Innovative Segmentation Approach Based on LRTM

S.Kezia, I.Shanti Prabha, V.VijayaKumar

Abstract— Texture refers to the variation of gray level tones in a local neighbourhood. The "local" texture information for a given pixel and its neighbourhood is characterized by the corresponding texture unit. This paper describes new statistical approaches for texture segmentation, based on minimum and maximum of fuzzy left and right texture unit matrix. In these methods, the "local" texture information for a given pixel and its neighbourhood is characterized by the corresponding fuzzy texture unit. The proposed Minimum Fuzzy Left and Right Texture Unit Matrix (MFLRTU) and Maximum Fuzzy Left and Right Texture Unit Matrix (MXFLRTU) segmentation methods overcome the computational complexity of Fuzzy Texture Unit (FTU) by reducing the texture unit from 2020 to 79. The proposed schemes are compared with the Wavelet Transform with Image Fusion (WTIF) in [20]. The results demonstrate the efficacy of the proposed methods.

Index Terms— Fuzzy Texture unit, Left Right Texture Unit Matrix, Texture Spectrum, Texture.

I. INTRODUCTION

An image texture can be defined as the local spatial variations in pixel intensities and orientation [19]. A texture is an ensemble of repetitive subpatterns, which follow a set of well-defined placement rules. These subpatterns themselves are made up of more fundamental units, called primitives. There are images, such as satellite images of the earth surface, which apparently do not possess such basic pattern primitives which are repeated in the overall pattern. Texture is a ubiquitous visual experience. It can describe a wide variety of surface characteristics such as terrain, plants, minerals, fur and skin. There are two types of textures: microtextures and macrotextures. This classification is based on the size of the primitives that constitute the textures. Both microtexture and macrotexture are composed of primitive elements with specific shapes, sizes and placements. Two important attributes of such textures are coarseness and directionality. Coarseness relates to the size of the texture elements. If the primitive element size is large, then the texture is termed a coarse texture or macro texture and if the size is small the resultant texture is a fine or micro texture. Directionality corresponds to the orientation of the texture elements and to their spatial arrangement. 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, 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.

Texture segmentation algorithms can roughly be categorised into five types of techniques for feature extraction. This list is strongly related to the list of the various approaches of describing textures. In statistical techniques the features for a pixel are constructed from the statistics of the region surrounding the pixel. Segmentation is done by deciding the most probable texture for every pixel, making use of the features for this pixel [1, 2, 3, 21, 22, 23, 24, 25, 26]. The model-based methods assume some underlying process for textures. The parameters for these processes are estimated, and constitute the feature set. Fractal textures are an example of model-based textures [2]. In structural techniques, textures are assumed to be composed of well defined texture elements with a spatial position according to a placement rule. The detection and the placement of these elements constitute the feature space on which segmentation will be based [2, 3].Neural network based technique is a new approach to texture segmentation. Neural networks can be trained to respond to their input in a certain way. A trained neural network decides the probability of a texture for a pixel. This constitutes the feature vector on which segmentation will be based [4, 5, 6]. The localised frequency techniques extract local frequency information for the regions surrounding the image pixels. The local frequency contents constitute the feature space on which the segmentation will be based [2, 3].

The present paper is organized as follows: The concepts of texture unit, texture spectrum and fuzzy texture spectrum are given in section II. The proposed methodology is given in section III. Section IV contains experimental results and conclusions are given in section V.

II. FUZZY TEXTURE SPECTRUM

The texture spectrum is a statistical way of describing texture feature of an image, was first conceived by He and Wang [11, 12, 13]. In this method a texture unit represents the local texture information for a given pixel and its neighborhood, and the global texture of an image is characterized by its texture spectrum [9].

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 neighborhood. 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 neighboring pixels. The local texture information for pixel is then extracted from the neighboring pixels, which form the elements of the 3 x 3 window with the pixel under consideration as the central one.

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It can be noted that the eight neighborhoods represents the smallest complete unit from which texture spectrum information can be obtained.

Given a neighborhood of 3 x 3 pixels, which are denoted by a set containing nine elements, V= {V_0, V_1,…, V_8}, where V_i (i = 0, 1, . . . , 8) represents the gray level of the i^{th} element in the neighborhood with V_0 representing the gray level of the central pixel [10]. It is important to note that the eight pixels in the neighborhood are always taken in some order and the subscripts might denote the direction in which a particular neighborhood pixel lies.

The corresponding texture unit (TU) of the pixel is then defined by a set containing eight elements. Thus, TU = { E_1 , E_2 , .. . , E_8}, and E_i (i = 1, 2,. . . ,8) is determined by the following description in base3 method:

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i = V_0 \\ 2 & \text{if } V_i > V_0 \end{cases} \quad (1)$$

Where the element E_i 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 3^8 = 6561 possible texture units in total. The algorithm labels these texture units by the following formula:

$N_{TU}=3^{i-1} E_i$, i=1, 2…, 8 (2)

Where N_{TU} 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 neighbors. 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 N_{TU} and the ordinate the frequency of its occurrence. In base5, the following equation 3 is used to determine the elements, E_i of texture unit

$$E_i = \begin{cases} 0 & \text{if} \quad V_i < V_0 \text{ and } V_i < x \\ 1 & \text{if} \quad V_i < V_0 \text{ and } V_i > V_x \\ 2 & \text{if} \quad V_i = V_0 \\ 3 & \text{if} \quad V_i > V_0 \text{ and } V_i > y \\ 4 & \text{if} \quad V_i > V_0 \text{ and } V_i < y \end{cases} \quad \text{for } i = 1,2,3,\dots,8 \quad (3)$$

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

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

III. 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, 14, 15, 16, 17, 18], 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 [8]. 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 E_1 and bottom most right texture element E_5 i.e., the texture unit which contains E_1 and E_5 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.

E_1		
E_8		
E_7	E_6	

E_1	E_2	
E_8		
E_7		

E_1	E_2	E_3
E_8		

E_1	E_2	E_3
		E_4

Fig.1 Representation of 4-patterns of LTU

	E2	E3
		E4
		E5

		E3
		E4
	E6	E5

		E4
E7	E6	E5

E8		
E7	E6	E5

Fig.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):

$N_{LTU}=E_{Li}*5^{(i-1/2)}$ (5)

$N_{RTU}=E_{Ri}*5^{(i-1/2)}$ (6)

Where N_{LTU} and N_{RTU} are the left texture unit number and right texture unit number respectively. The E_{Li} and E_{Ri} 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 labeled 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 methods shown in Fig. 4(a) & Fig. 4(b). Pixel wise minimum and pixel wise maximum is taken for the 4 resultant images corresponding to Fuzzy LTU (FLTU) patterns to obtain Minimum LTU (MLTU) and Maximum LTU (MXLTU) images respectively.

Similarly, pixel wise minimum and maximum is taken for the 4 resultant images corresponding to Fuzzy RTU (FRTU) patterns to obtain Minimum RTU (MRTU) and Maximum RTU (MXRTU) images respectively. The entire process is shown in Fig.4 (a) & Fig.4 (b).

Subimage

0	1	3
1		2
0	2	1

$0x5^{0}$	1x0	3x0
$1x5^{0.5}$		2x0
$0x5^{1}$	$2x5^{1.5}$	1x0

N_{LTU}=25

$0x5^{1.5}$	1x0	3x0
$1x5^{0}$		2x0
$0x5^{0.5}$	$2x5^{1}$	1x0

N_{LTU}=11

$0x5^{1}$	1x0	3x0
$1x5^{1.5}$		2x0
$0x5^{0}$	$2x5^{0.5}$	1x0

N_{LTU}=16

$0x5^{0.5}$	1x0	3x0
$1x5^{1}$		2x0
$0x5^{0.5}$	$2x5^{0}$	1x0

N_{LTU}=7

(b)

Subimage

0	1	3
1		2
0	2	1

0x0	$1x5^{0}$	$3x5^{0.5}$
1x0		$2x5^{1}$
0x0	2x0	$1x5^{1.5}$

N_{RTU}=29

0x0	$1x5^{1.5}$	$3x5^{0}$
1x0		$2x5^{0.5}$
0x0	2x0	$1x5^{1}$

N_{RTU}=24

0x0	$1x5^{1}$	$3x5^{1.5}$
1x0		$2x5^{0}$
0x0	2x0	$1x5^{0.5}$

N_{RTU}=43

0x0	$1x5^{0.5}$	$3x5^{1}$
1x0		$2x5^{1.5}$
0x0	2x0	$1x5^{0}$

N_{RTU}=41

(b)

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

IV. RESULTS AND DISCUSSIONS

The proposed methods MLTU, MRTU, MXLTU AND MXRTU are tested on Vistex & Brodatz textures of size 256x256. 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 schemes show well-defined borders. The results obtained are satisfactory. The proposed methods work well on images having two different textures and are able to differentiate clearly two textures. The methods are able to extract more details from dark texture images. The algorithms are 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 methods. The visual appearance of MLTU, MRTU, MXLTU and MXRTU outputs are identical. The outputs shown in Figs. 5-6 (f) clearly show that the WTIF method fails to distinguish two different textures. Results in Fig 7 show that the proposed schemes are able to segment dark regions of the texture. Fig. 8 (f) shows that WTIF method is unable to extract the suspected micro calcifications in mammograms.

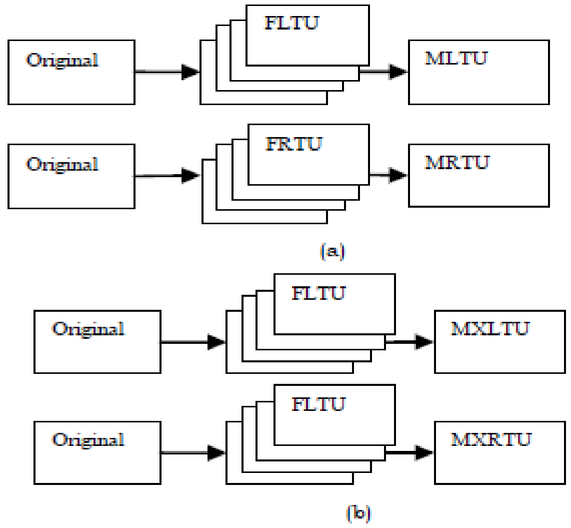

Fig.4Block diagram of the proposed method (a) MFLRTU (b) MXFLRTU

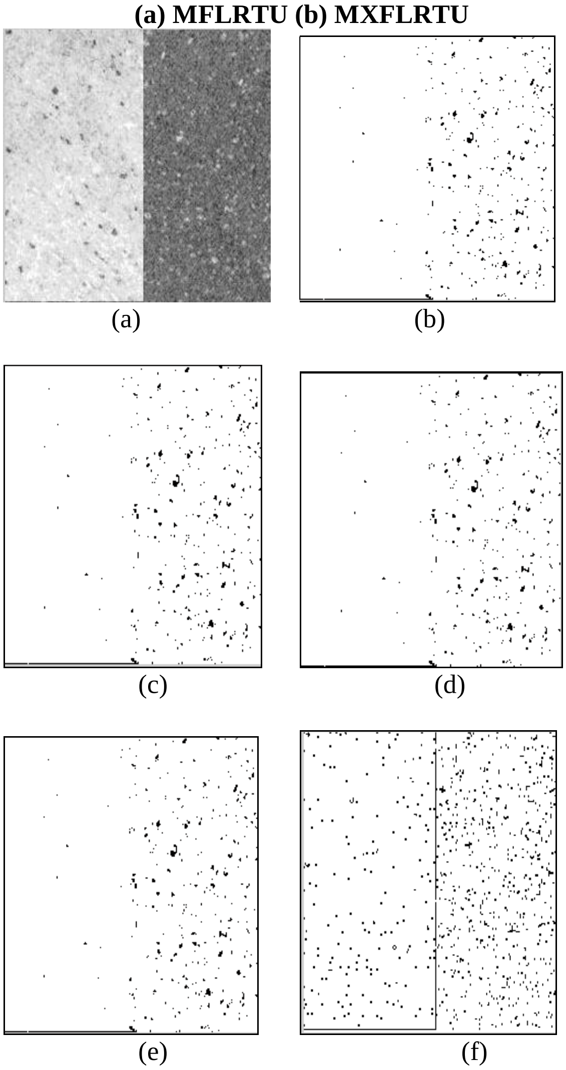

Fig.5 (a) Input image (b) MLTU (c) MRTU (d) MXLTU (e) MXRTU (f) WTIF

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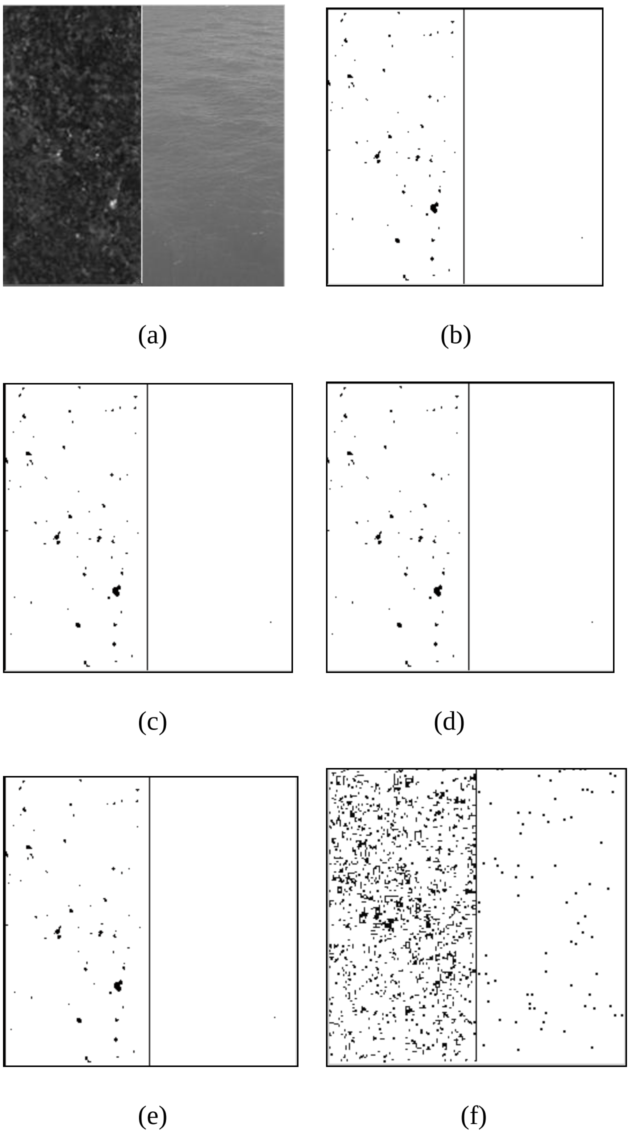
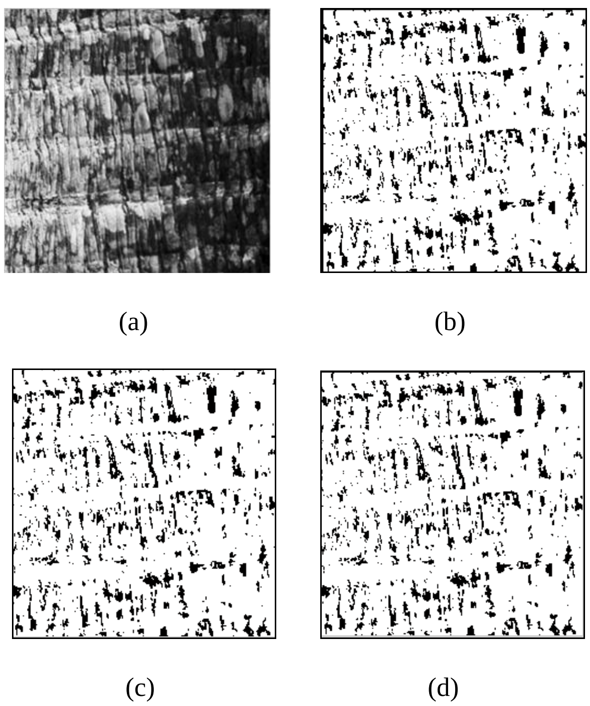


Fig.6 (a) Input image (b) MLTU (c) MRTU (d) MXLTU (e) MXRTU (f) WTIF



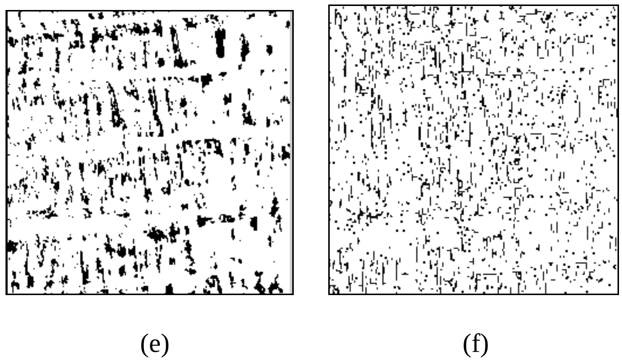


Fig.7 (a) Bark 0 image (b) MLTU (c) MRTU (d) MXLTU (e) MXRTU (f) WTIF

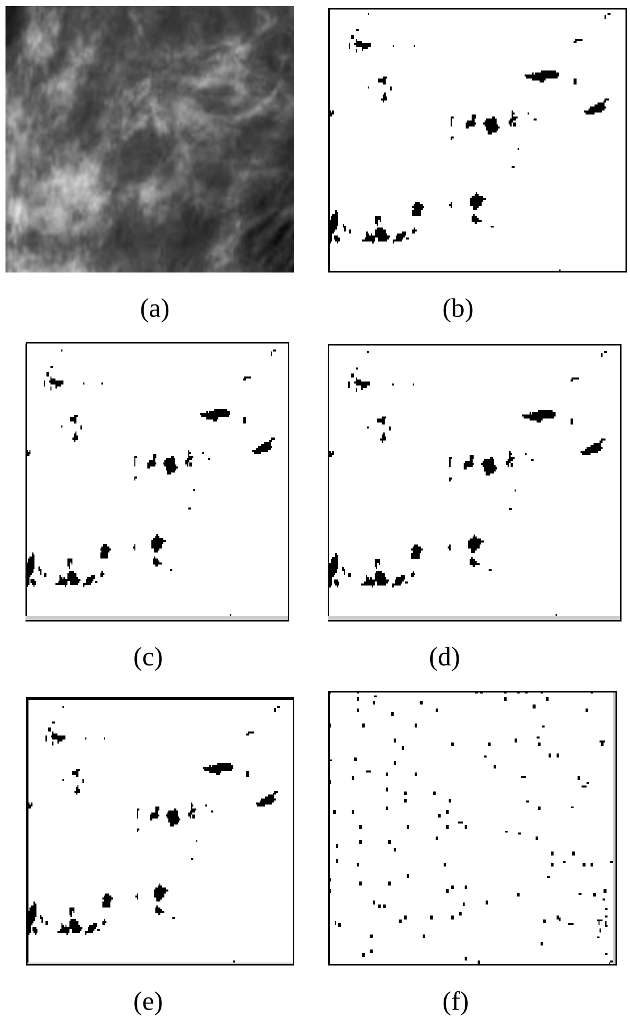


Fig.8 (a) Input image (b) MLTU(c) MRTU (d) MXLTU (e) MXRTU (f) WTIF

V. CONCLUSION

The proposed method resulted in good segmentation. The methods are able to distinguish clearly two different combined textures. The proposed methods are rotationally invariant because LRTM can be formed differently based on the position of LTU and RTU. The methods are efficient in segmenting bright areas on dark regions clearly rather than dark areas on bright regions. These algorithms work well for dark texture images.

The proposed methods can be applied to extract suspected micro calcifications in mammograms.

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