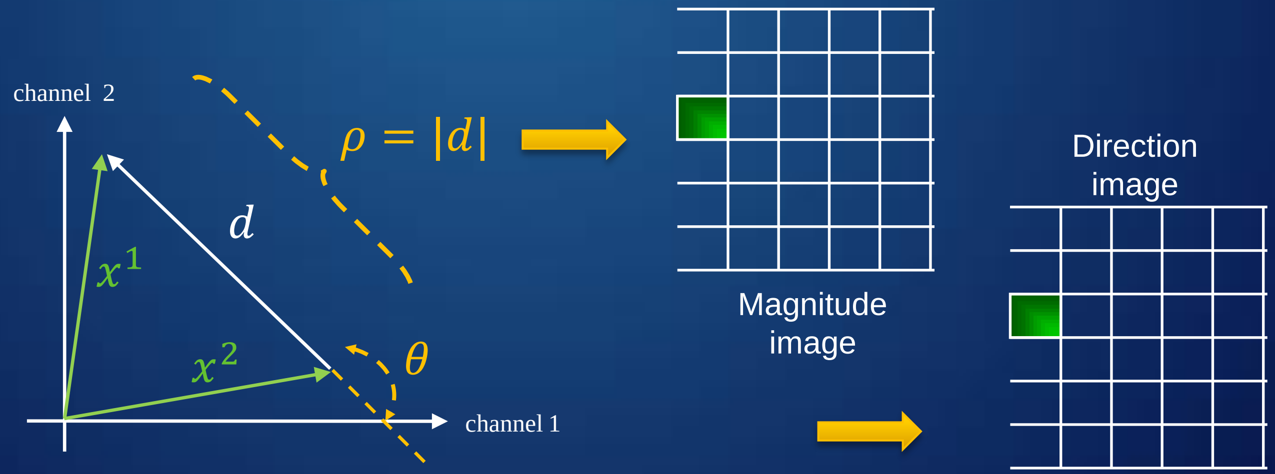
Satellite (sensor)	Geometrical resolution (m)	Swath (km)	Spectral bands (intervals)	Quant. (bits)	Revisit time (days)
Landsat 8 (OLI, TIRS)	15,30,100	183	11 (VNIR, SWIR, TIR, Coastal)	11	16
SPOT 6 – 7	1.5 (Pan), 6	60	5 (Pan, VNIR)	12	1 to 3
Sentinel 2 (MSI)	10,20,60	290	13 (VNIR, SWIR, RedEdge)	16	5

Change Vector Analysis (CVA)

We consider 2 spectral channels for each date (not a technical restriction).



Pixelwise representation of the polar decomposition in CVA



Statistical models and binary decision

- The distribution of $\rho = |d|$ is a mixture representing two classes

$$\mathrm{p}(\rho) = \mathrm{p}(\omega_n)\mathrm{p}(\rho|\omega_n) + \mathrm{p}(\omega_c)\mathrm{p}(\rho|\omega_c)$$

  where: ω_n unchanged pixels, and ω_c changed pixels.

- To infer the class given a value ρ, we need to estimate distribution parameters. This can be done via Expectation-Maximization (EM) algorithm.

- Binary decision based on Bayes rule (thresholding).

- SoA statistical models:
  - Standard approach [1] empirically assumes that classes are Gaussian.
  - More advanced model [2] derives the distribution (under certain assumptions) as a Rayleigh-Rice mixture.

[1] L. Bruzzone and D. F. Prieto. Automatic analysis of the dierence image for unsupervised change detection. IEEE Transactions on Geoscience and Remote Sensing, 38(3):1171{1182, 2000.
[2] F. Bovolo and L. Bruzzone. A theoretical framework for unsupervised change detection based on change vector analysis in the polar domain. IEEE Transactions on Geoscience and Remote Sensing, 45(1):218{236, 2007.

Proposed EM algorithm

- We devised a parameter estimation method for the Rayleigh-Rice mixture through an iterative formulation of the EM algorithm.
- Our approach is only based on independent parameters updating.
- The validity of the algorithm is very general.
- The method is fully unsupervised.

$$\alpha^{k+1} = \frac{1}{N} \sum_{x \in |X^D|} \mathrm{p}(\omega_n \mid x, \Psi^k)$$

$$(b^2)^{k+1} = \frac{\sum_x \mathrm{p}(\omega_n \mid x, \Psi^k)\, x^2}{2 \sum_x \mathrm{p}(\omega_n \mid x, \Psi^k)}$$

$$\nu^{k+1} = \frac{\sum_x \mathrm{p}(\omega_c \mid x, \Psi^k) \frac{\mathrm{I}_1\left(\frac{x\nu^k}{(\sigma^k)^2}\right)}{\mathrm{I}_0\left(\frac{x\nu^k}{(\sigma^k)^2}\right)} x}{\sum_x \mathrm{p}(\omega_c \mid x, \Psi^k)}$$

$$(\sigma^2)^{k+1} = \frac{\sum_x \mathrm{p}(\omega_c \mid x, \Psi^k) \left[x^2 + \left(\nu^k\right)^2 - 2x\nu^k \frac{\mathrm{I}_1\left(\frac{x\nu^k}{(\sigma^k)^2}\right)}{\mathrm{I}_0\left(\frac{x\nu^k}{(\sigma^k)^2}\right)} x \right]}{2 \sum_x \mathrm{p}(\omega_c \mid x, \Psi^k)}$$

Zanetti, M. and Bovolo, F. and Bruzzone, L. “Rayleigh-Rice mixture parameter estimation via EM algorithm for change detection in multispectral images”, IEEE Transactions on Image Processing, 24 (12), pp. 5004-5016, 2015.

Experimental results: dataset

Dataset A: Sensor: TM sensor – Landsat-5. Spatial resolution: 30 mt. Area: Lake Mulargia (Sardinia, Italy). Image size: 412 x 300. Change: lake enlargement

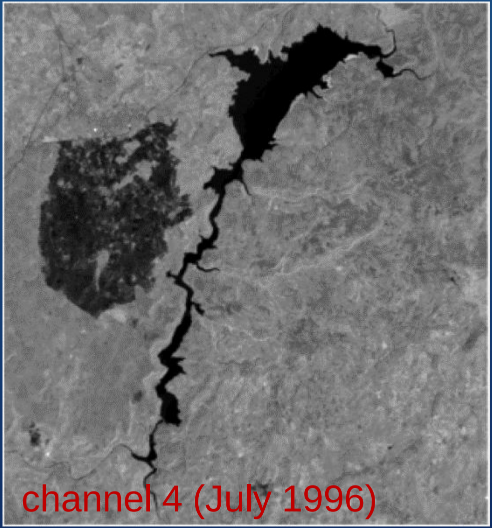

channel 4 (Sept. 1995)

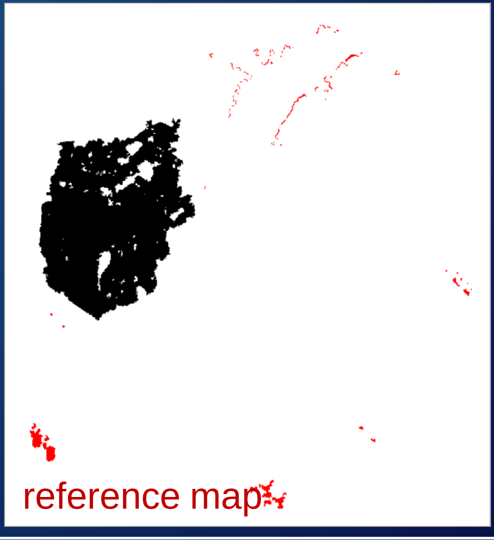

channel 4 (July 1996)


reference map

Dataset B: Sensor: OLI sensor - Landsat-8. Spatial resolution: 30 mt. Area: Lake Omodeo (Sardinia, Italy). Image size: 700 x 650. Change: fire.


channel 4 (Sept. 1995)

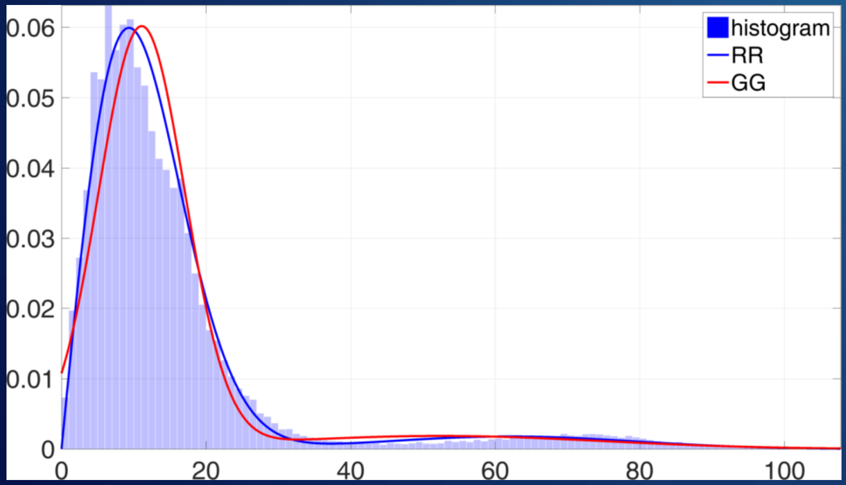

channel 4 (July 1996)


reference map

Exprerimental results: fitting performance

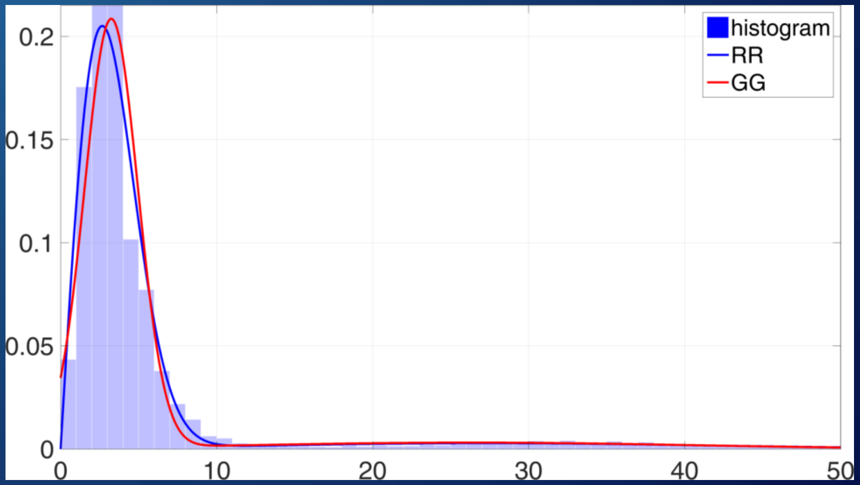
Dataset A

Mixture	X_P^2	KS
proposed Rayleigh-Rice	0,0136	0,0362
standard Gaussian	0,0420	0,0836



Dataset B

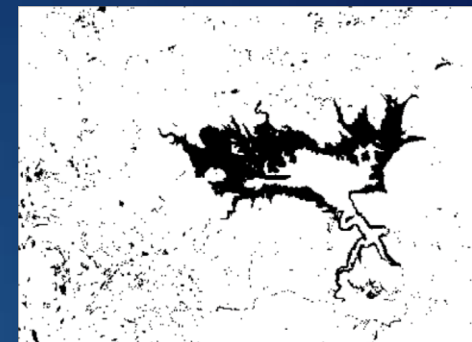
Mixture	X_P^2	KS
proposed Rayleigh-Rice	0,0215	0,0400
standard Gaussian	0,0500	0,0778



Experimental results: CD performance

optimal (OE = 0,62%)

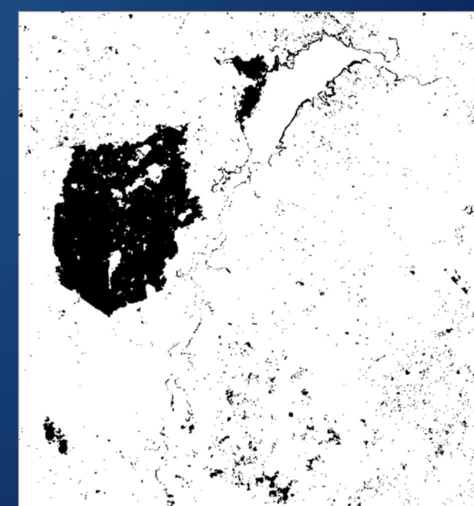
Rayleigh-Rice (OE = 1,47%)



Gaussian-mixture (OE = 3,22%)

optimal (OE = 1,02%)

Rayleigh-Rice (OE = 1,93%)



Gaussian-mixture (OE = 2,99%)

Future activities

Future activities

- Automatic detection of geometric features from objects represented by unstructured 3D point clouds (raw LiDAR points, TomoSAR). Requires proper handling of 2^{nd} –order differential operators via Finite Element Method.

- Provide mathematical quantification of the error in change detection methods based on the magnitude information.
  - Low discriminability when many class members are assumed;
  - Provide a lower bound in the selection of the number of bands for the calculation of the magnitude.

- Multiple change detection. It requires reduction of class-variance. This task can accomplished via variational methods. Preliminary results are very encouraging.