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Speckle reduction in polarimetric SAR imagery with stochastic distances and nonlocal means

Leonardo Torres [a,*], Sidnei J.S. Sant'Anna [a], Corina da Costa Freitas [a], Alejandro C. Frery [b]

[a] Instituto Nacional de Pesquisas Espaciais – INPE, Divisão de Processamento de Imagens – DPI, Av. dos Astronautas, 1758, 12227-010 São José dos Campos – SP, Brazil
[b] Universidade Federal de Alagoas – UFAL, CPMAT–LaCCAN, Av. Lourival Melo Mota, s/n, Tabuleiro dos Martins, 57072-900 Maceió – AL, Brazil

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ABSTRACT

This paper presents a technique for reducing speckle in Polarimetric Synthetic Aperture Radar (PolSAR) imagery using nonlocal means and a statistical test based on stochastic divergences. The main objective is to select homogeneous pixels in the filtering area through statistical tests between distributions. This proposal uses the complex Wishart model to describe PolSAR data, but the technique can be extended to other models. The weights of the location-variant linear filter are function of the *p*-values of tests which verify the hypothesis that two samples come from the same distribution and, therefore, can be used to compute a local mean. The test stems from the family of $(h\text{–}\phi)$ divergences which originated in Information Theory. This novel technique was compared with the Boxcar, Refined Lee and IDAN filters. Image quality assessment methods on simulated and real data are employed to validate the performance of this approach. We show that the proposed filter also enhances the polarimetric entropy and preserves the scattering information of the targets.

1. Introduction

Among the remote sensing technologies, Polarimetric Synthetic Aperture Radar (PolSAR) has achieved a prominent position. PolSAR imaging is a well-developed coherent microwave remote sensing technique for providing large-scale two-dimensional (2-D) high spatial resolution images of the Earth's surface dielectric properties [21].

In SAR systems, the value at each pixel is a complex number: the amplitude and phase information of the returned signal. Full PolSAR data is comprised of four complex channels which result from the combination of the horizontal and vertical transmission modes, and horizontal and vertical reception modes.

The speckle phenomenon in SAR data hinders the interpretation these data and reduces the accuracy of segmentation, classification and analysis of objects contained within the image. Therefore, reducing the noise effect is an important task, and multilook processing is often used for this purpose in single- and full-channel data. In the latter, such processing yields a covariance matrix in each pixel, but further noise reduction is frequently needed.

According to Lee and Pottier [21], Polarimetric SAR image smoothing requires preserving the target polarimetric signature. Such requirement can be posed as (i) each element of the image should be filtered in a similar way to multilook processing by averaging the covariance matrix of neighboring pixels; and (ii) homogeneous regions in the neighborhood should be adaptively selected to preserve resolution, edges and the image quality. The second requirement, i.e. selecting homogeneous areas given similarity criterion, is a common problem in pattern recognition. It boils down to identifying observations from different stationary stochastic processes.

Usually, the Boxcar filter is the standard choice because of its simple design. However, it has poor performance since it does not discriminate different targets. Lee et al. [18,19] propose techniques for speckle reduction based on the multiplicative noise model using the minimum mean-square error (MMSE) criterion. Lee et al. [20] proposed a methodology for selecting neighboring pixels with similar scattering characteristics, known as Refined Lee filter. Other techniques use the local linear minimum mean-squared error (LLMMSE) criterion proposed by Vasile et al. [37], in a similar adaptive technique, but the decision to select homogeneous areas is based on the intensity information of the polarimetric coherency matrices, namely intensity-driven adaptive-neighborhood (IDAN).

Çetin and Karl [4] presented a technique for image formation based on regularized image reconstruction. This approach employs a tomographic model which allows the incorporation of prior

* Corresponding author. Tel.: +55 12 82554626.
E-mail addresses: ljmtorres@gmail.com (L. Torres), sidnei@dpi.inpe.br (S.J.S. Sant'Anna), corina@dpi.inpe.br (C. da Costa Freitas), acfrery@gmail.com (A.C. Frery).
URLS: http://sites.google.com/site/ljmtorres (L. Torres), http://sites.google.com/site/acfrery (A.C. Frery).

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information about, among other features, the sensor. The resulting images have many desirable properties, reduced speckled among them. Our approach deals with data already produced and, thus, does not require interfering in the processing protocol of the data.

Osher et al. [26] presented a novel iterative regularization method for inverse problems based on the use of Bregman distances using a total variation denoising technique tailored to additive noise. The authors also propose a generalization for multiplicative noise, but no results with this kind of contamination are shown. The main contributions were the rigorous convergence results and effective stopping criteria for the general procedure, that provides information on how to obtain an approximation of the noise-free image intensity. Goldstein and Osher [16] presented an improvement of this work using the class of L_1-regularized optimization problems, that originated in functional analysis for finding extrema of convex functionals. The authors apply this technique to the Rudin–Osher–Fatemi model for image denoising and to a compressed sensing problem that arises in magnetic resonance imaging. Our work deals with full polarimetric data, for which, to the best of our knowledge, there are no similar results that take into account its particular nature: the pixels values are definite positive Hermitian complex matrices.

Soccorsi et al. [29] presented a despeckling technique for single-look complex SAR image using nonquadratic regularization. They use an image model, a gradient, and a prior model, to compute the objective function. We employ the full polarimetric information provided by the multilook scaled complex Wishart distribution.

Chambolle [5] proposed a total variation approach for a number of problems in image restoration (denoising, zooming and mean curvature motion), but under the Gaussian additive noise assumption.

Li et al. [22] propose the use of a particle swarm optimization algorithm and an extension of the curvelet transform for speckle reduction. They employ the homomorphic transformation, so their technique can be used either in amplitude or intensity data, but not in complex-valued imagery, as is the case we present here.

Wong and Fieguth [41] presented a novel approach for performing blind decorrelation of SAR data. They use a similarity technique between patches of the point-spread function using a Bayesian least squares estimation approach based on a Fisher–Tippett log-scatter model. In a similar way, Sølbo and Eltoft [30] assume a Gamma distribution in a wavelet-based speckle reduction procedure, and they estimate all the parameters locally without imposing a fixed number of looks (which they call "degree of heterogeneity") for the whole image.

Buades et al. [3] proposed a methodology, termed Nonlocal Means (NL-means), which consists of using similarities between patches as the weights of a mean filter; it is known to be well suited for combating additive Gaussian noise. Deledalle et al. [11] applied this methodology to PolSAR data using the Kullback–Leibler distance between two zero-mean complex circular Gaussian laws. Following the same strategy, Chen et al. [6] used the test for equality between two complex Wishart matrices proposed by Conradsen et al. [8].

This paper proposes a new approach for speckle noise filtering in PolSAR imagery: an adaptive nonlinear extension of the NL-means algorithm. This is an extension of previous works [33,34], where we used an approach similar to that of Nagao and Matsuyama [24]. Overlapping samples are compared based on stochastic distances between distributions, and the p-values resulting from such comparisons are used to build the weights of an adaptive linear filter. The goodness-of-fit tests are derived from the divergences discussed by Frery et al. [15] and Nascimento et al. [25]. The new proposal is called *Stochastic Distances Nonlocal Means* (SDNLM) and amounts to using those observations which are not rejected by a test seeking for a strong stationary process.

This paper is organized as follows. First, we summarize the basic principles that lead to the complex Wishart model for full polarimetric data. In Section 3 we recall the nonlocal means method. Our approach for reducing speckle in PolSAR data using stochastic distances between two complex Wishart distributions is proposed in Section 4. Image Quality Assessment is briefly discussed in Section 5. Results are presented in Section 6, while Section 7 concludes the paper.

2. The complex wishart distribution

PolSAR imaging results in a complex scattering matrix, which includes intensity and relative phase data [15]. Such matrices have usually four distinct complex elements, namely S_{VV}, S_{VH}, S_{HV}, and S_{HH}, where H and V refer to the horizontal and vertical wave polarization states, respectively. In a reciprocal medium, which is most common situation in remote sensing, $S_{VH}=S_{HV}$ so the complex signal backscattered from each resolution cell can be characterized by a scattering vector $\boldsymbol{Y}$ with three complex elements (see [36]).

Thus, we have a scattering complex random vector $\boldsymbol{Y}=[S_{HH},S_{VH},S_{VV}]^t$, where $[\cdot]^t$ indicates vector transposition. In general, PolSAR data are locally modeled by a multivariate zero-mean complex circular Gaussian distribution that characterize the scene reflectivity [35,36], whose probability density function is

$$f(\boldsymbol{Y};\boldsymbol{\Sigma})=\frac{1}{\pi^3|\boldsymbol{\Sigma}|}\exp\{-\boldsymbol{Y}^{*t}\boldsymbol{\Sigma}^{-1}\boldsymbol{Y}\},$$

where $|\cdot|$ is the determinant, and the superscript '$*$' denotes the complex conjugate of a vector; $\boldsymbol{\Sigma}$ is the covariance matrix of $\boldsymbol{Y}$. This distribution is defined on $\mathbb{C}^3$. The covariance matrix $\boldsymbol{\Sigma}$, besides being Hermitian and positive definite, has all the information which characterizes the scene under analysis.

Multilook processing enhances the signal-to-noise ratio. It is performed averaging over L ideally independent looks of the same scene, and it yields the sample covariance matrix $\boldsymbol{Z}$ given, in each pixel, by $\boldsymbol{Z}=L^{-1}\sum_{\ell=1}^{L}\boldsymbol{Y}_\ell\boldsymbol{Y}_\ell^{*}$, where L is the number of looks.

Goodman [17] proved that $\boldsymbol{Z}$ follows a scaled multilook complex Wishart distribution, denoted by $\boldsymbol{Z}\sim\mathcal{W}(\boldsymbol{\Sigma},L)$, and characterized by the following probability density function:

$$f_{\boldsymbol{Z}}(\boldsymbol{Z}';\boldsymbol{\Sigma},L)=\frac{L^{3L}|\boldsymbol{Z}'|^{L-3}}{|\boldsymbol{\Sigma}|^{L}\Gamma_3(L)}\exp\{-L\,\mathrm{tr}(\boldsymbol{\Sigma}^{-1}\boldsymbol{Z}')\},\tag{1}$$

where, for $L\geq 3$, $\Gamma_3(L)=\pi^3\prod_{i=0}^{2}\Gamma(L-i)$, $\Gamma(\cdot)$ is the gamma function, $\mathrm{tr}(\cdot)$ is the trace operator, and the covariance matrix $\boldsymbol{Z}$ is given by

$$\boldsymbol{\Sigma}=E\{\boldsymbol{Y}\boldsymbol{Y}^{*t}\}=\begin{bmatrix}E\{S_{HH}S_{HH}^{*}\} & E\{S_{HH}S_{VH}^{*}\} & E\{S_{HH}S_{VV}^{*}\}\\ E\{S_{VH}S_{HH}^{*}\} & E\{S_{VH}S_{VH}^{*}\} & E\{S_{VH}S_{VV}^{*}\}\\ E\{S_{VV}S_{HH}^{*}\} & E\{S_{VV}S_{VH}^{*}\} & E\{S_{VV}S_{VV}^{*}\}\end{bmatrix},$$

where $E\{\cdot\}$ denote expectation. Anfinsen et al. [2] removed the restriction $L\geq 3$. The resulting distribution has the same form as in (1) and is termed the "relaxed" Wishart. We assume this last model, and we allow variations of L along the image.

The support of this distribution is the cone of positive definite Hermitian complex matrices [13].

The parameters are usually estimated by maximum likelihood (ML) due to its statistical properties. Let $\boldsymbol{Z}_r$ be a random matrix which follows a $\mathcal{W}(\boldsymbol{\Sigma},L)$ law. Its log-likelihood function is given by

$$\ell_r(\boldsymbol{\Sigma},L)=3L\log L+(L-3)\log|\boldsymbol{Z}_r|-L\log|\boldsymbol{\Sigma}|-3\log\pi-\sum_{q=0}^{2}\log\Gamma(L-q)-L\,\mathrm{tr}(\boldsymbol{\Sigma}^{-1}\boldsymbol{Z}_r),$$