SOUTENANCE DE THÈSE

Image denoising beyond additive Gaussian noise

Patch-based estimators and their application to SAR imagery

Débruitage d'images au-delà du bruit additif gaussien

Estimateurs à patchs et leur application à l'imagerie SAR

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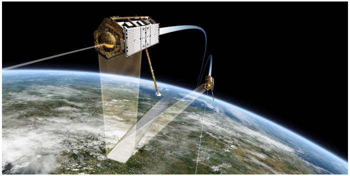
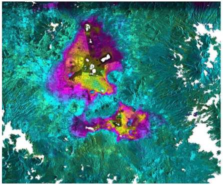
Synthetic aperture radar (SAR) imagery

- Ever-growing number of SAR sensors
- Need for automatic processing:
  - 3D reconstruction
  - Classification
  - Earth monitoring
- Limitation: **images are extremely noisy**



(a) TanDEM-X (©2010 DLR)

(b) Glacier melting

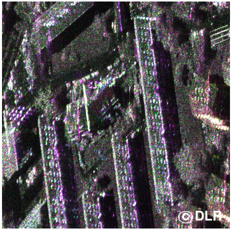


(c) Subsidence in Mexico

(d) 3D reconstruction of an urban area

Synthetic aperture radar (SAR) imagery

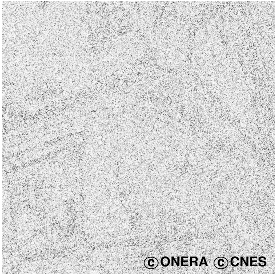
- Active sensor: emits a wave and measures its echoes
- SAR: A complex-valued image
  amplitude → **roughness**, . . .
- Interferometry: 2 SAR images
  phase difference → **elevation**, . . .
- Polarimetry: 3 SAR images
  complex correlation → **geophysical properties**



(a) Polarimetry

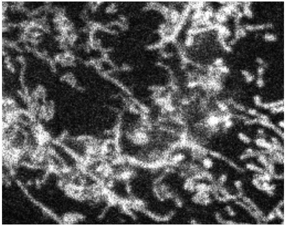
(b) Amplitude

(c) Phase

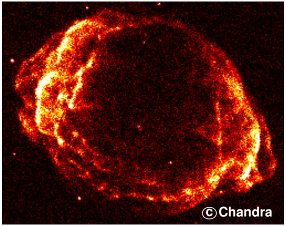


(d) Coherence

Different manifestations of noise in imagery

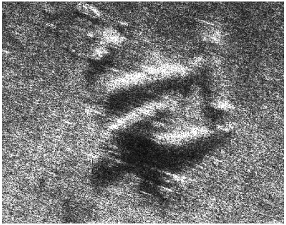


(a) Mitochondrion in microscopy

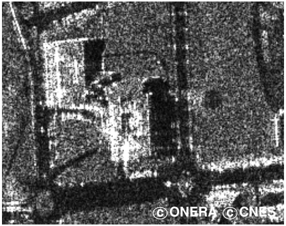


(b) Supernova in X-ray imagery

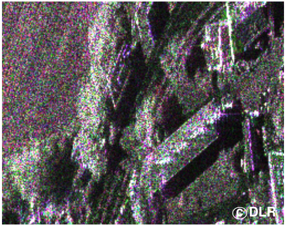
(c) Fetus using ultrasound imagery



(d) Plane wreckage in SONAR imagery



(e) Urban area using SAR imagery



(f) Polarimetric SAR imagery

Requirements for SAR image denoising methods

- Adapt to **non-Gaussian noise distributions**

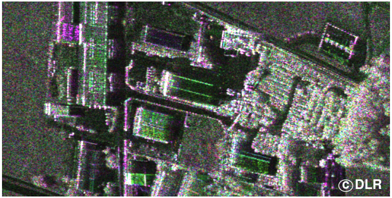
(a) Gaussian noise

(b) BM3D filter

(a) Signal-dependent noise

(b) BM3D filter

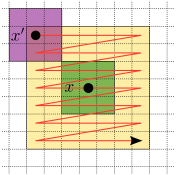
- Adapt to **complex-valued multivariate data**

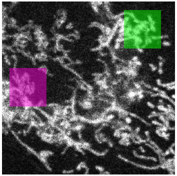


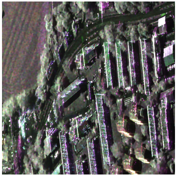
- Process large images in **reasonable time**
- Control **smoothing strength (noise reduction vs resolution loss tradeoff)**

Outline

1. Positioning and the limits of patch-based filtering
2. A new similarity criterion to compare noisy patches
3. Proposed methodology for non-Gaussian noise filtering
   - Iterative non-local filtering scheme
   - Automatic setting of the denoising parameters
4. Conclusion and perspectives







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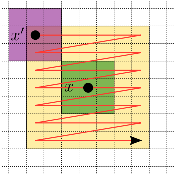
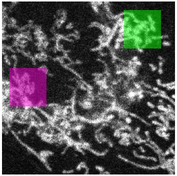
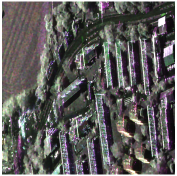






State-of-the-art of denoising approaches

BLS-GSM

[Donoho and Johnstone, 1994]
[Portilla et al., 2003]

Sparcifying transforms (wavelets, dictionnaries)

[Geman and Geman, 1984]
[Perona and Malik, 1990]
[Rudin et al., 1992]

Variational / Markovian Approaches

Anisotopic Diffusion

[Aharon et al., 2006]
[Dabov et al., 2007]
[Mairal et al., 2009]
[Chatterjee et al., 2011]

Sparsity and non-locality

Non-local Total Variation

[Gilboa and Osher, 2007]
[Peyré et al., 2008]

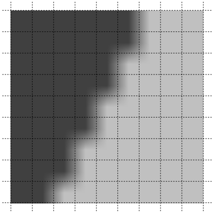
BM3D

Patch-based methods

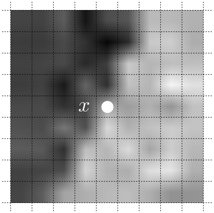
[Buades et al., 2005]
[Awate and Whitaker, 2006]

Non-local means

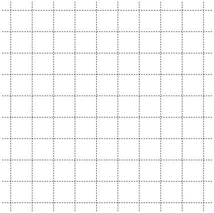
Patch-based approaches perform best (see review of [Katkovnik et al., 2010])



Unknown noise-free image u



Input noisy image v

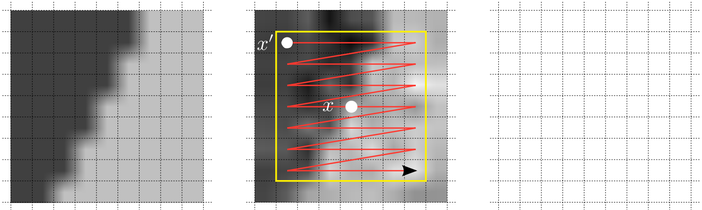


Output denoised image $\hat{u}$

General idea

- Goal: estimate the image u from the noisy image v
- Choose a pixel x to denoise
  - Inspect the pixels x' around the pixel of interest x
  - Select the suitable candidates x'
  - Average their values and update the value of x
- Repeat for all pixel x

Selection-based filtering



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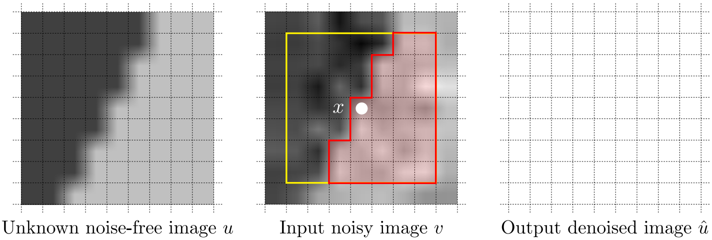

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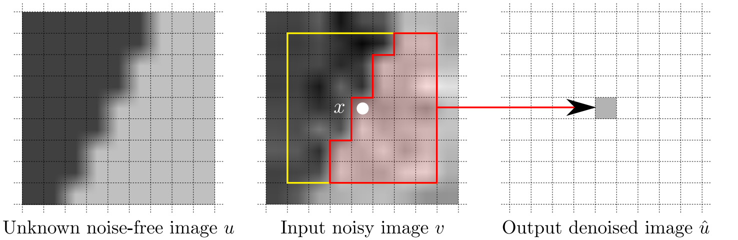

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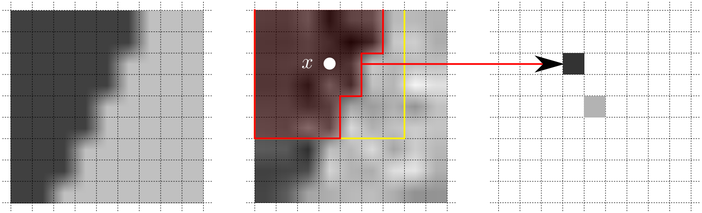

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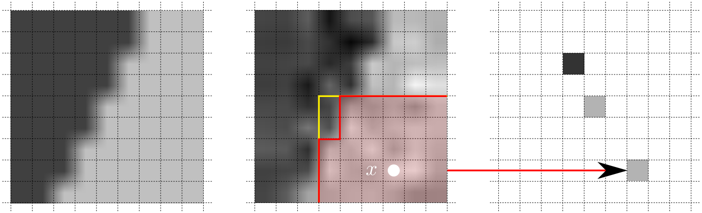

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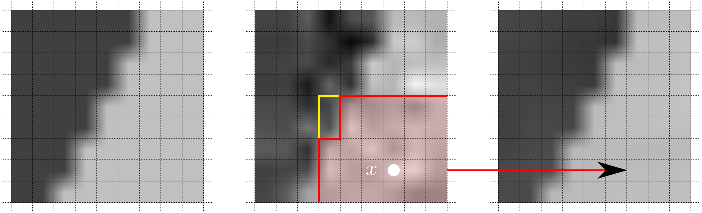

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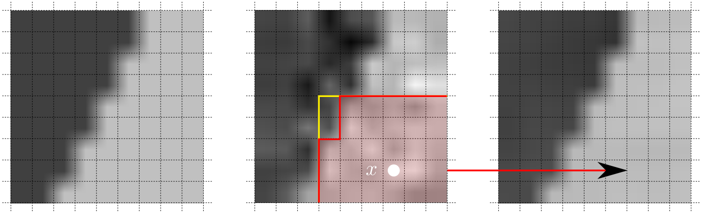

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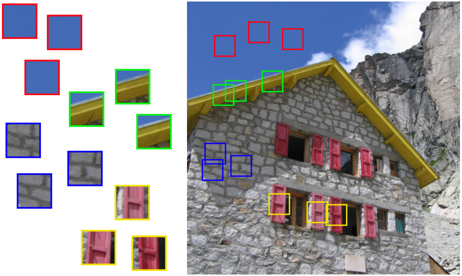
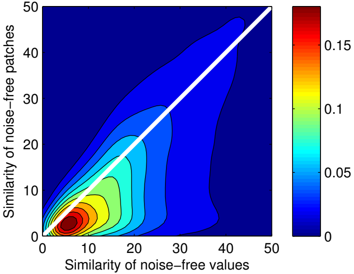
How to choose suitable pixels x' to combine?

Non-local approach [Buades et al., 2005]

- Local filters: select neighborhood pixels
- Non-local filters: select pixels being in a similar context





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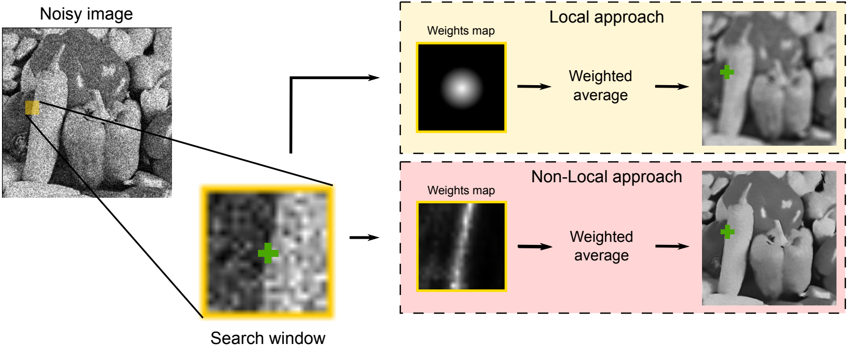

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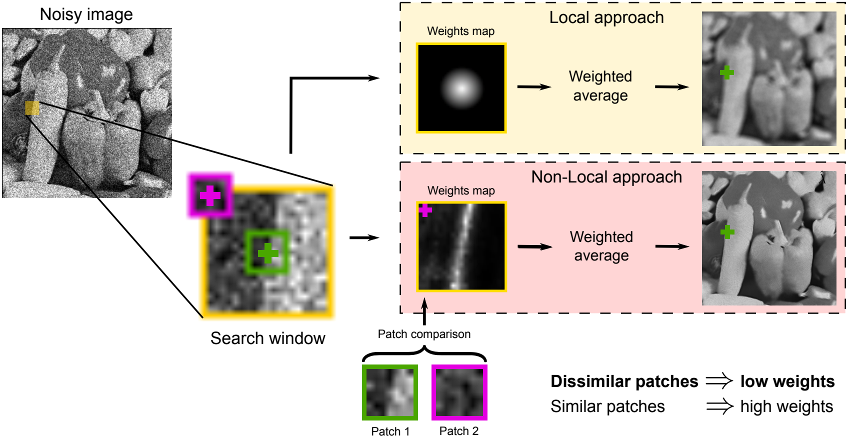

Dissimilar patches $\Rightarrow$ **low weights**
Similar patches $\Rightarrow$ high weights

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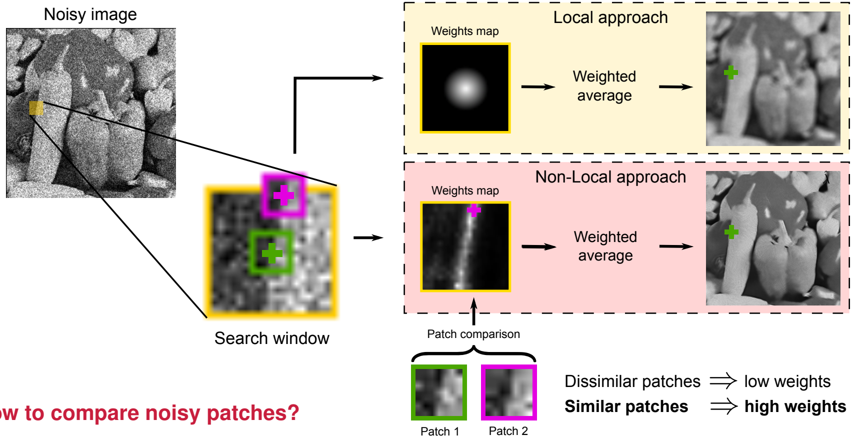
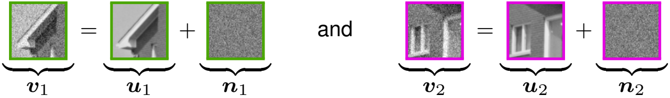


How to compare noisy patches?

Patch-similarity from the Euclidean distance

How to compare noisy patches?

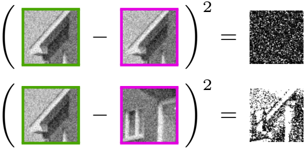
- Assume noise is additive and Gaussian such that:



- [Buades et al., 2005] suggest using the Euclidean distance:

when $\boldsymbol{u}_1 = \boldsymbol{u}_2$: … is low $\Rightarrow$ decide “similar”

when $\boldsymbol{u}_1 \neq \boldsymbol{u}_2$: … is high $\Rightarrow$ decide “dissimilar”



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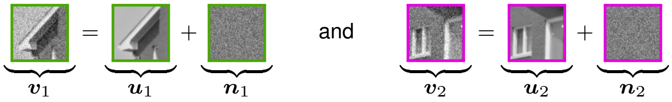

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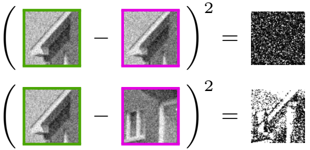

when $u_1 = u_2$: is low $\Rightarrow$ decide “similar”

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What about non-Gaussian noise?

Limits of the Euclidean distance

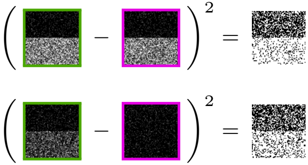
Beyond the Gaussian noise assumption

- Noise can be non-additive and/or non-Gaussian, e.g., for Poisson noise:

- The Euclidean distance **is no longer discriminant**:

when $\boldsymbol{u}_1 = \boldsymbol{u}_2$:

when $\boldsymbol{u}_1 \neq \boldsymbol{u}_2$:



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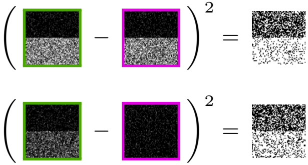
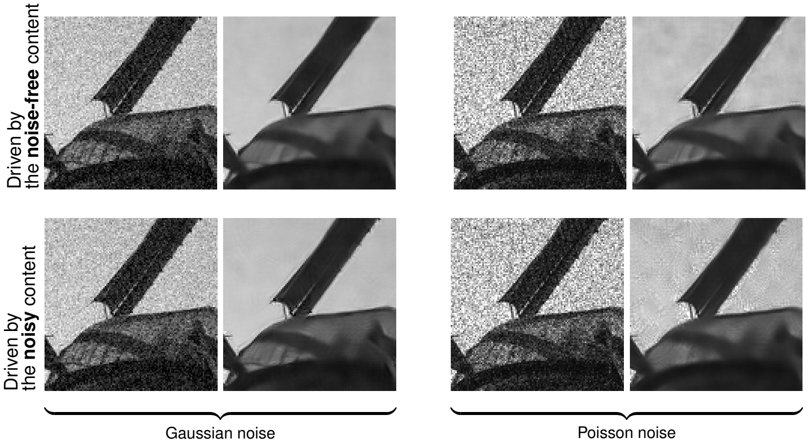


Consequence?

Beyond the Gaussian noise assumption – Illustration



When comparing noisy patches, one should take into account the noise distribution.

Some issues

Signal adaptation

- Tuning of global parameters (e.g., smoothing strength)
- Local adaptation (e.g., size and shape of patches)

Noise adaptation

- Use of pre-filtered data
- Patch comparison
- Estimator

Improvements

- Acceleration
- Filtering in patch space

Some issues

Signal adaptation

- Tuning of global parameters (e.g., smoothing strength)

  [Doré and Cheriet, 2009, Van De Ville and Kocher, 2009, Duval et al., 2011]

- Local adaptation (e.g., size and shape of patches)

  [Kervrann and Boulanger, 2006, Dabov et al., 2009]

Noise adaptation

- Use of pre-filtered data

  [Polzehl and Spokoiny, 2006, Brox et al., 2008, Azzabou et al., 2007, Dabov et al., 2007, Tasdizen, 2008, Goossens et al., 2008, Van De Ville and Kocher, 2011, Louchet and Moisan, 2011]

- Patch comparison

  [Polzehl and Spokoiny, 2006, Vasile et al., 2006, Alter et al., 2006, Matsushita and Lin, 2007, Teuber and Lang, 2011]

- Estimator [Polzehl and Spokoiny, 2006, He and Greenshields, 2009]

Improvements

- Acceleration

  [Mahmoudi and Sapiro, 2005, Coupe et al., 2006, Wang et al., 2006, Bilcu and Vehvilainen, 2007, Darbon et al., 2008, Pang et al., 2009]

- Filtering in patch space

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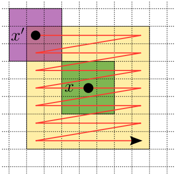
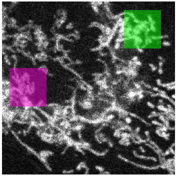
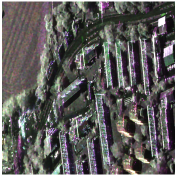
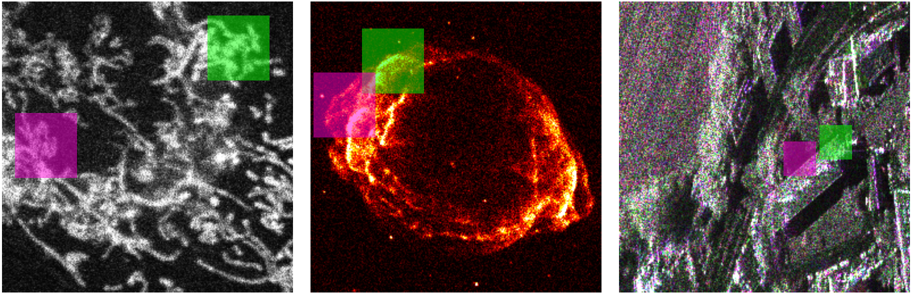


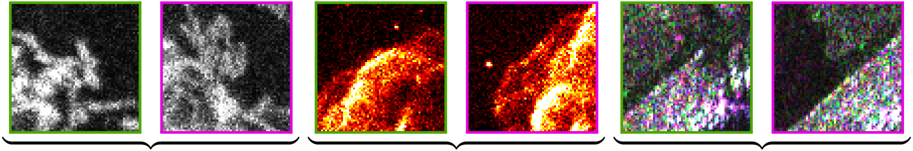




Motivation



(a) Microscopy (b) Astronomy (c) SAR polarimetry



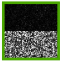
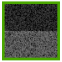
? ? ?

How to take into account the noise model?

Similarity through variance stabilization

Variance stabilization approach

- Use an application $\boldsymbol{s}$ which stabilizes the variance for a specific noise model
- Evaluate the Euclidean distance between the transformed patches:

$\Big(\boldsymbol{s}\Big($  $\Big) - \boldsymbol{s}\Big($  $\Big)\Big)^2 = \Big($  $-$  $\Big)^2,$

Example

- Gamma noise (multiplicative) and the homomorphic approach:

$$\boldsymbol{s}(V) = \log V$$

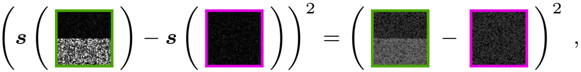
- Poisson noise and the Anscombe transform:

$$\boldsymbol{s}(V) = 2\sqrt{V + \frac{3}{8}}$$

Similarity through variance stabilization

Variance stabilization approach

- Use an application $\boldsymbol{s}$ which stabilizes the variance for a specific noise model
- Evaluate the Euclidean distance between the transformed patches:



Example

- Gamma noise (multiplicative) and the homomorphic approach:

$$\boldsymbol{s}(V) = \log V$$

- Poisson noise and the Anscombe transform:

$$\boldsymbol{s}(V) = 2\sqrt{V + \frac{3}{8}}$$

Limits

- Only heuristic
- No optimality results
- Does not take into account the statistics of the transformed data
- Does not apply to all noise distributions
  - e.g., multi-modal distributions like interferometric phase distribution

(a) Image with impulse noise

(b) SAR interferometric phase

Similarity in the light of detection theory

- Similarity can be defined as an hypothesis test (i.e., a parameter test):

$$\mathcal{H}_0 : \boldsymbol{u}_1 = \boldsymbol{u}_2 \equiv \boldsymbol{u}_{12} \qquad \text{(null hypothesis)}$$
$$\mathcal{H}_1 : \boldsymbol{u}_1 \neq \boldsymbol{u}_2 \qquad \text{(alternative hypothesis)}$$

- Its performance can be measured as:

$$P_{FA} = \mathbb{P}(\text{decide “dissimilar”} \mid \boldsymbol{u}_{12}, \mathcal{H}_0) \qquad \text{(false-alarm rate)}$$
$$P_D = \mathbb{P}(\text{decide “dissimilar”} \mid \boldsymbol{u}_1, \boldsymbol{u}_2, \mathcal{H}_1) \qquad \text{(detection rate)}$$

- The likelihood ratio (LR) test minimizes P_D for any P_{FA}:

$$L(\boldsymbol{v}_1, \boldsymbol{v}_2) = \frac{p(\boldsymbol{v}_1, \boldsymbol{v}_2 \mid \boldsymbol{u}_{12}, \mathcal{H}_0)}{p(\boldsymbol{v}_1, \boldsymbol{v}_2 \mid \boldsymbol{u}_1, \boldsymbol{u}_2, \mathcal{H}_1)} \qquad \leftarrow \text{given by the noise distribution model}$$

$\rightarrow$ Problem: $\boldsymbol{u}_{12}$, $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$ are unknown

Similarity in a detection framework

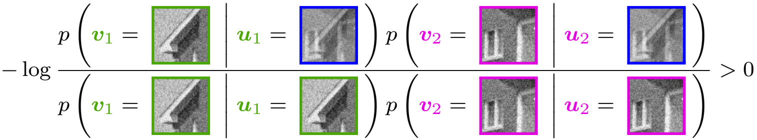
Generalized likelihood ratio (GLR)

- Replace $\boldsymbol{u}_{12}$, $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$ with maximum likelihood estimates (MLE)
- Define the (negative log) **generalized likelihood ratio** test:

$$
\begin{aligned}
-\log GLR(\boldsymbol{v}_1, \boldsymbol{v}_2) &= -\log \frac{\sup_{\boldsymbol{t}} p(\boldsymbol{v}_1, \boldsymbol{v}_2 \mid \boldsymbol{u}_{12} = \boldsymbol{t}, \mathcal{H}_0)}{\sup_{\boldsymbol{t}_1, \boldsymbol{t}_2} p(\boldsymbol{v}_1, \boldsymbol{v}_2 \mid \boldsymbol{u}_1 = \boldsymbol{t}_1, \boldsymbol{u}_2 = \boldsymbol{t}_2, \mathcal{H}_1)} \\
&= -\log \frac{p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \hat{\boldsymbol{t}}_{12})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \hat{\boldsymbol{t}}_{12})}{p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \hat{\boldsymbol{t}}_1)\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \hat{\boldsymbol{t}}_2)}
\end{aligned}
$$

Maximal self similarity

- Assume $\boldsymbol{v}_1 \neq \boldsymbol{v}_2$, then:



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\begin{aligned}
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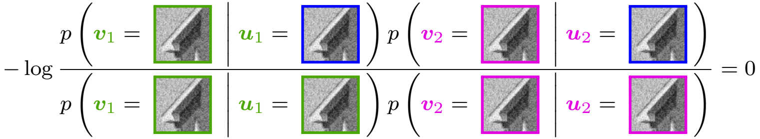
&= -\log \frac{p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \hat{\boldsymbol{t}}_{12})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \hat{\boldsymbol{t}}_{12})}{p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \hat{\boldsymbol{t}}_1)\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \hat{\boldsymbol{t}}_2)}
\end{aligned}
$$

Equal self similarity

- Assume $\boldsymbol{v}_1 = \boldsymbol{v}_2$, then:



- Other similarity criteria have been proposed:

Bayesian joint likelihood $\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})$ $\mathrm{d}\boldsymbol{t}$

[Deledalle et al., 2009b]

Similarity in a detection framework

- Other similarity criteria have been proposed:

Bayesian joint likelihood $$\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}$$

[Deledalle et al., 2009b]

[Yianilos, 1995, Matsushita and Lin, 2007]

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[Deledalle et al., 2009b]

[Yianilos, 1995, Matsushita and Lin, 2007]

Maximum joint likelihood $$\sup_{\boldsymbol{t}} p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})$$

[Alter et al., 2006]

Similarity in a detection framework

- Other similarity criteria have been proposed:

Bayesian joint likelihood

$$\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}$$

[Deledalle et al., 2009b]

[Yianilos, 1995, Matsushita and Lin, 2007]

Maximum joint likelihood

$$\sup_{\boldsymbol{t}} p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})$$

[Alter et al., 2006]

Bayesian likelihood ratio

$$\frac{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{u}_1 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t} \int p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_2 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}$$

[Minka, 1998, Minka, 2000]

Mutual information kernel

$$\frac{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}{\sqrt{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})^2\, p(\boldsymbol{u}_1 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t} \int p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})^2\, p(\boldsymbol{u}_2 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}}$$

[Seeger, 2002]

- Other similarity criteria have been proposed:

Bayesian joint likelihood

$$\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}$$

[Deledalle et al., 2009b]

[Yianilos, 1995, Matsushita and Lin, 2007]

Maximum joint likelihood

$$\sup_{\boldsymbol{t}} p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})$$

[Alter et al., 2006]

Bayesian likelihood ratio

$$\frac{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{u}_1 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t} \int p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_2 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}$$

[Minka, 1998, Minka, 2000]

Mutual information kernel

$$\frac{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})\, p(\boldsymbol{u}_{12} = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}{\sqrt{\int p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})^2\, p(\boldsymbol{u}_1 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t} \int p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})^2\, p(\boldsymbol{u}_2 = \boldsymbol{t})\, \mathrm{d}\boldsymbol{t}}}$$

[Seeger, 2002]

GLR

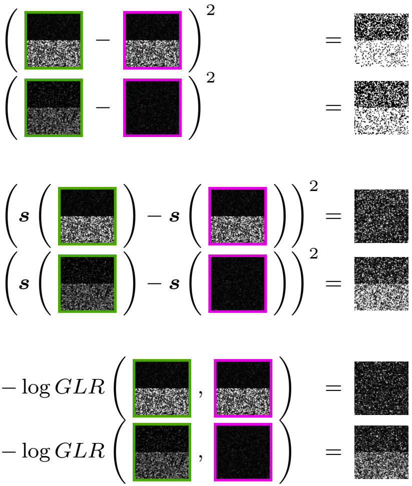
$$\frac{\sup_{\boldsymbol{t}} p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\, p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})}{\sup_{\boldsymbol{t}} p(\boldsymbol{v}_1 \mid \boldsymbol{u}_1 = \boldsymbol{t})\ \sup_{\boldsymbol{t}} p(\boldsymbol{v}_2 \mid \boldsymbol{u}_2 = \boldsymbol{t})}$$

Is GLR more discriminant?

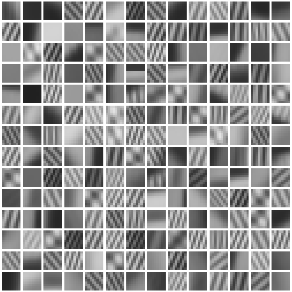
Euclidean distance
- when $\boldsymbol{u}_1 = \boldsymbol{u}_2$:
- when $\boldsymbol{u}_1 \neq \boldsymbol{u}_2$:

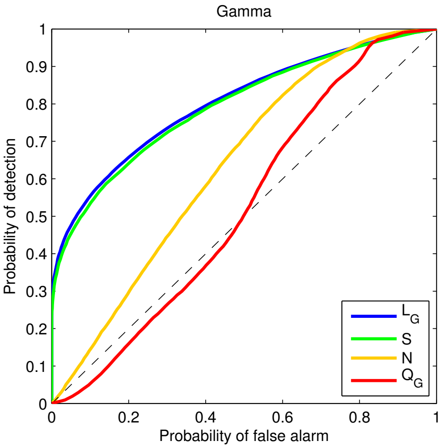
Variance stabilization
- when $\boldsymbol{u}_1 = \boldsymbol{u}_2$:
- when $\boldsymbol{u}_1 \neq \boldsymbol{u}_2$:

GLR
- when $\boldsymbol{u}_1 = \boldsymbol{u}_2$:
- when $\boldsymbol{u}_1 \neq \boldsymbol{u}_2$:



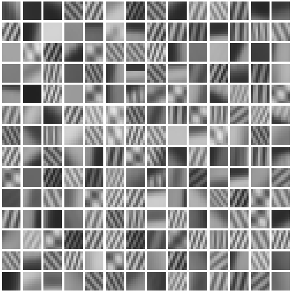
Evaluation of similarity criteria – Detection performance

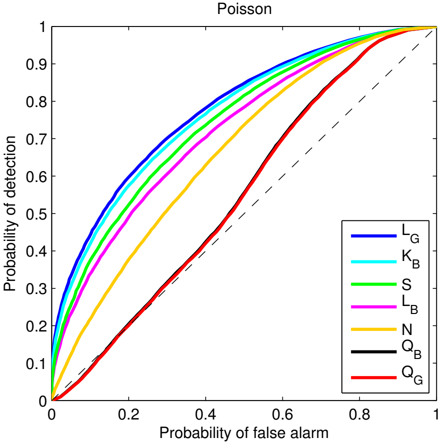




- Generalized likelihood ratio
- Variance stabilization
- Euclidean distance
- Maximum joint likelihood [Alter et al., 2006]
- Mutual information kernel [Seeger, 2002]
- Bayesian likelihood ratio [Minka, 1998, Minka, 2000]
- Bayesian joint likelihood [Yianilos, 1995, Matsushita and Lin, 2007]

Evaluation of similarity criteria – Detection performance





- Generalized likelihood ratio
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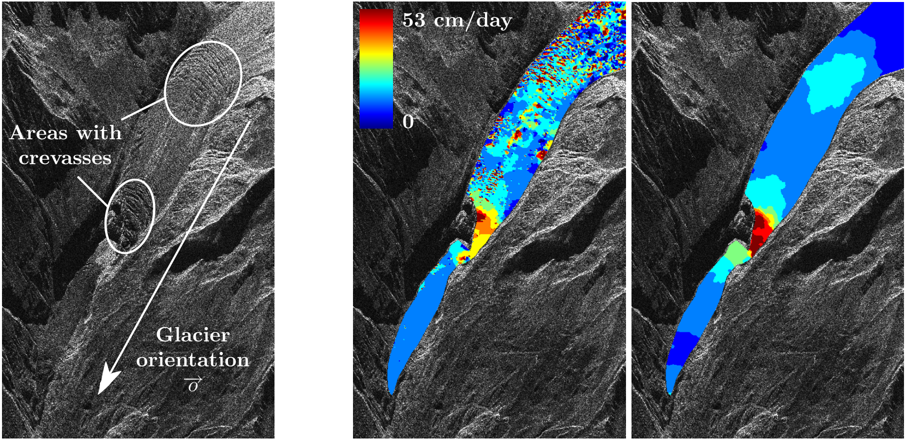
Evaluation of similarity criteria – Glacier monitoring



(a) Noisy image (b) Euclidean distance (c) Generalized lik. ratio

Figure: Glacier of Argentière. With GLR, the estimated speeds matches with the ground truth: average over the surface of 12.27 cm/day and a maximum of 41.12 cm/day in the areas with crevasses.

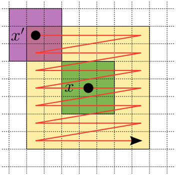
Conclusion

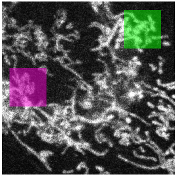
- Similarity between noisy patches expressed as an **hypothesis test**
- Among 7 similarity criteria, **GLR provides the best performance**
- Apply even when variance stabilization is not possible
- **Easy to derive** as long as the MLE is known in closed form
- Offers **good theoretical properties** (cf. manuscript):

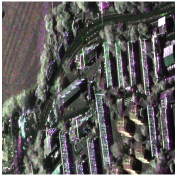
	Max. self sim.	Eq. self sim.	Id. of indiscernible	Invariance	Asym. CFAR	Asym. UMPI
Euclidean kernel	✓	✓	✓	×	×	×
Stabilization transform						×
Bayesian joint lik.	×	×	×	×	×	×
Maximum joint lik.	×	×	×	×	×	×
Bayesian lik. ratio	×	×	×	✓	×	×
Mutual info. kernel	✓	✓	✓	✓	×	×
GLR	✓	✓	✓	✓	✓	✓

[Deledalle et al., 2011] Deledalle, C., Tupin, F., Denis, L. (2011).
Patch similarity under non Gaussian noise.
IEEE ICIP, September 2011

Outline







Outline

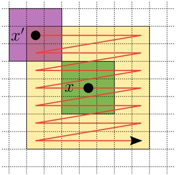
1 Positioning and the limits of patch-based filtering

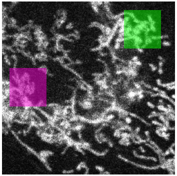
2 A new similarity criterion to compare noisy patches

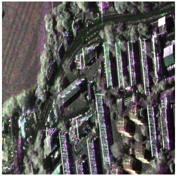
3 Proposed methodology for non-Gaussian noise filtering

- Iterative non-local filtering scheme
- Automatic setting of the denoising parameters

4 Conclusion and perspectives







Patch comparison: how to replace the squared differences?

- Weights have to select pixels with **close true values**
- Compare patches ⇔ test the hypotheses that noise-free patches have:

$\mathcal{H}_0$: same true values ,
$\mathcal{H}_1$: independent true values .

$$\frac{\mathbb{P}(\mathcal{H}_0 | \blacksquare_1, \blacksquare_2)}{\mathbb{P}(\mathcal{H}_1 | \blacksquare_1, \blacksquare_2)} = \frac{p(\blacksquare_1, \blacksquare_2 | \mathcal{H}_0)}{p(\blacksquare_1, \blacksquare_2 | \mathcal{H}_1)} \times \frac{\mathbb{P}(\mathcal{H}_0)}{\mathbb{P}(\mathcal{H}_1)}$$

Weight refinement in non-local filtering

Patch comparison: how to replace the squared differences?

- Weights have to select pixels with **close true values**
- Compare patches $\Leftrightarrow$ test the hypotheses that noise-free patches have:

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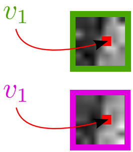
$$\frac{\mathbb{P}(\mathcal{H}_0 \,|\, \square_1, \square_2)}{\mathbb{P}(\mathcal{H}_1 \,|\, \square_1, \square_2)} = \boxed{\frac{p(\square_1, \square_2 \,|\mathcal{H}_0)}{p(\square_1, \square_2 \,|\mathcal{H}_1)}} \times \frac{\mathbb{P}(\mathcal{H}_0)}{\mathbb{P}(\mathcal{H}_1)}$$

1. Similarity between noisy patches

- Based on our comparison of several similarity criteria, we propose to evaluate the **generalized likelihood ratio (GLR)**

$\rightarrow$ For speckle noise:

$$-\log GLR(v_1, v_2) = 2 \log \left(\frac{v_1}{v_2} + \frac{v_1}{v_2} \right) - 2 \log 2$$



$\rightarrow$ For Poisson noise:

$$-\log GLR(v_1, v_2) = v_1 \log v_1 + v_2 \log v_2 - (v_1 + v_2) \log \left(\frac{v_1 + v_2}{2} \right) .$$

Patch comparison: how to replace the squared differences?

- Weights have to select pixels with **close true values**
- Compare patches $\Leftrightarrow$ test the hypotheses that noise-free patches have:

$\mathcal{H}_0$: same true values ,
$\mathcal{H}_1$: independent true values .

$$\frac{\mathbb{P}(\mathcal{H}_0 | \blacksquare_1, \blacksquare_2)}{\mathbb{P}(\mathcal{H}_1 | \blacksquare_1, \blacksquare_2)} = \frac{p(\blacksquare_1, \blacksquare_2 | \mathcal{H}_0)}{p(\blacksquare_1, \blacksquare_2 | \mathcal{H}_1)} \times \boxed{\frac{\mathbb{P}(\mathcal{H}_0)}{\mathbb{P}(\mathcal{H}_1)}}$$

2. Similarity between pre-filtered patches

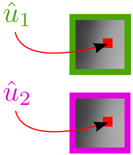
- We propose to refine weights by using the similarity between pre-filtered patches.
  Idea motivated by [Polzehl et al., 2006, Brox et al., 2007, Goossens et al., 2008, Louchet et al., 2008]
- A statistical test for the hypothesis $\mathcal{H}_0$: the **symmetrical Kullback-Leibler divergence**

→ For speckle noise:

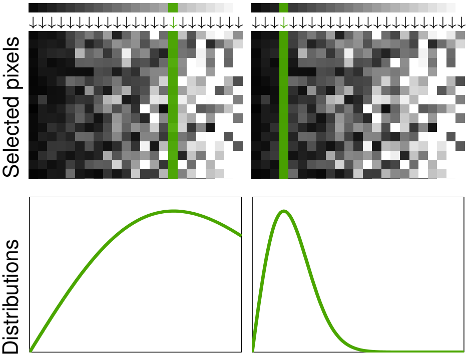
$$\mathcal{D}_{KL}(\hat{u}_1 \| \hat{u}_2) = \frac{\hat{u}_1}{\hat{u}_2} + \frac{\hat{u}_2}{\hat{u}_1} - 2$$

→ For Poisson noise:

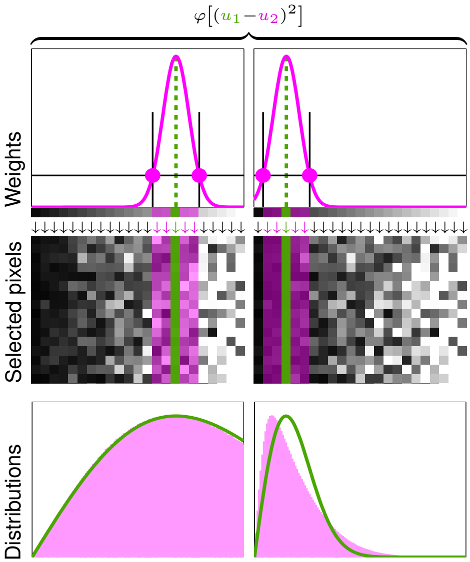
$$\mathcal{D}_{KL}(\hat{u}_1 \| \hat{u}_2) = (\hat{u}_1 - \hat{u}_2) \log \frac{\hat{u}_1}{\hat{u}_2} .$$



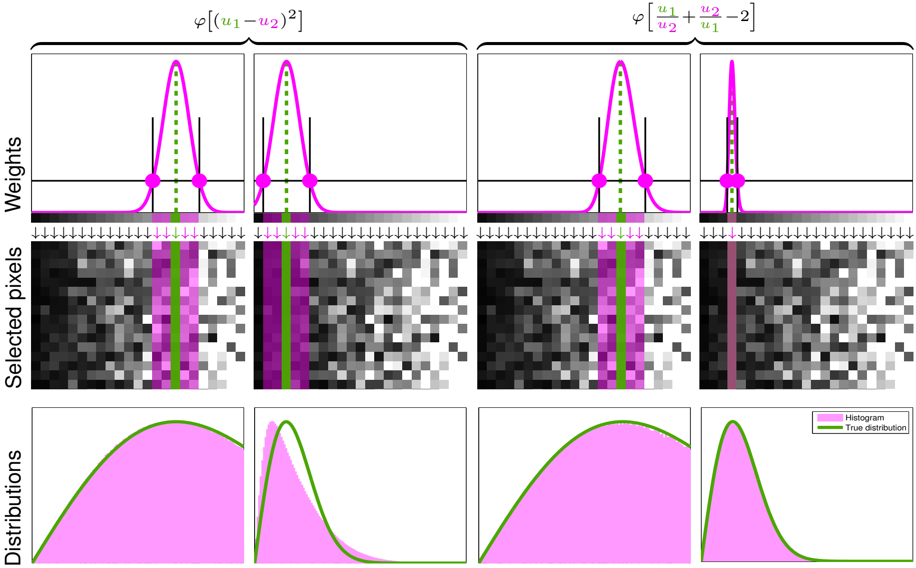
Weights refinement in non-local filtering



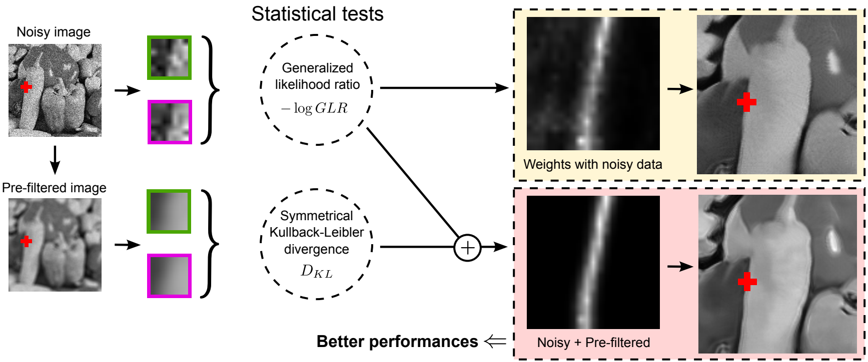
Weights refinement in non-local filtering



Weights refinement in non-local filtering

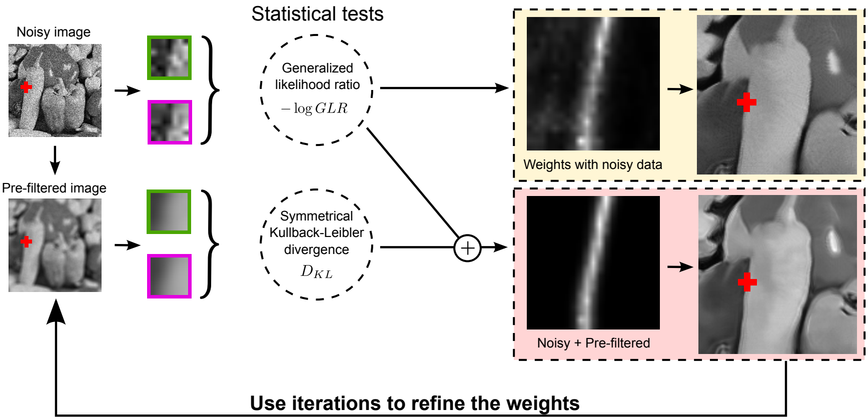


Weights refinement in non-local filtering



[Deledalle et al., 2009] Deledalle, C., Denis, L., and Tupin, F. (2009).
Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights.
IEEE Transactions on Image Processing, 18(12):2661–2672.

Weights refinement in non-local filtering



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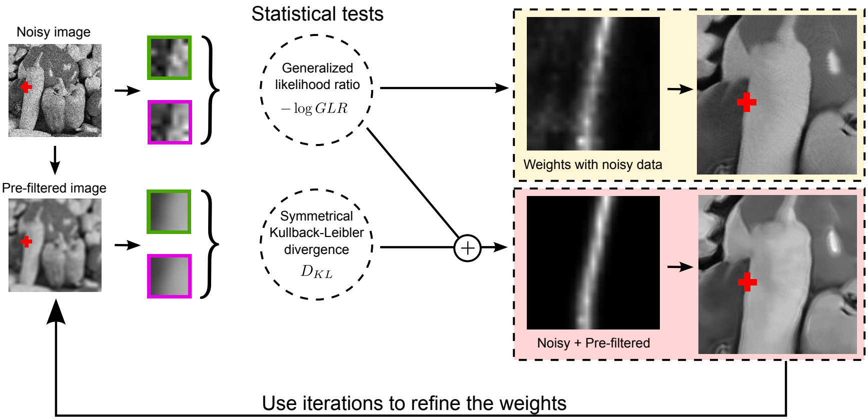
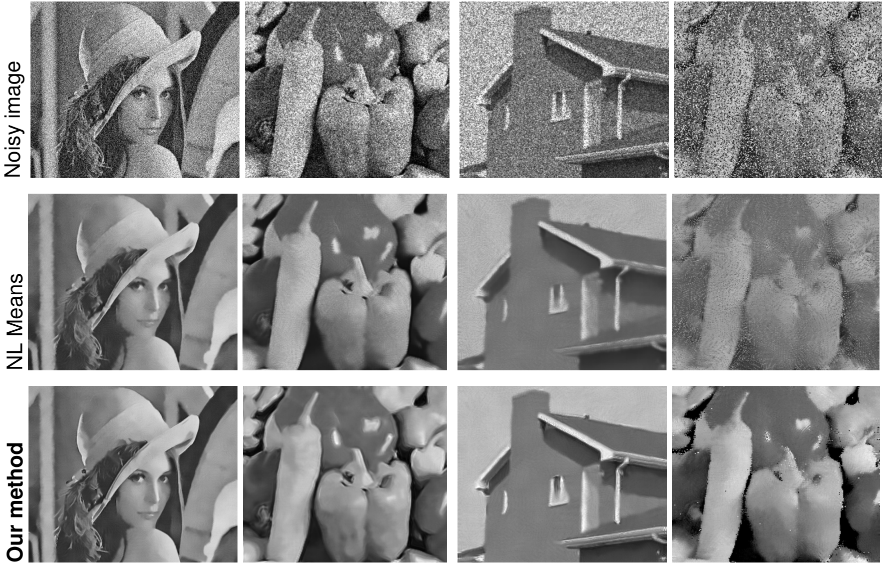


Let us illustrate the generality of the method

[Deledalle et al., 2009] Deledalle, C., Denis, L., and Tupin, F. (2009).
Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights.
IEEE Transactions on Image Processing, 18(12):2661–2672.

Illustration of the adaptivity of the proposed method



(a) Gaussien +0.87 dB   (b) Poisson +1.13 dB   (c) *Speckle* +4.00 dB   (d) Impuls. +3.82 dB

Application to multi-variate complex SAR images

Multi-variate complex SAR [Goodman, 1963]

- Parameter of interest: $\mathbf{\Sigma}(x)$ an $K \times K$ complex covariance matrix
- Observations: $\boldsymbol{C}(x)$ an $K \times K$ empirical covariance matrix s.t.:

$$p(\boldsymbol{C}|\mathbf{\Sigma}, L) = \frac{L^{LK}|\boldsymbol{C}|^{L-K}}{\Gamma_K(L)|\mathbf{\Sigma}|^L} \exp\left(-L\,\mathrm{tr}(\mathbf{\Sigma}^{-1}\boldsymbol{C})\right) \qquad \text{(Wishart distribution)}$$

- To denoise: to search for an estimate $\hat{\mathbf{\Sigma}}(x)$ of $\mathbf{\Sigma}(x)$

Comparison of patches

- Similarity between noisy patches:

$$-\log GLR(\boldsymbol{C}_1, \boldsymbol{C}_2) = 2L \log\left(\frac{|\boldsymbol{C}_1 + \boldsymbol{C}_2|}{\sqrt{|\boldsymbol{C}_1||\boldsymbol{C}_2|}}\right) - 2LK \log 2$$

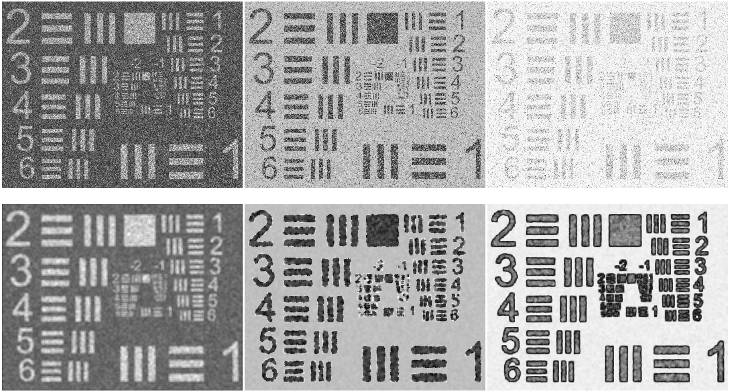
- Similarity between noise-free patches:

$$\mathcal{D}_{KL}(\hat{\mathbf{\Sigma}}_1 \| \hat{\mathbf{\Sigma}}_2) = L\mathrm{tr}\left(\hat{\mathbf{\Sigma}}_1{}^{-1}\hat{\mathbf{\Sigma}}_2 + \hat{\mathbf{\Sigma}}_2{}^{-1}\hat{\mathbf{\Sigma}}_1\right) - 2LK.$$

Experiments and results – Interferometric SAR data

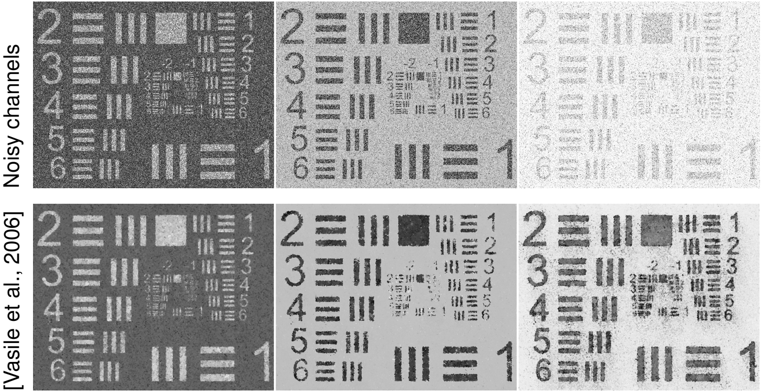
Noisy channels

Boxcar filter



[Deledalle et al., 2011a] Deledalle, C., Denis, L., and Tupin, F. (2011a).
NL-InSAR : Non-Local Interferogram Estimation.
IEEE Transactions on Geoscience and Remote Sensing, 49(4):1441–1452.

Experiments and results – Interferometric SAR data



[Deledalle et al., 2011a] Deledalle, C., Denis, L., and Tupin, F. (2011a).
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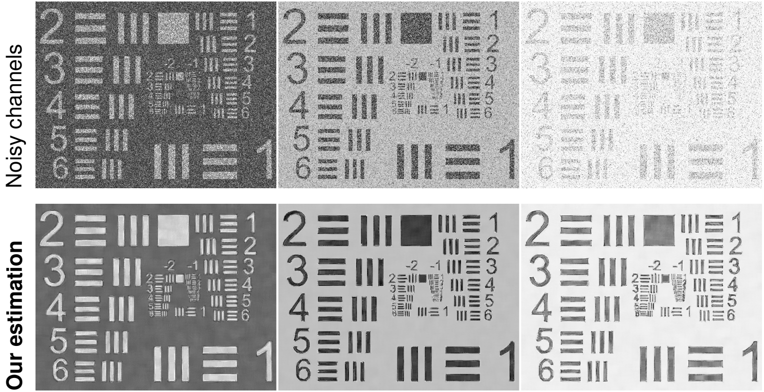

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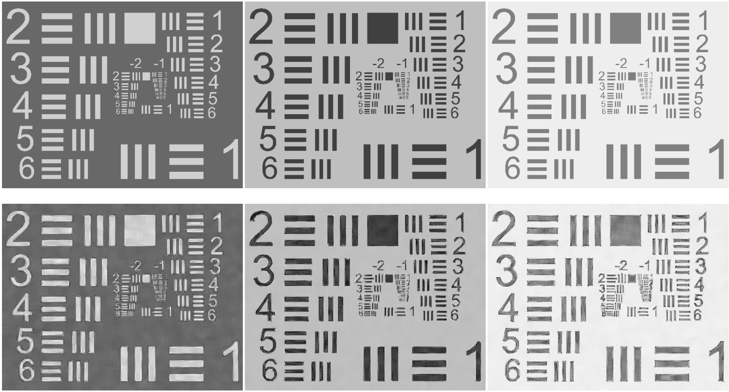
Experiments and results – Interferometric SAR data

True channels

Our estimation



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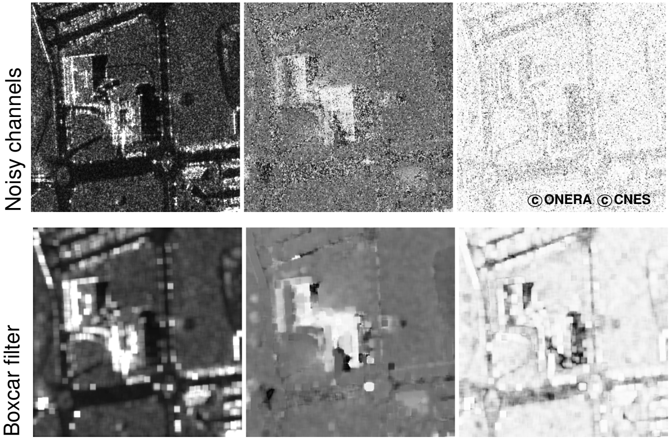

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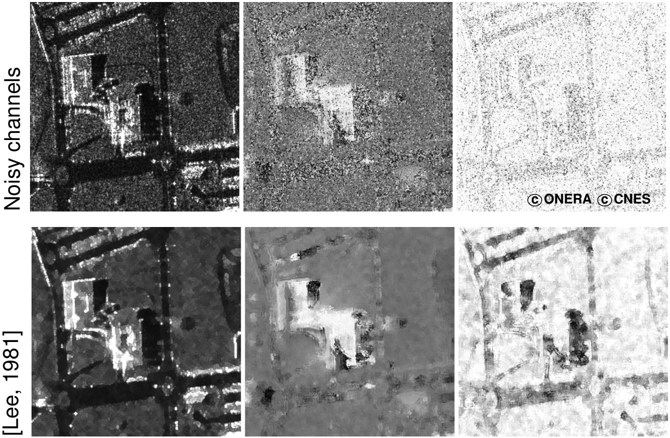

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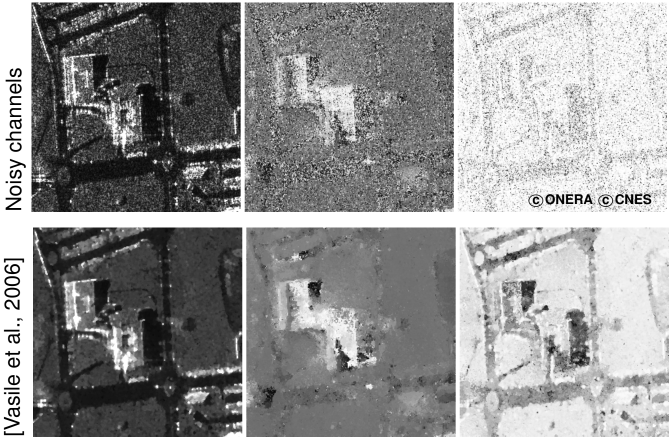

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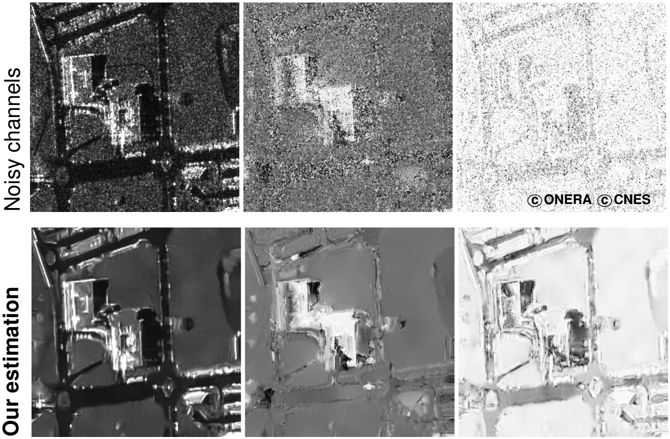

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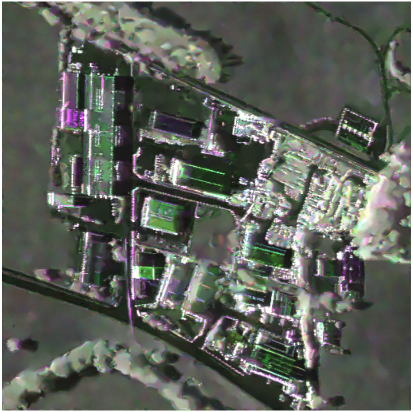
NL-InSAR : Non-Local Interferogram Estimation.
IEEE Transactions on Geoscience and Remote Sensing, 49(4):1441–1452.

Experiments and results – Polarimetric SAR data

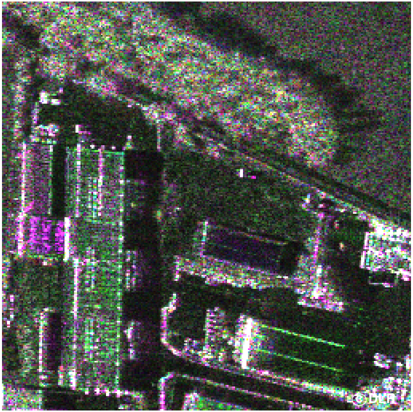
(a) High-resolution S-band SAR image



(b) **Our estimation**

[Deledalle et al., 2010b] Deledalle, C., Tupin, F., and Denis, L. (2010b).
Polarimetric SAR estimation based on non-local means.
In the proceedings of IGARSS, Honolulu, Hawaii, USA, July 2010.

Experiments and results – Polarimetric SAR data



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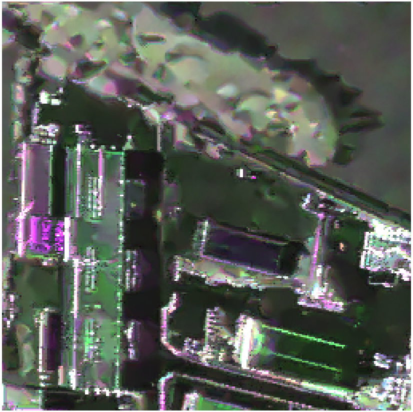

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Conclusion about iterative filtering

A general methodology that can

- Adapt to **signal-dependent noise** √
- Adapt to **complex-valued multivariate data** √
- Process huge images in **reasonable time** √

	File size	Image size	2 cores (3 GHz)	16 cores (2.27 GHz)
SAR	2.1 Mb	512×512	34 sec	-
InSAR	8.1 Mb	512×512	37 sec	27 sec
PolSAR	1.2 Gb	4096×4096	1h50	13.5 min

- Control **smoothing strength (noise reduction vs resolution loss tradeoff)** √

Search window size	11×11 to 21×21	image resolution
Patch size	3×3 to 9×9	object sizes
Number of iterations	1 to 4	level of noise
Fidelity to the estimation	$\lambda \in [0, 1]$	quality of the estimation
Filtering rate	around 95%	amount of filtering

Can we automatically tune the last two filtering parameters?

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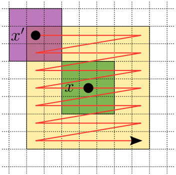
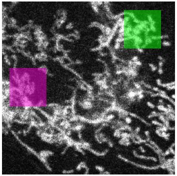
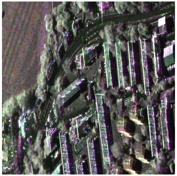
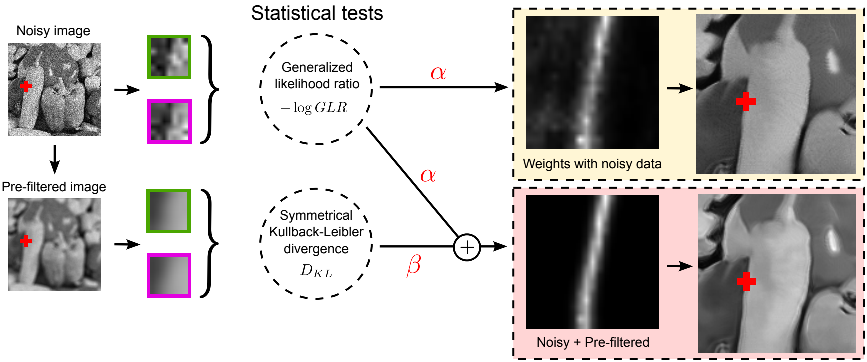
Outline





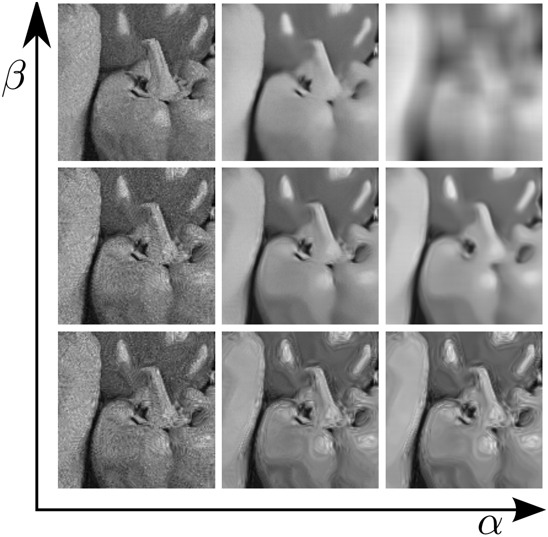


What about the denoising parameters?



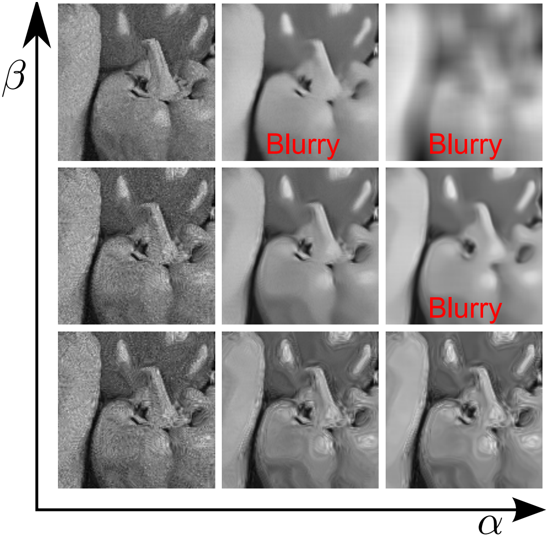
What is the influence of the denoising parameters?

What about the denoising parameters?



How to choose the parameters?
(trade-off noisy/pre-filtered)

What about the denoising parameters?



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Visually?

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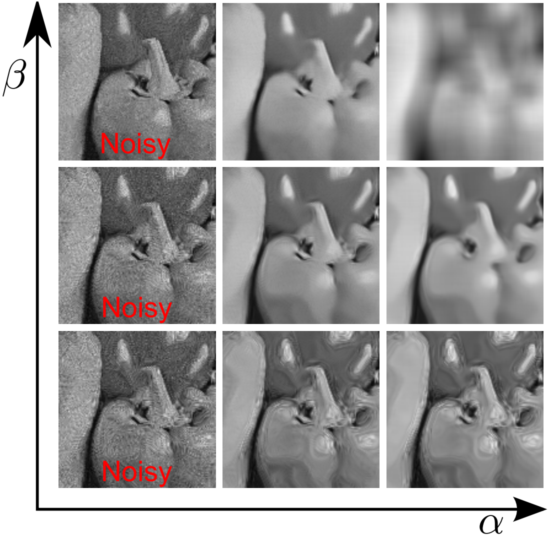

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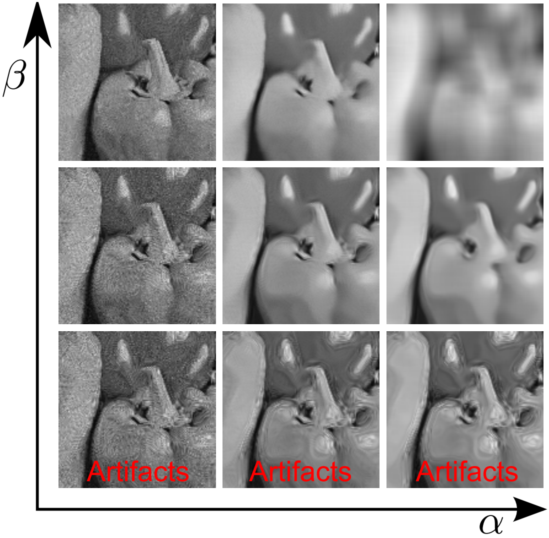

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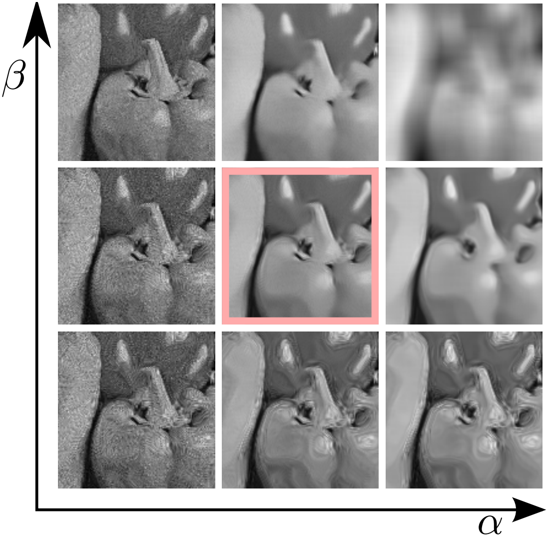

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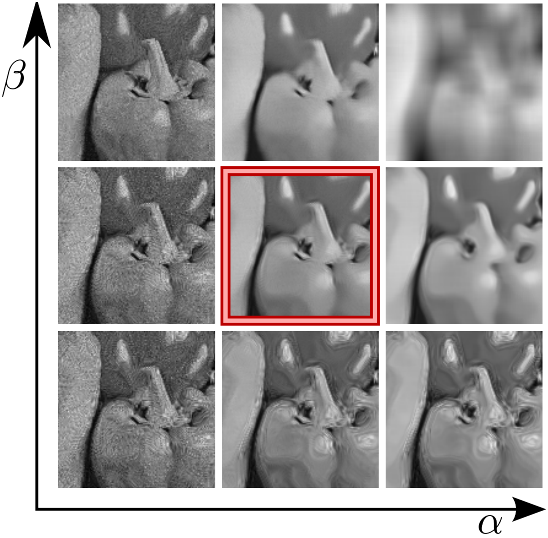
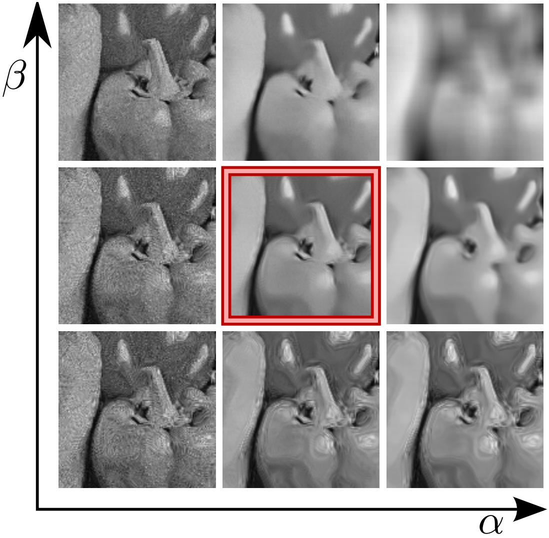


How to choose the parameters?
(trade-off noisy/pre-filtered)

Visually?

Mean squared error (MSE)?

What about the denoising parameters?



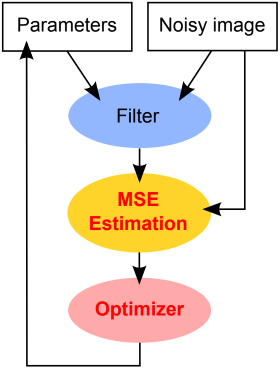
How to choose the parameters?
(trade-off noisy/pre-filtered)

Visually?

Mean squared error (MSE)?

How to estimate the MSE?

Automatic setting of the denoising parameters



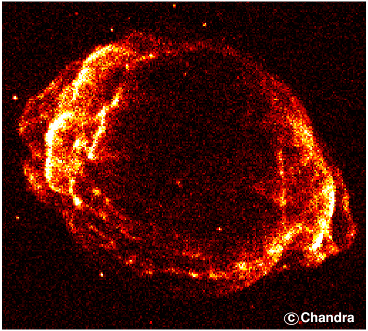
MSE estimators: unbiased risk estimators

Estimator	Gaussian	Poisson
General	SURE [Stein, 1973]	PURE [Chen, 1975]
Wavelet	SUREshrink [Donoho et al., 1995] SURE-LET [Blu et al., 2007]	PURE-LET [Luisier et al., 2010]
NL means	SURE based NL means [Van De Ville et al., 2009] Local-SURE NL means [Duval et al., 2010]	**Poisson NL means** [Deledalle et al., 2010c]

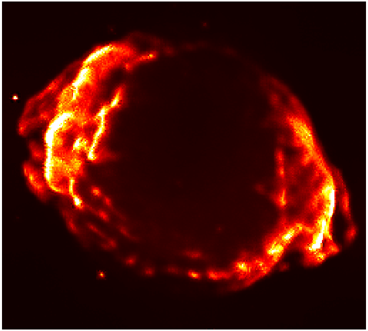
SURE: Stein's Unbiased Risk Estimator
PURE: Poisson Unbiased Risk Estimator

[Deledalle et al., 2010a] Deledalle, C., Tupin, F., and Denis, L. (2010a).
Poisson NL means: Unsupervised non local means for Poisson noise.
In *Image Processing (ICIP), 2010 17th IEEE International Conference on*, pages 801–804. IEEE.
Best student paper award

Experiments and results – Poisson noise

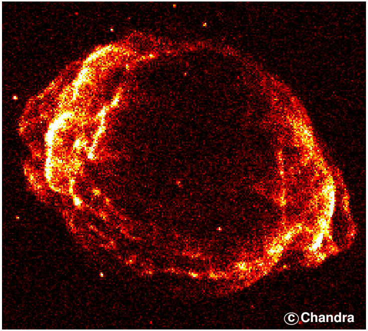


(a) Noisy image



(b) NL means

Experiments and results – Poisson noise



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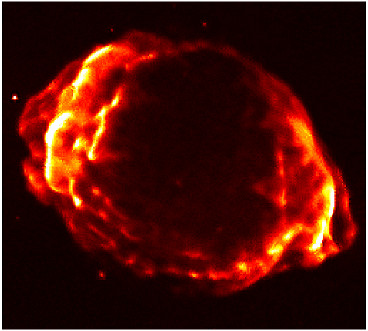
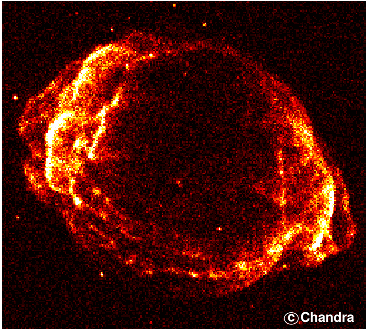


(b) **Our approach**

Experiments and results – Poisson noise



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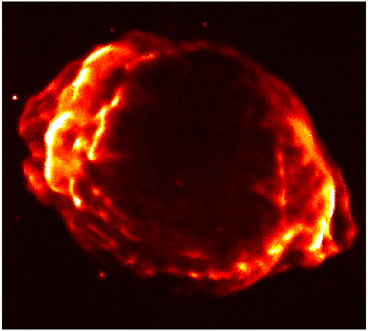
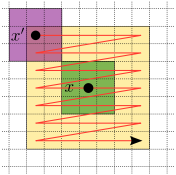
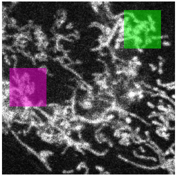


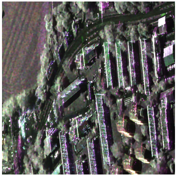
(b) **Our approach**

Conclusion about the unsupervised setting

- Find the best denoising level using similarities of noisy and pre-filtered patches
- Automatically choose to:
  - Trust the noisy image or favor the pre-estimate
  - Control smoothing strength w.r.t. the content
- Optimal parameters found in about 10 iterations


x'
x



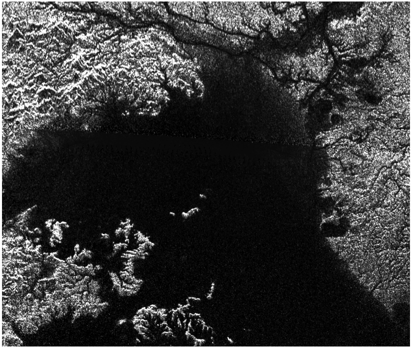


Main contributions

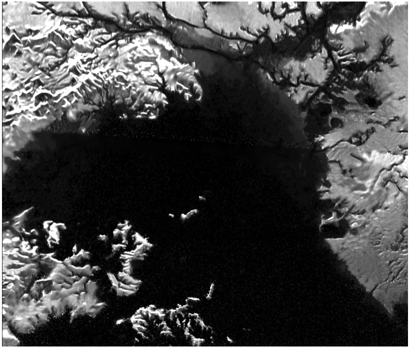
- A **general methodology** of patch-based denoising for:
  - non-Gaussian noise (e.g. Poisson noise)
  - complex-valued multivariate data (e.g. Wishart distributions)
- A **new similarity criterion** for noisy data:
  - asymptotically optimal
  - simple expression / easy to implement
- A powerful **iterative filtering** based on both:
  - Similarity between noisy patches
  - Similarity between noise-free patches
- An **unsupervised setting of parameters** for Poisson noise:
  - Derivation of PURE for NL means
  - Closed-form expression for Newton's method
- A **state-of-the-art** approach for (multi-variate) SAR imagery:
  - Collaboration with DLR (Andreas Reigber and Marc Jäger)
  - Validated on new high-resolution F-SAR data
  - Open source software: NL-SAR (CeCILL license)
  - On the way to be integrated into DLR's processing pipeline

Other contributions in SAR imagery

- Multi-temporal SAR analysis — with Sofiène Hachicha (URISA, SUPCOM)
- Polarimetric SAR classification — with Fang Cao (Telecom ParisTech)
- Study of Titan images — with Antoine Lucas and the Cassini radar team (Caltech)



(c) SAR image of Titan

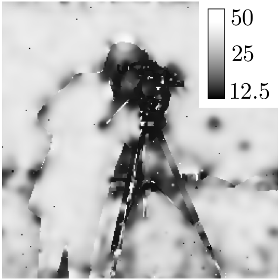


(d) Our estimation

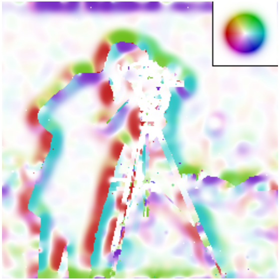
About signal adaptation

- Local adaptation of patch shapes and sizes
  with Vincent Duval (Telecom ParisTech) and Joseph Salmon (Duke University)
- Learning of local patch dictionary with Arnak Dalalyan (Univ. Paris Est) and Joseph Salmon

(e) Noisy image



(a) Patch sizes

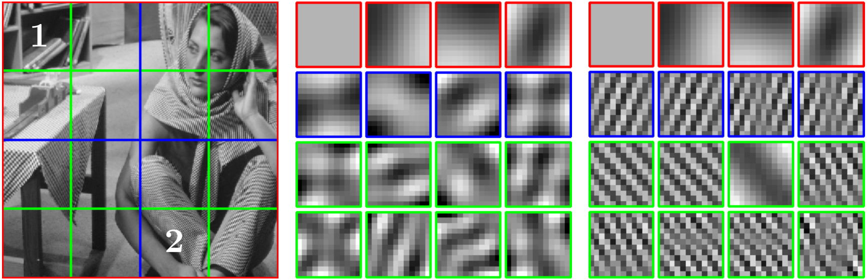


(b) Patch orientations

Other contributions and collaborations

About signal adaptation

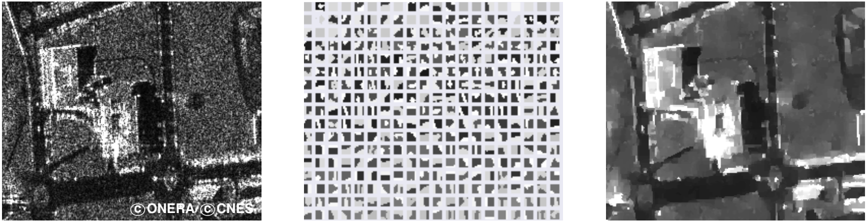
- Local adaptation of patch shapes and sizes
  with Vincent Duval (Telecom ParisTech) and Joseph Salmon (Duke University)
- Learning of local patch dictionary with Arnak Dalalyan (Univ. Paris Est) and Joseph Salmon



(a) Quadtree decomposition (b) 16 first axes in part 1 (c) 16 first axes in part 2

Future work – about the filtering of SAR data

- Learning of patch dictionary for non-Gaussian noise?



(a) Noisy image (b) Dictionary (c) Filtered image

- Extend BM3D-like approach to complex multi-variate images
- Regularize the result (e.g., for the phase in non-coherent areas)

Future work – about patch comparison

- For high SNR images, going beyond similarity detection
- Consider other choice for KL, e.g., the Bhattacharyya distance?
- Design contrast invariant criteria using GLR

Publication list

- 3 papers in refereed journals:

[Deledalle et al., 2009b] Deledalle, C.-A., Denis, L., and Tupin, F. (2009b).
Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights.
IEEE Trans. Image Process., 18(12):2661–2672.

[Deledalle et al., 2011b] Deledalle, C.-A., Denis, L., and Tupin, F. (2011b).
NL-InSAR : Non-Local Interferogram Estimation.
IEEE Trans. Geosci. Remote Sens., 49(4):1441–1452.

[Deledalle et al., 2011f] Deledalle, C.-A., Duval, V., and Salmon, J. (2011f).
Non-local Methods with Shape-Adaptive Patches (NLM-SAP).
Journal of Mathematical Imaging and Vision, pages 1–18.

- 12 papers in international conferences:
  - Image and computer vision: 2 ICIP, 1 BMVC, 1 SSVM
  - Geoscience and remote sensing: 5 IGARSS, 2 TITAN, 1 Multi-Temp
- 3 papers in french conferences
- 2 submitted papers
- 6 reviews for international refereed journals
- IEEE ICIP 2010 best student paper award!

Merci de votre attention.

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