IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 20, Issue 5, Ver. I (Sep - Oct 2018), PP 27-37
www.iosrjournals.org

Texture Classification Based On Variants of Fundamental Units of LBP Using Complete Text on Indexes

Y.Sowjanya Kumari[1], V. Vijaya Kumar[2,] Ch. Satyanarayana[3]
[1]Research Scholar JNT University Kakinada, Associate Professor, Dept. CSE, SACET, Chirala, Andhrapradesh, India
[2]Professor, Dean- Dept. CSE &IT ,Anurag Group of Institutions (Autonomous), Hyderabad, India
[3]Professor, Dept. CSE, Jawaharlal Nehru Technological University, Kakinada, India
Corresponding author; Y.Sowjanya Kumari

Abstract: *This paper presents a novel approach for texture classification, generalizing the well-known local binary pattern (LBP) approach. The local binary pattern (LBP) descriptor is widely used in texture analysis because of its computational simplicity and robustness to illumination changes. However, LBP has limitations to fully capture discriminating information. The uniform patterns derived on LBP have resulted with a medium classification rate. To overcome this and to make best use of ULBP, this paper proposed extended uniform patterns. In this paper, the variants of fundamental units of texture derived from uniform Local binary patterns are integrated with textons and statistical features are derived on them for a precise texture classification. This paper initially transformed the raw texture image into extended uniform patterns (EUP), the complete texton indexes are derived on EUP and GLCM features are derived on EUP-CTM for efficient classification. This paper derived three types of EUP and on each of this CTM is derived. The EU-CTM is a framework, which consists in encoding both contrast information and texton patterns of a 2 x 2 grid in a précised manner. Then, spatial relationships among the neighboring pixels are measures using GLCM. This allows producing a more discriminative encoding than several state-of-the art methods based only on intensity information. The proposed framework is compared with various methods and experimental results indicate the superiority of the proposed schemes.*

Keywords: *Uniform patterns, texton, Contrast, classification, texton, contrast*

Date of Submission: 05-09-2018 Date of acceptance: 21-09-2018

I. Introduction

Texture conveys essential characteristic of appearance of all natural surfaces and it is ubiquitous in natural images. One of active and challenging problems of texture analysis is the texture classification and texture classification plays a crucial role in many image processing and pattern recognition domains. Basically texture classification is a twostep process, in the first step the desired features have to be extracted and in the next step texture classification is performed based on the distance function or machine learning classifiers. Out of these two steps the feature extraction is the most crucial one. The feature extraction is often carried out based on features derived from local or region based methods. Most researchers bin texture classification kept their efforts in deriving significant and precise features on local neighborhoods. The important task of any texture classification lies on how effectively one represents the texture and its attributes. Texture representation can be carried out by various different approaches like: structural, geometrical, statistical, model based, signal processing etc..

The earlier texture classification methods derived statistical features and the popular ones include the co-occurrence matrix [1] and filtering based techniques [2]. The statistical methods exhibited good results and however the classification results are declined if the test and training images have different orientations. The real world images are prone to have arbitrary rotations and this will affect the classification rate of the statistical methods. Derivation of precise rotation invariant texture feature task is a difficult task and involves lot of complexity further it may require intermediate step. The rotation invariance is a crucial issue and this paper also focuses on this aspect. In the literature many researchers worked on this and derived various methods for invariant local texture representation based: on geometrical and photometrical representation [3–8]; using circular autoregressive dense approach [9] , Gaussian Markov model [10], hidden Markov model [11] , multi-resolution [12] etc.. Textons are proposed in the literature [13.] to derive rotation and iscale invariant features in the literature. The texton co-occurrence matrix(TCM) [14] , and multi texton matrix (MTH) [15] are proposed in the literature for CBIR and achieved a a precise retrieval rate. The TCM and MTH have derived rotational;

invariant patterns and however they have not represented complete texton patterns. In our earlier work we have derived complete textonmatix (CTM) [16] for texture classification.

Recently rotation and scale invariant texture images are classified more precisely using texton dictionary [4]. In the literature a texton based method that extracts features from local image intensity directly is also proposed [6]. In 1996 a local operator known as Local Binary Pattern (LBP) [17] was proposed and it has made a remarkable contribution in all fields of image processing. Various add-ons to LBP are proposed in the literature due to its immense success of LBP in pattern recognition and computer vision problems. The add-ons to LBP are DLBP [18], LBP variance (LBPV) [19] and completed LBP (CLBP) [20] to enhance the descriptive power and improve the texture classification. The Local derivative patterns (LDP) [21] have shown better performance than LBP since it can resist noise. A histogram feature vector for biomedical image retrieval based on new variant to LBP is proposed in the literature [22]. The directional information with LDP is also reported in the literature for CBIR[23]. The textons played a major role in evaluating the local features. This paper attempts to find how effective the textons on various variants of fundamental units of LBP and further this paper integrated the textons derived on variants of uniform patterns with statistical features for classification of textures.

This paper is organized as follows. The section 2 describes the proposed methods with a brief introduction to LBP and its disadvantages. The section 3 gives the experimental set up, brief discussion about the data bases and experimental findings. The section four concludes the paper.

II. Local Binary Patterns

In 1996 Ojala et al [17] contributed a great deal in deriving one of the most efficient, precise local operator, which is simple and powerful operator, that holds and extracts local attributes more significantly an precisely and this operator is named as the “Local Binary Pattern (LBP)”. And LBP played a dominant role in many image processing applications like CBIR [24,25,26], recognition and analysis of textures [27,28,29], age and other facial image applications[30, 31, 32, 33], medical imaging [34, 35] etc.. The LBP basically transforms the raw grey level image into a binary pattern image, where the pattern is represented with {1, 0}. This transformation is accomplished by LBP, by relating the central pixel value with each of the neighboring pixel. That is the grey level value of central pixel is treated as threshold value in LBP. Based on this relation a binary zero or one is assigned to the neighboring pixel. The neighboring pixels are multiplied by corresponding binary weights and summation of this will derive the LBP code as given in equation 1. The binary weights can be assigned in many possible ways as shown in Fig.1.

$$p_i = f(x) = \begin{cases} 0, & \text{if } (I(x_i, y_i) < I(x_i, y_i) \\ 1, & \text{otherwise} \end{cases} \qquad (1)$$

$$LBP_{p,r} = \sum_{i=0}^{i=7} p_i * 2^i \qquad (2)$$

The LBPP,R operator produces 2P different output values. P is the obtained binary code for the neighboring pixel Pi with co-ordinate positions (xi, yi) and I(xo, yo) represents the grey level value of the central pixel. In 1996 the ojala et al.[17] derived the LBP code on a 3*3 neighborhood and basically the LBP is denoted as LBP P,R where P symbolizes the number of neighborhood pixels over the radius R . This transformation process of raw image in to LBP coded image is given in 1 on a 3 x 3 neighborhood. Fig.1(a) shows the grey level values of a 3×3 neighborhood of an image. And the Fig. 1 (b) shows its corresponding binary labeling based on Equation 1.As each element of LBP has one of the two possible values, the combination of all the eight elements results in 28 = 256 possible local binary patterns ranging from 0 to 255. There is no unique way to label and order the 255 LBP on a 3×3 neighborhood.

The $LBP_{P,R}$ operator produces 2P different output values. P is the obtained binary code for the neighboring pixel Pi with co-ordinate positions (x_i, y_i) and I(x_o, y_o) represents the grey level value of the central pixel. In 1996 the Ojala et al.[17] derived the LBP code on a 3*3 neighborhood and basically the LBP is denoted as LBP P,R where P symbolizes the number of neighborhood pixels over the radius R . This transformation process of raw image in to LBP coded image is given in 1 on a 3 x 3 neighborhood. Fig.1(a) shows the grey level values of a 3×3 neighborhood of an image. And the Fig. 1 (b) shows its corresponding binary labeling based on Equation 1.As each element of LBP has one of the two possible values, the combination of all the eight elements results in 28 = 256 possible local binary patterns ranging from 0 to 255. There is no unique way to label and order the 255 LBP on a 3×3 neighborhood.

63	28	45
88	**40**	35
67	40	21

(a)

1	0	1
1		0
1	1	0

(b)

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(c)

1	0	2
128		0
64	32	0

(d)

Fig. 1 (a) Sample Grey level Neighborhood (b) Conversion of Fig. 1 (a) into Binary Neighborhood (c) Representation of Fig. 1 (a) Binary Weights (d) Represented Values with Binary Weights.

The sum of the resulting values of Fig 1 gives the LBP measure which is 227 in this case the central pixel 40 is replaced by the obtained LBP code value 227. A new LBP coded image is constructed by using the same process with a step length of one. The binary weights of Fig.1(c) can be given in many different ways; the Fig. 2 shows few of them and based on the ordering mechanism of these binary weights the LBP code changes.

20	21	22
27		23
26	25	24

(a)

27	20	21
26		22
25	24	23

(b)

26	27	20
25		21
24	23	22

(c)

25	26	27
24		20
23	22	21

(d)

24	25	26
23		27
22	21	20

(e)

23	24	25
22		26
21	20	27

(f)

22	23	24
21		25
20	27	26

(g)

21	22	23
20		24
27	26	25

(h)

Fig. 2.Eight different ways of calculating LBP on a 3×3 neighborhood.

Based on the above binary weights-ordering way the LBP code is evaluated for the sample neighborhood of 3 x 3 of Fig 1: LBP code is 227, 242, 121, 188, 94, 47, 151, and 203 respectively. The interesting point is that LBP code for P=8 and R=1 ranges from 0 to 255 whichever may be the ordering.

After observing the binary pattern trends on various types of image databases like different textures, human faces, medical and other images an interesting fact was noted down by ojala et al. [17] and this has made the discovery of fundamental or basic LBPs. The fundamental patterns are formed based on the transitions that occur from zeros to ones or vice versa on the neighboring pixel patterns. The fundamental patterns of LBP that have a maximum of two transitions, in a circular manner, from zero to one or one to zero are grouped as uniform LBP (ULBP) and the remaining patterns that exhibits more than two such circular transitions are named as noisy or non-uniform LBP (NULBP).For example the 8-bit binary pattern 11000000 is treated as ULBP since it is having two transitions in a circular manner, one is from 1 to 0 and the other is from 0 to1.On the other hand the 8-bit binary pattern 00101001 exhibiting a total of six transition, from 0 to 1 or 1 to 0, in a circular manner therefore it is treated as noisy or NULBP. The interesting observations made by ojala et al is most of the real time textures exhibits more than 85 % of ULBPS and thus they made a point that one can utilize only ULBPS for texture classification and for other domain applications. Out of 256 patterns of LBP 58 are ULBPS and the remaining 192 are NULBPS. Since NULBPs are noisy patterns and they occur very rarely or less frequently on an image texture, they are treated under one label called miscellaneous. Thus if an image is transformed in to a ULBP image then the transformed image will have code value or pixel values ranging from 0 to 58 (totally 59 codes; 58 from ULBP and one is for all NULBP codes). The advantage of this transformed ULBP image is it reduces the complexity by reducing the code-range from 0 to 58 instead of 0 to 255. This is because the consideration of circular transitions instead of different LBP codes for the same pattern as given in Fig .2, however on the other hand the ULBP approach treats the 192 out of 256 LBP as noisy and this looks odd because majority of the LBPs approximately the 75% of the local binary patterns are treated under one label and this results a problem of not describing precisely the stochastic attributes and characteristics of texture. The texture primitive information will be lost by this.

Several other attempts were also made in the literature to use non-uniform patterns to overcome limitation of the standard LBP [36, 37, 38, 39]. Some of the methods extracted rotation invariant non-uniform patterns [37, 38, 39]. The hierarchical multi-scale LBP is also explored in the literature [39]. This approach [39] enhanced the performance by obtaining information from the non-uniform bins. A further improvement of this classical LBP operator [36, 40] is to make efficient use of non-uniform patterns in an appropriate way. To fulfill this, all non-uniform patterns are classified into different subsets. In the literature Significant Non Uniform Local Binary Pattern (SNULBP) are derived after careful examination of NULBP'S [41]. The SNULBP holds a subgroup of NULBPS which are significant and derives more meaningful information of the image object. A set of NULBP's that holds the transitions that occur only from two or more consecutive zeros to two or more consecutive ones are named as SNULBP. And such transitions are stable because they are measured from two or more consecutive zeros or ones instead of single zero or one. The transitions that occur from a single zero to one i.e. a zero in between ones may be the result of a noise. For example 11101110 this pattern consists of a single zero in between three ones and such a dark or zero bit pattern in between intensity spots may not be visible. This kind of transition identifies a subset of 32 NULBPs as SNULBP out of 198 NULBPs. This paper combined the ULBPS with SNULBPs and derived "extended uniform patterns (EUP)". The number of patterns in EUP will be 90, out of which 58 are ULBPs, 32 are SNULBPs and all the remaining NULBPs are given a single code.

This paper also derived a new subset from NULBP and it is named as complementary to SNULBP (CSNULBP). The CSNULBP holds transitions of binary patterns that occur from two or more consecutive ones to two or more consecutive zeros and vice versa is not true. There CSNULBP derives exactly 32 patterns from NULBP. This paper combined the ULBPS with CSNULBPs and derived "comprehensive Uniform Patterns (CUP)". The number of patterns in CUP will be 90, out of which 58 are ULBPs, 32 are CSNULBPs and all the remaining NULBPs are given a single code. This paper derived strongly extended Uniform patterns (SEUP) by combining ULBPs, SNULBPs and CSNULBPS and this leads to a total of 122 patterns.

Recently we have derived complete texton approach for texture classification [13]. The complete texton matrix (CTM) has shown good results than earlier approaches like TCM [14] and MTH [15]. We have derived CTM on raw image.

The CTM approach defined all possible types of texton templates, i.e. 11 texton templates, on 2 x 2 grid and out of these, the texton types (T1, T2, T3, T4, T5) are exactly similar to the TCM and the texton types (T6, T7, T8 and T9) are exactly similar to that of MTH model. The texton types T10 and T11 are shown in Fig.3. The texton type T1 is formed if all the four pixel values of the 2x2 grid are same. The next four special type of textons T2,T3,T4,T5 are formed if three pixel values are identical in a 2 x 2 grid and the remaining six special types of textons T6,T7,T8,T9,T10 and T11 are defined when two pixels have identical values.

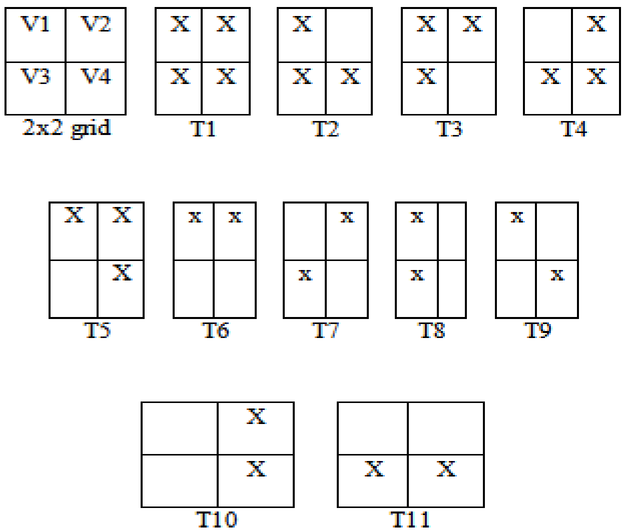


Fig.3: The defined texton types {T1,T11 }of CTM on a 2x2 grid..

The disadvantage of this CTM is it is difficult to integrate with statistical features such as co-occurrence matrix. To address this, this paper derives CTM on LBP, ULBP, EUP, CUP and SEUP coded images and constructed co-occurrence matrix. This process derived "complete texton co-occurrence matrix" on ULBP, EUP, CUP and SEUP and they are named as U-CTCM, EU-CTCM, CU-CTCM and SEU-CTCM respectively.

This paper derived GLCM features with three distance factors d=2, 3, 4. The GLCM is a second order statistical model. The spatial relationships between grey level tones are well established by GLCM and this is an important and very useful relationship for characterizing texture information more efficiently. The GLCM computation is given below: Let the image grey level ranges from 0 to g-1. Then, GLCM is computed from the transformed coded image by scanning the intensity of each pixel and its neighbours, defined by displacement d and angle ø.
The displacement, d could take a value of 1, 2, 3…n whereas an angle, ø is limited 0°, 45°, 90° and 135°. The following Fig.4 illustrates the formation of GLCM with different angles (0°, 45°, 90° and 135°) with d value as 1. The Fig.4 illustrates the basic mechanism of deriving GLCM with four different angles for d=1.

4	2	1
2	3	1
2	3	3

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

45o	1	2	3	4
1	0	0	0	0
2	0	1	1	0
3	1	0	1	0
4	0	0	0	0

90o	1	2	3	4
1	1	0	0	0
2	0	1	0	1
3	1	1	1	0
4	0	0	0	0

135o	1	2	3	4
1	0	1	0	0
2	0	0	0	0
3	0	1	1	1
4	0	0	0	0

Fig.4: An example of GLCM formation. (a): The sample window. The derived GLCM matrix with 0o, 45o, 90o and 135o with d=1.

The GLCM features i.e., Homogeneity, Energy, Contrast and Correlation (Eqns. 3 to 6) are derived under four rotation angles i.e., 00, 450, 900 and1350, for each d value. The average feature value on 00, 450, 900and1350 for each 'd' value is computed and considered for the classification purpose on machine learning classifiers like Liblinear, LibSVM and Naivebayes.

Homogeniety or Angular Second Moment (ASM):

$$ASM= \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}^2 \qquad (3)$$

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.

Energy :

$$\text{Energy} = \sum_{i,j} P(i,j)^2 \qquad (4)$$

Contrast :

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\right\}, |i-j| = n \qquad (5)$$

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

Correlation :

$$\text{Correlation} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{iXj\}XP(i,j)-\{\mu_x X\mu_y\}}{\sigma_x X\sigma_y} \qquad (6)$$

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

III. Experimental Results and Discussions

The present descriptor is evaluated against five other published state-of-art representative of LBP schemes such as uniform LBP(ULBP)[42], the LTP [43] descriptors, CLBP-SMC [44], TCM [14] and MTH[15], CTM[16]. The effectiveness of the proposed and other methods are investigated based on a series of experiments on three representative texture databases: Brodtaz[45], Outex [46] and UIUC[47]. The Brodtaz database consists of gray level images and the other databases contain color images (mostly in RGB). The images of these databases are captured under varying lighting, illumination and other conditions with varying sizes. Each database consists of various classes and each class consists of various images.

We selected 30 different texture images with a 512x512 pixels size from the Brodtaz database. The sample images are show in Fig.5. We divided each image into 16 non-overlapped texture images of size 128x128 and this results a dataset of 480 images (30x16). The present study used 60 images for training purpose (two images from each class). The remaining 420 texture images (14 texture image per class) are used for testing purpose.

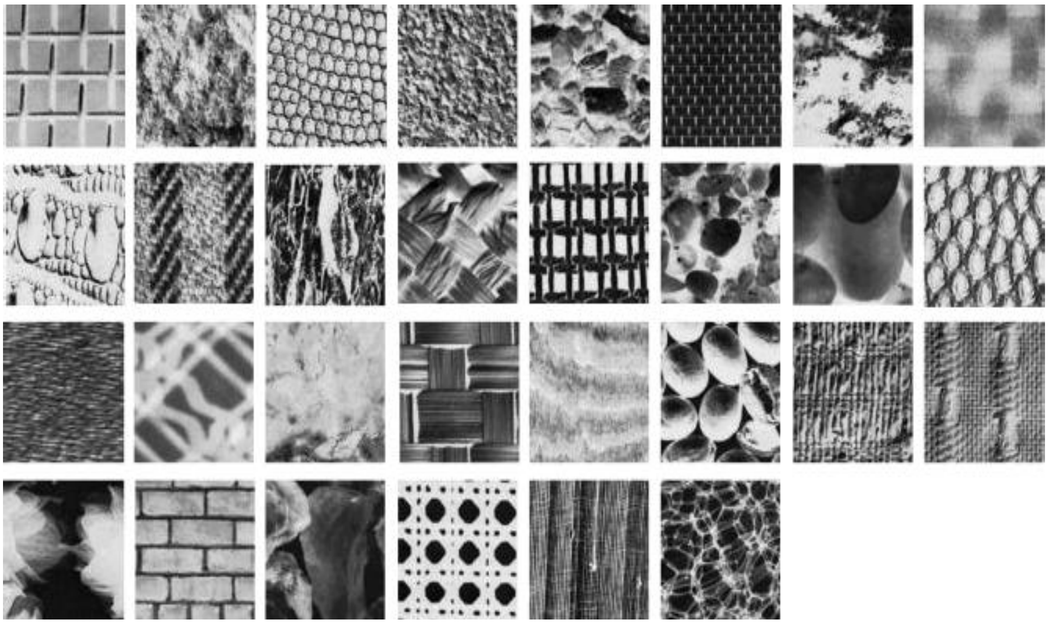


Fig.5: Samples of 30 classes randomly selected from the Brodatz database.

The Outex database contains two test suits: Outex-TC-10(TC12-000) and Outex-TC-12(TC12-001). There are 24 classes of texture images in both TC10 and TC12. These images are captured under three illumination conditions namely 1. "inca' 2. t184 3. Horizon with nine rotation angles i.e. 0o,5o,10o,15o,30o,45o,60o,75o,90o. The resolution of each image in TC10 and TC12 are 128x128 under each illumination condition and in each rotation angle, there are 20 images. The present paper considered the Outex images under illumination condition "inca" with 0o of rotation, for training purpose. The images with non-zero rotation angles with three illumination conditions are used for testing purpose. The sample images from Outex database are shown in Fig.6.

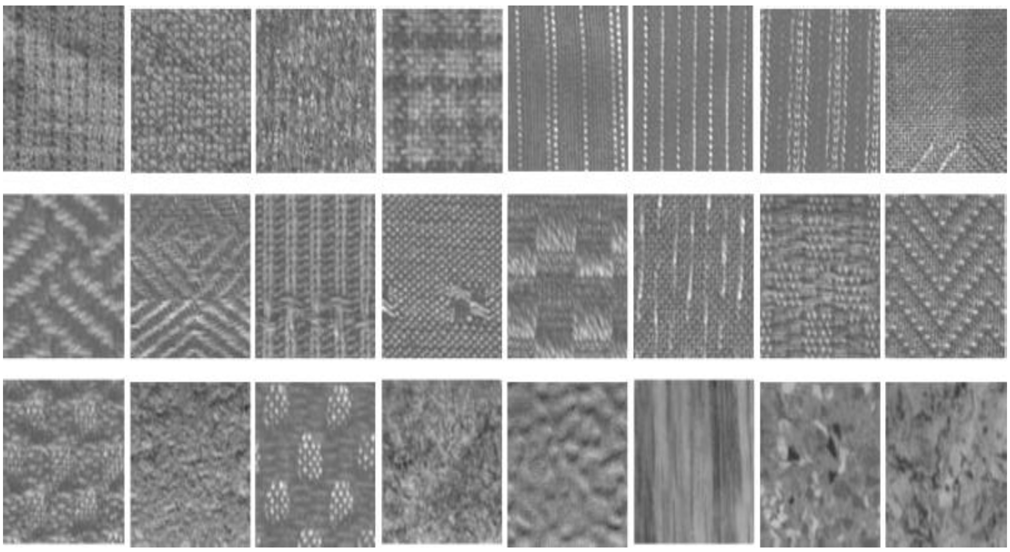


Fig. 6: The sample images of 24 classes from Outex database.

The sample images of UIUC database are shown in Fig.7. This database includes 25 classes and each class consists of 40 images resulting a total of 1000(25x40) texture images. The size of each image is 640x480. The present paper considered one texture image from each class and partitioned it into 15 non-overlapped images of size 128x128. This results a total of 375 (25x15) images and out of this 50 images (2 images from each class) are used for training purpose and reaming 325 images (25x13) are used for test purpose.

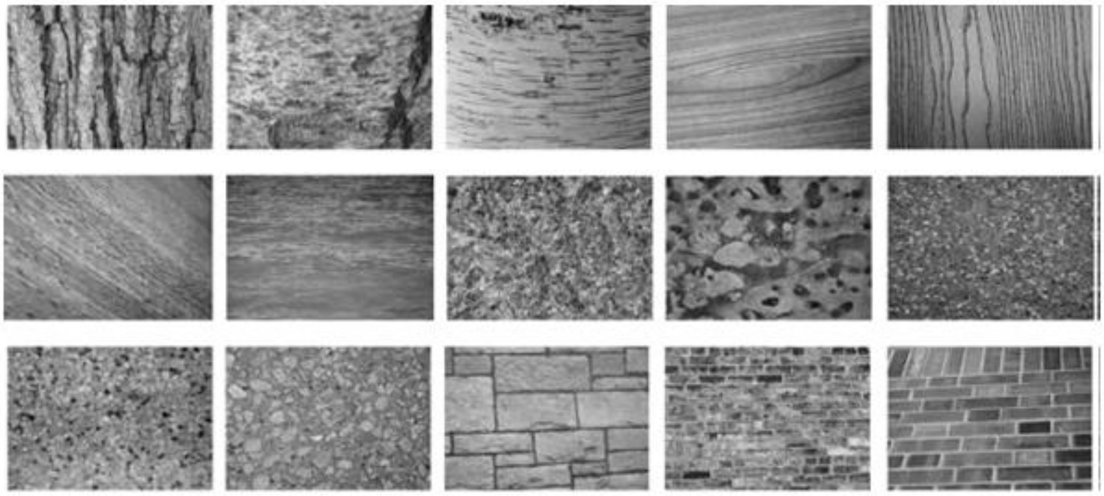


Fig. 7: Samples of 25 classes from the UIUC database.

This paper derived three methods using fundamental units of LBP. In method one this paper transformed the grey level image in to ULBP coded image and derived CTCM and it is named as U-CTCM. The other methods also transform the raw textures in to EUP, CUP and SEUP coded images and derives CTCM on these texture images and these methods are named as EU-CTCM, CU-CTCM and SEU-CTCM.

The average classification rates of each texture database on the proposed EU-CTCM, CU-CTCM and SEU-CTCM descriptors using Liblinear, LibSVM and Naivebaye's are computed with different d values. All the classification methods exhibited a high classification rate for a d value of 2, and the Table 1 shows the classification results of the proposed methods on various databases. The Liblinear exhibited a high classification rate which is almost 2 % higher than SVM and 3% to 4% higher than Naivebayes on all databases. In the rest of the paper, the classification rates of Liblinear are mentioned on the proposed EU-CTCM, CU-CTCM and SEU-CTCM descriptors and U-CTCM.

Table 1: average classification rate of EU-CTCM, CU-CTCM and SEU-CTCM on different databases using different classifiers for the d value=2.

Proposed Methods	Databases	Liblinear	LibSVM	Naivebayes
EU-CCTM	Brodtaz	92.45	90.01	87.62
	Outex _TC10	96.98	92.9	91.56
	Outex_TC12	92.56	89.12	88.57
	UIUC	91.78	88.56	86.92
	Average	93.44	90.15	88.67
CU-CTCM	Brodtaz	92.24	91.42	91.21
	Outex _TC10	96.45	92.56	91.07
	Outex_TC12	92.97	90.45	89.65
	UIUC	92.00	88.56	87.56
	Avg	93.42	90.75	89.87
SE-CTCM	Brodtaz	92.12	89.24	84.45
	Outex _TC10	94.24	90.47	86.45
	Outex_TC12	90.23	87.15	85.23
	UIUC	87.56	86.24	82.15
	Avg	91.04	88.28	84.57
U-CCTM	Brodtaz	75.22	73.14	72.12
	Outex _TC10	76.24	72.12	68.34
	Outex_TC12	71.00	69.98	64.56
	UIUC	71.68	65.34	61.34
	Avg	73.54	70.15	66.59

Table 2: The classification accuracy on the considered databases using different descriptors.

Methods	Classification rate on databases				
	Brodtaz	TC-10	TC-12		UIUC
			"t"	"h"	
ULBP[62]-	40.28	84.87	65.19	64.03	54.65
LTP[6]	57.50	94.14	75.88	73.96	67.16
CLBP_SMC[63]	85.23	96.56	90.30	92.29	87.64
TCM [53]	86.57	94.22	90.68	92.65	85.70
MTH[15]	87.25	93.56	89.8	91.87	87.83
CTM[18]	91.56	96.1	90.10	91.42	91.18
U-CCTM	75.22	76.24	71.00	77.56	74.68
EU-CCTM	92.45	96.98	92.56	91.89	91.78
CU-CTCM	92.24	96.45	92.97	91.68	92.00
SE-CTCM	92.12	94.24	90.23	89.25	87.56

The U-CTCM, EU-CTCM, CU-CTCM and SEU-CTCM descriptors outperform all the other techniques and shows large improvement than ULBP and LTP descriptors. However the CLBP-SMC, TCM, MTH descriptors have shown improved classification rate on Brodtaz textures. The performances of ULBP and LTP descriptors have shown improvement on this database when compared to Brodtaz texture database. The classification accuracy for TC_10 is significantly higher than that for TC12, because the training and testing images are under the same illumination. The classification rate is very poor for ULBP and LTP descriptors and moderate for CLBP-SMC [43], TCM [14] and MTH [15] this may be due to lot of orientation and scale changes in UIUC database however the proposed descriptors achieved high classification rate, this clearly indicates the proposed methods are more robust to orientation and scale changes. This is because the proposed methods integrated the merits of TCM and MTH and derived additional textons to capture more spatial information on fundamental units of texture to increase the classification accuracy. The ULBP and LTP showed the low classification results when compared to other descriptors because it is unable to capture magnitude information. The coarse quantization of the images limits the performance of non-texton based methods.

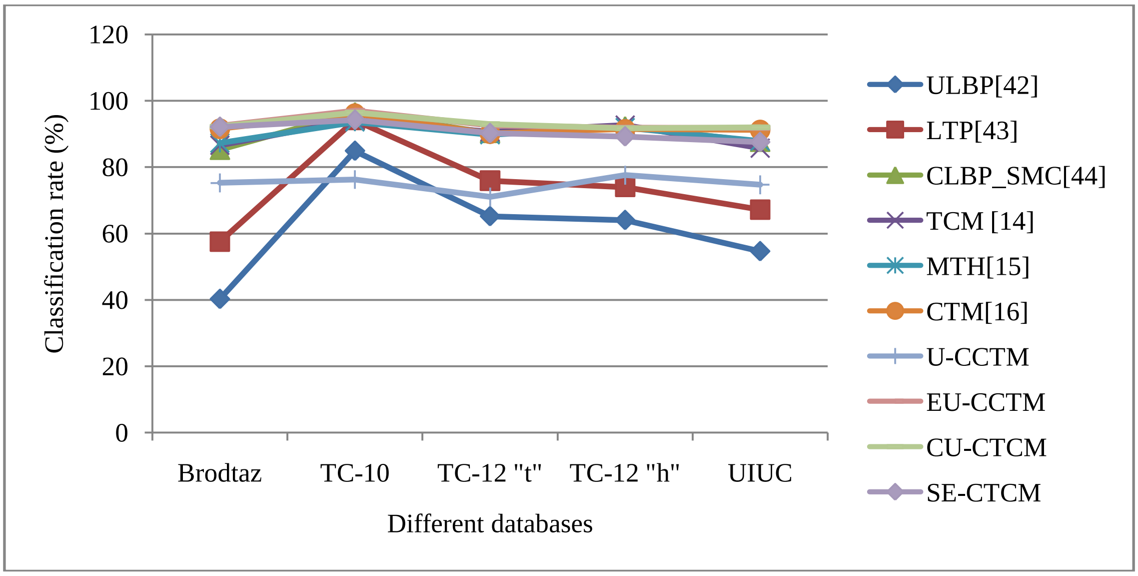


Fig.8: Performance comparison of proposed method and existing methods on considered databases.

The classification rate on all four databases using the proposed and other descriptors is plotted in Fig.8 and following are noted.

1. The performance of ULBP and LTP are too low on Brodtaz textures when compared to other three texture databases. Out of these two, ULBP has shown low performance.
2. The classification rate of all descriptors is little low on Brodtaz textures around 85% to 90%, however the proposed methods have achieved a classification rate around 92%.
3. The performance of all descriptors is high on Outex database when compared to Brodtaz and UIUC databases.
4. The performance of all the proposed descriptors is very high on all databases followed by other descriptors MTH, CLBP-SMC, TCM, LTP and ULBP.

III. Conclusion

We proposed four new descriptors namely the U-CTCM, EU-CTCM, CU-CTCM and SEU-CTCM descriptors, to describe image features that represent the fundamental local features, spatial correlation of texture orientation and texture color based on textons for efficient texture classification. The present paper derived The U-CTCM, EU-CTCM, CU-CTCM and SEU-CTCM descriptors to test the efficacy of the proposed compact CTM. The proposed fundamental local uniform complete texton co-occurrence approaches are different from CTM, TCM, and MTH approaches. In CTM the grey level range of image is quantized or partitioned in to ‘n’ groups, without any significance or without any predefined criteria. Further the CTM is not integrated with any statistical features. The TCM and MTH could not define all possible textons patterns, thus they failed to define all possible local attributes and features. The TCM is integrated with statistical features, however it computed with a step length of one thus it derives more complexity. In MTH the statistical features are not computed and only histograms were considered. The proposed methods initially quantized the image grey levels based on significant attributes of textures, i.e. the image is indexed with fundamental units and a subset from NULBPS. The dimensions of the proposed EU-CTCM, CU-CTCM, SEU-CTCM and U-CTCM descriptors are 90 x 90, 90 x 90, 112 x 112 and 59 x 59 respectively. The proposed descriptors achieved an average of 2% higher classification rate when compared CTM. The proposed descriptors considered all texton types on a 2 x 2 grid and they are very easy to implement and well suited for large-scale image dataset retrieval. The experiments were conducted on Brodtaz, Outex and UIUC natural images and the experimental results validated that our methods has strong discrimination power of color, texture and shape features, and outperforms other LBP based methods. The proposed EU-CTCM, CU-CTCM, SEU-CTCM and U-CTCM descriptors can express the spatial correlation of textons and has the discrimination power of texture, color, and shape features. Color and texture have close relationship via fundamental micro-structures in natural images.

References

[1]. R.M. Haralick , K. Shanmugam , et al. ,Textural features for image classification, IEEE Trans. Syst. Man Cybern. (6) (1973) 610–621.

[2]. T. Randen , J.H. Husoy , Filtering for texture classification: a comparative study, IEEE Trans. Pattern Anal. Mach. Intell. 21 (4) (1999) 291–310.

[3]. T. Ojala , M. Pietikainen , T. Maenpaa , Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, IEEE Trans. Pattern Anal. Mach. Intell. 24 (7) (2002) 971–987 .

[4]. M. Varma , A. Zisserman , A statistical approach to texture classification from single images, Int. J. Comput. Vis. 62 (1–2) (2005) 61–81 .

[5]. J. Zhang , M. Marszałek , S. Lazebnik , C. Schmid , Local features and kernels for classification of texture and object categories: a comprehensive study, Int. J. Comput. Vis. 73 (2) (2007) 213–238 .

[6]. M. Varma , A. Zisserman , A statistical approach to material classification using image patch exemplars, IEEE Trans. Pattern Anal. Mach. Intell. 31 (11) (2009) 2032–2047 .

[7]. M. Crosier , L.D. Griffin , Using basic image features for texture classification, Int. J. Comput. Vis. 88 (3) (2010) 447–460 .

[8]. L. Liu , P. Fieguth , Texture classification from random features, IEEE Trans. Pat- tern Anal. Mach. Intell. 34 (3) (2012) 574–586 .

[9]. R.L. Kashyap , A. Khotanzad , A model-based method for rotation invariant tex- ture classification, IEEE Trans. Pattern Anal. Mach. Intell. (4) (1986) 472–481 .

[10]. H. Deng , D.A. Clausi , Gaussian MRF rotation-invariant features for image clas- sification, IEEE Trans Pattern Anal Mach Intell 26 (7) (2004) 951–955 .

[11]. J.-L. Chen , A. Kundu ,Rotation and gray scale transform invariant texture iden- tification using wavelet decomposition and hidden Markov model, IEEE Trans. Pattern Anal. Mach. Intell. 16 (2) (1994) 208–214 .

[12]. J. Mao , A.K. Jain , Texture classification and segmentation using multiresolution simultaneous autoregressive models, Pattern Recognit. 25 (2) (1992) 173–188

[13]. JuleszB ,Textons, the elements of texture perception, and their interactions. Nature 290, 1981, 91-97

[14]. Guang-Hai Liu, Jing-Yu Yang, Image retrieval based on the texton co-occurrence matrix, Pattern Recognition , 41 (2008) 3521 – 3527

[15]. Guang-Hai Liu a, LeiZhang b, Ying-KunHou d, Zuo-YongLi c, Jing-YuYang, Image retrieval based on multi-texton histogram, Pattern Recognition, 43(2010),2380–2389

[16]. Y.SowjanyaKumari, V. Vijaya Kumar, Ch. Satyanarayana, Texture Classification Using Complete Texton Matrix, I.J. Image, Graphics and Signal Processing, 2017, 10, 60-68

[17]. Ojala, Timo, MattiPietikainen, and David Harwood. "A comparative study of texture measures with classification based on featured distributions." Pattern recognition 29, no. 1, (1996): 51-59.

[18]. S. Liao , M.W. Law , A.C. Chung , Dominant local binary patterns for texture clas- sification, IEEE Trans. Image Process. 18 (5) (2009) 1107–1118 .

[19]. Z. Guo , L. Zhang , D. Zhang , Rotation invariant texture classification using lbp variance (lbpv) with global matching, Pattern Recognit. 43 (3) (2010) 706–719 .

[20]. Z. Guo , L. Zhang , D. Zhang , A completed modeling of local binary pattern operator for texture classification, IEEE Trans. Image Process. 19 (6) (2010) 1657–1663 .

[21]. B. Zhang , Y. Gao , S. Zhao , J. Liu , Local derivative pattern versus local binary pattern: face recognition with high-order local pattern descriptor, IEEE Trans. Image Process. 19 (2) (2010) 533–544 .

[22]. S.R. Dubey , S.K. Singh , R.K. Singh , Local wavelet pattern: a new feature descrip- tor for image retrieval in medical ct databases, IEEE Trans. Image Process. 24 (12) (2015) 5892–5903

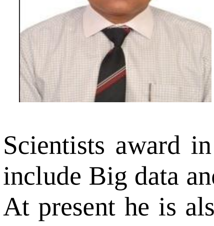
[23]. Z. Guo , Q. Li , J. You , D. Zhang , W. Liu , Local directional derivative pattern for rotation invariant texture classification, Neural Comput. Appl. 21 (8) (2012) 1893–1904

[24]. 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.
[25]. 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.
[26]. V.Vijaya Kumar, A. SrinivasaRao, YK Sundara Krishna, "Dual Transition Uniform LBP Matrix for Efficient Image Retrieval", I.J. Image, Graphics and Signal Processing (IJIGSP), Vol. 8, 2015, pp: 50-57.
[27]. V. Vijaya Kumar, K. Srinivasa Reddy, V. Venkata Krishna , "Face Recognition Using Prominent LBP Model", International Journal of Applied Engineering Research , Vol. 10, Iss. 2, 2015, pp. 4373-4384, ISSN: 0973-4562
[28]. B. Sujatha, V.Vijaya Kumar, P. Harini, "A new logical compact LBP co-occurrence matrix for texture analysis", International Journal of Scientific & Engineering Research (IJSER) , Vol.3, Iss.2, 2012, pp.1-5, ISSN 2229-5518.
[29]. K. Srinivasa Reddy, V.Vijaya Kumar, B.Eshwarareddy, "Face 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.
[30]. Ahonen, Timo, AbdenourHadid, and MattiPietikainen. "Face description with local binary patterns: Application to face recognition." Pattern Analysis and Machine Intelligence, IEEE Transactions on 28, no. 12, (2006): 2037-2041
[31]. Rodriguez, Yann, and Sebastien Marcel. "Face authentication using adapted local binary pattern histograms." In Computer Vision–ECCV 2006, pp. 321-332. Springer Berlin Heidelberg, 2006.
[32]. Ruiz-del-Solar, Javier, Rodrigo Verschae, and Mauricio Correa. "Recognition of faces in unconstrained environments: a comparative study." EURASIP Journal on Advances in Signal Processing 2009 (2009): pp. 1–20
[33]. Wolf, Lior, Tal Hassner, and YanivTaigman. "Descriptor based methods in the wild." In Workshop on Faces in'Real-Life'Images: Detection, Alignment, and Recognition. 2008.
[34]. 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.
[35]. 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.
[36]. A. Lucieer, P. Stein, Fisher, "Multivariate texture-based segmentation of remotely sensed imagery for extraction of objects and their uncertainty", International Journal of Remote Sensing, vol.26(14), pp.2917–2936, 2005.
[37]. M.Heikkila, M.Pietikainen, C. Schmid, "Description of interest regions with local binary patterns", Pattern Recognition, vol.42, pp.425–436, 2009.
[38]. S.Liao, A.C.S. Chung , "Face recognition by using Elongated local binary patterns with average maximum distance gradient magnitude", Computer Vision- ACCV, pp.672–679, 2007.
[39]. Z. Guo, L. Zhang, D. Zhang, X.Q. Mou, "Hierarchical multiscalelbp for face and palmprint recognition", ICIP, 2010.
[40]. Loris Nanni, Sheryl Brahnam, Alessandra Lumini, "A simple method for improving local binary patterns by considering non-uniform patterns", Pattern Recognition, pp.1-9, 2012
[41]. K. Srinivasa Reddy, V. Venkata Krishna, B. Eswara Reddy, "Facial Recognition using the combination of significant non uniform local binary patterns", ICGST-Graphics Vision and Image Processing (GVIP), Volume 15, Issue 1, pp.1-8, June, 2015.
[42]. R. L. Kashyap and A. Khotanzad, 1986, "A model-based method for rotation invariant texture classification," IEEE Trans. Pattern Anal. Mach. Intell., vol. 8, no. 4, pp. 472–481
[43]. Tan, X., Triggs, B., 2010. Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE Trans. Image Process. 19, 1635–1650
[44]. Z. Guo, L. Zhang, and D. Zhang, "A completed modeling of local binary pattern operator for texture classification," IEEE Trans. Image Process., vol. 9, no. 16, pp. 1657–1663, Jun. 2010
[45]. http://www.ux.uis.no/tranden/brodatz.htmlS.
[46]. http://www.outex.oulu.fi/index.php?page=image_databaseS.
[47]. Svetlana Lazebnik, CordeliaSchmid and Jean Ponce. A Sparse Texture Representation Using Local Affine region. IEEE Transactions on Pattern Analysis and Machine Intellignece, Vol.27, No.8, pp:1265-1278, August, 2005

Author's Profile

Mrs. Y.SowjanyaKumari working as Associate Professor in SACET (Affiliated to JNT University, Kakinada), Chirala, India and she has 13 years of teaching experience. Presently she is Pursuing Ph.D. in JNT University, Kakinada under the guidance of Dr. V.Vijaya Kumar. She has received M.Tech. in Computer Science & Engineering from JNTU, Kakinada A.P and B.Tech in Computer Science & Engineering from N.B.K.R.I.S.T, Vidyanagar, Nellore(dt) A.P. Her areas of interesting includes Digital image processing and Pattern recognition.

Dr. V. Vijaya Kumar is working as Professor & Dean Department of Computer Science & Engineering and Information technology in Anurag Group of Institutions (Autonomous) Hyderabad. He received integrated M.S.Engg, in CSE from USSR in 1989. He received his Ph.D. from Jawaharlal Nehru Technological University (JNTU), Hyderabad, India in 1998 in CSE and guided 33 research scholars for Ph.D. He acted as principle investigator for various R&D projects. He has served JNT University for 13 years as Assistant Professor, Associate Professor and Professor. He has received Distinguished Professor award from Computer Science of India (CSI), Mumbai, best researcher and best teacher award from JNT University, Kakinada, India, Leading Scientist of the WORLD -2009 and Top 100 Scientists award in 2010 from International Biographical Centre, Cambridge, England. His research interests include Big data and image analytics, image retrieval, texture analysis, author attribution, digital water marking. At present he is also acting as BoS member for various universities and institutions. He is the life member of



CSI, ISCA, ISTE, IE (I), IETE, ACCS, CRSI, IRS and REDCROSS. He published more than 120 research publications till now in various national, international journals and conferences. He has delivered key note addresses at various international conferences.

Dr. Ch. Satyanarayana is working as Director Academic Planning (DAP) and professor of CSE at Department at Jawaharlal Nehru Technological University -Kakinada. He has rich experience of teaching, research and administration and published more than 60 research articles and guided more than 10 research scholars for Ph.D .

Y.Sowjanya Kumari "Texture Classfication Based On Variants Of Fundamental Units Of Lbp Using Complete Texton Indexes " IOSR Journal of Computer Engineering (IOSR-JCE) 20.5 (2018):,, pp. 27-37