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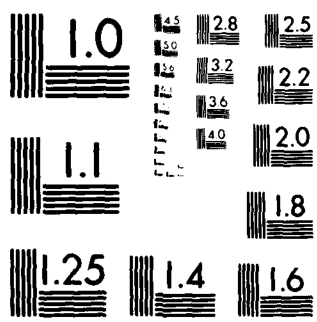

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Technical Report
Contract Number N00014-79-C-0494
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(6) A COMPARATIVE EVALUATION OF STATISTICAL IMAGE SEGMENTATION TECHNIQUES*

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*The support of the Statistics and Probability Program of the Office of Naval Research on this work is gratefully acknowledged.

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A Comparative Evaluation of Statistical Image Segmentation Techniques

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Abstract

Statistical image segmentation refers to the computer-oriented procedures that partition the image into meaningful parts by using the statistical pattern recognition techniques. Although most image segmentation works have been nonstatistical in nature, there is now strong interest in the use of the supervised and the unsupervised classification techniques for image segmentation. In this paper, a critical comparison is made on the supervised image segmentation techniques including the Fisher's linear discriminant, the auto-regressive moving-average modelling, the maximum likelihood region estimation, and the maximum a posteriori region estimation, as well as on the unsupervised image segmentation techniques including the cluster analysis, the estimation-theory based method, histogram directed segmentation techniques, and the decision-directed method using the conditional propulation mixture model. Some computer results are presented. The fundamental issues in the statistical image segmentation and the related topics are also reviewed.

A Comparative Evaluation of Statistical Image Segmentation Techniques

I. Introduction

Statistical image segmentation refers to computer-oriented procedures that partition the image into meaningful parts by using statistical pattern recognition techniques. Although most image segmentation work has been nonstatistical in nature, there is now strong and renewed interest on the use of supervised and unsupervised classification techniques for image segmentation. In this semi-tutorial paper, the fundamental issues on statistical image segmentation are examined. A critical comparison is made on supervised image segmentation techniques including the Fisher's linear discriminant, the autoregressive moving-average (ARMA) modelling, the maximum likelihood region estimation, and the maximum a posteriori region estimation, as well as on the unsupervised image segmentation techniques including the cluster analysis, the estimation-theory based method, histogram directed segmentation techniques, and the decision-directed method using the conditional population mixture model. Some computer results are presented. It is concluded that the supervised techniques, whenever applicable, generally can perform better than the unsupervised techniques. Presently the statistical approaches are limited to segmentation using pixel and local properties. The use of global information such as the statistical inter-region dependence as well as the mixed statistical-structural approach is also discussed.

It is noted that an earlier semi-tutorial paper on image segmentation [1] discussed the segmentation techniques from the standpoints of image models that include both statistical and spatial models. The present paper is limited to the discussion of statistical techniques in image segmentation.

II. Supervised Image Segmentation

1. Fisher's Linear Discriminant Method

Ahuja et. al. [2] recently presented detailed computer results on the pixel classification by using the Fisher's linear discriminant method. They use as features the gray levels in the neighborhood of a point. Further computer work performed by us [3] also indicates that the Fisher's linear discriminant is quite effective for the segmentation of infrared and reconnaissance images. A new form of theoretical error probability is proposed which compares very favorably with the experimental error rate. For illustrative purpose, Figs. 1-5 show the segmentation of a reconnaissance image. Figure 1 indicates the assignment of regions, I, II, III for the image considered. Figure 2a is the original image. All displays are in binary (or two-level) form. A neighborhood of size 3x3 is considered in this study. Without additive noise, Fig. 2b is the classified (segmented) result with M_1, M_2 learning samples taken from regions II and I respectively. Similarly Fig. 2c is the classified result with M_1, M_2 learning samples taken from regions III and I respectively. Each learning sample corresponds to the gray levels of a 3x3 neighborhood. Because of the gray level distribution in region II, the classified result given by Fig. 2c is better than that of Fig. 2b. Figures 3, 4, and 5 include additive white Gaussian noise with variance 1 and zero mean and with signal-to-noise ratios of 0.2, 1.0, 2.0 ıespectively. In these three sets of figures, b and c are classified results by using fixed weight matrix computed from original image of Fig. 2a, d and e are classified

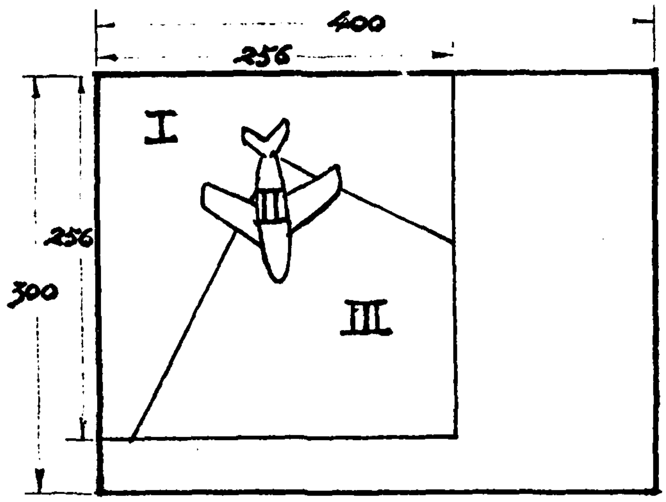

Figure 1

Fig. 2a
Th= 150

Fig. 2b M_1, M_2(II,I)

Fig. 2c M_1, M_2(III,I)

Fig. 3a
Th= 150
S/N= .2

Fig. 3b M_1, M_2(II,I)

Fig. 3c M_1, M_2(III,I)

Fig. 3d M_1, M_2(II,I)

Fig. 3e M_1, M_2(III,I)

Fig. 4a
Th= 150
S/N= 1.

Fig. 4b M_1, M_2(II,I)

Fig. 4c M_1, M_2(III,I)

Fig. 4d M_1, M_2(II,I)

Fig. 4e M_1, M_2(III,I)

Fig. 5a
Th= 150
S/N= 2.

Fig. 5b M_1, M_2(II,I)

Fig. 5c M_1, M_2(III,I)

Fig. 5d M_1, M_2(II,I)

Fig. 5e M_1, M_2(III,I)

results by using weight matrix computed from the noisy image provided. The experimental results clearly illustrate dependence of segmentation result on the selection of learning samples.

2. The ARMA modelling

One approach to model the spatial dependence of gray levels in an image is to consider the image as a sequence of random variables, each of which is dependent on some of the preceding ones. The approach uses the autoregressive moving-average (ARMA) model. For a given order of ARMA model, each region is characterized by a set of model parameters. A new image can be constructed from the predicted values of the ARMA model. An optimum threshold can then be determined to segment the predicted image into a binary image. Recently we employed a second order two-dimensional ARMA model for noise filtering and image segmentation [4]. For illustrative purpose, Fig. 6 shows the result of segmentation by ARMA model. Figure 6a is the original image (same scene as Fig. 2a) in two-level display along with the histogram of the original image. Figure 6b is the noisy image. Figures 6c and 6d are the segmented images after noise filtering. Histograms of the images before segmentation are also shown. The signal-to-noise ratio considered is 1.73. The result is comparable to that of Fig. 5, but the ARMA modeling requires much more computation. The above operations are in fact unsupervised. If classified learning samples of object and background are given, better pixel classification is expected by using model parameters (coefficients) as features. Further work is needed in this direction.

The ARMA models have been quite useful for texture analysis and synthesis ([5] and extensive references in this paper), and are thus particularly suitable for segmentation of textured images. The

Fig. 6a

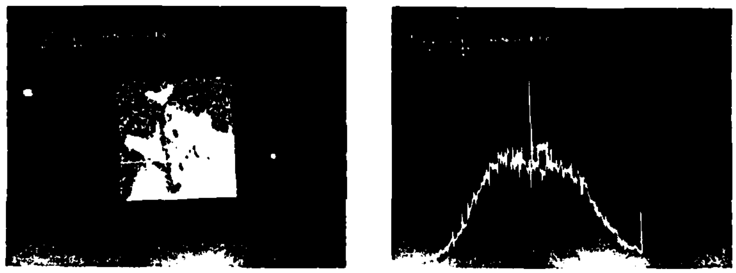

Fig. 6b

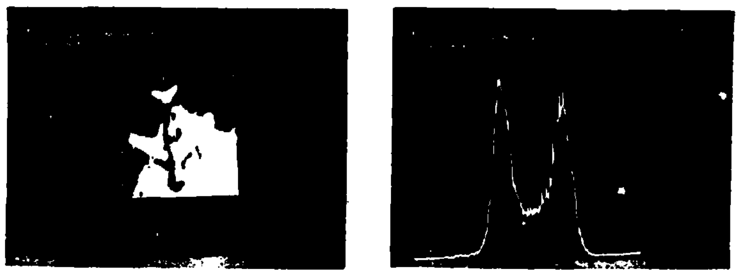

Fig. 6c

Fig. 6d

limitation of the models, as clearly pointed out in [1], is that symmetrical dependence is mathematically much less tractable.

3. Maximum Likelihood Estimation and Maximum a Posteriori Estimation

An algorithm involving comparison of linear predictive error residuals has been suggested by Haralick [5]. This approach can be shown to be equivalent to computing a maximum likelihood estimate for the regions when the textures are modeled by autoregressive processes driven by white noise sources with equal variances. Recently Therrien [6] indicated that the maximum likelihood procedure tends to produce an abundance of false regions. He proposed a maximum a posteriori region estimate as follows. Observe that a segmentation of the image is completely equivalent to an assignment of the pixels to 0 and 1. Such an assignment for a pixel is referred to as its state and assume that the states form a Markov chain with certain transition probabilities. By incorporating the transition probabilities in the probability density for the image, we can form the posterior probability of the state assignment. An iterative procedure is used to maximize the posterior probability. Experimentally Therrien was able to show that the maximum a posterior region estimate performs better than the maximum likelihood estimate. To segment the image into background and object, it is noted that learning samples from each class are needed in both maximum likelihood and maximum a posteriori estimates.

III. Unsupervised Image Segmentation

1. Cluster Analysis

A segmented image may be considered as a set of clustered points in a high dimensional space. Each cluster may possess certain distinctive characteristics such as the homogeneity to aid further analysis. Thus the clustering methods developed in the mathematical pattern recognition provide a promising approach to the image segmentation, although it has previously been believed that a pure clustering approach was too cumbersome computationally to implement. Computationally efficient algorithms have been developed for image segmentation (e.g. [6] [7] [8] [9]). The basic procedure is a K-means clustering algorithm which converges to a local minimum in the average squared intercluster distance for a specified number of clusters. Experimentally we have found that the algorithm is effective for certain images. To add flexibility to the algorithm, the test of cluster validity and reclustering must be incorporated in the segmentation process.

Preprocessing and feature selection are almost always needed. Preprocessing includes image smoothing and sharpening operation, decorrelations, etc. while the features selected may relate to the gray-level (brightness) and texture for several window sizes centered on every pixel. Feature evaluation and reduction can make use of the distance measures. For a discussion of the texture features, see [5] [10]. It is noted that the clustering analysis is an unsupervised approach to segmentation. Even though such segmentation may not be as satisfactory as human segmentation, it is necessary in some practical applications in which the classified learning samples may not be available or the real-time segmentation is required. The unsupervised approach may also reveal some characteristics in the image that were unobserved by human observers.

2. Estimation-theory Based Method

Image segmentation can be considered as an estimation problem. Chen and Pavlidis [11] proposed an estimation-decision process within the framework of a split-and-merge algorithm. After statistical parameter estimation, a region can be tested to determine its uniformity, i.e. homegeneity. Split-and-merge algorithm can be applied to grow or split regions as needed. After a sufficiently large number of iterations, small regions containing the boundary will remain. Curve fitting method can then be used to determine the boundary accurately. For the textured images, the authors also considered the use of correlation coefficients for segmentation [12] in terms of the split-and-merge algorithm.

3. Histogram Directed Segmentation

In spite of many recent research efforts in image segmentation, the simple histogram directed segmentation remains to be an effective segmentation method [13] as compared to the other methods such as the quadtree based method and the relaxation method. The histogram-directed segmentation may also be used as an initial segmentation which can be refined with other methods. The optimum threshold must be determined for the one-dimensional and multivariate histogram directed segmentation (see e.g. [14]).

4. Conditional Population-Mixture Model

The conditional population-mixture model as suggested by Sclove [15] is a decision-directed image segmentation or clustering technique. The K-means clustering algorithm is a special case of the model. By using a 2x2 image sample, the 4-dimensional feature space may be assumed to be multivariate Gaussian with the parameters iteratively estimated by decision directed learning samples. Assume that the background and object are two regions under consideration. As the mean vectors and covariant matrices are different for the two regions, the complete probability density rather than the Euclidean distance or weighted distance should be used for pixel classification. We have performed experimental study of this method for comparison with other statistical image segmentation methods. Figure 7b is the noisy image of a portion of airport scene (Fig. 7a) studied in Figs. 1-6. For the signal-to-noise ratio of 1.73 considered the decision directed segmentation result is shown in Fig. 7c. If the signal-to-noise ratio is reduced to 0.87 as shown in Fig. 7d, the segmented result as shown in Fig. 7e has more noise. If the noisy image is first preprocessed with median filtering and then by the conditional population-mixture model, the result is much improved as shown in Fig. 7f. Generally speaking the segmented result is noisier than those of Fisher's linear discriminant and the ARMA model. Furthermore the method requires considerably more computation and the convergence is slow.

IV. Review of the Fundamental Issues

The most fundamental issue in the statistical image segmentation as well as classification is the use of contextual information [16]. It is not possible in most cases to obtain the probability density of a set of neighborhood pixels without making simplifying assumption such as Markov dependence and ARMA modelling. Various methods of the statistical image segmentation have attempted to utilize the contextual information in the computationally feasible ways. In image analysis we often have too limited number of samples for the statistical analysis to provide a reliable segmentation. As discussed in the previous sections, good statistical descriptions of various regions are needed for effective segmentation. Iterative procedures are almost always used to establish accurate statistical information. Proper selection of image features is another problem area closely related to the statistical segmentation.

Fig. 7a

Fig. 7b

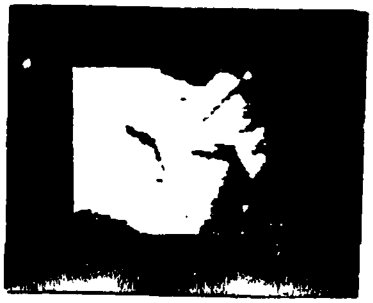

Fig. 7c

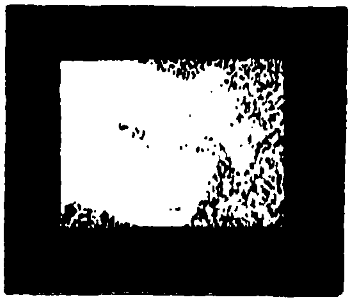

Fig. 7d

Fig. 7e

Fig. 7f

V. Related Topics

Many computer results have shown that the statistical image segmentation is very promising. There are fundamental limitations on what the statistical methods can accomplish. Presently the statistical approaches are limited to the segmentation using pixel and local properties as it is much easier to establish the statistical information of a pixel and its neighborhood. Such local statistical information is indeed important but not sufficient for the more complete characterization of an image. Statistical dependence among regions should be incorporated in the segmentation process. A simple technique is to use the correlation coefficient to test the similarity among regions.

It is important to note that the image also contains structural information which cannot be properly described statistically. How to utilize both statistical and structural information in an effective manner has been a difficult problem. However, some promising approach has now been available [17] and it has confirmed that the mixed statistical-structural approach can perform better than the use of the statistical or the structural approach alone.

Finally we would like to point out that a number of important works have been done at the edge (boundary) based statistical segmentation. This is a proper subject for a separate paper.

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) A Comparative Evaluation of Statistical Image Segmentation Techniques		5. TYPE OF REPORT & PERIOD COVERED Technical Report
		6. PERFORMING ORG. REPORT NUMBER SMU-EE-TR-81-3
7. AUTHOR(s) C. H. Chen		8. CONTRACT OR GRANT NUMBER(s) N00014-79-C-0494
9. PERFORMING ORGANIZATION NAME AND ADDRESS Electrical Engineering Department, Southeastern Massachusetts University, North Dartmouth, MA 02747		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR 042-422
11. CONTROLLING OFFICE NAME AND ADDRESS Statistics and Probability Program, Office of Naval Research, Code 436, Arlington, VA 22217		12. REPORT DATE January 26, 1981
		13. NUMBER OF PAGES 18
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

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17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

This paper will be presented at the IEEE Pattern Recognition and Image Processing Conference, August, 1981, Dallas, Texas.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Statistical image segmentation. Fisher's linear discriminant method.
The ARMA modelling. Cluster analysis. Estimation-theory image segmentation.
Conditional population-mixture model for image segmentation.
Supervised and unsupervised image segmentation.

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

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