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SEGMENTATION OF TEXTURED AREAS USING POLARIMETRIC SAR

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ABSTRACT

Segmentation of polarimetric SAR image is a difficult problem. We show that image segmentation can be viewed as a likelihood approximation problem. The optimum criterion is derived for a hierarchical segmentation process. The stepwise criteria are derived for polarimetric SAR images. The methods currently used for classification or segmentation of polarimetric SAR images are based on the multivariate complex Gaussian model for homogeneous scene. Their performances are significantly degraded in the presence of spatial texture. The optimum criterion is derived for segmentation of K-distributed textured polarimetric SAR images. Good results are shown for Convair-580 SAR data collected over the Ottawa region, Canada.

RÉSUMÉ

La segmentation d'images polarimétriques est un problème difficile. Nous montrons que la segmentation d'image peut être vue comme un problème d'approximation par une mesure de vraisemblance. Le critère optimum est dérivé pour un processus de segmentation hiérarchique. Nous dérivons le critère d'étape pour les images SAR polarimétriques. Les méthodes actuellement utilisées pour la classification et la segmentation des images polarimétriques sont basées sur un modèle multivarié gaussien complexe pour les scènes homogènes. Leurs performances sont significativement réduites lors de la présence de textures spatiales. Le critère optimum est dérivé pour la segmentation d'images SAR polarimétriques texturées suivant une distribution K. De bons résultats sont obtenus pour les données SAR du Convair-580 recueillies au-dessus de la région d'Ottawa, Canada.

INTRODUCTION

Segmentation of SAR (Synthetic Aperture Radar) images is greatly complicated by the presence of coherent speckle. All the methods currently in use for classification or segmentation of polarimetric SAR images are based on the multivariate complex Gaussian model (Lee 1999), (Lui 2000), (Conradsen 2003). Since their performances are significantly degraded in the presence of spatial texture, the application of these methods should be limited to "homogeneous"

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Gaussian areas.

In this study, a new method based on the hierarchical stepwise optimization is introduced for segmentation of K-distributed textured polarimetric SAR images. The product model is assessed and applied only within areas in which the model is valid.

The main approaches to image segmentation are based upon classifications, edges or regions. Image segmentation could result from the classification or the labelling of each pixel. Pixel classification does not involve generally the spatial aspect (Smith 1996). The image partition is a side effect of the classification. Markov random field and texture models have been used to include the spatial aspect into the class probabilistic models (Lee 1999), (Lui 2000). An edge detection process could also be used to define the boundaries of segment in which the signal is a wide-sense stationary process (Touzi 1988), (Touzi 2002).

We consider that truth image segmentation processes are based upon regions. The goal of the process is to identify regions (segments) that satisfy some criteria. Spatial aspects are involved in the criteria. It is often defined as hierarchical segmentation. A typical agglomerative approach involves the sequential growing of regions. The first techniques used threshold-based decision. More powerful techniques now use iterative optimization processes (Dong 1999), (Lira 1998), (Beaulieu 2001).

IMAGE SEGMENTATION AS A LIKELIHOOD APPROXIMATION PROBLEM

Image segmentation could be viewed as the transformation of the original image into a more complex description. The image is represented by a set of regions or segments. Each segment is described by a set of parameters, which are selected according to suitable image models. These models can be used to evaluate the image description or the segmentation result. A good description should explain the observed pixels values.

Maximum likelihood approach

Following a statistical approach, the image segmentation could be presented as a maximum likelihood estimation problem. Let $\boldsymbol{x}_i$ be the value of pixel i. The probability density function (pdf) of $\boldsymbol{x}_i$ is function of the segment S that contains the pixel i, ($i \in S$). The pdf are described by a set of parameters, θ. For the segment S, the pdf of $\boldsymbol{x}_i$ is $p(\boldsymbol{x}_i \mid \theta_S)$. We assume that the pdf of $\boldsymbol{x}_i$ is only a function of θ_S and is conditionally independent of other pixel values. Let X be the set of pixel values for the whole image, $X = \{ \boldsymbol{x}_i \mid i \in I \}$. Let Θ_P be the set of all θ_S for the partition P, $\Theta_P = \{ \theta_S \mid S \in P \}$. The likelihood function of Θ_P and P given X is

$$L(\Theta_P, P \mid X) = p(X \mid \Theta_P, P). \tag{1}$$

We could write the equation as a product of pixel pdfs because the probabilities of pixels are conditionally independent.

$$L(\Theta_P, P \mid X) = \prod_{i \in I} p(x_i \mid \theta_{S(i)}) \Big|_P \tag{2}$$

$S(i)$ is the segment containing the pixel i and the parameters are evaluated for the partition P. The parameter values that optimize the log likelihood function also optimize the likelihood function.

$$\ln\left(L(\Theta_P, P \mid X)\right) = \sum_{i \in I} \ln\left(p(x_i \mid \theta_{S(i)})\right)\Big|_P \tag{3}$$

In the maximum likelihood approach, we want to find the partition P and the segment descriptive parameters Θ_P that optimize the likelihood function. The likelihood function evaluates the probability of observing the pixel values X when the segments of the partition P are described by the parameters θ_S. The probability is a measure of the correspondence between the description and the image data. The best description is used to estimate the truth state of the nature.

Best parameter evaluation

For a segment S, the parameters θ_S could usually be evaluated from statistics calculated over the segment. For a given partition P, the log likelihood function value for the best parameters Θ_P could be defined as $LLF(P)$ and could be calculated rapidly. The function could be written as a sum of the maximum log likelihood values for each segment.

$$LLF(P) = \ln\left(L(\Theta_P, P \mid X)\right) = \sum_{S \in P} MLL(S) \tag{4}$$

where

$$MLL(S) = \sum_{i \in S} \ln\left(p(x_i \mid \theta_S)\right). \tag{5}$$

Eq. 4 shows that the difficult part of the optimization process is to find the best partition. Once we have a partition, it is easy to calculate the best descriptive parameters for this partition.

Finding the best partition

We cannot explore all image partitions with k segments to find a global optimum. A hierarchical framework is used to restrict the exploration space. In hierarchical segmentation, we start with an initial partition P_n and then produce a sequence of partition $P_n \ldots P_{k+1}, P_k \ldots P_1$ by merging two adjacent segments at each iteration. The partition P_k is produced by merging two segments of P_{k+1}. The optimization of LLF results then into a stepwise optimization process that finds the best merge at each iteration. This is a sub-optimum approach with the hierarchical segment merging constraint.

The used stepwise criterion should measure the decrease of LLF. If we consider the merging of segment S_i and S_j from partition P_{k+1} to produce the segment S_u ($= S_i \cup S_j$) in partition P_k then the difference between $LLF(P_{k+1})$ and $LLF(P_k)$ will only involve the segment S_i, S_j and S_u.

$$SC_{i,j} = MLL(S_i) + MLL(S_j) - MLL(S_u). \tag{6}$$

At each iteration, we should merge the segments that minimize the $SC_{i,j}$ criterion.

POLARIMETRIC SCENE-SPECKLE STATISTICS

The polarimetric scattering matrix measured by a polarimetric SAR consists of four complex elements. For a reciprocal medium, the two cross-polarized terms are identical and the polarimetric feature vector $\boldsymbol{x}$ has only three unique complex elements, $\boldsymbol{x} = (hh,\ hv,\ vv)^T$, where, for instance, hv is the horizontally polarized return signal, given that the transmitted signal is vertically polarized.

Homogeneous scene

For a homogeneous scene, the vector $\boldsymbol{x}$ is complex Gaussian-distributed with a covariance $\Sigma = E[\ \boldsymbol{x}\ \boldsymbol{x}^H]$. $E[\ ]$ denotes the expectation operator and the superscript H indicates the complex conjugate transpose.

$$p(x \mid \Sigma) = \frac{1}{\pi^3 |\Sigma|} \exp\left(-x^H \Sigma^{-1} x\right) \tag{7}$$

For a segment S with n_S pixels, the best estimate of the covariance matrix Σ is the sample covariance matrix, C_s (Goodman 1963).

$$C_S = \hat{\Sigma} = \frac{1}{n_S} \sum_{x \in S} x\ x^H \tag{8}$$

The maximum likelihood value for this segment is

$$MLL(S) = \sum_{x \in S} \ln\left(p(x \mid C_S)\right) = -n_S \ln\left|C_S\right| - n_S \ln \pi^3 - 3n_S\ . \tag{9}$$

We obtain the stepwise criterion

$$SC_{i,j} = (n_i + n_j) \ln\left|C_{Si \cup Sj}\right| - n_i \ln\left|C_{Si}\right| - n_j \ln\left|C_{Sj}\right| \tag{10}$$

where n_i and n_j are the sizes of segments S_i and S_j. At each iteration, the hierarchical segmentation algorithm merges the two segments that minimize this criterion.

For L-look image, we use the covariance matrix of the pixel Z_k instead of the complex vector $\boldsymbol{x}$ and $p(Z_k \mid \Sigma)$ instead of $p(x \mid \Sigma)$. Z_k follows a complex Wishart distribution within a Gaussian area (Goodman 1963). The stepwise criterion corresponds to Eq. 10 where the number of pixel of a segment is multiplied by the number of looks L. An equivalent criterion is used in (Conradsen 2003) for statistical hypothesis testing and is derived from a likelihood ratio test. In the present likelihood approximation framework, the stepwise criterion is related to a global measure of the image partition quality.

Textured scene

At the presence of texture, the product model was used in (Lopes 1997), (Oliver 1998) to derive the statistics of the covariance matrix for gamma-distributed scene signal:

$$p(Z\,|\,\Sigma)=\frac{2|Z|^{L-3}}{\pi^3\Gamma(L)\Gamma(L-1)\Gamma(L-2)}\times\frac{(\alpha L)^{\frac{(3L+\alpha)}{2}}}{\Gamma(\alpha)|\Sigma|^L}\times\frac{K_{3L-\alpha}\left(2\sqrt{\alpha L\,\mathrm{Tr}\left(\Sigma^{-1}Z\right)}\right)}{\mathrm{Tr}\left(\Sigma^{-1}Z\right)^{\frac{3L-\alpha}{2}}} \tag{11}$$

where α is the texture shape parameter and Σ is the covariance of the speckle without texture. K_γ is the modified Bessel function. There is no direct solution to calculate the best estimates of α and Σ that maximizes the likelihood function for a segment S. Approximate solutions have been proposed and are used in the current implementation (Backnell 1994). α is calculated by the Method of Moments (MoM) and $\hat{\Sigma}=C$. Removing the terms that will be cancelled in the stepwise criterion, the maximum log likelihood is

$$\begin{aligned}MLL(S)=&\,n(3L+\alpha)/2\;\ln\left(\alpha L\right)-n\ln(\Gamma(\alpha))-nL\ln(|C|)\\&-(3L-\alpha)/2\sum_{Z\in S}\ln(\mathrm{Tr}\left(C^{-1}Z\right))+\sum_{Z\in S}\ln(K_{3L-\alpha}\left(2\sqrt{\alpha L\,\mathrm{Tr}\left(C^{-1}Z\right)}\right))\end{aligned} \tag{12}$$

where n is the number of pixels of segment S. The stepwise criterion is calculated by (6). To evaluate Eq. 12, each pixel of the segment should be visited.

Unfortunately, this segmentation criterion is based on the product model that is limited to scenes where texture is independent of polarization (Touzi 2002). A more general algorithm is currently being developed for segmentation of scenes in which the product-model is not valid.

SEGMENTATION RESULTS

The likelihood approximation approach for image segmentation have been implemented and tested on polarimetric SAR images. A polarimetric Convair-580 SAR data set was collected over the Ottawa region. A test region in the Mer Bleu area is selected. The initial 1-look image has a resolution of 4m x 0.43m. A resolution of 4m x 4.88m is obtained by taking the average of the covariance matrix of 9 pixels. The resulting image (800x600 pixels) is shown in pseudo-color in Fig. 1 using the amplitude of the hh, vv and hv channels.

The image contains crop field areas and forest areas. Fig. 2 shows the result of the segmentation when Eqs. 9-10, which are derived from homogeneous scene statistics, are used. The figure shows a partition with 2000 segments. It shows that the partition is data driven. We should stress the hierarchical nature of the results and the difficulty to find an appropriate stopping point. For some parts of the image, more merging should have been done while, for other parts, less merging would be needed. Generally, field boundaries are correctly delimited. The segmentation is difficult task because of the importance of the noise in SAR images. The homogeneous scene criterion seems to give good results for crop fields. More merging is recommended for forest areas.

Fig. 3 presents the segmentation produced by the textured scene criterion (Eq. 12). This criterion should be used for forest areas. Statistics of crop fields should be calculated and used to know if the field is homogeneous or not (e.g. the amplitude variation coefficient). In Fig. 3, we see that

the textured scene criterion produces more merging in the forest areas. The segments in the forest areas are larger while the crop fields are more fragmented than in Fig. 2.

In the previous segmentation results, segment shape criteria have been used (Beaulieu 2001). In hierarchical segmentation, the accuracy of the decision process is related to the segment sizes. The first merging steps are critical and are error prone because of the small segment sizes and the high noise level of SAR images. If the first segments are not correctly delimited then the following steps will merge segments from different fields and produce contours delimiting speckle artefacts instead of the truth field boundaries. We use spatial constraints and contour shapes to improve the first segmentation steps. We have examined how the initial segments grow and developed criteria to control the spatial progression. See (Beaulieu 2001) for more details.

As an image contains both homogeneous and textured areas, we need to combine both criteria into the same segmentation program. For example, the amplitude variation coefficient could be used to select the appropriate criterion. More research is needed to evaluate the contribution of each criterion and to combine them.

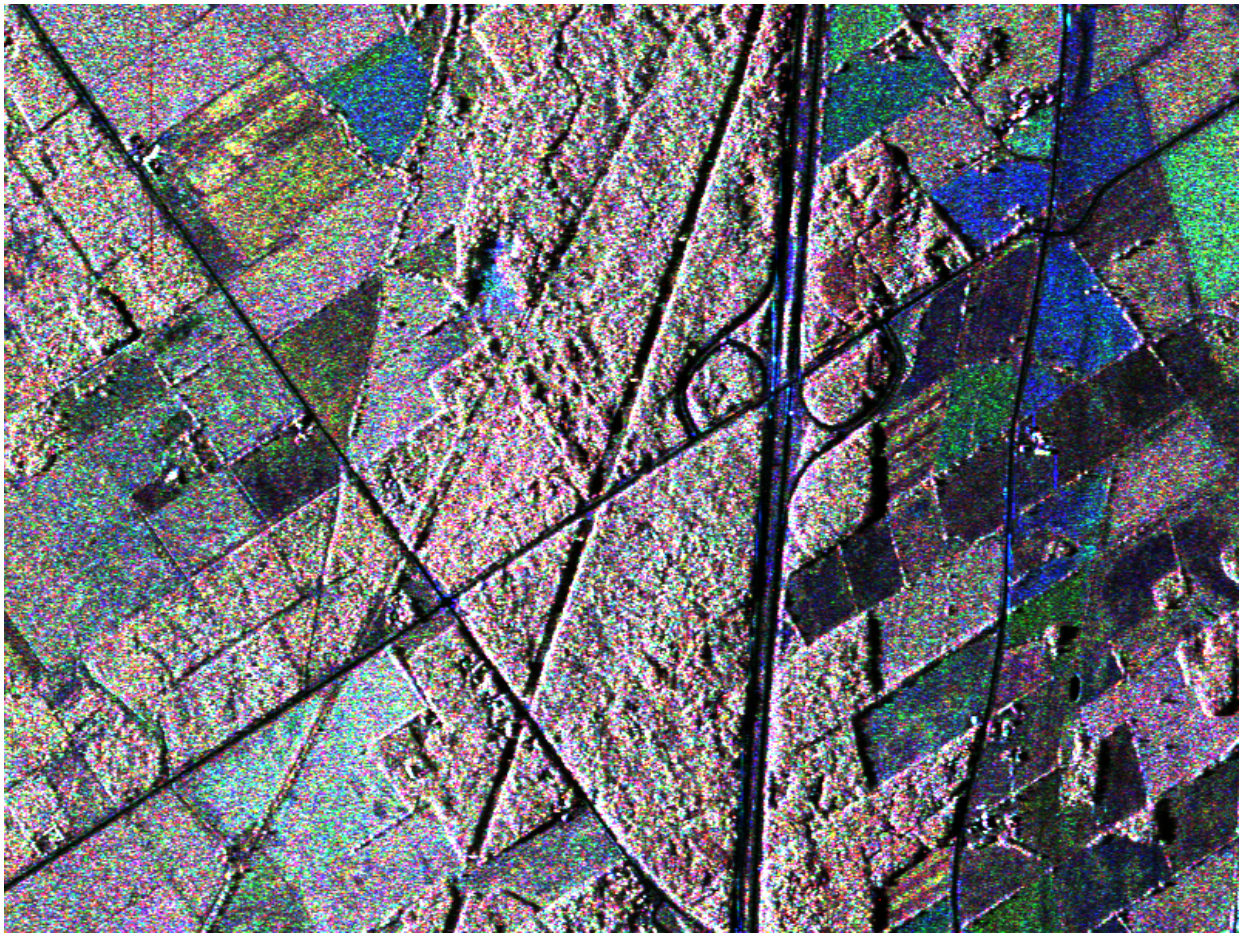

Fig. 1. Pseudo-color image of the Mer Bleu area (amplitude of hh, vv and hv, 800x600 pixels).

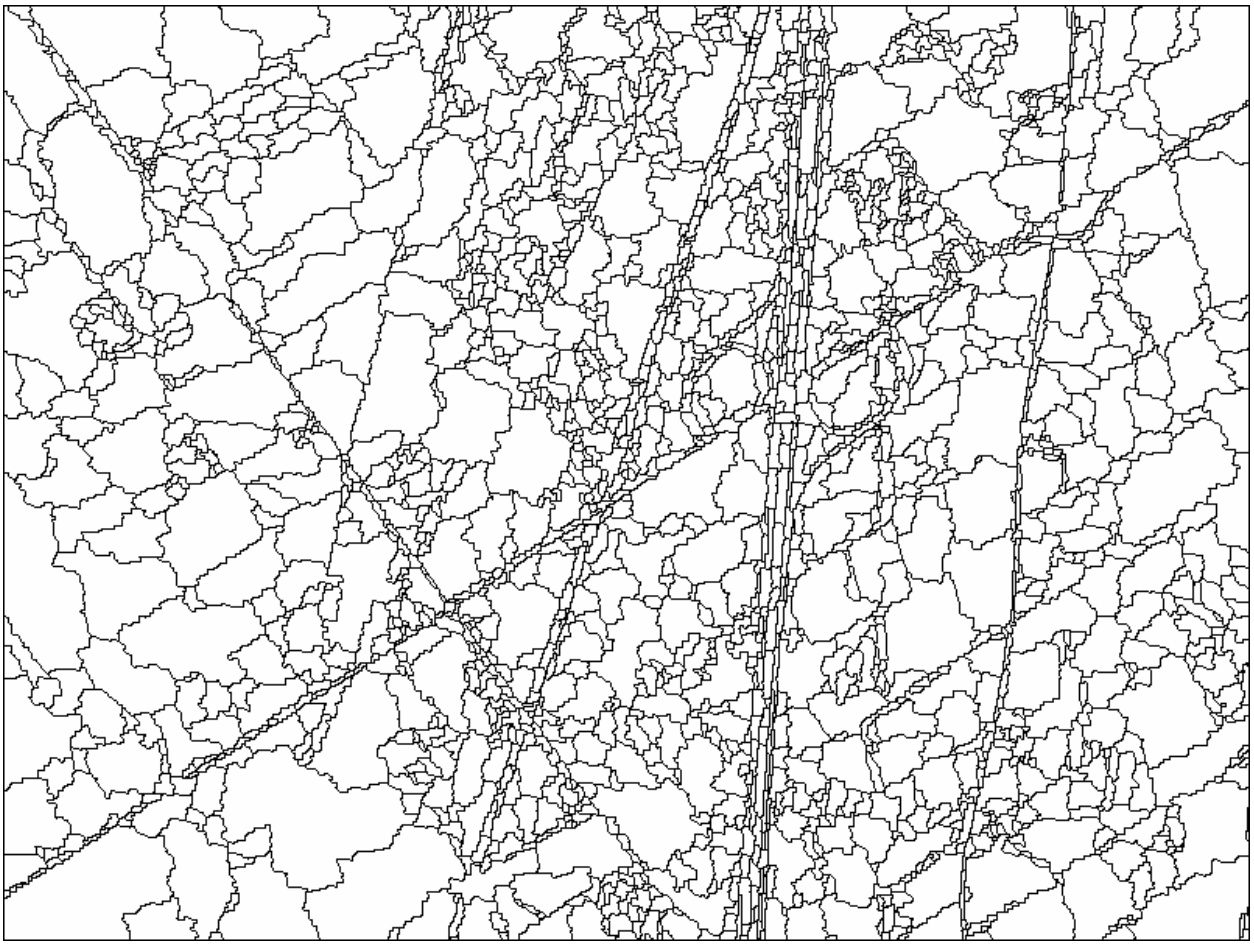

Fig. 2. Segmentation with the homogeneous scene criterion (Eqs. 9-10) (2000 regions).

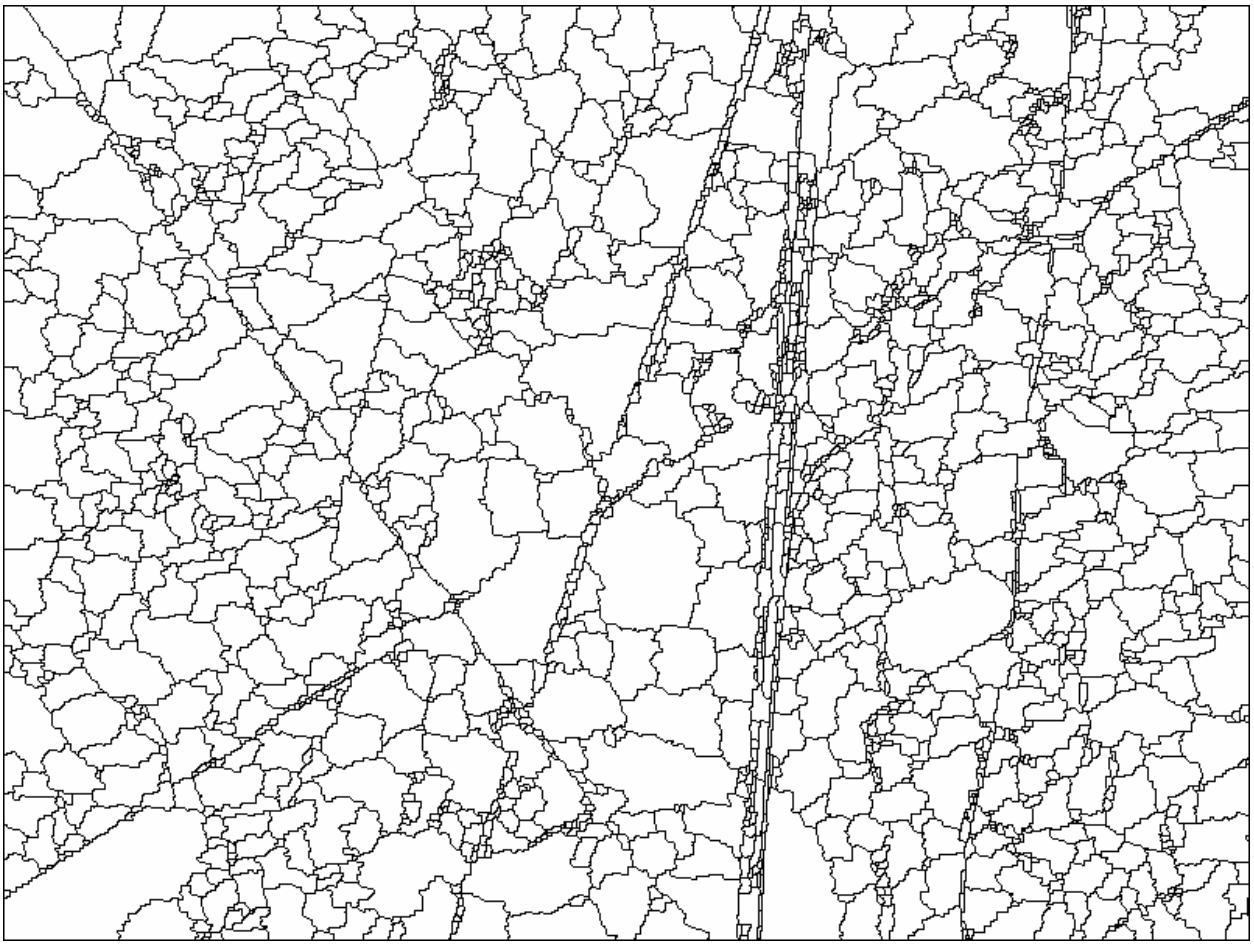

Fig. 3. Segmentation with the textured scene criterion (Eq. 12) (2000 regions).

CONCLUSION

Image segmentation has been presented as a likelihood approximation problem. The best criterion is derived for a hierarchical segmentation process. The stepwise criterion is derived for polarimetric SAR image with homogeneous or textured scene. Good results are shown for a Convair-580 SAR image.

REFERENCES

Backnell, D. 1994. Comparison of parameter estimators for K-distribution. *IEE Proc.-Radar, Sonar Navig.*, vol. 141, no. 1, pp. 45-52.

Beaulieu, J.M. 2004. Utilisation of Contour Criteria in Micro-Segmentation of SAR Images. *International Journal of Remote Sensing*, submitted May 2002.

Conradsen, K., Nielsen, A.A., Schou, J., and Skriver, H. 2003. A test statistic in the complex Wishart distribution and its application to change detection in polarimetric SAR data. *IEEE Trans. on Geoscience and Remote Sensing*, vol. 41, no. 1, pp. 4-19.

Dong, Y., Forester, B.C., and Milne, A.K. 1999. Segmentation of radar imagery using the Gaussian Markov random field model. *International Journal of Remote Sensing*, vol. 20, no. 8, pp. 1617-1639.

Goodman, J.W. 1963. Statistical analysis based on a certain multivariate complex Gaussian distribution. *Ann. Math. Stat.*, vol. 34, no. 152, pp. 152-180.

Lee, J.S., Grunes, M.R., Ainsworth, T.L., Du, L.J., Schuler, D.L., and Cloude, S.R. 1999. Unsupervised classification using polarimetric decomposition and the complex Wishart classifier. *IEEE Trans. on Geoscience and Remote Sensing*, vol. 37, no. 5, pp. 2249-2258.

Lira, J., and Frulla, L. 1998. An automated region growing algorithm for segmentation of texture regions in SAR images. *International Journal of Remote Sensing*, vol. 19, no. 18, pp. 3593-3606.

Liu, G., Xiong, H., and Huang, S. 2000. Study on segmentation and interpretation of multi-look polarimetric SAR images. *International Journal of Remote Sensing*, vol. 21, no. 8, pp. 1675-1691.

Lopes, A., and Sery, F. 1997. 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.

Oliver, C., and Quegan, S. 1998. *UNDERSTANDING SYNTHETIC APERTURE RADAR IMAGES.* Artech House, Boston.

Smith, D.M. 1996. Speckle reduction and segmentation of Synthetic Aperture Radar images. *International Journal of Remote Sensing*, vol. 17, no. 11, pp. 2043-2057.

Touzi, R. 2001. A review of speckle filtering in the context of estimation theory. *IEEE Trans. on Geoscience and Remote Sensing*, vol. 40, no. 11, pp. 2392-2404.

Touzi, R., Lopes, A., and Bousquet, P. 1988. A statistical and geometrical edge detector for SAR image. *IEEE Trans. on Geoscience and Remote Sensing*, vol. 26, no. 6, pp. 764-773.