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Segmentation of textured scenes using polarimetric SARs

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***Abstract*– The methods currently used for classification or segmentation of polarimetric SAR images are based on the multivariate complex Gaussian model. This should limit the application of these methods to "homogeneous" Gaussian areas, since their performances are significantly degraded in the presence of spatial texture. We show that image segmentation can be viewed as a likelihood approximation problem. The optimum criterion is derived 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 new method is validated for ice type segmentation using Convair-580 SAR data collected in 1993 over Cornwallis Island in Canada.**

I. 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 [1], [2], [3]. Since their performances are significantly degraded in the presence of spatial texture, the application of these methods should be limited to "homogeneous" 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 general flowchart of the segmentation method is described in the following Section III.

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 [4]. 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 [1], [2]. An edge detection process could also be used to define the boundaries of segment in 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 [6], [7], [8].

1 – Dr Beaulieu is presently at Canada Centre for Remote Sensing as visiting scientist on sabbatical leave.

II. 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.

A. 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

$$L(\Theta_P, P \mid X) = p(X \mid \Theta_P, P) \,. \quad (1)$$

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

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

$S(i)$ 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 evaluate 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.

B. 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

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

Equation (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.

C. 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.

III. 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.

A. Homogeneous scene

For a homogeneous scene, the vector $\boldsymbol{x}$ is complex Gaussian-distributed with a covariance $\boldsymbol{\Sigma} = E[\boldsymbol{x}\,\boldsymbol{x}^H]$. $E[\ ]$ 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 $\boldsymbol{\Sigma}$ is the sample covariance matrix, C_s [9].

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

The maximum likelihood value for this segment is

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

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 [9]. The stepwise criterion corresponds to (10) where the number of pixel of a segment is multiplied by the number of looks L. An equivalent criterion is used in [3] 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.

B. Textured scene

At the presence of texture, the product model was used in [10],[11] to derive the statistics of the covariance matrix for gamma-distributed scene signal:

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

where α is the texture shape parameter and Σ is the covariance of the speckle without texture. K_ν 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 [12]. 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 (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 [13]. A more general algorithm is currently being developed for segmentation of scenes in which the product-model is not valid. The flowchart below describes the segmentation strategy that will be adopted in this study. Illustrations using the polarimetric Convair-580 SAR data set collected over Cornwallis Island will be shown during the conference presentation.

REFERENCES

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

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

[3] K. Conradsen, A.A. Nielsen, J. Schou and H. Skriver, "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, Jan. 2003.

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

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

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

[7] J. Lira and L. Frulla, "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, 1998.

[8] J.M. Beaulieu, "Utilisation of Contour Criteria in Micro-Segmentation of SAR Images," *23rd Canadian Symposium on Remote Sensing*, Quebec, Canada, pp 91-100, Aug. 2001.

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

[10] 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, May 1997.

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

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

[13] R. Touzi, " 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, Nov. 2002.