SEGMENTATION OF IMAGES USING A RELAXATION TECHNIQUE

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ABSTRACT

A new approach to image segmentation via recursive region splitting is presented. The kernal of the proposed segmentation is based on the two class relaxation technique. An evaluation of this relaxation algorithm is made with respect to the signal to noise ratio, region size, and contrast of the objects present in the image. This establishes the validity of the two class segmentation technique for segmenting the objects of interest in a multiclass image, when applied on a local basis and recursive manner. The weaknesses and strengths of the multiclass segmentation are analyzed, and its performance on a natural scene is presented.

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, the segmentation provides a set of symbology and their interrelationships necessary for machine perception. Segmentation algorithms can be catagorized into three different types. These are: edge detection, clustering, and region splitting and merging. This paper employs region splitting via recursive application of the two class relaxation technique. The two class segmentation algorithm [1] allows control over the relaxation process, and provides automatic selection of the threshold. It does not directly depend on the peaks and valleys of the histogram to initiate the relaxation process (initial probability assignment), instead, it exploits the global statistics of the image. As a result, the initial step of the relaxation algorithm is simplified, since it is to be used over and over at the various levels of the region splitting hierarchy. In the recursive region splitting algorithms [2], often the partitioning is done arbitrarily namely, an image is divided into a set of sectors, and each sector is segmented and split further independently. The proposed algorithm allows the partitioning of the image to depend on the outcome of the two class relaxation technique, thus avoiding any heuristic and arbitrary measure for partitioning the image. Finally, the multiclass segmentation algorithm uses only the an intensity feature as opposed to color or texture features.

2. Two class relaxation algorithm: Suppose that N pixels are given, which fall into 2 classes λ_1 and λ_2, corresponding to white and black. To each pixel i, the set V_i of its 8 nearest neighbors is attached. The compatability function c is defined such that like reinforces like by

$$c(i,\lambda_k,j,\lambda_l) = 0, \quad k \neq l, \quad j \text{ in } V_i \text{ for all } i$$
$$c(i,\lambda_k,j,\lambda_k) = 1, \quad k=1,2 \quad j \text{ in } V_i \text{ for all } i \tag{1}$$

The consistency vector q is then defined as the mean neighborhood probability, given by

$$q_i(\lambda_k) = \frac{1}{8}\sum_{j\in V_i}\sum_{l=1}^{2} c(i,\lambda_k,j,\lambda_l)\, p_j(\lambda_l), \quad \begin{array}{l} k = 1,2 \\ i = 1,\ldots,N \end{array} \tag{2}$$

Based on the explicit use of consistency and ambiguity, a global criterion (3) is established, and maximized by using the gradient projection approach. The result is an iterative equation given by 4, with the initial probability assignment given by 5.

$$C(\vec{p}_1, \vec{p}_2, \ldots, \vec{p}_N) = \sum_{i=1}^{N} \vec{p}_i \cdot \vec{q}_i \tag{3}$$

$$p_i^{(n+1)}(\lambda_k) = p_i^{(n)}(\lambda_k) + \rho_i^{(n)}\left[2q_i(\lambda_k)-1\right] \tag{4}$$

$$p_i(\lambda_1) = FACT*\left(\frac{I(i)-\bar{I}}{255}\right)+0.5 \tag{5}$$

3. Evaluation of the two class segmentation algorithm: Since the two class relaxation algorithm [1] is used as a basis for the multiclass segmentation procedure, its performance needs to be understood and evaluated. In this context, the effect of signal to noise ratio, region size, and contrast are investigated. The following methodology analyzes the first two parameters.

i) A synthetic image is created to consist of a square region against the constant background. The size of the square is 50-by-50 with magnitude of 130 (intensity), and the background has the magnitude of 100 (on the gray scale of 0 to 255).

ii) White noise is added to the above image, and the signal to noise ratio is varied from 1 to 10. The signal to noise ratio is defined as the square of the strength of the signal (intensity of the target above the background) to the variance of the gaussian noise,

iii) 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 region pixels which are segmented as background,

and the number of background pixels which are segmented as the region pixels.
iv) The size of the square region is gradually reduced from 50-by-50 to 5-by-5 and steps 2 and 3 are repeated to estimate the effect of the region-size on the segmentation algorithm.

The results are shown in figures 1 to 3. This experiment reveals that 1) the segmentation algorithm has the noise cleaning effect; 2) most of the erroneous labelling occur at the boundary pixels, and 3) as the region-size is decreased, the number of mislabeled pixels in the background is increased. The noise cleaning effect is a major attribute of the relaxation techniques. 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 (except the corners pixels) are biased toward the inner square, since 5 out of 8 near neighbors are voting for brighter section. Finally, the result of shrinking the region size is a reduction in the global mean, which in turn increases the initial probability and compatability measure at each pixel location. Thus increasing the error rate.

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. The relaxation algorithm can partition the above synthetic images, as long as the signal-mean is approximately 25% above the background-mean. To enhance the performance at lower contrast, the estimation of the initial probability is revised to include both mean and variance of the image in such a way that as the variance of image is decreased, the initial probability assignment is increased.

4. Extension to multiclass: The multiclass segmentation algorithm is fundamentally a region splitting technique. Historically [2], these techniques rely on the analysis of the histogram. In this context, the image is split into separate parts along the regions of nonuniformity. Each part is then recursively split until it exhibits a homogenous intensity. The proposed multiclass segmentation algorithm depends on the recursive application of the two class segmentation algorithm. Consequently, partitioning 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 on the border pixels. An approach to this problem has been by "conservative thresholding" 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 and left of the corresponding threshold are labelled normally, whereas the pixels that lie between the two thresholds are not labelled. In this paper, the border pixels are masked off, and are not labelled initially. However, the border pixels are used in computation of the compatability 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, partitioning the image based on its global property, 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 (bimodal). This process continues recursively until a region is either nonpartitionable (unimodal), or its area is small enough that its further partitioning 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.

A natural image of size 200-by-200 is examined (figure 4). The segmentation results, shown in figures 5 and 6, indicates that the sky, roof, front wall , bushes, and windows are well segmented, and most of the details in the image are maintained. In particular, note that the left tree is not badly fragmanted. The poor segmentation has occured, however, at
i) the left corner of the roof, which is split into three parts,
ii) the left tree having merged with the left most window, and
iii) the side wall which is split into several parts.

5. Conclusions: In this paper, the performance of the two class relaxation algorithm was evaluated. The evidence indicates successful segmentation in the presence of the noise, low contrast, and the small region size. Next, the two class relaxation algorithm was employed as the basis for the recursive region splitting segmentation. The only shortcoming of the multiclass segmentation is the presence of fragmentation. However, fragmantation can be avoided by appending a merging algorithm at the end, i.e. split followed by a merge algorithm. A merging procedure, such as the one based on mere contrast difference between two adjacent regions, will remove most of the fragmentation, and improve the performance of the algorithm.

REFERENCES
[1] B. Bhanu, and O.D. Faugeras, "Segmentation of Images Having Unimodal Distribution," IEEE Trans. on PAMI, July 1982, pp. 408-419.
[2] C. K. Chow, and T. Kaneko, "Automatic Boundry Detection of the Left Ventricle from Cineangiograms," Computer Graphic and Biomedical Research, 5, 1972, pp. 388-410.

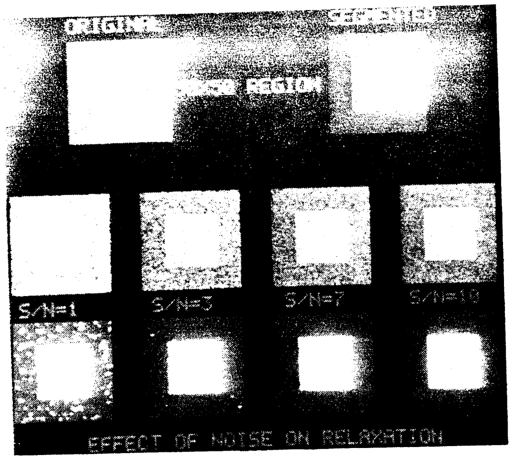


Figure 1

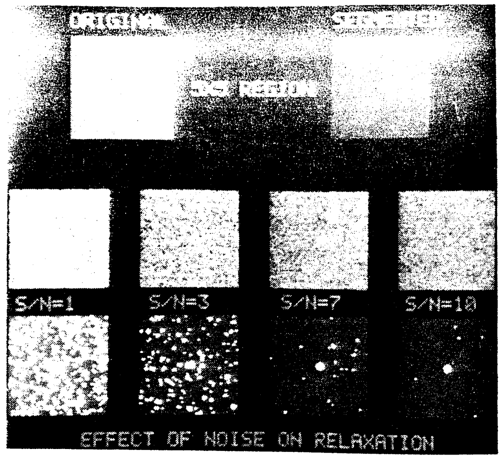


Figure 2

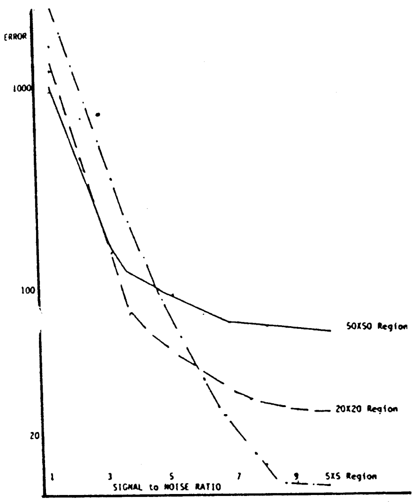
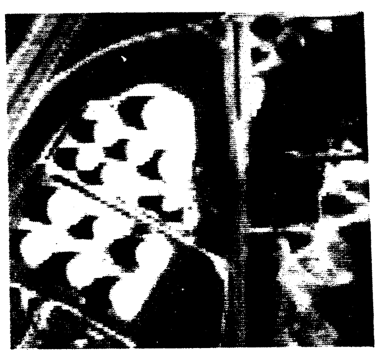


Figure 3

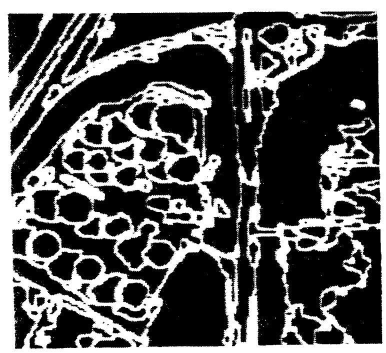
Figure 4

Figure 5

Figure 6
Edge Result



Aerial Image



Edge Result