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Texture Image Segmentation Based on threshold Techniques

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Abstract: Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is used to give the values of objects and boundaries of a selected image like lines, curves. The image segmentation plays a critical role in a variety of pattern recognition applications such as robot vision, cartography, criminal investigation, remote sensing, object identification and recognition, military surveillance, quality assurance in industries, facial recognition and medical imaging, etc. The main aim of this paper is to propose methods are improving image segmentation and give the clear object about the image by using different techniques. This article presents a brief outline of some of the most commonly used segmentation techniques like Thresholding, Region based and Edge detection methods. The proposed methods implemented in MATLAB.

Index Terms--- Segmentation, Edge Detection, Region Based, threshold-based segmentation techniques.

1. Introduction

Image segmentation divides an image in the form of groups of different regions depending on various attributes, such that every region is uniformly based on specific properties. Segmentation results can be used for further image analysis and processing like object classification and identification. Segmentation methods can classify into supervised or unsupervised. Unsupervised segmentation is one of the critical and demanding issues of the segmentation because no prior information about the image textures is available. That is why it has only limited success so far. Early methods of unsupervised segmentation are developed based on various methods like pyramid node linking [26], split-and-merge methods [40], a quadtree method [28] and particular feature smoothing with clustering [43]. Later the segmentation methods based on feature smoothing [32], local linear transforms, Markov random field models [4, 11], autoregressive models [38], fractal dimension [10], multichannel filtering [30], hidden Markov models [42], Markov random fields for color textures [22] are proposed. These methods achieved good results for a minute set of fine-grained texture like mosaics; however, they need to have prior knowledge of the image contents like some textures and regions. Moreover, some segmentation methods typically performed poor results for natural images containing non-uniform textures. The segmentation methodologies, including Edge based segmentation, threshold based image segmentation, and Region-based image segmentation [3]. To test the derived methods the present paper plans to work on four large databases, namely Indian facial expressions, WANG [32], official images from Google [33] and natural textures of Brodtaz album [34].

2. Image Segmentation Techniques

The segmentation methods are broadly divided into three categories:

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i. Edge-Based Segmentation
ii. Region Based Segmentation
iii. Thresholding Segmentation

(i) Edge-Based Segmentation

Edge detection is a fundamental tool for image segmentation. Edge detection methods transform original images into edge images benefits from the changes of gray tones in the picture. There are many edge detection techniques in the literature for image segmentation. The most commonly used discontinuity based edge detection techniques are reviewed in this section. Those techniques are Roberts edge detection, Sobel Edge Detection, Prewitt edge detection, Robinson edge detection, Marr-Hildreth edge detection, LoG edge detection and Canny Edge Detection.

a) Roberts Edge Detection

The Roberts edge detection is introduced by Lawrence Roberts (1965). It performs a simple, quick to compute, 2-D spatial gradient measurement on an image. This method emphasizes regions of high spatial frequency which often correspond to edges. The input to the operator is a grayscale image the same as to the output is the most common usage of this technique. Pixel values in every point in the output represent the estimated complete magnitude of the spatial gradient of the input image at that point. The Roberts gradient masks Gx and Gy given below.

Gx

-1	0
0	1

Gy

0	-1
1	0

b) Sobel Edge Detection

Sobel introduces the Sobel edge detection method in 1970 (Rafael C.Gonzalez (2004)). The Sobel method of edge detection for image segmentation finds edges using the Sobel approximation to the derivative. It precedes the edges at those points where the gradient is highest. The Sobel technique performs a 2-D spatial gradient quantity on an image, and so highlights regions of high spatial frequency that correspond to edges. In general, it is used to find the estimated absolute gradient magnitude at each point in n input grayscale image. In conjecture, at least the operator consists of a pair of 3x3 complication kernels as given away in under the table.

-1	-2	-1
0	0	0
1	2	1

Gx

-1	0	1
-2	0	2
-1	0	1

Gy

c) Prewitt Edge Detection

The Prewitt edge detection is proposed by Prewitt in 1970 (Rafael C.Gonzalez) [1]. To estimate the magnitude and orientation of an edge Prewitt is a correct way. Even though different gradient edge detection wants a quite time-consuming calculation to estimate the direction from the magnitudes in the x andy-directions, the compass edge detection obtains the direction directly from the kernel with the highest response. It is limited to 8 possible orientations; however, knowledge shows that most direct direction estimates are not much more perfect. This gradient-based edge detector is evaluated in the 3x3 neighborhood for eight directions. All the eight convolution masks are calculated.

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

[ii]. Region-Based Segmentation

A large number of segmentation approaches have been proposed in the literature [13, 14, 15, 16]. An excellent survey about their evaluation can be found in [17][18]. A list of unsupervised, supervised, and non-parametric region based segmentation algorithms are presented in this section, such as Mean Shift (MS), Fuzzy C-Means (FCM), KMeans, Expectation Maximization (EM), Spatial Constraint Fuzzy CMeans (SCFCM), Markov Random Fields (MRF), Pulse Coupled Neural Network (PCNN), and Support Vector

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Machine (SVM). In the next subsections, we will introduce some of these techniques briefly.

a) K-Means

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their fixed distance from each other. The iterative K-Means clustering algorithm was first proposed by MacQueen [19]. The algorithm aims at partitioning the data set, consisting of ℓ expression patterns {x1,..., xℓ} in an n-dimensional space, into k disjoint clusters, such that the expression patterns in each group are more similar to each other than to the expression patterns in other clusters[20]. There are two popular partitioned clustering strategies: square error and mixture modeling. The sum of the squared Euclidian distances between the samples in a cluster and the cluster center is called within-cluster variation. K-Means are widely used in many applications such as data extraction and image segmentation [21]. The K-Means method is an iterative algorithm that minimizes the sum of distances between each object and its cluster centroid.

b) Fuzzy C-Means (FCM)

Fuzzy C-Means (FCM) is an unsupervised fuzzy clustering algorithm[22]. Excerpted from the algorithm of C-means[23], it introduces the concept of fuzzy set in the definition of classes, each point in the dataset belongs to each cluster with a certain degree, and their center of gravity characterizes all clusters. The FCM clustering algorithm was first suggested by Dunn [24] and later improved by Bezdek [25].The FCM method proposes a fuzzy membership that assigns a degree of accession for each class by iteratively updating the cluster centers and the membership degrees for each data point. The cluster that has an associated pixel is one whose membership degree is highest.

c) Fuzzy C-Means algorithm with Spatial Constraint (SCFCM)

A fuzzy C-Means algorithm with Spatial Constraint (SCFCM) is based on the clustering algorithm FCM described above, two kinds of information in the image are used, the gray value and space distributed structure. Based on the relevance of near pixels, the neighbors in the set should be similar in feature value. Its effectiveness contributes not only to the introduction of fuzziness for belongingness of each pixel but also to the exploitation of spatial contextual information. SCFCM clustering algorithm preserves the homogeneity of the regions better than existing FCM techniques, which often have difficulties when tissues have overlapping intensity. To reduce the noise effect during segmentation, the proposed dimension feature space.

[iii].Thresholding Segmentation

Thresholding is a process of converting a grayscale input image to a bi-level image by using an optimal threshold. Threshold technique is one of the essential techniques in image segmentation. This technique can be expressed as:

$$T=T[x, y, p(x, y), f(x, y]$$

Where T is the threshold value. x, y are the coordinates of the threshold value point.p(x,y) ,f(x,y) are points the gray level image pixels [9].Threshold image g(x,y) can be defined:

$$g(x,y)=\begin{cases}1\ if\ f(x,y)>1\\0\ if\ f(x,y)\leq 0\end{cases}$$

Thresholding is classified into two types, namely Global Thresholding and Local Thresholding.

a) Otsu Method

The Otsu method, as proposed by [91] is based on the discriminate analysis. Otsu's method chooses the threshold by minimizing the within-class variance of the two groups of pixels separated by the thresholding operator. A measure of region homogeneity is variance (The areas with high homogeneity will have low variance). The advantage of Otsu threshold is it does not depend on modeling the probability density functions.

The Otsu threshold is based on a bimodal distribution (foreground pixels and background pixels) of gray-level values. The Otsu threshold operation performs the division of image pixels into two classes C0 and C1 (e.g., objects and background) at gray level t, i.e., C0 = {0, 1, 2, t} and C1 = {t + 1, t +2….L-1}.

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b)Histogram thresholding

Suppose that the gray-level histogram corresponds to an image, f(x,y), composed of dark objects in a light background, in such a way that purpose and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold 'T' that separates these modes. Then any point (x,y) for which f(x,y) > T is called an object point, otherwise, the point is referred to as a background point. For example, consider the following images and histogram equalization.

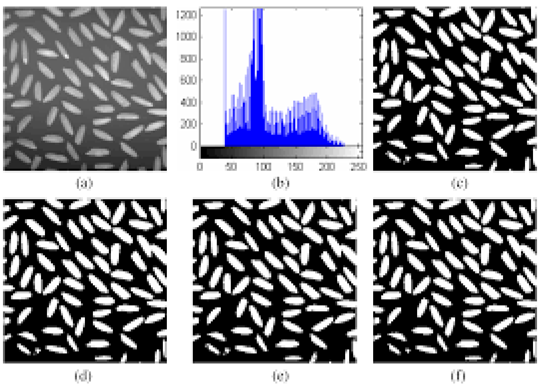

Fig 1: Thresholding segmentation results in a) Original image b) histogram c) us segmentation d) histogram thresholding segmentation e) global thresholding f) local thresholding.

3. Experimental Results and Discussion

The segmentation technique discussed in the previous section is applied to six different texture mosaic images of size 256 · 256, stitched from texture images of Brodatz (1966) texture album. The stitched texture mosaic images, shown in Fig. 2(a), consist of (i) leather, straw, grass and wood textures of square shape in clockwise direction; (ii) wood texture of square shape at the center of leather texture; (iii) leather texture of circular shape at the center of wood texture; (iv) leather and water textures of triangular shape with sand texture at the center; (v) water and sand textures of square shape with weave texture of circular shape

at the center and (vi) an irregular texture mosaic image consisting of leather, wood, and grass textures.

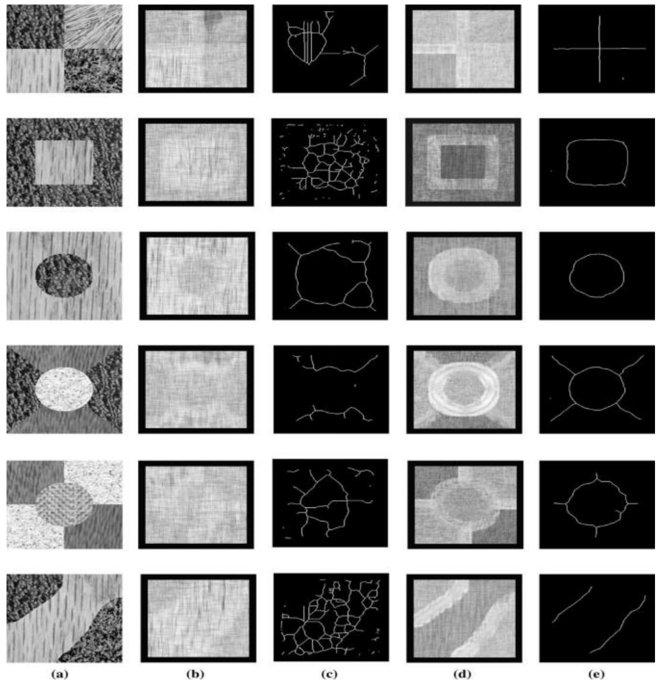

Fig. 2. Texture segmentation results. (a) Texture mosaic images. Texture spectrum technique: (b) segmented band, (c) thinned results. Proposed method: (d) segmented band, (e) thinned results.

The segmented band images are obtained from the above six images by applying the segmentation algorithm, given in Section 3, and are shown in Fig. 2(d). Then, thresholding and disk filtering techniques are applied to remove spurious noise spots.

4. Conclusion

The present paper proposed various innovative segmentation methods for natural, facial and texture images. The proposed segmentation methods are precise and accurate because they derived local attributes, edge responses significantly and they more robust to noisy and illumination effects. The morphological treatment and the Otsu threshold enhanced this process of segmentation by deriving more uniform regions. The various advantages of morphological methods are noise filtering, skeletonizing, thickening, object marking, shape simplification, thinning, convex hull, segmenting objects from the background, and quantitative description of objects (projections, area, and

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perimeter).

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