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Abstract

The hierarchical segmentation of SAR (Synthetic Aperture Radar) images is greatly complicated by the presence of coherent speckle. We are exploring the utilization of spatial constraints and contour shapes in order to improve the segmentation results. With standard merging criterion, the high noise level of SAR images results in the production of regions that have variable mean and variance values and irregular shapes. If the first segments are not correctly delimited then the following steps will merge segments from different fields. In examining the evolution of the initial segments, we see that the merging should take into account spatial aspects. Particularly, the segment contours should have good shapes. In this paper, we examine how the pseudo-convex envelope of a region can be used to evaluate the region contour. We present a pseudo-convex measure adapted to the geometry of image lattice. We show how the pseudo-convex envelope can be calculated. We present measures comparing contour shapes and using the perimeter, the area and the boundary length of segments. We use a hierarchical segmentation algorithm based upon stepwise optimization. A stepwise merging criterion is derived from the multiplicative speckle noise model. The shape measures are combined with the merging criterion in order to guide correctly the segment merging process. The new criterion produces good segmentation of SAR images. This is illustrated by synthetic and real image results.

1. 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. Supervised and unsupervised classifications are often based on probabilistic models. Markov random field models have been used to include the spatial aspect into the class probabilistic models [2]. Texture attributes and models are used for classification and segmentation [3].

An edge detection process could be used to define segment boundaries [4], [5]. A post-processing step could be needed to close segment boundaries. The active contour techniques look for the optimum position of a closed boundary by minimizing an energy function [6]. The watershed approach grows regions from a gradient image [7], [8].

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 optimisation processes [9], [10], [5], [11], [12], [13], [14]. Different techniques combine the information of regions and edges [15], [16]. Region growing could be combined with classification (spectral clustering) [17].

The processing of SAR images is difficult because of the large variance of the speckle multiplicative noise. The development of filters adapted to SAR images has required a sustained effort of many researchers [18], [19], [20]. The accurate detection of edges in SAR images is also a difficult task [13]. Similar difficulties are present in image segmentation. In SAR image processing, we need to average over a

large set of homogeneous pixels in order to obtain accurate measures because of the large speckle variance. However, we do not know in advance where the boundaries between homogeneous regions or fields are. Delimiting homogeneous regions is an important step or output of the process.

In this paper, we are exploring the utilisation of spatial constraints and contour shapes in order to improve the segmentation results. The complex structure of the SAR images requires the utilisation of a composite criterion for the segmentation. This criterion is particularly designed to be applied for the first segment mergers.

We use a standard hierarchical segmentation algorithm with an adapted criterion to the multiplicative nature of the speckle [9]. We start with each individual pixel as segments and then sequentially merge the segment pair that minimises the criterion. Segments grow by merging and first form small segments, that later will become larger segments. With standard merging criteria, the high noise level of SAR images results in the production of regions that have variable mean and variance values and irregular shapes. 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 [21]. In examining the evolution of the initial segments, we see that the merging should not only be based upon grey level values but should also take into account spatial aspects. Particularly, the segment contours should have good shapes.

In this paper, we examine how the pseudo-convex envelope of a region can be used to evaluate the region contour. We present a pseudo-convex measure adapted to the geometry of image lattice. We show how the pseudo-convex envelope can be calculated. We present three measures based upon contour shapes. These measures are combined with the adapted SAR criterion in order to guide correctly the segment merging process. The new criterion produces good segmentation of SAR images. This is illustrated by synthetic and real image results.

2. Hierarchical segmentation

A hierarchical segmentation algorithm [10], inspired from hierarchical data clustering and based upon stepwise optimisation is used in this paper. In a merging scheme, a hierarchical clustering starts with n clusters corresponding to each of the n data points, and sequentially reduces the number of clusters by merging. At each iteration, the similarity measures $d(G_i, G_j)$ are calculated for all clusters pairs (G_i, G_j)

and the clusters of the pair that minimises the measure are merged. This merging is repeated sequentially until the required number of clusters is obtained.

A hierarchical segmentation algorithm based upon stepwise optimisation is now presented [10]. A segment similarity measure, $C_{i,j}$, is defined as the stepwise criterion to optimise. For each iteration, the algorithm employs an optimisation process to find the two most similar segments, which are then merged. The algorithm can be defined as follows:

- i) Define an initial image partition.
- ii) For each adjacent segment pair, (S_i, S_j) , calculate the stepwise 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).

The algorithm is designed such as to reduce the computing time. In the initialisation step, the computing time is a function of the image size, the number of initial segments, and the number of neighbours per segment. On the other hand, the iterative steps are short and the computing time is mainly a function of the number of neighbours. The number of iterations depends upon the number of initial and final segments, each iteration reducing by one the number of segments. The algorithm requires substantial temporary memory space to store the current descriptive parameters, neighbour sets and criterion values. Usually, the initial partition contains one distinct segment for each pixel. The number of iterations to build the complete segment tree is equal to the number of pixels minus one. With an appropriate stepwise criterion, the average number of neighbours of created segments is small (≤ 8). In this case, the processing time of the algorithm grows rather linearly with the image size.

Radar images are mainly characterised by the presence of speckles. The radar signal can be modelled as a random process with a multiplicative speckle noise. The probability density function of the signal intensity or power, for a L -look signal follows a Gamma distribution. Using a likelihood approximation approach [9], it has been shown that the stepwise criterion for merging segments S_i and S_j is

$$C_{i,j} = (n_i + n_j) \ln(\mu_{S_i \cup S_j}) - n_i \ln(\mu_{S_i}) - n_j \ln(\mu_{S_j}).$$

where n_i and μ_{S_i} are the number of pixels and the mean value of segment S_i .

3. Pseudo-convex contour

To improve the segment growing process in the context of homogeneous regions with large grey level ranges, we should use spatial information to guide the process [21]. We will use segment contour and shape constraints to limit erratic expansions of segments. We will use the convex envelope of a region as the ideal shape and compare the region contour with the convex envelope. A contour is convex if for any 2 points on the contour, the line between the 2 points is inside the contour [22]. Another way to find the convex envelope is to take a straight line and make it rotate over the region. The convex area will be the space that can not be cover by the rotating line.

We can see the straight line as the limit case of a circle with a very large radius. If we reduce the radius and rotate the circle over the region, we obtain a pseudo-convex envelope. We can also replace the circle by another shape. We consider that a digital image is composed of square pixels. Each pixel has 4 adjacent pixels, one for each side. Therefore, adjacent pixels on a contour can define a straight vertical or horizontal line only. For other orientations, we have a stair like curve. The definition of an appropriate convex envelope should be adapted to the image geometry. We consider that $\pm 45^\circ$ contours are good. They have a very regular shape. The pseudo-convex envelope will be defined by an octagon with a very large radius. The octagon is moved over the region while preserving its orientation with horizontal, vertical and $\pm 45^\circ$ sides.

Figure 1 shows how the pseudo-convex envelope is calculated. A part of a region is shown in green with a black contour line. We first search for the pixels on the top line and select the 2 extreme pixels at left and right. They are pixels 1 and 2. In moving the octagon in this area, the "A" part of the octagon should be pushed against this part of the contour. We have to fill the space between the horizontal blue line and the region contour. We search next for pixel on the 45° line that is closest to the top left corner of the image and find pixels 3 and 4. For the region contour located between pixels 2 and 3, we use the "B" corner of the octagon. We push the "B" shape against the black contour and obtain the pseudo-convex blue line envelope. Between pixels 3 and 4, the octagon 45° side "C" (stair shape) is used. We search for pixel on the most left column and find pixels 5 and 6. Between pixels 4 and 5, the "D" corner is used and the vertical side "E" is used between pixel 5 and 6. The same approach is used for the remaining part of the region.

An advantage of the stepwise optimisation rule is its gradual aspect: the most similar segments are merged

first. However, in the context of homogeneous regions with large grey level variation as in SAR images, we have proved that spatial information should be used to guide the segment growing process [21]. We use segment contour and shape constraints to limit erratic expansions of segments. In [21], we compare the segment contour with its bonding box. The bonding box is 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

In this paper, we compare the segment contour with its pseudo-convex envelope. We use the perimeter, the area and the contour length to define three contour measures or factors, C_p , C_a and C_l . The three factors are combined in an ad hoc manner with the SAR stepwise criterion to produce the new stepwise criterion:

$$C_{ij}^{\text{contour}} = C_{ij} \times (1 + 20 C_p + 20 C_a) \times C_l$$

C_p is the difference between the perimeter of $S_i \cup S_j$ and the perimeter of the pseudo-convex envelope of $S_i \cup S_j$ over the pseudo-convex perimeter. C_a is the difference between the area of the pseudo-convex envelope and the area of the segment over the area of the segment. Let L_{\min} be the smallest of the contour lengths of S_i and S_j and L_{com} the length of the common boundary. C_l is equal to $(L_{\min} - L_{\text{com}}) / L_{\text{com}}$ [23].

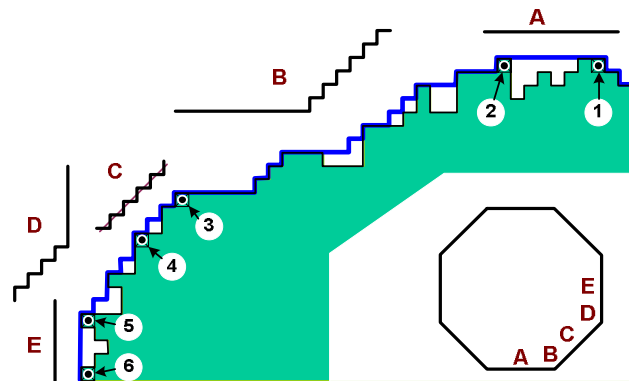


Figure 1. Detection of the pseudo-convex envelope (blue line) of an image region (green area).

4. Segmentation results

We examine the effects of the contour and shape criterion in image segmentation. The segmentation technique is applied on a 100x100 synthetic image

with four looks. Figure 2 shows the amplitude image composed of four regions with different mean values: 1.0, 1.4, 1.7 and 2.2. The SAR criterion $C_{i,j}$ without the shape criterion is first used to segment this image. The partition with 1000 segments (Figure 3) shows segments with irregular shapes. The segments are not compact, but have many branches. Many irregular segments are colored in black. Figure 4 shows that more regular segments are obtained when a segment shape criterion is included in the segmentation criterion. The pseudo-convex envelope is used in the shape criterion. Figure 5 shows the result when the shape criterion is based upon the bounding box as in [21]. There is an improvement in the segment shape when the pseudo-convex envelope is used instead of the bounding box. In both images, the black areas show that there are still some irregular segments. Their number and their size are smaller with the pseudo-convex criterion.

The synthetic image is difficult to segment because the difference between some regions is small and the multiplicative noise is important. Figure 6 shows partitions with 10 segments. Without a shape criterion, we can not obtain a good segmentation result (left

partition). Both the pseudo-convex criterion (center) and the bounding box criterion (right) produce good segmentation results. The result of the pseudo-convex criterion seems better.

The image segmentation approach is tested using polarimetric Convair-580 SAR data collected over the Ottawa region, Canada. A test region in the Mer Bleu area is selected. The initial 1-look image has a resolution of 5.6m x 0.63m. The covariance matrices of 9 pixels are averaged in azimuth to form a square pixel image. Only the amplitude of the hh, vv and hv channels is used for the segmentation. The image contains crop field areas and forest areas. Figure 7 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 a difficult task because of the presence of speckle in SAR images. The criterion seems to give good results for crop fields. More merging is recommended for forest areas.

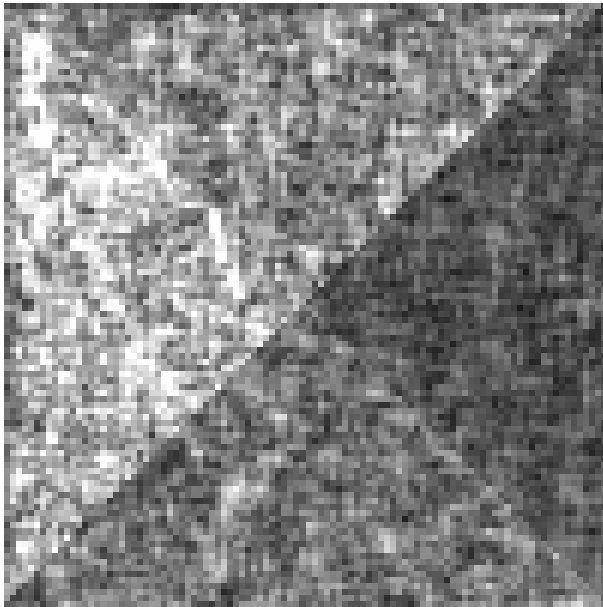


Figure 2. A synthetic 4-look 100x100 SAR image.

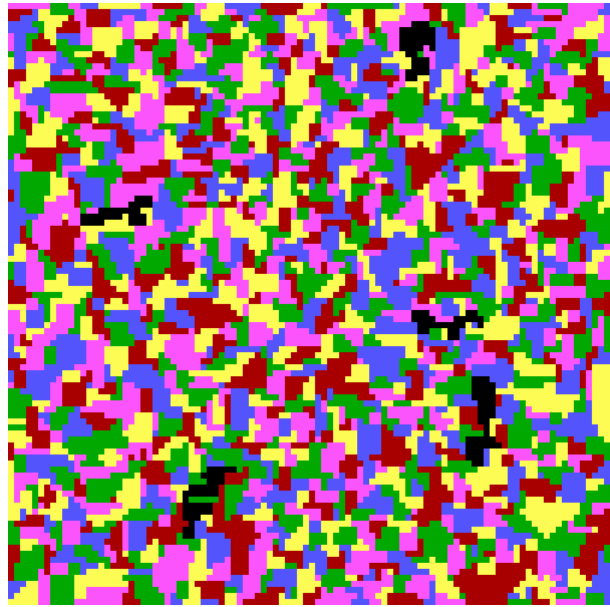


Figure 4. Partition with 1000 segments using the pseudo-convex envelope in the shape criterion.

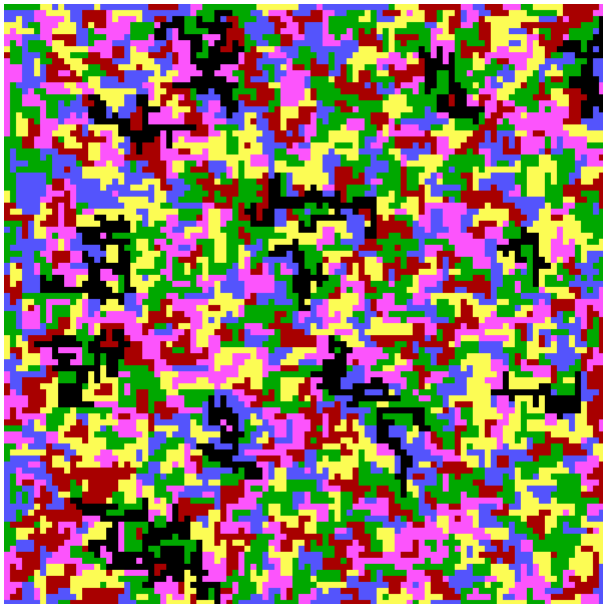


Figure 3. Partition with 1000 segments with no shape criterion.

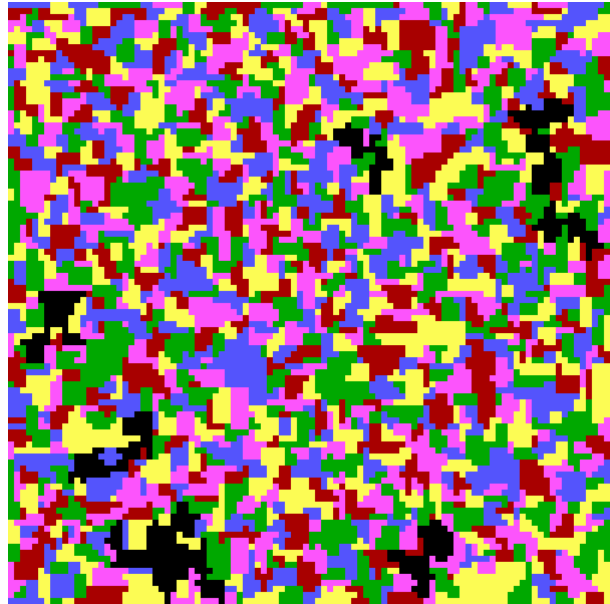


Figure 5. Partition with 1000 segments using the bounding box in the shape criterion.

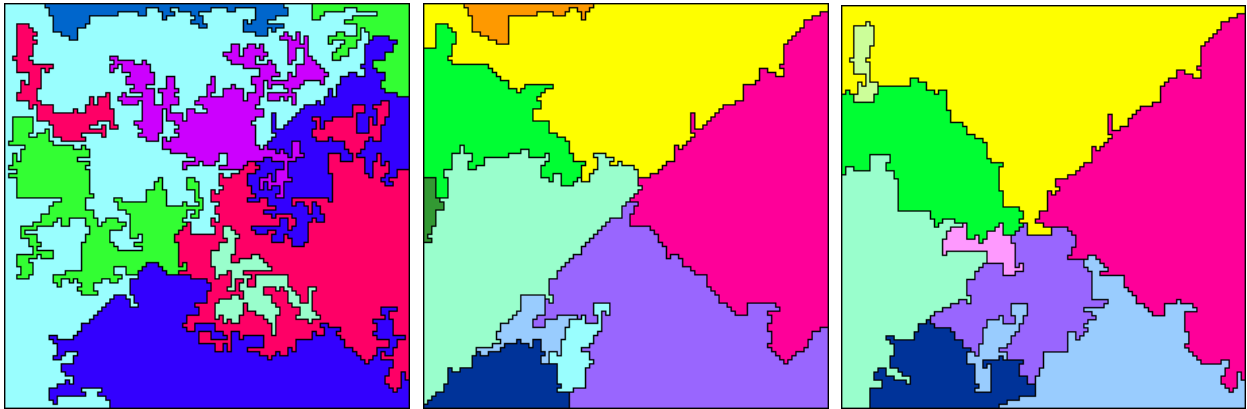


Figure 6. Partitions with 10 segments: (left) without shape criterion, (center) using pseudo-convex envelope and (right) using the bounding box.

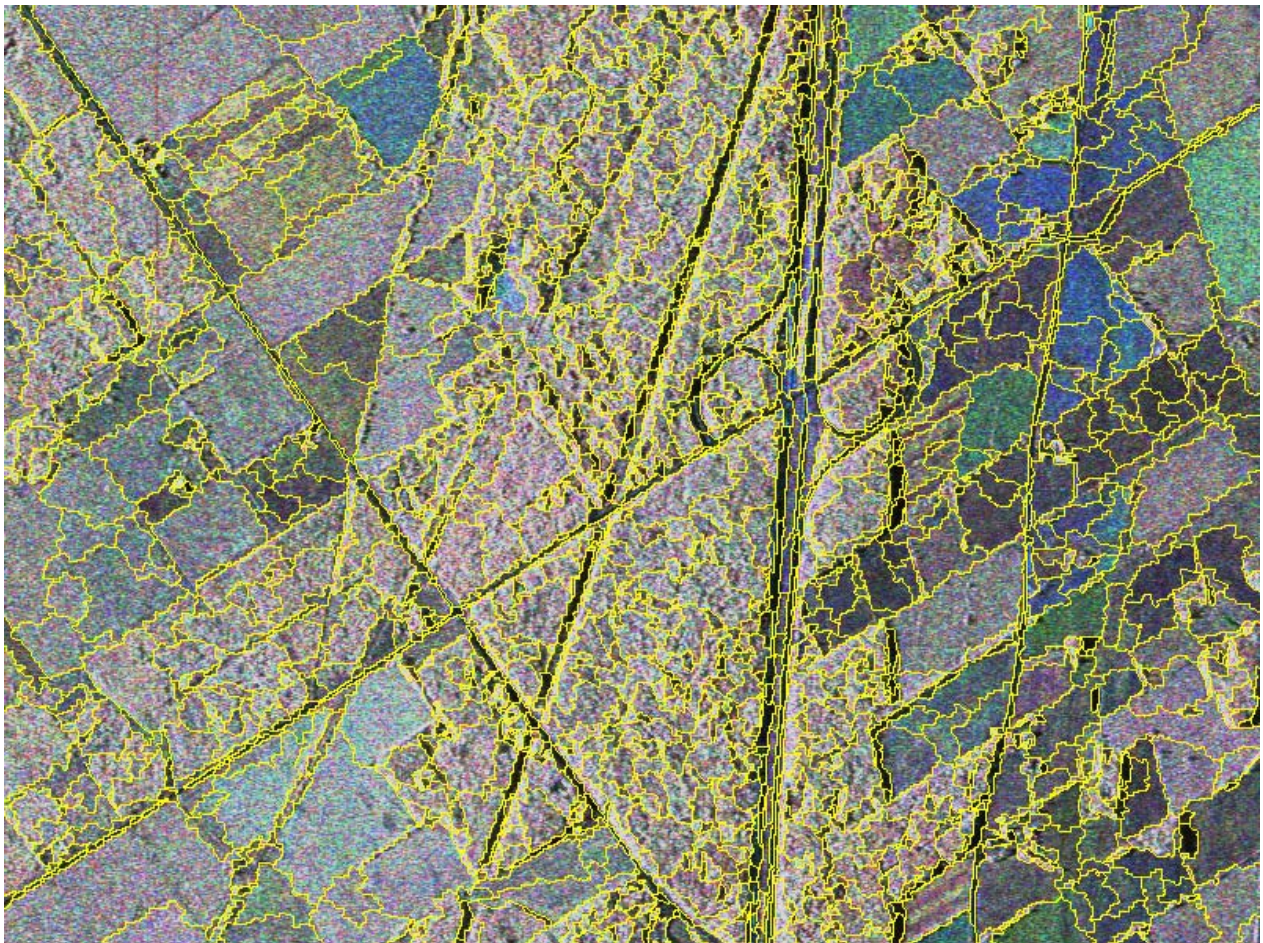


Figure 7. Partition of a 3 channel SAR image (polarimetric, 800x600 pixels) with 2000 segments.

5. Conclusion

This paper shows the contribution of pseudo-convex envelope for the evaluation of region shapes. Contour and shape criteria are important for the good segmentation of SAR images that have an important multiplicative noise.

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