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Hierarchical Segmentation of Polarimetric SAR Images

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***Abstract*– A hierarchical stepwise optimization process is used for polarimetric SAR image segmentation. The process starts with small sets of pixels as segments and then sequentially merges the segment pair that minimises a stepwise criterion. The polarimetric information could be represented by a covariance matrix. The proposed criterion is based upon the testing of the equality of covariance matrices of adjacent regions. The segmentation of SAR images is greatly complicated by the presence of coherent speckle. We are using spatial constraints and contour shapes in order to improve the segmentation results.**

I. Introduction

In remote sensing, a segmentation process could be used to detect land fields and to improve pixel classification. The segmentation of SAR (Synthetic Aperture Radar) images is greatly complicated by the presence of coherent speckle. The complex structure of the SAR images requires the utilisation of complex processes for the segmentation.

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. The main process is the classification of pixels where the spatial aspect is not usually considered [1]. 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 [2], [3]. An edge detection process could also be used to define segment boundaries [4].

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 [5], [6], [7].

II. Hierarchical Segmentation

A hierarchical segmentation algorithm, inspired from hierarchical data clustering and based upon stepwise optimization is used in this paper [7]. We start with a small set of pixels as a segment and then sequentially merge the segment pair that minimises a criterion. Segments grow by merging and first form small segments, that later will become larger segments. A segment similarity measure, $SC_{i,j}$, is defined as the stepwise criterion to optimize. At each iteration, the algorithm employs an optimization process to find the two most similar segments, which are then merged. The algorithm can be defined as follows:

i) Define an initial picture partition.
ii) For each adjacent segment pair, (S_i, S_j), calculate the stepwise criterion, $SC_{i,j}$; then find and merge the segments with the minimum criterion value.
iii) Stop, if no more merges are needed; otherwise, go to ii).

Different segment similarity measures (stepwise criteria) can be employed, each one corresponding to different definitions of the image segmentation task. A statistical hypothesis testing approach can be employed for image segmentation. An image is regarded as composed of regions with different pixel value probability density functions (pdf). Image segmentation can be produced by testing and merging two segments if they belong to the same region (i.e. the same statistical set). The derivation of the stepwise criterion from the distribution of the polarimetric signal is now examined.

III. Polarimetric Signal Distribution

The polarimetric scattering matrix measured by a polarimetric SAR consists of four complex elements [3]. 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. For a homogeneous scene, the vector $\boldsymbol{x}$ is complex Gaussian-distributed with a covariance $\boldsymbol{C} = E[\ \boldsymbol{x}\ \boldsymbol{x}^H]$. $E[\ ]$ denotes the expectation operator and the superscript H indicates the complex conjugate transpose. For any azimuthally symmetric medium, the ensemble average of the cross product of the copolarized and cross-polarized terms of the scattering matrix is negligible. The general form of the covariance $\boldsymbol{C}$ can be written as

$$\boldsymbol{C} = \begin{bmatrix} E[\ hh\ hh^*] & 0 & E[\ vv\ hh^*] \\ 0 & E[\ hv\ hv^*] & 0 \\ E[\ hh\ vv^*] & 0 & E[\ vv\ vv^*] \end{bmatrix} \tag{1}$$

where the superscript * indicates complex conjugation. The covariance matrix can be estimated from N independent samples from a homogeneous field:

$$\boldsymbol{X} = 1/N \ \Sigma \ \boldsymbol{x}\,\boldsymbol{x}^H \,. \tag{2}$$

$\boldsymbol{X}$ follows a complex Wishart distribution within a Gaussian area [9].

In hierarchical segmentation, we compare 2 adjacent segments and merge them if they are similar. We use a statistical hypothesis testing approach. It is assumed that an image is composed of distinct regions R_k defined by their covariance matrices $\boldsymbol{C}_k$. For 2 adjacent segments, S_i and S_j, we will test the hypothesis that they belong to the same region R_k ($\boldsymbol{C}_i = \boldsymbol{C}_j = \boldsymbol{C}_k$). We want to test the equality of the covariance matrices and use the hypothesis $\boldsymbol{C}_i = \boldsymbol{C}_j$ (see [8], p. 252). The test is based upon the estimates of the covariances for the 2 segments, $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$. The Likelihood ratio test was expressed as a function of the difference of determinant logarithms [8]:

$$TS_{i,j} = K \ \{ \ (N_i{+}N_j) \ln |\boldsymbol{X}_{i+j}| - N_i \ln |\boldsymbol{X}_i| - N_j \ln |\boldsymbol{X}_j| \ \} \tag{3}$$

where

$$K = 1 - 13/12 \ \{ \ 1/N_i + 1/N_j - 1/(N_i{+}N_j) \ \}. \tag{4}$$

$\boldsymbol{X}_{i+j}$ is the estimated covariance matrix of $S_i \cup S_j$, |Xi+j| its determinant, and N_i, N_j are the sizes of the segments. With the scaling factor K, the statistic is approximately distributed as a chi-squared variable with 6 degrees of freedom as N_i and N_j become large.

For a test of size α, we find the corresponding threshold t_α and merge segment S_i and S_j if the statistic $TS_{i,j}$ is lower than t_α. In hierarchical segmentation, we use an optimization process to find the best segment pair to merge at each step. The statistic $TS_{i,j}$ could be used as stepwise criterion. At each step, we merge the segment pair that minimizes $TS_{i,j}$. This ensures that each step does its best to minimize the probability of error. We only merge the most reliable segment pair.

IV. Contour Criteria

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. The approach is not based upon texture parameters. Instead, we have examined how the initial segments grow and developed criteria to control the spatial progression [7].

We use the segment perimeter, the segment area and the contour length to define 3 contour criteria, Cp, Ca and Cl. The criteria examine the shape of the segment produced by the merger, $S_i \cup S_j$. We define a bounding box containing the segment: a rectangle with left and right sides corresponding to the minimum and maximum values of the x coordinate of the segment and with the top and bottom sides corresponding to the minimum and maximum values of the y coordinate. The criteria are:

$$Cp = \frac{perimeter \ \ of \ \ S_i \cup S_j}{perimeter \ \ of \ \ bonding \ \ box}$$

$$Ca = \frac{area \ \ of \ \ bonding \ \ box}{area \ \ of \ \ S_i \cup S_j}$$

$$Cl = Min\left\{ \frac{lex_i}{Lc}, \frac{lex_j}{Lc} \right\} \tag{5}$$

Lc is the length of the boundary between both segments and lex_k is the length of S_k contour minus the common boundary.

The 3 shape criteria are combined in an ad hoc manner with the test statistic to produce the stepwise criterion:

$$SC_{i,j} = TS_{i,j} \cdot Cp^2 \cdot (\ (1{-}d) \cdot Ca \cdot Cl + d \ ) \tag{6}$$

where $d = Min(1, \ (N_i{+}N_j)/100)$. The shape criterion is very important for first mergers where the segments are small. Its contribution should decrease as the segments become larger. The decrease is controlled by the d parameter. Ca and Cl are not used when $N_i{+}N_j$ is larger than a user provided value (100).

V. Segmentation Results

The new segmentation method is validated using Convair-580 polarimetric 1-look SAR data. The image size is 5000x500 and the pixel resolution is 0.4m x 5.6m. For visualisation purposes, in the following figures, we have compressed the horizontal axis by 5 such that the pixel resolution is 2m x 5.6m. Fig. 1 shows a 1000x500 region of the amplitude component of the hh channel (compressed to 200x500). The hierarchical segmentation algorithm is applied on the initial 3 complex channel image. Initial segments of 5x1 pixels are used. A 10,000 segment partition is produced. Fig. 2 shows the partition for the selected region. The average segment size is 250 pixels. This is a good partition and the segments are really adapted to the image data. The utilisation of the polarimetric information with the testing of the equality of covariance matrices is appropriate and useful. This has produced better results than testing the equality of means of the 3 intensity channels ($|hh|^2$, $|hv|^2$, $|vv|^2$), (see [7]).

The hierarchical segmentation algorithm could be used to produce larger segments. A 1000 segment partition is produced and Fig. 3 shows the partition for the selected region of Fig. 1. The result shows the need for a more context sensitive approach. In some parts of the image, we should stop the segment merging earlier than in other parts. It has also been noted that the merging criterion depends on target brightness and more merging is achieved in brighter regions than in darker ones. The merging criterion, that does not look to be of constant probably of false alarms (CPFA), might be adapted to the multiplicative nature of speckle by replacing in equation (3) the covariances with the covariances normalized by the span. This idea is being currently investigated. We have tested a 2-stage approach. The first stage uses the polarimetric model to produce a 10,000 segment partition (Fig. 2). The second stage uses an image approximation criterion to continue the merging and to produce a 1000 segment partition (Fig. 4). We are using the Ward criterion on the 3 amplitude channels (|*hh*|, |*hv*|, |*vv*|) [7]. The Ward criterion minimizes the approximation error in hierarchical segmentation. Fig. 4 shows some improvements over Fig. 3 for some parts of the image. Further works are needed on this aspect.

VI. Conclusion

Good hierarchical segmentation results are obtained by testing the equality of polarimetric covariance matrices. The segment shape criteria are useful for the first segment mergers. We should look for appropriate higher lever criteria for the last mergers.

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Fig. 1. Amplitude of the *hh* channel.

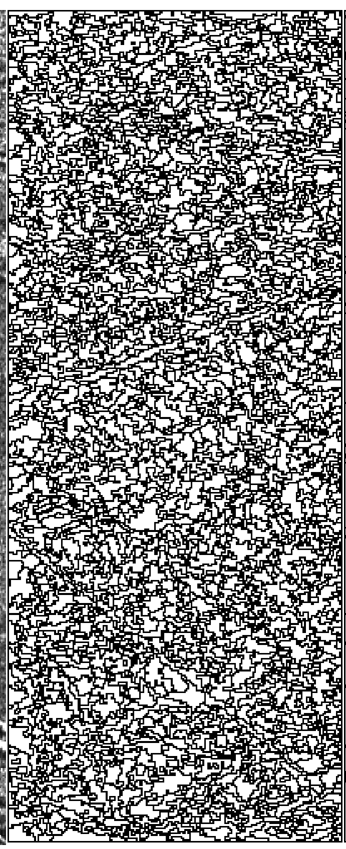

Fig. 2. Partition with 10,000 segments.

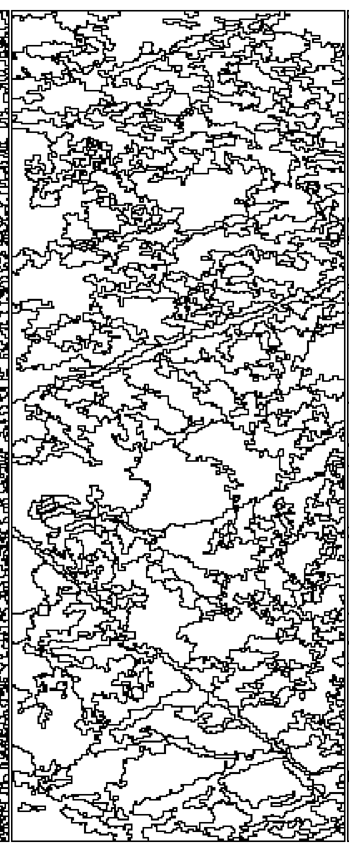

Fig. 3. Partition with 1000 segments.

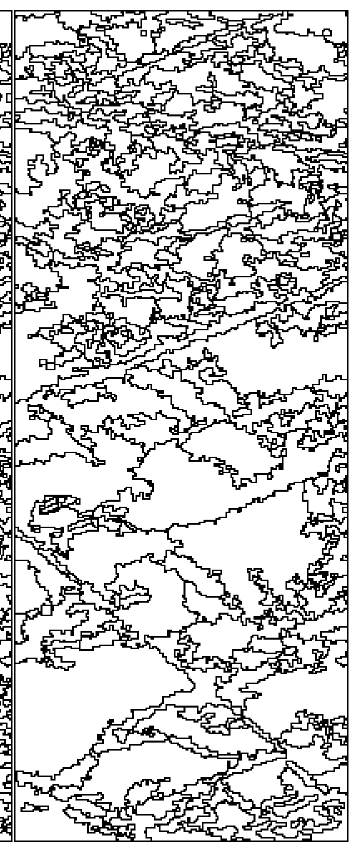

Fig. 4. Ward partition with 1000 segments.