Two Steps Multi-Temporal Non-Local Means for SAR Images

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Multi-Temporal SAR images & applications

Denoising:
1) Improve stable objects
2) Keep new objects

Change Detection:
• Environmental Monitoring;
• Disaster Evaluation;
• Urban Planning;
• ...

Classification:
• Land-cover Mapping;
• ...

Huge amount of SAR data
Various Denoising Methods

- **Spatial-Domain Methods**
  - Non-local means (NLM) for Gaussian noise, by Buades et al. [1]
  - NLM with adaptive search window, by Kervrann and Boulanger [2]
  - Iterative weighted maximum likelihood denoising with probabilistic patch-based weights (It-PPB), by Deledalle et al. [3]
  - K-SVD, by Elad and Aharon [4]
  - ... ... 

- **Transform-Domain Methods**
  - BM3D, by Dabov et al. [5]
  - An extension of BM3D to SAR image, by Parrilli et al. [6]
  - Denoising by fusing of wavelet Bayesian and Markov random field, by Xie et al. [7]
  - ... ... 

- **Multi-temporal SAR image denoising**
  - Adaptive-neighborhood speckle removal in multi-temporal SAR images, by Mihai Ciuc et al. [8]
  - ... ...
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Non-Local Means Denoising

• Estimate actual pixel intensities with image redundancy
  – Search similar pixels
  – Estimate a weighted maximum likelihood with similar pixels

• Image $I = \{y(i)\}$:
  – Additive Gaussian noise model:
    $y(i) = u(i) + n(i)$

    $y(i)$: the observed value;
    $u(i)$: the true value;
    $n(i)$: the noise;

Non-Local Means Denoising

- Estimate of true value $\hat{u}(i)$:
  \[ \hat{u}(i) = \sum_{j \in \Omega} w(i, j) y(j) \]

  - Weights:
    \[ w(i, j) = \frac{1}{Z} \exp \left( -\frac{S(i, j)}{h} \right) \]

  - Similarity (distances) between patches
    \[ S(i, j) = \sum_{k \in K} [y(i, k) - y(j, k)]^2 \]

$\Omega$: search window $\{21 \times 21\}$
$K$: patch $\{7 \times 7\}$
$Z$: normalization parameter
$h$: the decay parameter of weights

• Corrupted by the multiplicative Goodman speckle noise, the pixel intensities $Y$ are modeled as the following distribution:

$$p(y|u) = \frac{2LL^L}{\Gamma(L)u^L} y^{L-1/2} \exp \left( -\frac{Ly}{u} \right)$$

$y$: the pixel intensity; $u$: the true value (the reflectivity)
$L$: the (equivalent) number of looks

• The similarity between noisy patches (based on Generalized likelihood Ratio):

$$S(i, j) = \sum_{k \in K} \log \left( \frac{y(i, k) + y(j, k)}{y^{1/2}(i, k)y^{1/2}(j, k)} \right)$$

$K$: patch $\{7 \times 7\}$

Iterative Weighted Maximum Likelihood Denoising with Probability Patch-based Weights (It-PPB) for SAR Images

- **Estimate of $\mathcal{U}$**: 
  \[ \hat{u}(i) = \sum_{y(i) \in \Omega} w(i, j) y(j) \]
  
  $\Omega$: search window $\{21 \times 21\}$

- **The iterative weights $w(i, j)$**: 
  \[ w(i, j) = \frac{1}{Z} \exp \left[ -\frac{1}{h_0} S(i, j) - \frac{L}{h_1} R^{m-1}(i, j) \right] \]
  
  $h_0$: the decay parameter of similarity
  $h_1$: the decay parameter of iterative term

- **Iterative term (refines the weights)**: 
  \[ R^{m-1}(i, j) = \sum_{k \in K} \frac{[\hat{u}^{m-1}(i, k) - \hat{u}^{m-1}(j, k)]^2}{\hat{u}^{m-1}(i, k) \hat{u}^{m-1}(j, k)} \]
  
  $\hat{u}^{m-1}(i)$: the $(m - 1)$-th iterative denoising results

The temporal It-PPB for multi-temporal data (A direct extension of It-PPB)

The temporal It-PPB for multi-temporal data (A direct extension of It-PPB)

- The temporal image set: \( S = \{I_{t_1}, I_{t_2}, \ldots I_{t_N}\} \)
- The search cube (window): \( C = \{\Omega_{t_1}, \Omega_{t_2}, \ldots \Omega_{t_N}\} \)
- The estimate of true value \( \hat{u} \):

\[
\hat{u}_t(i) = \sum_{y_{t'}(j) \in C} w(i_t, j_{t'}) y_{t'}(j)
\]

\[
w(i_t, j_{t'}) = \frac{1}{Z} \exp \left[ - \frac{1}{h_0} S(i_t, j_{t'}) - \frac{L}{h_1} R^{m-1}(i_t, j_{t'}) \right]
\]

\[
S(i_t, j_{t'}) = \sum_{k \in K} \log \left[ \frac{y_t(i, k) + y_{t'}(j, k)}{\sqrt{y_t^{1/2}(i, k)y_{t'}^{1/2}(j, k)}} \right]
\]

\[
R^{m-1}(i_t, j_{t'}) = \sum_{k \in K} \frac{[\hat{u}_t^{m-1}(i, k) - \hat{u}_{t'}^{m-1}(j, k)]^2}{\hat{u}_t^{m-1}(i, k)\hat{u}_{t'}^{m-1}(j, k)}
\]
Test of the temporal It-PPB

• Image data (stable case)
  – Stable objects (no changes over time)
  – A synthetic set of multi-temporal SAR images \( \mathcal{S} = \{I_{t1}, I_{t2}, I_{t3}\} \)
  – 1-look speckle noise
  – \( \bar{\mathcal{S}} \): the temporal mean of \( \mathcal{S} \)

• Denoising methods
  – Exp.1: The temporal It-PPB on the multi-temporal images \( \mathcal{S} \)
  – Exp.2: The original It-PPB on the single image \( I_{t1} \)
  – Exp.3: The original It-PPB on the temporal means \( \bar{\mathcal{S}} \)

• The expected results
  – Exp.1 \( \approx \) Exp.3 \( >> \) Exp.2
  Is it true???
The actual results of stable case

Temporal It-PPB

Original It-PPB

SNR: 21.13dB  
Exp.1  
≈ 
Exp.2  
<<  
Exp.3

SNR: 20.75dB

SNR: 24.25dB
The actual results of stable case
Motivation and contribution

• Taking inspiration from the comparison experiment
  – Using the temporal information to acquire a lower-level noise image
  – Average the spatial pixels (Non local means)

• Contribution in multi-temporal SAR images denoising
  – Find a way to exploit more available information for stable pixels
  – Meanwhile, comparably keep new objects
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  – Step 1: Temporal average with binary weights
  – Step 2: Spatial Average

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Step 1: Temporal average with binary weights

- Similarity between temporal pixels (change criterion)
  - Denoise each image $I_{tn} = \{y_{tn}(i)\}$ in the multi-temporal image set $S$ and get the pre-denoising results $\hat{I}_{tn} = \{\hat{u}_{tn}(i)\}$
  - Compare pixels in different dates (images) but in same position
    $$P_i(t, t') = \begin{cases} 1, & \text{if } \frac{[\hat{u}_t(i) - \hat{u}_{t'}(i)]^2}{\hat{u}_t(i)\hat{u}_{t'}(i)} > T_{SA} \\ 0, & \text{otherwise} \end{cases}$$
    $T_{SA}$ denotes the temporal similarity threshold $\hat{u}_t(i)$ is the It-PPB denoising result of image $I_t$

- Temporal average
  $$\tilde{y}_t(i) = \frac{1}{Z} \sum_{t' \in [t_1, t_N]} P_i(t, t') y_{t'}(i)$$
  $$Z = \sum_{t' \in [t_1, t_N]} P_i(t, t')$$
Step 2: Spatial average

- The estimate of true value $\mathcal{U}$ using temporal average image $\widetilde{I}_{tn}$
  \[
  \hat{\mathcal{U}}'(i) = \sum_{\tilde{y}_t(j) \in \tilde{C}} \tilde{w}(i_t, j_t) \tilde{y}_t(j)
  \]

  - Weights:
    \[
    \tilde{w}(i_t, j_t) = \frac{1}{Z} \exp\left[ -\frac{1}{h_0} \tilde{S}(i_t, j_t) - \frac{L}{h_1} R^{m-1}(i_t, j_t) \right]
    \]

  - Similarity between X-looks noisy patches
    \[
    \tilde{S}(i_t, j_t) = \sum_{k \in K} \log \left[ \frac{\tilde{L}_{ti} \tilde{y}_t(i, k) + \tilde{L}_{tj} \tilde{y}_t(j, k)}{\tilde{L}_{ti} + \tilde{L}_{tj}} \right]
    \]

  $\tilde{L}_{ti}$ and $\tilde{L}_{tj}$ are the number of looks
The sketch map of the proposed method

- $\mathcal{S} = \{I_{t1}, I_{t2}, I_{t3}\}$: the original multi-temporal images
- $\hat{u}_{t1}$: the denoising result of $I_{t1}$ using It-PPB
- $P(t1, t2)$: the temporal relation between $I_{t1}$ and $I_{t2}$
- $\tilde{I}_{t1}$: the temporal average image
- $\hat{u}'_{t1}$: the final denoising result
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Data Sets

• Synthetic images
  – Noise free image: 100 looks SAR image © ONERA © CNES
  – 1-look multiplicative speckle noise
  – 3-dates: \( S = \{I_{t1}, I_{t2}, t_{t3}\} \)
  – A dark line and a bright target are added only to \( I_{t1} \)
    (in red rectangles)

\[ I_{t1} \text{ in } S \]

\[ I_{t2} \text{ in } S \ (I_{t3} \text{ is similar to } I_{t2}) \]
Data Sets

- **Real SAR images**
  - 2012 IEEE GRSS Data Fusion Contest
  - Single-look
  - TerraSAR X-bands data
  - 1m X 1m spatial resolution
  - 6 dates (images) in 2007 and 2011
  - Use the sensor parameters for image registration

\[ S = \{ I_{t1}, I_{t2}, I_{t3}, I_{t4}, I_{t5}, I_{t6} \} \]

Choice of Parameters

• Search window size and patch size enlarge with the increase of the number of iteration
  – Search window $\Omega \in \{3 \times 3, 7 \times 7, 11 \times 11, 21 \times 21\}$
  – Patch $K \in \{1 \times 1, 3 \times 3, 5 \times 5, 7 \times 7\}$

• Smooth parameter
  – $h_0 = \alpha$-quantile ($\alpha = 0.92$)
  – $h_1 = 0.2K$

• Temporal similarity similarity threshold
  – $T_{SA} = \alpha$-quantile ($0.98 < \alpha < 1$)
Results

- Comparably keep *new* objects
- Preserve more details for *stable* objects
Results

- Preserve more details for *stable* objects (dark lines)
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Conclusion and Future Works

• Conclusion
  – Present a two steps multi-temporal non-local means for SAR images denoising
    1) Exploit more available information for stable objects
    2) Comparably keep new objects

• Future works
  – Lower the requirement of input data, such as image registration;
  – Find more effective criterion for change detection;
  – Define new similarity for multi-temporal images;
References

Thanks for your attention
The actual results

Temporal It-PPB

Original It-PPB

Temporal Mean

It-PPB