UNSUPERVISED NONPARAMETRIC CLASSIFICATION OF POLARIMETRIC SAR DATA USING THE K-NEAREST NEIGHBOR GRAPH

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1. INTRODUCTION

Most classification methods make implicit assumptions about the shape of clusters in the polarimetric SAR data space, often through statistical assumptions, or by the classification scheme itself. These assumptions allow the problem to be solved quickly, but such methods may fail when dealing with highly nonlinear data exhibiting unusually shaped clusters. SAR classification algorithms are faced by this exact problem. Typically they initialize clusters in the Cloude-Pottier parameter space [1], and optimize clusters further in the coherency or covariance matrix space [2, 3]. However, as we will show, the Cloude-Pottier parameter space exhibits a highly nonlinear structure. Therefore, this initialization procedure will fail to separate certain types of land cover. This paper sets out to address this problem, by implementing a new data-driven clustering approach to detect clusters of arbitrary shape, for polarimetric SAR. In addition, some new information theoretic parameters will be employed to illustrate the potential of the new methodology to discriminate forest land cover types in a low dimensional space.

2. STUDY SITES AND POLARIMETRIC SAR DATA

Our study area located near the Chinchaga river in Alberta features mature forest stands, clear-cuts, and fire scars. The size of the area is approximately 1.66 million hectares. Multi-date ALOS PALSAR quad-pol data were collected during the summer of 2009 and processed through Faraday rotation compensation, speckle filtering, and polarimetric SAR decomposition. Selected decomposition parameters are later used as input data for the new classification scheme described in the following section.

3. APPROACH TO FIND NONLINEAR CLUSTERS

According to Wishart [4], clustering should resolve "data modes, independently of their shape and variance". Hartigan [5] clarified Wishart's idea using the notion of high density clusters (as maximally connected subsets of level sets of density in the feature space). Given a density function p and threshold λ, the level set for p and λ is given by:

$$L(\lambda; p) = \{x \mid p(x) > \lambda\}. \qquad (1)$$

The idea that clusters are regions of connected density motivates our approach. However, instead of assuming a density threshold in order to find clusters, we assume a level of detail, which we define implicitly by fixing a number of nearest neighboring points to consider around each data point. Stuetzle [6] gives a classification algorithm using the nearest neighbor density estimate, noting that density estimates based on the k-nearest neighboring points will improve the results. Since the clusters of the Cloude-Pottier parameter space are not well separated, it is necessary to follow Stuetzle's suggestion, estimating the density at a point x as a function of its k-nearest neighbors. In this work we test several density estimates, including the "max" estimate (2): where α is a scaling factor, we can estimate the density at x as proportional to the reciprocal of the greatest distance to a nearest neighbor of x (we denote the set of k-nearest neighbors of x by N, and denote a member of N as n):

$$\rho(x) = \alpha \frac{1}{\max_{n \in N} d(x, n)}. \qquad (2)$$

Moreover, the parameter k allows us to take the surrounding information of a point into consideration. When k=1, the density estimate is completely local, but as k is increased, the density estimate represents increasingly global information. As the k-nearest neighbors of all the points in the feature space are computed, a graph called the k-nearest neighbor graph is built, in which an edge connects each point with its k-nearest neighbors. The k-nearest neighbor graph is then searched recursively to locate the domains of attraction for which the density is maximal. One recursive iteration is performed for each point. If that point has a density greater than all of its neighbors, then it is deemed to be an attractive center of the data, and is given a new label. Otherwise, we continue to visit the highest density neighbor available until a new attractive center (or a previously labeled point) is reached. Then all points visited during the iteration are given the label of the new center (or the previously labeled point).

The attractive center and all points which have been "attracted" to it form a cluster representing a specific feature. Figure 1 shows an example of the k-nearest neighbor graph for k=40 (in which four clusters were found). Setting k too low produces too many clusters (due to the locality of the density estimate), while increasing k takes into account more global information and thus produces fewer clusters. It is necessary to repeat this procedure for several values of k, to verify that the attractive centers are consistent with the desired level of detail. The approach does not rely on a particular distance function (for example, the Wishart distance function [2]). Thus, it presents a vehicle for testing the consistency of the feature space initialization procedure with classification in the matrix space. In summary, density estimation followed by hill climbing on the k-nearest neighbors graph represents a novel classification approach, whereby the classification methodology is consistent with the density estimation technique employed.

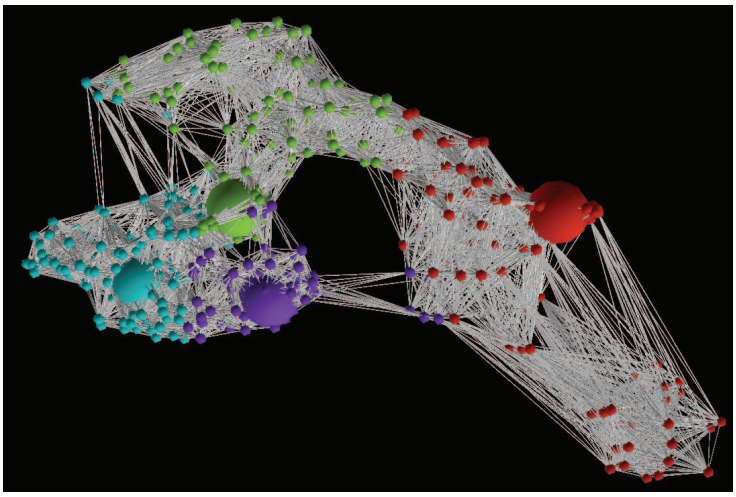
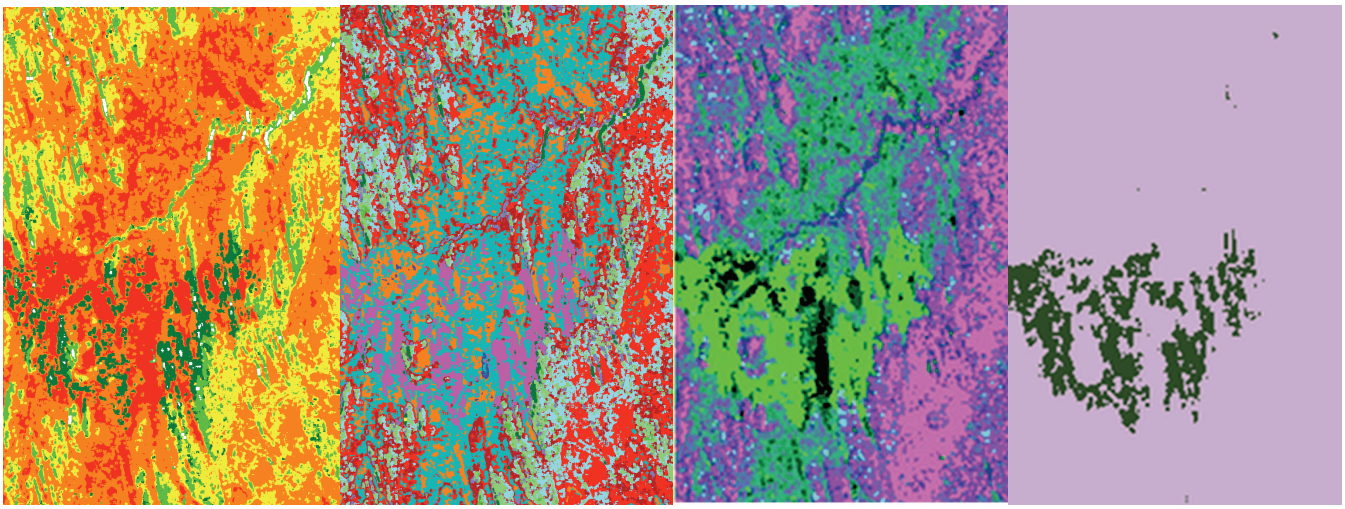


Figure 1: A 40-nearest neighbor graph of a subarea of the PALSAR data – the spheres represent points in the feature space. The spheres with the same color represent a cluster (region of attraction); the large spheres represent the attractive centers of the clusters.

For comparison with the graph based algorithm, an alternate approach was implemented, which assigns the data of the feature space to gridded bins. The attractive centers and regions of attraction are elucidated by climbing towards maxima in the binned density. A visualization suite including both the graph based algorithm, and the (fast) binned density climbing methodology, was implemented in C/C++ and OPENGL. The visualization suite is interactive so that the user can vary the parameter k at any time, and view the generated clusters on the fly.

4. PRELIMINARY RESULTS AND CONCLUSIONS

Preliminary classification results are shown using ALOS PALSAR quad-pol data over a sub area (image size 768x1140), featuring a 2002 fire scar in the Chinchaga study site. Using three of the decomposition parameters, which are Cloude Entropy, Shannon Entropy, and Cloude Alpha, the new classification approach was able to effectively resolve the burned forest scar from the other landcover types. See Fig. 2(c). Fig. 2(d) displays the fire scar class only. For the comparison, the Wishart-distance based classifiers were applied on the same data sets and the resulting classification images are show in Fig. 2 (a) and (b). We can see the Wishart-distance based classifiers certainly had difficulties separating the burned class from the other classes. The preliminary study results are encouraging and have shown the potential and effectiveness of our new classifier in segmenting and classifying radar polarimetric SAR data for forest applications, especially for fire scar detection. In [7] the results will be compared with those of a new coherence based geometrical detector [8]. The validity of the results on full PALSAR images is being further evaluated using GIS ground reference data and remote sensing data from a variety of sources.



(a) **(b)** **(c)** **(d)**

Figure 2: Classification of burned area. (a) Entropy/Alpha Wishart classification, (b) Entropy/Alpha/Anisotropy Wishart classification, (c) New binned classification approach, (d) Isolated forest burned class from (c) which matches historical fire scar GIS boundary.

5. REFERENCES

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