Jean-Marie Beaulieu

[BeaulieuJM.ca/publi/Bea2008a]

Classification of Polarimetric SAR Images using Radiometric and Texture Information

Authors: **Beaulieu** Jean-Marie, Ridha Touzi

Conference: IEEE International Geoscience and Remote Sensing Symposium IGARSS 2008

Boston, MA, USA

7-11 July 2008, vol. IV, pp. 29-32

ISBN: 978-1-4244-2807-6

URL: https://ieeexplore.ieee.org/document/4779648

DOI: 10.1109/IGARSS.2008.4779648

Classification of Polarimetric SAR Images using Radiometric and Texture Information,
Beaulieu Jean-Marie, Ridha Touzi,
IEEE International Geoscience and Remote Sensing Symposium IGARSS 2008, Boston, MA, USA, 7-11 July 2008, pp. 29-32.

DOWNLOAD **from the Publisher**

Published in: IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2008
Date of Conference: 7-11 July 2008
Date Added to IEEE *Xplore*: 10 February 2009
INSPEC Accession Number: 10472566
Conference Location: Boston, MA, USA
Publisher: IEEE

CLASSIFICATION OF POLARIMETRIC SAR IMAGES USING RADIOMETRIC AND TEXTURE INFORMATION : A SEGMENT CLUTERING APPROACH

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

ABSTRACT

Image segmentation and unsupervised classification are difficult problems. We propose 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. 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 and a good initial classification map. Multiplying the class map by the image of scalar texture component produces an image almost identical to the original where speckle 'color' noise variation is filtered out.

***Index Terms*—** Polarimetric SAR image, hierarchical segmentation, mean-shift, texture, classification, clustering.

1. INTRODUCTION

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 [5].

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

2.1. Iterative and hierarchical clustering

The agglomerative hierarchical clustering algorithm starts by assigning each data point to a distinct cluster [5]. For N data points, we initially have N clusters. Then, iteratively, the number of clusters is reduced by 1 by merging the 2 most similar clusters. At the end, there is 1 cluster containing all the data points. 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 result can be represented by a merging tree where the cluster produced by a merge (the father) is linked to the 2 merged clusters (the 2 sons). Partitions with varying number of clusters can be produced. A K cluster partition is produced by cutting the tree or stopping after N-K merges.

The algorithm is general but the distance D should be correctly defined for each application. D is a between cluster distance with varying clusters sizes. It could be related to inter-cluster distances d(x,y). The distance between cluster centers (mean values) is often used, D(Ci,Cj) = d(mi,mj) where mi is the mean value of cluster Ci data points.

Iterative clustering techniques start from an initial partition and iteratively improve it. The often used k-means algorithm starts with K center positions. Each data point is then assigned to the closest center. For each center, a new position is calculated from the mean values of points assigned to the center.

2.2. Polarimetric SAR data clustering

The distance measure is related to the used set of features or attributes. The attributes define the space of the data points. For multi-spectral images, each attribute could correspond to one of the spectral bands. Other attributes could be calculated from the 'primitive' values. For example, vegetation index are calculated from the spectral values. The objective is that the observed attribute values from different classes should occupied different regions of the attribute space.

For polarimetric SAR data, the covariance or the coherency matrices are the observed pixel values. Other attributes are obtained by signal decomposition such as the entropy, alpha and the anisotropy (H/α/A) [3], [6]. These attributes are used to identify volume diffusion, surface diffusion and double bound targets. Well defined threshold values have be identified and used to perform an initial

grouping of data. Iterative clustering was performed using the H/α/A attributes and/or the covariance/coherency matrix [3], [6]. The cluster mean covariance value is used as the best estimate of the population covariance Σ. The pixel value Z is then assigned to the cluster j that produces the highest probability for the observed value $p(Z|\Sigma j)$. For non textured (homogeneous) areas, the Wishart distribution is used.

Hierarchical clustering was also used. Different between cluster distances were proposed [3], [8]. The likelihood ratio statistic measures the probability of the observed values assuming 2 clusters over the probability for 1 cluster. Another approach is to measure the probability that the pixel values of one cluster belong to the population corresponding to the other cluster. The combined approach iterative/hierarchical clustering produces the better results.

2.3. Image segmentation and segment clustering

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. Clusters are image regions or segments. In the hierarchical approach, only adjacent regions could be merged as in region merging segmentation techniques [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.

2.4. Mean shift clustering

The mean shift approach could be viewed as a generalization of the k-means technique [4]. 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. At a data point, we can estimate the local probability density by using a Gaussian window kernel. The data point x is moved in the direction of higher density or in the direction of gradient assent. The direction is calculated from –(m-x) where m is the mean value of surrounding points weighted by Gaussian kernel centered on x. If the density is uniform then m=x. If there is a density gradient, then –(m-x) will point in the increased density direction. The m value will be located on the side of x with higher density. The point x should be moved toward the m value. The mean shift is an iterative technique where data points converge toward the local density modes. The used should specify the kernel window size. An advantage of the technique is that both radiometric and spatial information could be used in the weight calculation. The weight is related to difference in radiometric attributes and in spatial positions in the image.

2.4. Optimization in segmentation/clustering

Segmentation/clustering can be presented as an optimization problem: find the best data partition. It is usually difficult to relate the clustering distance measure D to a global objective function. We have presented the segmentation as a maximum likelihood approximation problem and have related the distance D to this global criterion for hierarchical segmentation [1]. D is the log of the likelihood ratio statistic:

$$D(Ci,Cj) = MLL(Ci) + MLL(Cj) - MLL(Ci \cup Cj) \qquad (1)$$

where MLL(C) is the maximum log likelihood value calculated over segment C.

Clustering techniques will look for 'local' optimum instead of global optimum because we cannot explore all the possible partitions. Iterative and hierarchical techniques have different way to explore the partition space. Iterative techniques move from a partition to a nearby one by moving a center or by moving a data point from one cluster to another. Hierarchical techniques modify the partition by merging 2 clusters. It seems advantageous to combine the 2 approach to obtain a better sub-optimum.

3. SEGMENTATION/CLUSTERING OF TEXTURED POLARIMETRIC SAR IMAGES

We propose to apply a clustering process over segment mean values. 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. Multiplying the class map by the image of scalar texture component produces an image almost identical to the original where speckle 'color' noise variation is filtered out.

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.

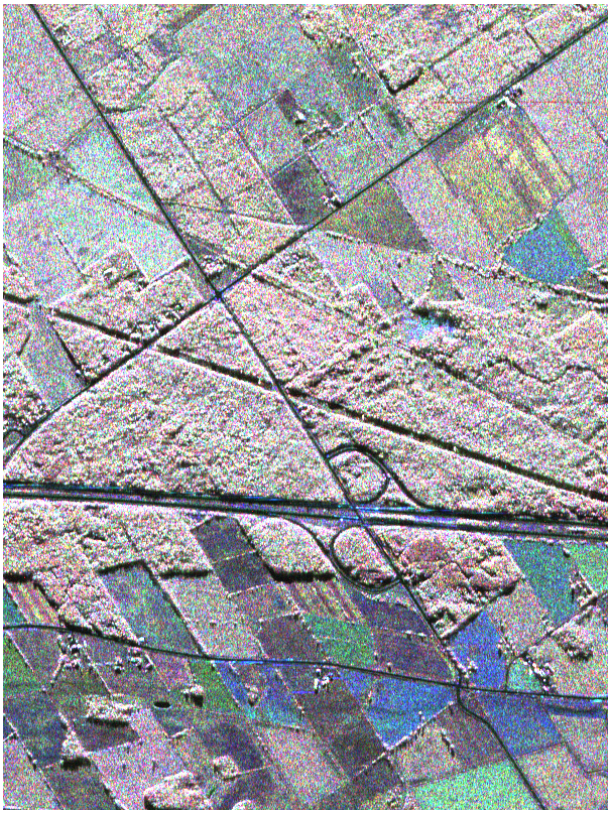

Fig 1 : Original polarimetric SAR image.

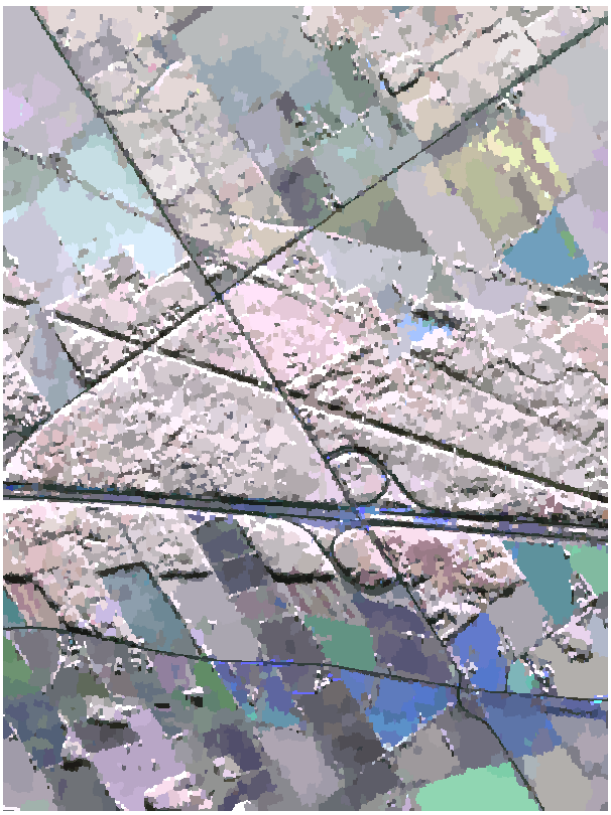

Fig 2 : Class map with 200 groups (7440 regions).

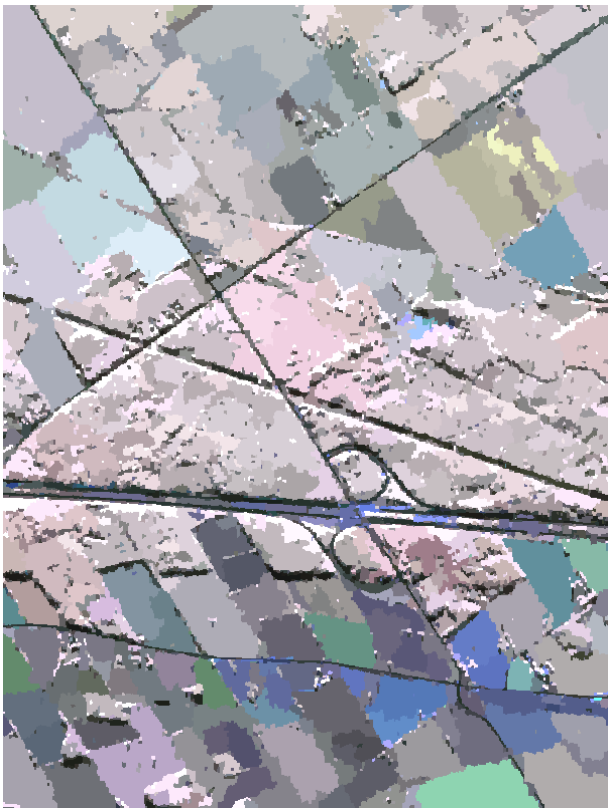

Fig 3 : Class map with 200 groups and 4849 regions.

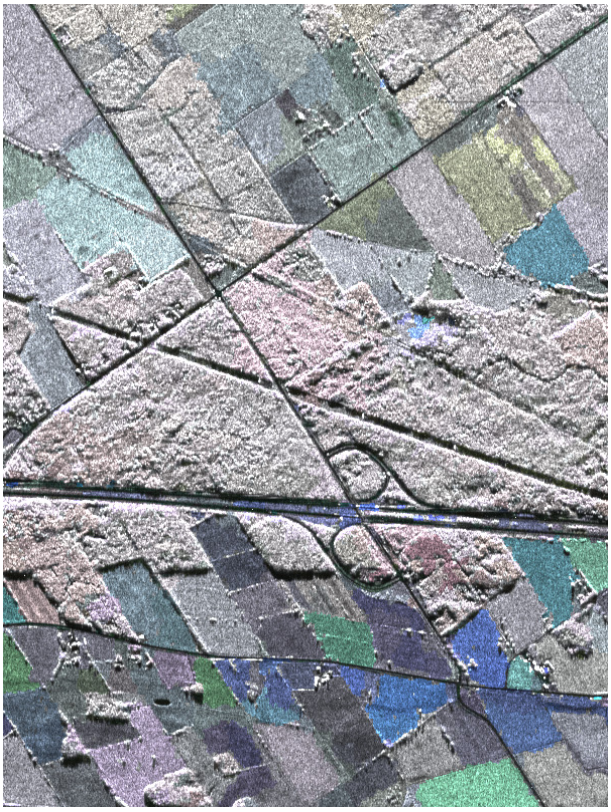

Fig 4 : Fig 3 multiplied by the image texture component.

A textured image model is used [1], [7]. Following the scalar product model, the observed covariance matrix, T = μ·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 α≤10 and non-textured if α≥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 of eq. (1). For non-textured region, the pixel covariance matrix Z follows the Wishart distribution and MLL(C)=$-nL\cdot\ln(|\Sigma|)$. For textured region, the pixel covariance matrix T follows the K distribution and

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

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 classification map with 200 groups is presented in Fig. 2. 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. In Fig. 2, we stopped at 200 region groups. We can continue the merges up to 50 or 20 groups and still get interesting results. 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. 3, the regions are larger and the fields are less subdivided. There are many small regions that should ideally be removed. Fig. 3 is not an appropriate classification map. User inputs are needed to define meaningful classes. However, this unsupervised classification could simplify the user work.

We have used the K distribution for textured scene. For each pixel in a group/class, Ti = μi·Zi, we can separate the texture and the speckle components [2], [7]. If we replace Zi by the class average Σ, we obtain a good approximation of the original image, Ti = μi·Σ, that need only a scalar texture value per pixel μi and a covariance matrix Σ per group. In Fig. 4, we see that the speckle 'color' variation have been averaged on a group/class basis.

4. 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] J.-M. Beaulieu and R. Touzi, "Segmentation of Polarimetric Sar Images Composed of Textured and Non-Textured Fields", *Advanced SAR Workshop 2005 (ASAR05)*, Canadian Space Agency, St-Hubert, PQ, Canada, November 15-17, 2005, CDrom.

[3] 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.

[4] 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.

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

[6] 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.

[7] 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.

[8] 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.