DUAL-IMAGE POLARIMETRIC SAR DATA ANALYSIS

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1. Introduction

There have been developed many algorithms and techniques to classify natural media from their polarimetric behavior [1]-[3]. Recently, techniques were introduced in order to investigate the intrinsic physical properties of a natural medium by evaluating the underlying scattering mechanisms [4][5]. All these approaches realize an interpretation of the change in polarization of the backscattered wave, and tend to establish a relation between the medium physical properties and structure, and some polarimetric transformations.

The use of multi-frequency polarimetric data sets has shown an important improvement in the interpretation capabilities in quantitative remote sensing of natural media. The ratio of the size of a scatterer with respect to the incident wavelength is a critical parameter which conditions the nature of the scattering mechanism. The variation of a target response when observed at different frequencies, like snow covered soils at L, C and X bands, permits to specify its structure, and to analyze its different physical properties [6].

Some multi-frequency full polarimetric classification approaches were developed based on various types of classification algorithms and techniques. In [7] is introduced a maximum likelihood decision rule based on the gaussian distribution of the elements of the coherent scattering matrix. In order to limit the effects of the speckle in polarimetric SAR images, data are generally processed through incoherent averaging procedures. The polarimetric information of the averaged targets is then represented under the form of distributed covariance or coherency matrices. In [8], is introduced an adaptation of the maximum likelihood decision rule to the incoherent case by using the Wishart distribution of sample coherency matrices. An iterative c-mean algorithm is run to iteratively assign the pixels of the POLSAR image to one of the different classes using the maximum likelihood rule. In [9] is proposed an improvement of the class distribution initialization by using the H-$\underline{\alpha}$ decomposition theorem, and is completed in [10] with the use of the anisotropy. Both approaches provide an accurate initial guess of the pixel distribution into the classes and permit a better convergence of the unsupervised adaptive classification algorithm.

In this paper, we propose an unsupervised classification of dual frequency POLSAR images by simultaneously considering the polarimetric information contained in each image. The construction of a 6 by 6 coherency operator permits to gather the coherency matrices from each image as well as their intercorrelation [12], [13]. This operator is shown to follow a Wishart distribution, and a maximum likelihood decision rule is derived. Similarly to the single image case, data sets are processed through a c-mean classifier after an initialization step achieved by the application of the H-$\underline{\alpha}$ classification procedure in each separate image. A class number reduction technique is applied on the 64 resulting clusters, to improve the efficiency of the interpretation and representation of each class characteristics.

This approaches is applied on full polarimetric SAR images

2. Unsupervised Wishart classifier

In a monostatic configuration, the (3×3) hermitian coherency matrix $\mathbf{T}$ of a target is defined from the elements of the scattering matrix $\mathbf{S}$ as follows:

$$\mathbf{T} = \mathbf{k}\mathbf{k}^{\mathbf{H}} \text{ with } \mathbf{k} = \frac{1}{\sqrt{2}}\left[S_{HH} + S_{VV} \; S_{HH} - S_{VV} \; 2S_{HV}\right]^T \tag{1}$$

where $\mathbf{k}$ is the target vector, and ^{H} denotes the conjugate transpose operator. It has been verified that when the radar illuminates an area of random surface of many elementary scatterers, $\mathbf{k}$ can be modeled as having a zero mean multivariate complex Gaussian probability density function $N_C(0, \Sigma)$, with $\Sigma = E(\mathbf{k}\mathbf{k}^{\mathbf{H}})$ the covariance matrix of $\mathbf{k}$.

In [7], is defined a maximum likelihood classification procedure based on this normal density function. A vector $\mathbf{k}$ is assigned to the class χ_m if the conditional probability of this class, knowing the vector $\mathbf{k}$, is superior to the conditional probability for other classes.

Data sets are generally processed using a large amount of incoherent techniques, due to SAR measurement principles, data compression and particularly speckle reduction. Multi-look data result from the averaging of independent single-look incoherent representations. The n-look sample coherency matrix is obtained from the n target vectors $\mathbf{k_i}$ as follows:

$$\langle \mathbf{T} \rangle = \frac{1}{n}\sum_{i=1}^{n} \mathbf{k}_i \mathbf{k}_i^H \tag{2}$$

It has been shown [9] that assuming that the target vectors have a $N_C(0, \Sigma)$ distribution, $\langle \mathbf{T} \rangle$ follows a complex Wishart probability density function with n degrees of freedom and covariance matrix $\Sigma_{\langle \mathbf{T} \rangle} = \Sigma / n$, $W_C(n, \Sigma_{\langle \mathbf{T} \rangle})$, defined by:

$$p(\langle \mathbf{T} \rangle) = \frac{|\langle \mathbf{T} \rangle|^{n-q} \exp(-\mathrm{tr}(\Sigma_{\langle \mathbf{T} \rangle}^{-1} \langle \mathbf{T} \rangle))}{K(n, q)\left|\Sigma_{\langle \mathbf{T} \rangle}\right|^n} \text{ with } K(n, q) = \pi^{q(q-1)/2} \prod_{i=1}^{q} \Gamma(n - i + 1) \tag{3}$$

with $\Gamma(\;)$ the gamma function, and q the number of elements of the target vector.

Similarly to the single-look case, a Bayes maximum likelihood classification leads to the definition of a decision rule. By taking the natural logarithm of (3), and assuming the *a priori* probabilities of the different classes to be equal, a sample covariance matrix of a pixel of the SAR image is assigned to the class χ_m if $d_1(\langle \mathbf{T} \rangle, \chi_m) \le d_1(\langle \mathbf{T} \rangle, \chi_j) \; \forall j \ne m$ with [9]

$$d_1(\mathbf{Z}, \chi_m) = \ln\left|\Sigma_{\mathbf{m}}\right| + \mathrm{tr}(\Sigma_{\mathbf{m}}^{-\mathbf{1}} \langle \mathbf{T} \rangle) \tag{4}$$

with $\Sigma_{\mathbf{m}}$ the coherency feature matrix of the class χ_m.

The method used to perform a classification of a single image polarimetric data set is based on the use of an iterative c-mean algorithm and is described in details in [8][9][10]. As indicated in [9][10], the critical step of the initialization of the pixel distribution over the different classes is achieved by the way of the unsupervised H-$\underline{\alpha}$ classification.

This pre-classification scheme consists in a projection into an arbitrarily segmented plane according to the values of $\underline{\alpha}$, the indicator of the scattering mechanism nature, and H, the random aspect of the global scattering phenomenon, obtained from an eigenvector-eigenvalue based decomposition of the distributed coherency matrix.

The arbitrarily fixed linear decision boundaries may not fit the data distribution in the classification plane and cause inaccurate results, nonetheless this classification scheme provides an interpretation of the global scattering leading to an understanding of the relation between the response of a medium and its mean physical characteristics and can be used as a first guess of the different scattering types met when observing a natural scene.

This unsupervised classification algorithm modify the decision boundaries in an adaptive way to better fit the natural distribution of the scattering mechanisms. The whole polarimetric information contained in coherency matrix representation is taken into account.

3. Unsupervised classification of dual polarimetric images

The classification procedure mentioned above deals with one image at a time. When comparing polarimetric images, one has to classify each image, and then analyze differences by a class to class migration observation from one image to the other [11].
In order to directly perform the comparison, we build a polarimetric incoherent representation gathering information from both images by the way of a $p = 2q$ complex element target vector $\mathbf{w}$:

$$\mathbf{w} = \begin{bmatrix}\mathbf{k_1} & \mathbf{k_2}\end{bmatrix}^T \tag{5}$$

where $\mathbf{k_1}$ and $\mathbf{k_2}$ are the target vectors belonging to the different images.

The corresponding $(p \times p)$ n-look sample hermitian covariance matrix $\mathbf{A}$ summarizes the joint information from both images and has the following structure.

$$\mathbf{A} = \frac{1}{n}\sum_{j=1}^{n} \mathbf{w_j}\mathbf{w_j^H} = \begin{bmatrix}\mathbf{A_{11}} & \mathbf{A_{12}} \\ \mathbf{A_{21}} & \mathbf{A_{22}}\end{bmatrix}, \text{ with } \mathbf{A_{12}} = \frac{1}{n}\sum_{j=1}^{n} \mathbf{k_{1j}}\mathbf{k_{2j}^H}. \tag{6}$$

The matrices $\mathbf{A_{11}} = \langle \mathbf{T_1} \rangle$ and $\mathbf{A_{22}} = \langle \mathbf{T_2} \rangle$ are the standard n-look $(q \times q)$ hermitian sample covariance matrices for separate images. $\mathbf{A_{12}} = \mathbf{A_{21}^H}$ is a $(q \times q)$ complex matrix which contains information about the polarimetric intercorrelation. Since both $\mathbf{k_1}$ and $\mathbf{k_2}$ verify the conditions stipulated in [9], the vector $\mathbf{w}$ follows a complex normal zero mean distribution $N_C(\mathbf{0}, \Sigma_\mathbf{w})$, with $\Sigma_w = E(\mathbf{w}\mathbf{w}^\mathbf{H})$ its $(p \times p)$ covariance matrix. The sample covariance matrix $\mathbf{A}$ has then a complex Wishart distribution $W_C(n, \Sigma_\mathbf{A})$, characterized by n degrees of freedom and by its covariance matrix $\Sigma_\mathbf{A} = \Sigma_w / n$.

$$p(\mathbf{A}) = \frac{|\mathbf{A}|^{n-p}\exp(-\mathrm{tr}(\Sigma_\mathbf{A}^{-1}\mathbf{A}))}{K(n, p)|\Sigma_\mathbf{A}|^n} \tag{7}$$

The advantage in using the $(p \times p)$ representation resides in the fact that according to (7) dual data sets can be simultaneously classified by using the maximum likelihood distance measure defined in (4), this, without any assumption concerning their independence.
Similarly to the 3 by 3 matrix case, the 6 by 6 matrix image is classified by the way of an unsupervised Wishart classifier.
The classes are initialized with the results of the Wishart classification over the separate images which constitute stable segmentations adapted to the data distribution within each image. The resulting number of classes is then 64, involving the use of a class merging procedure to be able to interpret and visually represent the classified information.
Considering the whole class set, the clusters to be merged are the ones presenting the lowest degree of separability. Two classes can be distinguished if they are compact and if the mean distance between their elements is high. We define the separability between classes i and j as the ratio of their inter-class distance to their intra-class dispersion as defined in [9].

4. Class characterization

Once the dual polarimetric images are classified, it is possible to analyze and give an interpretation of the particular media characteristics for each class.
This analysis may be achieved by the observation of the class H-A-$\underline{\alpha}$ decomposition parameters in both images. These parameters are highly related to the global underlying scattering phenomenon and give

information about the change in polarization between the images.
Another way to parameterize the polarization variation consists in determining the special unitary operator relating the coherency matrix from one image to the corresponding one in the other image. This operator can be parameterized using 8 Gell-Mann coefficients leading to an accurate description of the change in the observed medium response change [14].
We apply the classification procedures introduced in this paper to full polarimetric SAR images collected by the CRL/NASDA PISAR sensor.
The single image classification shows an important improvement in the classification accuracy, compared to the H-$\underline{\alpha}$ classification scheme, and permits a refined analysis of the mean scattering phenomenon. The use of several images provide more details and show results that better describe the distribution of the natural media features. The results are compared to the ones obtained using the independent image classification procedure, highlighting the gain in precision when simultaneously taking into account the polarimetric information from both images as well as their correlation.

5. Conclusion

In this paper we presented a new approach to polarimetric image comparison. This method simultaneously takes into account the polarimetric information from both images.
The unsupervised algorithm is based on a c-mean iterative classification procedure which assign a pixel to a class according to a maximum likelihood decision rule derived from the Wishart density function followed by a (6×6) polarimetric representation. This coherency matrix is formed by the separate image coherency matrix as well as their intercorrelation.
The effectiveness of this classification method is tested on several PISAR full polarimetric data sets.

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