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USE OF FUZZY SET IN TEXTURED IMAGE SEGMENTATION

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ABSTRACT

This paper presents an approach to texture segmentation by thresholding based on compactness measures of fuzzy sets to determine thresholds of an ill-defined image. The extension of fuzziness in the texture feature space provides more meaningful results than by considering fuzziness in gray scale domain. The effectiveness of the algorithm is demonstrated by comparison with other traditional non-fuzzy methods or the controversial fuzzy method in gray scale alone. In addition, the efficiency of our algorithm is further improved by parallel implementation using distributed shared memory workstations.

Key words: Texture segmentation, thresholding, fuzzy sets, fuzziness, fuzzy compactness, parallel implementation.

1. INTRODUCTION

An important component in image analysis is segmentation of the image into meaningful regions with certain properties. In computer vision, grouping parts of a generalized image into units that are homogeneous with respect to one or more characteristics (or features) results in a segmented image, which provides a fertile ground for vision theories to organize the scene into meaningful units as a significant step towards image understanding. During the past decades, various image segmentation techniques have been proposed [1]. Segmentation algorithms generally are based on one of two basic concepts of discontinuity and similarity. In the first category, an image is partitioned, in terms of abrupt changes in image features, by boundary detection associated with the detection of isolated points, lines and edges in an image. In the second category, the principal approaches are based on feature thresholding and clustering, region growing, region splitting and merging.

Thresholding is a technique extensively studied and widely used as a tool in image segmentation. The objective of histogram thresholding is to determine boundary value so as to partition the image space crisply into meaningful regions. A number of approaches to thresholding, including global, local and dynamic methods have been proposed in the past. However, when the regions in an image are ill-defined (i.e., fuzzy), some ideas based on fuzzy set have been proposed by assuming the segments to be fuzzy subsets of the image. Fuzzy geometric properties defined by Rosenfeld [2] are useful for such analysis. Pal [3] proposed a method to extract the fuzzy segmented version of an ill-defined image by minimizing compactness and fuzziness of the image in both the intensity and spatial domain. The advantages of such an algorithm has been demonstrated by considering the ambiguity in grey level through the concepts of index of fuzziness[4], entropy [5] and index of nonfuzziness (crispness) [6]. Nevertheless, this method cannot be applied directly to textured image because texture is characterized by its local features over some neighborhood rather than a pixel gray scale.

In this paper we extend the fuzzy compactness approach to segment textured images by incorporation of fuzziness in texture feature domain. Section 2 highlights two texture feature measurements — Skewness and Laws' texture energy. Section 3 introduces the fuzziness measurement in an image. The threshold selection procedure is described in Section 4 and the parallel implementation is summarized in Section 5. Finally the experimental results and conclusion are presented in Section 6 and Section 7.

2. TEXTURE FEATURE EXTRACTION

The aim of feature extraction is to represent an image by a set of numerical "features" so as to remove redundancy from the data and reduce the feature dimension. Historically, structural and statistical approaches have been adopted for texture feature extraction[8]. The structural approach assumes the texture is characterized by some primitives following a placement rule. In the statistical approach, texture is regarded as a sample from a probability distribution on the image space and defined by a stochastic model or characterized by a set of statistical features.

In this paper our emphasis is on the so called 'spatial-statistical' measurement of texture features, which involves the computation of statistics of various local image functions. These measures are spatial because they depend upon local window functions rather than single pixels. They are statistical in the sense that statistical moments of an image window are invariant to relative pixel positions. In our test, Skewness and Laws' texture energy are used as texture measurements[7]. Skewness is formulated as:

$$SKW = E[(I(r,c) - AVE)^3 / VAR^{3/2}]$$

where *AVE* denotes mean of pixel gray levels and *VAR* refers to variance of the pixel gray level distribution.

Laws introduced the notion of a single parameter, the local 'texture energy' as the measure of texture features in the spatial domain. Basically his method consists of two steps. The first step involves convolving [7]the whole image by a zero sum mask. The two-dimensional convolution of the image *I(i,j)* and mask *A(i, j)* with size 2a +1 by 2a +1 is given by the relation

$$F(i,j) = A(i,j) * I(i,j) = \sum_{k=-a}^{a}\sum_{l=-a}^{a} A(k,l) I(i+k, j+l),$$

for $i = 0, 1, \ldots, N-1$ and $j = 0, 1, \ldots, N-1$, where $*$ denotes two-dimensional convolution. After convolving the (signed) image *F(i, j)* has mean zero over a significantly large region of uniform texture. In most cases the size of the mask *A(i, j)* is 5 * 5. The convolution masks are intended to be sensitive to visual structure such as edges, ripples, and spots.

The second step involves determining the difference between the convolved image *F(i, j)* and the real image I(i, *j)*. For a zero-sum mask, the local texture measures are determined as statistical variances of the filtered image by computing the squared signal values in the filtered image. From the computational efficiency point of view, the sample mean deviation of the filtered image, called *ABSAVE,* is introduced as the most useful statistics by Laws. The *ABSAVE E(i, j)* is defined as the mean deviation within a 2n + 1 by 2n + 1 window at point (i, *j)* and is given by

$$E(i,j) = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n} | F(k,l) - M(i,j) |$$

where the mean $M(i,j)$ is given by

$$M(i,j) = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n} F(k,l)$$

The mean is zero over large window, therefore, the $ABSAVE\ E(i,j)$ becomes

$$E(i,j) = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n} | F(k,l) |,$$

which Laws called texture energy measure which is used in his test as the texture feature.

In the experiments reported here both Skewness and Laws' texture energy measures are used to determine the fuzziness in a texture feature image. The measures of fuzziness in such a feature image and the selection of threshold by minimizing fuzziness are detailed in next section.

3. FUZZINESS MEASUREMENT

Fuzzy sets were first introduced by Lotfi Zadeh [9] as a new way to represent vagueness in everyday life. Fuzzy interpretations of data structures in computational pattern recognition have been proved successful because they provide a very natural and intuitively plausible way to formulate and solve various problems. An image *I* of size *M * N* and *L* levels of brightness can be considered as an array of fuzzy singletons, where each associates a value of membership representing its degree of brightness relative to some brightness level *1,1* = 0, 1, 2, ..., *L 1*. Such an assumption can be expressed in the notation of fuzzy sets as below:

$$X = \{\mu_X(x_{ij}) = \mu_{ij}/x_{ij};\ i = 1, 2, \ldots, M;\ j = 1, 2, \ldots, N\}$$

where $\mu_X(x_{ij})$ or μ_{ij}/x_{ij} $(0 \leq \mu_{ij} \leq 1)$ denotes the grade of featuring some brightness property μ_{ij} by the (i,j)th pixel intensity x_{ij}.

In his previous work, Pal[3] introduced the index of fuzziness to reflect the average amount of ambiguity (fuzziness) present in an image I by measuring the distance between its fuzzy property μ_x and the nearest two-level property $\mu_{\underline{X}}$. A linear index of fuzziness is defined below:

$$\begin{aligned} v_l(X) &= \frac{2}{MN}\sum_i\sum_j |\mu_X(x_{ij}) - \mu_{\underline{X}}(x_{ij})| \\ &= \frac{2}{MN}\sum_i\sum_j \mu_{X\cap\overline{X}}(x_{ij}) \\ &= \frac{2}{MN}\sum_i\sum_j min(\mu_X(x_{ij}), 1 - \mu_X(x_{ij})) \\ m &= 1, 2, \ldots, M;\ n = 1, 2, \ldots, N, \end{aligned}$$

where $\mu_{\underline{x}}(x_{ij})$ denotes the nearest two-level version of X such that

$$\begin{aligned} \mu_{\underline{x}}(x_{ij}) &= 0 \text{ if } \mu_x(x_{ij}) < 0.5 \\ &= 1 \text{ otherwise.} \end{aligned}$$

In contrast to the conventional measurement of fuzziness in an gray scale image detailed above, we extended this approach by applying the distance measurement to texture feature image rather than the texture image in gray scale. Accordingly, *X* refers to the texture feature set and xi, represents the certain texture feature measurement. In the work reported here, both Skewness and Law's texture energy are calculated and mapped to different levels for the measure of index of fuzziness in the feature domain.

4. THRESHOLD SELECTION

There are a number of threshold selection schemes for segmenting an image which include global, local and dynamic methods. In general, a threshold operator can be viewed as an operation that involves tests against a function *T* of the form

$$T = T(i, j, N(i, j), I(i, j))$$

where I(*i, j)* is the gray level of point (*i, j)* and *N(i, j)* denotes some local property of the point (*i, j)* such as the average gray level of a neighborhood centered at *(i, j).* For each point *(i, j)* in the image I(*i, j*), if *I(i, j) > T(i, j, N(i, j), I(i, j))* then (*i, j)* is labeled as an object point; otherwise, *(i, j*) is labeled as a background point.

When an image is regarded as a fuzzy set as detailed in Section 3, an optimal threshold value can be determined by minimizing fuzziness, e.g $V_i(X)$. Based on the equation given in Section 3, it is seen that a proper selection of the cross-over point, i.e., the 0.5 value of μ_{Xx}, will result in a minimum value of v*(X)* which corresponds to the appropriate boundary between regions in *X.* Instead of processing the gray scale image, we consider the minimization of fuzziness in texture feature to select appropriate threshold value for segmentation. Such an algorithm is summarized as follows:

- Step 1: Convert the gray scale texture image to texture feature image by means of skewness or Laws' texture energy measurement. The maximum and minimum values are *lmax* and *lmin.*
- Step 2: Construct the "feature image" membership $\mu_{\underline{x}}$, where
  $\mu_{\underline{x}}(l) = S(1;\ a, c)$, $\quad$ lmin < l, l_i < lmax
  and\

$$\begin{aligned} S(l;a,b,c) &= 0 & l &\leq a, \\ &= 2[(l-a)/(c-a)]^2, & a &\leq l \leq b, \\ &= 1 - 2[(l-c)/(c-a)]^2, & b &\leq l \leq c, \\ &= 1 & l &\geq c \end{aligned}$$

with cross-over point $b = l_i = (a+c)/2$ and bandwidth $\Delta b = b - a = c - b$.

- Step 3: Obtain the linear index of fuzziness in texture feature image X by computing
  $v(X) \mid l_i = \frac{2}{MN}\sum_l T_i(l)h(l)$
  where
  $T_i(l) = min\{S(l;a,l_i,c,1-S(l;a,l_i,c)\}$
  and $h(l)$ denotes the number of occurrences of the level l.
- Step 4: Vary l_i from l_{min} to l_{max} and choose $l_i = l_c$ which corresponding to the minimum of $v(X)$.

For the purpose of fuzzy segmentation of the textured image, the cross-over point of *px* (smn which having minimum ambiguity is considered as the threshold value in texture feature image to identify regions.

5. PARALLEL IMPLEMENTATION

In contrast to the conventional parallel implementation where either the dedicated hardware or the software are required, our optimization of fuzziness for textured image segmentation is implemented in parallel using a workstation cluster. We adopt a divide-and-conquer policy, where a complex task is divided into a number of sub-tasks and those sub-tasks are mapped to computers for simultaneous implementation. In order to reduce the communication overheads, we conduct our experiment of parallel computing on networks of workstations using the TreadMarks distributed shared memory (DSM) system.

TreadMarks is a useful software which turns an existing network of workstations into a powerful shared-memory parallel computer for high performance. Based on the workstation's unmodified Unix operating system and standard compilers, TreadMarks creates a parallel programming environment that makes parallel computing convenient, inexpensive and efficient. In this section, we discuss our experience with parallel implementation of texture feature extraction and optimization of fuzziness on a network of workstations using the TreadMarks distributed shared memory (DSM) system. where the software provides facilities for process creation and destruction, synchronization, and shared memory allocation. The TreadMarks DSM system introduces lazy release consistency and multiple writer protocols to make sure that the shared memory abstraction does not result in a large amount of communication.

6. EXPERIMENTS

It has been confirmed that optimization of fuzziness in gray scale image provided a better solution to histogram thresholding for image segmentation[6]. We extend such an approach by introducing fuzziness to texture feature domain and partition the textured image into meaningful regions by thresholding. Figure 1 shows the comparison of histogram thresholding of a textured image. Our test results will show that the histogram of texture feature distribution *(em e.g.*, texture energy proves the potential use of simple thresholding in textured image segmentation.

The advantages and potentials of a general distributed shared memory system for parallel image processing is further demonstrated by the performance comparison listed in Table 1, where different numbers of processes were invoked by means of both PVM and DSM on the 512*512 size image. The parallel performance improvement is measured by the following ratio:

$$\gamma = \frac{T_P}{T_s}$$

where T_S refers to the sequential execution time and T_P, refers to the parallel execution time. It is clear that DSM increase the speed better due to its less communication overheads. It is expected that the overall performance will be further improved by introducing dynamic task scheduling for parallelism.

7. CONCLUSION

We conclude that the extended thresholding scheme by optimization of fuzziness provides more meaningful results for textured image segmentation. In addition, the parallel computing on networks of workstations using distributed shared memory is powerful to attain real-time performance. Our investigation shows that distributed shared memory computing can meet the high computational and memory access demands in real-time imaging.

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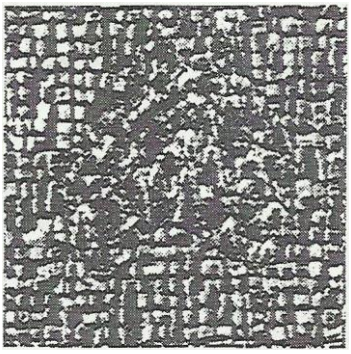
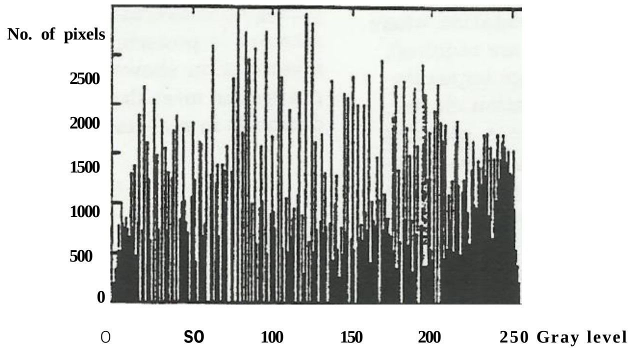
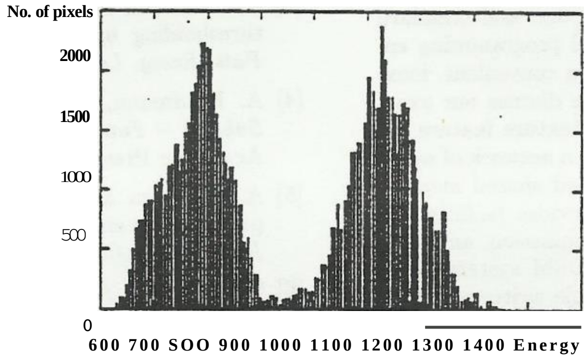


(a)



(o) Histogram of gray levels



(b) Histogram of local texture energies

Figure 1: (a) Texture image; (b), (c) Histogram

Table 1: The performance comparison of DSM and PVM

number of processes	execution time (DSM)	execution time (PVM)
1	1.45 sec.	1.77 sec.
2	0.80 sec.	1.41 sec.
4	0.52 sec.	1.17 sec.
8	0.48 sec.	1.13 sec.
16	0.22 sec.	0.27 sec.
32	0.12 sec.	0.27 sec.