A NOVEL APPROACH FOR TEXTURE SEGMENTATION BASED ON ROTATIONALLY INVARIANT PATTERNS

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ABSTRACT

Texture can be defined as a regular repetition of an element or pattern on a surface. It is a property that represents the surface and structure of an Image. A texture image can be represented as a set of essential small units termed as texture units, which characterize the local texture information for a given pixel and its neighbourhood. The statistics of all the texture units over the entire image reveal the global texture aspects. Texture segmentation can be considered the most important problem, since human can distinguish different textures quite easily, but the automatic segmentation is quit complex and it is still an open problem for research.This paper describes new statistical approach for texture segmentation, based on average of fuzzy left and right texture unit matrix. In this method, the "local" texture information for a given pixel and its neighbourhood is characterized by the corresponding fuzzy texture unit. The proposed Average Fuzzy Left and Right Texture Unit Matrix (AFLRTU) segmentation method overcomes the computational complexity of Fuzzy Texture Unit (FTU) by reducing the texture unit from 2020 to 79. Four patterns of Left Texture Unit (LTU) and four patterns of Right Texture Unit (RTU) are used for texture segmentation. Pixel wise averaging operation is performed on the resultant image obtained after adding all thee eight pattern images which leads to noise reduction. The proposed scheme is compared with the Wavelet Transform with Image Fusion (WTIF) in [17]. The results demonstrate the efficacy of the proposed method.

KEYWORDS: *FUZZY TEXTURE UNIT LEFT RIGHT TEXTURE UNIT* MATRIX, TEXTURE SPECTRUM, AND TEXTURE.

1. INTRODUCTION

An image texture can be defined as the local spatial variations in pixel intensities and orientation [19, 29]. A texture is an ensemble of repetitive sub patterns, which follow a set of well-defined placement rules. These sub patterns themselves are made up of more fundamental units, called primitives. Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. One immediate application of image texture is the recognition of image regions using texture properties. Texture is the most important visual cue in identifying these types of homogeneous regions. Image textures are complex visual patterns composed of entities or regions with sub-patterns with the characteristics of brightness, colour, shape, size, etc. An image region has a constant texture if a set of its characteristics are constant, slowly changing or approximately periodic [1]. Texture can be regarded as a similarity grouping in an image [2].

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. Segmentation is done by deciding the most probable texture for every pixel, making use of the features for this pixel [8, 9, 3, 10, 11, 12, 13, 14, 15, 31]. 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. The two general approaches to performing texture segmentation are analogous to methods for image segmentation: region-based approaches or boundary-based approaches. In a region-based approach, one tries to identify regions of the image which have a uniform texture. Pixels or small local regions are merged based on the similarity of some texture property. The regions having different textures are then considered to be segmented regions. This method has the advantage that the boundaries of regions are always closed and therefore, the regions with different textures are always well separated. It has the disadvantage, however, that in many region-based segmentation methods, one has to specify the number of distinct textures present in the image in advance. In addition, thresholds on similarity values are needed. The boundary-based approaches are based upon the detection of differences in texture in adjacent regions. Thus boundaries are detected where there are differences in texture. In this method, one does not need to know the number of textured regions in the image in advance. However, the boundaries may have gaps and two regions with different textures are not identified as separate closed regions. Strictly speaking, the boundary based methods result in segmentation only if all the boundaries detected form closed curves. Boundary based segmentation of textured images have been used by Tuceryan and Jain [16], Voorhees and Poggio [4], and Eom and Kashyap [5]. In all cases, the edges (or texture boundaries) are detected by taking two adjacent windows and deciding whether the textures in the two windows belong to the same texture or to different textures. If it is decided that the two textures are different, the point is marked as a boundary pixel. Du Buf and Kardan [6] studied and compared the performance of various texture segmentation techniques and their ability to localize the boundaries. Tuceryan and Jain [16] use the texture features computed from the Voronoi polygons in order to compare the textures in the two windows. The comparison is done using a Kolmogorov-Smirnoff test. A probabilistic relaxation labelling, which enforces border smoothness, is used to remove isolated edge pixels and fill boundary gaps. Voorhees and Poggio extract blobs and elongated structures from images (they suggest that these correspond to Julesz’s textons). The texture properties are based on blob characteristics such as their sizes, orientations, etc. They then decide whether the two sides of a pixel have the same texture using a statistical test called maximum frequency difference (MFD). The pixels where this statistic is sufficiently large are considered to be boundaries between different textures. Jain and Farrokhnia [7] gave an example of integrating a region-based and a boundary based method to obtain a cleaner and more robust texture segmentation method. They used the texture features computed from the bank of Gabor filters to perform region-based segmentation.

The present paper is organized as follows: The concepts of texture unit, texture spectrum and fuzzy texture spectrum are given in section 2. The proposed methodology is given in section 3. Section 4 contains experimental results and conclusions are given in section 5.

2. FUZZY TEXTURE SPECTRUM

The texture spectrum is a statistical way of describing texture feature of an image, was first introduced by He and Wang [20, 21, 22]. In this method a texture unit represents the local texture information for a given pixel and its neighbourhood, and the global texture of an image is characterized by its texture spectrum [18].

The basic concept is that a texture image can be represented as a set of essential small units termed as texture units, which characterize the local texture information for a given pixel and its neighbourhood. The statistics of all the texture units over the entire image reveal the global texture aspects. In a square raster digital image, each pixel is surrounded by eight neighbouring pixels. The local texture information for pixel is then extracted from the neighbouring pixels, which form the elements of the 3 x 3 window with the pixel under consideration as the central one. It can be noted that the eight neighbourhoods represents the smallest complete unit from which texture spectrum information can be obtained.

Given a neighbourhood of 3 x 3 pixels, which are denoted by a set containing nine elements, V= {V0, V1,…, V8}, where Vi (i = 0, 1, . . . , 8) represents the gray level of the i^{th} element in the neighbourhood with V0 representing the gray level of the central pixel [19]. It is important to note that the eight pixels in the neighbourhood are always taken in some order and the subscripts might denote the direction in which a particular neighbourhood pixel lies.

The corresponding texture unit (TU) of the pixel is then defined by a set containing eight elements. Thus, TU = { E1 , E2 , .. . , E8}, and Ei (i = 1, 2,. . . ,8) is determined by the following description in base3 method:

$$E_i = \begin{cases} 0 & \text{when } V_i < V_0 \\ 1 & \text{when } V_i = V_0 \\ 2 & \text{when } V_i > V_0 \end{cases} \tag{1}$$

where the element Ei occupies the same position as the pixel i. As each element of the TU has one of the three possible values, the combination of all the eight elements results in 38 = 6561 possible texture units in total. The algorithm labels these texture units by the following formula:

NTU=3i-1 Ei , i=1, 2…, 8 (2)

Where NTU represents the texture unit number. Each texture unit number describes the local texture aspect of a given pixel, which are the relative gray level relationships between the central pixel and its neighbours. Thus, the statistics on frequency of occurrence of all the texture unit numbers over a large region of an image should reveal texture information. With this background, the term texture spectrum is defined as the frequency distribution of all the texture unit (numbers) with the abscissa indicating the texture unit number NTU and the ordinate the frequency of its occurrence. In base5, the following equation 3 is used to determine the elements, Ei of texture unit

$$E_i = \left\{ \begin{matrix} 0 & \text{if} & V_i < V_0 & \text{and} & V_i < x \\ 1 & \text{if} & V_i < V_0 & \text{and} & V_i > V_x \\ 2 & \text{if} & V_i = V_0 & & \\ 3 & \text{if} & V_i > V_0 & \text{and} & V_i > y \\ 4 & \text{if} & V_i > V_0 & \text{and} & V_i < y \end{matrix} \right\} \quad \text{for } i = 1,2,3,\ldots,8 \tag{3}$$

where x, y are user-specified values. The FTU number (FTUn) is computed in Base5 as given in equation 4.

$$FTU_{n5} = \sum_{i=1}^{8} E_i * 5^{(i-1)/2} \tag{4}$$

3. METHODOLOGY

The GLCM method gives reasonable texture information of an image that can be obtained from two pixels. Further, a little work is reported in literature to produce strong texture information of an image by separating the neighbouring pixels into groups and to form a relationship among them. In the cross diagonal approach [7, 23, 24, 25, 26, 27,30], texture information of the image is evaluated by separating the neighbourhood pixels into diagonal and corner pixels. The corner pixels are not connected pixels. The cross diagonal approach is evaluated with original texture unit but not with the FTU information. To overcome these, Left Right Texture Unit Matrix (LRTM) on FTU is proposed recently [28]. The method divides the fuzzy texture information of an image by separating the neighbouring pixels into two well connected equal groups containing four pixels named as Left Texture Unit (LTU) and Right Texture Unit (RTU). This method further reduces the FTU from 2020 to 79 i.e., LTU and RTU values range from 0 to 78. This reduction is useful for decreasing the computational complexity.

The texture information is obtained by LTU and RTU from the mathematical model representing two groups of 4-connected texture elements is shown in Fig.1 & Fig.2. The LTU and RTU are named based on the position of top most left texture element E1 and bottom most right texture element E5 i.e., the texture unit which contains E1 and E5 are called as LTU and RTU respectively. A 3×3 grid can have four such patterns of LTU's and RTU's as shown in Fig.1 & Fig.2.

E1		
E8		
E7	E6	

E1	E2	
E8		
E7		

E1	E2	E3
E8		

E1	E2	E3
		E4

Figure 1. Representation of 4-patterns of LTU.

	E2	E3
		E4
		E5

		E3
		E4
	E6	E5

		E4
E7	E6	E5

E8		
E7	E6	E5

Figure 2. Representation of 4-patterns of RTU.

Each fuzzy texture element in the two groups has one of the five possible values {0, 1, 2, 3 and 4} as given in Eqs. (5) & (6):

$$NLTU=ELi*5(i-1/2) \quad (5)$$
$$NRTU=ERi*5(i-1/2) \quad (6)$$

Where NLTU and NRTU are the left texture unit number and right texture unit number respectively. The ELi and ERi are the i^{th} element of left texture unit and right texture unit respectively. The entire process of the proposed method is shown in Fig.3. The elements in the LTU and RTU may be ordered differently. The first element of each TU may take four possible positions. In the same manner, the remaining three elements also may take four possible positions. The values of LTU and RTU vary depending on the position of elements which can be labelled by using the Eqs. (5)& (6).

In the proposed methods, the texture unit number of first LTU pattern is calculated in 3x3 overlapping windows for the entire image to obtain first resultant image. The process is repeated for the remaining 3 patterns of LTU and 4 patterns of RTU to obtain 7 resultant images. At each pixel location of the original image, texture unit number is computed using the proposed method shown in Fig. 4. Pixel wise average is taken for the 4 resultant images corresponding to Fuzzy LTU (FLTU) patterns to obtain Average LTU (ALTU) image. Similarly, pixel wise average is taken for the 4 resultant images corresponding to Fuzzy RTU (FRTU) patterns to obtain Average RTU (ARTU) image. The entire process is shown in Fig.4. Finally, ALTU and ARTU images are averaged pixel wise to obtain the segmented output.

0x50	1x0	3x0
1x50.5		2x0
0x51	2x51.5	1x0

NLTU=25

0x0	1x50	3x50.5
1x0		2x51
0x0	2x0	1x51.5

NRTU=29

0x51.5	1x0	3x0
1x50		2x0

NLTU=11

0x0	1x51.5	3x50
1x0		2x50.5

NRTU=24

Sub image

0	1	3
1		2
0	2	1

(a)

0x50.5	2x51	1x0

0x51	1x0	3x0
1x51.5		2x0
0x50	2x50.5	1x0

NLTU=16

0x50.5	1x0	3x0
1x51		2x0
0x50.5	2x50	1x0

NLTU=7

(b)

0x0	2x0	1x51

0x0	1x51	3x51.5
1x0		2x50
0x0	2x0	1x50.5

NRTU=43

0x0	1x50.5	3x51
1x0		2x51.5
0x0	2x0	1x50

NRTU=41

Figure 3 (a) Four possible patterns for each LTU (b) Four possible patterns for each RTU

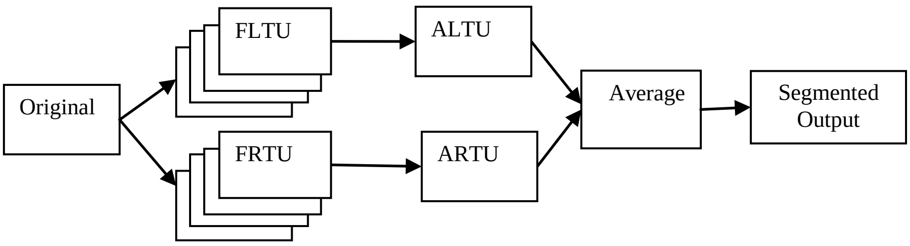
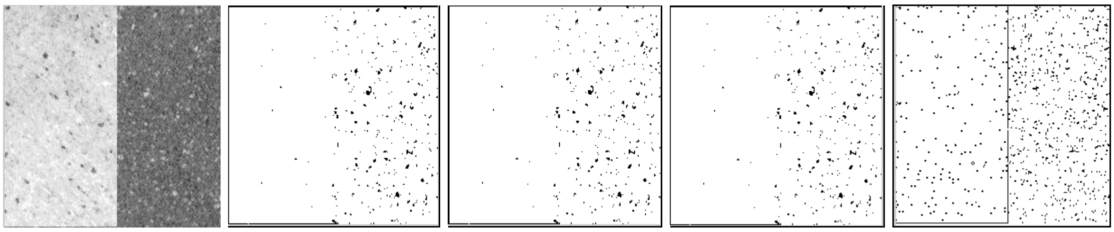


Figure 4. Block diagram of the proposed AFLRTU method

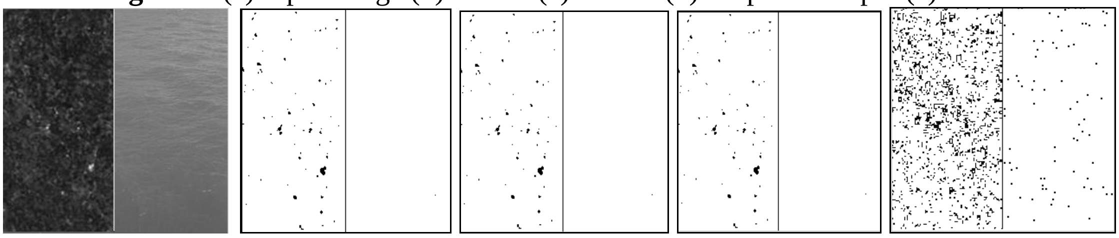
4. Results & Discussions

The proposed AFLRTU method is tested on Vistex & Brodatz textures of size 256x256. The AFLRTU method is compared with WTIF in [17]. The Figs. 5(a), 6(a), 7(a) and 8(a) show the input images of royalred and kashmirwhite, blackpearl and water 1, bark 0 and mammogram respectively. The resultant segmented images by the proposed scheme show well-defined borders. The results obtained are satisfactory. The proposed method works well on images having two different textures and are able to differentiate clearly two textures. The method is able to extract more details from dark texture images. The algorithm is also tested on medical images and the results are shown in Fig.8. The suspected micro calcifications are highlighted in the outputs of the proposed method. The visual appearance of ALTU, ARTU and AFLRTU is identical. Results in Fig 7 show that the proposed scheme is able to segment dark regions of the texture. The outputs shown in Figs. 5-6 (e) clearly show that the WTIF method fails to distinguish two different textures. Results in Fig 7 show that the proposed scheme is able to segment dark regions of the texture. Fig. 8 (e) shows that WTIF method is unable to extract the suspected micro calcifications in mammograms.



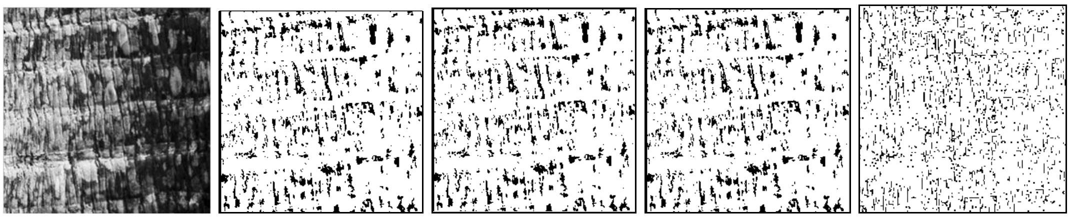
(a) (b) (c) (d) (e)

Figure 5. (a) Input image (b) ALTU (c) ARTU (d) Proposed output (e) WTIF



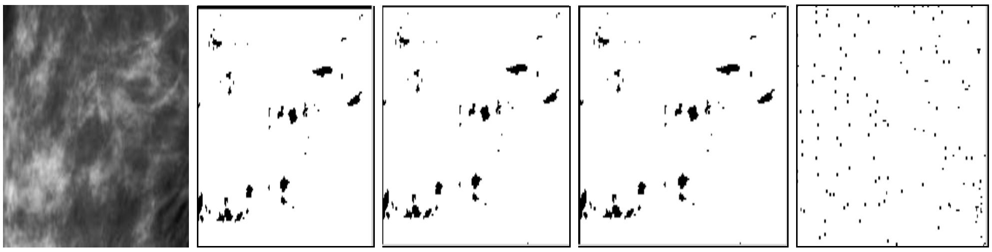
(a) (b) (c) (d) (e)

Figure 6. (a) Input image (b) ALTU (c) ARTU (d) Proposed output (e) WTIF



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

Figure 7. (a) Input image (b) ALTU (c) ARTU (d) Proposed output (e) WTIF



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

Figure 8 (a) Input image (b) ALTU (c) ARTU (d) Proposed output (e) WTIF

5. CONCLUSIONS

A novel approach based on LRTM as a feature for unsupervised texture segmentation is presented in this paper. Eight different patterns of texture unit are used for the segmentation of images thereby giving good segmentation results. The proposed algorithm reduces noise if present as pixel wise averaging is performed on the image obtained after addition of eight texture unit pattern images.The method is able to distinguish clearly two different combined textures. The proposed method is rotationally invariant because LRTM can be formed differently based on the position of LTU and RTU. The method is efficient in segmenting bright areas on dark regions clearly rather than dark areas on bright regions. This algorithm works well for dark texture images. The proposed method can be applied to extract suspected micro calcifications in mammograms.

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