Active Regions for Unsupervised Texture Segmentation Integrating Region and Boundary Information

X. Muñoz, J. Freixenet, J.Martí and X. Cufí

Abstract— **A novel approach to texture segmentation which unifies region and boundary information is presented. The algorithm uses a coarse detection of the texture boundaries to initialize a set of active regions. Therefore, the initial unsupervised segmentation problem is transformed to a supervised one, which allows us to accurately extract region and boundary information. Then, the regions compete for the image pixels in order to segment the whole image taking into account both information sources. The method is implemented on a multiresolution representation which ensures noise robustness as well as computation efficiency. Experimental results prove the performance of the proposed method.**

Keywords— **Texture segmentation, region-based segmentation, boundary-based segmentation, active region model.**

I. Introduction

Texture is a fundamental characteristic of natural images that, in addition to color, plays an important role in human visual perception and provides information for image understanding and scene interpretation.

The aim of texture segmentation, the problem considered in this paper, is the domain-independent partition of the image into a set of regions, which are visually distinct and uniform with respect to textural properties. Image segmentation methods are based on two basic properties of the pixels in relation to their local neighbourhood: discontinuity and similarity. Methods which are based on some discontinuity property are called boundary-based methods and their objective is to accurately extract the borders between texture regions in an image. Whereas, methods based on some similarity property, called region-based methods, try to part the image into a number of regions such that each region has the same textural properties.

In the task of segmentation of some complex pictures, such as outdoor and natural images, it is often difficult to obtain satisfactory results using only one approach of image segmentation. With the aim of improving the segmentation process, a large number of new algorithms which integrate region and boundary information have been proposed over the past few years. Although it is assumed that integration of both methods yields to get complementary information and, therefore, has long been a highly desirable goal [1], it becomes a non-trivial task due to the conflicts and incommensurate objectives it involves. Besides, the texture is generally forgotten as basic feature in the majority of these proposals, probably due to the difficulty of obtaining accurate boundary information when texture, which is a non-local image property, is considered.

X. Muñoz, J. Freixenet, J.Martí and X. Cufí are with the Computer Vision and Robotics Group. IIiA-University of Girona, Girona, Spain. E-mail:{xmunoz,jordif,joanm,xcuf}@eia.udg.es

In this paper we propose a new segmentation which integrates region and boundary information. Taking as a basis a previously developed segmentation algorithm [2], we have used the main contours of the image to adequately place the seeds in order to initialize the region models. Hence, the knowledge of the region's characteristics allows us to transform the initial unsupervised segmentation problem to a supervised way, in which region information is defined and accurate texture boundaries are extracted to provide the boundary information. Then, as these regions grow, they compete for the pixels of the image by using a decision criterion which ensures the homogeneity inside the region and the presence of edges at its boundary; finally, the method has been implemented on a multiresolution representation which allows us to refine the region boundaries from a coarse to a finer resolution.

The remainder of this paper is structured as follows: the related work concludes this introduction. Section II describes the proposed region segmentation technique, detailing the placement of the starting seeds, the definition of region and boundary information and the growing of the active regions. The multiresolution representation is presented in Section III, while experimental results proving the validity of our proposal appear in Section IV. Finally, conclusions are given in Section V.

A. Related Work

There is a large body of work on the fusion of region and boundary information in order to perform the image segmentation [3]. Although the textural properties are generally not considered, there are some relevant exceptions and this tendency seems to be changing in last years.

In [4], Philipp and Zamperoni proposed an image segmentation algorithm which starts with a high-resolution edge detection. Then, the boundaries are checked to distinguish between true and false contours by analyzing the texture characteristics at both sides of the contour in order to decide whether to suppress or prolong the boundary. A key work in multiresoltion strategy was developed by Wilson and Spann [5]. Their strategy uses a quadtree method using classification at the top level of the tree, followed by boundary refinement. A non-parametric clustering algorithm is used to perform classification at the top level, yielding to an initial boundary, followed by downward boundary estimation to refine the result. Following the multiresolution scheme, Hsu et al. [6] described in 2000 a texture segmentation algorithm, which uses a cooperative algorithm within the Multiresolution Fourier Transform (MFT) framework.

The most closely related work with this paper can be found in [7], where a supervised texture segmentation algorithm which unifies region and boundary-based information into a geodesic active region is proposed. However, this proposal is designed for supervised scenarios, where the occurring texture classes are known. So, an off-line step which creates multi-component probabilistic texture descriptors for the given set of texture patterns is required.

II. Active Region Segmentation

Recently, the concept of active regions as a way to combine the region and boundary information has been introduced. This model is a considerable extension on the active contour model since it incorporates region-based information with the aim of finding a partition where the interior and the exterior of the region preserve the desired image properties. The underlying idea is that the region moves through the image (shrinking or expanding) in order to contain a single, whole region.

The main contributions of our proposal are:

- Unsupervised region initialization: the seeds which allow us to initialize the statistical measurements which model the regions are automatically placed from a coarse boundary detection. Hence, it is not necessary user intervention or a previous learning phase.
- Integration of region and boundary information: the regions model allow to extract region and accurate boundary information, which are incorporated into the energy function.

A. Initialization

To obtain a sample of each region large enough to statistically model its behaviour, initial seeds have to be placed completely inside the regions. Boundary information allows us to extract these positions in the "core" of the regions by looking for places far away from the contours.

The problem of texture edge detection is considered as a classical edge detection scheme in the multidimensional set of k texture features which are used to represent the region characteristics [8]. So, boundaries of homogeneously textured regions are defined to be located where sudden changes in local texture characteristics occur. Nevertheless, as is well known, texture is an inherently non-local image property. All common texture descriptors, therefore, have a significant spatial support which renders classical edge detection schemes inadequate for the detection of texture boundaries. Hence, the result of this simple method are inaccurate and thick contours. However, this information is enough to perform the seed placement according to the algorithm proposed in [2], in which seeds are placed in zones free of contours or, in other words, the "core" of the regions.

Each region is modeled by a multivariate Gaussian distribution, so the mean vector and the covariance matrix, which are initialized from the seeds, describe the homogeneity region behaviour. From this point, we have transformed the considered problem of unsupervised segmentation to a supervised way, in which the characteristics of the regions are known a priori. Hence, it will be possible to make use of this knowledge to carry out the segmentation process and to accurately extract texture boundaries.

B. Region and Boundary Texture Information

The region information measures the homogeneity of the pixels into a texture region. The probability of a pixel j characterized by the texture features $\vec{x_j}$ of belonging to a region R_i is

$$P_H(\vec{x_j}|R_i) = \frac{1}{\sqrt{(2\pi)^k|\Sigma_i|}} \exp\{-\frac{1}{2}(\vec{x_j}-\vec{\mu_i})^T\Sigma_i^{-1}(\vec{x_j}-\vec{\mu_i})\} \quad (1)$$

where $\vec{\mu_i}$ is the mean vector of the region i and Σ_i its covariance matrix. The background is treated as a single region having uniform probability distribution P_0.

It is well know that the extraction of boundary information for textured images is a very tougher task. On the other hand, human performance in localizing texture edges is excellent, if (and only if) there is a larger patch of texture on each side available. Hence, as Will et al. [9] noted, texture model of the adjacent textures are required to enable precise localization. The previous initialization step of the regions model allows to dispose of this required knowledge.

We shall consider that a pixel constitutes a boundary between two adjacent regions, A and B, when the textural properties at both sides of the pixel are different and fit with the models of both regions. Textural features are computed at both sides (we will refer one side as m and its opposite as n) obtaining the feature vectors $\vec{x_m}$ and $\vec{x_n}$. Therefore, $P_H(\vec{x_m}|A)$ is the probability that the feature vector obtained in the side m belongs to region A, while $P_H(\vec{x_n}|B)$ is the probability that the side n corresponds to region B. Hence, the probability that the considered pixel is boundary between A and B is equal to $P_H(\vec{x_a}|A) \times P_H(\vec{x_b}|B)$. We consider four possible neighborhood partitions (the vertical, the horizontal and the two diagonals) as is showed in Fig. 1. So, the corresponding probability of a pixel j to be boundary, $P_B(\vec{x_j})$, is the maximum probability obtained on the four possible partitions.

C. Active Region Growing

The goal of image segmentation is to partition the image into subregions with homogeneous properties in its interior and a high discontinuity with neighbouring regions in its boundary. With the aim of integrating both conditions in an optimal segmentation, the global energy is defined with two basic terms. Boundary term measures the probability that boundary pixels are really edge pixels. Meanwhile, region term measures the homogeneity in the interior of the regions by the probability that these pixels belong to each corresponding region.

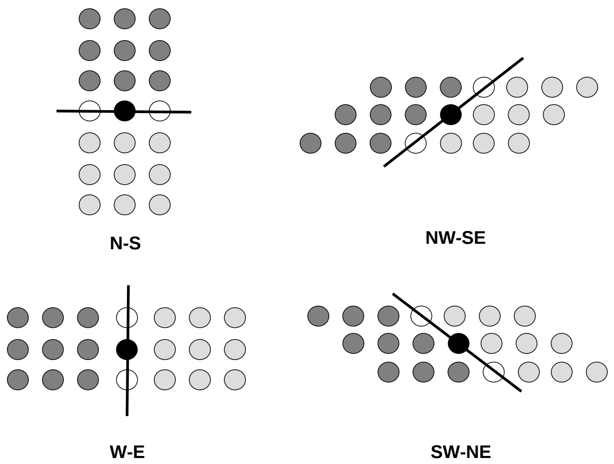


Fig. 1. Texture boundary information extraction. Textural features at both sides of the pixel are computed and compared with models of adjacent textures.

Some complementary definitions are required: let $\rho(R) = \{R_i : i\epsilon[0, N]\}$ be a partition of the image into $\{N+1\}$ non-overlapping regions, where R_0 is the region corresponding to the background region. Let $\partial\rho(R) = \{\partial R_i : i\epsilon[1, N]\}$ be the region boundaries of the partition $\rho(R)$. The energy function is defined as

$$\begin{aligned} E(\rho(R)) = \quad & (1-\alpha)\textstyle\sum_{i=1}^{N} P_B(\overrightarrow{x_j} : j\epsilon\partial R_i)) \\ & +\alpha \textstyle\sum_{i=0}^{N} P_H(\overrightarrow{x_j} : j\epsilon R_i|(\mu_i, \Sigma_i)) \end{aligned} \tag{2}$$

where α is a model parameter weighing the two terms: boundary probability and region homogeneity. This function is then optimized by a greedy algorithm which takes into account the neighbouring pixels to the current region boundaries $\partial\rho(R)$ to determine the next movement. Concretely, a region aggregates a neighbouring pixel when this new classification improves the energy of the segmentation.

Intuitively, all regions begin to move and grow, competing for the pixels of the image until an energy maximum is reached. When the maximization process finishes, if there is a background region R_0 not occupied by any seed regions, a new seed is placed in the background, and the energy maximization starts again.

III. MultiResolution Implementation

In order to further reduce the computational cost, a multiscale representation [5] is proposed which can be combined with the active region segmentation. Specifically, a pyramid of images at different scales is built upon the full resolution image. At lowest resolution level, the seeds are placed and start to compete for the image, obtaining a first segmentation result. This multiresolution structure is then used according to a coarse-to-fine strategy which assumes the invariance of region properties over a range of scales. Specifically, a boundary region is defined at coarsest level and then, at successive levels, the pixels not classified as boundary are used to initialize and model the regions. Further, segmentation by active region is performed to refine the candidate boundary by a factor of two using the multiresolution structure. As a result, the boundaries of the full image size are produced at the finest resolution.

Furthermore, the use of a multiresolution representation allows us to avoid the over-segmentation problems produced by the presence of noise in images. An initial coarse region segmentation is performed on a lower resolution achieving the effect of smoothing. Hence, the use of a multiresolution technique ensures noise robustness as well as computation efficiency.

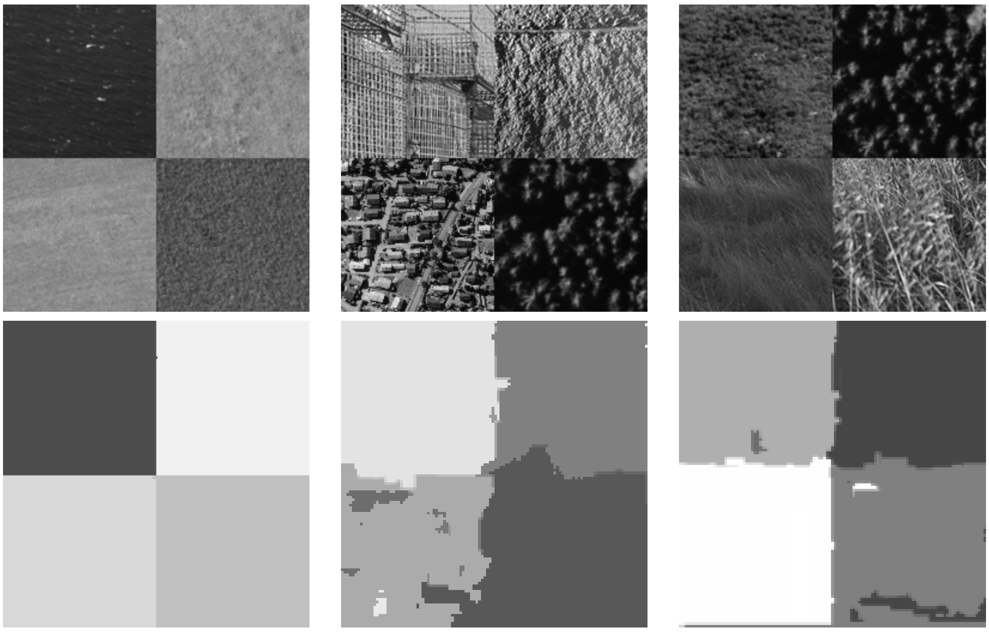
IV. Experimental Results

The described segmentation method can be performed over any set of textural features. Much of the texture segmentation work has concentrated on extracting features that are suitable for texture modeling. The result of comparing the relative merits of the different types of features have been nonconclusive and a clear winner has not emerged in all cases. For the experimental trials showed in this paper we used the co-occurrence matrices proposed by Haralick et al. [10]. Two of the most typical features, contrast and homogeneity, are computed for distance one and for $0°$,$45°$,$90°$ and $135°$ orientations to constitute a 8-dimensional feature vector.

The performance of our proposal has been evaluated over a set of three mosaic images created by assembling four subimages of size 128×128 of natural textures (see first row of the Fig. 2). Mosaic M1 contains (clockwise from the top left corner) water, red crop, green crop, and light green crop; M2 contains cage, wall, forest, town; finally M3 contains bushes, forest, long grass, grass. The segmentation results are showed in the second row of the Fig. 2. In order to evaluate the results, we use the quality parameters (region-based and boundary-based) proposed by Huang and Dom [11]. Two distance distribution signatures are used to measure the boundary quality, one from ground truth to the estimated, denoted by D_G^B, and the other from the estimated to ground truth, denoted by D_B^G. Instead, a region-based performance measure p based on normalized Hamming distance is defined. Moreover, two types of errors are defined: missing rate e_R^m and false alarm rate e_R^f. Table I shows the obtained quantitative results for each quadrant of the three mosaics. Quantitative results successfully demonstrate the validity of our proposal and the mosaic images are conveniently segmented. However, some important mistakes appear in the segmentation of the mosaic M2 due to the difficulty of the texture features used to model the textures existent in this image. Therefore, the identification of the best texture features for each application is required.

V. Conclusions

A new strategy for image segmentation which integrates region and boundary information has been described. The algorithm uses the contours of the image in order to initialize, in an unsupervised way, a set of active regions. The knowledge of these regions allows to define the region information and to extract accurate boundary information.



(a) (b) (c)

Fig. 2. Mosaic images of natural textures and segmentation results. First row shows the mosaic images (a) M1, (b) M2 and (c) M3. Second row shows the obtained segmentation results.

TABLE I

Quantitative segmentation results.

Mosaic	Region-based			Boundary-based			
	e_R^m	e_R^f	p	μD_G^B	σD_G^B	μD_B^G	σD_B^G
M1	0,000	0,000	1,000	0,008	0,089	0,008	0,089
	0,000	0,000	1,000	0,008	0,089	0,008	0,089
	0,000	0,000	0,999	0,048	0,279	0,072	0,383
	0,000	0,000	0,999	0,072	0,383	0,048	0,279
M2	0,013	0,023	0,982	1,737	2,048	2,113	2,484
	0,045	0,013	0,971	1,965	1,721	2,557	2,342
	0,214	0,005	0,890	3,652	3,003	8,619	7,620
	0,010	0,168	0,911	9,003	6,785	4,423	4,171
M3	0,047	0,017	0,968	3,123	2,806	2,089	2,573
	0,033	0,002	0,983	2,752	2,418	2,488	2,392
	0,000	0,095	0,953	0,860	0,720	0,836	1,741
	0,059	0,018	0,961	1,381	1,646	1,676	1,982

Then, region compete for the pixels maximizing an energy function which takes into account both region and boundary information. The method has been implemented on a multiresolution representation and has been tested on a set of synthetic and real images. The experimental results demonstrate the effectiveness of the proposed algorithm in estimating regions and their boundaries with high accuracy.

Future extensions of this work are oriented to testing our proposal with a different feature descriptor, as well as the integration of texture features with color properties to carry out the segmentation taken into account both information sources.

Acknowledgments

This study has been partially developed thanks to the support of the Departament d'Universitats, Recerca i Societat de la Informació de la Generalitat de Catalunya. Furthermore, we would like to thank M.-P. Dubuisson-Jolly at Imaging and Visualization Department, Siemens Corporate Research, for providing the texture mosaic images.

References

[1] T. Pavlidis and Y. Liow. Integrating region growing and edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(3):225–233, March 1990.

[2] X. Cufí, X. Muñoz, J. Freixenet, and J. Martí. A concurrent region growing algorithm guided by circumscribed contours. In *International Conference on Pattern Recognition*, volume I, pages 432–435, Barcelona, Spain, September 2000.

[3] X. Cufí, X. Muñoz, J. Freixenet, and J. Martí. A review on image segmentation techniques integrating region and boundary information. *Advances in Imaging and Electronics Physics*, 2002.

[4] S. Philipp and P. Zamperoni. Segmentation and contour closing of textured and non-textured images using distances between textures. In *International Conference on Image Processing*, volume C, pages 125–128, Lausanne, Switzerland, September 1996.

[5] R.G. Wilson and M. Spann. Finite prolate spheroidial sequences and their applications ii: Image feature description and segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 10(2):193–203, 1988.

[6] T.I. Hsu, J.L. Kuo, and R. Wilson. A multiresolution texture gradient method for unsupervised segmentation. *Pattern Recognition*, 32(11):1819–1833, 2000.

[7] N. Paragios and R. Deriche. Geodesic active regions for supervised texture segmentation. In *International Conference on Computer Vision*, volume II, pages 926–932, Corfou, Greece, September 1999.

[8] A. Khotanzad and J. Chen. Unsupervised segmentation of texture images by edge detection in multidimensional features. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(4):414–421, April 1989.

[9] S. Will, L. Hermes, J.M. Buhmann, and J. Puzicha. On learning texture edge detectors. In *International Conference on Image Processing*, volume III, pages 877–880, Vancouver, Canada, September 2000.

[10] R.M. Haralick, K. Shanmugan, and I. Dinstein. Texture features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, 3(6):610–621, November 1973.

[11] Q. Huang and B. Dom. Quantitative methods of evaluating image segmentation. In *International Conference on Image Processing*, volume III, pages 53–56, Washington DC, October 1995.