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Utilisation of Contour Criteria in Micro-Segmentation of SAR Images

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Utilisation of Contour Criteria in Micro-Segmentation of SAR Images

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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 utilisation 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 micro-regions that have variable mean and variance values and irregular shapes. If the micro-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. We present three criteria based upon contour shapes.

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. An 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 models have been used to include the spatial aspect into the class probabilistic models [2]. An edge detection process could also be used to define segment boundaries [3]. A post-processing step could be needed to close segment boundaries.

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 [4] [5] [6] [7] [8].

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 [9] [10] [11]. The accurate detection of edges in SAR images is also a difficult task [4]. 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 are the boundaries between homogeneous regions or fields. Delimiting homogeneous regions is an important step or output of the process. One approach is to reduce the speckle noise by reducing the resolution. Another approach is to apply an optimisation process with an appropriate signal model. More complex models have often the unproductive effect of requiring large averaging windows.

In hierarchical SAR image segmentation, the parameter accuracy problem is mostly present at the first segment mergers when the compared segments are small. Different techniques are used to obtain an initial partition with small segments: speckle filtering [6] [7], watershed process [4] [5], and wavelet transform [5]. The resolution (final locations) of segment boundaries is determined by the initial partition. Complex field models have been used for the description of segments such as texture model [6] [7].

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

We use a standard hierarchical segmentation algorithm with an adaptation of the Ward criterion to the multiplicative nature of the speckle. 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 micro-segments, that later will become larger segments. With standard merging criteria, the high noise level of SAR images results in the production of micro-regions that have variable mean and variance values and irregular shapes. If the micro-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. 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. We present three criteria based upon contour shapes. These criteria are combined with the adapted Ward criterion in order to guide correctly the segment merging process.

The new criterion produces good micro-segmentation of SAR images. The criterion could also be used in the following merges to produce good SAR image segmentations (larger segments). This is illustrated by synthetic and real image results.

2- Hierarchical segmentation of SAR images

A segmentation is a partition P of the image plane I into N disjoint regions $S_i \subseteq I$ such that $P = \{ S_1, S_2 .. S_N\}$, $S_i \cap S_j = \emptyset$ for $i \neq j$ and $\cup\ S_i = I$. A segment hierarchy can be represented by a tree where segments at lower levels are joined to form segments at higher levels. The ***i***th node at the ***τ***th level of the tree corresponds to the segment S_i^{τ}. The links between nodes indicate set inclusion. Hence, a link between a segment $S_k^{\tau+1}$ (ancestor or parent) and its disjoint subparts S_i^{τ} (descendants or sons) indicates that $S_i^{\tau} \subset S_k^{\tau+1}$. The root of the tree corresponds to I, the whole picture, and the leaves to pixels. An image partition, P, therefore corresponds to a node set $\{ S_1, S_2 .. S_N \}$, called a node cutset, which is the minimal set of nodes separating the root from all the leaves.

2.1- The Hierarchical Stepwise Optimisation algorithm

A hierarchical segmentation algorithm, 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 $d(c_i, c_j)$ are calculated for all clusters pairs (c_i, c_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.

An important limitation of the hierarchical clustering approach is its excessive computing time for large data set. If there are N clusters, then the similarity measure for N×(N-1) possible cluster pairs must be calculated. In image segmentation, however, only adjacent segments can be merged, reducing the number of potential segment pairs per iteration to N×M, where N is the number of segments, and M the average number of neighbours per segment. M is usually small ($4 \leq M \leq 8$) and is quite independent of N. Furthermore, a segment merge affects only the surrounding segments and only the pairs involving those segments need to be modified or updated. Thus, only a limited number of new segment pairs must be considered at each iteration.

A hierarchical segmentation algorithm based upon stepwise optimisation is now presented [8]. A segment similarity measure, $C_{i,j}$, is defined as the stepwise criterion to optimise. At 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 picture 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 picture 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.

2.2- Segmentation by hypothesis testing

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 grey level probability density functions (pdf). An image segmentation can be produced by testing and merging two segments if they belong to the same region.

It is assumed that an image f(x, y) is composed of distinct regions { R_k }, where each region is viewed as a statistical population and is defined by its probability density function, PDF_k. The goal of an image segmentation process is to find the truth picture partition {R_k }. Let S_i, designate any arbitrary subpart of a true region R_k, $S_i \subset R_k$. The merging of segments can be based upon hypothesis testing. As the characteristics of R_k are unknown, the statistical decision must consider whether the pixel values of two segments come from the same probability density function.

A test is usually described in terms of some statistic d that is a reduction of the observed data. Let d be a measure of the similarity of the estimated probability density functions of segments S_i and S_j. A statistical decision process can then be used to determine which one of the following two hypotheses is true.

H0: $d = 0$
H1: $d = d_{true}$

The hypothesis H0 indicates that the two segments belong to the same truth region, while the hypothesis H1 defines segments belonging to different regions. The statistical decision consists of accepting Ho if d is small, more precisely, if $d \leq t$, where t is a selected threshold. The performance of a test is judged according to its tendency to lead to wrong decisions. Two types of error are considered:

Type I: rejecting H0 when H0 is true
Type II: accepting H0 when H1 is true.

The probability of these two types of error are represented, respectively, by α and β. They must both be low for a good decision process The threshold value t can be modified such as to reduce either α or β, but not both simultaneously.

Hierarchical segmentation begins with many small segments that are sequentially merged to produce larger ones. Statistical decision can be employed to determine whether, or not, two adjacent segments must be merged. The sequential aspect of hierarchical segmentation must be considered in the design of the decision process. It can be noted that type II error results from merging of two different segments, and therefore, cannot be recovered by an agglomerative process. Whereas, type I error keeps separated two similar segments which can be corrected in a following step. Therefore, it seems preferable to keep β at a low level to avoid type II errors. The hierarchical segmentation could be regarded as a sequential testing process where we should consider the error probability of the final result, not the error probabilities of each individual test. It have been shown that in hierarchical segmentation, it is advantageous to keep β at an appropriately low level for each test, even if large α values must be used in the first tests [8].

2.3- Stepwise criterion

In hierarchical segmentation, it is preferable for each stage k to keep β_k, the probability of type II error, as low as possible. This is achieved by maximising α_k. At each stage or segment level, there are many possible segment mergers, which can be represented by segment pairs (Si, Sj). The segment similarity statistic, $d_{i,j}$, can be calculated for each pair. A statistical decision process accepts the hypothesis H0 and merges segments only if:

$$d_{i,j} \leq t(\alpha)$$

which can be rewritten as:

$$v_{i,j} \leq 1-\alpha \quad \text{or} \quad \alpha \leq 1-v_{i,j}$$

where $v_{i,j}$, is the confidence level associated with the interval (0, $d_{i,j}$), i.e., $v_{i,j}$ is the probability of obtaining a value d such that $d \leq d_{i,j}$:

$$v_{i,j} = \text{prob}\,(d \leq d_{i,j}\,;\,H0)$$

Defining v_{min} as the minimum over $v_{i,j}$, $v_{min} = \min(v_{i,j})$, the maximum allowed value for α is $\alpha_{max} = 1\text{-}v_{min}$, which results at least in one merger. Hence, a hierarchical segmentation algorithm can employ a stepwise process that finds the segment pair with the minimum confidence level $v_{i,j}$ and merges the corresponding segments. This will assure that, at each step, the probability of type II error β_k is kept to it lowest value.

2.4- Criterion for additive Gaussian noise

The Ward criterion is now derived. We assume that an ideal image is composed of constant value regions corrupted by a uniform Gaussian white noise. Each pixel value f(x, y) inside a region R_k, $(x, y) \in R_k$, is regarded as a random variable, with Gaussian distribution of mean m_k and variance σ^2, $N(m_k, \sigma^2)$. The difference of the segment means could be used to decide if two segments belong to the same region:

$$d_{i,j} = |\,\mu_i - \mu_j\,|$$

where μ_i and μ_j are the mean values of segments S_i and S_j.

If H0 is true, $d_{i,j}$ has a Gaussian distribution with a zero mean and a variance of σ_d^2:

$$\sigma_d^2 = (1/N_i + 1/N_j)\ \sigma^2$$

where N_i and N_j are, respectively, the sizes of segments S_i and S_j. The confidence level associated with the interval (0, $d_{i,j}$) under the H0 hypothesis is:

$$v_{i,j} = \text{prob}\,(d \leq d_{i,j}\,;\,H0)$$

$$v_{i,j} = \int_{-d_{i,j}}^{d_{i,j}} \frac{1}{\sqrt{2\pi}\,\sigma_d} \exp\left(\frac{-x^2}{2\sigma_d^2}\right) dx$$

$$v_{i,j} = 2\ \mathtt{erf}\,(d_{i,j} / \sigma_d)$$

The segment pair, S_i and S_j, that minimises $d_{i,j} / \sigma_d$ will also minimise $v_{i,j}$. Therefore, $d_{i,j} / \sigma_d$ could be used as a stepwise criterion:

$$C_{i,j}^{ward} = \frac{d_{i,j}}{\sigma_d} = \sqrt{\frac{N_i N_j}{N_i + N_j}}\ \frac{|\mu_i - \mu_j|}{\sigma}$$

σ is a constant value that can be removed from the criterion equation.

2.5- Criterion for SAR speckle noise

Radar images are mainly characterised by the presence of speckles. The radar signal can be modelled as a random process. The probability density function of the signal intensity or power, for a L-look signal follows a Gamma distribution:

$$p(f) = \frac{1}{\Gamma(L)}\left(\frac{L}{m}\right)^{L} f^{L-1} \exp\left(-Lf/m\right)$$

where m is the mean value of the signal intensity. The standard deviation σ increases with the mean value, $\sigma = m/\sqrt{,L}$.

The multiplicative aspect of the speckle noise is illustrated by the following model of the radar signal:

$$f(x,y) = m(x,y) \times u(x,y)$$

where f(x,y) is the observed image intensity and m(x,y) is the ground reflectivity. The multiplicative speckle noise, u(x,y), is statistically independent of m(x,y) and has a mean value of one.

As in the previous case, the difference of the segment means could be used to decide if two segments belong to the same region. Under the H0 hypothesis, we know that the segments S_i and S_j belong to the same region R_k with truth mean value m_k. The pdf of segment mean μ_i follows a Gamma distribution with $2N_iL$ degrees of freedom. We know that the mean of $d_{i,j}$ is zero. However, it is difficult to obtain its pdf.

For large N_iL values, the distribution of segment mean μ_i can be approximated by a Gaussian distribution with a mean value of m_k and a variance of $\sigma_i^2 = (m_k)^2 / N_i L$ [10]. Then, $d_{i,j}$ will have a Gaussian distribution with a zero mean and a variance of σ_d^2:

$$\sigma_d^2 = (1/N_i + 1/N_j)\,(m_k)^2 / L$$

where m_k could be estimated by the mean value μ_{i+j} of $S_i \cup S_j$. The confidence level associated with the interval $(0, d_{i,j})$ under the H0 hypothesis is:

$$v_{i,j} = 2\ \mathrm{erf}\,(d_{i,j} / \sigma_d)$$

Therefore, $d_{i,j} / \sigma_d$ could be used as the stepwise criterion for SAR image segmentation:

$$C_{i,j}^{sar} = \frac{d_{i,j}}{\sigma_d} = \sqrt{\frac{N_i N_j}{N_i + N_j}}\ \frac{|\mu_i - \mu_j|}{\mu_{i+j}}\ \sqrt{L}$$

where $\sqrt{,L}$ is a constant value that can be removed from the criterion equation.

This criterion has been appropriate for the segmentation of SAR images. There are other approaches for the development of stepwise criteria. This topic needs more studies.

3- Contour criteria

We have derived a stepwise criterion to take into account the multiplicative nature of speckle noise. The segmentation of SAR image is also complicated by the large amplitude of the noise. For a 4-look image, the standard deviation of the noise is half the mean value of the signal. It is difficult then to discriminate between regions with small mean value differences.

3.1- Micro-segment shapes in SAR images

An advantage of the stepwise optimisation rule is its gradual aspect: the most similar segments are merged first. The algorithm gradually merges segments starting with the ones having the smallest $C_{i,j}$ values. This assures that the first mergers produce segments corresponding to homogeneous regions. For SAR images, the range of grey level values inside homogeneous areas is large. The first mergers will produce micro-segments inside the homogeneous regions, each micro-segment including pixels from only a part of the grey level range of the region. The grey level ranges of adjacent regions will often overlap. This will result into the formation of micro-segments crossing the region boundaries and having pixels from different homogeneous regions. The merging of micro-segments across boundaries is possible because micro-segment grey level variances are small and do not correspond to the value ranges of homogeneous regions. It could then happen that the most similar neighbour of a micro-segment will be a micro-segment on the other side of the boundary and not one belonging to the same homogeneous region.

The first segment mergers should not cross distinct region boundaries. This can not be corrected in the following mergers and can only increase the confusion between adjacent regions. To illustrate this point, the segmentation technique is applied on a 100x100 synthetic image with 4 looks. Figure 1 shows the amplitude image composed of 4 regions with different mean values: 1.0, 1.4, 1.7 and 2.2. The SAR criterion previously developed, $C_{i,j}^{sar}$, is used to segment this image. In the partition with 10 segments (Figure 2), the shapes and boundaries are not well defined. The segments are not compact, but have many branches. The partition with 1000 segments (Figure 3) shows micro-segments with irregular shapes.

In a homogeneous region, we have local minima and maxima corresponding to pixels coming from the tails of the Gamma distribution. The extents of the micro-segments containing theses pixels are limited. Micro-segments with intermediary pixel values will try to expend between the extrema and could develop long branches (see marked segments in Figure 4).

3.2- Contour criteria

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. We will use segment contour and shape constraints to limit erratic expansions of segments. We use the segment perimeter, the segment area and the contour length to define 3 contour criteria, Cp, Ca and Cl. The 3 criteria are

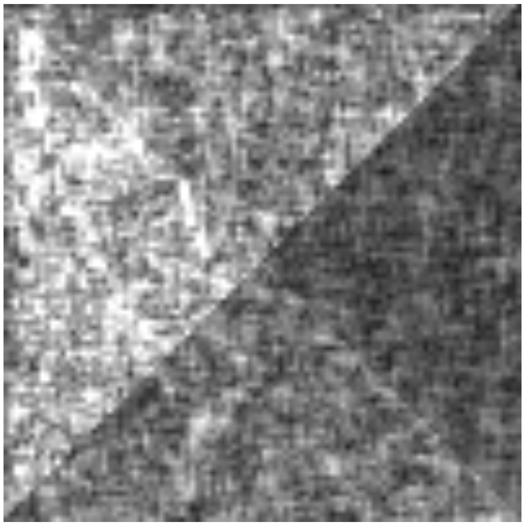


Figure 1: A synthetic 4-look 100x100 SAR image.

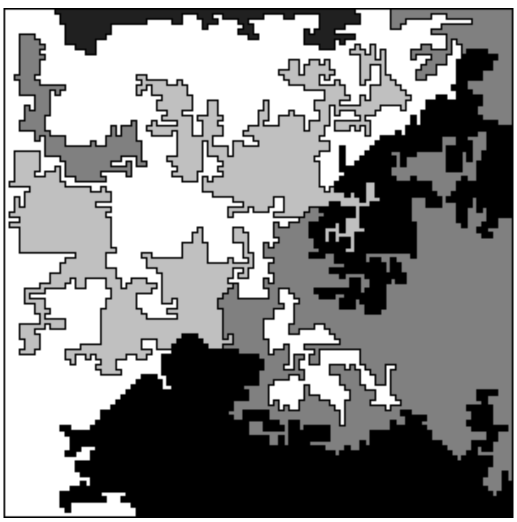


Figure 2: Partition with 10 segments.

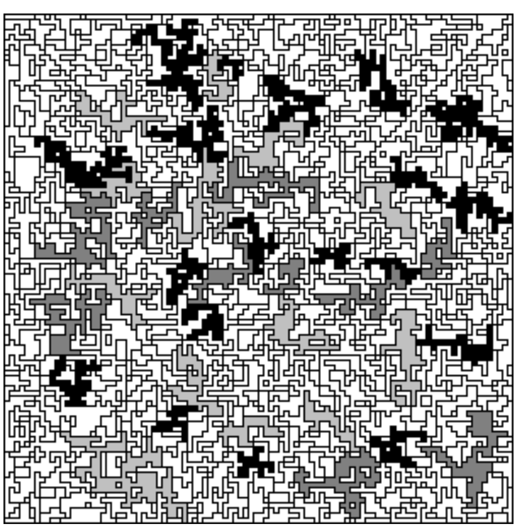


Figure 3: Partition with 1000 segments

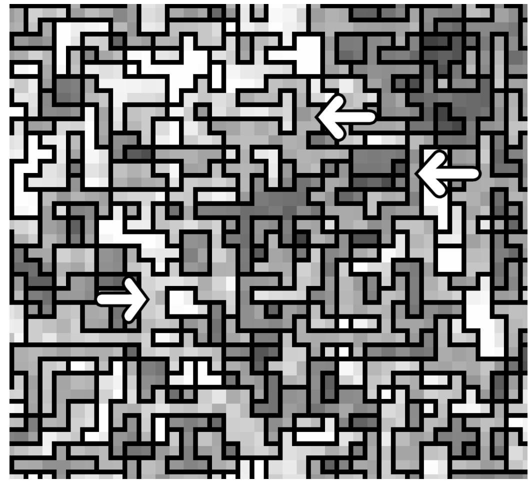


Figure 4: Shape of micro-segments.

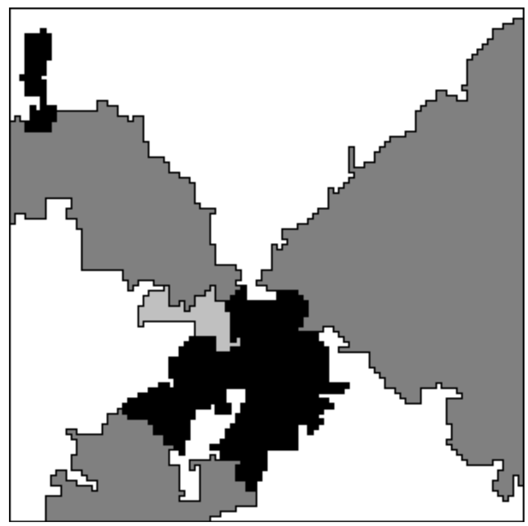


Figure 5:Partition with 10 segments from the contour criteria.

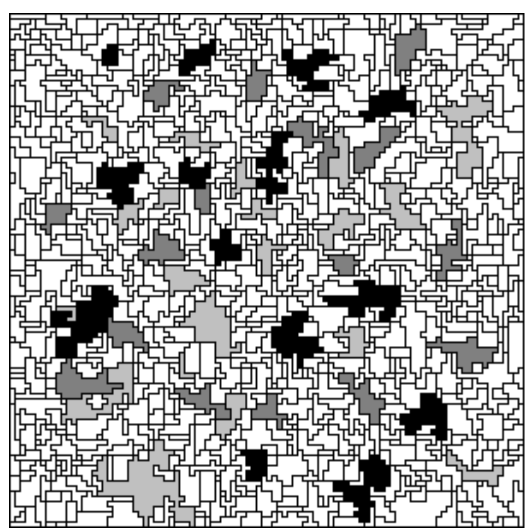


Figure 6: Partition with 1000 segments from the contour criteria.

combined in an ad hoc manner with the SAR stepwise criterion $C_{i,j}^{sar}$ to produce the new stepwise criterion:

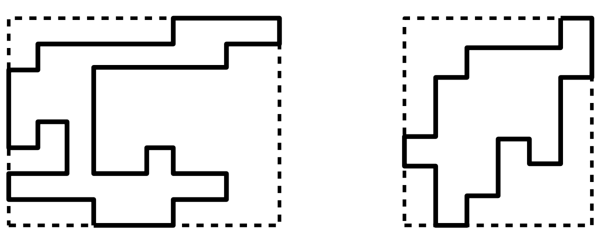
$$C_{i,j}^{contour} = C_{i,j}^{sar} \times Cp^2 \times Ca \times Cl$$

Figure 5 and Figure 6 show the improved segmentation results obtained with the new criterion on the synthetic image.

3.3- Segment perimeter criterion

We are examining the shape of the segment produced by the merger, $S_i \cup S_j$. We can 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. Each pixel corresponds to a square surface. The perimeter of a segment is a multiple of the pixel side length. If a segment is round or convex, the perimeters of the segment and the bounding box will have the same value. The perimeter will increase if a part of the contour is concave or forms deep bays. The perimeter criterion is defined as:

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

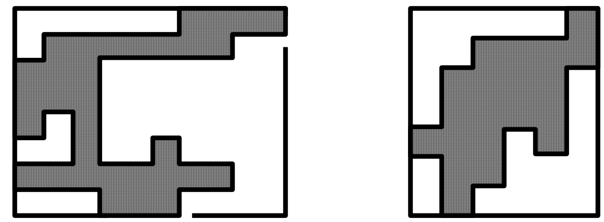


This criterion has a minimum value of one and the value will increase as the segment develops deep bays.

3.4- Segment area criterion

The area of the bounding box can also be compared with the area of the segment.

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



The criterion value will be one if the segment form a horizontal or vertical rectangle. The value will increase if the segment have many bays or if it is elongated in the diagonal directions.

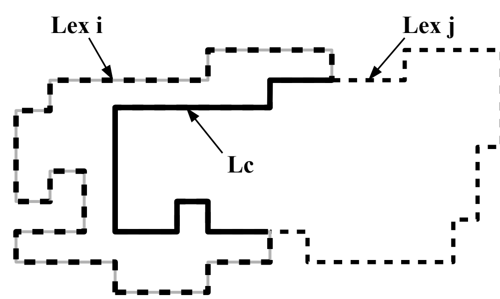
3.5- Contour length criterion

The contour length criterion will promote the merging of two segments if one is included or surrounded by the other one. In this case, the common boundary is important and corresponds to a large fraction of the total boundary of one or both segments.

$$Lc = \text{length of common part of contours}$$

$$lex_i = \text{length of exclusive part for } S_i$$

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



For 2 neighbour pixels, the criterion value is 3. For 2 rectangle segments, the value will be between 1 and 3 if the common boundary is one of the long sides and higher if it is one of the short sides. The value will be smaller than 1 if an important part of one segment is intruded inside the other.

4- Segmentation results

The hierarchical segmentation technique adapted for SAR image and with contour criteria is used to segment a 6-look ERS-1 image (1000x1000). The algorithm has produced good micro-segments with appropriate shapes. The same criterion is used in the following merges to produce larger segments. Good SAR image segmentations are produced. A partition with 1000 segments is obtained (average segment size is 1000 pixels). Figure 7 shows a 500x500 region of the SAR image and Figure 8 shows the segmentation result. In Figure 9, the segment boundaries are overlaid on the grey level image. We see that the segment formation is data driven. Looking at the grey level image, we see that segment boundaries are drawn between areas with different grey level values. The segmentation process produces good and appropriate results. A remaining problem is to define when to stop the segment mergers. The stopping time could be different for different part of the picture. This task should be performed by a higher level post-processing step.

To illustrate the importance of the contour criteria, we have produced an image partition with 1000 segments without the contour criteria. f10 shows a 500x500 area of the 1000x1000 image. This is a more complex figure than Figure 8 that has the same number of segments. The lengths of the contours are larger and the shapes are irregular. Segments have branches intruded inside other segments.

5- Conclusion

This paper has shown the importance of the first segment mergers in hierarchical SAR image segmentation. The proposed contour criteria are simple and effective in guiding the first mergers. These criteria could be useful for larger segments. For SAR images, we should look for appropriate high level criteria for the last mergers.

Acknowledgements

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Figure 7: ERS-1 4-look image (500x500).

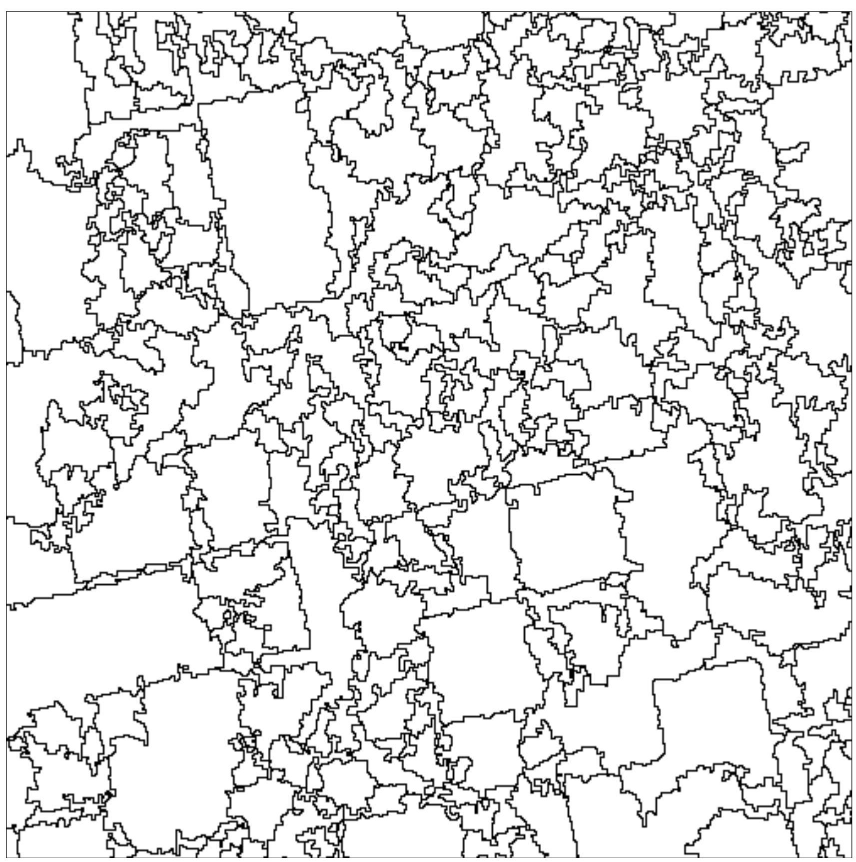

Figure 8: Partition with 1000 segments (500x500 region of the 1000x1000 image).

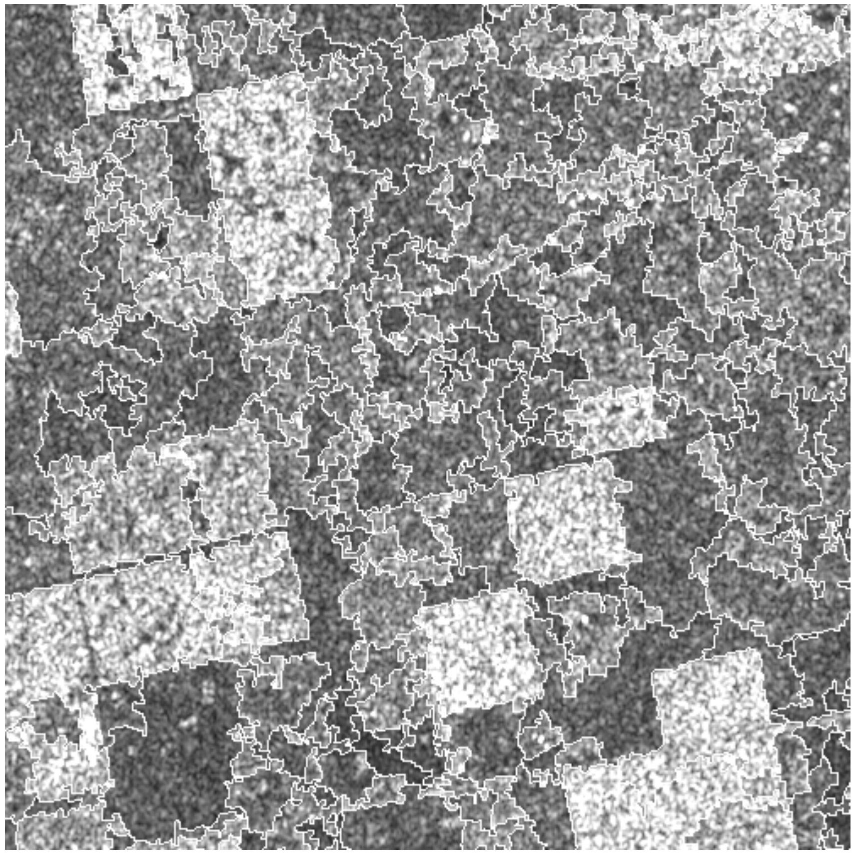

Figure 9:Overlay of the grey level image and the contour image (Figure 7 and 8).

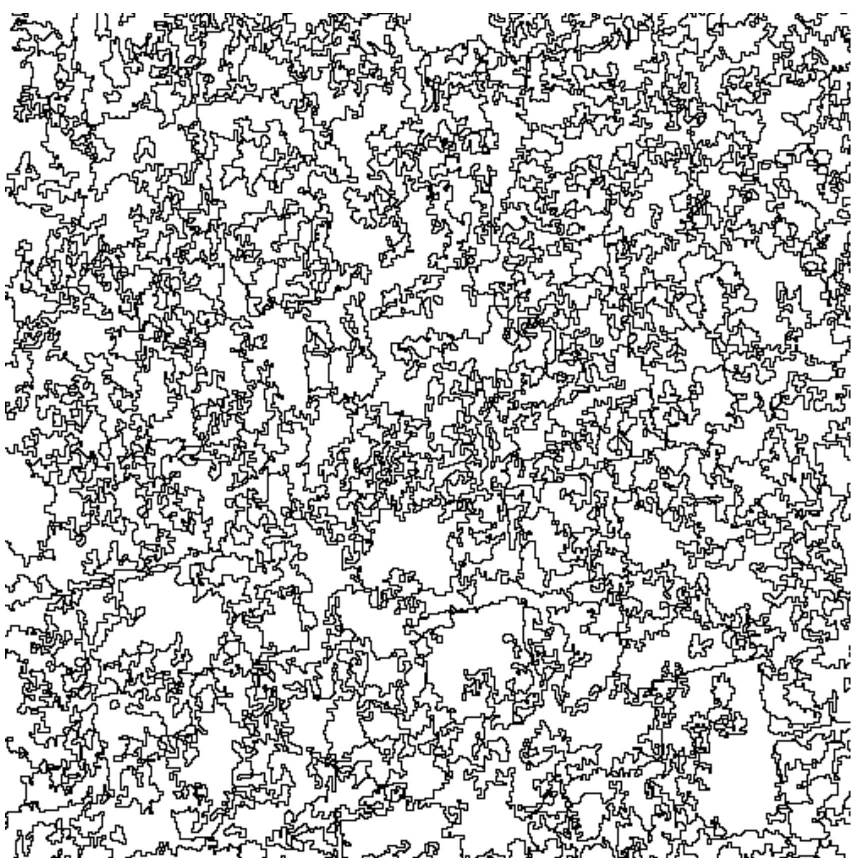

Figure 10: Segmentation without the contour critera (1000 segments as in Figure 8).