



[Bea1990b]

Hierarchical Segmentation of SAR Picture

Author: **Beaulieu Jean-Marie**

Conference: **Image'Com 90, Bordeaux**

Nov., 1990, pp. 392-397

Abstract: The segmentation of SAR (Synthetic Aperture Radar) pictures is greatly complicated by the presence of coherent speckle in the image. The complex structure of the SAR pictures requires the utilization of a composite criterion for the segmentation. This paper takes advantage of a powerful hierarchical segmentation technique based upon step-wise optimization. The algorithm could easily be adapted to complex criterion. We present a two stage approach. A constant approximation criterion is first employed to yield an initial partition of the image. Then, a composite criterion is employed to continue the merging. The segment means and variances are then exploited in the step-wise criterion (segment similarity measure). Moreover, the segment shape is employed to reduce the formation of random contours. Good segmentation results are obtained, and they compare advantageously with other segmentation approaches. The algorithm produces a good separation of regions, and in the same time, yields accurate boundary location.

Hierarchical Segmentation of SAR Picture,
Beaulieu Jean-Marie,
Image'Com 90, Bordeaux, Nov., 1990, pp. 392-397.

[\[Bibtex\]](#)

DOWNLOAD [the published version](#)

HIERARCHICAL SEGMENTATION OF SAR PICTURES

Jean-Marie Beaulieu
Département d'Informatique,
Université Laval, Québec,
Canada, G1K-7P4.

ABSTRACT:

The segmentation of SAR (Synthetic Aperture Radar) pictures is greatly complicated by the presence of coherent speckle in the image. The complex structure of the SAR pictures requires the utilization of a composite criterion for the segmentation. This paper takes advantage of a powerful hierarchical segmentation technique based upon step-wise optimization. The algorithm could easily be adapted to complex criterion. We present a two stage approach. A constant approximation criterion is first employed to yield an initial partition of the image. Then, a composite criterion is employed to continue the merging. The segment means and variances are then exploited in the step-wise criterion (segment similarity measure). Moreover, the segment shape is employed to reduce the formation of random contours. Good segmentation results are obtained, and they compare advantageously with other segmentation approaches. The algorithm produces a good separation of regions, and in the same time, yields accurate boundary location.

I - INTRODUCTION

A hierarchy of segments can be represented by a segment tree in which nodes correspond to segments. Each segment S_i^k is linked to segments of the lower level, S_j^{k-1} , which are disjoint sub-sets of S_i^k , and which are called "sons" of S_i^k . A picture partition thus corresponds to a sub-set of these tree nodes. Starting from the bottom of the tree, an agglomerative hierarchical segmentation algorithm climbs up the tree by merging similar segments. Different similarity measures can be used to decide if two adjacent segments must be merged.

Brice and Fennema [4] use two heuristics, based upon information from the segment boundaries, to evaluate the similarity of two segments: the phagocyte and the weakness

heuristics. The phagocyte heuristic guides the merging of regions in such a way as to smooth or shorten the resulting boundary. Two regions are merged if their common boundary is weak and if the segment boundary length does not increase too quickly. The weakness heuristic merges two regions if a prescribed portion of their common boundary is weak. The phagocyte heuristic is applied first, followed by the weakness one.

Horowitz and Pavlidis [8] propose a split-and-merge approach using a pyramidal data structure. The data structure defines the way in which segments can be merged or split. A pyramid is a stack of regular picture blocks of decreasing sizes. The picture blocks (or segments) of one level are split into four regular sub-parts to form the next lower level. A pyramid can be regarded as a segment tree where each node corresponds to a block of $2^k \times 2^k$ pixels. A segment is considered as homogeneous if the segment approximation error is smaller than a predefined threshold. The algorithm consists of 1) merging the homogeneous segments, if the resulting segments are also homogeneous, or 2) splitting the segments that are not homogeneous into their four sub-parts.

Chen and Pavlidis [5] employ a statistical decision process in the preceding split-and-merge approach. The segments of the initial partition are first tested for uniformity, and if not uniform, they are divided into smaller segments. The uniform segments are then subjected to a cluster analysis to identify similar types which are then merged.

Beaulieu and Goldberg [1],[2] propose a Hierarchical Step-Wise Optimization (HSWO) algorithm, which uses a hierarchical constraint to reduce the search space. It is shown that under this constraint the algorithm produces the best picture approximation. The algorithm is designed so as to reduce the computing time. Recalculations are avoided by 1) making explicit the information needed, and 2) updating the only values that are modified by a segment merger.

The Hierarchical Step-Wise Optimization (HSWO) algorithm is first presented in the next section. Then, we discuss the construction of complex segment similarity measures. The section IV presents a two phase segmentation approach for SAR pictures. Segmentation results are then presented, followed by an evaluation and a comparison with an other segmentation technique.

This work was done in collaboration with Dr. Morris Goldberg, Department of Electrical Engineering, Ottawa University, and the Canadian Center for Remote Sensing. It is supported by the Natural Science and Engineering Research Council of Canada.

II - THE HIERARCHICAL STEP-WISE OPTIMIZATION ALGORITHM

A hierarchical segmentation algorithm based upon step-wise optimization is used in this paper [1],[2]. A segment similarity measure, $C_{i,j}$, is defined as the step-wise criterion to optimize. At each iteration, the algorithm employs an optimization process to find the two most similar segments, which are then merged.

The Hierarchical Step-Wise Optimization (HSWO) algorithm can be defined as follows:

- i) Define an initial picture partition.
- ii) For each adjacent segment pair, (S_i, S_j) , calculate the step-wise criterion, $C_{i,j}$; 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 (step-wise criteria) can be employed, each one corresponding to different definitions of the picture segmentation task. Constant value picture approximation consists in approximating each segment by the mean μ_i . The approximation error, $H(S_i)$, for each segment is the sum of the squared deviations around the mean. The goal of picture approximation is then to find the partition, $\{S_i\}$, that minimizes the overall approximation error, $\sum H(S_i)$.

The segment similarity measure, thus, can be related to the increase of the approximation error produced by the merging of two segments, S_i and S_j :

$$C_{i,j} = H(S_i \cup S_j) - H(S_i) - H(S_j) \quad (1)$$

For the case of constant value approximation, we have:

$$C_{i,j} = \frac{N_i \times N_j}{N_i + N_j} (\mu_i - \mu_j)^2 \quad (2)$$

where N_i is the size of the segment S_i and μ_i is its mean value. The utilization of $C_{i,j}$ in the HSWO algorithm ensures that each iteration does it best to minimize the overall approximation error.

III - SIMILARITY MEASURE

The HSWO algorithm is now used to segment a SAR (Synthetic Aperture Radar) picture where the presence of speckle produces an important texture component. The one channel SAR picture used in this section is presented in Figure 1, [7]. This is an airborne X-band radar picture with vertical-vertical polarization, 256x256 pixels, and a 5 meter resolution. The picture covers a 1.28 km x 1.28 km area near Makofen, in the Federal Republic of Germany. It is an agricultural site composed of sugar beet, wheat, winter barley, potato, mixed hay and summer wheat, and corn fields. Good results are obtained, which demonstrate the versatility of the algorithm.

The presence of coherent speckle makes the picture noisy and greatly complicates the segmentation task. The derivation of the best picture model or step-wise criterion for this segmentation task seems difficult [3],[6],[11]. An ad-hoc approach is employed instead, where the picture characteristics are used in a more or less formal way to define step-wise criteria. The segmentation task is divided into two phases. A simple criterion is employed for an initial partition of the picture, then a composite criterion is used for the subsequent merging steps.

The complex structure of the SAR pictures requires the utilisation of a composite criterion for the segmentation. Zobrist and Thompson [12] point out that human vision employs many cues such as brightness, contour, color, texture and stereopsis to perform perceptual grouping. They stress the limitations of using only one cue at a time for computer grouping, and show the importance of studying mechanisms that combine many cues. For computer simulation of human perception, they derive from each cue a distance function that measures the similarity of two scene parts. Then, they perform a weighted sum of these distances to obtain a global perceptual distance.

In picture segmentation, an ordering of segment descriptions can also be considered [10]. For example, the pixel gray level can be employed to form small homogeneous regions, then more complex descriptors, such as segment contour shape, can be considered for forming larger regions. Many segment descriptors, such as contour shape, or higher order approximation coefficients, are meaningless for small regions and only become useful at a latter stage. In the hierarchical segmentation scheme, this corresponds to using a simple measure for the first merging steps, then, as we get to a higher level in the segment hierarchy, more complex measures, involving more complex segment descriptors, are introduced.

IV - SEGMENTATION CRITERION FOR SAR PICTURES

The proposed segmentation approach is now presented. It is composed of two phases. A simple criterion is employed for an initial partition of the picture, then a composite criterion is used for the subsequent merging steps.

First phase: initial segmentation

The first phase consists in the partition of the picture into 3000 segments using a simple criterion. The previously defined constant approximation criterion is employed. The criterion is not applied to the original SAR picture, but instead to an averaged version of this picture. The average picture is formed by assigning to each pixel the mean value of a 5x5 centered window (see Figure 2). The utilization of the average picture, by reducing the effect of noise (speckle), results in the division of the picture regions into more similar segments. It avoids, for example, the division of a homogeneous area into some segments which contain only the lighter pixels while the other segments are composed of the darker pixels, these two kinds of segments being interleaved. Note that, because of memory limitations, the picture is divided into four independent blocks of 128x128 pixels for the first segment mergers.

Second phase: composite criterion

The second phase employs a composite criterion applied to the original SAR picture to continue the merging of the initial 3000 segments. The segments can now be characterized by their means, μ_i , and their variances, σ_i^2 , which can be exploited in the derivation of a segment similarity measure (criterion). Moreover, the utilization of a segment shape parameter can be useful to reduce the formation of random contours, an artefact produced by the important noise component. Therefore, the employed composite criterion is composed of three parts:

$$C(\text{composite}) = C(\text{constant}) \times C(\text{variance}) \times C(\text{shape}) \quad (3)$$

where $C(\text{constant})$ is the previously defined constant value approximation criterion which takes account of the difference between segment means and of the segment sizes. $C(\text{variance})$ is defined as:

$$C(\text{variance}) = 1 + |\sigma_i - \sigma_j| \quad (4)$$

where σ_i is the gray level variance for segment S_i . The variances of the two segments are employed here in the evaluation of segment similarity. If two segments possess the same variance, then $C(\text{variance})$ is equal to one, which does not affect the composite result. If $|\sigma_i - \sigma_j|$ is equal to one or more, then the composite result is multiplied by 2 or more. Finally, $C(\text{shape})$ measures the compactness of the segment, S_k , produced by the merging of S_i and S_j , $S_k = S_i \cup S_j$. The following definition is used:

$$C(\text{shape}) = 1 + (1 + \sigma_x)(1 + \sigma_y) / N_k \quad (5)$$

where,

$$\sigma_x^2 = \frac{1}{N_k} \sum_{(x,y) \in S_k} x^2 - \left[\frac{1}{N_k} \sum_{(x,y) \in S_k} x \right]^2$$

$$\sigma_y^2 = \frac{1}{N_k} \sum_{(x,y) \in S_k} y^2 - \left[\frac{1}{N_k} \sum_{(x,y) \in S_k} y \right]^2$$

and where $N_k (=N_i+N_j)$ is the size of $S_k (=S_i \cup S_j)$. σ_x and σ_y measure the pixel dispersion along the x and y axes respectively. These values tend to be small when a segment is compact. Their product is divided by N_k to compensate for the segment size. A bias of one is added to σ_x and σ_y in order to secure the effect of any one even if the other is null.

V - SEGMENTATION RESULTS

The initial segmentation phase is applied to the SAR picture, and produces a 3000 segment partition. Then, the composite criterion is employed to continue the merging of segments. The resulting minimum criterion values, $C_{\min,k}$ are presented in Figure 3, while Figure 4 shows the corresponding picture partitions for 25, 37 and 86 segments. For 25 segments, the most prominent areas of the picture are correctly distinguished, but there remain a number of segments that are sub-parts of larger homogeneous regions. Some of these segments are marked by dots. They result from variations inside the homogeneous regions. These variations can be

regarded as noise effects and are smaller than the variations between the main regions.

In the 37 segment partition of Figure 4-b, finer picture components are considered. A number of the additional segments are distinct regions, and are indicated by a cross "X". The other additional segments result from variations inside homogeneous regions, some of which are marked by dots. In the 86 segment partition, most of the additional segments can be regarded as due to noise effects.

Using the composite criterion in a second phase improves the picture segmentation results. Figure 5 shows the results obtained by the utilization of the first phase only. The segment merging is performed with the constant approximation criterion of equation 2, until partitions of 25 and 37 segments are obtained. One evident difference is the occurrence of segments along the region boundaries. For example, in Figure 5, many region boundaries, indicated by arrows, are defined by double contour lines. These double lines delimit an area which must contain the true boundaries. However, the previous results with the composite criterion show better definition of the region boundaries.

VI - EVALUATION OF SEGMENTATION RESULTS

The segmentation results are now evaluated and compared. Goodenough et al [7] have used the Narendra and Goldberg algorithm [9] to segment the same picture. The different partitions obtained have been evaluated. An adaptive filter is first applied to the picture to reduce the multiplicative noise while preserving the edges. Different picture partitions result from the utilization of different window sizes for the adaptive filter, and different gradient operators and smoothing parameters for the segmentation algorithm.

Two criteria are used to evaluate the resulting picture partitions. First, it is determined if the manually defined boundaries are present in the segmentation results. From a manually draw edge image, a mask is created by thickening the edges by +2 pixels. The mask is applied to each picture segmentation in order to retain only the segment contours inside the edge mask. This is employed to determine the number of manually defined edges that are also present in the segmentation results. Only the continuous boundaries are counted for a maximum of 41 edges.

The second criterion evaluates the segmentation performance by the total number of segments created within known homogeneous fields. Segments inside eleven fields are counted for each picture segmentations. Partitions where these fields are broken into the fewest number of segments are considered to be the best.

The best picture partition obtained by Goodenough et al possesses 32 correctly identified edges, and has 404 segments inside the 11 homogeneous fields. This partition contains a total of 703 segments, and is produced by using a 11x11 window for the filter and a variance operator for the gradient image.

The same evaluation procedure is now applied to the results of the HSWO algorithm. A 703 segment partition is first used in order to facilitate the comparison. This partition possesses 33 correctly identified edges and has 361 segments inside the 11 homogeneous fields (see Table 1). The partition presented in Figure 4-c is also evaluated. In this case, 29 edges are correctly identified and the 11 homogeneous fields are split into 52 segments. This partition contains a total of 86 segments.

Table 1 : Picture partition evaluation.

| | identified edges | segments inside homogeneous fields |
|--|------------------|------------------------------------|
| Goodenough et al [7] (703 segments) | 32 | 404 |
| HSWO algorithm (703 segments) | 33 | 361 |
| (86 segments) | 29 | 52 |

These last results compare favorably with those of Goodenough et al [7]. They can be improved by using more appropriate step-wise criteria. The HSWO algorithm has the advantages that a partition with the required number of segments is easily produced, and that good results are obtained even for partitions with a small number of segments.

REFERENCES

- [1] J.M. Beaulieu & M. Goldberg, "Hierarchy in Picture segmentation: A Step-Wise Optimization Approach," IEEE Trans. on Pattern Analysis and Machine Intell., Vol. PAMI-11 (2), 1989, 150-163.
- [2] J.M. Beaulieu & M. Goldberg, "Step-Wise Optimization for Hierarchical Picture Segmentation," Conf. on Computer Vision and Pattern Recognition, Washington, D.C., 1983, 59-64.
- [3] D.H. Berger, "Texture as a Discriminant of Crops on Radar Imagery," IEEE Trans. on Geoscience Elect., Vol. GE-8 (4). 1970, 344-348.
- [4] C. Brice & C. Fennema, "Scene Analysis Using Regions," Artif. Intell. Vol. 1, 1970, 205-226.
- [5] P.C. Chen & T. Pavlidis, "Image Segmentation as an Estimation Problem," Comput. Graphics & Image Process., Vol. 12, 1980, 153-172.
- [6] V.S. Frost, J.A. Stiles K.S. Shanmugan & J.C. Holtzman, "A Model For Radar Images Filtering and its Application to Adaptive Digital Filtering of Multiplicative Noise," IEEE Trans. on Pattern Analysis & Machine Int., Vol. PAMI-4 (2), 1982, 157-166.

- [7] D.G. Goodenough, B. Guidon, J.F. Meunier & N.A. Swanberg, "Adaptive Filtering and Image Segmentation for SAR Analysis," Proc. of Machine Processing of Remotely Sensed Data Symposium, June 1984, 315-324.
- [8] S.L. Horowitz & T. Pavlidis, "Picture Segmentation by a Tree Traversal Algorithm," Journal of the Ass. of Computing Machinery, Vol. 23, 1976, 368-388.
- [9] P.M. Narendra & M. Goldberg, "Image Segmentation with Directed Trees," IEEE Trans. on Pattern Analysis & Machine Int., Vol. PAMI-2 (2), 1980, 185-191.
- [10] T. Pavlidis, "Hierarchies in Structural Pattern Recognition," Proceeding of IEEE, Vol. 67 (5), 1979, 737-744.
- [11] K.S. Shanmugan, V. Narayanan, V.S. Frost, J.A. Stiles & J.C. Holtzman, "Textural Features for Radar Image Analysis," IEEE Trans. on Geoscience & Remote Sensing, Vol. GE-19 (3), 1981, 153-156.
- [12] A.L. Zobrist & W.B. Thompson, "Building a Distance Function for Gestalt Grouping," IEEE Trans. on Computer, Vol. C-4, 1975, 718-728.

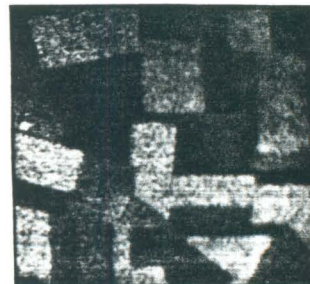


Figure 1 : The SAR picture (256x256 pixels).

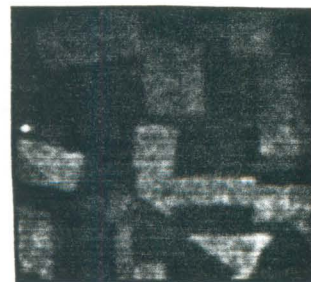


Figure 2 : The average picture calculated with a 5x5 window.

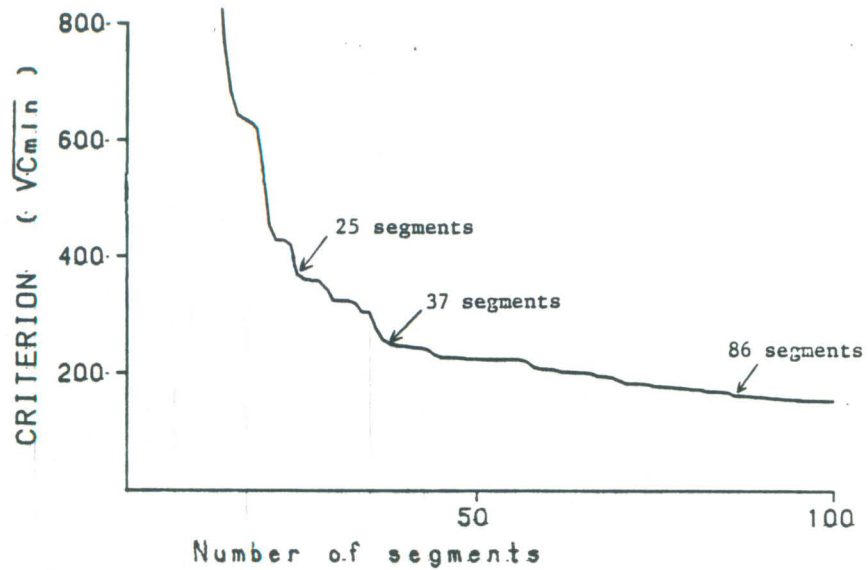
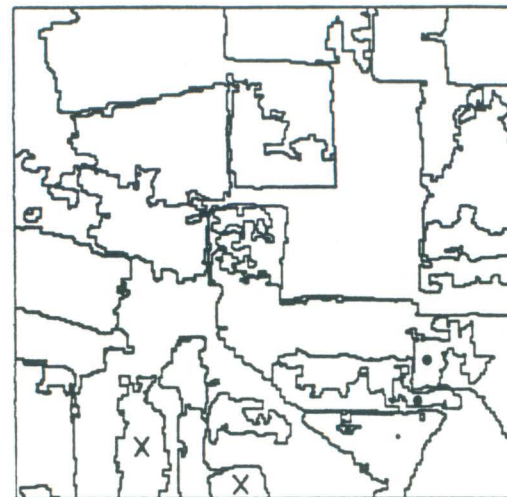
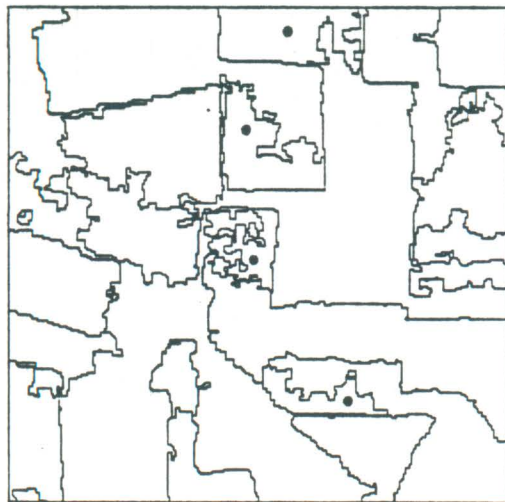


Figure 3 : Upper bound of the minimum criterion values.

b) 37 segments



a) 25 segments



c) 86 segments

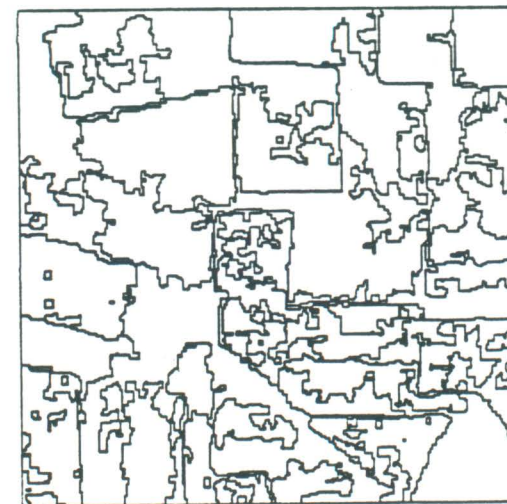
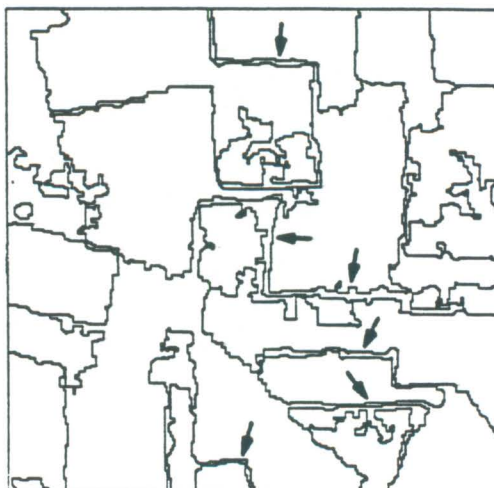


Figure 4 : Segmentations of the SAR picture with the composite criterion.

Figure 4 : (continued)

a) 25 segments



b) 37 segments

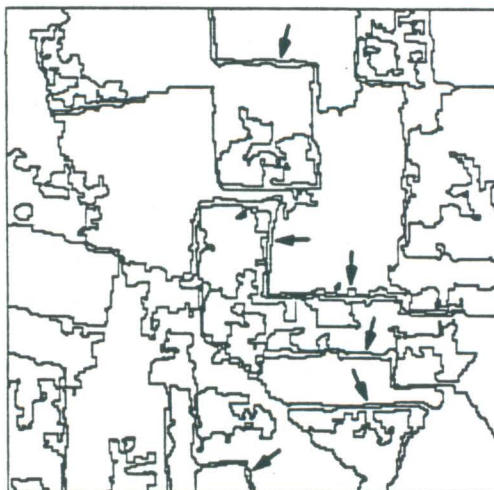


Figure 5 : Segmentations of the SAR picture with the constant approximation criterion only.