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UTILISATION OF SEGMENT BORDER INFORMATION IN HIERARCHICAL SEGMENTATION

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ABSTRACT

A multi-criterion approach is proposed for the segmentation of remote sensing images. Segmentation by region growing uses segment descriptors such as the mean value. We examine how the edge information could be combined with the segment descriptor in a hierarchical segmentation process. The multi-criterion decision measure is derived from the Ward measure for image approximation by constant value regions. Features as pixel value and gradient value are resolution dependant, adding a multi-resolution aspect to the approach. Segment contour shape features are also added for the segmentation of multi-channel SAR images. Good results are shown for Convair-580 SAR data collected over the Ottawa region, Canada.

RÉSUMÉ

Une approche multicritère est proposée pour la segmentation d'images de télédétection. La segmentation par croissance de régions utilise des descripteurs de segment comme la valeur moyenne. Nous examinons comment l'information d'arête peut être combinée avec un descripteur de segment dans un processus de segmentation hiérarchique. La mesure de décision multicritère est dérivée de la mesure de Ward qui intervient dans l'approximation d'une image par des régions de valeurs constantes. Des attributs comme la valeur d'un pixel et la mesure du gradient sont dépendantes de la résolution de l'image, ce qui ajoute un aspect multi résolution à notre approche. Des attributs de formes pour le contour des segments sont aussi ajoutés pour la segmentation d'images SAR multicanaux. De bons résultats sont obtenus pour les données SAR du Convair-580 recueillies au-dessus de la région d'Ottawa, Canada.

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‡ Dr. Beaulieu was visiting professor at Canada Centre for Remote Sensing, Ottawa, Canada, in 2001 and 2003.

INTRODUCTION

Two mains approaches in image segmentation are edge detection and region growing. Region based criteria use mainly information from the inside of a region, while edges should correspond to the boundaries of regions. We examine how both types of information could be combined in a hierarchical regions merging approach (Caves 1998), (Le Moigne 1995), (Zhu 1996). We should consider the size of the regions. For very small segments (e.g. one pixel segments), the region criterion could correspond to an edge measure. For example, the difference of segment means of two adjacent regions could be used as an edge measure particularly for small regions. On the other hand, using the mean value into segment similarity measure assumes that each region is uniform. It could be useful to relax this constraint and allow smooth variation inside a region. In this case, we should examine principally the pixels on both sides of the boundary between two regions to decide if they should be merged.

The combination of segment and edge information could be extended by a multi-criterion segmentation approach. For example, variation inside segment could be considered. In this paper, a multi-resolution aspect is added. The original image with two smoothed versions of the original image is presented to the segmentation algorithm. The segmentation criterion combines the information from the three input images. The similarity between regions is thus defined in a multi-resolution manner.

This paper takes advantage of a powerful hierarchical segmentation technique based upon step-wise optimization. A hierarchical decomposition of the picture is produced, witch is data driven with no restriction on the segment shape. It can be viewed as a tree where the nodes correspond to segment and where links between nodes indicate set inclusion. At each iteration, the algorithm merges the two most similar segments by optimizing a "stepwise criterion". The algorithm could easily be adapted to complex criterion.

This multi-criterion approach could be used for the segmentation of multi-spectral images. It could be more particularly useful for SAR images that are very noisy. To avoid the multiplicative nature of the speckle noise and simplify the measure combination, we take the logarithm of the SAR images.

The high noise level or texture of SAR image results in the production of micro-regions inside an homogeneous field after the first merges (Beaulieu 2004). These micro-regions have variable mean and variance values and irregular shapes. We should therefore impose the merging of these micro-regions inside a homogeneous field without merging parts of different fields. In order to take account of the high level noise, we should consider the inclusion of additional information and criteria. The segment shape is employed to reduce the formation of random contours. Segment shape parameters, such as the contour length, the smoothness of contour and the compactness of the region, are employed. Good segmentation results are obtained from this multi-creiterion approach.

THE HIERARCHICAL STEPWISE OPTIMISATION ALGORITHM

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

A hierarchical segmentation algorithm, inspired from hierarchical data clustering and based upon stepwise optimization 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 minimizes 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 k clusters, then the similarity measures for $k \times (k-1)$ 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 $k \times m$, where k is the number of segments, and m the average number of neighbors per segment. m is usually small $(4 \leq m \leq 8)$ and is quite independent of k. 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 optimization (HSO) is now presented (Beaulieu 1989). A segment similarity measure, $SC_{i,j}$, is defined as the stepwise criterion to optimize. For 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 image 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).

The algorithm is designed such as to reduce the computing time. In the initialization step, the computing time is a function of the image size, the number of initial segments, and the number of neighbors per segment. On the other hand, the iterative steps are short and the computing time is mainly a function of the number of neighbors. 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, neighbor sets and criterion values.

Different segment similarity measures (stepwise 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, $\Sigma\, H(S_i)$.

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:

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

For the case of constant value approximation, we have:

$$SC_{i,j} = \frac{N_i \times N_j}{N_i + N_j} \left(\mu_i - \mu_j\right)^2 \tag{2}$$

where N_i is the size of the segment S_i and μ_i is its mean value. $SC_{i,j}$ is called the Ward criterion. Its utilization in the HSO algorithm ensures that each iteration does it best to minimize the overall approximation error.

MULTICRITERION SEGMENTATION

The stepwise optimization algorithm can employ different criteria which correspond to different segmentation models. The Ward criterion uses a simple model. More complex models could be required by segmentation tasks. Complex models can be obtained from combinations of simpler ones. For example, the complex structure of the SAR images could require the utilisation of a composite criterion for the segmentation.

The human vision employs many cues such as brightness, contour, colour, texture and stereopsis to perform perceptual grouping. Computer grouping should not be limited to using only one cue at a time. We should examine ways to combine many cues. For computer simulation of human perception, (Zobrist 1975) 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 (Pavlidis 1979). For example, the pixel gray level can be employed to form small homogeneous regions, and 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.

POLARIMETRIC SAR IMAGE SEGMENTATION

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. We are exploring the utilisation of spatial constraints and of multi-resolution in order to improve the segmentation results.

Speckle in general does not lack information, and any attempt to simply smooth it out of the image is done at the expense of all the information about the spatial variability of the target scattering properties. SAR image is characterized by a high level multiplicative noise with eventually correlation between pixels. Therefore, a homogeneous cell or region of appropriate size is required to get valuable parameter estimation. However, we do not know, a priori, if the cell is homogeneous. The segmentation should therefore start from small regions, where the parameter estimation is poor. Additional constraints or information are then used to guide the first merges. The larger segments produced by merging should be homogeneous and have better parameter estimation.

A modification of eq. 2 is used to implement the multi-criterion approach:

$$SC_{i,j} = \frac{N_i \times N_j}{N_i + N_j} \sum_k w_k \times feature_k(i,j)^2 . \qquad (3)$$

Each criterion is associated with a feature difference measure, $feature_k(i,j)$, that calculates the difference of the feature between S_i and S_j. A weight is associated with each feature. The segmentation criterion is the weighted sum of the contribution of the different features. A factor is used to take into account the sizes of segments.

We will use the mean pixel values and the edge values for the segmentation. Those features are function of the image resolution. For example, edge measure could be calculated as the difference between two adjacent pixels. This is a high-pass filter that is noise sensitive. To reduce the noise effect, a low-pass filter (smoothing) is first applied. The overall result is a pass-band filter. We will use three resolution levels. The first level is the original image. The second level is the image smoothed by a 5x5 circular gaussian mask (0.05, 0.25, 0.40, 0.25, 0.05). The third level is the image smoothed by a 9x9 circular gaussian mask (0.0025, 0.025, 0.1025, 0.225, 0.29, 0.225, 0.1025, 0.025, 0.0025). To take into account the multiplicative nature of the SAR image noise and to simplify the combination of features, we take the logarithm of the signal intensity (after smoothing). There is also a summation over channels for a multi-channel image.

$$SC_{i,j} = \frac{N_i \times N_j}{N_i + N_j} \sum_{ch=1,2,3} \sum_{l=1,2,3} mw_l \times mdif_l(i,j,ch)^2 + ew_l \times edge_l(i,j,ch)^2 \qquad (4)$$

$mdif_l(i,j,ch)$ is the difference between the mean values of segments S_i and S_j for resolution level l and for channel ch. $edge_l(i,j,ch)$ is the mean value, along the border between S_i and S_j, of the difference between pixel on both sides, for resolution level l and for channel ch.

Eq. 4 is also combined with a segment contour shape criterion as described by (Beaulieu 2004). Because of the importance of the noise in SAR images, it is necessary to use the shape criterion to guide the segment merging.

SEGMENTATION RESULTS

The multi-criterion 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. We use only the intensity of the hh, vv and hv components as a three channel image. The amplitude of the resulting image (600x800 pixels) is shown in pseudo-color in Fig. 1.

A difficult aspect of the multi-criterion approach is to find the appropriate weighting factors for the different features. Fig. 2 shows the result of the segmentation when only the segment mean values are used. The figure shows a partition with 2000 segments. We give different weighting to the different resolution level in function of the size of the segment produced by the merge. For small segments, the smoothed images (level 2 and 3) are useful to reduce the noise effect. For large segments, it is better to use only the original image (level 1). The weight value is 2.0 for the three levels for small segments. The weights of levels 2 and 3 are progressively reduced to zero as the segments get larger.

Fig. 3 presents the segmentation produced when the edge criterion is included. The edge information is not reliable when the segments are too small. When the segments are large enough, levels 1 and 2 provide appropriate edge measures and the level 3 is not needed. We use a weight of 0.2 for the edge feature for large segments. No edge information is used when only 5000 merging steps are remaining. There is an improvement in the preservation of field boundaries.

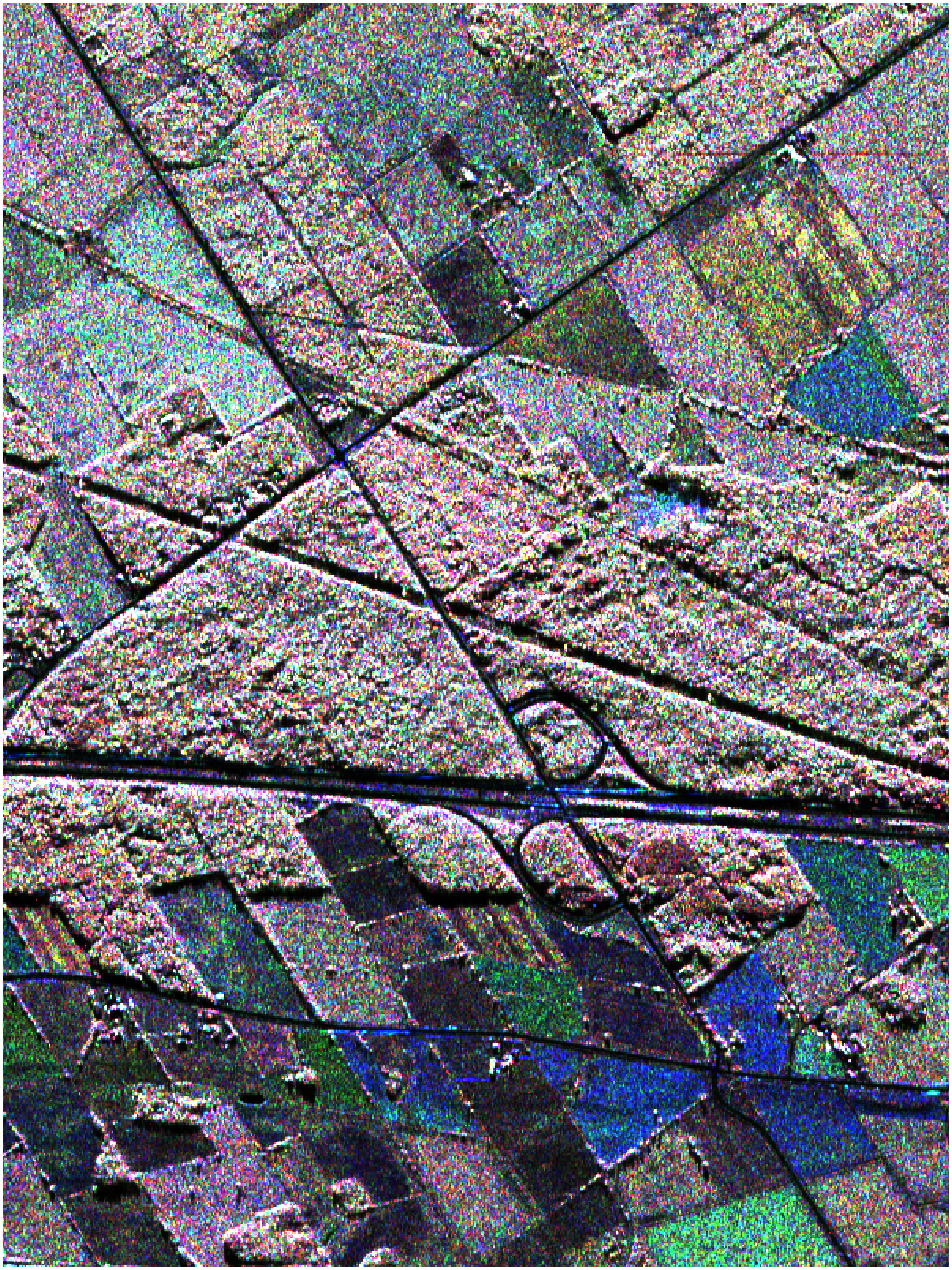

Fig. 1. Pseudo-color image of the Mer Bleu area (amplitude of hh, vv and hv, 600x800 pixels).

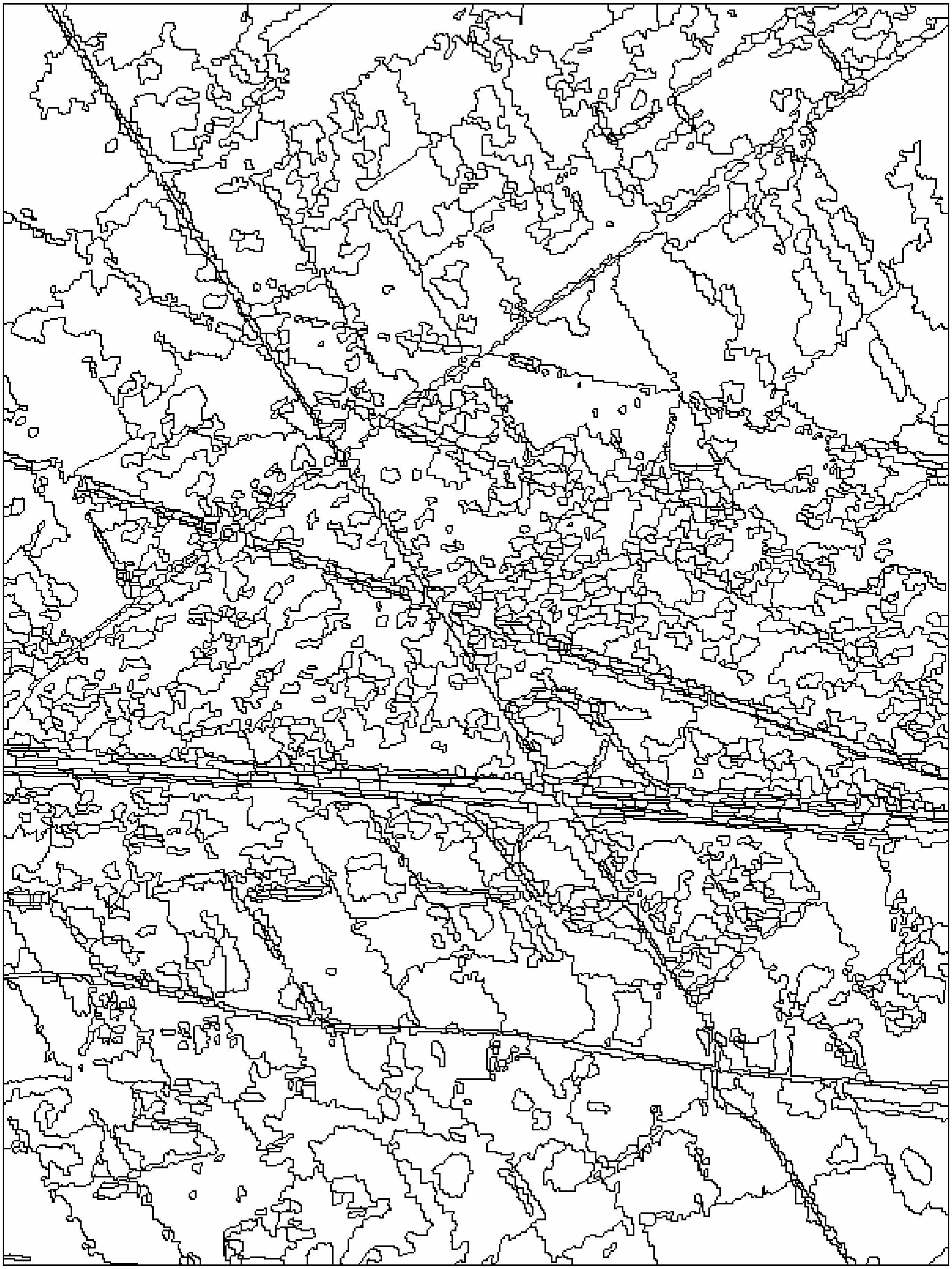

Fig. 2. Segmentation with only mean value criterion (2000 regions).

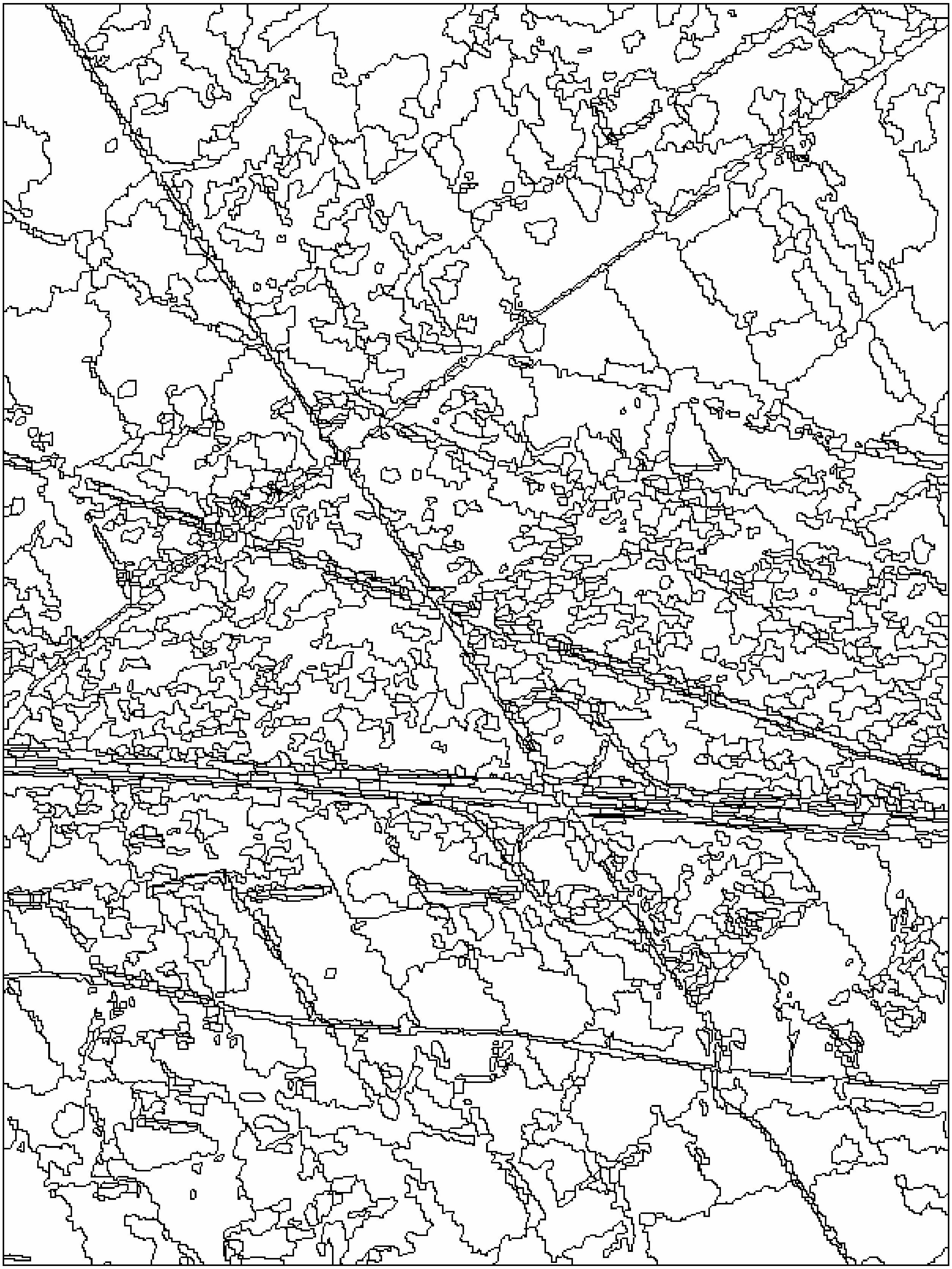

Fig. 3. Segmentation with mean value and edge criterion (2000 regions).

REFERENCES

Beaulieu, J.M. 2004. Utilisation of Contour Criteria in Micro-Segmentation of SAR Images. *International Journal of Remote Sensing*, submitted May 2002.

Beaulieu, J. M., and Goldberg, M. 1989. Hierarchy in picture segmentation: a step-wise optimization approach. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 11, 150-163.

Caves, R., Quegan, S. and White, R. 1998. Quantitative comparison of the performance of SAR segmentation algorithms. *IEEE Transactions on Image Processing*, Vol. 11, 1534-1546.

Le Moigne, J., and Tilton, J. C. 1995. Refining image segmentation by integration of edge and region data. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 33, 605-615.

Pavlidis, T. 1979. Hierarchies in Structural Pattern Recognition. *Proceeding of IEEE*, Vol. 67. no. 5, pp. 737-744.

Zhu, S. C., and Yuille, A., 1996, Region competition: unifying snakes, region growing, and Bayes/MDL for multiband image segmentation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 18, 884-900.

Zobrist, A.L., and Thompson, W.B. 1975. Building a Distance Function for Gestalt Grouping. *IEEE Trans. on Computer*, Vol. C-4, pp. 718-728.