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A New Texture Segmentation Approach for Medical Images

Saka.Kezia, Dr.I.Santi Prabha, Dr.V.VijayaKumar

Abstract— The problem of segmentation is to partition an image into a set of non-overlapping regions covering the entire image. Image segmentation has found its application directly or indirectly in tasks such as object detection, object tracking and recognition, content-based image retrieval and medical image analysis. The proposed paper presents a novel approach for image segmentation problems, based on simple morphological operations. The proposed technique divides the original image segmentation problem into seven simple steps. The proposed technique takes care of noise factors, interior segments and rotationally invariant features while segmenting the image. The present approach is tested on Brodatz and Vistex textures which resulted a fine and precise segmentation.

Index Terms— Filter, Morphology, Image complement, interior segments.

1 Introduction

An image texture can be defined as the local spatial variations in pixel intensities and orientation. In order to recognize objects and scenes in computer vision, it is essential to be able to partition an image into meaningful regions with respect to texture characteristics. This task, referred to as texture segmentation in the image processing literature, texture segmentation is a challenging problem due to the complexity and diversity of natural textures. Texture segmentation has a wide range of applications like content based image retrieval, medical diagnosis, analysis of satellite or aerial images, surface defect detection and terrain classification for mobile robot navigation. There are many different kinds of textures, and these have been classified in the form of taxonomy. Texture has been an active area for research of computer vision for over two decades [10,32]. Texture segmentation is a difficult problem because one usually does not know a priori what types of textures exist in an image, how many different textures there are and what regions in the image have which textures. In fact, one does not need to know which specific textures exist in the image in order to do texture segmentation. All that is needed is a way to tell that two textures (usually in adjacent regions of the images) are different. Many researchers have produced a large volume of research over the past three decades has addressed the problem of texture segmentation and has produced a number of review articles and comparative studies [34, 10, 32, 6 , 9, 8, 19, 26, 22,21, 2, and 25].

In the literature, various methods have been proposed for object segmentation and feature extraction. However, the design of robust and efficient segmentation algorithms is still a very challenging research topic, due to the variety and complexity of images. Image segmentation is defined as the partitioning of an image into non overlapped, consistent regions which are homogeneous in respect to some characteristics such as intensity, color, tone, texture, etc. The image segmentation can be divided into four categories: thresholding, clustering, edge detection and region extraction [35]. In the thresholding process, individual pixels in an image are marked as “object” pixels if their value is greater than some threshold value, otherwise the pixels are marked as “background” pixels. For thresholding technique, great efforts should be made in selecting threshold in order to ensure the quality and rapidity of segmentation. Moreover, it is sensitive to noise and has the disadvantage of spatial uncertainty as pixel location information is ignored. Clustering consists of identifying a homogeneous cluster of points in the feature space and then labelling each cluster as a different region. The disadvantage of this method is that the number of clusters is typically unknown. Additionally, it does not consider spatial interactions between neighbouring pixels. Edge detection is designed to detect edge boundaries of various regions by normally trying to locate points of abrupt change in intensity values. Now there are many edge detection algorithms, however, since not all edges produced by these operators are relevant, post-processing is still required to identify significant edges. Region extraction groups pixels into a set of regions based on similarity. Indeed, most segmentation techniques are based on region extraction. To reduce the competition cost of segmentation a four pass pipeline implementation scheme of segmentation method on cognate neighbourhood approach [29] is proposed. A segmentation method for finding interior borders is also proposed recently [30,31].Other conventional segmentation approaches range from the split-and-merge method to morphological segmentation. Among them, morphological segmentation techniques are of particular interest because they rely on morphological tools, which are very useful to deal with object-oriented criteria such as size and contrast. Much of the texture segmentation work has concentrated on extracting features that are suitable for texture modelling, followed by feature clustering or classification so that image regions of uniform texture may be identified [20]. Classic texture features include those derived from Laws filters [15], co-occurrence matrices (CO) [11, 4], and cortex transform modulation functions (CTMF) [27]. More recently, a number of new

- *S.Kezia is currently pursuing PhD(Research Scholar) in JNTUK University, India, email:sakakezia1981@gmail.com*
- *Dr.I.Shanti Prabha,Professor in ECE Dept.in JNTUCE,JNTUK University, Indi.,email: santiprabha@yahoo.com*

texture features have been considered for texture analysis and segmentation, including multiresolution simultaneous auto-regressive (MRSAR) models [18, 16, 5], Markov random field (MRF) models [7, 1, 17, 23] Gabor filters [12, 33], wavelet coefficients [14,3,28, 24], and fractal dimension [7, 13].

The present paper is organized as follows. The section 2 deals with the basic concepts of mathematical morphology, section 3 introduces thresholding and the section 4 deals with the methodology. Experimental results are discussed in section 5 and section 6 deals with conclusions.2 Procedure for Paper Submission

2 MATHEMATICAL MORPHOLOGY

Mathematical morphology is a set theory approach, developed by J.Serra and G. Matheron. It provides an approach to processing of digital images that is based on geometrical shape. Two fundamental morphological operations – erosion and dilation are based on Minkowski operations. There are two different types of notations for these operations: Serra/Matheron notation and Haralick/Sternberg notation. In this paper Haralick/Sternberg notation, which is probably more often used in practical applications, is used. In this notation erosion is defined as follows (Eq. 1) (Serra, 1982):

$$X \Theta B = \bigcap_{y \in B} X_y \tag{1}$$

And dilation (Eq. 2) as:

$$X \oplus B = \bigcup_{y \in B} X_y \tag{2}$$

Where:

$$X_y = \{ x + y : x \in X \} \tag{3}$$

$$\hat{B} = \{ b : -b \in B \} \tag{4}$$

B and $\hat{B}$ are structuring elements

Another important pair of morphological operations are opening and closing. They are defined in terms of dilation and erosion, by equations (5) and (6) respectively

$$X \circ B = (X \Theta B) \oplus B \tag{5}$$

$$X \bullet B = (X \oplus B) \Theta B \tag{6}$$

3 THRESHOLDING OTSU METHOD

This method, as proposed by [36] is based on discriminate analysis. The threshold operation is regarded as the partitioning of the pixels of an image into two classes C_0 and C_1 (e.g., objects and background) at grey-level t, i.e., $C_0 = \{0, 1, 2, t\}$ and $C_1 = \{t + 1, t +2,\ldots.L-1\}$. Let σ^2_W, σ^2_B and σ^2_T be the within-class variance, between-class variance, and the total variance, respectively. An optimal threshold can be determined by minimizing one of the following (equivalent) criterion functions with respect to:

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2}, \ \eta = \frac{\sigma_B^2}{\sigma_T^2}, \ \kappa = \frac{\sigma_T^2}{\sigma_W^2} \tag{7}$$

The optimal threshold t is defined as

$$t = \mathrm{ArgMin}\ \eta \tag{8}$$

$$\sigma_T^2 = \sum_{i=0}^{L-1}\left[1 - \mu_T\right]^2 P_i \ , \mu_T = \sum_{i=0}^{L-1}\left[iP_i\right] \tag{9}$$

$$\sigma_B^2 = W_0 W_1 \left(\mu_0 \mu_1\right)^2 \tag{10}$$

$$W_0 = \sum_{i=0}^{t} P_i \ , \qquad W_1 = 1 - W_0 \tag{11}$$

$$\mu_1 = \frac{\mu_T - \mu_t}{1 - \mu_0} \ , \ \mu_0 = \frac{\mu_t}{W_0} \ , \mu_t = \sum_{i=0}^{t}\left(iP_i\right) \tag{12}$$

$$P_i = \frac{n_i}{n} \tag{13}$$

Where n_i is the number of pixels with grey-level and n is the total number of pixels in a given image defined as

$$n = \sum_{i=0}^{L-1} n_i \tag{14}$$

Moreover, P_i is the probability of occurrence of grey-level i. For a selected threshold t of a given image, the class probabilities w0 and w1 indicate the portions of the areas occupied by the classes C_0 and C_1. The class means μ_0 and μ_1 serve as estimates of the mean levels of the classes in the original grey-level image. Moreover, the maximum value of η, denoted by η*, can be used as a measure to evaluate the separability of classes C_0 and C_1 in the original image or the bimodality of the histogram. This is a very significant measure because it is invariant under affine transformations of the grey-level scale. It is uniquely determined within the range $0 \leq \eta \leq 1$.

The lower bound (zero) is obtained when and only when a given image has a single constant grey level, and the upper bound (unity) is obtained when and only when two-valued images are given.

5 METHODOLOGY

Texture segmentation partitions an image into a set of disjoint regions based on texture properties. To deal the issues of segmentation the present paper divided the entire process of segmentation into seven steps. The first step estimates the significant regions of segmentation. For this image complement is used effectively. The image complement is a brightness function for a dark region. That is complement converts the dark regions and the regions covered with high noise that are not visible as bright regions. The image complement will brighten

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the dark regions regardless of their direction. This approach helps in estimating the significant regions for segmentation.

Further to deal with noise levels on segmented regions, LOG (Laplacian of Gaussian) is applied. Then to brighten the dark spots and to make precise segmentation in all directions again the resultant image is complemented. In the next step histogram equalization is performed to identify interior details and to enhance the contrast of the image. Then opening followed by a closing is applied to recognize interior segments. The opening operation can separate objects that are connected in a binary image. The closing operation can fill in small holes. Both operations generate a certain amount of smoothing on an object contour given a “smooth” structuring element. The opening smoothes from the inside of the object contour and the closing smoothes from the outside of the object contour. Finally thresholding is applied on step 6, to establish boundaries in the image that contain solid objects resting on a contrasting background. The proposed algorithm is presented below.

Algorithm

Begin

Step 1: Image complement

$$S_1 = (L-1)-r \tag{15}$$

where L is the number of gray levels in the given image, r is original, S_1 is complemented pixel value.

Step 2: To remove noise and edge detection in S1, the Laplacian of Gaussian filter is used.

$$S_2 = Laplacian(Gaussian_{\sigma=7/4}^{Width=7\ pixels}(S_1)) \tag{16}$$

Step 3: The same process of eq. (15) is applied on S_2 . S_3 is the resultant image.

Step 4: Histogram equalization is applied on S_3 to identify interior details. S_4 is the resultant image.

Step 5: Closing operation is performed on S_4 through the following transformation.

$$S_5 = (S_4 \oplus B)\Theta B \tag{17}$$

where B is3×3 structuring element.

Step 6: An opening operation is performed on S_5

$$S_6 = (S_5 \Theta B) \oplus B \tag{18}$$

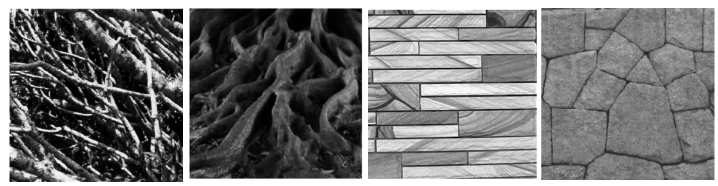
where B is 3×3 structuring element.S_6 gives segmented image.

Step 7: To establish boundaries in the image, thresholding is performed on S_6.

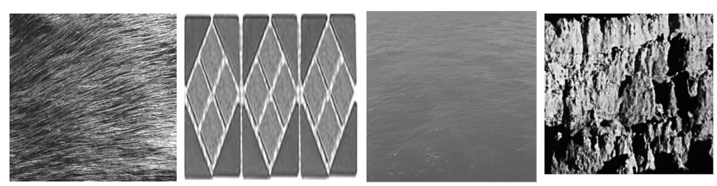
End

6 RESULTS AND DISCUSSIONS

The proposed algorithm is tested on a large database of textures taken directly from Brodatz and Vistex album. The typical size of the texture is 512×512. In this paper the results of eight Vistex textures are presented. The original texture images are shown in Figure 1(a)-1(h). The stepwise results of the proposed method for Bark.03 and Brick.04 textures are shown in figure 2 and 3. The results clearly indicate that image complement in step1 for all textures, enhanced the dark portions of the textures in all directions by segmenting the image. The second step i.e. LOG reduced the small bright noise and enhanced the interior segments. To fill the small holes and to connect borders of regions for a better segmentation closing is performed. Complement is applied second time to brighten the dark spots in all directions. To enhance the contrast further Histogram Equalization is applied in all images and this effect is clearly visible in figures of texture images 2(c) and 3(c).The proposed method is also applied on medical images of Figure 5(a)-5(b) and the corresponding output segmented images are shown from figure 5(c)-5(d).

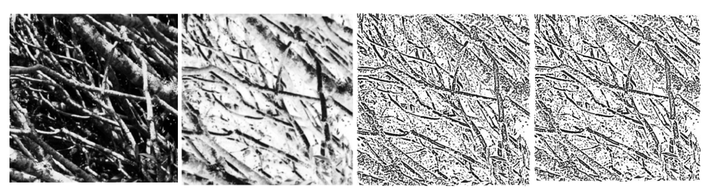


(a) (b) (c) (d)

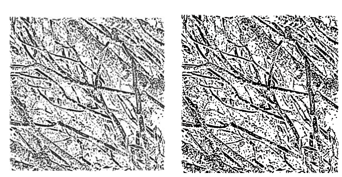


(e) (f) (g) (h)

Fig. 1. Original input textures. (a)Bark.03 (b)Bark.05 (c)Brick.02 (d)Brick.04 (e)Fabric.04 (f)Mosaic.01 (g)Water.01 (h)Stone.01.

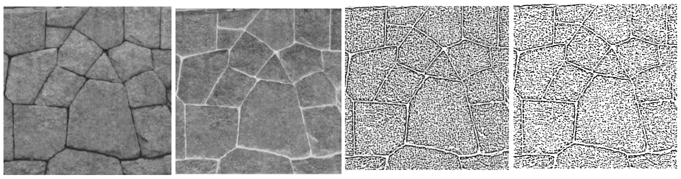


(a) (b) (c) (d)

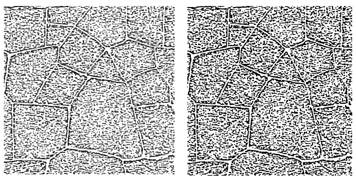


(e) (f)

Fig. 2. Step by step results of the proposed algorithm for Bark.03 (a) Original (b) Complement (c) after Hist.eq. (d) Closed (e) Opened (f) Thresholded.

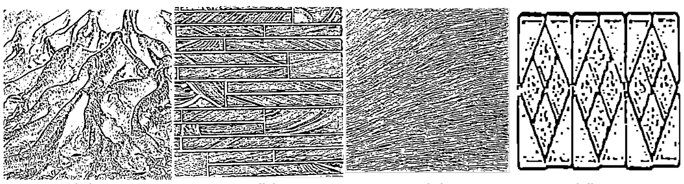


(a) (b) (c) (d)

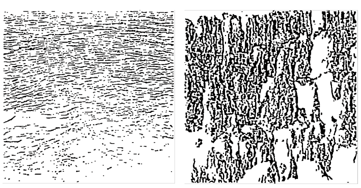


(e) **(f)**

Fig. 3. Step by step results of the proposed algorithm for Brick.04 teture (a)Original (b) Complement (c) after Hist.eq. (d)Closed (e) Opened (f) Thresholded.



(a) (b) (c) (d)

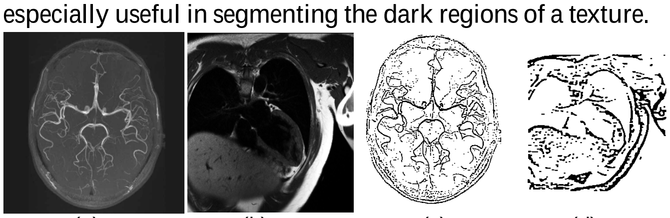


(e) (f)

Fig. 4. Final outputs of (a) Bark.05 (b) Brick.02 (c) Fabric.04 (d)Mosaic.01 (e) Water.01 (f) Stone.01

4 CONCLUSION

In this paper, a new texture segmentation method is proposed. The segmentation results are visually satisfactory as shown in figures 2 - 5. The whole process is autonomous and requires no supervision, which is one of the advantages of the proposed algorithm. The method guarantees best segmentation of textures in poor-quality images also. Image quality is enhanced by using histogram equalization step and morphological operations. By combining these different forms of image enhancement, the contrast was greatly increased. The proposed method segments the image along with enhancement. The influence of noise is of interest for a segmentation method. The proposed method removes the noise, if present and recognizes the interior segments. It is especially useful in segmenting the dark regions of a texture.



(a) (b) (c) (d)

Fig. 5. Results of the Proposed Algorithm for MRI Images. (a) and (b) Original input MRI Images (c) and (d) Corresponding outputs of proposed algorithm.

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