A Novel Polarimetric-Texture-Structure Descriptor for High-Resolution PolSAR Image Classification

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ABSTRACT

A novel Polarimetric-Texture-Structure descriptor for high-resolution PolSAR image is presented in this paper. More precisely, a PolSAR image is represented by a tree of shapes, each of which is associated with several polarimetric and texture attributes. We first extract the texture properties and polarimetric characteristics from each shape, then use the shape co-occurrence patterns (SCOPs) to characterize the shape relationships, and finally use the resulting SCOPs distributions as features for PolSAR image classification. The proposed method not only has the strong ability to depict the texture and polarimetric properties, but also encodes the shape relationships on the tree. We compare the proposed method with the cluster based statistical feature (CSF) and the scattering mechanism based statistical feature (SMSF). Experimental results on high-resolution PolSAR sample dataset and a large scene for classification demonstrate the effectiveness of the proposed method.

***Index Terms*—high-resolution, PolSAR, polarimetric, texture, structure, feature, classification.**

1. INTRODUCTION

High-resolution polarimetric SAR (PolSAR) image classification is one of the leading topics on understanding SAR images. Compared to low-resolution ones, high-resolution PolSAR image provides a richer scene and target information (such as polarimetric signatures, texture and geometric structure of the scenes and targets, etc.) for earth observation, but at the same time raises new problems and challenges for the interpretation of images. This study focuses on designing a novel Polarimetric-Texture-Structure Descriptor (PTSD) for characterizing high-resolution PolSAR images, which is presented to efficiently encode polarimetry, texture, structure, as well as local information. The proposed methodology relies on the BPT representation of PolSAR image [1, 2], which is obtained from keeping track of the merging the pair of most similar regions in each step. We first apply Freeman and Durden decomposition [3] and the polarimetric homogeneity measure to extract polarimetric information for each shape of the BPT. We then use the shape-based invariant texture analysis (SITA) method [4] to extract texture and structure information. Finally, we employ the shape co-occurrence patterns (SCOPs) [5] framework to achieve a more flexible statistical analysis and feature representation. Experimental results on high resolution PolSAR images demonstrate the effectiveness of the proposed approach.

In the rest of the paper, Section 2 presents the proposed Polarimetric-Texture-Structure Descriptor (PTSD) in detail. Section 3 shows the experimental results and analyses the performance. Section 4 ends up with conclusions and gives directions to future work.

2. METHODOLOGY

An overview of the proposed approach can be described as follows. First, a PolSAR image is represented by the Binary Partition Tree (BPT) of shapes. Then, polarimetric, texture, structure information is extracted from each shape of the BPT. Finally, a more flexible feature representation is obtained by using the SCOPs framework.

2.1 Binary Partition Tree

The BPT is created by keeping track of the merging steps. Starting from the initial pixels, the algorithm merges two most similar neighboring regions until a single region is obtained [1]. The construction process is given in Fig.1. The original image includes four pixels: A, B, C, D. Constructing the tree includes three steps. In the first step, the pair of most similar neighboring regions, for example A and C, are merged to create region E. Once E is created, the similarity between E and its neighboring regions (B and F) need to be evaluated. After the evaluation, assume that the most similar regions are B and E. Then B and E are merged and create region F. Finally, the last two regions D and F are merged to create region G, which represents the whole image.

Observing the construction process, we can find that the creation of BPT for PolSAR image implies two important notions: region model and merging criterion. The region model specifies how a region is represented and how to model the union of two regions. We choose average covariance matrix as the region model [2],

$$Z = \frac{1}{N}\sum_{i=1}^{N} C(i) \qquad (1)$$

where $C(i)$ is the one-look covariance matrix of the i-th pixel and N indicates the number of independent looks.

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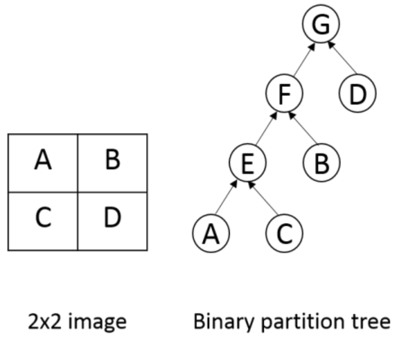

Fig.1. Illustration of the BPT construction

The merging criterion specifies the similarity between neighboring regions determining the merging order. We choose the symmetric revised wishart dissimilarity (RW) [2] to evaluate the similarity between regions,

$$d_{RW}(X,Y) = \left(tr(Z_X^{-1}Z_Y) + tr(Z_Y^{-1}Z_X)\right)(n_x + n_y) \qquad (2)$$

it defines the dissimilarities between two regions, X and Y, with average covariance matrices Z_X and Z_Y and size of n_x and n_y pixels, respectively.

2.2 Polarimetric-Texture-Structure Descriptor

Note that a shape is defined as a node in the BPT. As the BPT provides a complete representation of an image, the modeling of an image is converted to the modeling of the tree of shapes. Once the tree has been constructed, it has already contained some polarimetric information. Then, we use the shape-based invariant texture analysis (SITA) [4] to extract texture and structure information from the tree.

For p, q integer values, the two-dimensional (p+q)-th order central moment μ_{pq} of a shape s is defined as

$$\mu_{pq} = \iint_s (x-\bar{x})^p (y-\bar{y})^q d_x d_y \qquad (3)$$

where $(\bar{x},\bar{y})$ is the center of mass of s. Denote λ_1 and λ_2 as the two eigenvalues of the normalized inertia matrix of s, with $\lambda_1 \geq \lambda_2$, a as its area, $s^r, r \in [1,\dots,M]$ as the r-order ancestor of shape s in the tree, and a_{max}, a_{min} as two thresholds on shape area, the texture attributes used for characterizing shape s in this work are given in Table 1.

Table 1. Texture attributes for characterizing a shape s.

attribute	computation
Elongation	$\epsilon = \lambda_2/\lambda_1$
Ellipse-compactness	$\kappa_e = a/(4\pi\sqrt{\lambda_1\lambda_2})$
Scale ratio	$\alpha = Ma/(\sum_{r=1}^{M} a(s^r))$
Normalized area	$\theta = \frac{\ln a - \ln a_{min}}{\ln a_{max} - \ln a_{min}}$

To further make use of the polarimetric information, we use the Freeman and Durden decomposition, polarimetric homogeneity and span (or total power) to characterize the polarimetric information of the pixels in the shape.

The Freeman and Durden decomposition [3] can well illustrates the physical scattering mechanisms of the natural distributed target areas, which models the observed covariance matrix as a linear sum of surface scattering (P_s), double bounce scattering (P_d) and volume scattering (P_v)

$$P = P_s + P_d + P_v \qquad (4)$$

where P is the total power.

For the polarimetric homogeneity measure, we use the average error produced by representing each region X by its model Z_X[2]:

$$\emptyset_R(X) = \frac{1}{n_x}\sum_{i=1}^{n_x}\frac{\|X^i - Z_X\|^2}{\|Z_X\|^2} = \frac{1}{n_x\|Z_X\|^2}\sum_{i=1}^{n_x}\|X^i - Z_X\|^2 \qquad (5)$$

where X^i is the ith pixel in region X, and n_x is the number of pixels in X.

The span (or total power) is expressed as

$$span = k^H k \qquad (6)$$

where k represents the target vector and ^{H} is the complex conjugate transpose of a vector.

As a summarization, all the attributes of shape s can be written as

$$f(s) = [\,\epsilon, \kappa_e, \alpha, \theta, P_s, P_d, P_v, \phi, Span] \qquad (7)$$

2.3 Shapes co-occurrence patterns (SCOPs)

As discussed in [5], shape relationship plays an important role for image classification. In the BPT, the main relationships are sibling and conclusion, corresponding to small branches on the tree. Thus we use the SCOPs framework to describe the relationship of the shapes. In our context, the SCOPs reflect specific spatial organization in the BPT.

Denote s^r as the r-order ancestor of shape s, we use the following three SCOPs [5] as

single shape (P_1) : s,

shape-ancestor (P_2) : $s \to s^r$,

shape-ancestor-grandancestor (P_3) : $s \to s^r \to s^{2r}$.

For the three SCOPs $(P_k)_{k=1,2,3}$, the attributes are

attributes for P_1 : f(s),

attributes for P_2 : $[f(s), f(s^r)]$,

attributes for P_3 : $[f(s), f(s^r), f(s^{2r})]$,

where f(s) is the attributes of s.

3. EXPERIMENTS AND RESULTS

In this section, we evaluate the proposed method on two experiments. One is based on the CETC-38(China Electronics Technology Group Corporation) Institute PolSAR sample dataset which includes six-class samples selected from three large scenes. The three CETC-38 Institute full polarimetric SAR images are taken over Hainan, China, with size of 4901×7901 pixels, 4702×

7893 pixels, and 6185×7893 pixels, respectively. The six classes targets are forest (100), water (100), farmland (100), built-up areas (100), fruit trees (100), and grassland (100), and the size of all samples are 100×100 pixels. The samples of different classes of targets are shown in Fig.2. The other is based on a large scene acquired by DLR E-SAR, with size of 2800×1500 pixels collected in the Oberpfaffenhofen area, Germany. The image is shown in Fig.3 (a).

To investigate the classification performance of the proposed feature on the sample datasets, the cluster based statistical feature (CSF) [6] and the scattering mechanism based statistical feature (SMSF) [6] were adopted for comparison. The parameter r is estimated and set to be 5. The minimal area a_{min} and maximal area a_{max} of the shapes are chosen as 2 and 10000 respectively. The SVM classifier with the intersection kernel (HIK) is used to classify the images. Randomly select different number of samples (5, 10 and 20 in our experiment) from each class in the dataset and use these samples as the training set for classification. The final classification accuracy is the average of that achieved by 200 times random splitting of the datasets.

On the sample dataset, the proposed feature PTSD outperform the CSF and SMSF. Specially when the training size is 5, the PTSD method classification accuracy is 89.77%, much better than the CSF and SMSF approaches (about 5%). A quantitative comparison on classification performance of CSF [6], SMSF [6] and the proposed method is given in Table 2.

Table 2. Comparison of classification accuracies (%) on PolSAR sample datasets.

Training size	5	10	20
CSF	81.34(4.12)	88.84(2.82)	93.01(1.59)
SMSF	84.24(4.07)	90.90(2.72)	94.6(1.38)
PTSD	89.77(2.89)	93.85(1.78)	96.14(1.17)

To illustrate the applicability of our feature, we further carry out the experiment on a large PolSAR image. The experiment is on the patch level with size of 50×50, and K-means is used to unsupervised classify the image. The parameter r is estimated and set to be 2, and the minimal area a_{min} and maximal area a_{max} of the shapes are chosen as 2 and 2500 respectively. The number of clusters K is set to be 9. The classification result is shown in Fig.3 (b), we can find that our proposed descriptor can also achieve comparable classification performance.

4. CONCLUSIONS AND FUTURE WORK

In this paper, a novel feature descriptor, referred to PSTD, for characterizing high-resolution PolSAR images has been presented. The proposed method can efficiently encode polarimetry, texture, structure, as well as local information. The experimental results of classification on sample dataset and large image show very promising performance and the proposed feature significantly outperforms the CSF and SMSF features when limited training samples are available. In future work, we intend to use some other scattering mechanisms decomposition methods to achieve better performance.

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REFERENCE

[1] P. Salembier and L. Garrido, “Binary partition tree as an efficient representation for image processing, segmentation and information retrieval,” IEEE Trans. Image Process., vol. 9, no. 4, pp. 561–576, Apr. 2000.

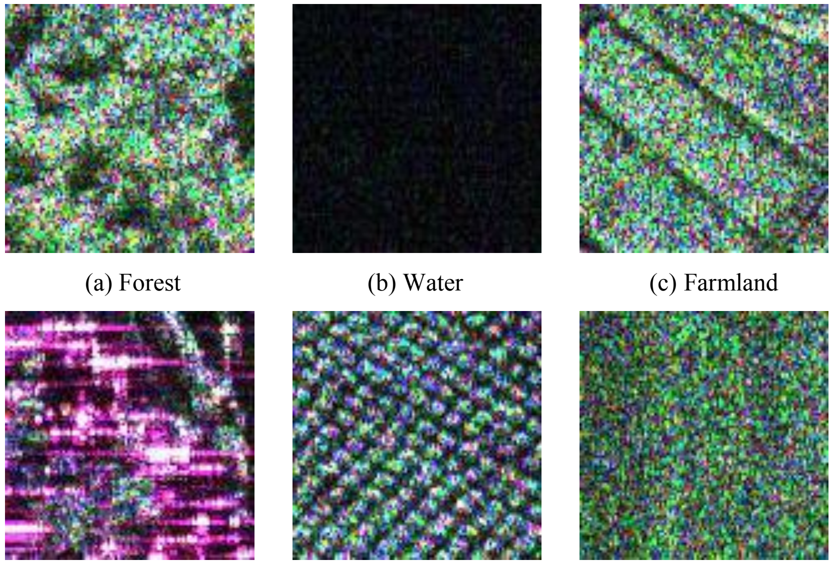
[2] A. Alonso-González, C. López-Martínez, P. Salembier, “Filtering and segmentation of polarimetric SAR data based on binary partition trees,” IEEE Transactions on Geoscience and Remote Sensing, vol. 50, no. 2, pp. 593–605, 2012.

[3] A. Freeman and S. L. Durden, “A three-component scattering model for polarimetric SAR data,” IEEE Trans. Geosci. Remote Sens., vol. 36, no.3, pp. 963–973, May 1998.

[4] G.-S. Xia, J. Delon, and Y. Gousseau, “Shape-based invariant texture indexing,” Int. J. Comput. Vision, vol. 88, no. 3, pp. 382–403, 2010.

[5] G. Liu, G.-S. Xia, W. Yang and L.-P. Zhang, “Texture analysis with shape co-occurrence patterns,” in Proceedings of ICPR, pp.1627-1632, August 24-28, 2014, Stockholm, Sweden.

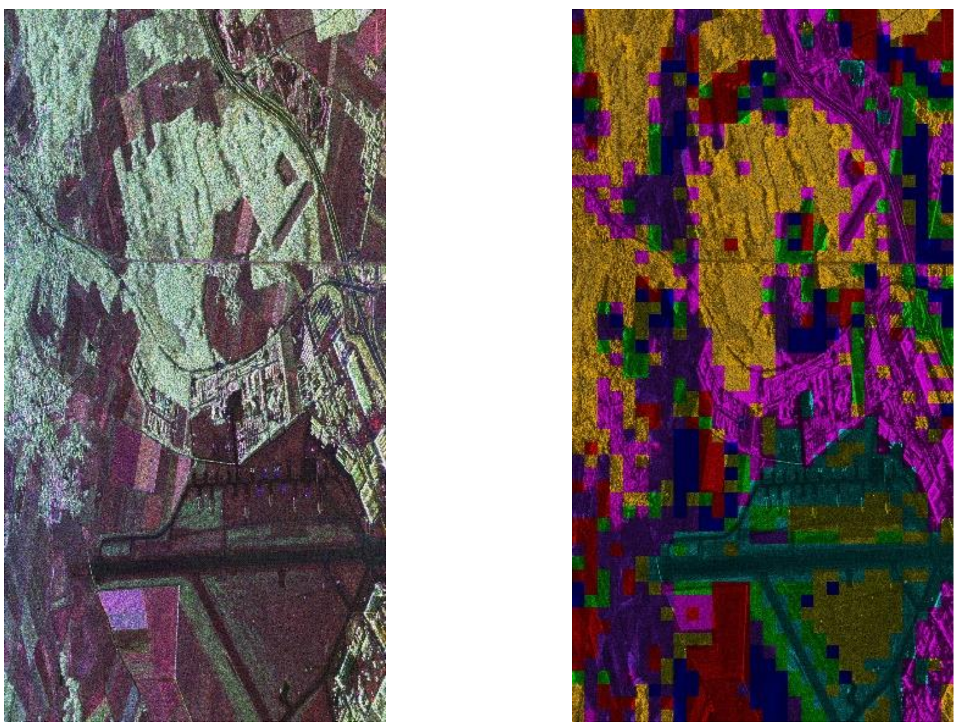
[6] W. Yang, Y. Liu, G.-S. Xia and X. Xu, “Statistical mid-level features for building-up area extraction from full polarimetric SAR imagery,” Progress In Electromagnetics Research, Vol. 132, pp. 233-254, 2012.



(a) Forest (b) Water (c) Farmland

(d) Built-up areas (e) Fruit trees (f) Grassland

Fig.2. PolSAR samples of different land covers



(a) E-SAR image (b) Classification result

Fig.3. The original E-SAR PolSAR image and classification result