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# SEGMENTATION OF POLARIMETRIC SAR IMAGES COMPOSED OF TEXTURED AND NON-TEXTURED FIELDS

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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 Wishart distribution 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. The likelihood value can be used to evaluate the segmentation results. With the step-wise optimization algorithm, we can observe the decrease of the likelihood value as segments are merged. Moreover, for a given partition, the log likelihood value can be calculated for each pixel of the image. Normalization is needed if we want to use the resulting image to visually evaluate the partition. This "likelihood" image can be calculated for the homogeneous criterion. For textured fields, we should separate the texture and the speckle components and calculate the "likelihood" image from the speckle component.

## 1. 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 Wishart distribution [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" areas.

A statistical hypothesis testing approach can be employed for image segmentation,. For homogeneous polarimetric images, two segments,  $S_i$  and  $S_j$ , could be merged if theirs covariance matrices are equal, which means that the observed sample covariance matrices could have been drawn from the same population. The modified likelihood ratio test is used for image segmentation and produces a test statistic of the form  $SC_{i,j} = (n_i + n_j) \ln |C_{S_i \cup S_j}| - n_i \ln |C_{S_i}| - n_j \ln |C_{S_j}|$  where  $C_s$  is the sample covariance matrix. The asymptotic distribution of  $SC_{i,j}$  is calculated in [3]. A test threshold value could then be calculated for a given false alarm rate.

In this study, we use a new method presented in [14] for the segmentation of K-distributed textured polarimetric SAR images. Image segmentation is presented as a maximum likelihood estimation problem and solved by a hierarchical stepwise optimization process. The product model is assessed and applied only within areas in which the model is valid. This study presents new ways to evaluate segmentation results for homogeneous (Wishart distribution) and textured (K distribution) scenes.

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 which the signal is a wide-sense stationary process [5], [13]. 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 [6], [7], [8].

## 2. IMAGE SEGMENTATION AS A LIKELIHOOD APPROXIMATION PROBLEM

Image segmentation could be viewed as the transformation of the original image into a more complex description. Beaulieu and Touzi [14] have developed a new approach that presents the image segmentation as a maximum likelihood estimation problem. 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 distribution models. These models can be used to evaluate the image description or the segmentation result. A good description should explain the observed pixels values by maximizing the likelihood value. We now present the result of [14] for the Wishart (homogeneous scene) and the K distribution (textured scene) models. The next section presents new ways to evaluate the segmentation results.

Let  $x_i$  be the value of pixel  $i$ . The probability density function (pdf) of  $x_i$  is function of the segment  $S$  that contains the pixel  $i$ , ( $i \in S$ ). The pdf are described by a set of parameters  $\theta$ . For the segment  $S$ , the pdf of  $x_i$  is  $p(x_i | \theta_S)$  and the best parameters  $\theta_S$  could usually be evaluated from statistics calculated over the segment. Let  $MLL(S) = \sum_{i \in S} \ln(p(x_i | \theta_S))$

be the maximum log likelihood for segment  $S$ . The log likelihood of the image,  $LLF(P)$ , is the sum over the segments of the partition  $P$ . We would like to find the best partition with  $k$  segments.

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  $P_n \dots P_{k+1}, P_k \dots P_1$  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  $LLF$ ,  $SC_{i,j} = MLL(S_i) + MLL(S_j) - MLL(S_u)$  where  $S_u = S_i \cup S_j$ . At each iteration, we should merge the segments that minimize the  $SC_{i,j}$  criterion.

The polarimetric scattering matrix measured by a polarimetric SAR for reciprocal medium consists of 3 complex elements,  $\mathbf{x} = (hh, hv, vv)^T$ . For  $L$ -look images, we use the covariance matrix of the pixel  $Z_k$ . For a homogeneous scene, the pixel covariance matrix follows a complex Wishart distribution [9]. The stepwise criterion is  $SC_{i,j} = (n_i + n_j) \ln|C_{S_i \cup S_j}| - n_i \ln|C_{S_i}| - n_j \ln|C_{S_j}|$  where  $n$  is the number of pixel of a segment multiplied by the number of look  $L$ . 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.

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:

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

where  $\alpha$  is the texture shape parameter and  $\Sigma$  is the covariance of the speckle without texture.  $K_V$  is the modified Bessel function. There is no direct solution to calculate the best estimates of  $\alpha$  and  $\Sigma$  that maximizes the likelihood function for a segment  $S$ . Approximate solutions have been proposed and are used in the current implementation [12].  $\alpha$  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

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

where  $n$  is the number of pixels of segment  $S$ . The stepwise criterion is  $SC_{i,j} = MLL(S_i) + MLL(S_j) - MLL(S_u)$ . To evaluate  $MLL(S)$  each pixel of the segment should be visited.

### 3. SEGMENTATION RESULTS AND EVALUATION

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. 2 using the amplitude of the hh, vv and hv channels.

The image contains crop field areas and forest areas. The top image of Fig. 2 shows the result of the segmentation when the homogeneous scene criterion is used. The figure shows partitions 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 homogeneous scene criterion seems to give good results for crop fields. More merging is recommended for forest areas.

The bottom image presents the segmentation produced by the textured scene criterion. This criterion should be used for forest areas. The texture shape parameter is used to know if the field is homogeneous or not. 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 the top image. Segment shape criteria have been used for the segmentation. See [8], [14] for more details.

Evaluation of image partition quality (segmentation results) is a difficult problem. We have presented the segmentation task as an optimisation problem: find the partition that optimize the log likelihood function  $LL(P)$ . Hence, the log likelihood can be used to measure the quality of a partition. Fig. 1 presents the average log likelihood as a function of the number of segment of the partition for the hierarchical segmentation process using the Wishart derived criterion. We start with segments of 1 pixels (480 000 segments) (left curve). The  $LL$  curve decreases smoothly as we reduce the number of segment by merging. The interesting part of the curve is between 500 and 10000 segments (central curve). In this area, we obtain a near linear curve if we use a log scale for the number of segment (right curve). This figure shows the good behaver of the segmentation process and can be used to find the appropriate partition (number of segment). A similar curve is obtained for the K distribution criterion (textured scene).

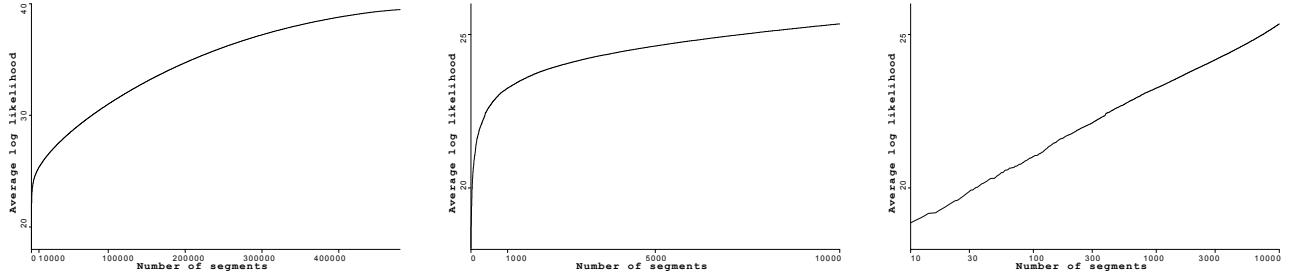


Fig. 1. Average log likelihood curves for partition with 0–480000 segment (left) and 0–10000 segments (middle and right) for the Wishart criterion (homogeneous scene).

For a given partition, the log likelihood value could be calculated for each pixel of the image. A normalisation is needed if we want to use the resulting image to visually evaluate the partition. The likelihood corresponds to a probability density that is function of the distribution width. Large likelihood values will be observed in areas where the determinant of the covariance matrix is small. The determinant ratio image has been previously proposed [15]. It uses the ratio of the determinant of the pixel covariance matrix  $Z_k$  over the determinant of the segment covariance matrix  $C_S$ . Unfortunately, this introduces some artefact by removing an inside segment varying term. See left image of Fig. 3. A better result is obtained by "normalizing" the pixel values such that the determinant of the segment covariance matrix is equal to one. For the Wishart distribution, we obtain the normalized log likelihood value of pixel  $Z_k$  as

$$LL^*(Z_k) = (L-3)(\ln|Z_k| - \ln|C_S|) - L \operatorname{tr}(C_S^{-1} Z_k) - \ln(\pi^3 \Gamma(L)\Gamma(L-1)\Gamma(L-2)/L^{3L}).$$

See the right image of Fig. 3. There are fluctuations produced by speckle. Information lost produced by assigning pixels to segments with different covariance matrices is also shown as dark linear features or spots. The quality of the segmentation is shows by the limited scope of the information lost. The normalized log likelihood image is more appropriate to reflect variations inside segments that the determinant ratio image.

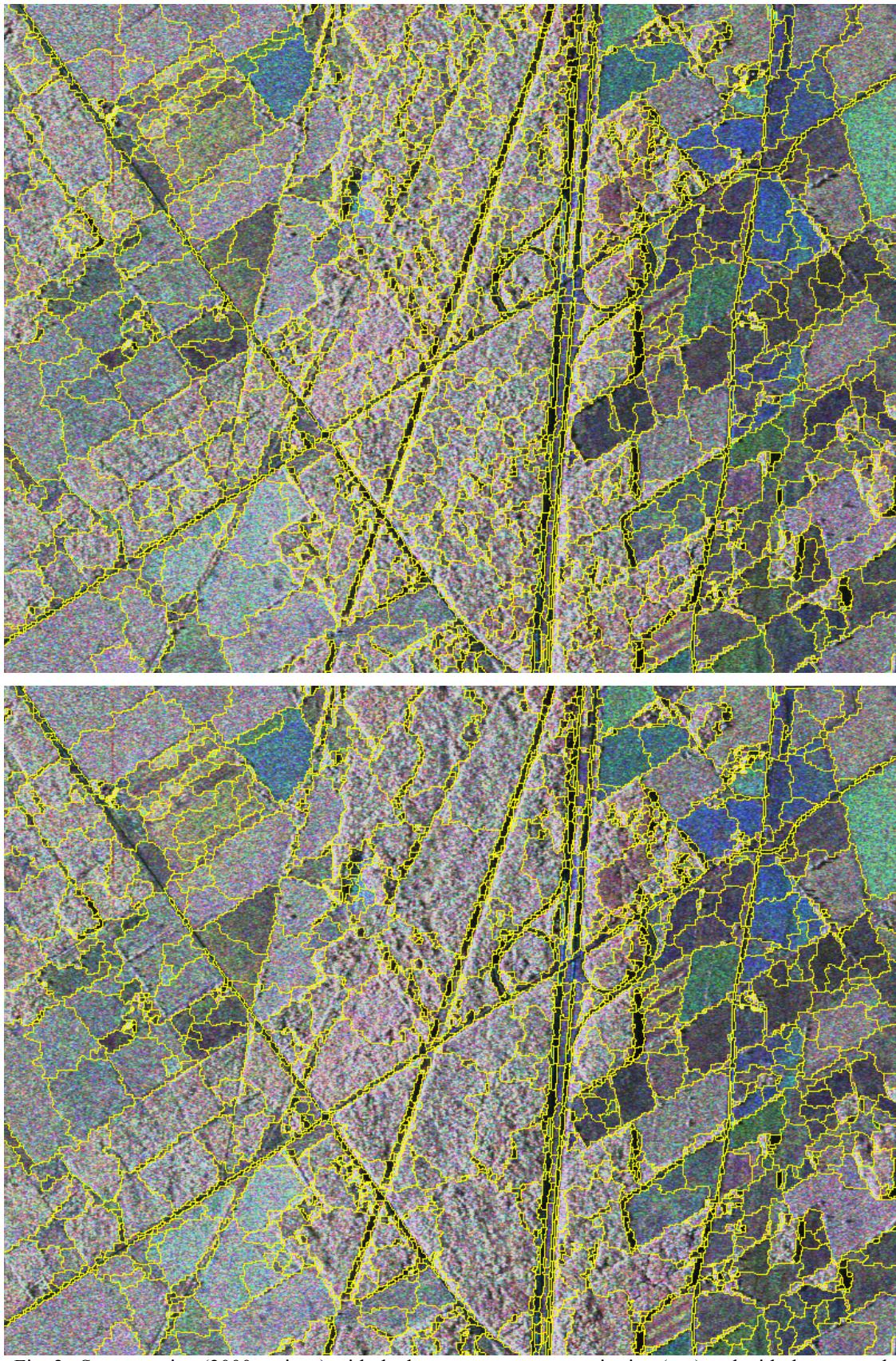


Fig. 2. Segmentation (2000 regions) with the homogeneous scene criterion (top) and with the textured scene criterion (bottom) of the Mer Bleu area image (800x600 pixels).

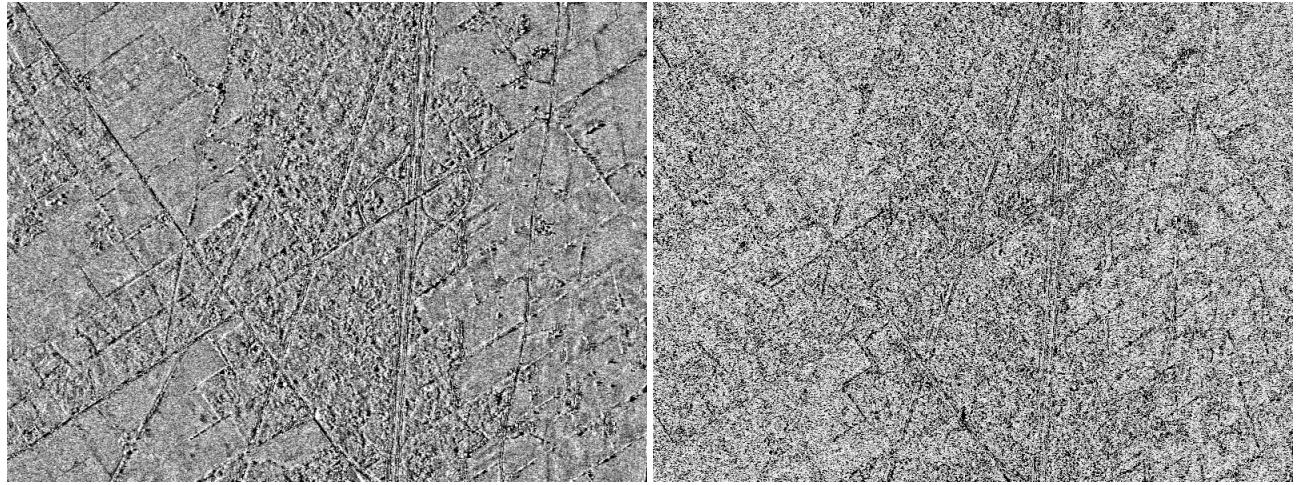


Fig. 3. Determinant ratio image (left) and normalized log likelihood image (right).

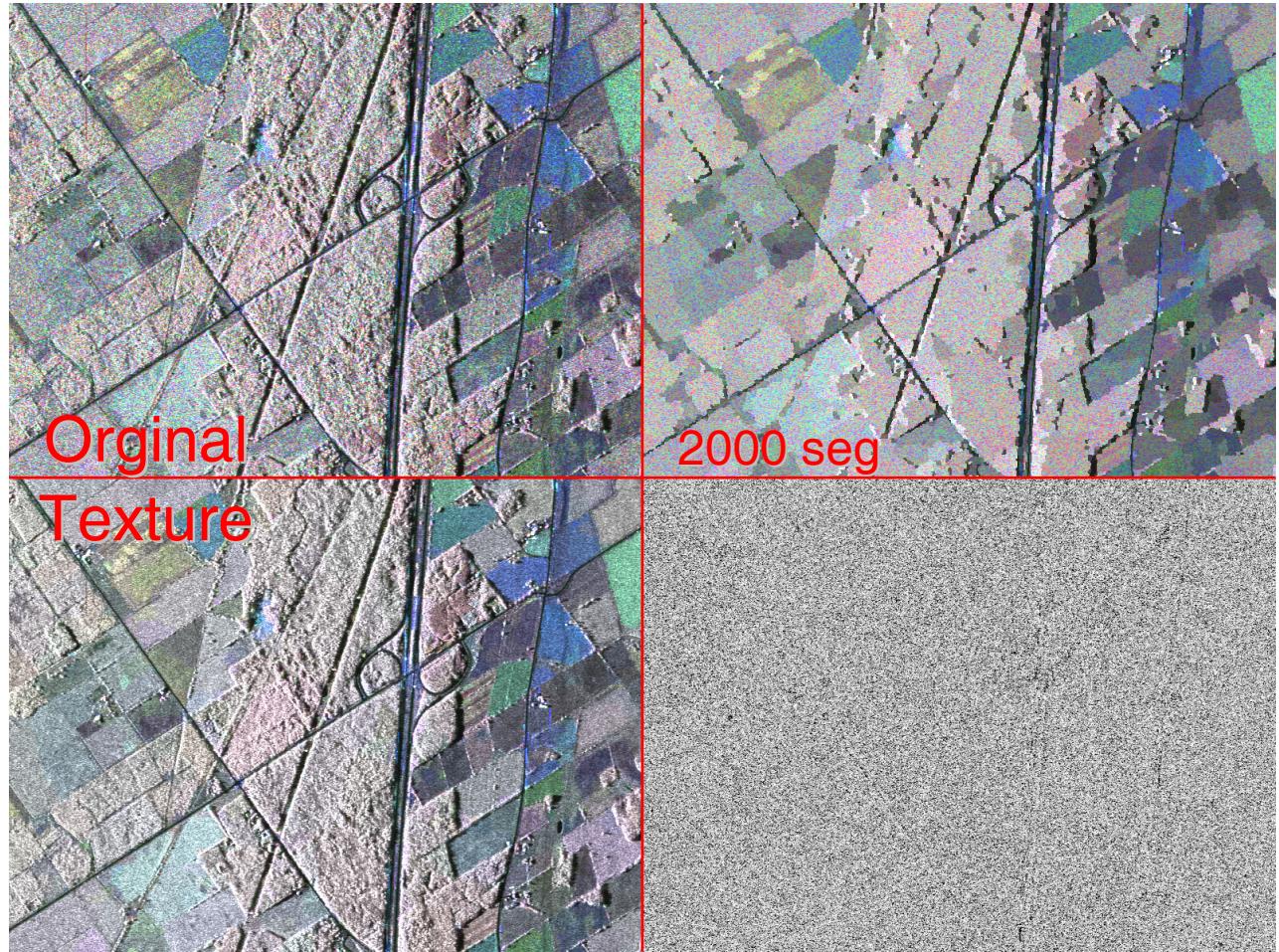


Fig. 4. Original image (top left), speckle image (top right), textured approximation image (bottom left) and normalized log likelihood image of the speckle (bottom right). The images are shown in pseudo-color using the amplitude of the hh, vv and hv channels

The previous pixel log likelihood normalisation could not be applied to the K distribution (textured scene). We propose to first separate the texture and the speckle components. We use an iterative process to simultaneously evaluate the pixel texture value and the segment covariance matrix of the K distribution [10]. We obtain a scalar texture image. We divide each the pixel covariance matrix by the pixel texture value to obtain the pixel speckle covariance matrix (top right)

image of Fig. 4). We obtain a segment average image by replacing each pixel value by the average of the speckle covariance over the segment. If we multiply this average image by the pixel texture value, we obtain a covariance image (bottom left image) that is a good approximation of the original image (top left image). This performs some kind of speckle filtering. Each segment has a uniform "color" and the pixel intensity is modulated by the texture value. We can now use the Wishart distribution with the speckle image and obtain the normalized log likelihood image (bottom right image). This image shows that the textured approximation image retains almost all the useful information of the image and the remaining speckle is mainly noise.

#### 4. 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. Interesting tools for partition evaluation are proposed.

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