

Fuzzy Based Texton Binary Shape Matrix (FTBSM) for Texture Classification

Dr. P.Chandra Sekhar Reddy¹ and B.Eswara Reddy²

¹ GIET, RAJAHMUNDY, A.P, INDIA.

Received: 13 February 2012 Accepted: 29 February 2012 Published: 15 March 2012

Abstract

Texton is a extensively applied approach for texture analysis. This technique shows a strong dependence on certain number of parameters. Unfortunately, each variation of values of any parameter may affect the texture characterization performance. Moreover, micro structure texton is unable to extract texture features which also have a negative effect on the classification task. This paper, deals with a new descriptor which avoids the drawbacks mentioned above. To address the above, the present paper derives a new descriptor called Fuzzy Based Texton Binary Shape Matrix (FTBSM) for clear variation of any feature/parameter. The proposed FTBSM are defined based on similarity of neighboring edges on a 3×3 neighborhood. With micro-structures serving as a bridge for extracting shape features and it effectively integrates color, texture and shape component information as a whole for texture classification. The proposed FTBSM algorithm exhibits low dimensionality. The proposed FTBSM method is tested on Vistex and Akarmarble texture datasets of natural images. The results demonstrate that it is much more efficient and effective than representative feature descriptors, such as logical operators and GLCM and LBP, for texture classification.

Index terms— texton, micro structure, fuzzy, shape component.

1 Introduction

Texture classification is a fundamental issue in computer vision and image processing, playing a significant role in a wide range of applications that include medical image analysis, remote sensing, object recognition, document analysis, environment modeling, content-based image retrieval etc. [1]. For four decades, texture analysis has been an area of intense research, however analyzing real world textures has proven to be surprisingly difficult, in many cases caused by natural texture in-homogeneity of varying illumination, scale changes and variability in surface shape.

Many researchers have put forward various algorithms to extract color, texture and shape features for texture classification. Color is the most dominant and distinguishing visual feature. Texture features provide an important information of the smoothness, coarseness and regularity of many real-world objects such as fruit, skin, clouds, trees, bricks and fabric, etc. [10], and texture based algorithms are also widely used in CBIR systems, including the gray co-occurrence matrixes [2],

Markov random field (MRF) model [3], simultaneous auto-regressive (SAR) model [4], Wold decomposition model [5], Gabor filtering [6,7] and wavelet decomposition [8,9] and so on. Tang [11] demonstrated that textural features extracted from a new run-length matrix can produce great classification results over traditional run-length techniques. Chen et al. Proposed a set of statistical geometrical features based on the statistics of geometrical properties of connected regions in a sequence of binary images.

Textures are classified recently by edge direction movements [12], classification and recognition of handwritten digits using mathematical wavelet transforms using first and second order statistics [13], skeleton extraction [14]

and avoiding complex patterns [15]. Fuzzy based methods also proposed in the analysis of textures [16,17], age classification problems are also proposed [18,19,20] in the literature based on texture features. The above methods captured different topological configurations and texture properties of the image. As a consequence, their performance is best suited for the analysis of textures.

The term "texton" is conceptually proposed by Julesz [21] and it is a very useful concept in texture analysis and has been utilized to develop efficient models in the context of texture recognition or object recognition [22,23]. The texton [21] has been used in several classification problems [24,25], age classification problem, face recognition, image retrieval [26]. These methods need high classification rate, which is however still an open problem. The present paper put forward a new method of Fuzzy Texton Binary Matrix to describe texture features for texture classification. This method can express the spatial correlation of micro structure textons.

The rest of this 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 by conducting two experiments over the Vistex texture database of MIT, Akarmarble images and those images which come from web. Section 4 concludes the paper. Various algorithms are proposed by many researchers 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 drawback of this is, it lacks spatial information. Texture patterns can provide significant and abundance of texture and shape information. The proposed method consists of three steps which are listed below. In the first step the color image is converted in to grey level image by using any HSV color model. The following section describes the RGB to HSV conversion procedure.

2 a) RGB to HSV Color Model Conversion

In color image processing, there are various color models in use today. The RGB model is mostly used in hardware oriented application such as color monitor. In the RGB model, images are represented by three components, one for each primary color -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 nonlinear transform from RGB color space that can describe perceptual color relationship more accurately than RGB color space. In this paper, HSV color space is adopted.

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. Thus it can be seen that HSV color space is different from RGB color space in color variations. When a color pixelvalue in RGB color space is adjusted, intensities of red channel, green channel, and blue channel of this color pixel are modified. That means color, intensity, and saturation of a pixel is involved in color variations. It is difficult to observe the color variation in complex color environment or content. However, HSV color space separates the color into hue, saturation, and value which means observation of color variation can be individually discriminated. Based on the above the proposed method adopted HSV descriptor for color space because it describes colour intensity and brightness's in a significant manner. In order to transform RGB color space to HSV color space, the transformation is described as follows:

The transformation equations from RGB to HSV color model conversion is given below 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.

3 b) Fuzzy Texton Matrix Detection

In natural images, due to the presence of 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 avoid this imprecision and be able to represent the vagueness within the processes, the present paper made use of fuzzy logic and fuzzy techniques in deriving fuzzy texton binary matrix for 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 Binary Shape Window (FTBSM) 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 6 and the fuzzy membership function is represented as shown in Fig. ???. From Fig. ??, 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. To address this, the present study considered fuzzy based texton approach is used for classification of textures. The proposed Fuzzy 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 Texton Binary Shape Matrix (FTBSM). The FTBSM is 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 binary matrix method is illustrated in Fig. 3. 4. Evaluate fuzzy texton binary matrix using fuzzy code and texton as explained in Section II. 5. Represent the given shape components on a 3×3 neighborhood, where $i=1$ to 5 as shown in Fig. ?? 6. Compute frequency occurrence (FPI) of each shape component by convolving the entire texture image (Tk). Repeat the procedure for all shape components of all texture images. 7. Compute the percentage of occurrence of each shape component (SPI, $i=1$ to 5) for each of the texture Tk, $k=1:24$.

8. Classify textures using distance function of Step 7. 9. Calculate the average percentage of occurrence (APOi) of each shape component of all textures.

10. A texture Tk will be placed in one of the two classes C1 or C2 in the following way.

4 III.

5 Results and discussions

To evaluate a good classification based on the fuzzy shape components, the present study initially computed the frequency occurrences of each shape component. The proposed methodology is tested with a set of different groups of textures as shown in Fig. ?? The frequency occurrences of the derived fuzzy shape components are counted for all the original textures and the results are furnished in Table ??.

Table ?? : Frequency occurrences of fuzzy shape components on a 3×3 neighborhood of different groups of textures

From the results of Table ??, texture classification can be done by distance function. 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 are furnished in Table ?? The distance measure of different groups of textures is tabulated in Table ??, Table ??, Table ?? and Table ?? respectively. The classification group of textures with lag value for all textures is shown in Table ??, Table ?? and Table ?? By observing the results of Tables 6 to 10 the following facts are noted down. Table ?? clearly indicates that, it shows a uniform distance between each of them. The following facts are noted down from the classification tables of Table ?? The facts indicate that a good, precise and accurate stone classification is observed by the proposed FTBSM using diagonal shape components. The proposed method FTBSM also analyzed the percentage occurrence of each shape component represented in the Table 11. The Table 11 evaluated on FTBSM reveals that diagonal shape component classifies brick, granite and marble texture images accurately.

6 Conclusions

The present study created a new direction for classification of textures based on texture features derived from shape components on a 3×3 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 FTBSM method concludes that one need not necessarily count the other shape components except the diagonal shape. Therefore the present study reduced a lot of complexity in the selection of shape components for classification purpose.

¹© 2012 Global Journals Inc. (US) © 2012 Global Journals Inc. (US)

²© 2012 Global Journals Inc. (US)

³© 2012 Global Journals Inc. (US) Global Journal of Computer Science and Technology



Figure 1:

$$V = \max(R, G, B) \tag{1}$$
$$S = \frac{V - \min(R, G, B)}{V} \tag{2}$$
$$H = \frac{G - B}{6S} \text{ if } V = R \tag{3}$$

12

Figure 2: Fig. 1 :Fig. 2 :

$$H = \frac{1}{3} + \frac{B - R}{6S} \text{ if } V = G \tag{4}$$
$$H = \frac{1}{3} + \frac{R - G}{6S} \text{ if } V = B \tag{5}$$

3

Figure 3: Fig. 3 :

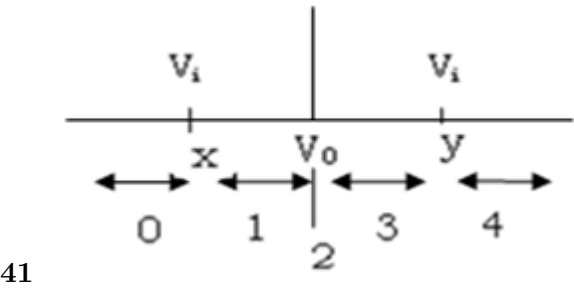


Figure 4: Fig. 4 : 1 .

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \text{ and } V_i < x \\ 1 & \text{if } V_i < V_0 \text{ and } V_i > x \\ 2 & \text{if } V_i = V_0 \\ 3 & \text{if } V_i > V_0 \text{ and } V_i > y \\ 4 & \text{if } V_i > V_0 \text{ and } V_i < y \end{cases} \quad \text{for } i = 1, 2, 3, \dots, 8 \quad (6)$$

Figure 5:

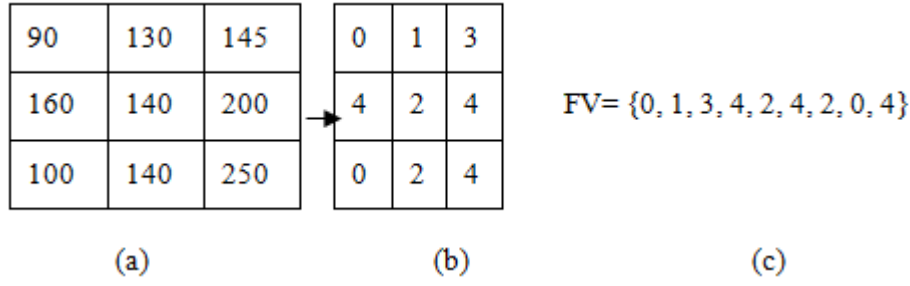


Figure 6:

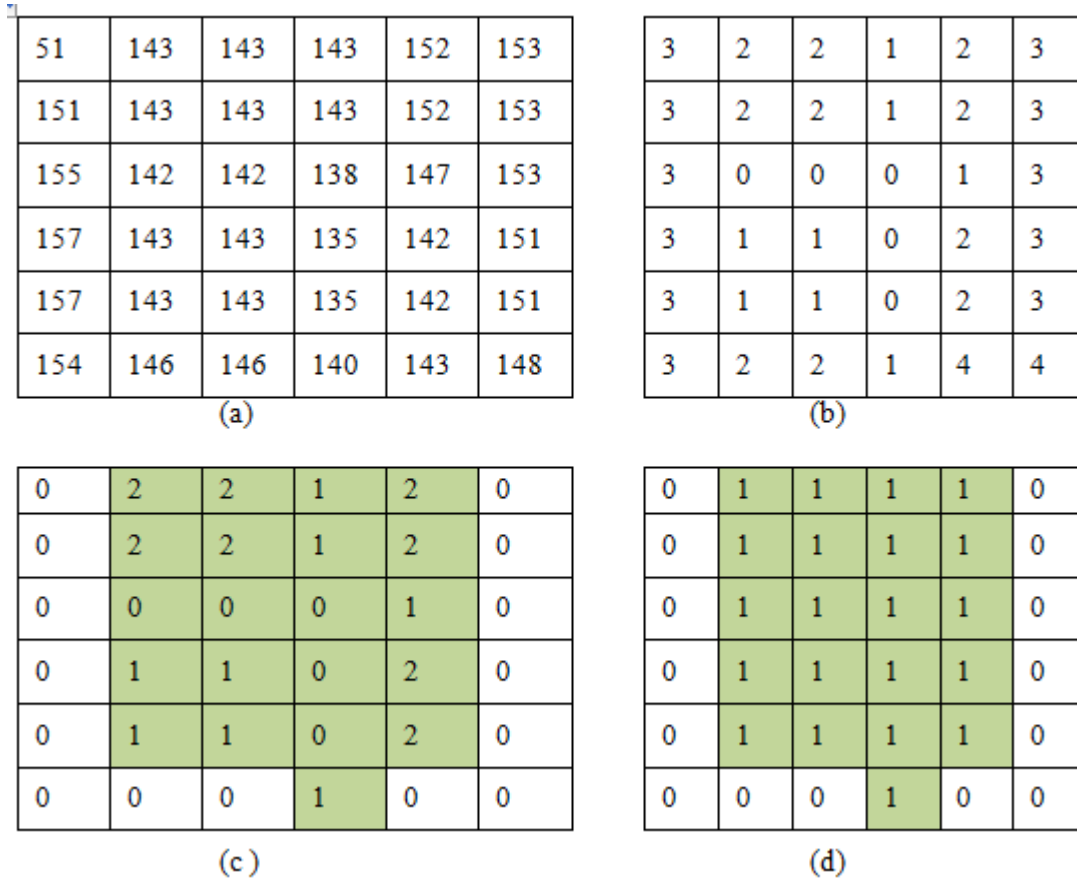


Figure 7:

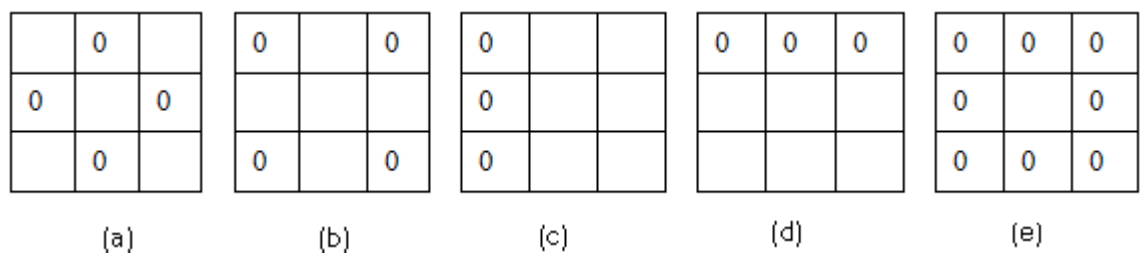


Figure 8:

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

Figure 9:

$$APO_i = \frac{\forall_{i=1}^5 \sum_{k=1}^n T_k sp_i}{\max(k)}$$

Figure 10:

Figure 11:

Figure 12:

Figure 13: Table 11 :

.1 Acknowledgment

The authors would like to express their gratitude to Sri K.V.V. Satyanarayana Raju, Chairman, and Sri K. Sasi Kiran Varma, Managing Director, Chaitanya group of Institutions for encouraging to work at SRRF-GIET Advanced labs.

[Lee et al.] , W.-L Lee , - C Yung , Chen , - C Ying , K.-S Chen .

[Feng et al. ()] ‘A Coarse-to-Fine Classification Scheme for Facial Expression Recognition’. X Feng , A Hadid , M Pietikainen . *ICIAR 2004 Proceedings*, Lecture Notes in Computer Science 3212 II 2004. p. . (Image Analysis and Recognition)

[Ojala et al.] *A comparative study of texture measures with classification based*, T Ojala , M Pietikäinen , D Harwood .

[Hadid et al. ()] ‘A Discriminative Feature Space for Detecting and Recognizing Faces’. A Hadid , M Pietikainen , T Ahonen . *IEEE Conference on Computer Vision and Pattern Recognition II*, 2004. p. .

[Jiji and Ganesan ()] ‘A new approach for unsupervised segmentation’. Wiselin Jiji , G Ganesan , L . *Applied Soft Computing* 2010. 10 p. .

[Reed and Buf ()] ‘A review of recent texture segmentation and feature extraction techniques’. T R Reed , J M H Buf . *CVGIP: Image Understanding* 1993. 57 p. .

[He et al. ()] ‘An enhanced LBP feature based on facial expression recognition’. L H He , C R Zou , L Zhao , D Hu . *Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, (the 2005 IEEE Engineering in Medicine and Biology 27th Annual ConferenceShanghai) 2005. p. .

[Jiji and Ganesan ()] ‘Comparative analysis of colour models for colour textures based on feature extraction’. Wiselin Jiji , G Ganesan , L . *Int. Jour. of Soft computing* 2007. 2 (3) p. .

[Ahmed et al.] *Compound Local Binary Pattern (CLBP) for Facial Expression Recognition*, Faisal Ahmed , A S M Bari , Emam Hossain . p. 2011.

[Kumar et al. (2009)] ‘Employing Long Linear Patterns for Texture Classification relying on Wavelets’. Vijaya Kumar , .V , U S N Raju , Chandra Sekaran , V V Krishna . *ICGST-GVIP Journal* 1687-398X. January 2009. (8) p. .

[Ahonen et al. ()] ‘Face description with local binary patterns: application to face recognition’. T Ahonen , A Hadid , M Pietikäinen . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2006. 28 (12) p. .

[Ahonen et al. ()] ‘Face Recognition Based on the Appearance of Local Regions’. T Ahonen , M Pietikainen , A Hadid , T Maenpaa . *17th International Conference on Pattern Recognition III*, 2004. p. .

[Ahonen et al. ()] ‘Face Recognition with Local Binary Patterns’. T Ahonen , A Hadid , M Pietikainen . *Computer Vision, ECCV Proceedings*, 2004. p. .

[Feng et al. ()] ‘Facial Expression Recognition with Local Binary Patterns and Linear Programming’. X Feng , M Pietikainen , A Hadid . *Pattern Recognition and Image Analysis* 2005. 15 p. .

[Dash and Liu ()] *Feature Selection for Classification. Intelligent Data Analysis*, M Dash , H Liu . 1997. Elsevier. p. .

[Belur et al. (1981)] ‘Image characterizations based on joint gray level-run length distributions’. V Belur , Edwin B Dasarathy , Holder . *Pattern Recognition Letters* 1981. August 1991. 12 p. .

[Chan and Chang ()] ‘Image matching using run-length feature’. Yung-Kaun Chan , Chin-Chen Chang . *Pattern Recognition Letters* 2001. 22 p. .

[Zhang et al. ()] ‘Learning optimal filter representation for texture classification’. P Zhang , J Peng , B Buckles . *International Conference on Pattern Recognition*, (Hong Kong) 2006. 2 p. .

[Lucieer et al. ()] ‘Multivariate texturebased segmentation of remotely sensed imagery for extraction of objects and their uncertainty’. A Lucieer , A Stein , P Fisher . *International Journal of Remote Sensing* 2005. 26 (14) p. .

[Jafari-Khouzani and Soltanian-Zadeh ()] ‘Radon transform orientation estimation for rotation invariant texture analysis’. K Jafari-Khouzani , H Soltanian-Zadeh . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2005. 27 (6) p. .

[Lahdenoja et al. ()] ‘Reducing the feature vector length local binary pattern based face recognition’. M O Lahdenoja , A Laiho , Paasio . *ICIP 2005, IEEE International Conference on Publication*, 2005. 2 p. .

[Pietikäinen et al. ()] ‘Rotation-invariant texture classification using feature distribution’. M Pietikäinen , T Ojala , Z Xu . *Pattern Recognition* 2000. 33 p. .

[Paclik et al. ()] ‘Supervised segmentation of textures in backscatter images’. P Paclik , R Duin , G Van Kempen , R Kohlus . *Proceedings of the 16th International Conference on Pattern Recognition*, (the 16th International Conference on Pattern RecognitionQuebec City) 2002. p. .

- [Garcia and Balu ()] ‘Supervised texture classification by integration of multiple texture methods and evaluation windows’. M A Garcia , D Balu . *Image and Vision Computing* 2007. 25 p. .
- [Galloway (1975)] ‘Texture analysis using gray level run lengths’. M M Galloway . *Comput. Graphics Image Process* June 1975. 4 p. .
- [Samal et al. ()] ‘Texture as the basis for individual tree identification’. A Samal , J R Brandle , D S Zhang . *Information Sciences* 2006. 176 p. .
- [Raju et al. ()] ‘Texture Classification Based On Extraction Of Skeleton Primitives Using Wavelets’. U S N Raju , Eswar Reddy , Vijaya Kumar , B Sujatha . *Information Technology Journal* 2008. (7) p. .
- [Reddy et al. (2007)] ‘Texture Classification by Simple Patterns on Edge Direction Movements’. Eswara Reddy , B , A Rao , A Suresh , V Vijaya , Kumar . *IJCSNS International Journal of Computer Science and Network Security* November 2007. 7 (11) p. .
- [Marzabal et al. ()] ‘Textured-based characterization of defects in automobile engine valves’. A Marzabal , C Torrens , A Grau . *Proceedings of the Ninth Symposium on Pattern Recognition and Image Processing*, (the Ninth Symposium on Pattern Recognition and Image Processing) 2001. p. .
- [Tuceryan and Jain ()] ‘The Handbook of Pattern Recognition and Computer Vision’. M Tuceryan , A K Jain . *Texture analysis*, C H Chen, L F Pau, P S P Wang (ed.) (Singapore) 1998. World Scientific. p. . (second ed.)
- [Koller and Sahami ()] ‘Toward optimal feature selection’. D Koller , M Sahami . *Proceedings of the 13th International Conference on Machine Learning*, (the 13th International Conference on Machine LearningBari, Italy) 1996. p. .
- [Hsieh ()] ‘Unsupervised segmentation of ultrasonic liver images by multiresolution fractal feature vector’. Hsieh . *Information Sciences* 2005. 175 p. .
- [Chu et al. ()] ‘Use of gray value distribution of run lengths for texture analysis’. A Chu , C M A Sehgal , J F Greenleaf . *Pattern Recognition Letters* 1990. 11 (6) p. .