Segmentation of Complex Outdoor Scenes

Bahram A. Parvin and Bir Bhanu

UUCS 85-110

August 31, 1985

Department of Computer Science

University of Utah

Salt Lake City, Utah 84112

Abstract

A new simpler approach to image segmentation via recursive region splitting and merging is presented. Unlike other techniques the kernel of splitting is based on a generalization of a two class gradient relaxation method and merging uses a statistical analysis of variance.

Index Terms - Image Understanding, Multiclass Images, Outdoor Natural Scenes, Relaxation, Image Segmentation, Split and Merge, Thresholding

Name and Present Address of the Corresponding author:

Bir Bhanu, Department of Computer Science, 3160 Merrill Engg. Building, University of Utah, Salt Lake City, Utah 84112

1. Introduction

Image segmentation is one of the crucial steps in image analysis. The goal of a segmentation algorithm is to partition an image into regions, each having a homogeneous property such as intensity, color, texture etc. Ultimately, segmentation provides a set of symbols and their interrelationships necessary for machine perception. Segmentation algorithms can be categorized into three different types: edge detection, clustering and region splitting and merging. Recursive segmentation based on the analysis of distribution of features is one of the most popular and commonly used techniques for image segmentation [7, 8, 11, 13]. Many of these techniques make use of an elaborate peak location and selection procedure [7, 8] which provides threshold values for the purpose of image segmentation. As an example Ohlander, Price and Reddy [8] select peak from the histogram of 9 features of a color image using a seven step peak precedence description. The computation of peak maxima and minima is complicated since minor changes must be distinguished from major ones. One of the shortcomings of these techniques is that small regions in a large image may not show a distinct peak in the histogram, even if they are distinct from their immediate neighborhood. Therefore, in the application of these techniques normally the image is partitioned artificially into a set of subimages and each subimage is segmented and split further independently [5, 7, 8]. As a result a remerging measure may be required [7] to merge regions that are arbitrarily broken at the subimage boundaries. Very often this merging step leads to some regions which remain unmerged or overmerged.

In complex natural scenes with many different regions due either to the increased size of the image or to the decreased size of the regions, the gray level histogram may have only one peak because the range of intensities for each region will probably overlap with the ranges of other regions. As a result of this overlap, the histogram is usually almost unimodal. In [2] we presented a two class gradient relaxation algorithm for the segmentation of images having unimodal gray level distributions. This basic algorithm has been compared with the Rosenfeld, Hummel and Zucker algorithm [12] and has been successfully used in the extraction of objects from biomedical images, aerial images and tactical images [3, 4]. The tactical images being both in the visible and infrared spectrum. This algorithm allows control over the segmentation results and rate of convergence of the relaxation process. It provides automatic selection of the threshold for binarization. In this paper we generalize the use of this algorithm for the segmentation of complex natural scenes [1, 9, 10]. Region splitting is accomplished via recursive application of the two class gradient relaxation algorithm [2]. It is followed by merging which attempts to resolve fragmentation. Two adjacent regions are merged if they have equal mean values. The test for equal mean value is achieved by one way analysis of variance from a subset of pixels in each region.

Since the technique presented here allows the splitting of the image to depend on the outcome of the two class gradient relaxation technique [1, 2], it avoids any heuristic and arbitrary measures for partitioning the image. Thus it does not suffer from the fact that some of the regions may be artificially broken at the subimage boundaries and does not require a robust merging step in order to remove the boundary artifacts [7]. It does not require the detailed peak location and selection procedure. Further as it does not directly depend on the peaks and valleys of the gray level histogram to initiate the relaxation process (initial probability assignment), and uses image statistics, the initial step of the relaxation process is a simple one, which is to be used over and over at the various levels of the region splitting hierarchy.

2. Two Class Gradient Relaxation Algorithm

Bhanu and Faugeras [1, 2] proposed a gradient relaxation algorithm for the segmentation of images having unimodal distributions. These distributions are typically obtained when the image consists mostly of a large background area with other small but significant regions. In such cases the selection and location of the valley in the histogram is nontrivial. Since two-class method is used as the basis for the segmentation of multiclass images, a brief description of the algorithm is given below.

Suppose a set of N pixels i= 1,2,...,N fall into two classes λ_1 and λ_2 corresponding to the white (gray value = 255) and black (gray value = 0). Reduced inconsistency and ambiguity of pixels with respect to their neighbors are achieved by maximizing the global criterion,

$$C(\mathbf{p}_1,\dots,\mathbf{p}_N)=\Sigma^{N}_{i=1}\mathbf{p}_i\bullet\mathbf{q}_i \quad (1)$$

subject to the constraint that $\mathbf{p}_i$'s are probability vectors. $\mathbf{p}_i$ is the probability that the ith pixel belongs to class λ_1 and λ_2. $\mathbf{q}_i$, the compatibility vector, is a function of $\mathbf{p}_i$'s. It is defined as,

$$q_i(\lambda_k)=(1/V_i)\Sigma_{j\epsilon V_i}\Sigma^{2}_{i=1}c(i,\lambda_k,j,\lambda_l)p_j(\lambda_l);\ k=1,2;\ i=1,\dots,N \quad (2)$$

where compatibility,

$$c(i,\lambda_k,j,\lambda_l)=\{\ 0;\ k = l;\ k=1,2\ ;\ j\ \epsilon V_i,\ \text{for all } i$$
$$\{\ 1;\ k = l\ ;\ k=1,2;\ j\ \epsilon V_i,\ \text{for all } i \quad (3)$$

and V_i is the set of 8 nearest neighbors of the ith pixel. $\mathbf{q}_i(\lambda_k)$ is in effect the average of $\mathbf{p}_i(\lambda_k)$ of eight nearest neighbors.

Initially at every pixel the assignment of probabilities is done by,

$$p_i(\lambda_1)=FACT*((I(i)-IBAR)/255) + 0.5 \quad (4)$$

where, IBAR is the mean of the image and FACT a function of intensity which is taken to be equal to 1 if I(i)>IBAR, otherwise normally it is taken between 0.7 and 1. The process is iterated using equations,

$$p_i^{n+1}(\lambda_1)=p_i^n(\lambda_1)[1-\alpha_1]+\alpha_1; q_i(\lambda_1) > 0.5; \quad 0 < \alpha_1 < 1.0 \qquad (5)$$

$$p_i^{n+1}(\lambda_1)=p_i^n(\lambda_1)[1-\alpha_2]; q_i(\lambda_1) < 0.5; \quad 0 < \alpha_2 < 1.0 \qquad (6)$$

The magnitude of α's control the degree of smoothing at each iteration and their ratio control the bias to a class. The magnitude of FACT controls the initial assignment of probabilities. After a few iterations the gray level histogram becomes bimodal with two well separated peaks and the image is segmented into black and white classes.

2.1. Evaluation of the Two Class Gradient Relaxation Algorithm

Since the two class gradient relaxation technique is used as the basis for the region splitting procedure, its performance needs to be understood and evaluated. Three factors are used to evaluate the performance: signal-to-noise ratio, region size and contrast. The following methodology analyzes the first two parameters.

1) A 100x100 synthetic image is created to consist of a square region against the constant background. The size of the square is 50x50 pixels with magnitude of 130 for intensity, and the background has a magnitude of 100 on the gray scale of 0-255. This image is noise-free, and the objective is to extract the square from its immediate background (see Fig. 1(a) top left image).

2) White noise is added to the original image and the signal-to-noise ratio is varied from 1 to 10. It is defined as the square of the step edge amplitude divided by the standard deviation of Gaussian white noise.

3) A *figure of merit* is established to assess the amount of deviation between the noise-free segmentation, and the segmentation obtained on the noisy images. It is defined as the number of the square region pixels which are segmented as background,

and the number of background pixels which are segmented as the square region pixels.

4) The size of the square region is gradually reduced from 50x50 to 5x5 and steps 2 and 3 are repeated to estimate the effect of the region-sizes on the segmentation algorithm.

The results are shown in Fig. 1 for the region-sizes of 50x50, 20x20, and 5x5. The *figure of merit* is plotted in Fig. 2. It shows the error versus the signal-to-noise ratio. Using these figures, this experiment reveals that a) the segmentation algorithm has the noise cleaning effect; b) most of the erroneous labelling occur at the boundary pixels, and c) as the region-size is decreased, the number of mislabeled pixels in the background are increased.

The noise cleaning effect is a major attribute of the relaxation technique. The iterative relaxation process allows the labelling at any pixel location, to depend on the results of the previous iteration. Thus, the process is better informed as the analysis proceeds. The erroneous labelling of the border pixels is due to their inherent instability. For example, all the border pixels in the inner square (with the exception of the corner pixels) are biased toward the inner square, since 5 out of 8 nearest neighbors are voting for the brighter square region. This results from a slight noise distortion in the vicinity of the border data created by shifting the pixel balance, thus producing a wrong assignment. The effect of shrinking the region-size is evident in Fig. 1(a) through 1(c). As the region-size is reduced, the contribution of the smaller region is decreased in the global mean, thus, increasing the initial probability and compatibility measure at each pixel location. Therefore, it increased the number of mislabelled pixels.

The contrast can be defined as a function of the mean difference between the delineated square region and the background. In other words, it is a measure of the overall variance of the image. It was found through experiments that the relaxation algorithm, as defined by equations (4) to (6) can partition the above synthetic images (Fig. 1) provided that the signal-mean is approximately 25% above the background-mean. Fig. 3 shows the effect of contrast and noise on the region extraction. To enhance the performance of the segmentation algorithm, the estimation of the initial probability (equation (4)) was revised to include both mean and variance of the image. This is done by replacing IBAR with (IBAR-bias) where bias is defined in Fig. 4, and its value is obtained in such a way that the segmentation error across a wide range of the contrast is minimized. With this change the lower contrast image with signal intensity=110 and background intensity=100, small square region, was successfully extracted. Consider what has occurred: as the variance of the image is decreased, the value of the bias is increased, thus, increasing the initial probability assignment and local compatibility measure. Consequently, this change forces region extraction from the background.

2.2. A Real time Architecture for the Two Class Gradient Relaxation Algorithm

To emphasize the simplicity of the two class segmentation algorithm, its real time implementation is also examined and evaluated. The implementation shown in Fig. 3 is of a pipelined architecture, and consists of three components:

1. Computation of the initial probability,
2. Computation of the compatibility vector, and
3. Updating the probability vector.

Since the computation of the initial probability depends on the global mean and variance of the image, it is assumed that these two variables are computed on the previous frame. In other words, the global mean and variance do not change significantly on the frame to frame basis. In many image understanding problems such as biomedical data analysis, the computation of mean and variance is not necessary, since, either the mean and variance are known apriori, or they have to be computed only once. The second component of the relaxation algorithm is the computation of compatibility vector which is defined as the mean probability of the neighborhood. To align the eight near neighbors, two shift-registers and nine registers are employed (Fig. 5), and a tree of carry-save-adders is used to compute the local mean. Next, the most significant bit of the compatibility measure is checked to either increase or decrease the current probability assignment.

This architecture enables the application of the relaxation algorithm a viable approach to image segmentation in real time environment. Currently the VLSI implementation of this algorithm is in progress.

3. Extension to Multiclass

3.1. Recursive Region Splitting

The multiclass segmentation algorithm is fundamentally a region splitting technique. Historically [8, 13], these techniques rely on the analysis of the gray level (or Color) histogram. In this context, the image is split into separate parts along the regions of nonuniformity. The location of the sharp boundary variation is determined either by locating the valley in the histogram which often requires histogram smoothing to eliminate small peaks, or partitioning the histogram into intervals where each interval satisfies an elaborate set of rules [13] such as,

i) the interval must contain a marked peak, ii) the area of the interval is above a prespecified threshold, iii) the highest peak in an interval is above a certain amplitude, and iv) the valleys on each side of the interval are sufficiently low.

The splitting is done by finding a well separated peak. If no split can be done, then either the region is considered to be segmented or in cases where there is a lack of spectral features such as monochromatic images, arbitrary partitioning of the image is done and the splitting is done recursively.

The proposed multiclass segmentation algorithm depends on the recursive application of the two class segmentation algorithm discussed earlier. Consequently, splitting of the image based on mere global histogram is avoided, and the segmentation at each level of the hierarchy, is allowed to depend on local neighborhood activity.

Another important issue in region splitting is the ambiguity of the border (edge data) pixels. An approach to this problem is "conservative thresholding" [13] where the original threshold is actually replaced by two thresholds, one to left and the other one to the right of the original threshold. The pixels to the right of the rightmost threshold and left of the leftmost threshold are labelled normally, whereas the pixels that lie between the two thresholds are not labelled and region growing is used to fill in the labels for these pixels. In the proposed multiclass segmentation algorithm, the border pixels are masked off, and are not labelled initially. However, the border pixels are used in computation of the compatibility coefficients for the pixels directly adjacent to them. After the segmentation process, region growing is used to fill in for the border pixels.

In summary, the two class segmentation algorithm is applied to the entire image, splitting the image based on its global and local properties, into two distinct classes. Next, all the connected-components of the segmented image are isolated and labelled. Then each connected-component is used as a binary mask on the original image to partition it further. A region is said to be partitionable if it has a valley in its histogram, and as it will be shown later by an example, if such a valley exists, its selection is trivial. This process continues recursively until a region is either nonpartitionable (unimodal), or its area is small enough that its further partioning is of no interest. Currently, any region that has an area of less than one percent of the total image area is not partitioned further. In addition, any region that is less than 0.05% of the total image area is not labelled at all. These holes are either due to noise or sharp local intensity variation, and are filled in during the final analysis. The multiclass segmentation algorithm is formally defined below. Note that only the local variables are pushed onto the stack.

```
procedure SEGMENT (image, mask, border_mask, 2_class_image)

global       image                  :2_D array; /*original image*/
             mask                   :2_D array; /*initialized 'true'*/
             border_mask            :2-D array; /*array of border pixels*/
             2-class_image          :2_D array; /*2 class segmentation image*/
             split_flag             :boolean;
local        connected_component    :2_D array;
             label                  :1_D array;
/* 'label[i]' is an array which maintains the area of the labeled-region 'i'*/

begin
      MARK_BORDER_PIXELS (mask, border_mask); /*set all the border pixels
of the 'mask' array true, return the border pixels in 'border_mask'*/

      2_CLASS_SEGMENT (image, mask, border_mask, 2_class_image); /* apply
the 2 class segmentation algorithm to the 'image' where ever 'mask' is true
and border_mask is false.*/

      REGION_GROW (2_class_image, border_mask); /* perform region growing
on the segmentation result where ever the border pixels 'border_mask' is
true*/

      LABEL_CONNECTED_COMPONENT (2_class_image, mask, connected_component,
label, split_flag); /* find all the connected-components, and create a
list of the assigned 'label'.  Set 'split_flag' true, if more than one
connected-component is found.  i.e. the two class segmentation did
split the image.*/
      i : = 1;
      while label[i] not null do
              begin
              if split_flag then
                      begin
                      if label [i] > threshold_area then
                               begin
                               SET_MASK(LABEL[i]); /* Set mask true where
ever the connected-component array has value equal to label [i].*/
   SEGMENT(image, mask, border_mask, 2_class_image);
                                 end;
                        end
                        else ASSIGN_LABEL(i);
/* Region i is not partitionable, assign a label to it */
                 i = i + 1;
                 end;
end;
end SEGMENT
```

Note that the recursive segmentation algorithm, described above, does not assume a known number of classes. In other words, it is unsupervised, and allows classes to be generated as required. This is accomplished by first extracting the dominant regions based on the global feature activity and then using these regions to structure finer segmentation in a hierarchical manner so that the local feature activity is revealed.

3.2. Region Merging

A side effect of any pure recursive region splitting algorithm is fragmentation and it may lead to poor segmentation results for some images [6]. Therefore, we use a merging step which removes fragmentation and improves the performance of the relaxation algorithm for a much wider class of images.

After the splitting algorithm has been applied, the image consists of a set of regions where each of them is uniquely labelled. The goal of merging is to test whether the histogram of two adjacent regions is unimodal. If the test is successful then the two regions are merged; otherwise they remain intact. Such a test is usually achieved by measuring the gray scale variance of the adjacent regions. Assuming that adjacent regions X1 and X2 are of size n1 and n2 pixels respectively. then there are (n1+n2)!/(n1!)*(n2!) ways to merge the two regions. Since n! grows as n^n, a simple test [14] was defined to be:

$$C_{12} = V_0^{n1+n2}/(V_1^{n1} \cdot V_2^{n2})$$

where

V0 = the standard deviation across region X1 and X2,
V1 = the standard deviation across region X1 and
V2 = the standard deviation across region X2

C12 is a confidence measure that regions X1 and X2 are separable.

Several variations of this criterion have been used for merging [7]. In this paper, adjacent regions are merged if they have equal means. The test for equal mean is based on the analysis of variance. The technique is as follows:

1a. Compute mean of each region,

$$X_i=(1/n_i)\Sigma^{n_i}_{j=1}x_{ij},$$ where x_{ij} is jth pixel intensity of region i.

1b. Compute mean of the combined regions,

$$X=(1/n)\Sigma^{2}_{i=1}n_iX_i$$

2a. Compute sum of squares between the means of the regions and the mean of the combined regions,

$$Q1=\Sigma^{2}_{i=1}n_i(X_i-X)^2$$

2b. Compute sum of squares within region,

$$Q2=\Sigma^{2}_{i=1}\Sigma^{n_i}_{k=1}(X_{ik}-X_i)^2$$

2c. Compute the quotient $V = Q1(N-2)/Q2$, where $N=n1+n2$

3. Choose a significant level of α at 5% and determine the solution c of the equation $p(V <=c)=1-\alpha$.

4. From the F-distribution table with (1,n-2) degrees of freedom find the value of c; if $V <= c$ then accept the unimodality hypothesis and merge the two regions.

The above methodology assumes that all n1 and n2 pixels are independent. Obviously, the intensity information in a given image is spatially correlated. For this reason only a fraction of pixels are used to compute the statistic of the adjacent regions This fraction is 5% of pixels in each region. Further, if regions X1 and X2 are merged then statistic of the new region is updated and all of the new neighbors are recursively examined for further merging.

Note that since we are not arbitrarily partitioning the image, it is possible to avoid this merging step altogether if a smoothing operation (expansion and contraction) is carried out on the binary mask to eliminate small regions, holes and thin connections between regions.

3.3. Results of the Multiclass Technique on Synthetic & Natural Scenes

Synthetic Images: Three synthetic images are used to evaluate the performance of the multiclass segmentation algorithm. These images have also been used by Nagin et. al. and Price [7, 11].

Example 1: Fig. 6(a) shows a synthetic image with its gray level histogram. There are four regions in this image. The means are R1=10 and R2=25 for the top outer and inner rectangles and R3=40 and R4=14 for the bottom ones with standard deviation=3 for all cases. The histogram reveals three distinct peaks, as the distribution of the R2 and R4 is represented by the same peak. However, since R2 and R4 are not spatially adjacent, they are labelled as two separate regions. Note that R1 and R4 would merge together if they were spatially adjacent. In Fig. 6(b) left image is the original image and the right image shows the segmentation results after region splitting. The multiclass technique produces results which are similar to those of [7, 11].

This experiment is repeated by changing the intensity of the region R4 from 14 to 17, and the multiclass segmentation algorithm produced an identical result. The importance of this test is that as the intensity of R4 is changed to 17, its distribution becomes completely ambiguous in the histogram. As a result, the techniques that depend solely on the global histogram peaks for initial probability assignment are subject to failure [7].

Example 2: Fig. 7(a) shows the previous image with R4 replaced with a ramp function which varies from 11 to 18 from the top to the bottom. The result is shown in Fig. 7(b). Evidently, the relaxation scheme did not correctly label a very small number of pixels. This is due to the very low contrast variation in R4.

Natural Images: Two natural images of approximate size 200x200 pixels are examined. The first one is a green component of the color house image. It is shown in Fig. 8 together with its gray level histogram. The same image has been used by many researchers. Fig. 9 shows the results of the two class gradient relaxation algorithm on the original house image. It is evident from Fig. 9(b) that the selection of the binarization threshold is trivial. Fig. 10(a) shows the segmentation results following region splitting. Fig. 10(b) shows the outline of the regions obtained after the split and merge process. The results indicate that the sky, roof, front wall, bushes and windows are well segmented and most of the details in the images are maintained. Segmentation problems have occurred, however, at three locations: i) the left corner of the roof where it is split into three parts; ii) the left tree where it is merged with the left window; and iii) the roof which is merged with the right tree.

The second natural image is shown in Fig. 11 together with its histogram. It is an aerial image consisting of several roads and a storage tank complex. The segmentation results after recursive region splitting are shown in Fig. 12(a) and the boundaries of the extracted regions after the split and merge process are shown in Fig. 12(b). Note that the results indicate that the tank complex, main highway, curved road and the background are well extracted. However, some parts of the highway are merged with the background; this is due to the small width of the road.

4. Conclusions

In this paper, the performance of the two class gradient relaxation algorithm was evaluated. The evidence indicates successful segmentation in the presence of noise, low contrast and small region size. The simplicity of the algorithm was demonstrated by providing a real-time architecture. The implementation is possible on the ground that the algorithm requires only local processing for updating the initial probabilities in a subimage. Next, the two class gradient relaxation algorithm was used as the basis for the recursive region splitting which was followed by region merging to resolve fragmentation. One shortcoming of the proposed technique is its inability to extract narrow line segments as required for roads and highways. One possible solution is to make use of the intensity and edge information in an integrated manner [3].

The multiclass segmentation technique presented here is a much simpler and conceptually straight forward technique and provides at least as good results on complex natural scenes as the techniques presented in [7, 8]. It uses only the intensity feature as opposed to color or texture features.

References

[1] B. Bhanu.
Shape Matching and Image Segmentation Using Stochastic Labeling.
Technical Report USCIPI 1030, USC Image Processing Institute, Los Angeles, California, August, 1981.

[2] B. Bhanu and O.D. Faugeras.
Segmentation of Images Having Unimodal Distributions.
IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-4(4):408-419, July, 1982.

[3] B. Bhanu and R.D. Holben.
Model Based Segmentation of FLIR Images.
In A.G. Tescher (editor), *Proc. SPIE, Applications of Digital Image Processing VII, Number 504*, pages 10-18. August, 1984.

[4] B. Bhanu, A.S. Politopoulos and B.A. Parvin.
Intelligent Autocueing of Tactical Targets.
In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 502-503. June, 1983.

[5] C.K. Chow and T. Kaneko.
Automatic Boundary Detection of the Left Ventricle from Cineangiograms.
Computer Graphics and Biomedical Research 5:388-410, 1972.

[6] A.R. Hanson, E.M. Riseman and P.A. Nagin.
Author's Reply.
IEEE Trans. on Pattern Analysis and Machine Intelligence PAMI-6:249, March, 1984.

[7] P. Nagin, A. Hanson and E. Riseman.
Studies in Global and Local Histogram Guided Relaxation Algorithms.
IEEE Transactions on Pattern Analysis and Machine Intelligence :263-276, May, 1982.

[8] R. Ohlander, K. Price and D.R. Reddy.
Picture Segmentation Using a Recursive Region Splitting Method.
Computer Graphics and Image Processing 8:313-333, 1978.

[9] B.A. Parvin and B. Bhanu.
Segmentation of Images Using a Relaxation Technique.
In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 151-153. June, 1983.

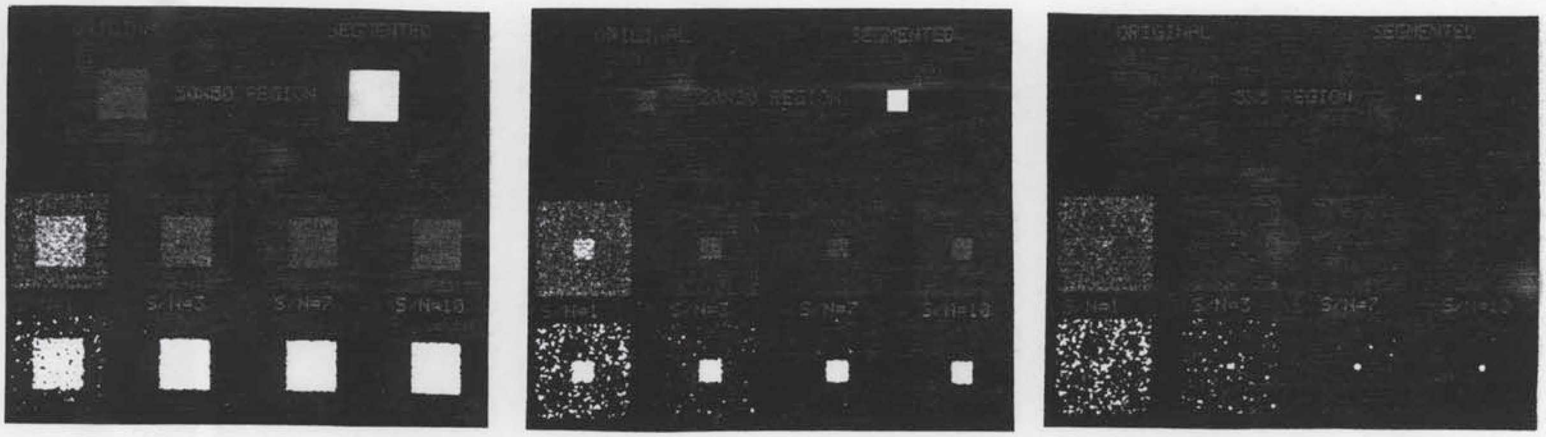
[10] B.A. Parvin.
A Split and Merge Algorithm for Segmentation of Natural Scenes.
In *Seventh International Conference on Pattern Recognition*, pages 294-296. 1984.

[11] K. Price.
A Comment on - Studies in Global and Local Histogram Guided Relaxation Algorithms.
IEEE Transactions on Pattern Analysis and Machine Intelligence :247-249, March, 1984.

[12] A. Rosenfeld, R. Hummel and S. Zucker.
Scene Labeling by Relaxation Operations.
IEEE Transactions on Systems, Man, and Cybernetics SMC-6(6):420-433, June, 1976.

[13] S. Shafer and T. Kanade.
Recursive Region Segmentation by Analysis of the Histogram.
In *International Conference on Acoustics, Speech and Signal Processing*, pages 1166-1171. May, 1982.

[14] Y. Yakimovsky.
Boundary and Object Detection in Real World Images.
Journal of Assoc. Comput. Mach. 23(4):599-618, 1976.



(a) region size 50x50 (b) region size 20x20 (c) region size 5x5

Fig. 1 Effect of noise on the 2 class gradient relaxation technique for regions of various sizes with varying amount of signal-to-noise ratio.

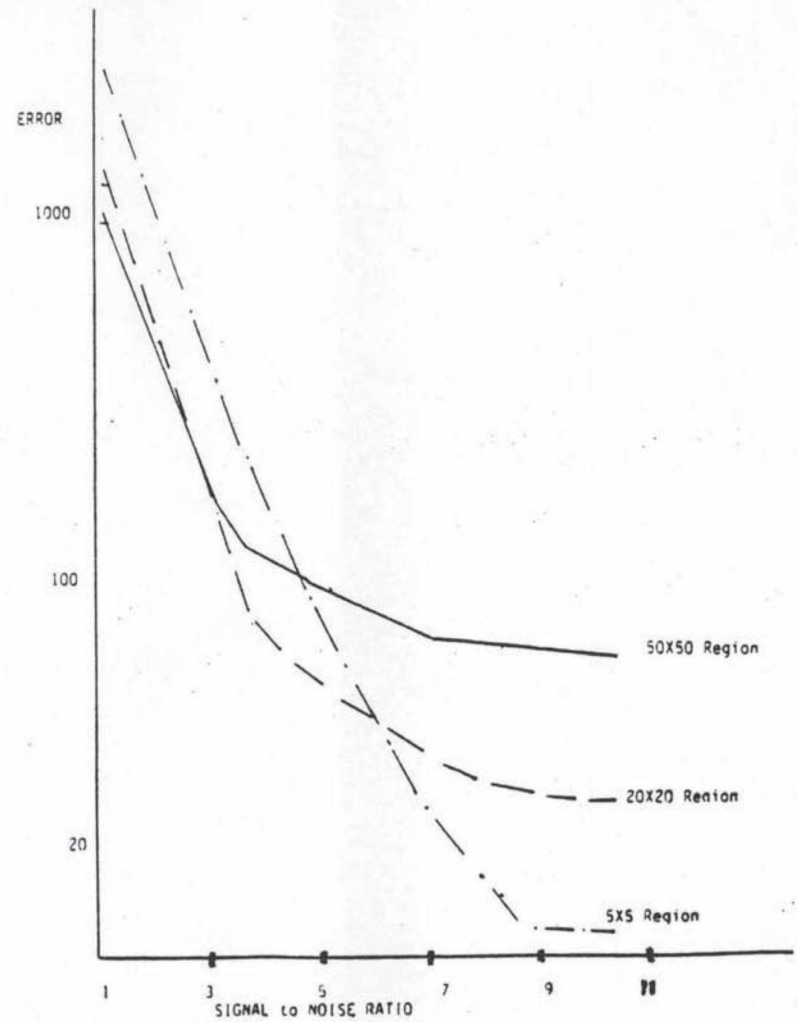
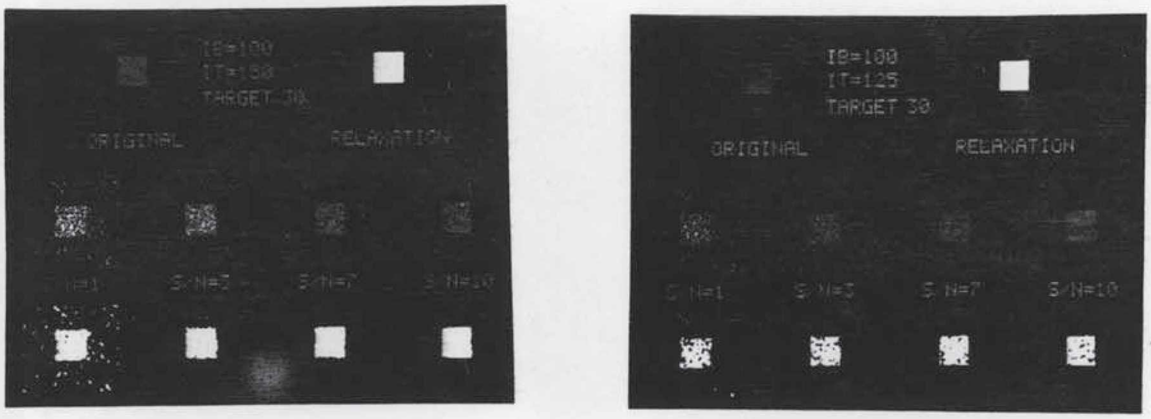


Fig. 2 Pixel classification error versus signal-to-noise ratio for the images in Fig. 1.



(a) (b)

Fig. 3 Effect of contrast and noise on target extraction
(a) target size 30x30, target intensity 150, background intensity 100
(b) target size 30x30, target intensity 125, background intensity 100

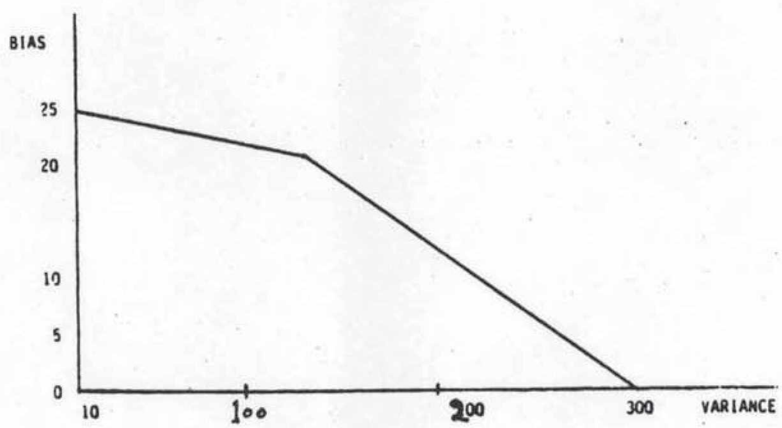


Fig. 4 Relation between bias and variance used in the initial assignment of probabilities.

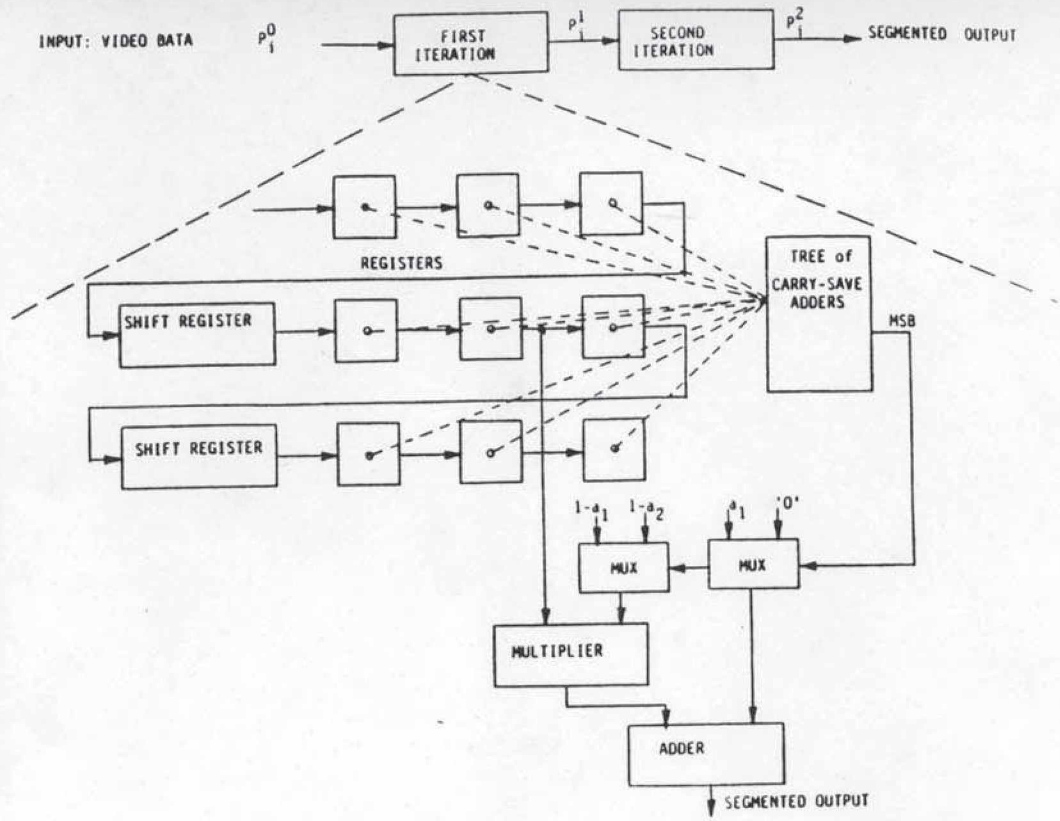


Fig. 5 Real-time implementation of 2 class gradient relaxation algorithm

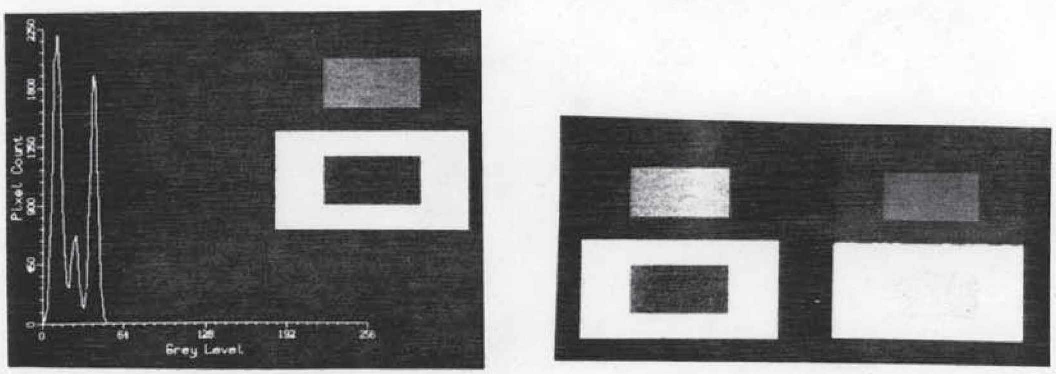


Fig. 6 Case 1. (a) An artificial image and its histogram. The means are 10 and 25 for the top outer and inner rectangles and 40 and 14 for the bottom ones (with standard deviation=3 for all cases). (b) Segmentation results using the recursive region splitting technique.

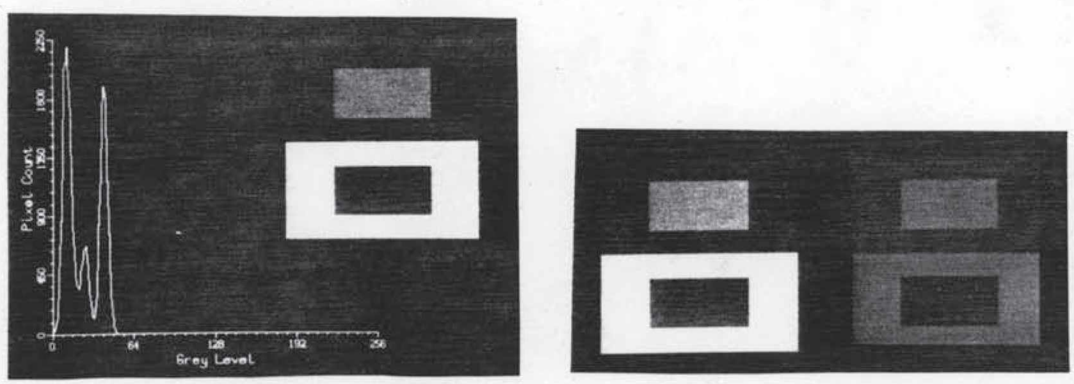


Fig. 7 Case 3. (a) An artificial image and its histogram. The image is the same as in Fig. 6(a) except that the mean for the lower inner rectangle increases from 11 to 18 from the top to the bottom. (b) Segmentation results using the recursive region splitting technique.

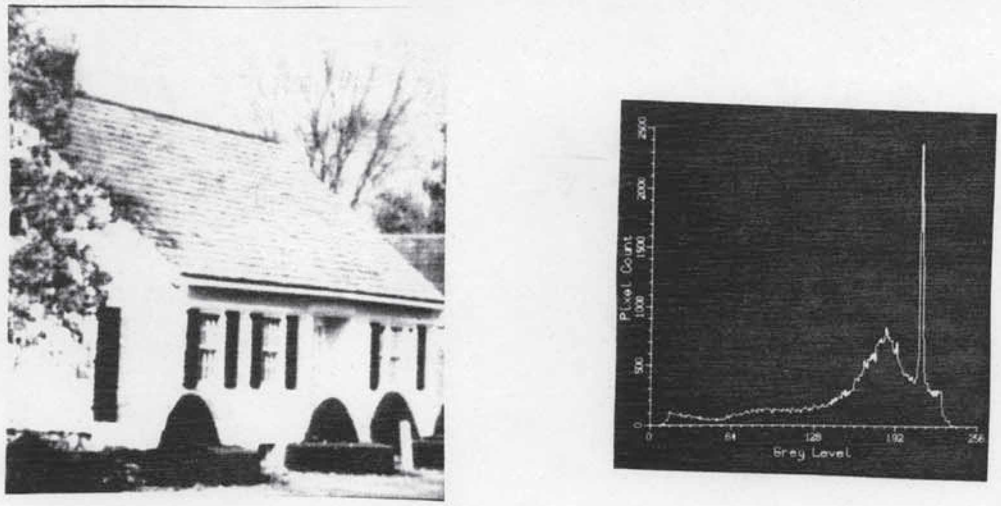
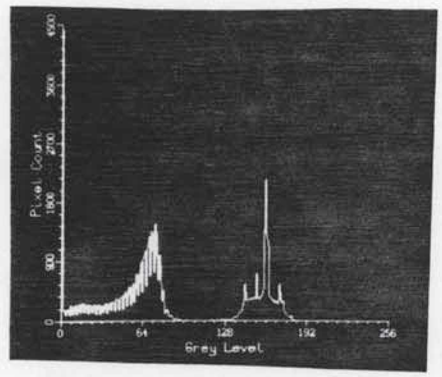


Fig. 8 A house image and its gray level histogram.

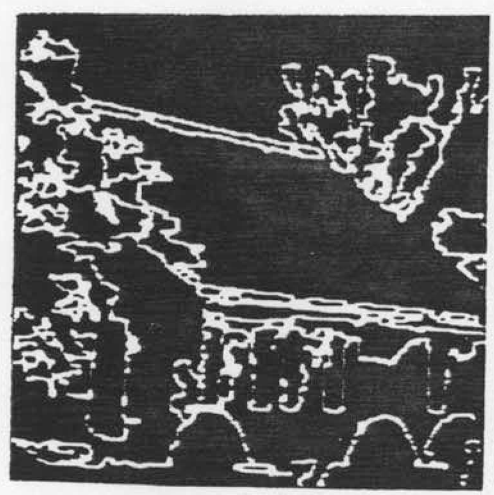
(a)



(b)

Fig. 9 (a) Effect of two class gradient relaxation algorithm on the house image.
(b) Histogram of the image corresponding to Fig. 9(a).

(a)



(b)

Fig. 10 (a) Results of recursive region splitting.
(b) Edge results of the segmented image following the region merging step.

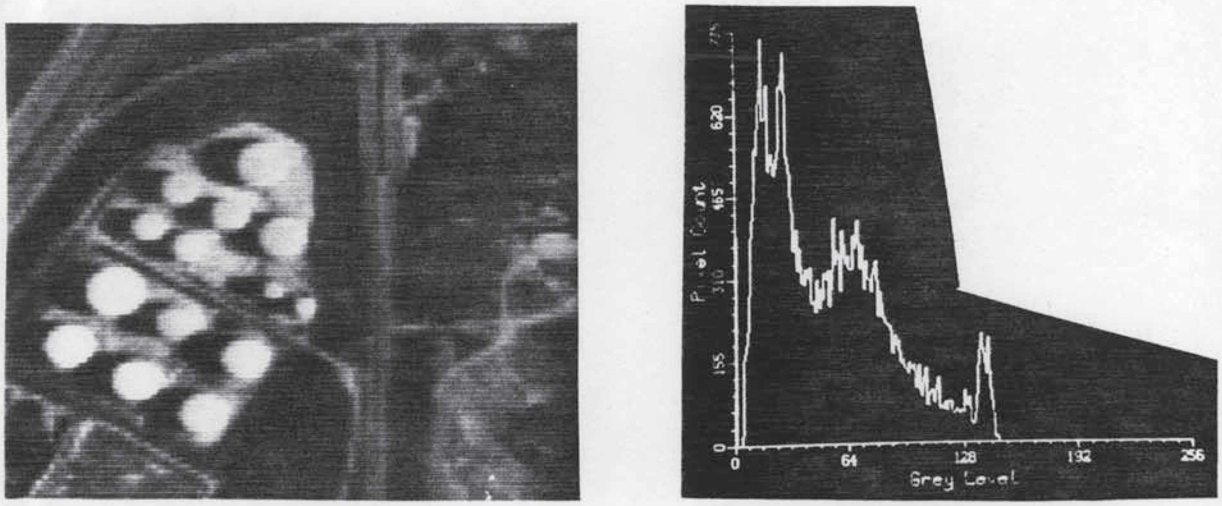
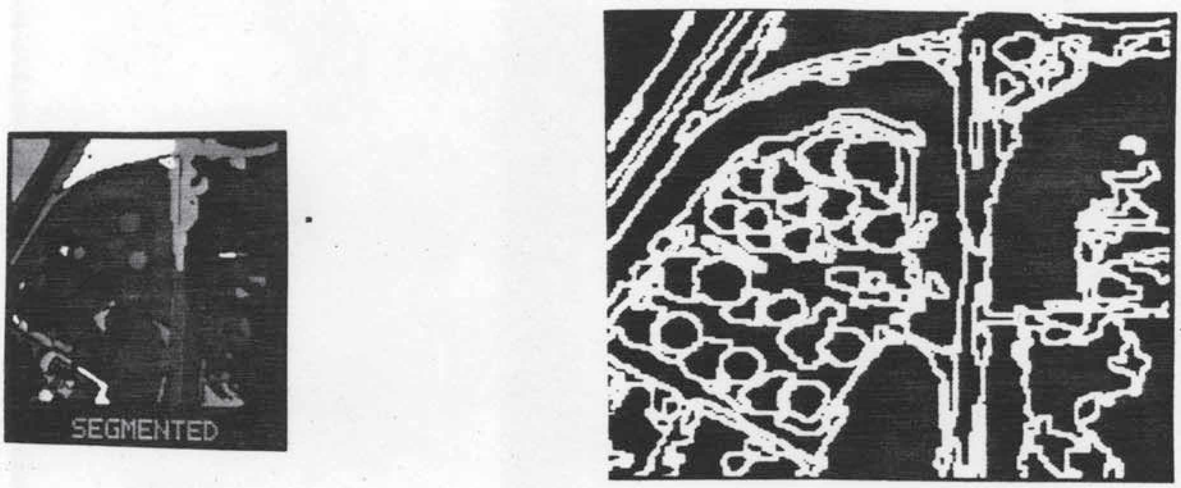


Fig. 11 An aerial image and its gray level histogram.



(a) (b)

Fig. 12 (a) Results of recursive region splitting.
(b) Edge results of the segmented image following the region merging step.

List of Figures

Table of Contents