MEAN-SHIFT AND HIERARCHICAL CLUSTERING FOR TEXTURED POLARIMETRIC SAR IMAGE SEGMENTATION/CLASSIFICATION

Jean-Marie Beaulieu *and* *Ridha Touzi*

Dép. informatique et génie logiciel
Laval University, Quebec, PQ, G1V0A6, Canada

Canadian Center of Remote Sensing, NRCan
588 Booth St., Ottawa, Ont., K1A0Y7, Canada

1. INTRODUCTION

We have developed a powerful hierarchical segmentation approach for polarimetric SAR images [1]. Hoever, image segmentation and unsupervised classification are difficult problems. This paper proposes to combine both. A clustering process is applied over segment mean values. Only large segments are considered. The clustering is composed of a mean-shift step and a hierarchical clustering step. A new hierarchical clustering approach that integrates the mean-shift spatial constraint will be presented. The approach is applied on a 9-look polarimetric SAR image. Textured and non-textured image regions are considered. The K and Wishart distributions are used respectively. The obtained region groups constitute an important simplification of the image data. The fields are correctly delimited and small variations inside homogeneous areas are recognized

The main task in remote sensing is the interpretation of the image. There is a need for tools to facilitate the realization of this complex task. This is the objective of automatic (unsupervised) classification techniques. In the more general framework of data analysis (any kind of data, not only images), this is referred to as clustering techniques [4]. In the next section, we will examine the relation between iterative clustering, hierarchical clustering and image segmentation and how we can move between them. Then, we present the segment clustering approach and it application on a textured polarimetric SAR image.

2. CLUSTERING AND IMAGE SEGMENTATION

The agglomerative hierarchical clustering algorithm starts by assigning each data point to a distinct cluster [4]. For N data points, we initially have N clusters. At each iteration, we consider all pairs of cluster (Ci, Cj), calculate a similarity measure or distance for each pair (Di,j = D(Ci,Cj)) and merge the 2 clusters which are the most similar or have the smallest distance. The iterative mean-shift [3] approach could be viewed as a generalization of the k-means technique [2], [5]. We can consider that the k centers are moved toward the modes of the probability density function (pdf). The mean shift could move every data points toward the modes.

Image segmentation is a special case of clustering where clusters contain only connected pixels, i.e. for each pixel, you can go to any other pixel of the cluster by following a path inside the cluster [1]. It could be advantageous to used segmentation instead of clustering because of the utilization of spatial information. Pixels inside the same image field should be inside the same cluster, especially adjacent pixels. Grouping adjacent pixels should reduce the noise if they belong to the same field or class. It should be easier to cluster segment mean values than pixel values.

At some point, we should consider grouping regions that are not adjacent, i.e. perform region clustering. Image regions with the same land use class could be in different parts of the image. Clustering regions produces region aggregates or region groups. Aggregates will have better estimation of the region common land use parameters. The discrimination between land use classes will then be improved.

3. SEGMENTATION/CLUSTERING OF TEXTURED POLARIMETRIC SAR IMAGES

We propose to apply a clustering process over segment mean values. The partition is produced by a powerful hierarchical segmentation approach previously developed [1]. We consider only large segments. The clustering is composed of a mean-shift step where region mean values are moved toward density mode and a hierarchical clustering step that produce K region groups/clusters. Small segments are then assigned to the closest region group. The obtained region groups constitute an important simplification of the image and a good initial classification map.

The approach is applied on a 9-look polarimetric Convair-580 SAR image of the Mer Bleu area, Ottawa, Canada. The image (800x600 pixels) is show in Fig. 1 using the amplitude of the hh, vv and hv channels. The image contains crop field areas and forest areas.

A textured image model is used [1], [6]. Following the scalar product model, the observed covariance matrix, $T = \mu \cdot Z$, is the product of 2 random variables: a scalar texture component μ with a gamma distribution and the speckle complex covariance matrix Z with a Wishart distribution. T follows the K distribution. For a region, the shape parameter α is estimated by the method of moment. We consider that the region is textured if $\alpha \leq 10$ and non-textured if $\alpha \geq 20$. Between these 2 values, we use a weighted sum of the distance measures of both cases. The distance D used in the hierarchical segmentation, the hierarchical clustering and the mean shift processes is the likelihood ratio statistic $D(Ci,Cj) = MLL(Ci) + MLL(Cj) - MLL(Ci \cup Cj)$ where MLL(C) is the maximum log likelihood value calculated over segment/cluster C. For non-textured region, the pixel covariance matrix Z follows the Wishart distribution and $MLL(C) = -nL \cdot \ln(|\Sigma|)$ [7]. For textured region, the pixel covariance matrix T follows the K distribution and

$$MLL(C) = n(3L+\alpha)/2\ \ln\left(\alpha L\right) - n\ln(\Gamma(\alpha)) - nL\ln(|\Sigma|) - (3L-\alpha)/2\sum_{T\in C}\ln(\mathrm{Tr}\left(\Sigma^{-1}T\right)) + \sum_{T\in C}\ln(K_{3L-\alpha}\left(2\sqrt{\alpha L\,\mathrm{Tr}\left(\Sigma^{-1}T\right)}\right))$$

where n and Σ are the region size and covariance matrix [1]. Kν is the modified Bessel function. L is the number of look.

The following steps are applied to the test image (Fig. 1).

1) The hierarchical segmentation algorithm is first used. We obtain a partition with 10,000 segments. Only segments of 20 pixels or more are used in the 2 following steps.
2) The mean-shift algorithm is applied to modify the segment mean values. Values are moved toward higher probability density zone (the density mode). This is a kind of adaptive value filtering.
3) The modified large segment values are clustered by hierarchical clustering. We obtain partitions with 200, 50 and 20 groups of segments.
4) The small segments are assigned to one of the region groups after mean shift filtering and maximum likelihood classification. The mean value of the covariance matrix for each group is calculated and assigned to every pixel in the group.

The first merges in hierarchical clustering and segmentation are easy. The last merges involve segments or groups that are not really similar but can still belong to a same field or class. There is a large uncertainty about if it is a good merge or not. With 200 groups, many fields (image regions) are divided into parts belonging to different groups. This corresponds to identifying sub-class inside the field class. If we continue cluster merging, the sub-class will be merged with other sub-classes, but will not necessary form the field class and the field will remain divided into parts. We decided to switch from cluster to segment merging to merge only adjacent segments. This is followed by clustering to obtain again 200 region groups. In Fig. 2, the regions are larger and the fields are less subdivided. There are many small regions that should ideally be removed. Fig. 2 represents good unsupervised classification result. The important fields are correctly delimited. The process was able to recognize small variation inside what we would have considered as homogeneous areas, for example, in the top right corner of the image.

4. CONCLUSION

Combination of iterative mean shift clustering with hierarchical clustering and segmentation has produced good unsupervised classification results. The important fields are correctly delimited and small variations inside homogeneous areas are recognized. A new hierarchical clustering approach that integrates the mean-shift spatial constraint is currently developed and will be presented.

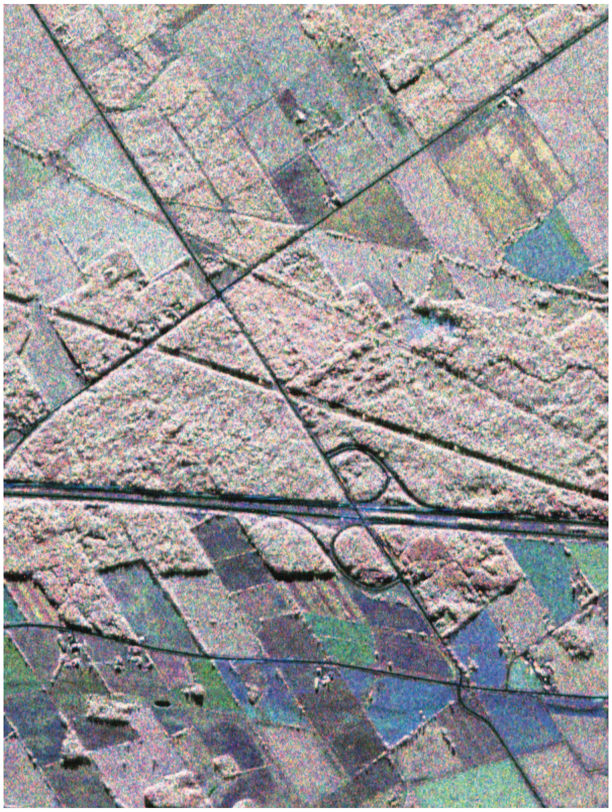

Fig 1 : Original polarimetric SAR image.

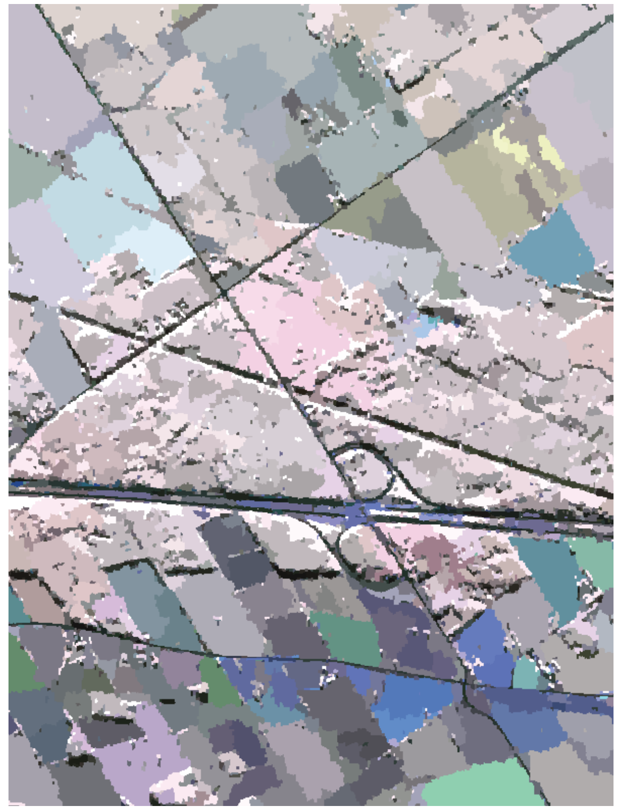

Fig 2 : Class map with 200 groups and 4849 regions.

5. REFERENCES

[1] J.-M. Beaulieu, and R. Touzi, "Segmentation of Textured Polarimetric SAR Scenes by Likelihood Approximation," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 10, pp. 2063-2072, 2004.

[2] F. Cao, W. Hong, Y. Wu, and E. Pottier, "An Unsupervised Segmentation With an Adaptive Number of Clusters Using the SPAN/H/α/A Space and the Complex Wishart Clustering for Fully Polarimetric SAR Data Analysis," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 11, pp. 3454-3467, 2007.

[3] D. Comaniciu, and P. Meer, "Mean Shift: A Robust Approach Toward Feature Space Analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 5, pp. 603-619, 2002.

[4] R.O. Duda, P.E. Hart and D.G. Stork, ***Pattern Classification***, 2nd ed., John Wiley and Sons, 2000, 654 pages.

[5] J.S. Lee, M.R. Grues, E. Pottier, and L. Ferro-Famil, "Unsupervised terrain classification preserving scattering characteristics," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 4, pp. 722-731, 2004.

[6] A. Lopes and F. Sery, "Optimal speckle reduction for the product model in multilook polarimetric SAR imagery and the Wishart distribution," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 35, no. 3, pp. 632-647, 1997.

[7] H. Skriver, A.A. Nielsen and K. Conradsen, "Evaluation of the Wishart test statistics for polarimetric SAR data," in *Proceeding of IGARSS'03*, Toulouse, France, July 2003.