SEQUENTIAL ESTIMATION OF BOUNDARIES IN TEXTURE IMAGES

Dragana Brzakovic
Dept. of Electrical Engr.
The University of Tennessee
Knoxville, TN 37996-2100

Antonios Liakopoulos
System Dynamics Inc.
1219 N. W. 10th Ave.
Gainesville, FL 32608

ABSTRACT

In this paper we describe a method for estimating boundaries between perceptually distinct regions in an image. The method is a two step procedure which first identifies image regions which exhibit uniformity. Boundaries between uniform regions are approximated by a complete cubic spline function and the linear recursive filter is used to estimate the values of the function at the knots. Boundaries are assumed to be smooth; however, abrupt changes in boundary location may infrequently occur. In these exceptional cases flexibility of boundary approximation is achieved by adding additional knots at the positions where abrupt changes occur.

KEYWORDS: segmentation, splines, texture, linear recursive filter.

1. INTRODUCTION

Determination of boundaries delimiting objects and their parts in an image is recognized to be a crutial link between an image and its interpretation. It is well recognized that boundary detection in images wherein meaningful regions exhibit textural properties is a difficult task. Regions in such images can be identified by region based segmentation operators, e.g. [10,11]. However, determination of boundaries between texture regions requires further processing. Recently, attempts have been made to develop estimation theory-based boundary detectors [1,4].

This paper describes the design, implementation and performance of an estimation theory-based segmentation operator for noisy images which contain regions of uniform intensity as well as texture regions. The operator performs segmentation at the signal level and it assumes no a priori knowledge on images considered. Its essence is incorporation of region based segmentation with curve fitting to find boundaries between perceptually distinct regions in an image. First, dominant regions which exhibit uniformity and which are called cue regions are identified. Then, boundaries lying between cue regions are estimated globally.Boundaries are approximated by a complete cubic spline function. The flexibility of boundary approximation is achieved by adding additional knots at positions where boundary location changes abruptly.

The function of this segmentation operator corresponds to early vision in humans and it is viewed as a part of a multi-level modular segmentation scheme. At the first level of segmentation hierarchy this operator is employed to perform rough segmentation of an image. The obtained result is then used as an input to subsequent levels of segmentation which take advantage of knowledge on the scene domain and are task dependent. Their function is to perform refined segmentation, label cue regions and identify smaller objects that are of interest.

The method underlying identification of cue regions is described in Section 2. Boundary approximation and estimation schemes are the subject of Section 3. Results and future work are discussed in Section 4.

2. IDENTIFICATION OF CUE REGIONS

The first task of the segmentation operator is to identify cue regions and intermediate zones where boundaries between cue regions lie. Consequently, the problem of boundary estimation between regions of unknown properties reduces to the problem of boundary estimation in the ambiguity zone between two regions of known properties.

Since most of textures appearing in nature are viewed as "uniform" only as a whole while locally they exhibit various statistical and structural irregularities images are subjected to pre-processing prior to region identification. The purpose of this procedure is to eliminate minor textural detail and map texture regions into regions which exhibit higher degree of ergodicity Figure 1(b). This task is accomplished by using Gaussian filter applied locally over a pixel neighborhood and as a result local image variances decrease as a function of σ. The filter is implemented by using method of hierarchical discrete correlation [3] which performs filtering in stages and approximates Gaussian by weighted sums over small neighborhoods.

The identification of uniform regions involves generation of a T image in which each pixel (x,y) is replaced by

$$T(x,y) = \frac{1}{(2P+1)(2Q+1)} \sum_{q=-Q}^{Q} \sum_{p=-P}^{P} \Big(I(x,y) - I(x+p, y+q) \Big)^2$$

Generation of a T image is a form of primitive segmentation since T(x,y) is constant within a homogeneous region and increases at the boundary between two homogeneous regions. (Examples of T images are shown in Figure 1 (c)). Cue regions and ambiguity zones where boundaries between cue regions lie can be easily extracted from a T image using thresholding techniques. Results obtained by using method proposed by Otsu[9] are shown in Figure 1 (d).

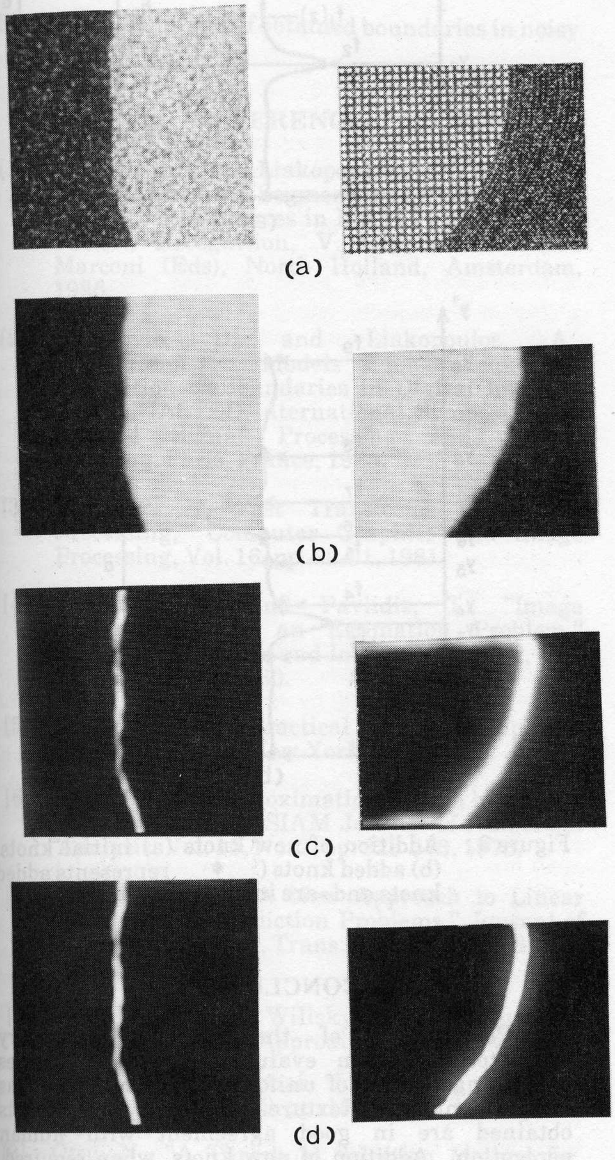

Figure 1. Cue region identification:
(a) original images, (b) filtered images, (c) T images, (d) identified ambiguity zones.

In essence, described procedure is a region merging method where intensity in the T image is used as the merging criterion. However, it does not employ region splitting; instead, pixels which can not be assigned to cue regions constitute ambiguity zones where boundaries between cue region lie. This design decision is governed by the fact that this operator aimes at estimation of boundaries between dominant and thus large regions which exhibit statistical homogeneity. Furthermore, reliability of statistical measurements for texture regions falls with decrease of region size.

3. BOUNDARY ESTIMATION

A boundary f(y) (Figure 2) is approximated, as in an earlier work [1], by a cubic spline function g(y) with (n+1) knots. The function g(y) is explicitely determined by the function values at the knots and derivatives at the interval ends, i.e.

$$g_i(z) = \sum_{m=1}^{n+1} K_{m,i}(z)\, f_m + \Lambda_i(z)\, f'_1 + \Omega_i(z)\, f'_{n+1} \tag{1}$$

The task of boundary estimator is then to estimate f_i, f'_j $i=1,2,\ldots, n+1$, $j=1, n+1$. This task is accomplished by the linear recursive filter [7] under assumption that state vector evolves according to

$$\underline{x}_k = \underline{x}_{k-1} + \underline{w}_k ,$$

$\underline{w}_k$ is the process noise and

$$\underline{x}^T = [f_1, f_2, \ldots, f_{n+1}, f'_1, f'_{n+1}].$$

Vector $\underline{x}$ is estimated by considering M simultaneous measurements in the ambiguity zone between two uniform regions. The measurement model takes form

$$\underline{z}_k = H_k \underline{x}_k + \underline{v}_k \tag{2}$$

where H_k is the measurement matrix and $\underline{v}_k$ is the measurement noise. A measurement performed in the ambiguity zone (in pre-processed image between regions R_1 and R_2) is modeled as

$$z = \frac{p_1 \delta + (\rho - 2\delta)\, p_2}{\rho} + \eta \tag{3}$$

where p_1 and p_2 are measured properties of regions R_1 and R_2 respectively, η is the measurement noise and ρ and δ are as shown in Figure 2. Based on equations (1), (2) and (3) the measurement matrix is

$$H = \frac{p_1 - p_2}{\delta} \begin{bmatrix} K_{1,1} & K_{2,1} & \ldots & K_{n+1,1} & \Lambda_1 & \Omega_1 \\ K_{1,2} & K_{2,2} & \ldots & K_{n+1,2} & \Lambda_2 & \Omega_2 \\ \vdots & & & & & \\ K_{1,M} & K_{2,M} & \ldots & K_{n+1,M} & \Lambda_M & \Omega_M \end{bmatrix}$$

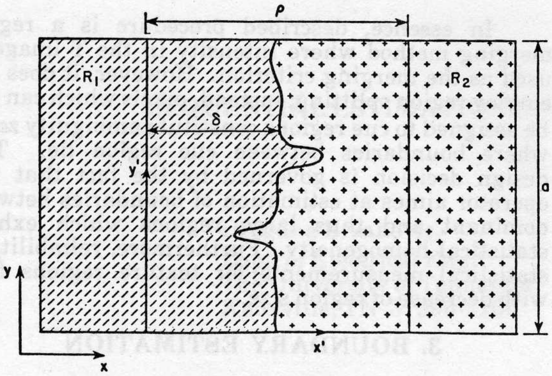

Figure 2. Boundary estimation nomenclature.

The success of the described scheme depends on two major factors: (1) choice of property p to be measured and (2) positioning of the knots. Various measurement schemes are described in [2]. (Results shown in this paper are generated by using mean measured along adjacent strips in regions R_1, R_2 and ambiguity zone). In this paper we shall consider the role of knot positions.

The approximation to functions by splines is well know to depend on number and positions of the knots. Smooth curves, such as those considered in [1], can be adequately approximated by small number of equidistant knots. However, if abrupt changes are expected it is desirable to utilize large number of knots and it is particularly important that the knots be placed at the positions where significant changes occur. An approach to obtaining desired flexibility is to consider knots to be free parameters. Different schemes for handling variable knots have been described by Jupp [6] and De Boor [5]. Muth and Willsky [8] have designed a variable knot recursive scheme to approximate wave forms by splines. This method utilizes age-weighted linear recursive filter to change the locations of the knots. The scheme is designed to work on functions which have a large number of jumps.

In this work the assumption is that boundaries are generally smooth and abrupt changes occur infrequently. Therefore, it is more computationally efficient to achieve the flexibility of boundary approximation by knot additions rather than variations in the location of a given number of knots. The boundary estimation procedure starts with $(I+1)$ equidistant knots and the new knot is added to segment h_j at position r if $z_r - z_{r\pm1} > \Delta$ (Δ is the threshold value and z_r is the measurement taken along strip located at r). In this way new knots are added at the positions where abrupt changes in the first derivative occur or where maxima and minima are expected. The reliability of the measurement is increased by considering m previous and n new measurements around position r. While it is possible to consider large number of previous and new measurements, we have found $m=n=2$ to be sufficient. The dimensionality of the vectors (equations (1), (2), (3)) is increased by one for each additional knot and all vectors are appropriately augmented. The final boundary is approximated by $N+1 \geqslant I+1$ knots. Addition of new knots is illustrated in Figure 3, while results obtained are shown in Figure 4.

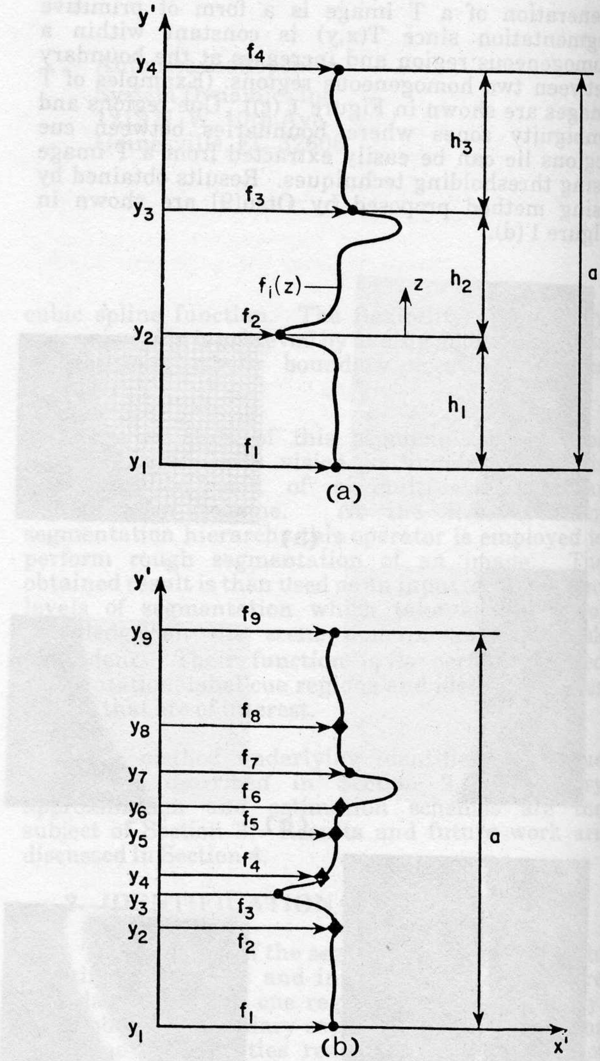

Figure 3. Addition of new knots (a) initial knots, (b) added knots (♦ represents added knots and • are initial knots).

4. CONCLUSIONS

Performance of the described boundary estimator has been evaluated on noisy images containing regions of uniform intensity as well as images containing texture. Generally, the results obtained are in good agreement with human perception. Addition of new knots, when required, allows good boundary approximation in cases where boundary location changes abruptly without adding significant computational burden. Development of the method is subject of further research. At present we are investigating usage of multiple properties in the measurement scheme, i.e. both statistical and texture properties, to increase reliability of the measurements.

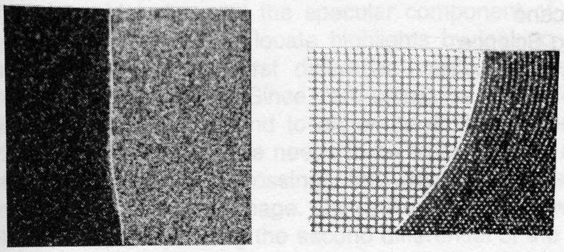

Figure 4. Examples of obtained boundaries in noisy images.

REFERENCES

[1] Brzakovic, D. and Liakopoulos, A., "Estimation Theory Based Segmentation of Texture Images," in Advances in Image Processing and Pattern Recognition, V. Cappellini and R. Marconi (Eds), North Holland, Amsterdam, 1986.

[2] Brzakovic, D. and Liakopoulos, A., "Measurement Models for Sequential Estimation of Boundaries in Digital Images," Proc. of IASTED International Symposium on Applied Signal Processing and Digital Filtering, Paris, France, 1985.

[3] Burt, P. J. "Fast Transforms for Image Processing," Computer Graphics and Image Processing, Vol. 16, pp. 20-51, 1981.

[4] Chen, P. C. and Pavlidis, T., "Image Segmentation as an Estimation Problem," Computer Graphics and Image Processing, Vol. 12, pp. 153-172, 1980.

[5] DeBoor, C. A. Practical Guide to Splines, Springer-Verlag, New York, N.Y., 1978.

[6] Jupp, D.L.B. "Approximation to Data by Splines with Free Knots," SIAM Journal of Numerical Analysis, Vol. 15, No. 2, pp. 328-373, 1978.

[7] Kalman, R. E., "A New Approach to Linear Filtering and Prediction Problems," Journal of Basic Engineering, Trans. ASME, Vol. D-82, pp. 35-45, 1960.

[8] Muth, A.M.M. and Willsky, A. S., "A Sequential Method for Spline Approximation with Variable Knots," International Journal of Systems Science, Vol. 9, No. 9, pp. 1055-1067, 1978.

[9] Otsu, N., "A Threshold Selection Method for Gray-level Histograms," IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-9, pp. 62-66, 1979.

[10] Pavlidis, T., "Structural Pattern Recognition," New York, Springer-Verlag, 1977.

[11] Zucker, S. W., "Region Growing: Childhood and Adolescence," Computer Graphics and Image Processing, Vol. 5, pp. 382-399, 1976.