Classification of Polarimetric SAR Data Using Spectral Graph Partitioning

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***Abstract*— A new approach for classification of Polarimetric Synthetic Aperture Radar (POLSAR) data is proposed using segmentation that is formulated as a graph partitioning problem. This work is motivated by the fact that human experts are very good at visual interpretation and segmentation of POLSAR data, which is often challenging for automated analysis techniques. Spectral graph partitioning, a framework that has recently emerged in computer vision for solving grouping problems with perceptually plausible results, is used with modifications necessary to accommodate POLSAR data. Using the similarity of edge-aligned patch histograms and spatial proximity, classification performance that is superior to the Wishart classifier is achieved. This approach also provides a way to combine region-based and contour-based segmentation techniques, as it can accommodate different representations of polarimetric data as well as other data sources (e.g., optical imagery).**

I. Introduction

In the last two decades, Synthetic Aperture Radar (SAR) polarimetry has shown promise through airborne research campaigns, which lead to the planning of space-borne missions that offer fully polarimetric modes (i.e., ALOS-PALSAR, TerraSAR-X and RADARSAT-2). Once these space-borne systems become operational, (1) large volumes of data will be available on a daily basis, whose manual interpretation will not be feasible and (2) many end-users that have limited or no expertise will start using these data. Therefore, automated analysis procedures are required, which typically involve the classification task. However, SAR data classification is known to be challenging due to speckle, that results in large variation of the backscatter across neighboring pixels within the same distributed target (e.g., a field of wheat). Even after speckle reduction, a considerable amount of within-class variation remains. Thus, pixel-based classification schemes are often unreliable.

In radar polarimetry literature, there have been attempts to improve the classification accuracy through different representations, many features were suggested as candidates to discriminate between targets. A widely accepted technique uses the maximum likelihood classification based on the complex Wishart distribution (a.k.a. Wishart classifier) in an iterative scheme [1], [2]. However these techniques are pixel-based and therefore are not able to capture and utilize spatial information in the image data.

To achieve improved classification performance, a segmentation step could be introduced to aid the task by forming groups of pixels that represent homogeneous regions. However, segmentation of SAR image data is challenging for automated systems, while being relatively easy for human experts. This is generally the case for many problems in computer vision, where the ultimate goal is to achieve the performance of the human vision system. This may only become possible through a good understanding of how humans handle the task. Therefore, it is important to recognize that for humans, an image represents more than a collection of pixels: it is a meaningful organization of objects or patterns. In late 1930s, Gestalt psychologists have studied this important phenomenon, *perceptual organization*, and reported several factors that contribute to this process. These factors (e.g., similarity, proximity, continuity, closure) are known as *cues* in psychology literature.

Over the last two decades, research in computer vision has sought methodologies that can utilize these ideas and in the last few years a promising technique for grouping applications, spectral graph partitioning, has emerged [3], [4]. This approach has been shown to perform well on image segmentation problems as well as recovering complicated manifold structures in the feature space. Spectral graph partitioning is a pair-wise grouping technique. It enables the combination of several cues and allows flexibility in the definition of affinity functions that measure the similarity between pairs. Utilizing multiple cues that contribute to perceptual grouping process (i.e., similarity in brightness, color or texture, proximity, and contour continuity) results in segmentations that are perceptually plausible (i.e., consistent with what humans perceive).

Our proposed scheme uses the spectral graph partitioning framework with modifications that were found necessary for classification of Polarimetric SAR data. Preliminary results obtained using the similarity of patch-based features and proximity are found to be superior to the Wishart classifier. Detailed analysis of different aspects of the proposed scheme and validation for multiple data sets is underway.

II. Spectral Graph Partitioning

Both clustering and image segmentation can be formulated as a graph partitioning problem, by representing a set of points in an arbitrary feature space using an undirected graph $G = \{V, E\}$, where V and E represent the nodes and the edges (i.e., connections) respectively. Each node on the graph

corresponds to a data point in feature space and the edge between two nodes, u and v, is associated with a *weight*, $\omega(u, v)$, that indicates the *similarity* of that pair. In general, G is a fully connected graph (i.e., each node is connected to all the other nodes). For partitioning such a graph, it is intuitive to minimize the similarity across candidate partitions V_1 and V_2, which can be quantified by a *cut* (i.e., sum of weights between the nodes in V_1 and the nodes in V_2).

$$cut(V_1, V_2) = \sum_{u \in V_1, v \in V_2} \omega(u, v) \tag{1}$$

However, minimizing this cost function favors partitions with single nodes. To avoid this bias, Shi and Malik [3] suggested to minimize the *Normalized Cut* (*NCut*) defined as follows:

$$NCut(V_1, V_2) = \frac{cut(V_1, V_2)}{assoc(V_1, V)} + \frac{cut(V_1, V_2)}{assoc(V_2, V)} \tag{2}$$

where $assoc(V_1, V)$ is the sum of the weights from the nodes in V_1 to all the nodes in the graph, V. An optimal partitioning can be found by minimizing this cost function, which can be shown to be equivalent to solving the following:

$$y = \text{argmin}_y \frac{y^T (D - W)\, y}{y^T D\, y} \tag{3}$$

where $y = \{a, b\}^N$ is a binary indicator vector specifying the group identity for each point (i.e., $y_i = a$ if node i belongs to V_1 and $y_j = b$ if node j belongs to V_2). N is the number of nodes, W is the $N \times N$ matrix whose entries are the weights, $\omega(i, j)$, and D is a diagonal matrix, where its diagonal elements are the sum of the rows of W.

Note that the expression in (3) is the *Rayleigh quotient*, and if the condition on y is relaxed so that it can take on real values, the solution can be obtained by solving the *generalized eigenvalue system*,

$$(D - W)y = \lambda\, D\, y \tag{4}$$

where $D - W$ is known as the *graph Laplacian*. Using $z = D^{\frac{1}{2}} y$, (4) can be rewritten as:

$$D^{-\frac{1}{2}} (D - W) D^{-\frac{1}{2}} z = \lambda\, z \tag{5}$$

where $D^{-\frac{1}{2}}(D-W)D^{-\frac{1}{2}}$ is the *normalized graph Laplacian*, $\mathcal{L}$, which is symmetric positive semi-definite (p.s.d.). The eigenvector that corresponds to the second smallest eigenvalue is the real valued solution for (3). Therefore, this eigenvector can be used to bi-partition the graph as suggested in [3]. Also note that the second smallest eigenvalue of $\mathcal{L}$ corresponds to the second largest eigenvalue of $I - \mathcal{L}$ or $D^{-\frac{1}{2}}\, W\, D^{-\frac{1}{2}}$, where I is the identity matrix.

A. An algorithm for k-way partitioning: Spectral Clustering

Based on the approach described in the previous section, the spectral clustering algorithm given by Ng *et al.* [4] provides k-way partitioning. A slightly different notation is used, where the matrix W is now called the affinity matrix, A, and $I - \mathcal{L}$ is replaced with L, the normalized affinity matrix. Therefore the eigenvectors that correspond to the largest eigenvalues are used instead of the smallest ones. For a set of points, $S = \{s_1, ..., s_N\}$ in R^ℓ, and number of clusters, k, the algorithm involves the following steps:

1) Form the affinity matrix $A \in R^{N \times N}$ whose entries are defined by:

$$A_{ij} = \begin{cases} \exp\left\{\frac{-d^2(s_i, s_j)}{2\sigma^2}\right\}, & \text{if} \quad i \neq j \\ 0, & \text{if} \quad i = j \end{cases} \tag{6}$$

where σ is the scaling parameter (i.e, kernel bandwidth) and $d(s_i, s_j)$ is the Euclidian distance and represents the *dissimilarity* between points s_i and s_j.

2) Construct the normalized affinity matrix, L using,

$$L = D^{-\frac{1}{2}} A\, D^{-\frac{1}{2}} \tag{7}$$

where D is a diagonal matrix with $D_{ii} = \sum_{j=1}^{N} A_{ij}$.

3) Form matrix $X = [x_1\, x_2 .. x_n \;\; .. x_k] \in R^{N \times k}$, whose columns x_n are the eigenvectors that correspond to the k largest eigenvalues of matrix L.

4) Normalize the rows of X and form matrix Y (i.e., $Y_{ij} = X_{ij} / (\sum_j X_{ij}^2)^{-\frac{1}{2}}$)

5) Cluster rows of Y using the K-means algorithm

Since pairwise similarities are used to determine the groups, it becomes possible to recover complicated manifold structures in the feature space, which can not be achieved by central grouping techniques (e.g., k-means or EM) that require each group member to be close to a prototype (i.e., the cluster center). A synthetic data set that contains concentric circles in a two-dimensional feature space is often used to demonstrate the ability of spectral clustering to overcome the limitation of those techniques and correctly solve the perceptual grouping problem (i.e., group points as two circles like humans do). However, the scaling parameter, σ, plays an important role in obtaining successful results. The potential problems due to manual parameter tuning can be circumvented by using *local scaling* as suggested in [5]. This procedure automates the parameter selection and provides good results by adaptively choosing a scaling parameter σ_i for each point s_i. The affinity function in Eq. 6 is modified as follows:

$$\widehat{A}_{ij} = \exp\left(\frac{-d^2(s_i, s_j)}{2\, \sigma_i\, \sigma_j}\right) \tag{8}$$

and σ_i, the local scaling parameter for point s_i is given by

$$\sigma_i = \text{median}_{s_n \in N(s_i)} \{\, d(s_i, s_n) \,\} \tag{9}$$

where $N(s_i)$ is the set of n_{LS} nearest neighbors of s_i in the feature space.

B. Computational Complexity and Fast Approximate Solutions

The spectral graph partitioning framework involves solving the eigenvalue problem for the normalized affinity matrix, of size $N \times N$, where N is the number of points (or pixels for image segmentation problems). In the case of a fully

connected graph, the entries of this matrix are potentially non-zero, and the time complexity of solving the eigenvalue problem is $O(N^3)$. The computational cost of this dense solution quickly becomes prohibitive for images of useful size. However the following techniques can decrease the time and space complexity at the expense of an approximate solution:

1) Iterative methods: Spectral clustering requires only the first few eigenvectors. Therefore, an iterative method (e.g., Lanczos) can be used to obtain the solution with the time complexity of $O(N^2)$;

2) Sparse representation: For image segmentation problems, the number of connections from each pixel can be set to a small constant, so that the graph has very few connections in comparison to the fully connected case and the affinity matrix is sparse. This will reduce the complexity to O(N);

3) Nyström Method: The Nyström extension is a technique to find numerical approximations for eigenvalue problems. In the context of solving the eigenvalue problem for the normalized affinity matrix, this turns out to be very useful. The eigenvectors that are computed using a small set of sample points can be extrapolated to obtain the eigenvectors of the matrix. The details of this method with application to spectral clustering can be found in [6].

III. Proposed Scheme for Classification of Polarimetric SAR data

Our proposed scheme for classification of POLSAR data is based on the spectral clustering algorithm:

- Perform multi-looking on single look complex (SLC) data (i.e., for Convair-580 data set, use 10 azimuth looks)
- Apply a polarimetric SAR speckle filter, as suggested in Lee *et al.* [7] (i.e., use window size of 7×7)
- Apply the spectral clustering algorithm with the following modifications:

1) Form an affinity matrix for each data channel (i.e., $|HH|^2$, $|HV|^2$, $|VV|^2$, ρ_{HHVV} and ϕ_{HHVV}) independently using the following weights:

$$W_{ij}^{b} = \exp\left(\frac{-\chi^2(h_i, h_j)}{2\,\sigma_i\,\sigma_j}\right) \tag{10}$$

where $\chi^2(h_i, h_j)$ represents the dissimilarity between the histograms h_i and h_j that are associated with pixels s_i and s_j:

$$\chi^2(h_i, h_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \tag{11}$$

For a pixel of interest s_i, the histogram h_i is computed from an edge-aligned window (patch), where the window mask is chosen using the procedure described in Lee *et al.* [7] for polarimetric SAR speckle filtering. The definition of the local scaling parameter, σ_i is also modified as follows:

$$\sigma_i = \mathrm{median}_{h_n \in N(h_i)}\{\,\chi^2(h_i, h_n)\,\} \tag{12}$$

2) Define an affinity matrix that represents the proximity of pixel pairs in the image domain using the following scheme:

$$W_{ij}^{P} = \begin{cases} 1 - \frac{||l_i - l_j||_2}{r}, & \text{if } ||l_i - l_j||_2 < r \\ 0, & \text{if } ||l_i - l_j||_2 \geq r \end{cases} \tag{13}$$

where r is the maximum distance allowed between pairs to have a non-zero affinity (i.e., longest pairwise connection allowed in the graph) and l_i represents the location of pixel i in the image plane.

3) Form the combined affinity matrix, W_{ij}^{tot}, by element-wise multiplication of the affinity matrices as follows:

$$W_{ij}^{tot} = W_{ij}^{P} \times \prod_{b=1}^{N_b} W_{ij}^{b} \tag{14}$$

where N_b is the number of channels.

4) Perform Steps 2 to 5 in the spectral clustering algorithm as in Section II-A (i.e., form matrix D and L, calculate the first k eigenvectors of L, form matrix X, normalize its rows and cluster using the K-means algorithm).

IV. Results and Discussion

The results presented in this section are obtained using a subset of the Westham Island scene shown in Figure 1. This C-band data set was acquired on 30 September 2004 by the Canadian Convair-580. This scene covers the agricultural fields on Westham Island, which is located in the south of Vancouver, Canada. The area contains fields of corn, potatoes, variety of berries, hay, bare soil, some barley, wheat, pumpkin, turnip, red cabbage, broccoli, and grass. However, detailed ground truth was only collected at a limited number of locations and the rest is considered unknown. Therefore we have chosen the region of interest (ROI) shown in Figure 1(b), where most of the fields have ground truth information given in Figure 1(d).

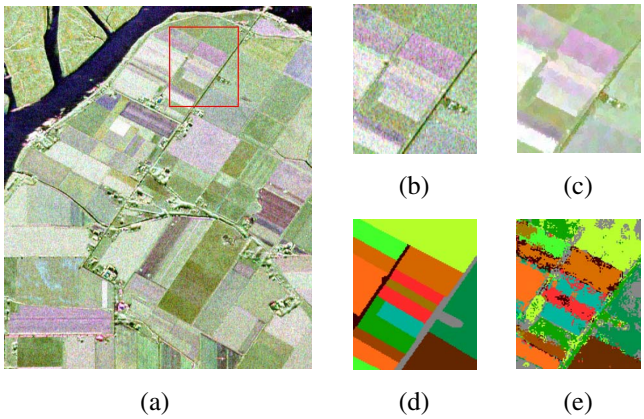

Fig. 1. Westham Island Scene acquired by the Convair-580 ©CSA (a) RGB color composite [HH-HV-VV] (b) Region of Interest (ROI) (c) ROI after speckle filtering (d) Ground Truth (e) Wishart classifier result [63.1%]

A number of results have been obtained for different values of the patch size ($d = 11, 15$ and 21) and the neighborhood

TABLE I

OVERALL CLASSIFICATION ACCURACY USING THE PROPOSED SCHEME

r	n_{LS}	d = 11	d = 15	d = 21
N/A	5	71	69	72
	25	71	71	73
45	5	75	72	74
	25	75	75	73

size ($n_{LS} = 5$ and 25). Also two cases for proximity are considered: (1) $r = N/A$ (or $r = \infty$), i.e., proximity does not have any affect on the total affinity matrix (or $W_{ij}^P = 1$), and (2) $r = 45$ is used to form W_{ij}^P as defined in (13).

The Nyström method, is used to obtain all the results presented here. Since it involves random selection of sample points, 10 runs were performed for each case mentions above. The classification accuracy results shown in Table I are the average values obtained from multiple runs. The overall accuracy for each run is defined as the percentage of the total number of correctly classified pixels in the image.

Figure 2 shows a set of results obtained using the proposed scheme and the Wishart classifier. It can be concluded that $d = 11$ provides the most accurate result and the performance can be improved if proximity is included (i.e., $r = 45$). This is also confirmed by the results given in Table I. Increasing the patch size results in the blue and red regions being merged, since they are rather small. However, all of these cases perform better than the Wishart classifier, whose accuracy was 63.1%.

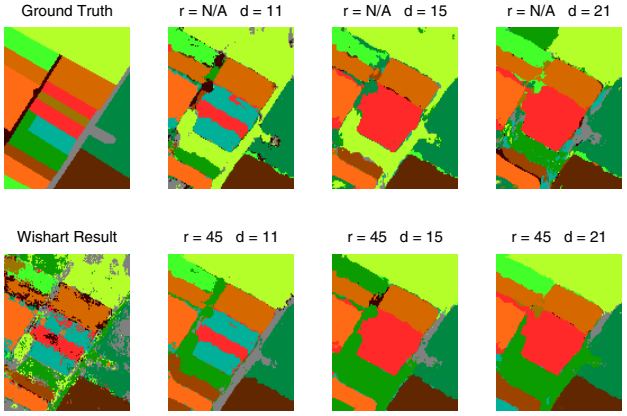

Fig. 2. One set of results used to obtain the average classification accuracy results given in Table I. For this Figure $n_{LS} = 25$

Figure 3 shows the normalized eigenvectors of L that correspond to the first k eigenvalues. These eigenvectors are used as input to the last step of the spectral clustering algorithm (i.e., k-means). This figure demonstrates how these normalized eigenvectors can be used to obtain "SC Result" in Figure 3.

Future work involves using contour continuity together with the patch-based similarity and proximity. An edge map obtained using the oriented energy will be used to determine the affinity matrix, where the weights will be small if there is an edge passing between the two pixels. Evaluating the proposed scheme on different data sets is also underway.

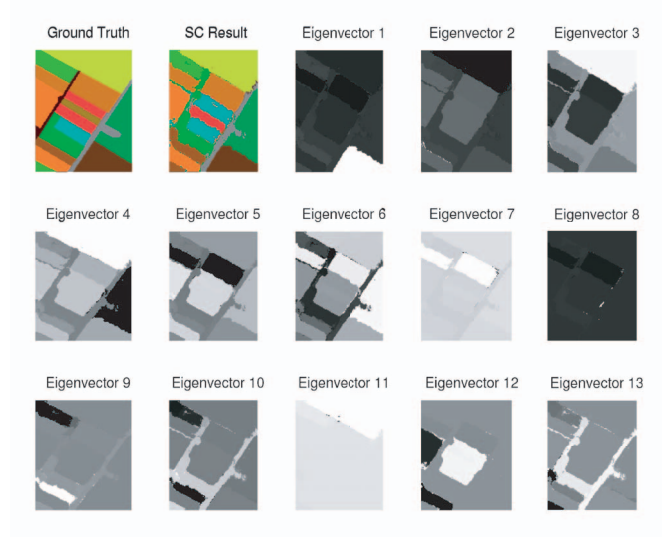

Fig. 3. Ground truth, a classification result obtained using the proposed scheme, and the first k eigenvectors of matrix L after normalization

V. CONCLUSION

A new technique based on spectral graph partitioning is proposed for polarimetric SAR data classification and the spectral clustering algorithm is modified to account for the properties of such data. Edge-aligned patch-based similarity measured by the χ^2 distance between histograms and spatial proximity of pixels are used to form the affinity matrix. It is shown that this approach not only outperforms the Wishart classifier, but also allows further improvement by offering flexibility in using additional cues (e.g., continuity, texture, optical data) and different affinity functions.

ACKNOWLEDGMENT

The authors acknowledge that the original source of the data is the Canadian Space Agency (CSA) with the cooperation of Environment Canada, Natural Resources Canada (Canada Center for Remote Sensing), Defense Research and Development Canada - Ottawa, and Radarsat International.

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