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
  \[ \text{amplitude} \rightarrow \text{roughness}, \ldots \]
- Interferometry: 2 SAR images
  \[ \text{phase difference} \rightarrow \text{elevation}, \ldots \]
- Polarimetry: 3 SAR images
  \[ \text{complex correlation} \rightarrow \text{geophysical properties} \]
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)**
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
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
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4 Conclusion and perspectives
State-of-the-art of denoising approaches

Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Proposed methodology for non-Gaussian noise filtering

Sparcifying transforms (wavelets, dictionaries)

Variational / Markovian Approaches

Patch-based methods

BLS-GSM

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

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

Sparsity and non-locality

Non-local Total Variation

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

BM3D Non-local means

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

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

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

**Unknown noise-free image** $u$

**Input noisy image** $v$

**Output denoised image** $\hat{u}$
**Selection-based filtering**

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- **Goal:** estimate the image $u$ from the noisy image $v$
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  - Select the suitable candidates $x'$
  - Average their values and update the value of $x$
- **Repeat for all pixel $x$**

---

**How to choose suitable pixels $x'$ to combine?**
Non-local approach

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

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

- Local filters: select neighborhood pixels
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How to compare noisy patches?

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

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

How to compare noisy patches?

[Buades et al., 2005]
How to compare noisy patches?

■ Assume noise is additive and Gaussian such that:

\[
\begin{align*}
\mathbf{v}_1 &= \mathbf{u}_1 + \mathbf{n}_1 \quad \text{and} \quad \mathbf{v}_2 &= \mathbf{u}_2 + \mathbf{n}_2
\end{align*}
\]

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

\[
\begin{align*}
\text{when } \mathbf{u}_1 &= \mathbf{u}_2 : \\
& \quad \left( \frac{\mathbf{v}_1}{\mathbf{u}_1} - \frac{\mathbf{v}_2}{\mathbf{u}_2} \right)^2 = \text{is low } \Rightarrow \text{ decide “similar”} \\
\text{when } \mathbf{u}_1 &\neq \mathbf{u}_2 : \\
& \quad \left( \frac{\mathbf{v}_1}{\mathbf{u}_1} - \frac{\mathbf{v}_2}{\mathbf{u}_2} \right)^2 = \text{is high } \Rightarrow \text{ decide “dissimilar”}
\end{align*}
\]
How to compare noisy patches?

- Assume noise is additive and Gaussian such that:

\[ v_1 = u_1 + n_1 \]

and

\[ v_2 = u_2 + n_2 \]

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

\[
\begin{align*}
\text{when } u_1 &= u_2 : & 2 \left( \begin{array}{c} v_1 \setminus u_1 \\ n_1 \end{array} \right)^2 &= \begin{array}{c} \text{is low } \Rightarrow \text{ decide } \text{“similar”} \\
\end{array} \\
\text{when } u_1 \neq u_2 : & 2 \left( \begin{array}{c} v_2 \setminus u_1 \\ n_2 \end{array} \right)^2 &= \begin{array}{c} \text{is high } \Rightarrow \text{ decide } \text{“dissimilar”} \\
\end{array}
\end{align*}
\]

What about non-Gaussian noise?
Beyond the Gaussian noise assumption

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

\[
\begin{align*}
\mathbf{v}_1 &= \mathbf{u}_1 + \mathbf{n}_1 \\
\mathbf{v}_2 &= \mathbf{u}_2 + \mathbf{n}_2
\end{align*}
\]

- The Euclidean distance is no longer discriminant:

\[
\begin{align*}
\text{when } \mathbf{u}_1 &= \mathbf{u}_2 & \left( \mathbf{v}_1 - \mathbf{v}_2 \right)^2 &= \text{noise} \\
\text{when } \mathbf{u}_1 &\neq \mathbf{u}_2 & \left( \mathbf{v}_1 - \mathbf{v}_2 \right)^2 &= \text{noise}
\end{align*}
\]
Beyond the Gaussian noise assumption

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

\[ v_1 = u_1 + n_1 \quad \text{and} \quad v_2 = u_2 + n_2 \]

- The Euclidean distance is no longer discriminant:

  when \( u_1 = u_2 \):
  \[ \left( \begin{array}{c}
  v_1 \\
  v_2
\end{array} \right) - \left( \begin{array}{c}
  u_1 \\
  u_2
\end{array} \right)^2 = \]

  when \( u_1 \neq u_2 \):
  \[ \left( \begin{array}{c}
  v_1 \\
  v_2
\end{array} \right) - \left( \begin{array}{c}
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\end{array} \right)^2 = \]

Consequence?
When comparing noisy patches, one should take into account the noise distribution.
Some issues
Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Proposed methodology for non-Gaussian noise filtering

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
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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

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

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  [Buades et al., 2005, Aharon et al., 2006, Dabov et al., 2007, Mairal et al., 2009, Salmon and Strozecki, 2010]
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  [Buades et al., 2005, Aharon et al., 2006, Dabov et al., 2007, Mairal et al., 2009, Salmon and Strozecki, 2010]
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- **Acceleration**

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  [Buades et al., 2005, Aharon et al., 2006, Dabov et al., 2007, Mairal et al., 2009, Salmon and Strozecki, 2010]
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
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4. Conclusion and perspectives
Motivation

Positioning and the limits of patch-based filtering
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How to take into account the noise model?
**Variance stabilization approach**

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

$$\left( s\left(\begin{array}{c}
\text{image 1}
\end{array}\right) - s\left(\begin{array}{c}
\text{image 2}
\end{array}\right) \right)^2 = \left(\begin{array}{c}
\text{transform 1}
\end{array}\right) - \left(\begin{array}{c}
\text{transform 2}
\end{array}\right)^2,$$

**Example**

- **Gamma noise (multiplicative) and the homomorphic approach:**
  
  $$s(V) = \log V$$

- **Poisson noise and the Anscombe transform:**
  
  $$s(V) = 2\sqrt{V + \frac{3}{8}}$$
Variance stabilization approach

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

$\left( s\left( \begin{array}{c} \text{patch 1} \\ \text{patch 2} \end{array} \right) - s\left( \begin{array}{c} \text{patch 3} \\ \text{patch 4} \end{array} \right) \right)^2 = \left( \begin{array}{c} \text{patch 5} \\ \text{patch 6} \end{array} \right)^2$

Example

- Gamma noise (multiplicative) and the homomorphic approach:

$s(V) = \log V$

- Poisson noise and the Anscombe transform:

$s(V) = 2\sqrt{V + \frac{3}{8}}$
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
Similarity in the light of detection theory

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

\[ H_0 : u_1 = u_2 \equiv u_{12} \]  (null hypothesis)
\[ H_1 : u_1 \neq u_2 \]  (alternative hypothesis)

- Its performance can be measured as:

\[ P_{FA} = P(\text{decide “dissimilar”} \mid u_{12}, H_0) \]  (false-alarm rate)
\[ P_D = P(\text{decide “dissimilar”} \mid u_1, u_2, H_1) \]  (detection rate)

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

\[
L(v_1, v_2) = \frac{p(v_1, v_2 \mid u_{12}, H_0)}{p(v_1, v_2 \mid u_1, u_2, H_1)} \quad \leftarrow \text{given by the noise distribution model}
\]

\[ \rightarrow \text{Problem: } u_{12}, u_1 \text{ and } u_2 \text{ are unknown} \]
Generalized likelihood ratio (GLR)

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

$$- \log GLR(v_1, v_2) = - \log \frac{\sup_t p(v_1, v_2 | \mathbf{u}_{12} = t, \mathcal{H}_0)}{\sup_{t_1, t_2} p(v_1, v_2 | \mathbf{u}_1 = t_1, \mathbf{u}_2 = t_2, \mathcal{H}_1)}$$

$$= - \log \frac{p(v_1 | \mathbf{u}_1 = \hat{t}_{12}) p(v_2 | \mathbf{u}_2 = \hat{t}_{12})}{p(v_1 | \mathbf{u}_1 = \hat{t}_1) p(v_2 | \mathbf{u}_2 = \hat{t}_2)}$$

Maximal self similarity

- Assume $v_1 \neq v_2$, then:

$$- \log \frac{p \left( v_1 = \text{\includegraphics[width=0.2\textwidth]{image1}} \mid \mathbf{u}_1 = \text{\includegraphics[width=0.2\textwidth]{image2}} \right) p \left( v_2 = \text{\includegraphics[width=0.2\textwidth]{image3}} \mid \mathbf{u}_2 = \text{\includegraphics[width=0.2\textwidth]{image4}} \right)}{p \left( v_1 = \text{\includegraphics[width=0.2\textwidth]{image1}} \mid \mathbf{u}_1 = \text{\includegraphics[width=0.2\textwidth]{image2}} \right) p \left( v_2 = \text{\includegraphics[width=0.2\textwidth]{image3}} \mid \mathbf{u}_2 = \text{\includegraphics[width=0.2\textwidth]{image4}} \right)} > 0$$
Generalized likelihood ratio (GLR)

- Replace $u_{12}$, $u_1$ and $u_2$ with maximum likelihood estimates (MLE)
- Define the (negative log) generalized likelihood ratio test:

$$-\log GLR(v_1, v_2) = -\log \frac{\sup_t p(v_1, v_2 \mid u_{12} = t, \mathcal{H}_0)}{\sup_{t_1, t_2} p(v_1, v_2 \mid u_1 = t_1, u_2 = t_2, \mathcal{H}_1)}$$

$$= -\log \frac{p(v_1 \mid u_1 = \hat{t}_{12}) p(v_2 \mid u_2 = \hat{t}_{12})}{p(v_1 \mid u_1 = \hat{t}_1) p(v_2 \mid u_2 = \hat{t}_2)}$$

Equal self similarity

- Assume $v_1 = v_2$, then:

$$-\log \frac{p(v_1 = \text{[image]}}{p(v_1 = \text{[image]})} = 0$$
Other similarity criteria have been proposed:

Bayesian joint likelihood

\[ \int p(v_1 \mid u_1 = t) \ p(v_2 \mid u_2 = t) \ dt \]

[Deledalle et al., 2009b]
Other similarity criteria have been proposed:

Bayesian joint likelihood

\[
\int p(v_1 | u_1 = t) p(v_2 | u_2 = t) p(u_{12} = t) \, dt
\]

[Deledalle et al., 2009b]

[Yianilos, 1995, Matsushita and Lin, 2007]
Other similarity criteria have been proposed:

- **Bayesian joint likelihood**
  \[
  \int p(v_1 | u_1 = t) \ p(v_2 | u_2 = t) \ p(u_{12} = t) \ dt
  \]
  [Deledalle et al., 2009b]
  [Yianilos, 1995, Matsushita and Lin, 2007]

- **Maximum joint likelihood**
  \[
  \sup_t p(v_1 | u_1 = t) \ p(v_2 | u_2 = t)
  \]
  [Alter et al., 2006]
Other similarity criteria have been proposed:

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  \]
  [Deledalle et al., 2009b]
  [Yianilos, 1995, Matsushita and Lin, 2007]

- **Maximum joint likelihood**
  \[
  \sup_t p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t)
  \]
  [Alter et al., 2006]

- **Bayesian likelihood ratio**
  \[
  \frac{\int p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t) \, p(u_{12} = t) \, dt}{\int p(v_1 \mid u_1 = t) \, p(u_1 = t) \, dt \int p(v_2 \mid u_2 = t) \, p(u_2 = t) \, dt}
  \]

- **Mutual information kernel**
  \[
  \frac{\int p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t) \, p(u_{12} = t) \, dt}{\sqrt{\int p(v_1 \mid u_1 = t)^2 \, p(u_1 = t) \, dt \int p(v_2 \mid u_2 = t)^2 \, p(u_2 = t) \, dt}}
  \]
  [Seeger, 2002]
Other similarity criteria have been proposed:

- **Bayesian joint likelihood**
  \[ \int p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t) \, p(u_{12} = t) \, dt \]
  \[ \text{[Deledalle et al., 2009b]} \]
  \[ \text{[Yianilos, 1995, Matsushita and Lin, 2007]} \]

- **Maximum joint likelihood**
  \[ \sup_t p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t) \]
  \[ \text{[Alter et al., 2006]} \]

- **Bayesian likelihood ratio**
  \[ \frac{\int p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t) \, p(u_{12} = t) \, dt}{\int p(v_1 \mid u_1 = t) \, p(u_1 = t) \, dt \int p(v_2 \mid u_2 = t) \, p(u_2 = t) \, dt} \]
  \[ \text{[Minka, 1998, Minka, 2000]} \]

- **Mutual information kernel**
  \[ \frac{\int p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t) \, p(u_{12} = t) \, dt}{\sqrt{\int p(v_1 \mid u_1 = t)^2 \, p(u_1 = t) \, dt \int p(v_2 \mid u_2 = t)^2 \, p(u_2 = t) \, dt}} \]
  \[ \text{[Seeger, 2002]} \]

- **GLR**
  \[ \frac{\sup_t p(v_1 \mid u_1 = t) \, p(v_2 \mid u_2 = t)}{\sup_t p(v_1 \mid u_1 = t) \, \sup_t p(v_2 \mid u_2 = t)} \]
Is GLR more discriminant?

Euclidean distance

- When $u_1 = u_2$:
  \[
  \left( \begin{array}{cc}
  s & - s \\
  \end{array} \right) \left( \begin{array}{c}
  s \\
  \end{array} \right) = \frac{1}{2}
  \]
- When $u_1 \neq u_2$:
  \[
  \left( \begin{array}{cc}
  s & - s \\
  \end{array} \right) \left( \begin{array}{c}
  -s \\
  \end{array} \right) = \frac{1}{2}
  \]

Variance stabilization

- When $u_1 = u_2$:
  \[
  \left( \begin{array}{c}
  s \\
  \end{array} \right) \left( \begin{array}{c}
  s \\
  \end{array} \right) = \frac{1}{2}
  \]
- When $u_1 \neq u_2$:
  \[
  \left( \begin{array}{c}
  s \\
  \end{array} \right) \left( \begin{array}{c}
  -s \\
  \end{array} \right) = \frac{1}{2}
  \]

GLR

- When $u_1 = u_2$:
  \[
  - \log GLR \left( \begin{array}{cc}
  s & - s \\
  \end{array} \right) = \frac{1}{2}
  \]
- When $u_1 \neq u_2$:
  \[
  - \log GLR \left( \begin{array}{cc}
  s & - s \\
  \end{array} \right) = \frac{1}{2}
  \]
**Evaluation of similarity criteria – Detection performance**

Positioning and the limits of patch-based filtering

A new similarity criterion to compare noisy patches

Proposed methodology for non-Gaussian noise filtering

Conclusion and perspectives

- Generalized likelihood ratio
- Variance stabilization
- Euclidean distance
- Maximum joint likelihood
- Mutual information kernel
- Bayesian likelihood ratio
- Bayesian joint likelihood

[Alter et al., 2006]
[Seeger, 2002]
[Yianilos, 1995, Matsushita and Lin, 2007]
- Generalized likelihood ratio
- Variance stabilization
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[Alter et al., 2006]
[Seeger, 2002]
[Yianilos, 1995, Matsushita and Lin, 2007]
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):

<table>
<thead>
<tr>
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<th>Max. self sim.</th>
<th>Eq. self sim.</th>
<th>Id. of indiscernible</th>
<th>Invariance</th>
<th>Asym. CFAR</th>
<th>Asym. UMPI</th>
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<td>Maximum joint lik.</td>
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<td>✓</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tr>
</tbody>
</table>

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
Outline

1. Positioning and the limits of patch-based filtering
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4. Conclusion and perspectives
Patch comparison: how to replace the squared differences?

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

\[
\begin{align*}
\mathcal{H}_0 : & \text{ same true values} , \\
\mathcal{H}_1 : & \text{ independent true values} . \\
\frac{P(\mathcal{H}_0 | \overrightarrow{I}_1, \overrightarrow{I}_2)}{P(\mathcal{H}_1 | \overrightarrow{I}_1, \overrightarrow{I}_2)} &= \frac{p(\overrightarrow{I}_1, \overrightarrow{I}_2 | \mathcal{H}_0)}{p(\overrightarrow{I}_1, \overrightarrow{I}_2 | \mathcal{H}_1)} \times \frac{P(\mathcal{H}_0)}{P(\mathcal{H}_1)}
\end{align*}
\]
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:

\[
\mathcal{H}_0 : \text{same true values}, \quad \mathbb{P}(\mathcal{H}_0 | \mathbf{v}_1, \mathbf{v}_2) = \frac{p(\mathbf{v}_1, \mathbf{v}_2 | \mathcal{H}_0)}{p(\mathbf{v}_1, \mathbf{v}_2 | \mathcal{H}_1)} \times \frac{\mathbb{P}(\mathcal{H}_0)}{\mathbb{P}(\mathcal{H}_1)}
\]

1. Similarity between noisy patches

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

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

\[ -\log GLR(v_1, v_2) = v_1 \log v_1 + v_2 \log v_2 - (v_1 + v_2) \log \left( \frac{v_1 + v_2}{2} \right) . \]
Patch comparison: how to replace the squared differences?

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

\[
H_0 : \text{same true values}, \quad \frac{P(H_0 \mid \hat{u}_1, \hat{u}_2)}{P(H_1 \mid \hat{u}_1, \hat{u}_2)} = \frac{p(\hat{u}_1, \hat{u}_2 \mid H_0)}{p(\hat{u}_1, \hat{u}_2 \mid H_1)} \times \frac{P(H_0)}{P(H_1)}
\]

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 \( H_0 \): the **symmetrical Kullback-Leibler divergence**

\[ D_{KL}(\hat{u}_1 \mid \hat{u}_2) = \frac{\hat{u}_1}{\hat{u}_2} + \frac{\hat{u}_2}{\hat{u}_1} - 2 \]

\[ D_{KL}(\hat{u}_1 \mid \hat{u}_2) = (\hat{u}_1 - \hat{u}_2) \log \frac{\hat{u}_1}{\hat{u}_2} \]
Weights refinement in non-local filtering

- Positioning and the limits of patch-based filtering
- A new similarity criterion to compare noisy patches
- Proposed methodology for non-Gaussian noise filtering

\[
\phi \left[ (u_1 - u_2)^2 \right] \quad \phi \left[ u_1 u_2 + u_2 u_1 - 2 \right]
\]
Weights refinement in non-local filtering

Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Proposed methodology for non-Gaussian noise filtering

\[ \varphi[(u_1 - u_2)^2] \]
Weights refinement in non-local filtering

Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Prosposed methodology for non-Gaussian noise filtering

\[ \varphi[(u_1 - u_2)^2] \]

\[ \varphi\left[\frac{u_1}{u_2} + \frac{u_2}{u_1} - 2\right] \]

Selected pixels

Distributions

Histogram

True distribution

Selected pixels

Distributions

Histogram

True distribution

Histogram

True distribution

Histogram

True distribution

PhD defense

C.-A. DELEDALLE

page 25/40
Weights refinement in non-local filtering

Positioning and the limits of patch-based filtering A new similarity criterion to compare noisy patches Proposed methodology for non-Gaussian noise filtering

Statistical tests

Generalized likelihood ratio
\[- \log \text{GLR}\]

Symmetrical Kullback-Leibler divergence
\[D_{KL}\]

Better performances


Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights.

Weights refinement in non-local filtering

Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Proposed methodology for non-Gaussian noise filtering

Statistical tests:
- Generalized likelihood ratio: $- \log GLR$
- Symmetrical Kullback-Leibler divergence: $D_{KL}$

Use iterations to refine the weights

Weights refinement in non-local filtering

Positioning and the limits of patch-based filtering  A new similarity criterion to compare noisy patches  Proposed methodology for non-Gaussian noise filtering

Use iterations to refine the weights

Let us illustrate the generality of the method

Illustration of the adaptivity of the proposed method

Noisy image

NL Means

Our method

(a) Gaussien +0.87 dB  (b) Poisson +1.13 dB  (c) Speckle +4.00 dB  (d) Impuls. +3.82 dB
Multi-variate complex SAR

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

\[
p(C|\Sigma, L) = \frac{L^{LK} |C|^{L-K}}{\Gamma_K(L)|\Sigma|^L} \exp(-L \text{tr}(\Sigma^{-1}C)) \quad \text{(Wishart distribution)}
\]

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

Comparison of patches

- Similarity between noisy patches:

\[
- \log GLR(C_1, C_2) = 2L \log \left( \frac{|C_1 + C_2|}{\sqrt{|C_1||C_2|}} \right) - 2LK \log 2
\]

- Similarity between noise-free patches:

\[
\mathcal{D}_{KL}(\hat{\Sigma}_1 || \hat{\Sigma}_2) = L \text{tr} \left( \hat{\Sigma}_1^{-1} \hat{\Sigma}_2 + \hat{\Sigma}_2^{-1} \hat{\Sigma}_1 \right) - 2LK.
\]
Experiments and results – Interferometric SAR data

Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Proposed methodology for non-Gaussian noise filtering

Noisy channels

Boxcar filter

NL-InSAR : Non-Local Interferogram Estimation.
Experiments and results – Interferometric SAR data

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NL-InSAR : Non-Local Interferogram Estimation.

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Our estimation

NL-InSAR : Non-Local Interferogram Estimation.
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True channels

Our estimation

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Boxcar filter

[c] ONERA [c] CNES

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Noisy channels

[Vasile et al., 2006]


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NL-InSAR : Non-Local Interferogram Estimation.  
Experiments and results – Polarimetric SAR data

Positioning and the limits of patch-based filtering
A new similarity criterion to compare noisy patches
Proposed methodology for non-Gaussian noise filtering

---

(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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[Deledalle et al., 2010b] Deledalle, C., Tupin, F., and Denis, L. (2010b).
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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**

<table>
<thead>
<tr>
<th>File size</th>
<th>Image size</th>
<th>2 cores (3 GHz)</th>
<th>16 cores (2.27 GHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAR</td>
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</tr>
<tr>
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<td>37 sec</td>
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<td>PolSAR</td>
<td>1.2 Gb</td>
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<td>1h50</td>
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</tbody>
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- **Control smoothing strength** (**noise reduction vs resolution loss tradeoff**)

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

Can we automatically tune the last two filtering parameters?
Conclusion about iterative filtering

A general methodology that can

- Adapt to **signal-dependent noise** ✓
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- Control **smoothing strength (noise reduction vs resolution loss tradeoff)** ✓

- Search window size: 11 × 11 to 21 × 21
- Patch size: 3 × 3 to 9 × 9
- Number of iterations: 1 to 4
- Fidelity to the estimation: \( \lambda \in [0, 1] \)
- Filtering rate: around 95%

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

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Outline

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2. A new similarity criterion to compare noisy patches
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4. Conclusion and perspectives
What about the denoising parameters?

- Symmetrical Kullback-Leibler divergence
- Generalized likelihood ratio

Statistical tests

Noisy image

Pre-filtered image

Weights with noisy data

Noisy + Pre-filtered

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?

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

Visually?
What about the denoising parameters?

Positioning and the limits of patch-based filtering

A new similarity criterion to compare noisy patches

Proposed methodology for non-Gaussian noise filtering

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

Visually?
What about the denoising parameters?

How to choose the parameters?
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Visually?
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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?
### MSE estimators: unbiased risk estimators

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Gaussian</th>
<th>Poisson</th>
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<tbody>
<tr>
<td>General</td>
<td>SURE [Stein, 1973]</td>
<td>PURE [Chen, 1975]</td>
</tr>
<tr>
<td>Wavelet</td>
<td>SUREshrink</td>
<td></td>
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<tr>
<td></td>
<td>[Donoho et al., 1995]</td>
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<tr>
<td></td>
<td>SURE-LET</td>
<td>PURE-LET</td>
</tr>
<tr>
<td></td>
<td>[Blu et al., 2007]</td>
<td>[Luisier et al., 2010]</td>
</tr>
<tr>
<td>NL means</td>
<td>SURE based NL means</td>
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<tr>
<td></td>
<td>[Van De Ville et al., 2009]</td>
<td></td>
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<tr>
<td></td>
<td>Local-SURE NL means</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[Duval et al., 2010]</td>
<td></td>
</tr>
</tbody>
</table>

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

---

**References**


**Best student paper award**
Experiments and results – Poisson noise

(a) Noisy image
(b) NL means

■ 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
Experiments and results – Poisson noise

Positioning and the limits of patch-based filtering

A new similarity criterion to compare noisy patches

Proposed methodology for non-Gaussian noise filtering

(a) Noisy image

(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
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Positioning and the limits of patch-based filtering

A new similarity criterion to compare noisy patches

Proposed methodology for non-Gaussian noise filtering

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

Conclusion and perspectives
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 and collaborations

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)
Other contributions and collaborations

Positioning and the limits of patch-based filtering
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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
About signal adaptation

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(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?
  
  - 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
3 papers in refereed journals:

   Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights.

   NL-InSAR : Non-Local Interferogram Estimation.

   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.
K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation.

An intensity similarity measure in low-light conditions.

Image denoising based on adapted dictionary computation.

Fast nonlocal means for image denoising.
volume 6502, page 65020R. SPIE.

Efficient Nonlocal Means for Denoising of Textural Patterns.

A review of image denoising algorithms, with a new one.

Poisson approximation for dependent trials.

Fast Non Local Means Denoising for 3D MR Images.

BM3D Image Denoising with Shape-Adaptive Principal Component Analysis.
In *Signal Processing with Adaptive Sparse Structured Representations (SPARS)*.

Image denoising by sparse 3-D transform-domain collaborative filtering.
  Fast nonlocal filtering applied to electron cryomicroscopy.
  In *IEEE Int. Symposium on Biomedical Imaging (ISBI)*, pages 1331–1334. IEEE.

  Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights.

  Poisson NL means: Unsupervised non local means for Poisson noise.

  Robust NL-means filter with optimal pixel-wise smoothing parameter for statistical image denoising.

  A bias-variance approach for the non-local means.

  Statistical analysis based on a certain multivariate complex Gaussian distribution (an introduction).

  An improved non-local denoising algorithm.
  In *Local and Non-Local Approximation (LNLA)*, pages 143–156.

  Bhattacharyya distance as a contrast parameter for statistical processing of noisy optical images.


  From local kernel to nonlocal multiple-model image denoising.
Optimal spatial adaptation for patch-based image denoising.

A variational approach to reconstructing images corrupted by poisson noise.

Speckle analysis and smoothing of synthetic aperture radar images.

Information theory and mixing least-squares regressions.

Total variation as a local filter.

Fast interscale wavelet denoising of Poisson-corrupted images.

Fast image and video denoising via nonlocal means of similar neighborhoods.

Non-local sparse models for image restoration.
International Conference on Computer Vision (ICCV), pages 2272–2279.

A Probabilistic Intensity Similarity Measure based on Noise Distributions.
In IEEE Comput. Vis. and Pattern Recognition (CVPR), pages 1–8. IEEE.

Bayesian Inference, Entropy, and the Multinomial Distribution.
Distance measures as prior probabilities.

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