TEMPORAL POLSAR IMAGE SERIES EXPLOITATION WITH BINARY PARTITION TREES

Alberto Alonso-González, Carlos López-Martínez, Philippe Salembier

Universistat Politècnica de Catalunya (UPC), Signal Theory and Communications Dept. (TSC)
Jordi Girona 1-3, 08034 Barcelona, Tlf. +34 934016785 Email: alberto.alonso@tsc.upc.edu

ABSTRACT

In this paper, the processing of temporal PolSAR image series is addressed through a region-based and multi-scale data representation, the Binary Partition Tree (BPT). This structure contains useful information related to the data structure at different detail levels that may be employed for different applications. The construction of this structure ans its exploitation is addressed in this work in the context of the speckle filtering and data segmentation applications. A new region model and processing strategy are defined to tackle with the temporal dimension of the data. Finally, to illustrate the capabilities of the proposed technique, results are shown with a real RADARSAT-2 dataset.

***Index Terms*—** Temporal series, SAR Polarimetry, Binary Partition Tree, Segmentation, Change detection

1. INTRODUCTION

Polarimetric Synthetic Aperture Radar (PolSAR) is a type of multidimensional radar where different combinations of polarization are applied to the transmitted and received radar echoes to achieve diversity. PolSAR has demonstrated its importance to extract useful geophysical and biophysical information from the Earth surface. In the last decade, the presence of some space-borne PolSAR sensors has empowered the building of large datasets containing different acquisitions of the same scene at different dates. In this paper, a processing scheme is proposed, based on a Binary Partition Tree representation, to extract information of these datasets.

2. BINARY PARTITION TREE REPRESENTATION

The Binary Partition Tree (BPT) structure was introduced in [1] as an image representation. BPT can be seen as a *region-based* and *multi-scale* data representation. It contains information related to the data structure at a different detail levels organized as a hierarchical structure. In the BPT, each node represents a connected region of the data; the tree leaves represent single pixels of the original data whereas the other nodes represent the merging of its two child nodes. Then, the root of the tree represents the whole data and within the root and the leaves there are a lot of nodes representing different regions of the data at different detail levels. Consequently, the BPT contains a large amount of information related to the data structure that can be exploited for different applications.

Recently, the BPT has been employed for PolSAR data filtering and segmentation [2][3][4], showing its ability to detect, at the same time, large structures of the scene while also preserving the contours and small details. Additionally, it has been extended to the temporal dimension [5], conforming a tool to exploit PolSAR temporal series. In this approach, a three-dimensional representation of the data is obtained, where each region of the BPT represents a connected area of the dataset with an arbitrary shape in space and time domains.

In this paper, a different approach is presented to deal with the temporal dimension of the data. Instead of maintaining the same region model and construct the tree simultaneously in the space-time domain, the temporal dimension of the data will be included within the region model. The resulting BPT representation will contain spatial regions of the data and will be sensitive not only to the polarimetric information but also to its temporal evolution among different acquisitions.

3. BPT PROCESSING

In this work, the proposed BPT representation has been employed to process a RADARSAT-2 Fine Quad-Pol dataset corresponding to a test-site in Flevoland, the Netherlands. The dataset was acquired during the ESA AgriSAR 2009 campaign, devoted to analyze the agricultural fields temporal evolution with PolSAR. The scene is composed mainly by an area of agricultural fields and some sea surface and urban areas. A subset of 8 images has been selected, corresponding to different acquisitions with the same incidence angle (beam FQ13) and ascending passes. The resulting subset is composed of images from April 4th, 2009 to September 29th, 2009 with an acquisition every 24 days.

A cut of 4000 by 2000 pixels has been selected and coregistered, conforming the full dataset presented in Fig. 1.

3.1. Region model

Assuming the complex Gaussian SAR data model, the estimated covariance matrix $\mathbf{Z}$ is employed to measure the region

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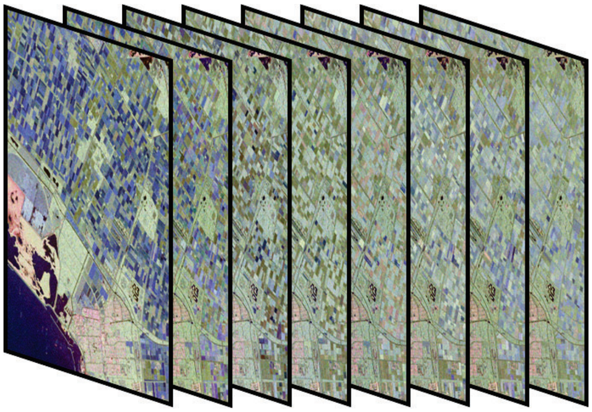


Fig. 1: Full dataset with 8 temporal acquisitions.

statistical information for all the temporal acquisitions

$$\mathbf{Z} = \langle \mathbf{k}\mathbf{k}^H \rangle_n = \frac{1}{n}\sum_{i=1}^{n} \mathbf{k}_i \mathbf{k}_i^H \qquad (1)$$

where $\mathbf{k}_i$ represents the scattering vector of the *i*-th pixel among all the acquisitions, n represents the region size in pixels and ^{H} represents the complex hermitian transpose. Consequently, the estimated covariance matrix $\mathbf{Z}$ can be decomposed into

$$\mathbf{Z} = \begin{pmatrix} \mathbf{C}_{11} & \mathbf{\Omega}_{12} & \cdots & \mathbf{\Omega}_{1N} \\ \mathbf{\Omega}_{12}^H & \mathbf{C}_{22} & \cdots & \mathbf{\Omega}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{\Omega}_{1N}^H & \mathbf{\Omega}_{2N}^H & \cdots & \mathbf{C}_{NN} \end{pmatrix} \qquad (2)$$

where N represents the number of temporal acquisitions of the dataset, $\mathbf{C}_{ii}$ is a 3 by 3 covariance matrix representing the polarimetric information of the *i*-th acquisition and $\mathbf{\Omega}_{ij}$ is a 3 by 3 complex matrix representing the interferometric information among the acquisitions *i* and *j*.

3.2. BPT construction

As proposed in [1], the BPT can be constructed with an iterative algorithm in a bottom-up approach. At each step of the construction process, the two most similar neighboring regions are merged, and this process is repeated iteratively until the root of the tree is generated. Then, to apply this BPT construction scheme, a similarity measure on the region model space $d(X, Y)$ has to be defined to compare each pair of neighboring regions X and Y. Different similarity measures were analyzed and compared in [4][3], where d_{sg}, based on the positive definite matrix cone geometry [6], resulted into the best performance in the case of spatial BPT-based PolSAR data filtering

$$d_{sg}(X, Y) = \|log\left(\mathbf{Z}_X^{-1/2}\mathbf{Z}_Y\mathbf{Z}_X^{-1/2}\right)\|_F + ln\left(\frac{2n_x n_y}{n_x + n_y}\right) \quad (3)$$

where $\mathbf{Z}_X$ and $\mathbf{Z}_Y$ represent the estimated covariance matrices for regions X and Y, respectively, n_x and n_y represent their number of pixels, $\|.\|_F$ represents the Frobenius matrix norm, $log(.)$ represents the matrix logarithm and $ln(.)$ represents the natural logarithm.

However, d_{sg} was proposed and analyzed in the context of the 3 by 3 covariance matrices representing the polarimetric information of a single acquisition. One possible solution to extend this measure to the region model presented in (2) is to apply this measure to all the different 3 by 3 covariance matrices $\mathbf{C}_{ii}$ and sum all the contributions

$$d_g(X, Y) = \sum_{i=1}^{N} d_{sg}(\mathbf{C}_{X_{ii}}, \mathbf{C}_{Y_{ii}}) \qquad (4)$$

where $\mathbf{C}_{X_{ii}}$ represents the $\mathbf{C}_{ii}$ component of the X region, as shown on (2).

Note that the d_g measure presented in (4) is sensitive to the temporal evolution of the polarimetric information, since the whole sequence of $\mathbf{C}_{ii}$ matrices is compared. Then, during the BPT construction process regions having a similar temporal evolution of their polarimetric information will be merged. This is an important advantage respect to the space-time BPT method presented in [5].

Mathematically, the d_{sg} measure in (3) could be applied directly to the whole $\mathbf{Z}$ matrix presented in (2). However, this approach has some important inconveniences. On one hand, the interferometric information stored within the $\mathbf{\Omega}_{ij}$ matrices has a completely different nature and interpretation than the polarimetric information. On the other hand, note that the d_{sg} measure requires a full rank matrix in order to compute its inverse. This will lead to an initial regularization or filtering process with at least $3N$ pixels which may be too high for a small number of acquisitions N. With the d_g measure presented in (4) a simpler regularization process may be applied with at least only 3 pixels, since the interferometric information $\mathbf{\Omega}_{ij}$ is not employed for BPT construction.

3.3. BPT pruning

To extract useful information from the BPT a tree pruning process is proposed in [1]. It can be seen as the selection of the useful nodes for a particular application from all the nodes present within the BPT structure. Then, this is an application dependent process; for filtering and segmentation applications, a region homogeneity based pruning has been proposed in [2][3][4] following a top-down approach. By means of this method, a set of regions are obtained from the BPT that can be considered as the bigger possible homogeneous regions within the scene. A region homogeneity criterion ϕ_R has to be defined to apply this pruning mechanism. Following a similar approach than with the d_g measure presented before, the pruning criteria presented in [2][3][4] can be extended to the region model in (2)

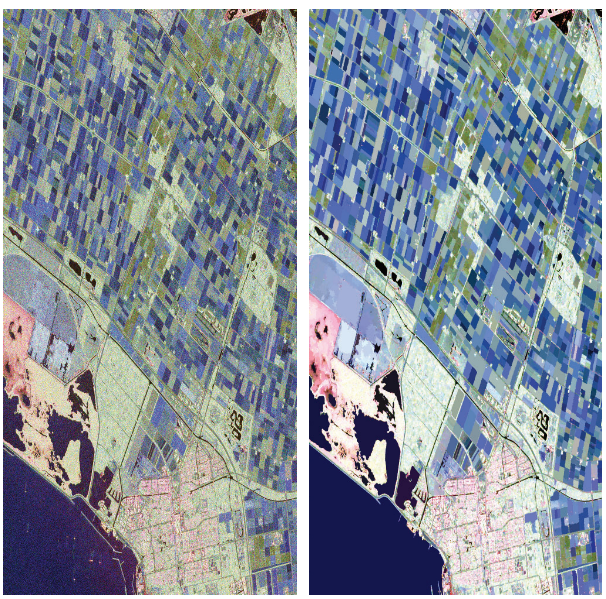
$$\phi_R(X) = \frac{1}{n_x}\sum_{i=1}^{n_x} \frac{\sum_{j=1}^{N} \|\mathbf{C}_{jj}^i - \mathbf{C}_{X_{jj}}\|_F^2}{\sum_{j=1}^{N} \|\mathbf{C}_{X_{jj}}\|_F^2} < \delta_p \qquad (5)$$

where $\mathbf{C}^i_{jj}$ is the $\mathbf{C}_{jj}$ covariance matrix for the *i*-th pixel within region X, $\mathbf{C}_{X_{jj}}$ is the $\mathbf{C}_{jj}$ covariance matrix of the region model $\mathbf{Z}$ for the X region and δ_p is the pruning factor, usually expressed in dB.

The ϕ_R measure defined in (5) can be interpreted as the relative mean squared error produced at representing all the pixels from the region X by its region model $\mathbf{Z}_X$. Note that this pruning criteria is sensitive to the whole polarimetric information present within the $\mathbf{C}_{jj}$ covariance matrices, assuming the complex Gaussian PolSAR model.

4. RESULTS

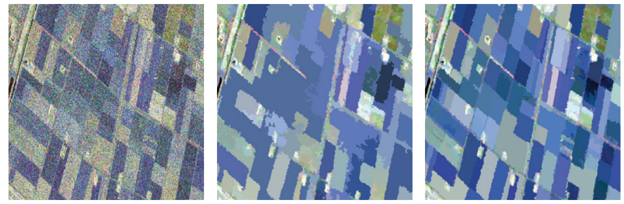
The proposed BPT processing technique has been employed with the dataset presented in Fig. 1, and the results for the first acquisition are shown on Fig. 2. Note that the region model $\mathbf{Z}$ contains the information related to all the acquisitions but, to simplify the plots, only the data of the first acquisition ($\mathbf{C}_{11}$ sub-matrix from $\mathbf{Z}$) is shown.



(a) Original (b) $\delta_p = -3dB$

Fig. 2: First acquisition processed with with the proposed method.

As it can be seen, qualitatively the same colors and contours are observed over the filtered image in Fig. 2b than in the original Fig. 2a. To see the results in detail, a 512 by 512 pixel size crop of the full image is presented on Fig. 3. The original data is represented on Fig. 3a. Figs. 3b and 3c show the results for a pruning factor $\delta_p = -3dB$ after applying the proposed method with a single image, $N = 1$, and with the whole dataset, corresponding to $N = 8$. Note that the proposed method for $N = 1$ is equivalent to the one defined in [2][3][4].

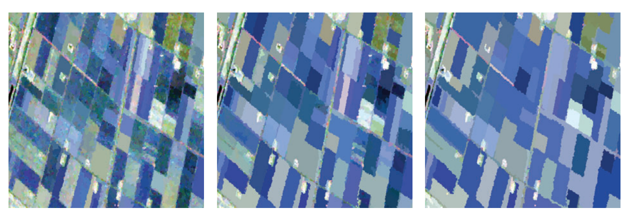


(a) Original (b) $N = 1$ (c) $N = 8$

Fig. 3: Detailed area of the first acquisition (a) filtered with one image (b) and with the full dataset (c) with $\delta_p = -3dB$.

The benefit of combining the information from different acquisitions for the BPT can be clearly seen when comparing the contours of Figs. 3b and 3c. The contours of neighboring fields with similar values appear noisy or they become merged with $N = 1$, but when employing the 8 acquisitions, with $N = 8$, they appear clear and well defined. This improvement may be produced by a combination of two different factors. On one hand, different realizations of the contours are available through the temporal acquisitions, resulting in clearer contours. On the other hand, the contours become stronger when taking into account the temporal evolution of the neighboring agricultural fields, that can be completely different across all the acquisitions.

Fig. 4 shows the effect of the pruning factor δ_p in the results obtained. Increasing δ_p results into larger regions, as the allowed relative mean squared error ϕ_R per region gets increased and vice versa. Note that all the pruning results are performed over the same BPT, then all the regions appearing in Fig. 4 are stored within the same tree, showing its multi-scale nature.

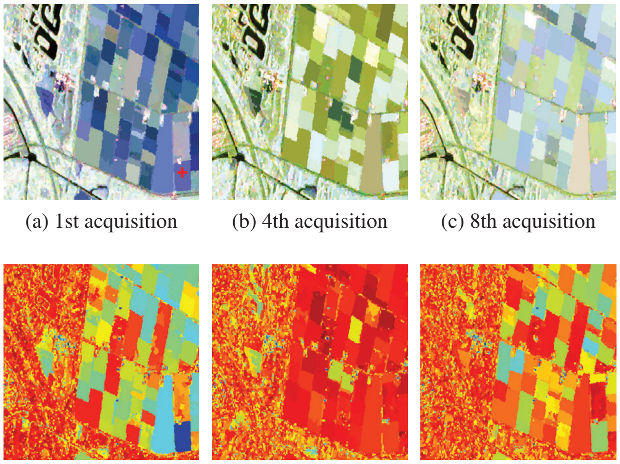


(a) $\delta_p = -4dB$ (b) $\delta_p = -3dB$ (c) $\delta_p = -2dB$

Fig. 4: Results over the first acquisition for different tree pruning processes with different δ_p over the BPT constructed with $N = 8$.

As mentioned before, the region model presented in (2) stores all the evolution of the polarimetric information along the temporal dimension within the $\mathbf{C}_{ii}$ matrices. To show the ability of the proposed to preserve this information, Fig. 5 shows the Pauli and entropy (H) eigen-decomposition parameter images for different acquisitions, corresponding to the different $\mathbf{C}_{ii}$.

Fig. 6 shows the evolution of the H/A/$\bar{\alpha}$ parameters for the agricultural field marked with a red cross in Fig 5a with the



(a) 1st acquisition (b) 4th acquisition (c) 8th acquisition

(d) H, 1st acquisition (e) H, 4th acquisition (f) H, 8th acquisition

Fig. 5: Pauli and entropy H images for different acquisitions. The dataset has been processed with $\delta_p = -3dB$ and employing $N = 8$.

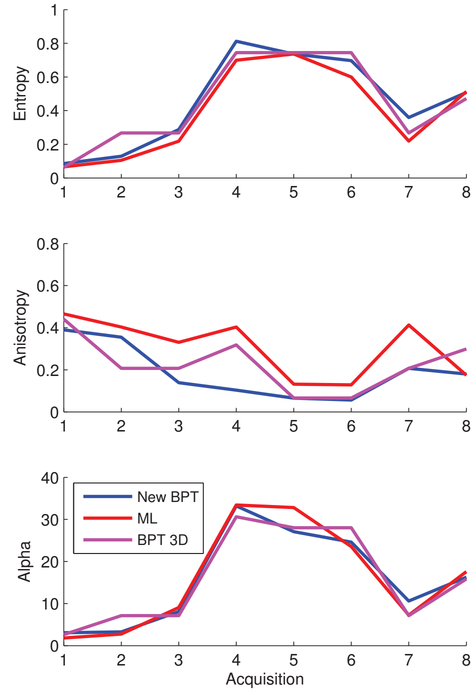


Fig. 6: Evolution of the H/A/$\bar{\alpha}$ parameters for an agricultural field for all the $\mathbf{C}_{ii}$ matrices processed with the BPT-based proposed method, with a 7x7 multilook filter and with the 3D BPT method defined in [5]. For the BPT pruning $\delta_p = -3dB$ has been employed.

proposed method, with the classical 7 by 7 multilook filter and with the space-time 3-dimensional BPT proposed in [5]. As it can be seen, the evolution of all the parameters is very similar, indicating that the BPT-based filtering is able to preserve the polarimetric information over all the acquisitions.

5. CONCLUSIONS

In this paper, a new processing scheme has been defined to analyze PolSAR image series datasets. It is based on the BPT, a region-based and multi-scale data representation. To extend it to the temporal dimension, the region model has been augmented to include this information within. This region model has proven to have important advantages, allowing the construction of a BPT structure taking into account not only the polarimetric information but also its temporal evolution.

When applying a BPT pruning process in the context of the speckle filtering application, the advantage of employing simultaneously all the acquisitions appears as a much more clear and precise spatial contours while also preserving accurately the small details. To assess that the temporal evolution of the polarimetric information is preserved it has been compared with the multilook filter, showing very similar trends. Finally, it is worth to notice that the filtering technique proposed is sensitive to the whole polarimetric information, assuming the complex Gaussian model.

6. REFERENCES

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