POLSAR IMAGES CHARACTERIZATION THROUGH BLIND SOURCES SEPARATION TECHNIQUES

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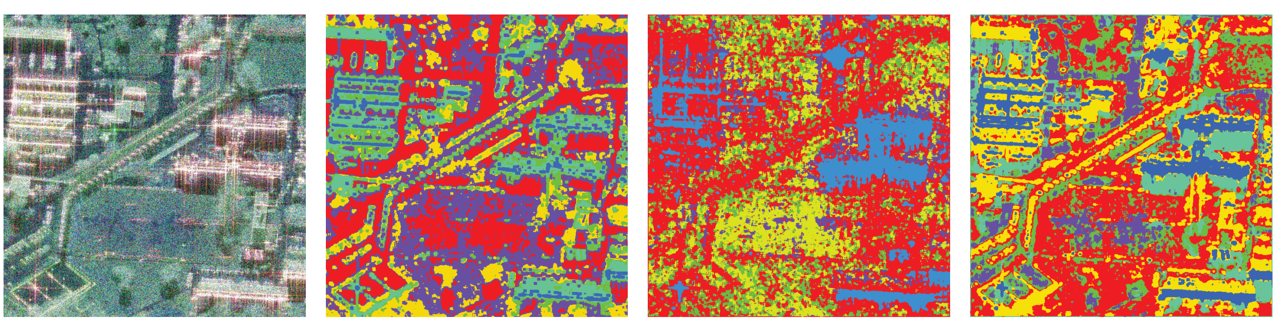
1. INTRODUCTION

Appropriate backscattered signal stochastic models are essential for correctly segmenting high-resolution Polarimetric SAR (POLSAR) images. Modelling using multivariate, centered, circular Gaussian random process is no longer acceptable for the new high quality images, since the reduced dimensions of the resolution cells increase the heterogeneity of the observed scene and obsoletes the Gaussian polarimetric model. Examples of advanced, non-Gaussian polarimetric stochastic models are the SIRV model and various submodels (e.g. the KummerU model [1]).

During classification of image pixels in POLSAR, each pixel receive the label of a class. This is illustrated in Fig. 1 [1] (classes are coded with colours). The segmentation algorithm essentially relies on the underlying stochastic model assumed for the backscattered radar signal (e.g. Gaussian, SIRV/KummerU, etc.). As such, homogeneity of determined classes is based on the statistical distribution of POLSAR image pixels, and the physical characteristics of the objects in the image are not considered at this stage.

In order to complement the stochastically-based pixel classification, physical characterization may be also used. Since the backscattered signal is intrinsically linked with the physical characteristics of the objects in the image, valuable information may be extracted therefrom. The paper focus is to propose a new physical characterization of the scattering target, inspired by the Blind Sources Separation techniques.



(a) (b) (c) (d)

Fig. 1. Classification results for the X-band RAMSES data over the Toulouse test-site (700 × 700 pixels) : (a) Colored composition of the target vector $[k]_1$-$[k]_3$-$[k]_2$, (b) Wishart criterion, (c) SIRV criterion, (d) KummerU criterion

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2. PHYSICAL CHARACTERIZATION

Efforts have been made in direction of characterizing the physical structure of the objects observed by a radar from their polarimetric echos. Several such decompositions have been proposed: the Huynen decomposition [2], the H/α/A decomposition [3], the Target Scattering Vector Model (TSVM) decomposition [4], etc. The fundamental idea of those decomposition is that each elementar reflector (surface, sphere, dihedral, ...) has a particular backscattering mechanism and that each target may be described as a superposition of such elementary reflectors.

2.1. H/α/A and TSVM decompositions

In the monostatic case ($S_{HV} = S_{VH}$), the scattering vector is defined as a vectorization of the scattering matrix $\mathbf{S}$:

$$\vec{k_P} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{bmatrix} \quad (1)$$

The coherency matrix $\mathbf{T}$ is defined as:

$$\mathbf{T} = E\left[\vec{k}_P \cdot \vec{k}_P^{\dagger}\right] \quad (2)$$

Many incoherent target decompositions (ICTD) theorems have been proposed in the litterature to compute polarimetric parameters from the coherency matrix $\mathbf{T}$. The H/α/A and TSVM-ICTD decompositions extract a first set of parameters computed from the eigenvalues of $\mathbf{T}$, and a second set of parameters which is computed from the eigenvectors of $\mathbf{T}$, using either the α/β model (for the H/α/A decomposition) [3] or the TSVM model [4].

Since $\mathbf{T}$ is hermitian and positive semidefinite, it is possible to write:

$$\mathbf{T} = \mathbf{V}\mathbf{\Sigma}\mathbf{V}^{\dagger} \quad (3)$$

where $\mathbf{\Sigma}$ is the diagonal matrix of the eigenvalues of $\mathbf{T}$ (arranged in decreasing order), while $\mathbf{V}$ is the complex matrix whose columns are the corresponding eigenvectors of $\mathbf{T}$.

Three roll-invariant parameters can be extracted from the eigenvalues of $\mathbf{T}$, namely the span: $span = \sum_{i=1}^{3} \lambda_i$; the entropy: $H = \sum_{i=1}^{3} -p_i \log_3 p_i$ where the pseudoprobabilities p_i are given by $p_i = \frac{\lambda_i}{\sum_{j=1}^{3} \lambda_j}$ and the anisotropy: $A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} = \frac{p_2 - p_3}{p_2 + p_3}$.

The parameters computed from the eigenvectors vary according to the retained model.

In the α/β model [3], each eigenvector $\mathbf{k_i}$ of the coherence matrix $\mathbf{T}$ is parametrized using five angles $(\alpha_i, \beta_i, \gamma_i, \delta_i, \theta_i)$:

$$\mathbf{k_i} = e^{j\theta_i} \begin{bmatrix} \cos\alpha_i \\ \sin\alpha_i \cos\beta_i e^{j\delta_i} \\ \sin\alpha_i \sin\beta_i e^{j\gamma_i} \end{bmatrix} \quad (4)$$

The TSVM, proposed by Touzi in 2007, consists in the projection in the Pauli basis of the scattering matrix con-diagonalized by the Takagi method (see [4] for details). It leads:

$$\overrightarrow{e_T}^{\mathbf{SV}} = e^{j\Phi_s} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(2\psi) & -\sin(2\psi) \\ 0 & \sin(2\psi) & \cos(2\psi) \end{bmatrix} \begin{bmatrix} \cos\alpha_s \cos(2\tau_m) \\ \sin\alpha_s e^{j\Phi_{\alpha_s}} \\ -j\cos\alpha_s \sin(2\tau_m) \end{bmatrix} \quad (5)$$

The rotation angle ψ is used for the subtraction of the target orientation from the target vector. τ_m is the target helicity, it characterizes the symmetry of the target. α_s and Φ_{α_s} are the symmetric scattering type magnitude and phase. They are derived from the coneigenvalues μ_1 and μ_2 of the scattering matrix $\mathbf{S}$ by:

$$\tan(\alpha_s)\, e^{j\Phi_{\alpha_s}} = \frac{\mu_1 - \mu_2}{\mu_1 + \mu_2}. \tag{6}$$

For the α/β model, only α_i angle is roll-invariant whereas for the TSVM three parameters, namley α_s, Φ_{α_s} and τ_m, are roll-invariant (independent of ψ).

3. BLIND SOURCES SEPARATION TECHNIQUES

An alternative to the physical decompositions based on the covariance matrix is to use the techniques dedicated for blind source separation (BSS). In its simplest form, the latter assumes that a number of sensor record different linear combinations of an equal number of sources. Making use of relative weak hypothesis on the original sources (e.g. the statistical independence of the random sources), the BSS techniques attempt to retrieve the coefficients of the linear combinations (e.g. the mixing matrices) and, correspondly, the signals transmitted by the sources.

Under the hypothesis that POLSAR image pixels are realizations of a multivariate (three-dimensional) stochastic process (for example, the KummerU model [1]), whose components are linear combinations of one-dimensional sources, the scattering vectors may be written as:

$$\vec{k_P} = \begin{bmatrix} S_{HH} \\ S_{VV} \\ \sqrt{2}S_{HV} \end{bmatrix} = \mathbf{A} \begin{bmatrix} \xi \\ \eta \\ \zeta \end{bmatrix} \tag{7}$$

where $\mathbf{A}$ is the 3×3 mixing matrix.

Under the BSS model, the matrix $\mathbf{A}$ is retrieved in such way that sources represented by ξ, η, ζ are independent (also known as the Independent Component Analysis or ICA). One algorithm that may be used to retrieve the matrix $\mathbf{A}$ and the independent stochastic sources ξ, η, ζ is the FastICA method [5].

Based on (7), the coherence matrix $\mathbf{T} = E\left[\vec{k}_P \cdot \vec{k}_P^{\dagger}\right]$ may be now written as:

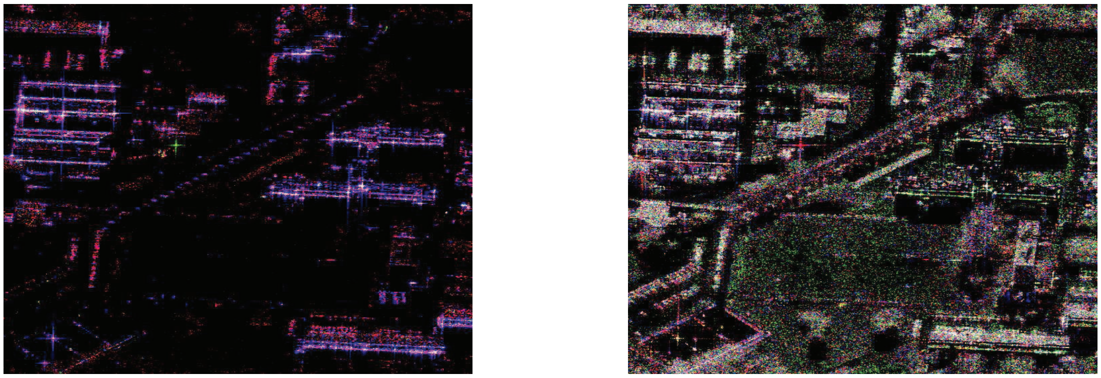
$$\mathbf{T} = \mathbf{A}E\left[\begin{bmatrix} \xi \\ \eta \\ \zeta \end{bmatrix}\begin{bmatrix} \xi^* & \eta^* & \zeta^* \end{bmatrix}\right]\mathbf{A}^H \tag{8}$$

This is an alternative writing for (3), which is the basis on which the H/α/A and the TSVM decompositions rely on. Since variables ξ, η, ζ are independent, their correlation matrix is diagonal, which further enhance the similarity with (3).

4. FUTURE WORK AND PROSPECTED RESULTS

This work is in progress. Preliminary results are presented in Fig. 2, where intensities of the independent components resulting from (7) are shown against the original components of the original target vector. Note that the ξ, η, ζ planes bear no more information about their coupling, as this information is now completely transferred to the mixing matrix of each class (a number of 6 classes [1] has been identified).

The final paper will propose alternative physical decompositions, following the general lines of the H/α/A and the TSVM decompositions, but relying on (8) instead of (3). A common framework for expressing the H/α/A and the TSVM decompositions will also be studied, exploiting the fact that the stochastic independence is an alternative (and stronger) hypothesis than decorrelation. The decorrelation is achieved through various techniques, for example the Principal Component Analysis,



(a) (b)

Fig. 2. Classification results for the X-band RAMSES data over the Toulouse test-site (700 × 700 pixels) : (a) Colored composition of the original target vector components $[k]_1$-$[k]_3$-$[k]_2$ in logarithmic representation, (b) colored composition of the independent components ξ-ζ-η in logarithmic representation

strongly linked with decomposition (3). An extensive comparison between the H/α/A, TSVM and the newly-proposed ICA based decomposition, under the new common framework, will also be included.

5. REFERENCES

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