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Contribution of Information Geometry for Polarimetric SAR Classification in Heterogeneous Areas

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Abstract: *We discuss in the paper the use of the Riemannian mean given by the differential geometric tools. This geometric mean is used in this paper for computing the centers of class in the polarimetric H/α unsupervised classification process. We can show that the centers of class will remain more stable during the iteration process, leading to a different interpretation of the H/α/A classification. This technique can be applied both on classical SCM and on Fixed Point covariance matrices. Used jointly with the Fixed Point CM estimate, this technique can give nice results when dealing with high resolution and highly textured polarimetric SAR images classification.*

1. Introduction

The recently launched POLSAR systems are now capable of producing high quality polarimetric SAR images of the Earth surface under meter resolution. The additional polarimetric information allows the discrimination of different scattering mechanisms. In [1] was introduced the entropy-alpha (H/α) classification based on the eigenvalues of the polarimetric (or coherency) covariance matrix (CM). This CM is usually estimated, under homogeneous and Gaussian assumptions, with the well known Sample Covariance Matrix (SCM) which is Wishart distributed. Based on this decomposition, the unsupervised classification of the SAR images can be performed by an iterative algorithm [2] based on complex Wishart density function. It uses the H/α decomposition results to get an initial segmentation into eight clusters, followed by a K-means clustering. This technique needs to derive by a classical Euclidian mean operation the averaged CM of each class. The use of a more rigorous Riemannian metric, which is adapted to the structure of the space of CM, to compute the class centers will be discussed and results on real images will be presented.

2. SIRV model

For high resolution SAR images, recent studies have shown that the spatial heterogeneity of the scene lead to a non-Gaussian model of the clutter. A commonly used non-Gaussian clutter model is the compound model: the spatial heterogeneity is accounted for by modeling the clutter polarimetric information m-vector $\mathbf{k}$, by a SIRV (Spherically Invariant Random Vector). A SIRV is the product between the square root of a positive random variable τ, called texture and an independent, zero-mean gaussian vector $\mathbf{z}$, called speckle, and characterized by its CM $\mathbf{M}$:

$$\mathbf{k} = \sqrt{\tau}\,\mathbf{z}, \tag{1}$$

In this model, τ represents the local variation of intensity of $\mathbf{k}$ from one pixel to another. All the polarimetric information (phase relationships in the vector $\mathbf{k}$) is contained in the CM $\mathbf{M}$.

Under homogeneous and Gaussian assumption, the texture τ is supposed to be constant and the same for all pixels. In that case, the N-sample of secondary data $\mathbf{k}_i$, $i \in [1, N]$ is Gaussian-distributed and the Maximum Likelihood Estimator (MLE) of the MC is the SCM:

$$\widehat{M}_{SCM} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{k}_i\,\mathbf{k}_i^H \tag{2}$$

Under SIRV hypothesis, the CM is usually an unknown parameter which can be estimated by a ML process. Gini et al. derived in [3] the MLE $\widehat{\mathbf{M}}_{FP}$ of the CM $\mathbf{M}$ for deterministic texture, which is the solution of the following equation:

$$\widehat{\mathbf{M}}_{FP} = f(\mathbf{M}) = \frac{m}{N}\sum_{i=1}^{N} \frac{\mathbf{k}_i\,\mathbf{k}_i^H}{\mathbf{k}_i^H\,\widehat{\mathbf{M}}_{FP}^{-1}\,\mathbf{k}_i}, \tag{3}$$

This approach has been used in [4] by Conte et al. to derive an algorithm allowing to compute the solution matrix, called the Fixed Point Estimate (FPE). This algorithm computes the fixed point of f by using the sequence $\mathbf{M}_{i+1} = f(\mathbf{M}_i)$ and $\mathbf{M}_0 = \mathbf{I}$. In [3] and [4], it has been proven that the estimation process of Eq. (3) yields an approximate MLE under stochastic texture hypothesis. This study has been completed with the works of Pascal et al. [5] who established the existence and unicity of the FPE, as well as the convergence of the algorithm whatever the initialisation. Moreover, the FPE is asymptotically Wishart-distributed.

3. Polarimetric classification in non-Gaussian environment

Classical polarimetric classification processes use a K-means algorithm[2]. Each pixel, represented by its CM, is assigned to a class. Each class is represented by its class center (mean of

all its elements). A distance is used to reassign pixels after each iteration. In the Gaussian case, the Wishart distance between the CM $\widehat{\mathbf{M}}_i$ and the class center $\widehat{\mathbf{M}}_\omega$, derived in [2], is used:

$$D_W\left(\widehat{\mathbf{M}}_i, \widehat{\mathbf{M}}_\omega\right) = \ln \frac{|\widehat{\mathbf{M}}_\omega|}{|\widehat{\mathbf{M}}_i|} + \mathrm{Tr}\left(\widehat{\mathbf{M}}_\omega^{-1}\, \widehat{\mathbf{M}}_i\right)$$

In the SIRV case, Vasile et al. derived a suitable distance in [6]:

$$D_S\left(\widehat{\mathbf{M}}_i, \widehat{\mathbf{M}}_\omega\right) = \ln \frac{|\widehat{\mathbf{M}}_\omega|}{|\widehat{\mathbf{M}}_i|} + \frac{m}{N}\sum_{n=1}^{N} \frac{\mathbf{k}_n^H\, \widehat{\mathbf{M}}_\omega^{-1}\, \mathbf{k}_n}{\mathbf{k}_n^H\, \widehat{\mathbf{M}}_i^{-1}\, \mathbf{k}_n}$$

This expression can be rewritten as:

$$D_S\left(\widehat{\mathbf{M}}_i, \widehat{\mathbf{M}}_\omega\right) = D_W\left(\widehat{\mathbf{M}}_i, \widehat{\mathbf{M}}_\omega\right) \tag{4}$$

Note this is the same expression as in the Gaussian case. This distance is used to reassign pixels into classes after each iteration. Class centers $\widehat{\mathbf{M}}_\omega$ are then recomputed using a euclidean metric, i.e. the usual arithmetical mean:

$$\widehat{\mathbf{M}}_{\omega_l} = \frac{1}{K}\sum_{k=1}^{K} \widehat{\mathbf{M}}_k^l \tag{5}$$

with $\widehat{\mathbf{M}}_k^l$, $k \in [1, K]$ the K CM of the pixels belonging to class ω_l. After several iterations of the algorithm, class centers move significantly from their original position in the H-α plane, which makes the physical interpretation of the classification result harder.

4. Geometry of information contribution

A recent theory [7, 8] allows to account for the fact the space of CM is not euclidean. Rigorously, the mean of the CM of a class cannot be computed by Eq. (5).

The mean associated to the riemannian metric is the geometric mean defined by:

$$\mathbf{M}_{\omega_l} = \underset{\mathbf{M}_\omega \in \mathcal{P}(m)}{\arg\min} \sum_{k=1}^{K} \left|\left|\log\left(\mathbf{M}_\omega\, {\mathbf{M}_k^l}^{-1}\right)\right|\right|_F^2 \tag{6}$$

with $||.||_F$ the Frobenius norm and $\mathcal{P}(m)$ the space of Hermitian definite positive matrices of size m. A gradient descent method easily yields a solution to this equation.

The rieamannian geometry of $\mathcal{P}(m)$ can also be used to compute a distance between two matrices:

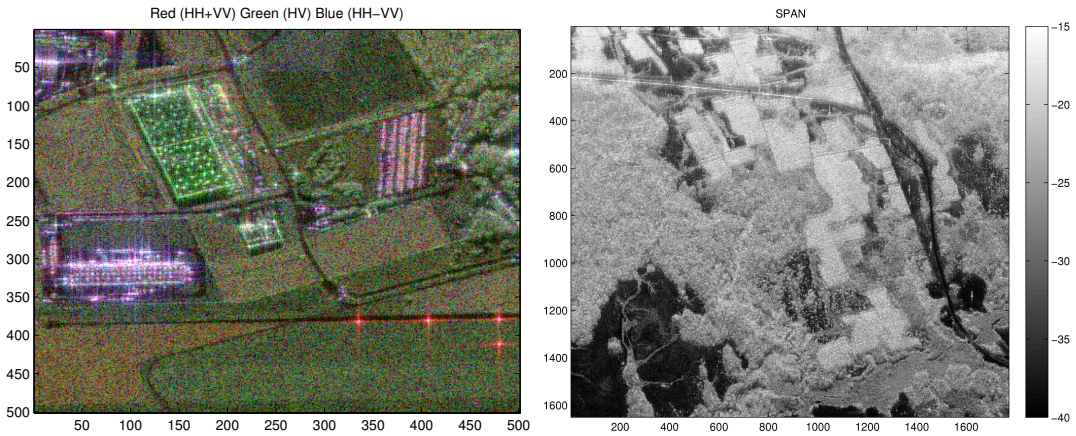
$$d_G(\mathbf{P}_1, \mathbf{P}_2) = \left\|\log(\mathbf{P}_1^{-1}\mathbf{P}_2\right\|_F \tag{7}$$

5. Results on real data

Fig. 1 presents the data sets used: a dataset acquired in Brétigny, France by the ONERA RAMSES sytem in X band and a dataset acquired in Paracou, French Guyana by the ONERA SETHI sytem in UHF band. In both cases, the ground resolution is 1.3x1.3m.

Fig. 2 presents the comparison between the classification results obtained with the FPE using the arithmetical mean or the geometrical mean on the data set presented on Fig. 1(a). When using the geometrical mean, the corner reflectors used for the calibration in the lower right corner of the image stand out more by being the only pixels in the class 8. Urban areas, more heterogeneous, are represented by classes 1, 3, 6 and 7 while more homogeneous areas (fields and forests) are in the remaining classes.

Fig. 3 shows the classification results obtained with the FPE using the arithmetical mean or the geometrical mean on the data set presented on Fig. 1(b). Using the geometrical mean allows to refine the classification of specific areas on this dataset. On the whole, the number of pixels in class 8 has reduced compared with the arithmetical mean. The pixels that left class 8 have been attributed to neighbouring classes, mostly classes 4 and 5. This reordering increases when the distance from Eq. (7) is used in place of the SIRV distance of Eq. (4), as seen in Fig. 3 (c). Class 8 is only composed of a straight line in the top left corner, which is a road, and an unidentified area in the top right corner. Without detailed ground truth, it is difficult to provide a more detailed interpretation but on both datasets, using geometry of information brings additional information.



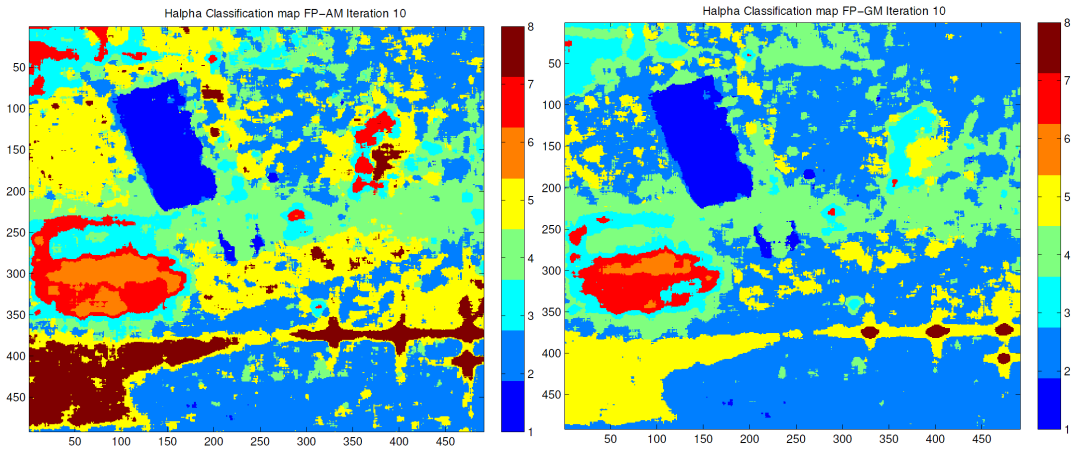
(a) Brétigny, Pauli representation (b) Paracou, span.

Figure 1: Data sets.

6. Conclusions

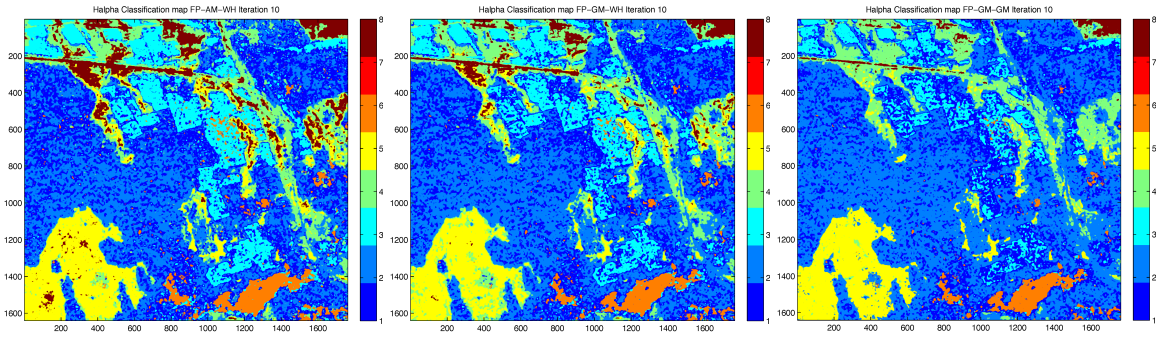
First results using the Riemannian metric for PolSAR classification are encouraging and suggest an improvement of the classifications by using these methods more intently. Simulations will

be done in order to quantify the contribution of this method.



(a) FPE, arithmetical mean (b) FPE, geometrical mean

Figure 2: Comparison between classification results with FPE after 10 iterations for arithmetical and geometrical means.



(a) FPE and arithmetical mean (b) FPE, geometrical mean (c) FPE, geometrical mean, geometrical distance

Figure 3: Comparison between classification results with FPE after 10 iterations for arithmetical and geometrical means.

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