Speckle reduction in PolSAR by multi-channel variance stabilization and Gaussian denoising: MuLoG

Charles-Alban Deledalle, Loïc Denis, Florence Tupin, Sylvain Lobry

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DELEDALLE Charles-Alban, IMB, CNRS, Univ Bordeaux, Bordeaux INP, F-33405 Talence, France
charles-alban.deledalle@math.u-bordeaux.fr

DENIS Loïc, Univ Lyon, UJM-Saint-Etienne, CNRS, Institut d Optique Graduate School, Laboratoire Hubert Curien UMR 5516, F-42023, Saint-Etienne, France
loic.denis@univ-st-etienne.fr

TUPIN Florence, LTCI, Telecom ParisTech, Université Paris-Saclay, 75013, Paris, France
florence.tupin@telecom-paristech.fr

LOBRY Sylvain, Laboratory of Geo-information Science and Remote Sensing, Wageningen University, 6708 PB Wageningen, The Netherlands
work@sylvainlobry.com

Abstract

Due to speckle phenomenon, some form of filtering must be applied to SAR data prior to performing any polarimetric analysis. Beyond the simple multilooking operation (i.e., moving average), several methods have been designed specifically for PolSAR filtering. The specifics of speckle noise and the correlations between polarimetric channels make PolSAR filtering more challenging than usual image restoration problems. Despite their striking performance, existing image denoising algorithms, mostly designed for additive white Gaussian noise, cannot be directly applied to PolSAR data. We bridge this gap with MuLoG by providing a general scheme that stabilizes the variance of the polarimetric channels and that can embed almost any Gaussian denoiser. We describe MuLoG approach and illustrate its performance on airborne PolSAR data using a very recent Gaussian denoiser based on a convolutional neural network.

1 Introduction

Image restoration is an old topic in image processing that has been periodically revived by methodological breakthroughs such as the neighborhood filters (developed by Lee and Yaroslavsky in the 80s), Markov random fields, total variation minimization, wavelets filtering, sparse representations, patch-based methods, and most recently, deep neural networks. These methodologies have been adapted to SAR intensity images to reduce fluctuations due to speckle. Many adaptations are based on a log transform that turns speckle fluctuations into an additive component that is approximately Gaussian. The extension of these methodologies to polarimetric SAR images is more challenging due to the lack of such variance stabilization transform. Only a few methodologies could be applied to PolSAR filtering, mostly "selection" type algorithms that perform a (weighted) average over pixels identified as sufficiently similar (notably, Lee's filters, IDAN [9], Pretest [3] and NL-SAR[5]).

The aim of this paper is to show that there exists a transformation that (approximately) stabilizes the variance of PolSAR data and that an alternating optimization scheme can be applied to include very easily, like a "black-box", almost any Gaussian denoiser. The general framework of the method, called MuLoG, has been very recently described in [4]. We illustrate it here in the case of PolSAR data and show that it can successfully include a denoiser based on a deep neural network, trained over natural images, because such a network encodes information about geometrical and textural patterns encountered in all images.

The paper structure is the following: we first introduce the variance stabilization transform, then we describe MuLoG algorithm and analyze its performance with a denoiser based on deep learning for PolSAR covariance estimation.

2 PolSAR variance stabilization

Due to the interference between echoes retro-diffused by the scatterers located within the same radar resolution cell, the diffusion vector $\vec{k} = (k_{\mathrm{HH}}\ k_{\mathrm{HV}}\ k_{\mathrm{VV}})^t \in \mathbb{C}^3$ is highly sensitive to the configuration of scatterers. Changes in this configuration lead to fluctuations of the diffusion vector. Under Goodman's fully-developed speckle model, these fluctuations can be modeled by a multivariate complex circular Gaussian distribution. The covariance of this Gaussian distribution carries information about the polarimetric behavior of the medium within the resolution cell.

A polarimetric covariance matrix $\mathbf{\Sigma}$ can be estimated from L samples of diffusion vectors $\vec{k}_1, \ldots, \vec{k}_L$ by computing the empirical covariance:

$$\boldsymbol{C} = \frac{1}{L} \sum_{t=1}^{L} \vec{k}_t . \vec{k}_t^* \,, \tag{1}$$

where $*$ denotes the Hermitian transpose. If vectors $\vec{k}_t$

are supposed to be Gaussian-distributed then the empirical covariance $\boldsymbol{C}$ follows a circular complex Wishart distribution, for $L \geq D$:

$$p_{\boldsymbol{C}}(\boldsymbol{C}|\boldsymbol{\Sigma}) = \frac{L^{LD}|\boldsymbol{C}|^{L-D}}{\Gamma_D(L)|\boldsymbol{\Sigma}|^L} \exp\left(-L\,\mathrm{tr}(\boldsymbol{\Sigma}^{-1}\boldsymbol{C})\right) , \quad (2)$$

where D is the dimension of the diffusion vector ($D = 3$ under the reciprocity assumption considered in this paper, and $D = 2$ for dual polarization), L is the number of looks, Γ stands for the multivariate gamma function and tr() denotes the matrix trace.
The empirical covariance matrix is unbiased ($\mathbb{E}[\boldsymbol{C}] = \boldsymbol{\Sigma}$), but the fluctuations of the empirical covariance matrix $\boldsymbol{C}$ depend on $\boldsymbol{\Sigma}$. In particular, according to [6], $\mathrm{Var}[\mathrm{tr}(\boldsymbol{C})] = \frac{1}{L}\mathrm{tr}(\boldsymbol{\Sigma}^2)$, which shows that speckle fluctuations cannot be considered as a stationary additive contribution to the signal of interest.

Speckle fluctuations can be made almost signal-independent by the matrix logarithm transform:

$$\boldsymbol{C} \;\mapsto\; \tilde{\boldsymbol{C}} = \log \boldsymbol{C} = \mathbf{E}\,\mathrm{diag}(\tilde{\boldsymbol{\Lambda}})\mathbf{E}^{-1} , \quad (3)$$

where $\tilde{\boldsymbol{\Lambda}}_i = \log \boldsymbol{\Lambda}_i$, $\mathbf{E} \in \mathbb{C}^{D\times D}$ is the matrix whose column vectors are eigenvectors (with unit norm) of $\boldsymbol{C}$, $\boldsymbol{\Lambda} \in \mathbb{R}_+^D$ is the vector of corresponding eigenvalues, such that $\boldsymbol{C} = \mathbf{E}\,\mathrm{diag}(\boldsymbol{\Lambda})\mathbf{E}^{-1}$, and $\tilde{\boldsymbol{\Lambda}} \in \mathbb{R}^D$. Its inverse transform is the matrix exponential defined similarly. Log-transformed covariance matrices $\tilde{\boldsymbol{C}}$ are distributed according to a Wishart-Fisher-Tippett distribution [4]:

$$p_{\tilde{\boldsymbol{C}}}(\tilde{\boldsymbol{C}}|\tilde{\boldsymbol{\Sigma}}) = \kappa e^{L\,\mathrm{tr}(\tilde{\boldsymbol{C}}-\tilde{\boldsymbol{\Sigma}})} \exp\left(-L\,\mathrm{tr}(e^{\tilde{\boldsymbol{C}}}e^{-\tilde{\boldsymbol{\Sigma}}})\right) , \quad (4)$$

with κ a scalar that depends only on D, L and $\tilde{\boldsymbol{C}}$ and that will be irrelevant when estimating $\tilde{\boldsymbol{\Sigma}}$ from a given $\tilde{\boldsymbol{C}}$. This distribution is the polarimetric generalization of the well-known Fisher-Tippett distribution of log-transformed intensity images corrupted by speckle. The first two moments of the trace of $\tilde{\boldsymbol{C}}$ are known in closed form [1]:

$$\mathbb{E}[\mathrm{tr}\,\tilde{\boldsymbol{C}}] = \mathrm{tr}\,\tilde{\boldsymbol{\Sigma}} + \sum_{i=1}^{D}\Psi(0, L-i+1) - D\log L ,$$
$$\text{and}\quad \mathrm{Var}[\mathrm{tr}\,\tilde{\boldsymbol{C}}] = \sum_{i=1}^{D}\Psi(1, L-i+1) , \quad (5)$$

which shows that, (i) like in the case of a single-channel intensity image, a bias is present when averaging log-transformed data, and (ii) the variance (of the trace) is signal-independent (i.e., independent from $\boldsymbol{\Sigma}$). Numerical experiments show that not only the variance of the trace is stabilized, but the variance of each term of the covariance matrix $\boldsymbol{C}$ is approximately signal-independent. The matrix logarithm is thus a good candidate to extend Gaussian denoisers to PolSAR covariance estimation.

3 MuLoG framework

We give here a summarized presentation of MuLoG approach in the case of polarimetric images. More technical details are available in [4]. We then show how to include a denoising step based on a deep neural network.

The general scheme of MuLoG is depicted in figure 1. Several ingredients are combined in order to include a Gaussian denoiser within a generic approach for PolSAR covariance estimation:

1. speckle fluctuations are made almost signal-independent by applying a matrix logarithm on the data,
2. the complex entries of the covariance matrices are decomposed into real-valued channels,
3. these channels are whitened and equalized,
4. the log-likelihood of log-transformed covariances is maximized while enforcing some form of regularization using alternating minimization.

Prior to performing the matrix logarithm transformation, off-diagonal elements of the covariance matrices are shrunk so as to ensure that all covariance matrices are full rank (starting from SLC PolSAR images, the covariance matrix at pixel t is initially the rank-one matrix $\vec{k}_t.\vec{k}_t^*$). Channels whitening is performed so that each channel be processed independently by the Gaussian denoiser while introducing as few artifacts as possible. A whitening transform is defined based on a principal component analysis of the real-valued channels extracted from the matrix logarithm of the speckle-corrupted data. We define by $\Omega : \boldsymbol{x} \mapsto \tilde{\boldsymbol{\Sigma}}$ the affine mapping that transforms whitened and equalized channels $\boldsymbol{x}$ back into a complex-valued covariance (in matrix-log domain). Figure 2 illustrates how a single look PolSAR image (shown with Pauli color-coding in Fig.2(a)) can be decomposed into variance-stabilized and whitened real-valued channels (first 3 channels shown in L*a*b* color-coding in Fig.2(e), last 3 channels shown in Fig.2(f)). The estimation of the matrix-log transform of (speckle-free) covariance matrices $\hat{\boldsymbol{x}}$ from the noisy matrix-log-transformed channels $\boldsymbol{y} = \Omega^{-1}(\tilde{\boldsymbol{C}})$ can be formulated within the maximum a posteriori framework as the following minimization problem:

$$\hat{\boldsymbol{x}} \in \underset{\boldsymbol{x}}{\mathrm{argmin}}\; -\log p_{\boldsymbol{y}}(\boldsymbol{y}|\boldsymbol{x}) + \sum_{i=1}^{D^2}\mathcal{R}(x^i) , \quad (6)$$

where, from (4), we have (up to a constant)

$$-\log p_{\boldsymbol{y}}(\boldsymbol{y}|\boldsymbol{x}) = L\sum_{k=1}^{n}\mathrm{tr}\left(\Omega(\boldsymbol{x}_k) + e^{\Omega(\boldsymbol{y}_k)}e^{-\Omega(\boldsymbol{x}_k)}\right) \quad (7)$$

and the final estimate $\hat{\boldsymbol{\Sigma}}_k$ at pixel index k is defined as $\hat{\boldsymbol{\Sigma}}_k = \exp\Omega(\hat{\boldsymbol{x}}_k)$. The same regularization $\mathcal{R}$ is applied separately to each (real-valued) channel since after whitening and equalization these channels are approximately i.i.d. By applying the variable splitting $\boldsymbol{z} = \boldsymbol{x}$ and the alternating directions method of multipliers

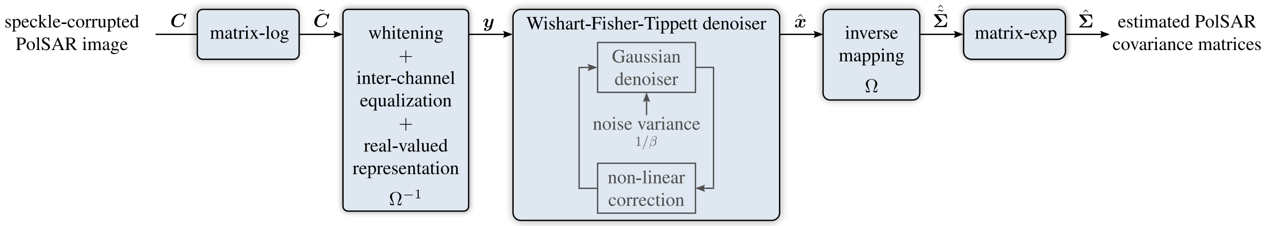

Figure 1: MuLoG approach to speckle reduction in PolSAR data.

(ADMM), the minimization problem is turned into the following sequence of steps:

$$\hat{\boldsymbol{z}} \leftarrow \underset{\boldsymbol{z}}{\operatorname{argmin}} \, \frac{\beta}{2}\|\boldsymbol{z} - \hat{\boldsymbol{x}} + \hat{\boldsymbol{d}}\|^2 + \sum_{i=1}^{D^2} \mathcal{R}(z^i) \,, \tag{8}$$

$$\hat{\boldsymbol{d}} \leftarrow \hat{\boldsymbol{d}} + \hat{\boldsymbol{z}} - \hat{\boldsymbol{x}} \,, \tag{9}$$

$$\hat{\boldsymbol{x}} \leftarrow \underset{\boldsymbol{x}}{\operatorname{argmin}} \, \frac{\beta}{2}\|\boldsymbol{x} - \hat{\boldsymbol{z}} - \hat{\boldsymbol{d}}\|^2 - \log p_{\boldsymbol{y}}(\boldsymbol{y}|\boldsymbol{x}) \,, \tag{10}$$

where the first step amounts to a Gaussian denoising, the second step is an update of so-called scaled Lagrange multipliers, and the third step is a non-linear processing performed independently at each pixel. Because of the matrix exponentials that involve eigen-decompositions, this last step is not trivial. An iterative procedure is described in [4].

Since (8) corresponds to a Gaussian denoising step of each channel of the images $\hat{\boldsymbol{x}} - \hat{\boldsymbol{d}}$ for a noise variance equal to $1/\beta$, the idea of plug-and-play ADMM methods is to perform (8) using an off-the-shelf Gaussian denoiser [2, 4] (the regularization $\mathcal{R}$ is then not explicitly defined). In this paper, we consider a very recent Gaussian denoiser based on a deep convolutional neural network described in [11]. The neural network combines several elements that have proven very effective: batch normalization [8] (normalization of the output of each layer to improve the learning speed), residual learning [7] (i.e., learning of how to recover the noise to remove to obtain a restored image, rather than learning how to directly restore the image) and dilated convolutions [10] (to capture multi-scale features without resorting to dimension reduction/augmentation). This network has been trained over a set of more than 5000 natural images.

4 Results and discussion

We illustrate MuLoG on an airborne full-polar SAR image obtained with the E-SAR sensor of the DLR (image over Oberpfaffenhofen provided with PolSARpro). In order to reduce speckle correlation, we downsampled by a factor 2 the image prior to filtering. Figure 2 illustrates the original image (region of interest of size 351×351 pixels), the result of a boxcar filtering (i.e., multilooking) over a 3×3 window, the result of NL-SAR [5] which can be considered as a state-of-the-art speckle reduction technique for PolSAR data (the processing took 20s with the default parameters on a laptop with a quad-core i7-4980HQ CPU @ 2.80GHz) and the result using MuLoG with the deep CNN of [11] (the processing took 2min with a CPU implementation of the CNN on Matlab). The multi-looking process degrades the resolution: point-like targets are spread and small details are lost while homogeneous regions are insufficiently smoothed. In contrast, both NL-SAR and MuLoG preserve the resolution while performing a strong smoothing of homogeneous areas. Some residual noise can be observed on the NL-SAR result in the regions where too few similar patches could be found, while MuLoG offers a strong smoothing everywhere. The two results are in good agreement in most regions. Small discrepancies can be observed on some isolated targets that are sometimes suppressed in MuLoG. The texture of the vegetated area also does not seem very natural with MuLoG. The performance of MuLoG+CNN could most probably be improved by performing a training specific to PolSAR images. Even with a network trained over natural images, the performance is very good which seems to indicate that the network captured information about points, lines, edges or textures that is general enough to be common to several image modalities.

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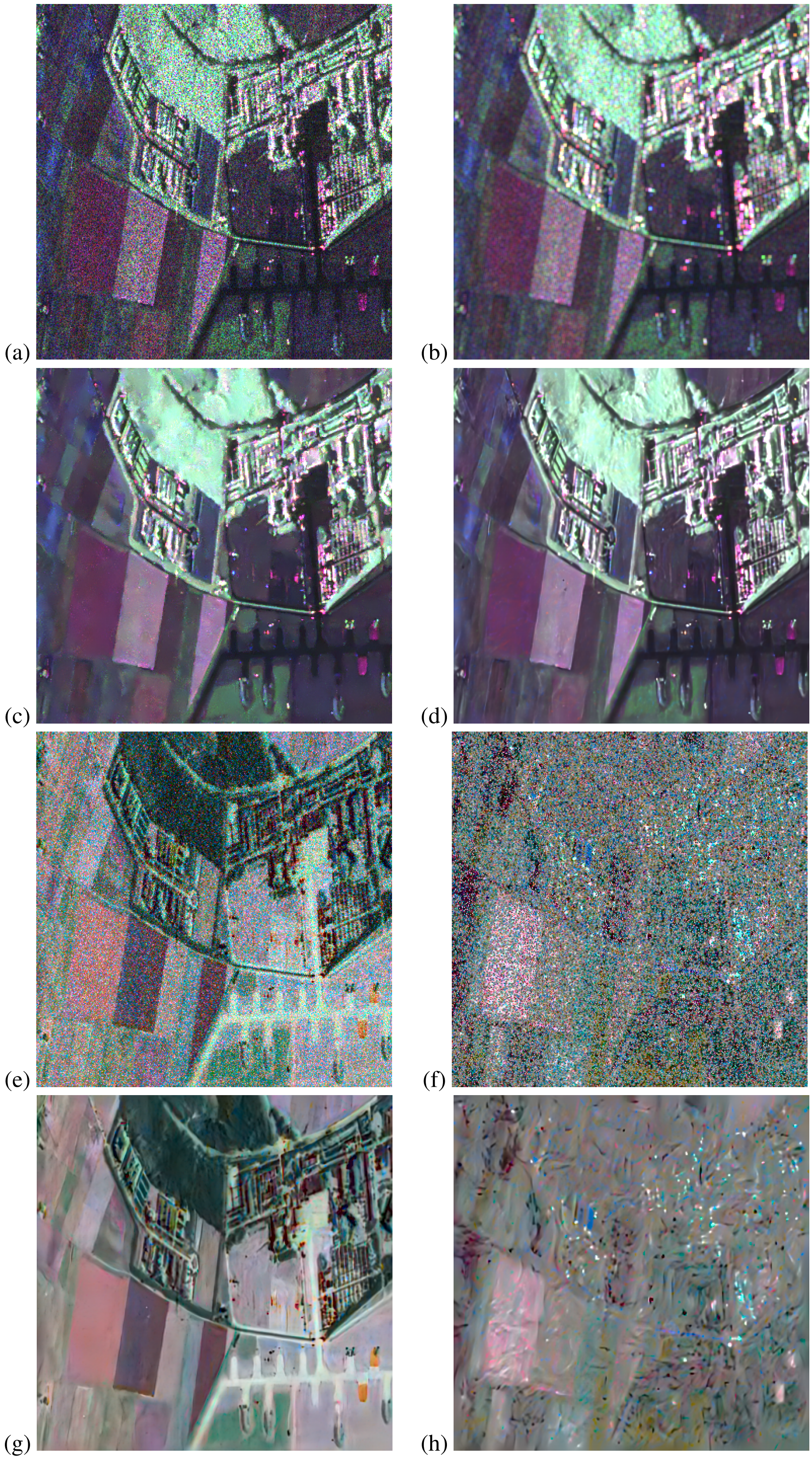

Figure 2: Application of MuLoG with the Gaussian denoiser based on the deep neural network described in [11]: (a) single-look E-SAR image of Oberpfaffenhofen (©DLR, source: PolSARPro sample datasets); (b) 3×3 multilooking; (c) denoising result with NL-SAR [5]; (d) denoising result with the proposed method: MuLoG + deep CNN; (e) and (g) color composition of the first 3 channels after matrix logarithm and whitening, at the beginning (e) and at the end (g) of the denoising procedure; (f) and (h) color composition of the last 3 channels (i.e., the least significant channels according to the PCA).

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