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A New Approach for Texture Segmentation Using Gray Level Textons

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Abstract

Texture analysis such as segmentation and classification plays a vital role in computer vision and pattern recognition and is widely applied to many areas such as industrial automation, bio-medical image processing and remote sensing. Over the last decade, several studies on texture analysis propose to model texture as a probabilistic process that generates small texture patches. In these studies, texture is represented by means of a frequency histogram that measures how often texture patches from a codebook occur in the texture. In the codebook, the texture patches are represented by a collection of filter bank responses. The resulting representations are called textons. A recent study claims that textons based on gray values outperform textons based on filter responses. Textons refer to fundamental micro structures in natural images and are considered as the atoms of pre-attentive human visual perception. This paper describes a novel technique of image segmentation for texture images based on six different texton patterns and morphological transforms.

Keywords: *Texton pattern, Texture, Segmentation*

1. Introduction

Texture [1, 4] can be seen in many images from multispectral remote sensed data to microscopic photography. Despite its importance, there is no unique and precise definition of texture. Each texture analysis method characterizes image texture in terms of the features it extracts from the image. Therefore, it depends not only on studying the images but also on the goal for which the image texture is used and the features that are extracted from the image. A number of definitions have been proposed for texture and used by various researchers in their context of analysis. Few schemes for texture analysis have been suggested. They are statistical, structural and spectral approaches. Using statistical approaches, several schemes have been suggested right from Co-occurrence matrix, run length matrix based, auto correlation, auto regression, MRF based, moments based etc. as found in literature [5-9]. Radius and angular histogram features obtained by computing Discrete Fourier Transform of the texture image signal was used for content based image retrieval [10]. A texture representation is designed which is invariant to any geometric transformation that can be locally approximated by a sparse set of affine models [11].

Texture analysis is one of the most important techniques used in the analysis and interpretation of images, consisting of repetition or quasi repetition of some fundamental image elements [2]. There are three primary issues in texture analysis, such as texture classification, texture segmentation and shape recovery from texture. In texture classification, the problem is identifying the given texture region from a given set of texture classes. As opposed to texture classification, in which the class label of a single homogeneous region is determined using distinguishing features derived from the region, texture segmentation is concerned with automatically determining the boundaries between various textured regions in an image [3].

Image segmentation is essentially the process of dividing an image into small pieces or objects that have a common attribute, *e.g.*, color, brightness, texture, boundary continuity and so on. Moreover, the resulting segments must be "visually meaningful" [12] although it is quite hard to give "visually meaningful" a precise and quantitative definition. Different people may like to divide the same image in different ways according to their practical purposes. Furthermore, huge diversity of images in the real world are getting more and more complicated with advances of photography techniques and painting tools. Therefore, image segmentation is still a very difficult problem. Traditionally, there are two main approaches to address this challenging task: the edge-based and region-based approaches. The idea of edge-based segmentation is to detect the locations of discontinuities in brightness, color, texture *etc*. However, the resulting image by edge detection is essentially "not" a segmentation result yet [13, 18, 19], because the edge fragments need to be linked into closed boundaries that correspond to meaningful objects in the further processing stages. In contrast, the region based algorithms group the pixels with similarities into subregions directly, *e.g.*, the K-means clustering and GMM based approaches [14-17], and thus the boundaries can be easily obtained from the constructed subregions. The basic idea behind region-based approaches is to segment the images into regions with maximum homogeneity. Various criteria for homogeneity can be utilized such as intensity, color, texture, shape, model (using semantic information) and so on [19].

For some typical applications, particularly in medical images, segmentation based on gray level does not give the desired results, in such applications, segmentation based on textural feature methods gives more reliable results. Therefore, texture-based analysis is extensively used in analysis of medical images [21-24]. Image segmentation based on texture feature of an image is still a complex and challenging problem. Texture can be defined as something consisting of mutually related elements. Further, texture can be defined as spatial arrangement of texture primitives or texture element, sometimes also called texton, arranged in periodic manner, where texture primitive is a group of pixels representing the simplest or basic subpattern. A texture may be fine, coarse, smooth, or grained, depending upon its tone and structure, where tone is based on pixel intensity properties in primitive while structure is the spatial relationship between primitives [25].

Various researchers have proposed texture analysis algorithms on texton patterns. In [26] texton based segmentation of retinal vessels is described. Methods for analyzing general texture surfaces based on 3D textons have been studied in [27-29]. Varma and Zisserman [30] proposed a statistical learning based algorithm, namely maximal response 8 (MR8), with which a rotation invariant texton library is first built from a training set and then an unknown texture image is classified according to its texton distribution. LBP and MR8 are two typical local rotation invariant features, while their underlying local invariance is different: the former extracts an isotropic feature, as it does not consider any local dominant orientation; the latter selects an anisotropic feature, as it defines a dominant orientation from six orientations and keeps the response at that orientation only. To investigate whether local dominant orientation is important for local rotation invariant, a complex response 8 (CR8) is proposed. Instead of getting the maximal response among six orientations, average and standard deviation of responses are computed and an 8-dimensional feature is extracted. After that, similar to MR8, a complex texton library is built from a training set by k-means clustering algorithm and then an texton distribution is computed for a given texture image. Since CR8 and MR8 use the same filters and feature extraction scheme, it is relatively fair to evaluate the role of local dominant orientation in texture classification. The method used in [31] combined texton and Local Binary Pattern features for texture analysis. Texture classification using gray level textons is described in [32]. Texton based texture classifiers are studied in [33-35].

In the present paper Section II gives brief introduction of mathematical morphology, Section III describes methodology, results and discussions are given in Section IV and finally conclusions are given in Section V.

2. Mathematical Morphology

Mathematical morphology used to extract image components that are useful in the representation and description of region shape, such as boundaries extraction, skeletons, convex hull, morphological filtering, *etc.* It is based on set theory and set in mathematic morphology represent objects in an image. In binary images (0 = black, 1 =white) the element of the set is the coordinates (x, y) of pixel belong to the object Z^2 and in gray-scaled images the element of the set is the coordinates (x, y) of pixel belong to the object and the gray levels Z^3. The basic operations in mathematical morphology are dilation and erosion and in gray-scaled images, they defined as equations (1) and (2) respectively:

$$(f \oplus b)(s, t) = max\left\{f(s-x, y-t) + b(x,y) \mid (s-x),(t-x) \in D_f; (x,y) \in D_b\right\} \quad (1)$$

$$(f \Theta b)(s, t) = max\left\{f(s+x, y+t) - b(x,y) \mid (s+x),(t+y) \in D_f; (x,y) \in D_b\right\} \quad (2)$$

Where f(x, y) is the input image, b(x, y) is a structuring element, and D_f, D_b are the domains of f and b, respectively. Combining these operations produces another two useful operators, which are opening and closing:

$$f \circ b = (f \ \Theta\ b) \oplus b \quad (3)$$

$$f \bullet b = (f \oplus b) \ \Theta\ b \quad (4)$$

In opening, the structuring element is rolled underside the surface of ‘f’ and all the peaks that are narrow with respect to the diameter of the structuring element will be reduced in amplitude and sharpness. Therefore, opening is used to remove small light details, while leaving the overall gray levels and larger bright features relatively undisturbed. The initial erosion removes the details, but it also darkens the image. The subsequent dilation again increases the overall intensity of the image without reintroducing the details totally removed by erosion [20].In closing the structuring element is rolled on top of the surface of f and peaks essentially are left in their original form (assume that their separation at the narrowest points exceeds the diameter of the structuring element). So, closing is used to remove small dark details, while leaving bright features relatively undisturbed. The initial dilation removes the dark details and brightens the image and the subsequent erosion darkens the image without reintroducing the details totally removed by dilation [20].

3. Methodology

In the current work, image based textons are used for segmentation. In the literature [35], it was proved that image based textons performance is better when compared to textons based on filter bank responses. In Figure 1, the four pixels of a 2×2 grid are denoted as V1, V2, V3 and V4. If two pixels are highlighted in gray color of same value then the grid will form a texton. The six texton types denoted as TP1, TP2, TP3, TP4, TP5 and TP6 are shown in Figure 1(b) to 1(g). In step one ,for every 2x2 overlapping block of the entire input image, the first texton pattern is identified, the pixels satisfying TP1 pattern are replaced with ones and remaining pixels are made zeros thereby generating IP1 image. Similarly, images corresponding to the remaining texton types are generated thereby giving a total of six images. The images corresponding to TP2,TP3,TP4,TP5,TP6 are IP2,IP3,IP4,IP5,IP6 respectively. In step two, IP2 to IP6 images are added and the result is subtracted from IP1 to eliminate the common pixels. Eq. (4) is applied on the output image of step two in 5x5 non-overlapping blocks to obtain final segmented ouput image. The example of computing texton images is shown in Figure 2.

$$\textit{Output image} = ((f(x, y) \oplus SE) + (f(x, y)\Theta SE)) - (0.2(((f(x, y) \oplus SE) - (f(x, y)\Theta SE))/2) \quad (5)$$

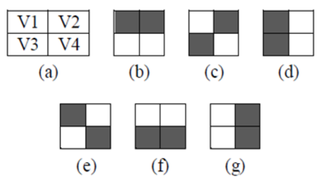

Figure 1. Six Special Types of Textons: a) 2×2 grid b) TP1 c) TP2 d) TP3 e) TP4 f) TP5 g) TP6

(a)

2	3	4	4	5
1	2	3	3	4
9	8	4	4	4
0	3	4	5	5
9	9	0	0	9

(b)

0	0	1	1	0
0	0	1	1	0
0	0	1	1	1
0	0	0	1	1
1	1	0	0	0

(c)

0	0	0	0	0
0	0	0	0	1
0	0	0	1	0
0	0	0	0	0
0	0	0	0	0

(d)

0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	1	0	0
0	0	0	0	0

(e)

1	1	0	1	0
0	1	1	0	1
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0

(f)

0	0	0	0	0
0	0	1	1	0
0	0	1	1	1
0	0	0	1	1
1	1	1	1	0

(g)

0	0	0	0	0
0	0	0	0	1
0	0	1	0	1
0	0	1	0	0
0	0	0	0	0

Figure 2. Example for Generation of Texton Images (a) Original Image (b) Texton Image IP1 (c) Texton Image IP2 (d) Texton Image IP3 (e) Texton Image IP4 (f) Texton Image IP5 (g) Texton Image IP6

4. Results and Discussions

The proposed algorithm is tested on a large database of smoke textures. The typical size of the texture is 256×256. In this paper, the results of six textures are presented. The original texture images are shown in Figure 3(a)-3(f). The stepwise results of the proposed method for smoke 1041 and smoke 1049 textures are shown in Figure 4 and 5 respectively. The results shown in Figure 4(b)-(g) and Figure 5(b)-(g) clearly indicate that the output of step one i.e.

IP1 to IP6 images give texton patterns in six different directions. The output of step two, which is shown in Figure 4(h) & Figure 5(h) resulted in background subtraction. The final segmented output shown in Figure 4(i) & Figure 5(i) resulted in enhancement and detection of interior segments of the smoke textures. Figure 6. Show the final outputs of smoke 1057, 1011, smoke 1037 and 1061. The algorithm is also tested on medical images and the results are shown in Figure 7. The results clearly indicate that the dark background appears brighter and the smoke region appears darker in the IP1 to IP6 images thereby enhancing the contrast of the image. The texton patterns appear brighter in the dark smoke region of IP1 to IP6 images, which are shown in Figures 4, 5(b)-(g). The background appears similar in all the texton images IP1 to IP6. Figures 4-5(h) images clearly show the elimination of background by subtraction operation. Figures 4-5(i) images show further enhancement of the texton patterns in smoke textures. The final outputs of the proposed algorithm are shown in Figure 6.

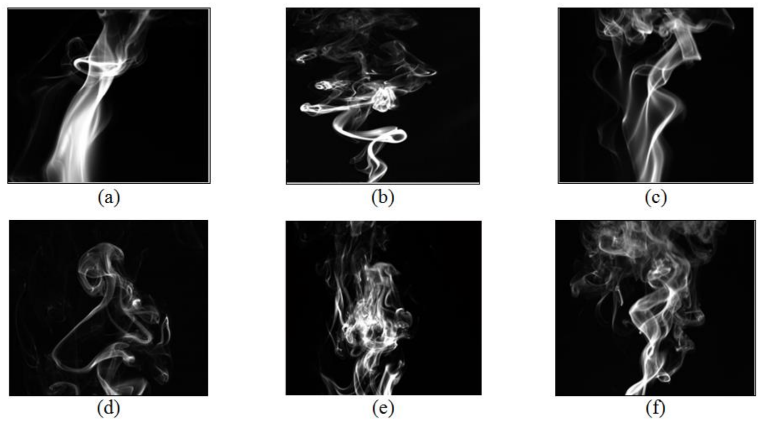

Figure 3. (a) Smoke 1057 (b) Smoke 1011 (c) Smoke 1037 (d) Smoke 1061 (e) Smoke 1049 (f) Smoke 1041

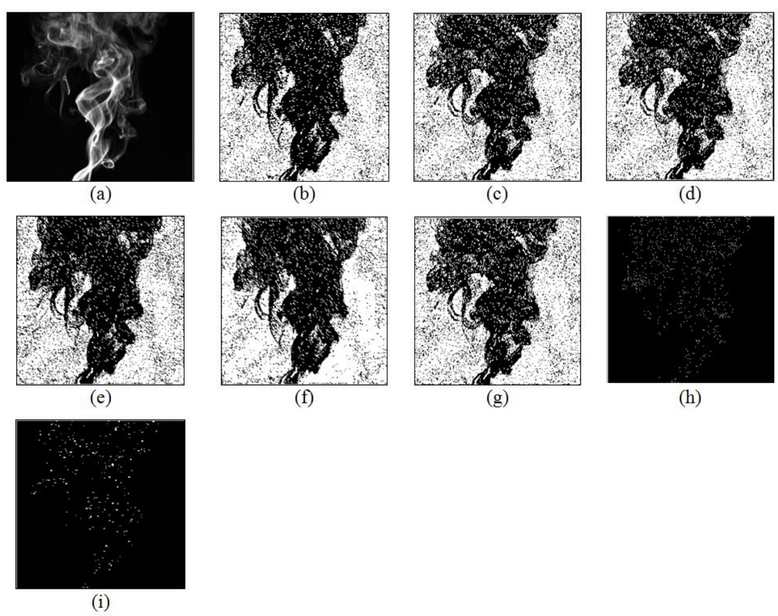

Figure 4. (a) Original Smoke 1041 Image (b) IP1 (c) IP2 (d) IP3 (e) IP4 (f) IP5 (g) IP6 (h) Step Two Output (i) Segmented Image

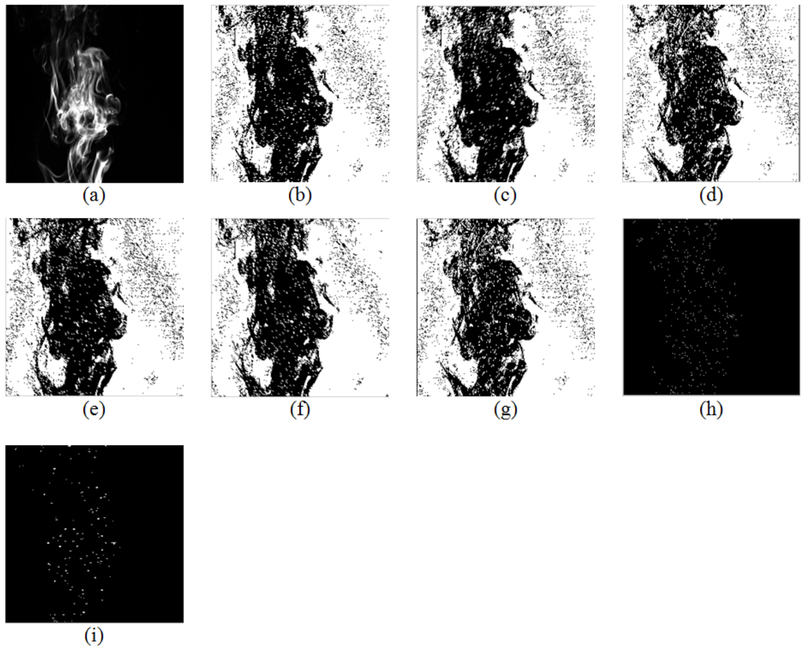

Figure 5. (a) Original Smoke 1049 Image (b) IP1 (c) IP2 (d) IP3 (e) IP4 (f) IP5 (g) IP6 (h) Step Two Output (i) Segmented Image

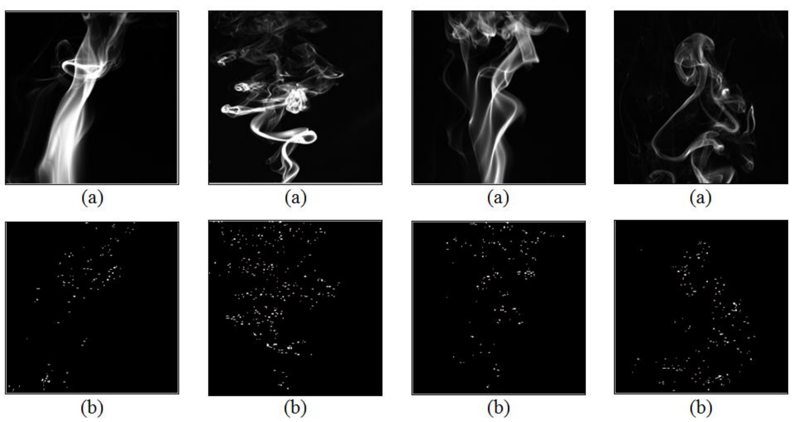

Figure 6. (a) Original Smoke Image (b) Final Segmented Images Corresponding to (a)

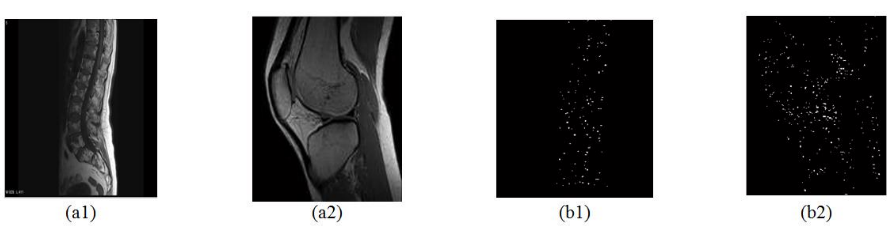

Figure 7. (a1), (a2) Original MRI Images (b1), (b2) Final Segmented Images Corresponding to (a1) (a2)

5. Conclusions

Textons are considered as texture primitives. Different textons may form various image features. Based on the texton features the present paper evaluated a new texture segmentation approach, which is rotationally invariant. The segmentation results are visually satisfactory. 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 as the algorithm also does enhancement. Image quality is enhanced by using morphological operations. By combining these different forms of image enhancement, the contrast was greatly increased. The proposed method segments the image along with enhancement. It is especially useful in segmenting the bright regions of a texture. The algorithm proved to be efficient in obtaining the internal patterns of textures.

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