ACKNOWLEDGMENT

The author is grateful to Prof. T. Cover of Stanford University for many helpful discussions.

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Adaptive Image Region-Growing

Yian-Leng Chang and Xiaobo Li

***Abstract*— We propose a simple, yet general and powerful, region-growing framework for image segmentation. The region-growing process is guided by regional feature analysis; no parameter tuning or *a priori* knowledge about the image is required. To decide if two regions should be merged, instead of comparing the difference of region feature means with a predefined threshold, we adaptively assess region homogeneity from region feature distributions. This results in an algorithm that is robust with respect to various image characteristics. Our merge criterion also minimizes the number of merge rejections and results in a fast region-growing process that is amenable to parallelization.**

Manuscript received September 14, 1993; revised May 17, 1994. This work was supported by the Canadian Natural Sciences and Engineering Research Council under Grant OG9198. The associate editor coordinating the review of this paper and approving it for publication was Prof. Roland T. Chin.

The authors are with the Department of Computing Science, University of Alberta, Edmonton, Alberta, Canada T6G 2H1.

IEEE Log Number 9404451.

I. INTRODUCTION

In this project, we studied the region-growing approach to segmentation. The decision to merge regions is often based on comparing the difference of their feature measures with a predefined value known as the segmentation threshold. Threshold determination is a difficult problem, yet the selection of an appropriate threshold is crucial to the success of a region-growing process. In the existing methods, threshold determination is either based on *a priori* knowledge, histogram analysis, or is a tedious trial and error process. Although single thresholds may be sufficient to segment simple images, it has long been realized that multiple thresholds are required to produce segmentation of more complex images. Existing multiple-threshold region-growing algorithms apply either position-varied [4], [7] or time-varied [8] thresholds in their segmentation processes. In the former approach, position-dependent thresholds, determined using *a priori* knowledge about an image or by local thresholding techniques, are applied on different parts of the image. Time-varied threshold region-growing refers to the application of varying thresholds during different stages of the region-growing process.

Our algorithm differs from the existing adaptive methods in the simplicity and generality of our adaptive homogeneity test. Unlike the existing methods, our adaptive algorithm does not require *a priori* knowledge, nor does it depend on local thresholds obtained from regular sized subimages. Our algorithm uses both position- and time-varied thresholds that are dynamically and automatically computed in the region-growing process. To select the most suitable threshold for merging two regions, feature histogram analysis is performed on the fly based on regions being formed in the merging process. Also, unlike the hypothesis model given by Chen, *et al* [4], our adaptive test can be applied on features having nonnormal, arbitrary distributions.

In this study, we compare our simple and general purpose adaptive approach with the simple and still widely used fixed threshold method. Fixed threshold refers to the use of static threshold(s) applied globally or locally on an image in the segmentation process. The reader is referred to [2] for timing results and parallel implementations of the algorithm. Also, we only focus on the pure merge region-growing approach. On implementations where a split-and-merge approach may result in shorter processing time, a split phase can be easily incorporated into our algorithm.

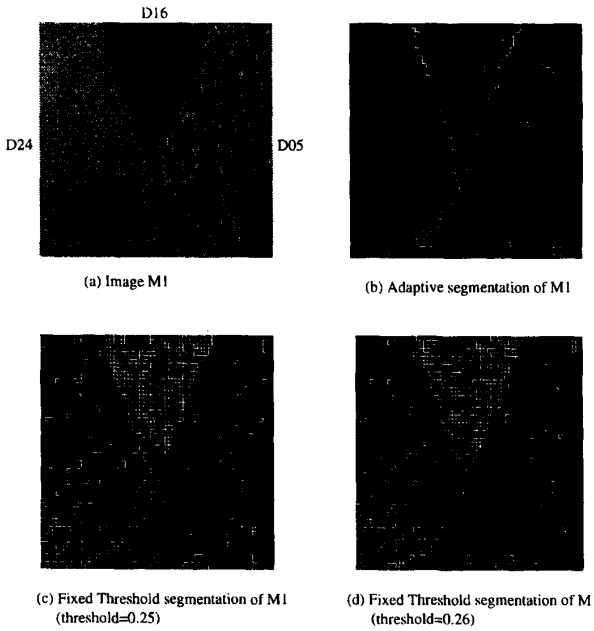
II. THE ADAPTIVE HOMOGENEITY TEST

In region-growing segmentation, an image is first divided into many small, usually equal sized, *primitive regions* that are assumed to be homogeneous. These primitive regions are then repeatedly merged to form larger regions until no merges will produce a homogeneous region. A *region* is a spatially connected set of primitive regions.

In the existing region-growing algorithms [3], [4], [6], [9], a predefined, fixed threshold ϵ is applied throughout the process on the entire image or on every regular subdivision of the image.

We refer to these methods as *fixed threshold region-growing*. Let R_i and R_j be two regions that are made up of n and m primitive regions, respectively. That is, $R_i = \{X_1, \ldots, X_n\}$ and $R_j = \{Y_1, \ldots, Y_m\}$ where the X_i's and Y_j's represent feature values of the primitive regions. Also, let $\overline{X}$ and $\overline{Y}$ denote feature means of R_i and R_j. Then, the *fixed threshold homogeneity test* ($\mathcal{FIX}$) with threshold ϵ on the regions R_i and R_j is defined as

$$\mathcal{FIX}\left(R_i \bigcup R_j\right) = \begin{cases} \text{true} & \text{if } |\overline{X} - \overline{Y}| < \epsilon, \\ \text{false} & \text{otherwise.} \end{cases} \tag{1}$$



(a) Image M1
(b) Adaptive segmentation of M1
(c) Fixed Threshold segmentation of M1 (threshold=0.25)
(d) Fixed Threshold segmentation of M1 (threshold=0.26)

Fig. 1. Fixed threshold and adaptive segmentations.

If an optimal threshold is known, the fixed threshold test is simple and efficient to implement. However, in many cases there may not be an optimal threshold which possesses the ideal separating power for the entire image or image subdivision due to the diversity of regional feature homogeneities. Even if an optimal threshold does exist for an image or subimage, there is no reliable method for finding it. As an example, test image M1 as shown in Fig. 1 is composed of three texture segments with different feature variations. Fig. 1(c)–(d) gives the segmentations of the fixed threshold method using different thresholds. Despite careful adjustments on the threshold, the fixed threshold method fails to produce a satisfactory segmentation.

Stated loosely, a threshold specifies the allowance for which feature values within a region can deviate. A segmentation threshold is therefore a feature- and region-dependent parameter. In our adaptive homogeneity test, we base the homogeneity decision on the feature distributions of the two regions under examination. From the feature histogram of a region, we estimate a range, called the adaptive range (ℓ_1, ℓ_2), within which the central λ portion of the region feature values lie. The user-defined parameter $\lambda (0 \leq \lambda \leq 1)$ is called the adaptive parameter. Suppose a region R_i is composed of n primitive regions with feature values $\{X_1, \ldots, X_n\}$ where each X_j is identically distributed, and the feature mean of R_i is $\overline{X} = \sum_{j=1}^{n} X_j/n$. Given a λ, for each region R_i in the image, we define the region's adaptive range (ℓ_{i1}, ℓ_{i2}) by the following relations:

$$\Pr(\ell_{i1} < X_j < \ell_{i2}) = \lambda \tag{2}$$

$$\text{and} \qquad \Pr(\ell_{i2} \leq X_j) = \Pr(X_j \leq \ell_{i1}) = \frac{1-\lambda}{2}. \tag{3}$$

For two regions to be considered homogeneous, we require that each region's feature mean falls within the other region's adaptive range. For region $R_j = \{Y_1, \ldots, Y_m\}$, the *adaptive homogeneity test* $(\mathcal{ADAP})$ on regions R_i and R_j is defined as

$$\mathcal{ADAP}\Big(R_i \bigcup R_j\Big) = \begin{cases} \text{true} & \text{if } \ell_{j1} < \overline{X} < \ell_{j2} \text{ and } \ell_{i1} < \overline{Y} < \ell_{i2}, \\ \text{false} & \text{otherwise.} \end{cases} \tag{4}$$

TABLE I
HOMOGENEITY TEST PROCEDURE

Conditions	Test Applied
$s_1 < n_1$ and $s_2 < n_1$ (both very small regions)	Fast-merge – R_1 merges with its closest neighbor.
$s_1 + s_2 < n_2$ (both small regions)	Mann-Whitney test – nonparametric test on feature distributions.
$s_1 < n_3$ and $s_1 + s_2 > n_4$ (one small region)	Modified Adaptive test – check if the feature mean of R_1 falls within R_2's adaptive range.
Otherwise	The regular Adaptive test

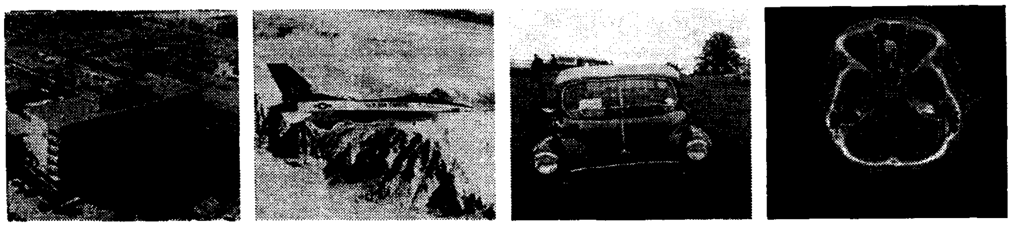
s_1, s_2: sizes of regions R_1, R_2; n_1 to n_4: preset constants (eg. $n_1 = 3, n_2 = 16, n_3 = 7$, and $n_4 = 30$).

For example, if $\lambda = 0.80$, the adaptive homogeneity test in (4) states that regions R_i and R_j are considered homogeneous if $\overline{X}$ falls within the central 80% range of R_j, and $\overline{Y}$ falls within that of R_i. It was found that $\lambda \in (0.80, 0.85)$ produced good segmentations on a wide range of images. Actually, $\lambda = 0.80$ was used throughout our experiments and analysis. There is no parameter tuning in our adaptive region growing process and λ can in fact be treated as a constant.

We performed an analytical study on the fixed threshold and adaptive tests [2] with the assumption that feature values are independently distributed. In addition, all features within the same region are assumed to be identically and normally distributed. The validity of the normality assumption is substantiated by the Shapiro-Wilk test performed on five feature measures over 20 textures from the Brodatz album (we found only an 8% rejection rate at the 10% quantile). Although our analysis requires the normality assumption, it should be noted that the application of the FAS algorithm is not restricted to normally distributed features. In the case of normal distribution, the adaptive threshold $k\sigma$ can be used to simplify computation.

The first theorem in our analysis states that regardless of the feature distribution parameters, it is guaranteed that the probability of two homogeneous regions passing the adaptive test is at least λ^2, or around $0.64 (\lambda = 0.80)$ in practice. On the other hand, probability of the same event on the fixed threshold test reduces with feature variation; the larger the standard deviation of the feature distribution, the lower the probability. Besides allowing homogeneous regions to merge, it is equally important for a good homogeneity test to ascertain that nonhomogeneous regions would not be merged. We proved in [2] that if a fixed threshold test and an adaptive test are equally good in merging homogeneous regions, and if either of two conditions on regions' sizes and feature standard deviations is satisfied, then this adaptive test would have a lower probability than the fixed threshold test of merging two nonhomogeneous regions (see Section 3.3 of [2]).

The adaptive test discussed above based merge decisions on the analysis of region feature histograms. When regions are small, reliable adaptive ranges cannot be determined for the test because of the low number of feature values. In our implementation, we augment the adaptive test with the test procedure given in Table I. At the beginning of the process, fast-merge is used to guarantee merges between very small regions and their most homogeneous neighbors, which are also very small regions. On two moderately small regions, the Mann-Whitney test is applied to assess if the two feature distributions are similar enough. The Mann-Whitney test is a nonparametric test that has been demonstrated to work well even on small samples [5]. When only one of the regions to be tested for a merge is small, we modify our adaptive test so that no adaptive range is required on this small region.



M7 M8 M9 M10

Fig. 2. The grayscale test image set.

III. The Merge Criteria

A decision function, called the *merge criterion*, determines whether two regions should be merged. The main focus of our study is on the ways merge criteria affect the quality of segmentation and the processing time. A merge criterion consists of two parts: a homogeneity test and a selection policy. Two adjacent regions need to pass the homogeneity test in order to be merged. When several neighboring regions pass the homogeneity test to merge with a given region, a selection policy is applied to choose one region from the several candidates to participate in the merge.

As in the image graph model used in [9], we represent an image as a disjoint set of regions (vertices), and a set of edges connecting adjacent regions. Initial studies on using the merge selection to improve segmentation are presented in [9]. They applied the *best-merge* paradigm which requires the edge connecting two merging regions to be minimum with respect to *both* regions. The strength of the best-merge approach is that different parallel runs on the same image would produce the same segmentation due to the ordering imposed on the merge sequence. We use the *fast-merge* policy in our algorithm. That is, two regions which pass the homogeneity test are merged if the value of the edge connecting them is a minimum with respect to *either* (not necessarily both) of the regions. The most important improvement of fast-merge over best-merge is the reduction in processing time. Also, as shown in our experiment, fast-merge helps to improve region mergeability.

An experiment was designed to evaluate the merge criteria based on four important aspects on segmentation results: *region mergeability* refers to the degree to which regions that should be merged are merged. We measure region mergeability using the number of regions in the final segmentation. It is equally important that regions that should not be merged remain as separate regions throughout the process. In our experiment where the exact locations of region boundaries are known, *boundary accuracy* is measured in the number of boundary units found in these expected locations. Unlike the number of successful merges, the number of *merge rejections* in a region-growing process depends heavily on the merge criterion used. The number of failed merges is therefore an important measure in the evaluation of merge criteria speed performance. The number of *iterations* required in the region-growing process is an indicator on the length of its parallel processing time. In our experiment, we used simple 50×50 images. Each image has two equal-sized regions that share a simple straight 50-unit boundary. We randomly generated data for the two regions from a pair of normal distributions having different means and variances. For each pair of normal distributions, we generated 100 test images. Three sets of distribution pairs with different distances between the two means were used. The same 300 images were used to assess the four merge criteria formed by the two homogeneity tests and two selection policies. Detailed results of this experiment are given in [2]. A summary is presented in Table II. The adaptive homogeneity test together with the fast-merge selection policy have provided consistently good performance in the four aspects of evaluation.

TABLE II
Summary of Merge Criteria Performance

	Fixed Threshold		Adaptive	
Fast-merge	o	Partially fragmented 96% with 10 to 50 regions	+	Merge well 86% with < 5 regions
	o	Fair boundary 20% has < 5% error	+	Good boundary 34% has < 5% error
	+	Low merge rejections 16% failure	+	Low merge rejections 12% failure
	+	Few iterations average 9 iterations	+	Few iterations average 13 iterations
Best-merge	−	Very fragmented 86% with > 100 regions	−	Very fragmented 79% with > 100 regions
	+	Good boundary 32% has < 5% error	+	Good boundary 45% has < 5% error
	−	High merge rejections 85% failure	−	High merge rejections 80% failure
	−	Many iterations average 46 iterations	−	Many iterations average 44 iterations

+ desirable − undesirable o tolerable

IV. Segmentation Results

Extensive experiments were performed on textured and grayscale images to assess the performance of the FAS algorithm. The textured images used in our experiments were created using real textures obtained from the Brodatz album [1]. The co-occurrence measures were used although other texture measures (e.g., Gabor filters, Law's energy masks, fractal measures) can also be applied. Grayscale images which represent different domains of natural scenes, such as test images M7 to M10 in Fig. 2, are also used in our experiment.

Figs. 3 and 4 show segmentations produced by the existing best-merge fixed threshold segmentation algorithm (BFS) [9] and our FAS algorithm. All FAS segmentations are obtained using $\lambda = 0.8$. Different thresholds are applied in the BFS algorithm and the most satisfactory BFS results are given in the figures. For some images, no satisfactory segmentation can be obtained using the BFS

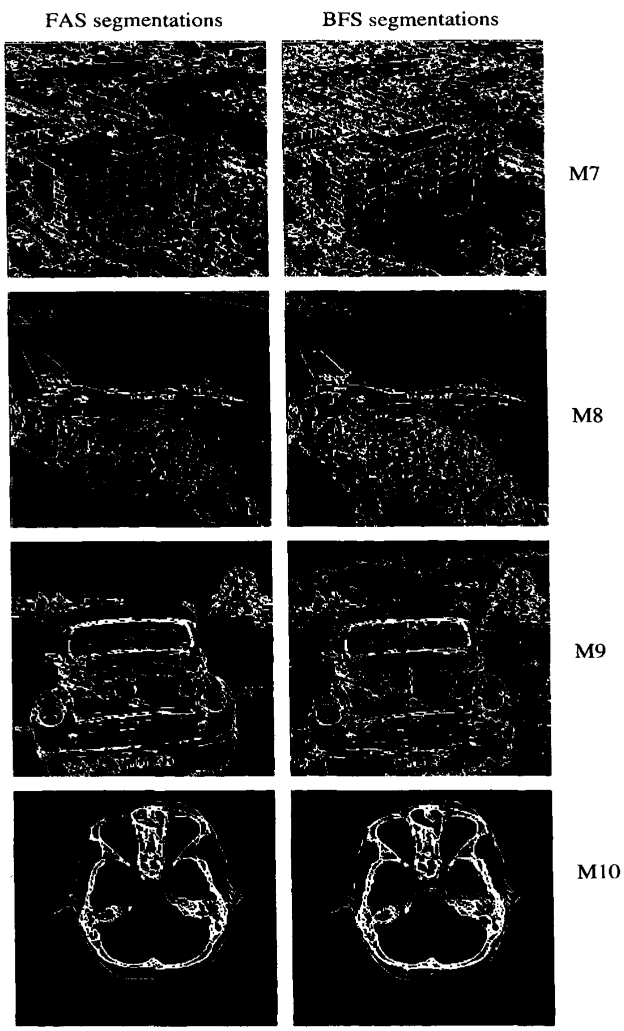
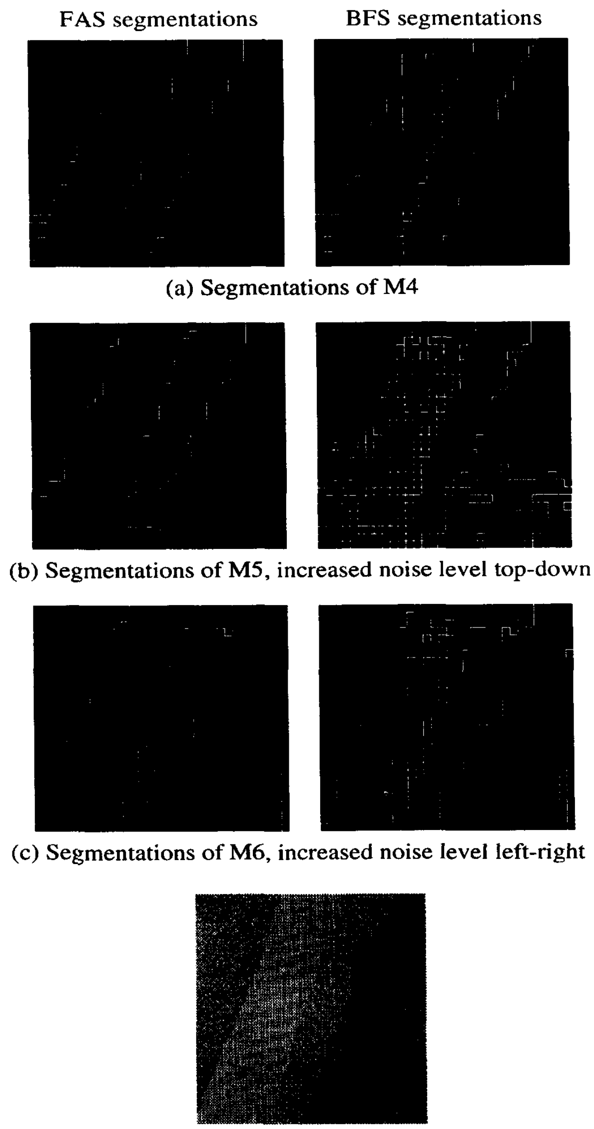


Fig. 3. Grayscale segmentations.



(d) Image M4

Fig. 4. Robustness of noisy images.

algorithm. For example, on the BFS segmentations of image M7, the background is fragmented regardless of the threshold applied; relaxing the threshold causes details on the building to be lost.

We have also tested the robustness of the FAS algorithm with respect to different degrees of random noise. Test images M4 (Fig. 4), M5, and M6 are four-region textured images with M5 and M6 produced from M4 with random noise added, with increasing intensities in the top-down and left-right directions, respectively. On the noisy images M5 and M6, we can see that the segmentations from the BFS algorithm degrade more severely with noise intensity compared to those from the FAS algorithm (Fig. 4(b)–(c)). The reader is referred to [2] for experimental results on small-region sensitivity and multiple-feature incorporation of the algorithms.

Both the FAS and the BFS algorithms were implemented on the BBN TC2000 shared memory multiprocessing system. On the parallel FAS algorithm, an average 15-fold speedup over the sequential FAS algorithm on the same machine was achieved. Only a five-fold speedup (over the sequential BFS algorithm) was attainable using the parallel BFS algorithm. This is because the stringent best-merge policy results in a highly ordered and sequential merge process—before a processor carries out a certain obstructive merge, another processor cannot perform its merges. The number of merge rejections performed by the processors are data-dependent, thus resulting in a highly imbalanced load on the multiprocessing system. On the other hand, the relaxed fast-merge policy allows merges to be carried out in parallel and few merge rejections are encountered. As a result, an efficient parallel process with a well-balanced load is achievable using the FAS algorithm. Our experiments also show that compared to the FAS algorithm, the time performance of the BFS algorithm is very sensitive to feature distribution, region size, and shape. Detailed discussions on timing results can be found in [2].

V. Conclusion

We studied several merge criteria and proposed a simple and general adaptive region-merging decision test that automatically computes segmentation thresholds based on local feature analysis. Our region growing scheme, called the fast adaptive segmentation (FAS) algorithm, has proved to be robust and produced high-quality segmentations on a wide range of textured and grayscale images. It is a general segmentation framework which can be easily adapted to different image applications by substituting the suitable feature measures.

As mentioned in Section II, a limitation of the FAS algorithm is the applicability of the adaptive homogeneity test on very small regions. Another undesirable characteristic of the FAS algorithm is the order dependency of its segmentation results. Different parallel executions on the same image may result in slightly different segmentations due to the different merging orders adopted by the processes. In our study, however, such differences in segmentation results have shown to be minute and insignificant.

Although the segmentation does not require *a priori* knowledge, domain-specific knowledge could be utilized when available, which is one possible avenue for further study. Also, multiregion merge instead of binary merge could be used to further improve the speed.

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