HIERARCHICAL UNSUPERVISED NONPARAMETRIC CLASSIFICATION OF POLARIMETRIC SAR TIME SERIES DATA

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1. INTRODUCTION

1.1. Problem

Data classification approaches for Polarimetric SAR (Pol-SAR) typically make assumptions about the shape of clusters. Established Pol-SAR classification methods [1,2,3] that initialize clusters in decomposition parameter spaces [4] and subsequently refine clusters by k-means Wishart optimization in the coherency matrix (T3) space are not exceptions. Indeed representing a cluster by the mean is extremely successful provided that clusters in the data are compact, well separated, and approximately round. Such assumptions are computationally effective but may yield poor results when highly nonlinear features and unusually shaped clusters are encountered. This is the challenge we address here.

1.2. Method

Pol-SAR classification tools should ideally represent arbitrarily shaped clusters. Accordingly, an unsupervised nonparametric density based clustering scheme for Pol-SAR data was presented [5] based on "mode seeking", and applied successfully to space-borne Pol-SAR data for automatic isolation of previously burned forest areas. For increasingly accurate and automatic Pol-SAR clustering this paper demonstrates improvements to the method [5] such as: high performance implementation, improved density estimation, and full hierarchical operation. The "mode seeking" approach considered here, unlike typical "mean shift" [6] implementations, uses K-nearest neighbor density estimation in conjunction with hill climbing on the K-nearest neighbor graph. Thus it is locally adaptive in the sense that no bandwidth is explicitly assumed (effectively, there is a locally varying bandwidth). Furthermore, the method is non-iterative, and does not require initialization. The "mode seeking" is performed using a data-driven step size: only displacements between a given point and one of its K-nearest neighbors are permitted. The density estimate is evaluated only at data points. There is only one parameter: the number K of neighboring points to consider about each point. As the cluster boundaries are always motivated in terms of statistical density, the results show good stability with respect to the choice of K.

2. STUDY AREA AND POLARIMETRIC SAR DATA

2.1. Data Acquisitions

A time series of Radarsat-2 images (FQ-17 mode, ascending, look angle ~37°) were collected over a study area in northern Alberta (center geo-coordinates 57°35'N, 117°45'W) near the Keg River, as follows:

Date	**18-02-13**	**14-03-13**	**07-04-13**	**01-05-13**	**25-05-13**	**18-06-13**	**05-08-13**	**22-09-13**	**16-10-13**	**09-11-13**	**03-12-13**
Interval	*(days)*	*24*	*24*	*24*	*24*	*24*	*48*	*48*	*24*	*24*	*24*

Figure 1: Radarsat-2 FQ17 Acquisition Dates.

Forests (predominantly coniferous) are prominent within the Keg River study area, which features an extensive recorded history of fires (multiple fires in every decade since 1950). The most recent is the Keg River wild fire, which burned over 4830 hectares in 2002. This is the primary region of interest for this study.

2.2. Data Processing

To accomplish speckle reduction and simultaneous reduction of data volume, multi-looking was applied to each date (4 in range and 2 in azimuth), resulting in 4x4 covariance (C4) matrices. Subsequently, 5x5 box filtering was applied. Next, correlation techniques were utilized to co-register all other dates to a master (14-03-13). The master was selected by minimizing (over all possible masters) the grand sum of the magnitudes of those displacement vectors terminating at each slave image center and originating at the center of the master.

Figure 2: The time series ensemble visualized using the encoding H,S,V=(Alpha, Shannon entropy, Span)

Decomposition parameters were produced for all of the co-registered dates, using C++ code adapted from PolSARPro. Moreover, the same parameters were calculated also for the time series ensemble (the time-averaged covariance matrix). To these parameters, a further 2x2 multi-look was applied, resulting in decomposition products of dimension 670x875 pixels with spatial resolution of 44x19m. Ultimately, each time-varying decomposition product was temporally filtered. This was accomplished by calculating the minimum, maximum, median, and median absolute deviation (MAD) for each parameter, over time. Selected parameters were used as input for the unsupervised classification scheme.

3. APPROACH TO FIND ARBITRARILY SHAPED CLUSTERS

3.1. Distance Matrix Evaluation

As input to the unsupervised scheme, we take vectors in n-dimensional Euclidean space. Each vector represents a pixel, and each dimension corresponds to one of the selected parameters. For convenience we first linearly scale each of the dimensions so that they are normalized to the interval [0,1]. This step is justified since the approach represents estimation of the cluster tree of a density: the cluster tree is topologically invariant under affine transformations of the feature space [7]. Next, we calculate the matrix of (pairwise) distances. We alleviate the computational expense of this operation by using multi-threaded acceleration,

1) a max-heap to retain references to only the KMAX-nearest points to a given point (where KMAX is some relatively small number) and,
2) storing, for each point, references to the KMAX-nearest points, for further use.

The parameter KMAX is taken sufficiently large to permit the user to vary the parameter K, below.

3.2. Density Estimation

Next, we estimate the density for each point. This step involves the parameter K. Although more sophisticated methods exist [8], a simple and effective strategy is to take the density estimate at a point x, as proportional to the reciprocal of the average of the distances to the K-nearest neighbors of x:

$$\rho(x) = \frac{1}{\frac{1}{K}\sum_{n\in N} d(x,n)}.$$

Here, N denotes the set of K-nearest neighbors of x, to which n belongs. Thus, larger values of K entail that the density estimate is more global, leading to coarser-grained results (fewer clusters). Accordingly, smaller values of K result in increasingly local estimates, resulting in a greater number of fine-grained clusters.

3.3. Hill Climbing

For the density estimate at each point, a label is assigned according to the following recursive function:

myLabel(**x**):

- If **x** is of highest density (among its K-nearest neighbors) we define myLabel(**x**) to be a new label.
- Else, **x** has a higher density neighbor **y**, and we define myLabel(**x**) to be mLabel(**y**).

3.2. Cluster Merging and Interactive Visualization

The previous step resulted in each pixel being assigned a label, corresponding to the associated cluster. The final result will be a dendrogram (tree) for hierarchical cluster representation. Formally this is an estimate of the cluster tree of a density [7]. The hierarchical merges are (unlike model-based approaches) motivated by observed density. Indeed, the splits in the tree are ordered in terms of density. We construct the tree according to the following algorithm:

1) Find the interfaces between clusters.
2) Perform merging with respect to the order of the density of the interfaces (highest first). For efficiency, we use a disjoint set-forest data structure (with path flattening).

4. PRELIMINARY RESULT AND CONCLUSIONS

We will process the full frame on a desktop workstation and present the result in the final paper. For the preliminary result edge areas were trimmed and an additional 2x2 multi-look factor was applied, producing a test chip of 220x260 pixels (spatial resolution 87x36m). Sixteen bands were selected: the temporal minimum, maximum, mean, and standard deviation for each of the parameters: Entropy, Alpha, Shannon Entropy, and Span. The 220x260x16 image cube was then input to the unsupervised scheme. An ordinary laptop computed the distance matrix in five minutes. According to the hierarchical clustering result, each cluster C is contained within a greater cluster C* (with the exception of the root, which represents the totality of pixels). The operation "*" is a real-time user-interactive aspect of the image display (implemented in C++ and OpenGL). Pixel selection (hence, cluster selection) and variation of the parameter K are also features of the image display. We selected a fire scar cluster C (a leaf of the tree). The constituent pixels of C***** (the cluster arrived at from C by taking five steps along the tree in the direction of the root) are depicted in Fig. 3 b) in white.

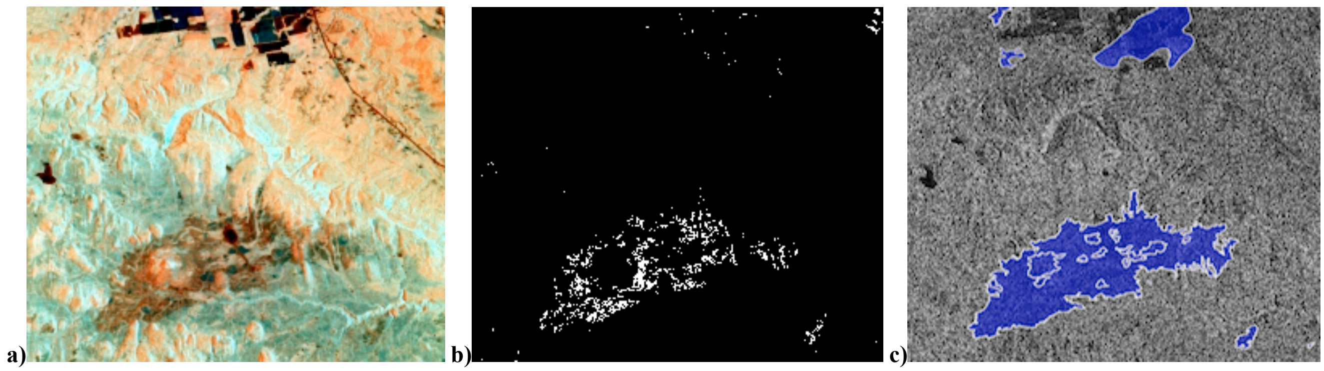

Figure 3: a) (R,G,B)=(Average entropy, Average Shannon Entropy, Average Span), b) Binary fire scar classification result (with K=50 and after 5 merges), c) |HH| overlaid with polygons from the Alberta Wild Fire database.

The 2002 Keg River fire scar is clearly identified in Fig. 3 b). This shows excellent agreement with the 2002 Keg River fire polygon (the largest polygon within Fig. 3 c)). The object detected in the lower right hand corner of Fig. 3 b) is another recent fire. The polygons in the upper half of Fig. 3 c) represent fires that are not recent. The preliminary result demonstrates the potential and effectiveness of the new method for forest applications, especially for detection of historical fire scars. Detailed results will be presented and analyzed in the full paper.

5. REFERENCES

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