BINARY PARTITION TREE AS A POLARIMETRIC SAR DATA REPRESENTATION IN THE SPACE-TIME DOMAIN

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ABSTRACT

The aim of this paper is to present a Polarimetric Synthetic Aperture Radar data processing technique on the space-time domain. This approach is based on a Binary Partition Tree (BPT), which is a region-based and multi-scale data representation. Results with series of RADARSAT-2 real data are analyzed from the point of view of speckle filtering and change detection applications, to illustrate the capabilities to detect and preserve spatial and temporal contours.

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

1. INTRODUCTION

Within the last decade Polarimetric Synthetic Aperture Radar (PolSAR) has demonstrated its capabilities to extract useful geophysical and biophysical information from the Earth surface. A set of complex radar echoes are coherently processed to achieve a high spatial resolution image. As a consequence of this coherent processing and the fact that the resolution cell contains a certain number of elementary targets, the received signal is the coherent sum of all these echoes inducing the speckle term. Despite the speckle term is determined by the scattering process itself, its complexity makes necessary to consider it from a stochastic point of view and then, to assume the speckle term as a noise term. The speckle is a drawback in SAR imagery processing and information extraction and consequently some speckle filtering process is needed.

An important point in PolSAR image processing is that the data are non stationary since they reflect the complexity of the environment. Therefore, PolSAR filters must adapt to this non stationarity. Some recent state-of-the-art filtering techniques are based on this approach [1][2] by defining a homogeneous neighborhood for each pixel. In [3] a new PolSAR data filtering scheme was introduced based on a Binary Partition Tree (BPT) representation of the image [4]. This processing strategy employs a region-based and multi-scale data representation which is able to detect homogeneous regions of the data at different detail levels.

In the last years, the presence of a number of PolSAR space-borne systems has empowered the construction of PolSAR image datasets containing images of the same scene at different times. In this work we propose an extension of the BPT technique to employ series of coregistered PolSAR images to construct a representation of the data in the space-time domain. This data representation considers the full dataset as a single three-dimensional figure of the same scene. This novel representation is useful to identify homogeneous regions over space and time, allowing a better characterization and a temporal evolution analysis of the scatters, by means of merging efficiently all the data in the different time acquisitions.

2. BINARY PARTITION TREE REPRESENTATION

The Binary Partition Tree (BPT) was introduced in [4] as an image representation. Recently, it has been employed for PolSAR data filtering and segmentation in [3][5]. BPT is a region-based and multi-scale data representation. It is a hierarchical structure containing information about the data structure at different detail levels. Each node of the tree represents a region of the data; the tree leaves represent single pixels, whereas other nodes represent the merging of its two child regions. Consequently, the root node of the tree represents the whole data. The edges of the tree describe the inclusion relationship between regions. The BPT contains a large number of regions between the leaves and the root, having useful information about the data structure that may be employed for different applications.

In this paper, the BPT representation is extended to the time dimension represented by a series of images of the same site acquired at different dates. As a consequence, a region of the tree will represent a set of pixels covering different images. Then, a region conceptually represents a space-time area of the data.

3. BPT PROCESSING

In this paper, the proposed BPT space-time representation has been employed to process a RADARSAT-2 Fine Quad-Pol dataset corresponding to a test-site in Flevoland, Nether-

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lands. 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.

3.1. Pre-processing

To process the dataset correctly, a 4000 by 2000 pixel cut of the original image has been selected and a coregistration process has been done to ensure that all the pixels are aligned in the time dimension. The full dataset coregistrated, containing 4000 x 2000 x 8 pixel is represented in Fig. 1.

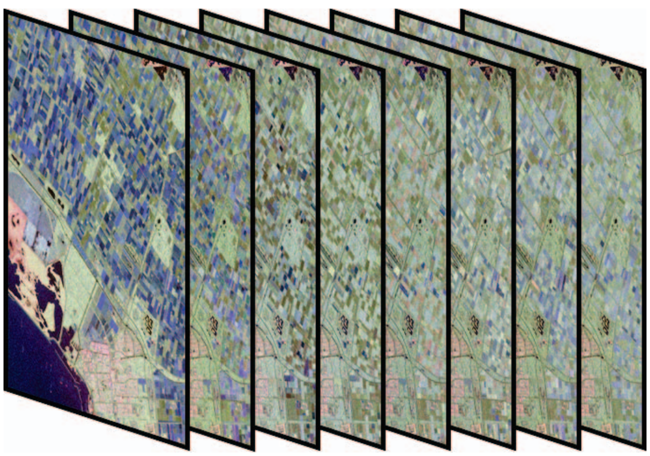


Fig. 1: Full 3-dimensional data set

3.2. BPT Construction

The BPT can be constructed with an iterative algorithm in a bottom-up approach [4]. In the initial state of the algorithm every pixel of the dataset becomes a one-pixel region. At each step of the construction process the two most similar neighboring regions are merged. This process is repeated iteratively until the root of the tree is generated. In this case, since the dataset is covering the space and time dimensions, a neighborhood has to be defined within this context. In this work, we propose the 10 connectivity shown in Fig. 2. Each pixel is connected with its 8 neighbors in space, to be able to preserve small diagonal details properly, and with the pixel in the same position in the images immediately before and after in the time dimension.

As mentioned in [3], the following additional elements have to be defined to apply the BPT construction process:

1. A region model: traditionally, under the complex Gaussian PolSAR model, the 3x3 estimated covariance matrix $\mathbf{Z}$ is employed to measure the region polarimetric information

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

where $\mathbf{k}_i$ represents the scattering vector of the i-th pixel and n represents the region size in pixels.

2. A similarity measure on the region model space to compare two neighboring regions $d(X,Y)$. In this work we will employ the d_{sg} measure based on the positive definite matrix cone geometry [6]. Different similarity measures were analyzed and compared in [5], where d_{sg} resulted into the best performance in the case of spatial BPT-based PolSAR data filtering

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

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.

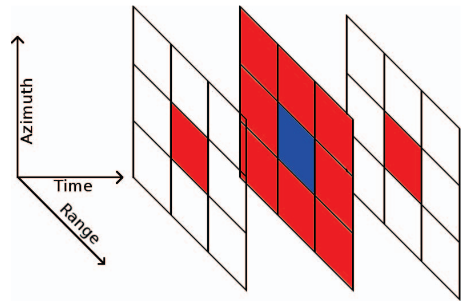


Fig. 2: Pixel connectivity for the dataset. Each pixel, in blue, has 10 neighbors, in red

3.3. BPT Pruning

A data processing may be obtained by a tree pruning process over the full BPT, as stated in [4]. This is an application dependent process. For filtering and segmentation, a homogeneity based tree pruning has been proposed and evaluated in [3][5]. A homogeneity criterion is introduced and the biggest regions of the tree that fulfill this criterion are selected from the BPT

$$\phi_R(X) = \frac{1}{n_x}\sum_{i=1}^{n_x}\frac{\|\mathbf{X}^i - \mathbf{Z}_X\|_F^2}{\|\mathbf{Z}_X\|_F^2} < \delta_p \quad (3)$$

where $\mathbf{X}^i$ is the estimated covariance matrix for the i-th pixel within region X and δ_p is the pruning factor, usually expressed in dB.

Note that the region model, the similarity measure and the pruning criterion employed for the BPT based processing are sensitive to the full estimated covariance matrix, so this processing is employing systematically all the polarimetric information, assuming the complex Gaussian PolSAR model.

4. RESULTS

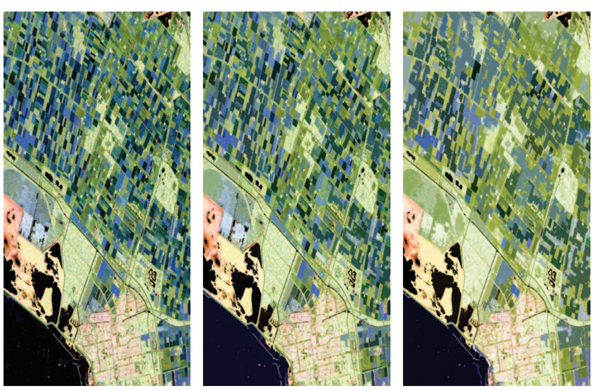
The mentioned BPT processing strategy has been employed with the full dataset presented in Fig. 1. In this case, because of the dimensionality of the original data, a space-time segmentation is obtained, representing homogeneous regions in this domain.

In the following, the results obtained will be interpreted from the point of view of speckle filtering application and change detection.

4.1. Filtering results

For the speckle filtering application, the BPT processing can benefit from a space-time segmentation, since additional samples can be employed from different images to estimate the covariance matrix if the region is homogeneous in time.

Fig. 3 shows filtering results for the first image, corresponding to the first acquisition image, for different pruning factors δ_p. As expected, when increasing the pruning factor δ_p bigger regions are obtained since less homogeneous regions are accepted and pruned. Note that, as discussed before, these filtering results are obtained by averaging pixels corresponding to different acquisitions, depending on the region extent in the time dimension.



(a) $\delta_p = -5dB$ (b) $\delta_p = -3dB$ (c) $\delta_p = -1dB$

Fig. 3: First image processed with space-time filtering for different pruning factors δ_p

To assess the gain obtained when filtering an image employing the full dataset with respect to a 2 dimensional case, the average region depth in the time dimension is shown in Table 1. This parameter is calculated as the relation between the number of pixels contained in all the regions intersecting the first acquisition and the pixels contained in a single image. Note that, for example, when $\delta_p = -3dB$ the first acquisition can be filtered employing approximately 4 times more samples than with a single acquisition.

δ_p	Regions	Average depth
-5 dB	359371	2.067
-4 dB	223969	2.652
-3 dB	127957	4.068
-2 dB	52077	6.727
-1 dB	14660	7.758
0 dB	4666	7.921

Table 1: Number of regions and average region depth in time dimension over homogeneous regions intersecting the first acquisition for different pruning factors

Fig. 4 shows the temporal evolution of the entropy (H) parameter for two different agricultural fields of potatoes and onions. The results obtained with the BPT for $\delta_p = 0dB$ and $\delta_p = -3dB$ are compared with those obtained with the 7x7 multilook. As it can be seen, qualitatively the evolution of the parameter is similar for all the cases. Differences are produced by estimating the parameter over regions of different sizes in space and time, and not only in space. The flat zones that appear with the BPT based processing are produced when the same region appears over different acquisitions, conforming an homogeneous region that spans various images in the time dimension.

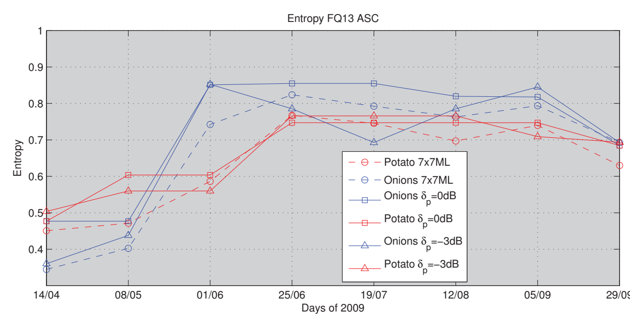
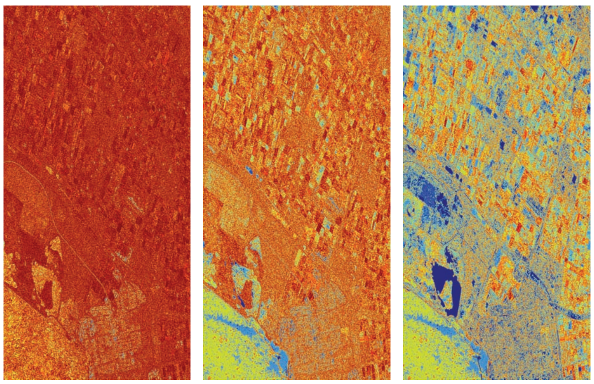


Fig. 4: Estimated entropy (H) temporal evolution over two different agricultural fields with 7x7 multilook and BPT homogeneity based pruning

4.2. Change detection results

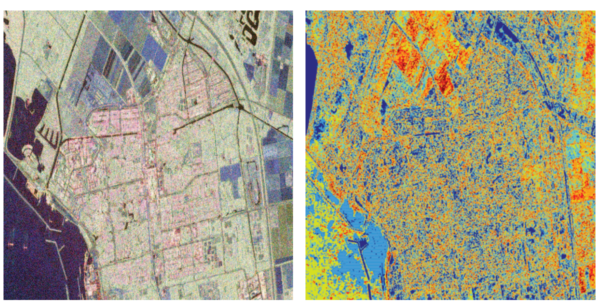
In the previous section some filtering results have been presented showing the spatial contours of the homogeneous areas within the BPT corresponding to the first acquisition. In this section we will focus on the contours in the time dimension, interpreted as changes between different acquisitions.

Fig. 5 shows, for different δ_p, the number of changes, or contours in the time dimension, for each pixel, ranging from no changes, represented in blue, to 7 changes, in red. Again, increasing the pruning factor δ_p results in bigger regions also in the time domain, and a smaller number of changes is detected for each pixel. Analyzing the results closely, some small blue dots can be seen over urban areas even at $\delta_p = -5dB$, corresponding to point scatters of the buildings that have no change in time. When increasing the pruning factor some other areas appear also in blue, as some regions of closed water, which roughness is less affected by wind. On the other hand, some agricultural fields appear more reddish, indicating that they are changing substantially along different acquisitions. A detailed area showing this behavior is shown in Fig. 6.



(a) $\delta_p = -5dB$ (b) $\delta_p = -3dB$ (c) $\delta_p = -1dB$

Fig. 5: Temporal changes detection for different pruning factors δ_p. No changes is represented in blue and 7 changes in red.



(a) Pauli image (b) Changes detected

Fig. 6: Detail of changes detection around urban area

Note that, since this processing strategy is employing all the information within the covariance matrix, the change detection application is also sensitive to all this information, identifying indirectly a concept of region temporal stability in terms of all the polarimetric information assuming the Gaussian polarimetric model.

5. CONCLUSIONS

In this paper a region-based and multi-scale data representation has been proposed simultaneously in the space and time dimensions. It is based on a BPT representation extended to the temporal dimension. Region homogeneity based pruning has been applied to obtain homogeneous regions of the tree in the space-time domain. It has proven to be able to adapt to the spatial and temporal information, preserving the polarimetric information. For the filtering application, this technique is able to increase the number of samples of homogeneous regions by efficiently employing pixels of different acquisitions, conforming an important gain in terms of the speckle filtering application.

Another application that automatically arises when segmenting a space-time dataset is temporal change detection. Some maps have been generated showing the number of changes detected in the time dimension. Although this changes cannot be physically confirmed, because of the absence of ground-truth, the temporal evolution of the entropy (H) parameter over some fields has shown to follow similar trends than the individual images filtered.

Consequently, a new processing tool has been introduced that systematically exploits PolSAR image series. Due to the BPT processing generic formulation, the same BPT construction and pruning algorithms can be employed for a single image or a set of images; only a new pixel neighboring scheme is needed to generate the initial state of the construction process. Moreover, the BPT based processing is not restricted to any region model, similarity measure or pruning criterion.

6. REFERENCES

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