Texture Classification Based On Fuzzy Similarity Texton Co-Occurrence Matrix

J.Srinivas, Ahmed Abdul Moiz Qyser, B. Eswara Reddy

Abstract*: In the existing texton based methods a texton is derived in a grid by a collection of pixels exhibiting exactly the similar grey level values/color/attributes. The disadvantage of this approach is they fail in recognizing textons, whenever a small random noise changes the pixels intensity values slightly. This paper addresses this by deriving a fuzzy similarity 'S' in identification of texton patterns. The proposed Fuzzy similarity Texton Co-occurrence Matrix (FSTCM) framework considers the pixels whose gray level value falls within the fuzzy similarity index value as texton pattern. The FSTCM divides initially the texture image into micro regions of size 2x2, identifies the textons and transforms the texture image into a fuzzy texton image. This paper derives gray level co-occurrence matrix (GLCM) features on FSTCM and the proposed method is tested on five popular texture image databases. The experimental investigation reveals the high performance of the proposed method over the state of art local based and texton based methods.

Keywords: texton, similarity; micro region; GLCM features; random noise.

I. INTRODUCTION

Texture classification is treated as one of the important and crucial problems of image processing, pattern recognition and computer vision tasks. Texture classification (TC) is one of the long standing research problems and it has lot of significance and also treated as the major problem of texture analysis. Texture classification has a wide range of applications include document, classification, age classification, bio-metrics, content based image retrieval (CBIR), remote sensing etc. Texture classification is also treated as a classical problem of pattern recognition. Texture classification consists of two critical steps: feature extraction and the design of classifiers [30]. Out of these two steps the extraction of significant texture features is treated as more important and crucial. The best classifiers will result in a poor classification if the extracted texture features are very poor or non-significant. That is the reason most of the research in Texture classification concentrates on how to extract the best features. A good number of researchers carried out significant surveys on texture classification [30, 31] and these surveys listed out various texture feature extraction methods with their merits and demerits. The existing methods mostly attained good texture classification performance on small and medium size databases. This has lead towards more research on Texture classification to deal with large databases, non-ideal environmental images and for real time applications. The texture classification methods need to address the difficulties in extracting texture features i.e. need to balance between extraction of powerful features and computational complexity. The texture classification need to manage the tradeoff between distinctiveness due to wide range of classes and robustness due to large intra class variations like rotations, scale, blur occlusion, noise illumination etc. These days texture classification is applied to numerous fields like writer identification and verification [1] classification of forest spices [2, 3], agriculture [4, 5], gas [6-8], medical diagnosis [9, 10], geo processing [11] etc. Texture is a surface properly and the research defines textures as a varying distribution of intensity or gray levels or colors. Texture features also plays a major role in video indexing [12], lip reading [13], web search [14] and sound event classification [15]. The texture classification methods are broadly divided into statistical and structural methods.

The structural methods can be local based or region based or global based methods. Out of these local based methods have become more popular and these are used predominantly in texture classification especially after the derivation of local binary pattern (LBP) [16]. The other local descriptors are scale invariant feature transforms (SIFT) [17] and histogram oriented gradients (HOG) [18]. The local binary pattern (LBP) [16] is one of the popular descriptors of texture classification due to its advantages like ease of understanding and implementation and rotational invariance. The LBP was initially derived for texture analysis and however the LBP based methods have successfully applied in many divested applications like CBIR [32-34], texture recognition [35-37], age classification [38, 39], texture classification [41-43], bio medical image analysis [43, 44], environmental modeling [45, 46].Many variants are proposed to LBP in the literature to improve its performance and the popular LBP variants include [19, 20, 21]. The advantages of these local descriptors are [20, 21, 22], they are handcrafted methods and they can easily incorporate with other complex methods [23, 24]. That is the LBP and its variants can be easily integrated with other statistical descriptors to drive more meaningful and discriminate features. The LBP is initially derived on a 3 x 3 neighborhood with 8 sampling points (P=8) over a center pixel of radius one (R=1). Further, LBP is also derived with P=12 and R=1 ; P=16 and R=2, to improve overall robustness to noise [22, 23, 24, 25]. The computation process of generating binary patterns are also changed over the years i.e. instead of sign differences, researchers used median, average, symmetric relations etc. to generate binary patterns [25, 26].

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A texture contains repetitive patterns/patches. The patch based classification methods also played a vital role in texture classification [27,28,29]. The patch based approaches divides each image into smaller grids/patches and each patch is considered as a feature or observation. The patch based approaches instead of deriving features from the whole image derives multiple patches and by observing these patches classification is performed. The patch based classification systems are divided into two levels (category). The multiple patches are combined at the classification level in the first category. The patch level classifications of all patches are combined by fusing with the help of a classifier. The patch based approaches are also becoming popular in the literature [27, 28, 29].

Texton based methods played a vital role in content based image retrieval and in texture analysis. Texton based methods derived discriminative texture features with robustness and ease of computation. The textons construct filter banks and make use of their responses to represent texture patterns [55, 56]. The texton based methods can be easily integrated with other complex methods like co-occurrence matrix etc. The popular texton based methods are texton co-occurrence matrix (TCM)[57], multi texton histogram (MTH) [58], complete texton matrix (CTM) [59]. These methods are good at detecting local structures such as oriented edges. The TCM and MTH models are used for CBIR and CTM is derived for texture classification. These models detected a texton on a 2 x 2 grid, if two or more adjacent pixels represent exactly the similar intensity value. This paper derived a new model of deriving textons using fuzzy similarity index.

The rest of the paper is organized as follows: section 2 describes about proposed method, section 3 and section 4 gives results and discussions and conclusions respectively.

II. DERIVATION OF THE PROPOSED FUZZY SIMILARITY TEXTON CO-OCCURRENCE MATRIX (FSTCM) FRAMEWORK

The Patten trends play a major role in various image processing applications like Texture classification [40-42], content based image retrieval (CBIR) [32-34], texture recognition [35-37], age classification [38, 39] etc… In the literature pixel based methods are not popular, since they derive attributes related to only that pixel, thus they fail in deriving more significant information. The existence of texture and its definition clearly states that the attributes of a pixel not only depend on that pixel, and they also depend on the adjacent pixels that are surrounding the current pixel. That is the reason neighborhood based methods are developed. The local based approaches are mostly based on neighborhood properties i.e. the features are extracted from neighborhoods.

Textons have become popular for more than 20 years [60] and they are most popular local based approaches. A texton is basically a texture property. A texton represents a pattern. A pattern on a texture is formed if two or more adjacent pixels in the neighborhood hold the similar properties i.e. exhibit similar intensity, color, gradient values etc. The textons represents a structure on a 2 x 2 micro grid and basically textons represent a pattern and the advantage of textons is one can easily represent the complex patterns based on the simple patterns of textons. The textons are used in many applications of image and computer vision i.e., texture analysis [61, 62], texture classification [63], age classification [61], content based image retrieval (CBIR)[57, 58] and other applications of texture [41, 42]. Textons derive rotational and scale invariant local features. The proposed fuzzy similarity texton (FST) frame work establishes the spatial correlation of textons with a minor similarity difference. The FST derives the texture and shape features of FST. The derivation of co-occurrence matrix and the extraction of GLCM features on FSTCM derived more discriminate information required for a high classification rate.

The proposed fuzzy based texton model derives textons on a 2x2 grid. In the literature various texton models are proposed and the popular ones are TCM [57], MTH [58] and CTM [59]. The TCM, MTH and CTM have derived textons with exactly similar grey level/color values: with three or four pixels, with few patterns of two pixels and with complete set of patterns respectively. This paper modifies the process of formation of textons and derives the textons based on fuzzy similarly value‘s’. That is a texton is formed even if the adjacent pixels differs with a value less than or equal to‘s’. The advantage of the proposed fuzzy based similarity texton model is i) It over comes the noise effect in the image. A small/ random noise may change pixel intensity slightly and in such case the similar pixel will differ in gray level intensities and thus formation of textons will be affected. ii) Pixels with similar brightness under different shades will exhibits a small difference in intensity levels. The existing models of textons fail in representing such textons. The proposed model can recognize such textons.

The texton co-occurrence matrix (TCM) defined the following types of five textons on a 2x2 grid.

g_1	g_2
g_4	g_3

A 2x2 grid

t	t
t	t

T_1

t	t
	t

T_2

t	t
t	

T_3

t	
t	t

T_4

	t
t	t

T_5

Fig.1: The texton patterns of TCM model.

The proposed fuzzy Similarity Texton Co-occurrence Matrix (FSTCM) defined the similar type of textons as in the case of TCM (Fig.1), however with a Fuzzy similarity index value ‘s’ and they are named as (FT1, FT2, FT3, FT4, FT5) on a 2x2 grid.

g_1	g_2
g_4	g_3

A 2x2 grid

g ±t	g±t
g±t	g±t

FT_1

g±t	g±t
	g±t

FT_2

g±t	g±t
g±t	

FT_3

g±t	
g±t	g±t

FT_4

	g±t
g±t	g±t

FT_5

Fig.2: The texton patterns of fuzzy similarity texton model.

40	40
40	24

(a)

40	41
42	39

(b)

22	21
20	19

(c)

Fig. 3: The recognition process of textons in TCM vs. proposed FSTCM.

The figure 3 establishes the difference between the identification process of textons in TCM and the proposed FSTCM.

1. The TCM and FSTCM recognize a texton with 3 identical pixels in Fig. 3(a).
2. Fig 3(b): The TCM does not identify any texton in Fig. 3(b), though the pixels g_1, g_2, g_3 and g_4 represents mostly similar gray level value though not exactly the same. The TCM identifies a texton type with three or four pixels if and only if all three or four pixels represent exactly similar grey/colour value. The proposed FSTCM identifies the pixels with exactly similar or mostly similar gray levels values using a fuzzy similarity index 's' value for the formation of a texton. The proposed FSTCM identifies the Fig. 3(b) as a texton with four similar values for a fuzzy similarity index's' value equals to 2 (s=2). That is by considering the top leftmost pixel g1 with gray level value 40 the FSTCM identifies the pixels with gray level range from 38 to 42 for s =2. Thus all the four pixels of the 2x2 grid of Fig. 3(b) fall into the range of 38 to 42. Thus the proposed FSTCM identifies the Fig.3(b) as a texton type FT1 with four similar values based on fuzzy similarity index "s=2" and the four pixels are replaced by grey level value 40.
3. Fig 3 b): By considering the fuzzy similarity index S=1 the proposed FST framework identifies the three pixels g1,g2 and g3 as similar values. The fuzzy similarity index value S =1 for the top most left pixel with the grey level value g1= 40, identifies all the pixels with the range 39 to 41 as similar grey levels. Thus the structural pattern or texton pattern FT2 will be formed by using g_1,g_2 and g_3 pixels and the texton structure is replaced with the value 40.
4. Fig 3(c): No texton is identified according to TCM. The FSTCM by considering g1 i.e. the gray level value 22 with s=2(the range will be 20 to 24) identifies a texton type with three similar values g1, g2 and g4 i.e. the texton type FT2. However by considering g3 with grey level value 20 and fuzzy similarity index value s=2 (the similarity range will be 18 to 22) identifies the texton type with four identical pixels i.e. FT1. In this case the FSTCM recognizes the grid as FT1 and the four pixels of the grid are replaced by a value 20 (the pixel value of g3). Thus the FSTCM initially tries to recognize the texton type FT1 with four identical pixels by inspecting all four pixels g1,g2,g3 and g4 of the 2x2 grid. If it is not recognized then it tries to recognize for FT2 or FT3 or FT4. If FT1 is recognized then other three are not verified since all of them are only of 3-similar pixel values.

The texton detection process of TCM and FSTCM are also different. The TCM frame work scans every 2x2 grid of the image from top to bottom and left to right by shifting one column at each instance until the end of all columns and shifting one row bottom until the end of the image. This process is known is as moving the window object in an overlapped manner by a step length of one. The TCM approach initially scans the image for the texton type T1 where all the four pixels have exactly the same brightness. This process will be continued on the entire image with a step length of one. The same process is repeated for the remaining four types of textons T2, T3, T4 and T5 for TCM frame work. If the texton type is identified then the TCM frame work retains the pixel values which are part of the textons and assigns zero value to those pixels which are not part of textons on a 2x2 grid. This results a five copies of the texture image each one is representing a different type of textons from T1 to T5. The TCM frame work fuses these five textons type images into one to realize the final texton image. The Framework of texton detection and final derivation of texton image in TCM is shown in the Fig.5. The Fig.5 shows the derivation process of the TCM frame work for the 6 x 6 image patch of Fig. 4.

The proposed FSTCM initially divides the image into micro grids of size 2x2 i.e. with a step length of two in a non-overlapped manner. In each micro grid the FSTCM framework initially tries to identifies the texton type FT_1 with four similar values with fuzzy similarity index value 's', if it is found then FSTCM moves to the next micro grid. If it is not detected then FSTCM identifies the texton types FT_2, FT_3, FT_4, FT_5 with three similar values with a fuzzy index value's'. If a texton type is identified then it moves to the next grid. The FSTCM places zero value to the pixel locations of 2x2 micro grid which are not part of the texton formation and retains all the pixels that are part of texton, with exactly the same value of the pixel on which the fuzzy similarity index 's' is applied and on which the fuzzy texton is derived. The derivation of FST for an image patch of Fig.4, is shown in Fig. 6(a) and Fig. 6(b) for S=1 and S=2 respectively.

22	21	18	28	12	14
20	19	18	18	13	15
15	15	15	11	14	20
15	7	15	13	21	19
9	7	7	12	14	12
15	7	7	14	14	10

Fig.4: the sample sub image of 6x6.

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	7	7	0	0	0
0	7	7	0	0	0

(a) Texton type T_1 of TCM

0	0	0	0	0	0
0	0	0	0	0	0
0	15	15	0	0	0
0	0	15	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

(b) Texton type T_2 of TCM

0	0	0	0	0	0
15	15	0	0	0	0
15	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

(c)Texton type T_3 of TCM

0	0	18	0	0	0
0	0	18	18	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

(d) Texton type T_4 of TCM

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	14	0
0	0	0	14	14	0

(e) Texton type T_5 of TCM

0	0	18	0	0	0
0	0	18	18	0	0
15	15	15	0	0	0
15	0	15	0	0	0
0	7	7	0	14	0
0	7	7	14	14	0

(f) Final TCM matrix

Fig: 5: a to e - the detection process of textons T1 to T5 respectively; (f) the final Texton image of TCM.

21	21	18	0	0	14
21	0	18	18	14	14
15	15	0	0	0	20
15	7	0	0	20	20
0	0	0	0	0	0
0	0	0	0	0	0

(a) FST framework for s=1

20	20	18	0	13	13
20	20	18	18	13	13
15	15	13	0	0	20
15	0	13	13	20	20
9	9	0	0	12	12
0	9	0	0	12	12

(b) FST framework for s=2

Fig. 6: The frame work of FSTCM.

The paper derived a co-occurrence matrix on fuzzy similarity texton indexed image and this result a FSTCM. This paper derived five gray level co-occurrence matrix (GLCM) features on FSTCM and the GLCM features are derived (Equations 2 to 5) on FSTCM with a distance value d=1 and 2.

On each distance value four FSTCM's are extracted with an angle of 0o, 45o,90o and 135o and this paper computed five GLCM features on each of this angle and the average value is considered under each distance for texture classification purpose.

Table 1: Summary of the image databases.

No.	Name of the Database	Size of the image	Number of classes	Number of images per category	Total number of images
1	Brodatz 640[44]	128x128	40	16	640
2	UIUC	640 x 480	25	40	1000
3	Outex-TC-10	128 x 128	24	vary	4320
4	Outex-TC-12	128 x 128	24	vary	4320
5	KTH-TIPS	128x 128	10	81	810
6	ALOT	384x256	250	100	2500
No.	Name of the Database	Size of the image	Number of classes	Number of images per category	Total number of images

The five GLCM features are given below:

Contrast :

$$\sum_{n=0}^{M-1} n^2 \left\{\sum_{i=1}^{M} \sum_{j=1}^{N} X(i,j)\right\}, |i-j| = n \qquad (1)$$

This measure of contrast or local intensity variation will favor contributions from P (i, j) away from the diagonal, i.e. i ! = j.

Correlation :

$$\text{Correlation} = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \frac{\{iXj\}XX(i,j)-\{\Box_x X \Box_y\}}{\sigma_x X \sigma_y} \qquad (2)$$

Correlation is a measure of grey level linear dependence between the pixels at the specified positions relative to each other.

Entropy :

$$\text{Entropy} = \sum_{i,j} \log(X(i,j).\ X(i,j) \qquad (3)$$

Inhomogeneous scenes have low first order entropy, while a homogeneous scene has high entropy.

Homogeniety, Angular Second Moment (ASM):

$$\text{ASM}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{X(i,j)\}^2 \qquad (4)$$

ASM is a measure of homogeneity of an image. A homogeneous scene will contain only a few grey levels, giving a GLCM with only a few but relatively high values of P (i, j). Thus, the sum of squares will be high.

5. Local Homogeneity, Inverse Difference Moment (IDM)

$$\text{IDM}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \qquad (5)$$

IDM is also influenced by the homogeneity of the image. Because of the weighting factor (1+(i−j)2)−1 IDM will get small contributions from inhomogeneous areas (i != j). The result is a low IDM value for inhomogeneous images, and a relatively higher value for homogeneous images.

For classification purpose this paper computed the average feature value from each distance value and it is given as input to different classifiers. This paper used Naive Bayes classifier, multi-layer perceptron (MLP), liblinear and J48 classifiers on WEKA tool for classification purpose.

III. RESULTS AND DISCUSSIONS

To evaluate the performance, this paper compared the classification rates of the proposed FSTCM descriptor with LBP based descriptors i.e. LBP[16], LTP[19], CS-LBP[65] , CLBP-SMC[46] and texton based descriptors TCM[57] and MTh[58]. The experiments are conducted on five different popular data bases namely, Brodatz [66], UIUC [67], Outex-TC-10[68], Outex-TC-12[68], KTH-TIPS [69] and ALOT[70]. The summary of these databases are given in table 1. The sample images of these databases are shown from figures 7 to 12.

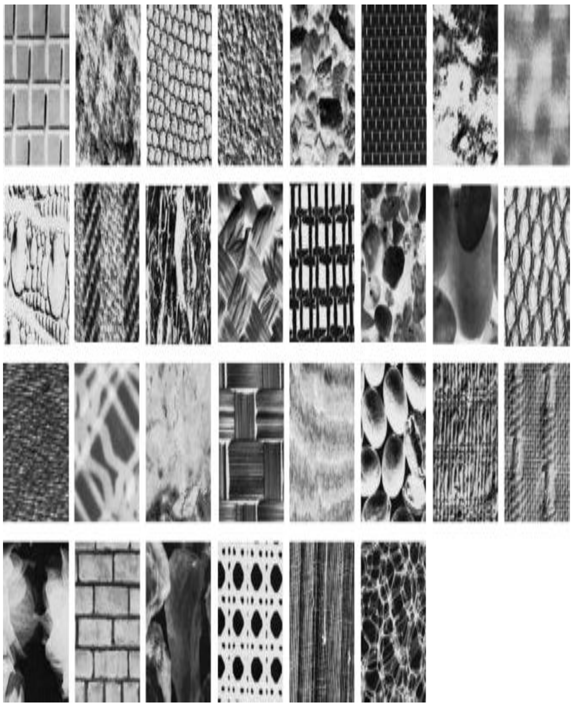

Fig. 7: Samples of the 30 classes randomly selected from the Brodatz database.

Fig. 8: Sample images from the UIUC database.

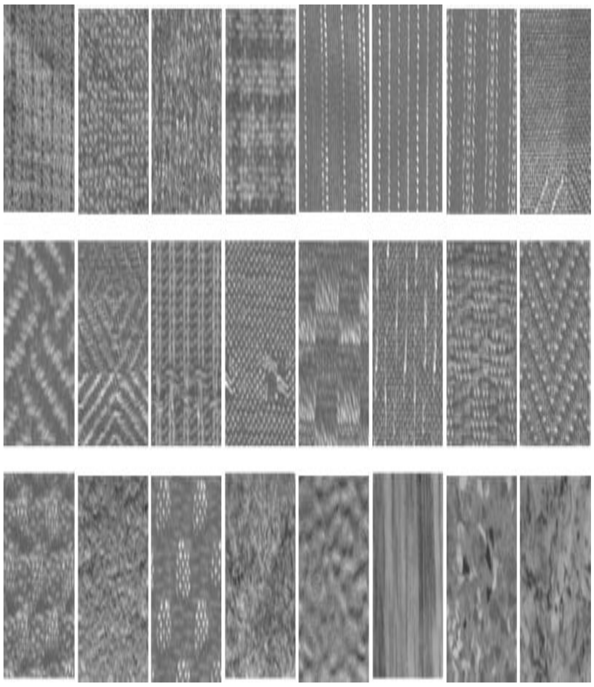

Fig.9: The sample images of 24 classes from Outex database.

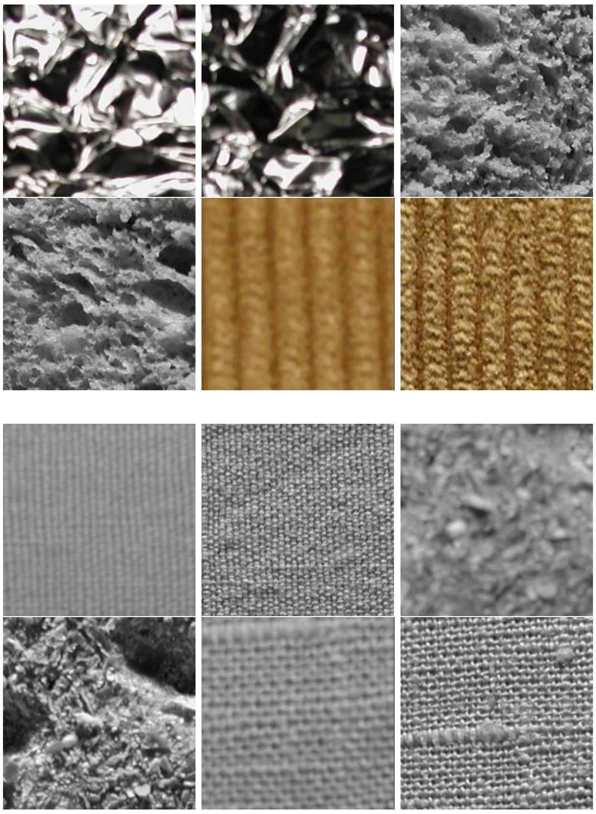

Fig. 10: Sample images of KTU-TIPS texture database.

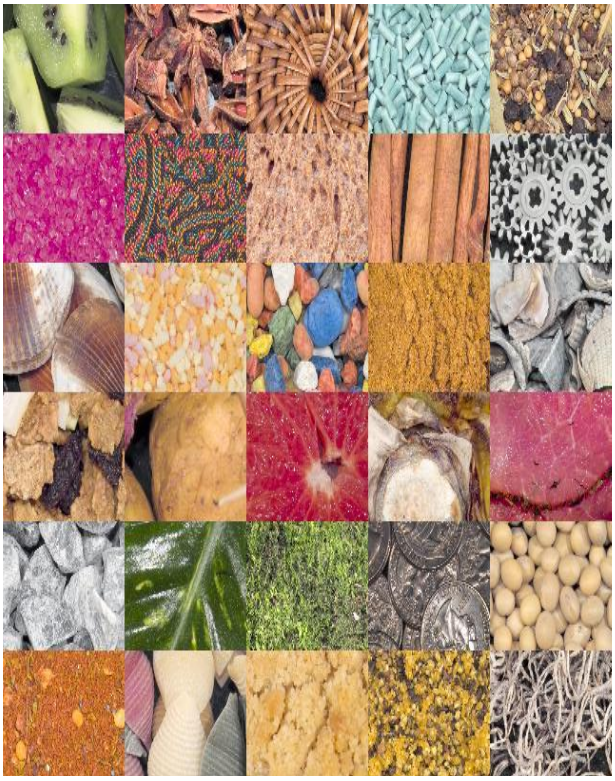

Fig. 11: ALOT texture database.

This paper initially transforms the given image into grey level image. This paper divided the image in to local micro grids of size 2 x2. On each region extracted the fuzzy similarity textons as defined in this paper. Thus the given raw texture image is transformed in to a fuzzy similarity texton image and this image overcomes the noise affect and other illumination variations. The derivation of GLCM features on FSTCM extracted more meaningful information required for texture classification.

The proposed FSTCM descriptors have shown high classification rate for similarity index value one and the distance value d=2 on all four classifiers and on all considered databases. The multilayer perceptron exhibits a high classification rate for d value=2 on all databases, when compared to other classifiers on the proposed descriptor (from table 1). For comparison purpose with the other existing descriptors, now onwards the classification rates of multilayer perceptron for similarity index s=1 is quoted for the proposed descriptor.

The fuzzy texton similarity index s=1 has given high classification rate when compared to S=2, the reason for this is the number of textons identified by S=1 are little higher than TCM frame work and far less than for S value =2. More number of textons will be resulted for fuzzy similarity texton index S=2 and this may result a poor classification rate especially for homogeneous textures.

Table 1: Average classification rate of the proposed FSTCM with s=1 on different databases using different classifiers for d=2

Proposed Method	Databases	Naviebayes	Multilayer-perceptron	Ibk	J48
Proposed FSTCM	Brodtaz [66]	79.64	85.46	83.77	82.68
	UIUC[67]	76.64	83.33	81.56	79.88
	Outex-TC-10[68]	71.52	80.41	77.32	74.21
	Outex-TC-12[68]	72.5	81.49	78.25	75.84
	KTH[69]	86.63	91.37	90.02	88.84
	A LOT[70]	76.14	81.67	80.02	79.18
	AVERAGE	77.18	83.96	81.82	80.11

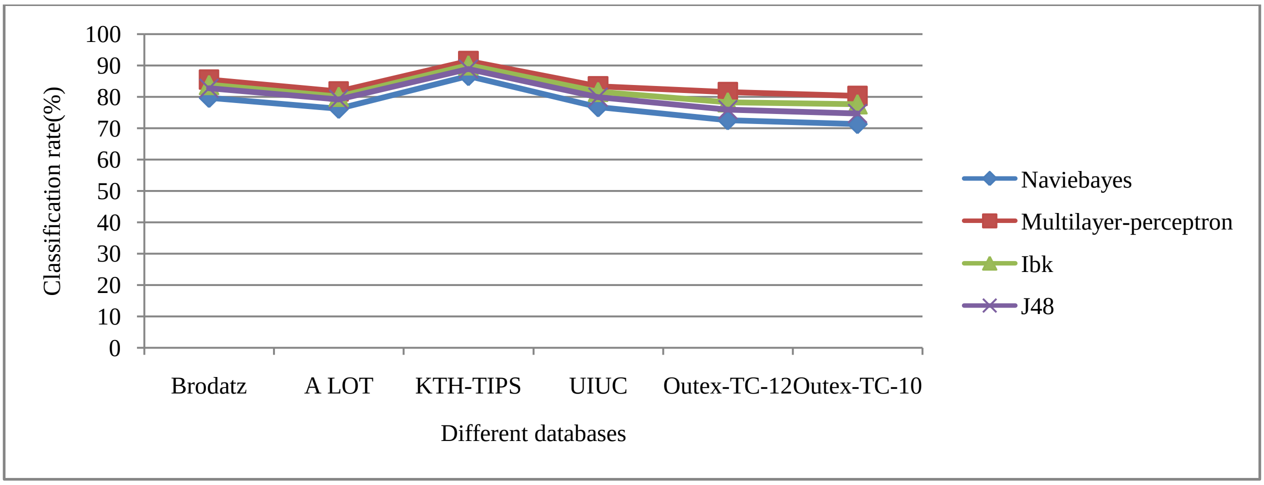

Fig. 12: Classification rate (%) of proposed method on different databases.

Table 2: Classification rate of proposed and existing methods.

Database	LBP[16]	LTP[15]	CLBP-SMC[46]	CS-LBP[65]	MTH[58]	TCM[57]	Proposed FSTCM
Brodtaz	54.28	57.50	85.23	74.56	87.25	86.57	88.23
UIUC	62.86	67.16	87.64	74.24	87.83	85.7	86.45
Outex-TC-10	55.62	74.12	89.85	73.47	90.12	91.14	91.88
Outex-Tc-12	56.19	75.88	90.30	74.64	91.87	92.65	92.53
KTH-TIPS	64.16	66.18	89.14	72.14	87.89	87.51	90.11
ALOT	52.26	56.24	80.46	70.14	85.65	86.10	88.66

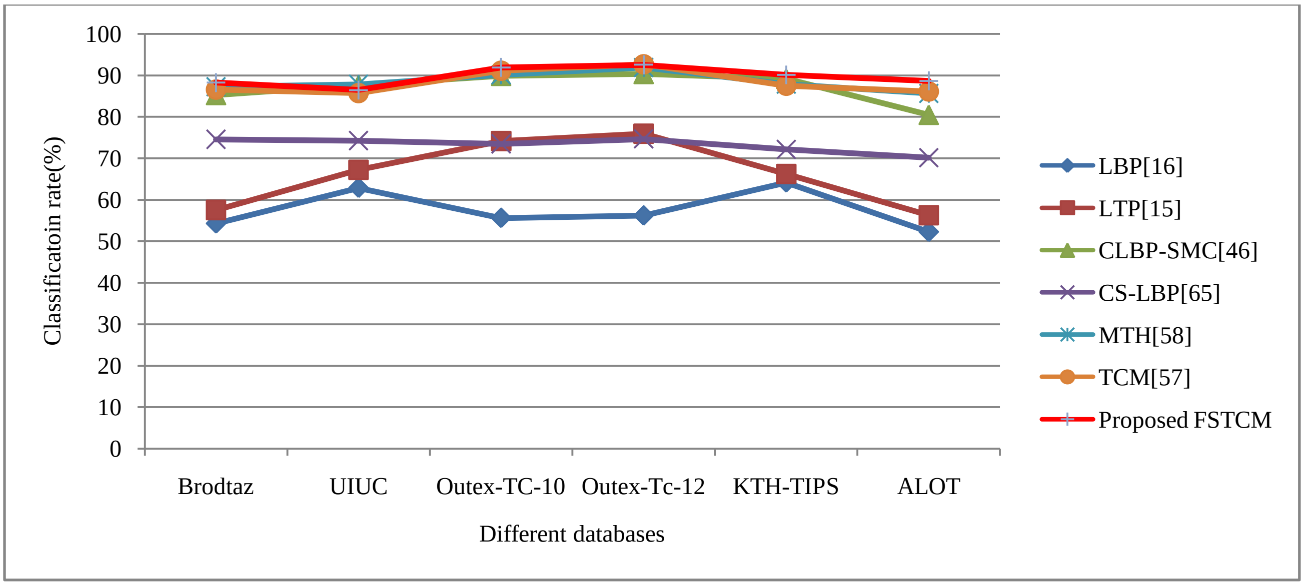

Fig.13: Comparison graph of proposed method with existing methods.

The major contribution of this paper

1. Derivation of textons using a fuzzy similarity index, instead of exactly similar gray levels on a grid.
2. The division of texture images into 2x2 micro grids and deriving fuzzy similarity texton patterns on each grid. This operation avoids the complex fusing operation, as in the case of TCM.
3. The proposed texton frame work can derive texton pattern even on a noisy texture images, more efficiently.
4. The proposed FSTCM frame work assigns the similar gray level values to all the pixels of the texton pattern and this assignment is carried based on the pixel gray level value on which the fuzzy similarity index value is applied.
5. The FSTCM derives more number of textons than TCM approach and thus extracts more spatial information while constructing co-occurrence matrix.

The proposed FSTCM has exhibited a good enhancement in texture classification rate than LBP, LTP and CS-LBP approaches on all databases. The proposed descriptor attained better classification accuracy when compared to the state of art texton based methods. The main reason for this due to the introduction of fuzzy similarity index value s and recognizing local patterns that falls within certain grey level range of a pixel. The UIUC database images are more prone to scale and orientation changes and that's why they have shown 2 to 4% less classification rate when compared to other databases on all methods. The proposed method attained a high classification rate than existing methods on several types of popular databases; this clearly indicates the efficacy and significance of fuzzy similarity index in texton derivation.

The limitations of the existing texture features LBP, ULBP, CS-LBP and LTP, for texture classification are analyzed. LBP, UBLP and LTP differentiate a bright object against a dark background and vice-versa. This differentiation makes the object intra-class variation larger. The CS-LBP though measures the symmetric relations of neighbors but it yields a poor classification rates due to its short code on the other hand LBP, ULBP and LTP when integrated with GLCM produces a huge dimensions and this makes them too complex and not suitable to real time applications. The proposed FSTCM is proposed by carefully

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analyzing the weakness of existing texton based methods. The proposed descriptor alleviates the problem of existing descriptors of textons by introducing the fuzzy similarity index representation.

IV. CONCLUSIONS

This paper derived a new variant to the existing texton based methods. The concept of fuzzy similarity between gray level values of the pixels with in a micro gird is introduced. The advantage of this, it is more tolerable to noise fluctuations. The proposed FSTCM derived more texton grids than existing texton frame works. This derives a better spatial relationship among and between texton patterns. The GLCM features derived on FSTCM extract more meaningful and discriminant texture features. That's why the proposed method exhibited high classification rate than the existing methods on the popular databases. The better performance of the proposed FSTCM approach on different types of texture databases where the images are captured under different varying conditions and the experimental analysis on the large datasets clearly indicates that the FSTCM approach is more robust and compact to various variations like illumination conditions, lighting conditions etc., than the existing classification methods. The proposed method can also be extended to CBIR.

REFERENCES

1. D. Bertolini, L. Oliveira, E. Justino, and R. Sabourin, "Texture-based descriptors for writer identification and verification," Expert Syst. Appl., vol. 40, no. 6, pp. 2069–2080, May 2013. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2012.10.016
2. P. L. Paula Filho, L. S. Oliveira, A. S. Britto, and R. Sabourin, "Forest species recognition using color-based features," in Proceedings of the 20th International Conference on Pattern Recognition, Instanbul, Turkey, 2010, pp. 4178–4181.
3. M. Nasirzadeh, A. A. Khazael, and M. b. Khalid, "Woods recognition system based on local binary pattern," in 2010 2nd International Conference on Computational Intelligence, Communication Systems and Networks, July 2010, pp. 308–313.
4. M. Jhuria, A. Kumar, and R. Borse, "Image processing for smart farming: Detection of disease and fruit grading," in 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013), Dec 2013, pp. 521–526.
5. J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, "Image processing based detection of fungal diseases in plants," Procedia Computer Science, vol. 46, pp. 1802 – 1808, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S187705091500201X
6. D. Gao, "Latest developments in seismic texture analysis for subsurtexture structure, facies, and reservoir characterization: A review," GEOPHYSICS, vol. 76, no. 2, pp. W1–W13, 2011. [Online]. Available: http://dx.doi.org/10.1190/1.3553479
7. A. Amin and M. Deriche, "A hybrid approach for salt dome detection in 2d and 3d seismic data," in 2015 IEEE International Conference on Image Processing (ICIP), Sept 2015, pp. 2537–2541.
8. R. D. S. Ferreira, A. B. Mattos, E. V. Brazil, R. Cerqueira, M. Ferraz, and S. Cersosimo, "Multi-scale evaluation of texture features for salt dome detection," in 2016 IEEE International Symposium on Multimedia(ISM), Dec 2016, pp. 632–635.
9. R. N. Sutton and E. L. Hall, "Texture measures for automatic classification of pulmonary disease," IEEE Trans. Comput., vol. 21, no. 7, pp. 667–676, Jul. 1972. [Online]. Available: http://dx.doi.org/10.1109/T-C.1972.223572
10. F. Spanhol, L. S. Oliveira, C. Petitjean, and L. Heutte, "Breast cancer histopathological image classification using convolutional neural network," in Proc. of the International Joint Conference on Neural Networks (IJCNN 2016), Vancouver, Canada, 2016.
11. R. Haralick, K. Shanmugam, and I. Dinstein, "Texture features for image classification," IEEE Transactions on Systems, Man, and Cybernetics, vol. 3, no. 6, 1973.
12. M. Haas, J. Rijsdam, B. Thomee, and M. S. Lew, "Relevance feedback: perceptual learning and retrieval in bio-computing, photos, and video,"in Proceedings of the 6th ACM SIGMM International Workshop on Multimedia Information Retrieval. ACM, 2004, pp. 151–156.
13. G. Zhao, M. Barnard, and M. Pietikainen, "Lip-reading with local
14. spatiotemporal descriptors," IEEE Transactions on Multimedia, vol. 11, no. 7, pp. 1254–1265, 2009.
15. X. Wang, C. Zhang, and Z. Zhang, "Boosted multi-task learning for texture verification with applications to web image and video search," in Computer Vision and Pattern Recognition, IEEE Conference on. IEEE, 2009, pp. 142–149.
16. J. Ren, X. Jiang, J. Yuan, and N. Magnenat-Thalmann, "Sound-event classification using robust texture features for robot hearing," IEEE Transactions on Multimedia, 2016.
17. T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971–987, 2002.
18. D. G. Lowe, "Distinctive image features from scale-invariant keypoints," International Journal of Computer Vision, vol. 60, no. 2, pp. 91–110, 2004.
19. N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Computer Vision and Pattern Recognition, IEEE Conference on, vol. 1. IEEE, 2005, pp. 886–893.
20. X. Tan and B. Triggs, "Enhanced local texture feature sets for texture
21. recognition under difficult lighting conditions," IEEE Transactions on Image Processing, vol. 19, no. 6, pp. 1635–1650, 2010.
22. X. Wu and J. Sun, "Joint-scale lbp: a new feature descriptor for texture classification," The Visual Computer, pp. 1–13, 2015.
23. L. Liu, P. Fieguth, Y. Guo, X. Wang, and M. Pietik¨ainen, "Local binary features for texture classification: Taxonomy and experimental study," Pattern Recognition, vol. 62, pp. 135–160, 2017.
24. M. Cimpoi, S. Maji, and A. Vedaldi, "Deep filter banks for texture recognition and segmentation," in Computer Vision and Pattern Recognition, IEEE Conference on, 2015, pp. 3828–3836
25. L. Sifre and S. Mallat, "Rotation, scaling and deformation invariant scattering for texture discrimination," in Computer Vision and Pattern Recognition, IEEE Conference on, 2013, pp. 1233–1240.
26. N. Zhang, R. Farrell, F. Iandola, and T. Darrell, "Deformable part
27. descriptors for fine-grained recognition and attribute prediction," in Computer Vision, IEEE International Conference on. IEEE, 2013, pp. 729–736.
28. T.-Y. Lin and S. Maji, "Visualizing and understanding deep texture
29. representations," in Computer Vision and Pattern Recognition, IEEE Conference on, 2016, pp. 2791–2799.
30. J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell, "Decaf: A deep convolutional activation feature for generic visual recognition," arXiv preprint arXiv:1310.1531, 2013.
31. M. S. Allili, N. Baaziz, and M. Mejri, "Texture modeling using contourlets and finite mixtures of generalized gaussian distributions and applications," IEEE Transactions on Multimedia, vol. 16, no. 3, pp. 772–784, 2014
32. X. Qi, R. Xiao, C.-G. Li, Y. Qiao, J. Guo, and X. Tang, "Pairwise
33. rotation invariant co-occurrence local binary pattern," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, no. 11, pp. 2199– 2213, 2014.
34. L. Liu, P. Fieguth, G. Kuang, and H. Zha, "Sorted random projections for robust texture classification," in Computer Vision, IEEE International Conference on. IEEE, 2011, pp. 391–398.
35. M. Pietikäinen and G. Zhao, "Two decades of local binary patterns: A survey," in Advances in Independent Component Analysis and Learning Machines. Amsterdam, The Netherlands: Elsevier, 2015.
36. S. Brahnam, L. C. Jain, L. Nanni, and A. Lumini, Eds., Local Binary Patterns: New Variants and Applications. London, U.K.: Springer, 2014.
37. A.Obulesu, V. Vijay Kumar, L. Sumalatha, "Content based Image Retrieval Using Multi Motif Co-Occurrence Matrix" , I.J. Image, Graphics and Signal Processing, 2018, 4, 59-72.
38. A.Obulesu, V. Vijay Kumar, L. Sumalatha , "Image Retrieval based Local Motif Patterns Code ", I.J. Image, Graphics and Signal Processing, 2018, 6, 68-78.
39. A.Obulesu,V. Vijay Kumar,L. Sumalatha, "Cross Diagonal Derivation Direction Matrix for Efficient Image Retrieval", Jour of Adv Research in Dynamical & Control Systems, Vol. 10, No. 4, pg.284-295, 2018

40. K. Srinivasa Reddy, V.Vijaya Kumar, B.Eshwara reddy, "Texture Recognition based on Texture Features using Local Ternary Patterns", I.J. Image, Graphics and Signal Processing (IJIGSP), Vol.10, 2015, pp: 37-46, ISSN: 2074-9082.
41. V. Vijaya Kumar, K. Srinivasa Reddy, V. Venkata Krishna , "Texture Recognition Using Prominent LBP Model", International Journal of Applied Engineering Research , Vol. 10, Iss. 2, 2015, pp. 4373-4384, ISSN: 0973-4562
42. P. Chandra SekharReddy,B. Eswara Reddy, V. Vijaya Kumar, "Fuzzy based image dimensionality reduction using shape primitives for efficient texture recognition", ICTACT- Journal On Image And Video Processing, Vol. 04, Iss. 02, 2013, pp. 695-701, ISSN: 0976-9102.
43. V.Vijaya Kumar, P.J.S. Kumar , Pullela S V V S R Kumar, "Age classification of texture images using third order neighbourhood Local Binary Pattern" , International Journal of Applied Engineering Research (IJAER), Vol. 10, Iss.15, 2015, pp: 35704-35713, ISSN 0973-4562.
44. P.J.S. Kumar , V. Venkata Krishna ,V.Vijaya Kumar, "A dynamic transform noise Resistant uniform Local Binary Pattern (DTNR-ULBP) for Age Classification", International Journal of Applied Engineering Research (IJAER), Vol. 11, Iss.1, 2016, pp: 55-60. ISSN 0973-4562.
45. B. Sujatha, V. VijayaKumar, M. Chandra Mohan, "Rotationally invariant texture classification using LRTM based on fuzzy approach", International Journal of Computer Applications (IJCA), Vol.33, Iss.4, 2011, pp.1-5, ISSN: 0975 – 8887
46. M. Srinivasa Rao, V.Vijaya Kumar, MHM Krishna Prasad, Texture Classification Based On Statistical Properties Of Local Units, Journal of Theoretical and Applied Information Technology, 30th November 2016. Vol.93. No.2
47. M. Srinivasa Rao, V.Vijaya Kumar, MHM Krishna Prasad ,Texture Classification based on First Order Local Ternary Direction Patterns, I.J. Image, Graphics and Signal Processing, 2017, 2, 46-54
48. V. Vijaya Kumar, SakaKezia, I. SantiPrabha, "A new texture segmentation approach for medical images", International Journal of Scientific & Engineering Research (IJSER), Vol. 4, Iss.1, 2013, pp.1-5, ISSN: 2229-5518.
49. C.M.Sheela Rani, V.VijayaKumar, "Block based image fusion technique using lifting wavelet transform and neural networks on medical images", IRACST - International journal of computer science and information technology & security (IJCSITS), Vol. 2, Iss.5, 2012, pp.980-986, ISSN: 2249-9555.
50. L. Liu, L. Zhao, Y. Long, G. Kuang, and P. Fieguth, "Extended local binary patterns for texture classification," Image Vis. Comput., vol. 30, no. 2, pp. 86–99, Feb. 2012.
51. Z. Guo, L. Zhang, and D. Zhang, "A completed modeling of local binary pattern operator for texture classification," IEEE Trans. Image Process., vol. 19, no. 6, pp. 1657–1663, Jun. 2010.
52. Yadong Mu, Shuicheng Yan, Yi Liu, Thomas Huang, Discriminative local binary patterns for human detection in personal album , 2008 IEEE Conference on Computer Vision and Pattern Recognition, 23-28 June 2008, DOI: 10.1109/CVPR.2008.4587800
53. S. Liao, Max W. K. Law, and Albert C. S. Chung, Dominant Local Binary Patterns for Texture Classification, IEEE Transactions On Image Processing, VOL. 18, NO. 5, MAY 2009
54. S Murala, R Maheshwari, R Balasubramanian, Local tetra patterns: a new feature descriptor for content-based image retrieval. IEEE Trans. Image Process. 21(5), 2874–2886 (2012)
55. V. Ojansivu, E. Rahtu, and J. Heikkilä, "Rotation invariant local phase quantization for blur insensitive texture analysis," in Proc. IEEE Int. Conf. Pattern Recognit. (ICPR), Dec. 2008, pp. 1–4.
56. D. K. Iakovidis, E. G. Keramidas, and D. Maroulis, "Fuzzy local binary patterns for ultrasound texture characterization," in Image Analysis and Recognition (Lecture Notes in Computer Science), A. Campilho and M. Kamel, Eds. Berlin, Germany: Springer, 2008, pp. 750–759.
57. J. Ren, X. Jiang, and J. Yuan, "Noise-resistant local binary pattern with an embedded error-correction mechanism," IEEE Trans. Image Process., vol. 22, no. 10, pp. 4049–4060, Oct. 2013.
58. J. Chen, V. Kellokumpu, G. Zhao, and M. Pietikänen, "RLBP: Robust local binary pattern," in Proc. Brit. Vis. Conf. Comput. Vis. (BMVC), 2013, pp. 1–10.
59. A. Fathi and A. R. Naghsh-Nilchi, "Noise tolerant local binary pattern operator for efficient texture analysis," Pattern Recognit. Lett., vol. 33, no. 9, pp. 1093–1100, Jul. 2012.
60. D.-C. He and L. Wang, "Texture unit, texture spectrum, and texture analysis," IEEE Trans. Geosci. Remote Sens., vol. 28, no. 4, pp. 509–512, Jul. 1990.
61. E. Cernadas, P.Carrión, P.G.Rodríguez, E.Muriel, T.Antequera, Analyzing magnetic resonance images of Iberian pork loin to predict its sensorial characteristics, Comput. Vis. Image Underst.98 (2005)345–361
62. G.H. Liu, J.Y. Yang, Image retrieval based on the texton co-occurrence matrix, Pattern Recogn. 41 (12) (2008) 3521–3527.
63. G.H. Liu, L. Zhang, Y.K. Hou, Z.Y. Li, J.Y. Yang, Image retrieval based on multi-texton histogram, Pattern Recogn. 43 (7) (2010) 2380–2389.
64. Y.Sowjanya Kumari , V. Vijaya Kumar, Ch. Satyanarayana, Texture Classification Using Complete Texton Matrix, I.J. Image, Graphics and Signal Processing, 2017, 10, 60-68.
65. Julesz B (1981): Textons, the elements of texture perception, and their interactions. Nature 290:91-97.
66. B.Eswara Reddy, P.Chandra Sekhar Reddy, V.Vijaya Kumar, 2012 "Texton based shape features on local binary pattern for age classification", International journal of image, graphics and signal processing (IJIGSP), Vol. 7, No.4, pp.54-60.
67. M Varma, A Zisserman, in Proceedings of the 7th European Conference on Computer Vision, Copenhagen, Denmark. Computer Vision, 3. Classifying images of materials: Achieving viewpoint and illumination independence (SpringerBerlin, 2002), pp. 255–271.
68. M. Varma and A. Zisserman, 2009, "A statistical approach to material classification using image patch exemplars," IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 11, pp. 2032–2047, 2009.
69. R. L. Kashyap and A. Khotanzad, "A model-based method for rotation invariant texture classification," IEEE Trans. Pattern Anal. Mach. Intell., vol. 8, no. 4, pp. 472–481, Jul. 1986.
70. Marko Heikkil¨a1, Matti Pietik¨ainen1, and Cordelia Schmid2, Description of Interest Regions with Center-Symmetric Local Binary Patterns, ICVGIP 2006, LNCS 4338, pp. 58–69, 2006.
71. P. Brodatz, Textures: A Photographic Album for Artists and Designers. New York, NY, USA: Dover, 1996.
72. [67] S. Lazebnik, C. Schmid, and J. Ponce, "A sparse texture representation using local affine regions," IEEE Trans. Pattern Anal. Mach. Intell.,vol. 27, no. 8, pp. 1265–1278, Aug. 2005
73. http://www.outex.oulu.fi/index.php?page=image_databaseS.
74. E. Hayman, B. Caputo, M. Fritz, and J. Eklundh, "On the significance of real-world conditions for material classification," in European Conference on Computer Vision (ECCV), 2004, pp. 253–266.
75. G. J. Burghouts and J.-M. Geusebroek, "Material-specific adaptation of color invariant features," Pattern Recognit. Lett., vol. 30, no. 3,pp. 306–313, Feb. 2009.
76. Jun-Da Txia, Chung-Lin Huang, Age estimation using AAM and local facialfeatures, in: International conference on Intelligent Information Hiding and Multimedia Signal Processing (2009) 885–888
77. A. Mallikarjuna Reddy, V. Venkata Krishna, L. Sumalatha, Efficient Face Recognition by Compact Symmetric Elliptical Texture Matrix (CSETM), Jour of Adv Research in Dynamical & Control Systems, Vol. 10, 4-Regular Issue, 2018.
78. T. Ojala, M. Pietikainen and T. Maenpaa, "Multi-resolution gray- scale and rotation invariant texture classification with local binary patterns," PAMI, 24 (7), 971–987, 2002.
79. K. Subba Reddy , V. Vijaya Kumar, A.P. Siva Kumar, Classification of Textures Using a New Descriptor Circular and Elliptical-LBP (CE-ELBP), International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 19 (2017) pp. 8844-8853