Fuzzy Based Texton Matrix with Shape Components for Texture Analysis and Texture Classification

Dr.G.Karuna
Associate Professor, Department of Computer Science and Engineering, Gokaraju Rangaraju Institute of Engineering and Technology, Telangana, India

Abstract

Texture Analysis and classification is one of the challenging issue in computer vision and image processing. Texture Classification plays very important role for a wide range of applications. The novel approach texton based technique is very useful in Texture analysis and classification and this technique shows highly dependence on few parameters. However, the variation in values of any of these parameter may greatly influenced the texture characterization performance. And the micro structure texton is unable to capture the texture features which also shown a negative effect on the classification task. The present work mainly intended to overcome such limitations. The proposed paper derives a novel descriptor called Fuzzy Based Texton Matrix with Shape Components (FBTMSC) to avoid the variation of any parameter. The proposed FBTMSC is defined based on similarity of neighboring edges on a 3×3 matrix and the micro-structures serving as a channel for capturing shape features and it also effectively incorporates shape, color and texture information for texture classification. The proposed FBTMSC algorithm shows low dimensionality and verified on texture datasets of natural images. The results are evaluated and determined that this technique is more efficient and gives better performance than existing feature descriptors, such as LBP etc, for texture classification.

Keywords: fuzzy, texton, texture classification, shape features

I. INTRODUCTION

In Image Processing and Pattern Recognition, Texture analysis and classification is a fundamental issue and texture analysis has been an area of intense research from past five decades. It plays a significant role for different kinds of applications that include medical image analysis, remote sensing, object recognition, document analysis, environment modeling, content-based image retrieval etc. [1]. Analyzing real world textures has a challenging task and in most of the cases caused by texture in-homogeneity of varying scale changes, variability in surface shape.

II. RELATED WORK

Many researchers have been developed various algorithms to extract color, texture and shape features for texture classification. Texture features provide an important information of the coarseness, smoothness and regularity of many real-world objects such as skin, clouds, trees, bricks etc. [2], and texture based algorithms are also widely used in CBIR systems, including the gray co-occurrence matrixes [3], Wold decomposition model [4], Markov random field model [5], simultaneous auto-regressive model [6], and wavelet decomposition [7] and many more existed in literature. Tang [8] discussed that textural features extracted from a new run-length matrix can produce great classification results over traditional run-length techniques. Textures are classified most recently by edge direction movements [9]. Fuzzy based methods also proposed in the analysis of textures [10, 11], age classification problems are also proposed [12] in the literature based on texture features. The above methods captured different topological configurations and texture properties of the image. The term "texton" is conceptually proposed by Julesz [13] and it is a most useful technique in texture analysis to develop efficient models in the context of texture recognition or object recognition [14]. The texton has been used in several classification problems [15], age classification problem, face recognition etc. The present paper focused on Fuzzy Based Texton Binary Matrix to describe texture features for texture analysis and classification.

The remaining paper is organized as follows. In Section 2, the proposed methodology is introduced. In Section 3, the texture classification performance resulted from logical operators, GLCM, LBP and our proposed method is compared over the Vistex texture database of MIT, Akarmarble images and those images taken from web. Section 4 concludes this paper.

III. PROPOSED METHODOLOGY

A novel Fuzzy Based Texton Matrix with Shape Components (FBTMSC)

Many researchers developed various algorithms to extract color, texture and other features. Color is the most distinguishing important and dominant visual feature. That's why color histogram techniques remain popular in the literature. The main limitation of this is, lack of spatial information. Texture patterns can provide significant and abundance of texture and shape information. The proposed method explained in below given sections. In the first section the color image is converted in to grey level image by using any HSV color model. This section describes how the RGB image is converted in to the HSV model.

2.2.1 Conversion of RGB Color Model to HSV Color Model

The RGB model is mostly used in hardware oriented application such as color monitor. In the RGB model, images are represented by three components, red, green and blue. However, RGB color space is not sensitive to human visual perception or statistical analysis. Moreover, a color is not simply formed by these three primary colors. HSV color space is a non-linear transform from RGB color space that can describe perceptual color relationship more accurately than RGB color space. HSV color space is formed by hue (H), saturation (S) and value (V). Hue denotes the property of color such as blue, green, red, and so on. Saturation denotes the perceived intensity of a specific color. Value denotes brightness perception of a specific color. When a color pixel-value in RGB color space is adjusted, intensities of red channel, green channel, and blue channel of this color pixel are modified. However, HSV color space separates the color into hue, saturation, and value which means observation of color variation can be individually discriminated. In order to transform RGB color space to HSV color space, the transformation is described as follows:

$$V = \max(R, G, B) \qquad \text{--} \qquad \text{(i)}$$

$$S = \frac{V - min(R,G,B)}{V} \qquad \text{--} \qquad \text{(ii)}$$

$$\mathrm{H} = \frac{\mathrm{G-B}}{6\mathrm{S}} \quad if \quad \mathrm{V = R} \qquad \text{--} \qquad \text{(iii)}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{B-R}}{6\mathrm{S}} \quad if \quad \mathrm{V = G} \qquad \text{--} \qquad \text{(iv)}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{R-G}}{6\mathrm{S}} \quad if \quad \mathrm{V = B} \qquad \text{--} \qquad \text{(v)}$$

Where R, G, B are Red, Green and Blue normalized in value [0, 1]. In order to quantize the range of the H plane is normalized with value [0, 255] for extracting features specifically.

2.2.2 Fuzzy Based Texton Matrix

In general for the images, due to noise, different illumination levels and various conversion factors between neighboring pixels of a window represent as equal, though they rarely have exactly the same intensity value. To eliminate this imprecision and be able to represent the vagueness within the processes, the present work focused on fuzzy logic and fuzzy techniques in order to derive fuzzy based texton matrix for analysis and classification of textures. To deal classification effect by different shape components, with regions of natural images perceived as homogeneous by human beings, the present paper proposes a Fuzzy Based Texton Matrix encoding.

The present paper labels eight neighbors of a 3×3 neighborhood using five possible fuzzy patterns or values {0, 1, 2, 3 and 4} derived from the fuzzy code as depicted in Equation 2.1 and the fuzzy membership function is represented as shown in Fig.1. The element V_i represent the intensity values of the eight neighboring pixels on a 3×3 neighborhood, V_0 represents the intensity value of central pixel, x and y are the user-specified lag values.

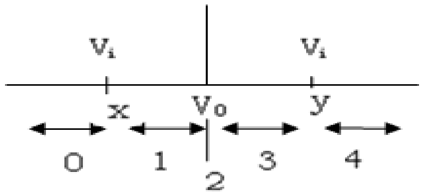

Fig.1: Fuzzy texture number (Base-5) representation.

$$E_i = \begin{cases} 0 & \text{if} \quad V_i < V_0 \quad \text{and} \quad V_i < x \\ 1 & \text{if} \quad V_i < V_0 \quad \text{and} \quad V_i > x \\ 2 & \text{if} \quad V_i = V_0 \\ 3 & \text{if} \quad V_i > V_0 \quad \text{and} \quad V_i > y \\ 4 & \text{if} \quad V_i > V_0 \quad \text{and} \quad V_i < y \end{cases} \quad \text{for } i = 1,2,3,\dots,8 \qquad (2.1)$$

Ex: The process of evaluating fuzzy values on a 3×3 neighborhood is shown in Fig.2.

80	130	250
155	140	200
100	140	160

(a)

→

0	1	4
3	2	4
0	2	3

(b)

FV= {0, 1, 4, 4, 2, 3, 2, 0, 3}

(c)

Fig.2: Representation of (a) a 3×3 matrix (b) fuzzy values (c) set of fuzzy values.

2.2.3 Finding Texton Micro-structure

Textons are fundamental micro structures and have more powerful description ability than the pixels themselves. Texton are defined as a set of blobs or emergent patterns sharing a common property all over the image [16]. If the textons in the image are small and the tonal difference between neighbouring textons is large, a fine texture may result. If the textons are larger and concise of several pixels, a coarse texture may result. If the textons in image are large and consists of few texton categories, an obvious shape may result. If the textons are greatly expanded in one orientation, pre-attentive discrimination is somewhat reduced. If elongated elements are not jittered in orientation, the texton gradients at the texture boundaries are increased. To address this, the present study considered fuzzy based texton approach is used for classification of textures. The proposed Fuzzy based texton approach utilized to detect micro-structures blocks from left-to-right and top-to-bottom through- out the image.

A fuzzy code is applied for overlapped window of the texton micro-structure for the construction of Fuzzy based Texton Matrix with Shape components (FBTMSC) and used for detection of shapes for classification of textures. In a 3×3 block, if one of the eight nearest neighbors has the same value as the center pixel, then it is kept unchanged and marked with green color as shown in Fig.3(c); otherwise set it to '0'. Incase if the centre pixel is zero and one of the eight nearest neighbors has the same value as the center pixel, then these pixel values are also set to '1'. If all the eight nearest neighboring pixels are '0', then the 3×3 block is not considered as a micro structure. The marked pixels are treated as micro-structure and this structure is set to '1'. The working mechanism of proposed fuzzy texton matrix method is illustrated in Fig.3.

150	142	142	142	151	152
150	142	142	142	151	152
154	141	141	137	147	152
156	142	142	134	141	150
156	142	142	134	133	150
153	146	141	140	142	147

(a)

3	2	2	1	2	3
3	2	2	1	2	3
3	0	0	0	1	3
3	1	1	0	2	3
3	1	1	0	0	3
3	2	2	1	4	4

(b)

0	2	2	1	2	0
0	2	2	1	2	0
0	0	0	0	1	0
0	1	1	0	2	0
0	1	1	0	0	0
0	0	1	1	0	0

(c)

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

(d)

Fig. 3: Illustration of the Fuzzy Texton Shape Matrix (a) Original texture image (b) Detection of fuzzy values (c) Fuzzy texton mapping process on a 3×3 neighborhood d) Fuzzy texton binary image.

2.2.4 Apply Fuzzy Texture Features on FBTMSC

The present work predicted fuzzy texture features for classification of textures based on proposed FBTMSC. It consists of a 3×3 neighborhood for evaluating fuzzy shape components. This derived five different fuzzy shape components named as Diamond, Diagonal, Vertical Line, Horizontal Line and Blob on a 3×3 neighborhood and is represented as shown in Fig.5.

	0	
0		0
	0	

0		0
0		0

0		
0		
0		

0	0	0

0	0	0
0		0
0	0	0

Fig.4: Representation of fuzzy shape components (a) Diamond (b) Diagonal (c) Vertical Line (d) Horizontal Line (e) Blob.

For the classification of textures the frequency occurrences of each of the fuzzy shape component with different texture patterns is counted using the Algorithm. The novelty of the present work is it uses only five different types of fuzzy shape components using the proposed FBTMSC.

Proposed FBTMSC Algorithm:

begin

Step 1: Take input image and read the original textures T_j, where j=1: n with dimension M×N.

Step 2: Convert the color texture image in to gray image by using HSV model

Step 3: Convert each 3×3 neighborhood matrix of the gray level texture image into fuzzy values (0, 1, 2, 3 or 4) by using fuzzy code.

Step 4: Compute fuzzy texton matrix using fuzzy code and texton.

Step 5: Apply shape components on a 3×3 neighborhood, where i = 1 to 5.

Step 6: Calculate frequency occurrence (FO_i) of each shape component for entire texture image (Tj). Repeat the same process for all shape components of all texture images.

Step 7: Calculate the percentage of occurrence of each shape component (SC_i, i =1 to 5) for each of the texture T_j, j = 1 : 24.

$$\forall_{i=1}^{5} sc_i = \frac{FC_i}{(M-2)\times(N-2)} \times 100$$

Step 8: Classify textures using the function given in Step 7.

Step 9: Compute the average percentage of occurrence (AO_i) of each shape component of all the textures. $AO_i = \frac{\forall_{i=1}^{5} \sum_{j=1}^{m} T_j sc_i}{\max(j)}$

Step 10. A texture Tj will be placed in any one of the two classes specified as

Class one (C_1) or Class two (C_2) as given below.

for Tj, j = 1 : m

begin

if ($\forall_{i=1}^{5} T_j sc_i == 1$) T_j is assigned to C_1

else T_j is assigned to C_2

end

end

IV. EXPERIMENTAL RESULTS

The present study initially computed the frequency occurrences of each shape component to obtain good classification accuracy. The proposed work is evaluated with a set of different groups of textures as shown in Fig.6. The frequency occurrences of the derived fuzzy shape components are counted for all the original textures and the results are shown in Table 1.

Fig.5: Original textures groups of brick (B), granite (G), marble(M) and fabric(F)

The Frequency occurrences of fuzzy shape components on a 3×3 neighborhood of different groups of textures are shown in Table1.

Texture Name	Diamond	Diagonal	Horizontal Line	Vertical Line	Blob
B1	102	55	195	151	165
B2	296	185	497	269	337
B3	404	277	519	343	439
B4	42	21	131	62	84
B5	73	113	162	177	151
B6	471	249	625	310	568
B7	140	235	226	348	196
B8	163	464	256	554	224
G1	52	58	142	155	114
G2	98	34	184	103	167
G3	32	76	110	177	85
G4	43	8	158	40	147
G5	55	27	158	71	144
G6	3	4	28	8	18
G7	28	41	107	118	88
G8	137	94	222	194	219
M1	19	5	56	21	54
M2	12	19	79	54	80
M3	133	113	280	185	237
M4	64	57	184	153	155
M5	89	664	106	845	100
M6	98	400	142	552	140
M7	322	199	492	258	472
M8	302	148	465	214	422
F1	182	372	250	448	268
F2	508	412	592	433	575
F3	401	409	507	423	501
F4	440	365	542	393	533
F5	351	251	562	81	485
F6	321	192	545	70	471
F7	330	297	425	443	391
F8	342	337	475	408	422

Table 1. Frequency occurrences of fuzzy shape components on different textures

By using distance function, two textures are similar count the number of textures and the result are stored in the training database. The present study, classified textures based on the proposed method using distance function with a lag value. The distance among all groups of textures based on number of frequency occurrences of different shape components are calculated and the classification group of textures with lag value for all textures is incorporated from Table 2 to Table 6 respectively.

Texture Group	Class	Textures that are classified
Brick	C_1	{B1, B2, B3, B5, B7, B8}
	C_2	{B4, B6}
Granite	C_1	{G1, G2, G3, G4,G5, G7, G8}
	C_2	{G6}
Marble	C_1	{M3, M4, M6, M7, M8}
	C_2	{M1, M2, M3, M5}
Mosaic	C_1	{F1, F2, F3, F4, F7, F8}
	C_2	{F5, F6}

Table 2: Texture classes for proposed method using lag value of Diamond shape component

Texture Group	Class	Textures that are classified
Brick	C_1	{B1, B2, B3, B4, B6, B7, B8}
	C_2	{B5}
Granite	C_1	{G1, G2, G3, G4,G5, G6, G7, G8}
	C_2	-----
Marble	C_1	{M1.M2, M3, M4,M5, M6, M7, M8}
	C_2	-----
Mosaic	C_1	{F3, F4, F5, F6, F7, F8}
	C_2	{F1, F2}

Table 3: Texture classes for proposed method using lag value of Diagonal shape component

Texture Group	Class	Textures that are classified
Brick	C_1	{B1, B2, B3, B5, B7, B8}
	C_2	{B4,B6}
Granite	C_1	{G1, G2, G4,G5, G6, G7, G8}
	C_2	{G3}
Marble	C_1	{ M4, M6, M8}
	C_2	{M1.M2, M3, M5, M7}
Mosaic	C_1	{F1, F2, F3, F4, F7, F8}
	C_2	{F5, F6}

Table 4: Texture classes for proposed method using lag value of Horizontal Line shape component

Texture Group	Class	Textures that are classified
Brick	C_1	{ B5, B7, B8}
	C_2	{B1, B2, B3, B4, B6}
Granite	C_1	{ G4,G5, G7, G8}
	C_2	{ G1, G2, G3, G6}
Marble	C_1	{ M1.M2, M3, M4, M6, M8}
	C_2	{ M5, M7}
Mosaic	C_1	{F2,F3, F4, F7, F8}
	C_2	{F1, F5, F6}

Table 5: Texture classes for proposed method using lag value of Vertical Line shape component

Texture Group	Class	Textures that are classified
Brick	C_1	{B1, B2, B3, B4, B5, B8}
	C_2	{B1,B6}
Granite	C_1	{ G1, G2, G4,G5, G6,G7, G8}
	C_2	{ G3}
Marble	C_1	{ M1.M2, M3, M4, M6, M8}
	C_2	{ M1, M5, M7}
Mosaic	C_1	{, F3, F7, F8}
	C_2	{ F1, F2, F4, F5, F6}

Table 6: Texture classes for proposed method using lag value of Blob shape component

Based on observations from the above results the following facts are identified. Table3 clearly indicates that, it shows a uniform distance between each of them. The extracted diamond shape component of Table 2 classified each of the Brick, Granite, Marble and Fabric textures into two classes. Table 3 classified each of the Brick, Granite and Marble textures into separate class only, and it classified the fabric textures into two classes. Table 4 classified each of the Brick, Granite, Marble and Mosaic textures into two classes. Table 5, 6 classified each of the Brick, Granite, Marble and Fabric textures into two classes. The facts indicate that a good, precise and accurate stone classification is observed by the proposed FBTMSC using diagonal shape components and it also analyzed the percentage occurrence of each shape component represented in the Table 7. The Table 7 evaluated on FBTMSC reveals that diagonal shape component classifies brick, granite and marble texture images accurately.

Shape Component	Brick	Granite	Marble	Fabric	Average
Diamond	76	86.5	66	76	76.125
Diagonal	100	100	99.5	76	93.875
Horizontal Line	76	89	65	75	76.25
Vertical Line	65	51	77	64	64.25
Blob	73	87	65	64	72.25

Table 7: Percentage occurrences of each shape component with every group of textures.

V. CONCLUSIONS

Texture classification using texton micro-structure with shape components produced efficient results than other existing methods. The present paper derived a new direction for classification of textures based on texture features derived from shape components on a 3×3 matrix neighborhood. By investigating texture classification using different shape components with fuzzy logic the present study concludes that diagonal shape component contains more classification information than other shape components. Based on the experimental results the proposed FBTMSC method determines that one need not necessarily count the other shape components except the diagonal shape. The present study reduced complexity in the selection of shape components for texture classification.

REFERENCES

1. M. Tuceryan, A.K. Jain, Texture analysis, in: C.H. Chen, L.F. Pau, P.S.P. Wang (Eds.), Handbook Pattern Recognition and Computer Vision, World Scientific, Singapore, 1993, pp. 235–276.
2. Xiaoou Tang, “Texture information in runlength matrices”, IEEE Transactions in image processing, vol.7(11), pp:1602-1609, 1998.
3. R.M. Haralick, K. Shangmugam, I. Dinstein, Textural feature for image classification, IEEE Trans. Syst. Man Cybern. SMC-3 (6) (1973) 610–621.
4. F. Liu, R. Picard, Periodicity, directionality, and randomness: wold features for image modeling and retrieval, IEEE Trans. Pattern Anal. Mach. Intell. 18 (7) (1996) 722–733.
5. G. Cross, A. Jain, Markov random field texture models, IEEE Trans. Pattern Anal. Mach. Intell. 5 (1) (1983) 25–39.
6. J. Mao, A. Jain, Texture classification and segmentation using multi-resolution simultaneous autoregressive models, Pattern Recognition 25 (2) (1992) 173–188.

7. T. Chang, C.C. Jay Kuo, Texture analysis and classification with tree-structured wavelet transform, IEEE Trans. Image Process. 2 (4) (1993) 429–441.
8. B. Eswara Reddy, A. Nagaraja Rao, A. Suresh, V. Vijaya Kumar, “Texture Classification by Simple Patterns on Edge Direction Movements,” IJCSNS International Journal of Computer Science and Network Security, VOL.7 No.11, November 2007.
9. V.Vijaya Kumar, A.Srikrishna, M.Radhika Mani, B.Raveendra Babu, “Classification and Recognition of Handwritten Digits by Using Mathematical Morphology”, *Sadhana* Vol. 35, Part 4, August 2010, pp. 419–426. © Indian Academy of Sciences.
10. Aina Barceloa, Eduard Montseny, Pilar Sobrevilla, “Fuzzy texture unit and fuzzy texture spectrum for texture characterization,” Fuzzy Sets and Systems, vol.158 pp: 239-252, 2007.
11. Chandra Mohan M., Vijaya Kumar V. and Damodaram A., ”Novel Method of Adulthood Classification based on Geometrical Features of Face,” Accepted by GVIP Journal of Graphics, Vision and Image Processing, 2010.
12. Chandra Mohan M., Vijaya Kumar V. and Sujatha B., ”Classification of Child and Adult Based on Geometric Features of Face Using Linear Wavelets,” Communicated to International Journal of Signal and Image Processing (IJSIP), 2010.
13. V.Vijaya Kumar, A.Srikrishna, M.Radhika Mani, B.Raveendra Babu, “Classification and Recognition of Handwritten Digits by Using Mathematical Morphology”, *Sadhana* Vol. 35, Part 4, August 2010, pp. 419–426. © Indian Academy of Sciences.
14. J. Winn, A. Criminisi, T. Minka, “Object categorization by learned universal visual dictionary, in: Proceedings of the 10th IEEE International Conference on Computer Vision, (2005) pp. 1800–1807.
15. Sujatha.B, Chandra Sekhar Reddy, P Kiran Kumar Reddy, “Texture Classification Using Texton Co-Occurrence Matrix Derived From Texture Orientation,” International Journal of Soft Computing and Engineering (IJSCE), 2012.
16. T. Leung, J. Malik, “Representing and recognizing the visual appearance of materials using three-dimensional textons,” International Journal of Computer Vision 43 (1) (2001) 29–44.