Rotationally Invariant Texture Classification using LRTM based on Fuzzy Approach

B. Sujatha
Assoc. Prof., Dept. of CSE
G.I.E.T, Rajahmundry
Andhra Pradesh, India

Dr. V. VijayaKumar
Dean,Dept. of Comp.Sciences
Head, SRRF- G.I.E.T
Rajahmundry, A.P, India

M. Chandra Mohan
Associate Prof., Dept. of CSE
J.N.T.U- H college of Engg.
JNTU Hyderabad, A.P, India

ABSTRACT
Texture is an important spatial feature, useful for identifying objects or regions of interest in an image. One of the most popular statistical methods used to measure the textural information of images is the grey-level co-occurrence matrix (GLCM). The other statistical approach to texture analysis is the texture spectrum approach. The present paper combines the fuzzy texture unit and GLCM approach to derive a Left Right Texture Unit Matrix (LRTM). The LRTM approach considers the two sets of four connected texture elements on a 3×3 grid for evaluating the TU instead of non-connected or corner texture elements as in the case of Cross Diagonal Texture Unit Matrix (CDTM). The co-occurrence features extracted from the LRTM provide complete texture information about an image, which is useful for classification. The performance of these features for classification/discrimination of the texture images has been evaluated. The LRTM texture features are compared with original texture spectrum features in discriminating/classification of some of the VisTex natural texture images. The proposed LRTM reduces the size of the matrix from 6561 to 79 as in the case of original texture spectrum and 2020 to 79 as in the case of fuzzy texture spectrum approach. Thus it reduces the overall complexity. The experimental results indicate the efficacy of the proposed method.

Keywords
Grey-level co-occurrence matrix, Cross Diagonal Texture Unit Matrix, Left Right Texture Unit Matrix, texture spectrum.

1. INTRODUCTION
Texture Analysis plays an important role in the interpretation and understanding of terrain, biomedical or microscopic images. The main aim of texture analysis is an important cue to the recognition of objects. It requires proper identification of attributes or features that differentiate the textures for classification, segmentation and recognition. There are several methods for defining the textural features. Each method has its own way to define the features that are used in the classification problem. In practice, structural and statistical approaches [1] are the two major methods for extracting textural features. Structural approaches, where texture is considered to be a repetition of some basic primitive patterns with a certain rule of placement [2, 3], the problems appear when trying to identify the primitives and the placement rules in natural images. Statistical approaches yield characterizations of textures as smooth, coarse, grainy, and so on, by means stochastic properties of the spatial distribution of gray level in an image. The most common features used in practice are the measures derived from the spatial grey tone co-occurrence matrix [4-7], that is, Haralick features [6], or Conner's features [7], for which the correct classification rate of 60% to 70% was only reported in the literature. Sometimes second-order grey-level co-occurrence matrix (GLCM) produces unsatisfactory results. Some reasons for this are as follows. First, the matrix depends not only on the spatial relationships of grey levels but also on the regional intensity background variation within the image. Secondly, the co-occurrence matrix reveals textural information of the image in a given displacement vector $V = (\Delta x, \Delta y)$ so that the choice of this vector is somewhat problematic. Textural features also extracted from texture spectrum (TS) have been used in texture description and discrimination [9, 10].

He and Wang have proposed the texture spectrum (TS) approach for texture analysis [8,9,11,12]. The TS methodology [11, 12, 13, 14] has been applied to texture characterization and texture classification showing its promising discrimination performance. But a major inconvenient of this descriptor is the large range of its possible values (there are 6561) at the same time that these values are not correlated. Moreover, as images of the same underlying texture can vary significantly, textural features must be invariant to (large) image variations, and at the same time sensitive to intrinsic spatial structures that define textures. To alleviate the above drawbacks of TU recently a Fuzzy Texture Spectrum (FTS) was proposed in [15]. This will dramatically reduce the total number of texture units to 2020. However, the high dimension of 2020 is a computational burden. One way to simplify this is to combine the fuzzy texture unit and GLCM approach to derive a new method named as LRTM. The proposed LRTM reduces the number of texture units and also reduces the computational complexity of the texture classification problem.

The 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.

2. TEXTURE SPECTRUM
In a square raster digital image, each pixel is surrounded by eight neighboring pixels. The local texture information for a pixel can be extracted from a neighborhood of 3x3 pixels, which represents the smallest complete unit. A texture image can be decomposed into a set of essential small units called texture units (TU), which characterize the local texture information for a

given pixel and its neighborhood. The occurrence distribution of texture units is called the texture spectrum (TS).

Given a neighborhood of 3x3 pixels, which will be denoted by a set containing nine elements: $V= \{V_0,V_1,...,V_8\}$, where V_0 represents the intensity value of the central pixel and V_i $\{i=1,2,\ldots,8\}$, is the intensity value of the neighboring pixel i as shown in Fig.1 and the corresponding texture unit (TU) by a set containing eight elements, $TU = \{E_1, E_2,\ldots,E_8\}$, where E_i $(i=1,2,\ldots 8)$ is determined by the following Equation 1.

$$E_i = \begin{cases} 0 \text{ if } & V_i < V_0 \\ 1 \text{ if } & V_i = V_0 \quad \text{for} \quad i = 1,2,3,\ldots,8 \\ 2 \text{ if } & V_i > V_0 \end{cases} \qquad (1)$$

and each element E_i occupies the same position as the pixel i.

V_1	V_2	V_3
V_8		V_4
V_7	V_6	V_5

E_1	E_2	E_3
E_8		E_4
E_7	E_6	E_5

Fig 1: Representation of Texture Elements

As each element of TU has one of the three possible values {0, 1, 2}, the combination of all the eight elements results in 3^8 = 6561 possible texture units in total. There is no unique way to label and order the 6561 texture units. These texture units are labeled by using the following Equation 2.

$$N_{TU} = \sum_{i=1}^{8} E_i \, 3^{i-1}, \qquad N_{TU} \in \{0,1,2,\ldots(N^{8-1})\} \qquad (2)$$

where N_{TU} represents the texture unit number and E_i is the i^{th} element of texture unit set $TU = \{E_1, E_2,\ldots, E_8\}$.
The TS is able to reveal texture information in digital images and has promising discriminating performance for different textures. In addition, when compared with the other statistical methods, texture unit method extracts the local texture information for a given pixel from a neighborhood of 3x3 pixels, i.e., in all the eight directions from the centre pixel instead of only computing one displacement vector as in the GLCM. One of the major inconveniences of this descriptor is the large range of its possible values (there are 6561 possible TU) at the same time that these values are not correlated.

After exploring the concept of TU and trying to alleviate its drawbacks and problems a new texture spectrum method called Fuzzy Texture Spectrum (FTS) was proposed in [15] which retain TS discriminatory power considering entire spectrum. Moreover, in natural images, due to the presence of noise and the different processes of caption and digitization, even if the human eye perceives two neighboring pixels as equal, they rarely have exactly the same intensity value. However, the desirable situation would be that TU of homogeneous images, contain more number of one's because that is what the human eye perceives. Therefore, if there is a lack of ones, the TU will take only values of 0 and 2, which means that the real number of possible textures is 2^8, that is 256 out of the of 6561, as proposed in [16], and the spectrum will be never totally covered, which misuses the power of the TS method. To avoid this imprecision and be able to represent the vagueness within the TS, the proposed method improves the use of the entire spectrum, by using a fuzzy logic.

2.1 Fuzzy Texture Spectrum (FTS)

For preserving the discriminatory power of the TS and incrementing its robustness it will be necessary to give some kind of mathematical formalization to the concepts 'exactly equal', 'exactly greater' and 'exactly smaller' accordingly to human eye perception.

As in the case of the TS method, the aim of the Fuzzy Texture Unit (FTU) is the extraction of local texture information from the pixels for characterizing the textural aspect of a digital image. To reduce the number of texture units two more membership functions (Greater, Lesser quantities) were introduced in FTU. The texture unit is reduced to 2020, so that the computation time is very less when compared to previous approach of TU. Greater or lesser quantities are further quantized using fuzzy logic approach as follows. Here two more levels of comparison are introduced. A texture unit is represented by eight elements, each of which has only five possible values {0, 1, 2, 3 and 4} obtained from a neighborhood of 3x3 image region. The elements are ordered clockwise around the centre pixel as shown in Fig.1. The fuzzy texture membership function is represented as shown in Fig.2. In Base5, the following Equation 3 is used to determine the elements, E_i of texture unit.

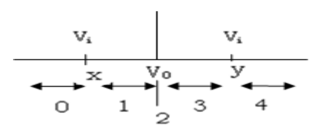

Fig 2: Fuzzy Texture Number (base-5) Representation

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

where x, y are user-specified values.

The FTU number (FTU_n) is computed in base5 as given in Equation 4.

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

The total texture numbers range from 0 to 2020.
For example

90	130	145
160	140	200
100	140	250

0	1	3
4		4
0	2	4

FTU= {0, 1, 3, 4, 4, 2, 0, 4}, FTU_{n5} = 1292

Fig 3: Transformation of a 3×3 neighborhood to a FTU

Fuzzy Texture Spectrum (FTS) is termed as the frequency of distribution of all fuzzy texture units, with the abscissa indicating the texture unit number and the ordinate representing its occurrence frequency. FTS is the extraction of local texture information from the pixels for describing the textural aspect of a digital image; it should be good to detect the classes having highest relevance for deciding the existence of a concrete textural feature within an image.

3. PROPOSED METHOD: LEFT RIGHT TEXTURE UNIT MATRIX (LRTM)

The texture spectrum method of texture analysis gives the texture information using the eight neighbouring pixels around the central pixel. The level of this information depends on the ordering of the neighbouring pixels. The GLCM method gives reasonable texture information of an image that can be obtained between two pixels. Further a little work has been reported in the literature to produce strong texture information of an image by separating the neighbouring pixels into groups and form a relationship between them. In the cross diagonal approach [17] 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 on the normal texture unit but not on the fuzzy texture unit information. To overcome these, a new method of texture analysis called Left Right Texture Unit Matrix (LRTM) is proposed on fuzzy texture unit (FTU). The proposed method divides the fuzzy texture information of an image by separating the neighbouring pixels into two well connected equal groups of 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 formation of a GLCM, by which a good classification can be obtained by reducing computational complexity.

The texture information can be obtained from the mathematical model representing two groups of 4-connected texture elements as shown in Fig.4. 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. That is the texture unit that contains E_1 and E_5 are called as LTU and RTU respectively. A 3x3 grid can have four such patterns of LTU's and RTU's as shown in Fig.4.

E_1			E_1	E_2		E_1	E_2	E_3	E_1	E_2	E_3
E_8			E_8			E_8					E_4
E_7	E_6		E_7								

Fig 4: (a) Representation of 4-patterns of LTU

	E_2	E_3			E_3						
		E_4			E_4			E_4	E_8		
		E_5		E_6	E_5	E_7	E_6	E_5	E_7	E_6	E_5

Fig 4: (b) Representation of 4-patterns of RTU

Each fuzzy texture element in the two groups has one of five possible values (0, 1, 2, 3 and 4) as given in the Eqn.5 and Equation 6. Both the LTU and RTU are labeled by using the following Equations 5&6.

$$N_{LTU} = \sum_{i=1}^{4} E_{L_i}\, 5^{(i-1/2)} \qquad (5)$$

$$N_{RTU} = \sum_{i=1}^{4} E_{R_i}\, 5^{(i-1/2)} \qquad (6)$$

where N_{LTU} the left-texture unit number, N_{RTU} is the right-texture unit number, E_{Li} and E_{Ri} are the i^{th} element of left-texture unit right-texture unit respectively. The entire process of transforming an image neighborhood into LTU and RTU is shown in Fig. 5. The elements in the LTU and RTU may be ordered differently. The first element of each texture unit may take four possible positions. In the same manner, the second, third and fourth element also may take four possible positions. The values of LTU and RTU vary depending on position of elements can be labeled by using equations 5 and 6.

0		
4		
0	2	

$0x5^0$		
$4x5^{0.5}$		
$0x5^1$	$2x5^{1.5}$	

N_{LTU}=31

$0x5^{1.5}$		
$4x5^0$		
$0x5^{0.5}$	$2x5^1$	

N_{LTU}=14

$0x5^1$		
$4x5^{1.5}$		
$0x5^0$	$2x5^{0.5}$	

N_{LTU}=49

$0x5^{0.5}$		
$4x5^1$		
$0x5^{0.5}$	$2x5^0$	

N_{LTU}=22

Fig 5: (a) The four possible patterns of LTU

	1	3
		4
		4

	$1x5^0$	$3x5^{0.5}$
		$4x5^1$
		$4x5^{1.5}$

N_{RTU}=72

	$1x5^{1.5}$	$3x5^0$
		$4x5^{0.5}$
		$4x5^1$

N_{RTU}=43

	$1x5^1$	$3x5^{1.5}$
		$4x5^0$
		$4x5^{0.5}$

N_{RTU}=52

	$1x5^{0.5}$	$3x5^1$
		$4x5^{1.5}$
		$4x5^0$

N_{RTU}=66

Fig 5: (b) The four possible patterns of RTU

A LRTM is obtained with LTU values on X-axis and RTU values on the Y-axis as shown in Fig.6 (b). This LRTM has elements of relative frequencies in both LTU and RTU as in Fig.6 (a). Since the values of LTU and RTU ranges from 0 to 78, then the LRTM will have a fixed size of 79×79. From this LRTM, a set of Haralick features are extracted to give the texture information about the image. This new method combines the merits of both GLCM and TS methods of texture analysis and hence it gives the complete texture information about an image. The size of the GLCM depends on the gray level range of the image. The LRTM irrespective of the gray level range of the image it has a fixed size of 79×79. The proposed LRTM reduced the computational time complexity, because of the reduced size of the LRTM from 6561 to 79 as in the case of original texture spectrum [9] and 2020 to 79 as in the case of fuzzy texture spectrum [18].

NTu1	f1
0	
1	
2	
.	
.	
.	
51	

NTu2	f2
0	
1	
2	
.	
.	
.	
51	

(a)

	0	.	.	.	78
0					
1					
2					
.					
.					
.					
78					

(b)

Fig 6: (a) Frequency occurrence of Left Right Texture Unit (b) Left Right Texture Unit Matrix

4. EXPERIMENTAL RESULTS

Experiments are conducted with two different datasets obtained from VisTex[19] and google [20] color images each of size 512×512. Color images are converted into gray images by using simple MatLab command. For each texture group, 10 texture samples are used to design the classifier. Seven Haralick features i.e. entropy, energy, contrast, correlation, homogeneity, cluster shade and cluster prominence is evaluated on LRTM and General Texture Spectrum (GTS) using 0, 45, 90, 135 degrees of rotation. This leads to a total of 4x7=28 features for each texture sample. For classification, LOOM classifier is used to guarantee strict separation of test and training set with the maximization of the number of training images. Table 1 and Table 2 show the mean percentage classification rate for each group of textures by using the proposed LRTM and GTS method on VisTex and Google database images respectively. From these tables it is clearly evident that the proposed LRTM exhibits a high classification rate than the GTS method. The graphical analysis of the percentage mean classification rate for the proposed LRTM and GTS methods of two databases are shown in Fig.7.

Table 1. VisTex Database: Mean % classification rate of each group of rotations of textures

Texture Name	GTS				LRTM			
	R1	R2	R3	R4	R1	R2	R3	R4
Bark	86.7	83.2	84.6	84.7	95.1	93.8	92.2	89.8
Brick	84.5	82.7	84.1	85.3	93.4	90.3	92	92.1
Leaves	79.3	78.3	77	74.1	88.3	86.6	86.7	89.6
Fabric	87.6	81.1	86.7	84	95.2	92.1	93.4	93.1
Stone	82.7	81.4	77.5	78.4	91.9	90.7	88.4	90.3
Avg	84.15	81.34	81.97	81.3	92.74	90.71	90.54	90.97

Table 2. Google Database: Mean % classification rate of each group of rotations of textures

Texture Name	GTS				LRTM			
	R1	R2	R3	R4	R1	R2	R3	R4
Bark	85.48	87.07	85.5	84.9	94.55	94.95	93.62	92.6
Granite	84.88	85.38	82.05	87.6	92.75	90.17	91.03	92.26
Leaves	79.51	79.24	78.96	75.7	91.18	90.5	90.1	90.32
Marble	82.12	80.25	79.19	86	92.55	91.54	91.47	92.67
Stone	84.39	78.1	80.93	82.9	91.86	91.09	91.52	90.94
Average	83.27	82	81.32	83.4	92.57	91.65	91.54	91.75

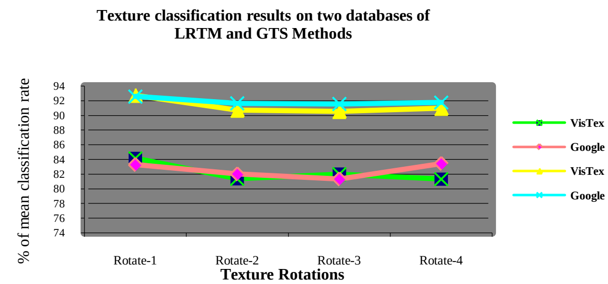

Fig 7. Comparative analysis of LRTM and GTS

5. CONCLUSIONS

The proposed LRTM reduced the computational time complexity, because of the reduced size i.e. 6561 to 79 as in the case of original texture spectrum [9] and 2020 to 79 as in the case of fuzzy texture spectrum [18]. This reduction helps in evaluating GLCM features for classification purpose, which is not possible in the previous TS method. The proposed method is rotationally invariant because LRTM can be formed differently based on the position of LTU and RTU. The results and graph clearly indicates the efficacy of the proposed method when compared to other methods.

6. ACKNOWLEDGMENTS

The authors would like to express their cordial thanks to Dr. K.V.V. Satya Narayana Raju, MLC and Chairman for providing facility to work at the advanced labs of Srinivasa Ramanujan Research Forum (SRRF)-GIET and Sri. K. Sasi Kiran Varma, Managing Director, Chaitanya Group of Institutions for providing moral support and encouragement towards research.

7. REFERENCES

[1] R.M. Haralick, "Statistical and structural approaches to texture," Proc. of IEEE, Vol.67, pp.786-804, 1979.

[2] C. S. Lu, P.C. Chung and C.F. Chen, “Unsupervised texture segmentation via wavelet transform,” Pattern Recognition, Vol. 30, no. 5, pp. 729-742, 1997.

[3] O. Pichler, A. Teuner and B. J. Hosticka, “A comparison of texture extraction using adaptive Gabor filtering, pyramidal and tree structured wavelet transforms,” Pattern Recognition, Vol. 29, no. 5, pp.733-742,1996.

[4] B. Julesz, “Visual pattern discrimination," IRE Trans. Inform. Theory, Vol.8, pp.84-92, 1962.

[5] A. Gagalowicz, "Visual discrimination of stochastic texture fields based upon second order statistics," Proc. 5Th Int.

Joint Conf. Pattern Recog., Miami Beach, pp.786- 789, 1980.

[6] R.M. Haralick, K. Shanmugan and I. Dinstein, "Textural features for image classification," IEEE Trans. Sysr., Man., Cybern., Vol. SMC-3, pp.610-621, 1973.

[7] R.W. Conners, "Towards a set of statistical features which measure visually perceivable qualities of texture," Proc. Pattern Recognition Image Processing Conf. pp.382-390, 1979.

[8] D.C.He, L.Wang and J.Guibert, "Texture features extraction," Pattern Recognition Letters. Vol.6, pp.269-273, 1987.

[9] Dong-Chen He and Li Wang, "Texture unit, texture spectrum and Texture, IEEE Transactions on geoscience and Remote Sensing, Vol. 28, July 1990.

[10] D.C.He, L.Wang, "Texture features based on texture spectrum," Pattern Recognition, Vol.24, pp. 391-399, 1991.

[11] D.C.He and L.Wang, "Texture unit, texture spectrum and texture analysis," Proc of IGARSS.89, Vancouver, Canada, 1989, Vo1.5, pp.2769-2772.

[12] L.Wang, D.C.He, "A new statistical approach to texture analysis," Photogrammetrics Eng. and Remote Sensing, pp.61-65, 1990.

[13] L. Wang, D.C. He and A. Fabbri, "Textural filtering for SAR image processing," Proc. of IGARSS'89, Vancouver, Canada, 1989, Vol.5, pp. 2785-2788, 1989.

[14] L.Wang and D.C.He, "Texture classification using texture spectrum," Pattern Recognition, 1989.

[15] A.Barcelo, E.Montseny and P.Sobrevilla. "On Fuzzy Texture Spectrum for Natural Microtextures Characterization," Proceedings EUSFLAT-LFA, pp. 685-690, 2005.

[16] T. Ojala, M. Pietiknen, D. Harwood, "A comparative study of texture measures with classification based on feature distributions," Pattern Recognition, Vol.29, pp.51-59, 1996

[17] Abdulrahman Al-Janobi, "Performance evaluation of cross-diagonal texture matrix method of texture analysis," Pattern Recognition, Vol. 34, pp.171-180, 2001.

[18] G.Wiselin Jiji, L.Ganesan, "A new approach for unsupervised segmentation," Applied Soft Computing, Vol.10, pp.689-693, 2010.

[19] VisTex.ColourImageDatabase http://www.whitemedia.mit.edu/vismod/imagery/VisionTexture.

[20] Paul Bourke Texture and Colour, available at http://paulbourke.net/texture_colour/bark/

7. AUTHORS PROFILE

B.Sujatha received the B.Tech. degree from JNT University, Kakinada in 1997 and received her M. Tech. (Computer Science & Engineering) from Andhra University in 2002. She is having 10 years of teaching experience. Presently she is working as an Assoc. Professor in GIET, Rajahmundary. She has published 8 research publications in various National and Inter National Journals and conferences. She is a member of Srinivasa Ramanujan Research Forum SRRF-GIET, Rajahmundry. She is pursuing her Ph.D from Mysore University in Computer Science under the guidance of Dr. V.Vijaya Kumar at SRRF Labs. Her research interest includes Image Processing and Pattern Recognition. She is a Life member of ISCA.

Dr.Vakulabharanam Vijay Kumar received integrated M.S. Engg, degree from Tashkent Polytechnic Institute (USSR) in 1989. He received his Ph.D. degree in Computer Science from Jawaharlal Nehru Technological University (JNTU) in 1998.He has served the JNT University for 13 years as Assistant Professor and Associate Professor and taught courses for M.Tech students. He has published more than 80 research publications in various National, International conferences, proceedings and Journals. He has established Srinivasa Ramanujan Research Forum (SRRF) at GIET, Rajahmundry, India for promoting research activities. At present he is working as Dean and Head for Dept of Computer Sciences at Godavari Institute of Engineering and Technology since April, 2007. His research interests includes Image Processing, Pattern Recognition, Digital Water Marking and Image Retrieval Systems. He is a life member for CSI, ISTE, IE, IRS, ACS and CS.

M. Chandra Mohan received B.E. (EEE) degree from Osmania University in 1994. He worked as an Assistant Engineer in AP State Electricity Board (APSEB) for 7 years (1994-2001). Mean while he completed his M. Tech. (CS&E) from Osmania University in 2000 by availing study leave. He is working in JNT University Hyderabad since 2001. Presently he is working as an Associate Professor in Dept of CS&E in JNTUH College of Engineering Hyderabad, JNT University Hyderabad. He is the recipient of 3 Gold Medals from Osmania University at the graduate level by securing University first rank. He is pursuing his Ph.D. from JNT University Hyderabad in Computer Science under the guidance of Dr V. Vijaya Kumar. He has published four research publications in various National and International conferences.