Local Texton Centre Symmetric Pattern Matrix (Ltcspm) On Wavelet Domain for Texture Classification

B. Kishore , V. Vijaya Kumar

Abstract*: This paper proposes a novel local descriptor, local texton center symmetric texture matrix (LTCSTM) for texture classification on wavelet domain. The proposed LTCSTM extracts i) structural features from texton representation ii) Local texton center symmetric pattern (LTCSP) code iii) integrates the above two features with gray level co-occurrence matrix (GLCM) features. The texture classification is performed using machine learning classifiers. Initially the raw image is transformed in to wavelet based image. The LL-1 image is sub divided in to local regions of size 2 x 2 and each region is replaced with texton index. The LTCSP is derived on texton index image. The LTCSP code replaces the center pixel of the 3x3 window. The derivation of co-occurrence matrix on this LTCSP coded image derives the proposed LTCSTM. The GLCM features on LTCSTM are used for texture classification. The proposed LTCSTM is compared with state-of-art of texton based methods and local descriptors of LBP on five popular databases. The experimental evidence clearly indicates the efficiency of the proposed method over the rest of the state-of-art methods.

Keywords: Local binary pattern, GLCM features, classifiers, integrated features, wavelet domain.

I. INTRODUCTION

Classification of texture images is one of the most important and crucial task of computer vision. The texture classification basically consists of two major steps as shown in Fig.1.

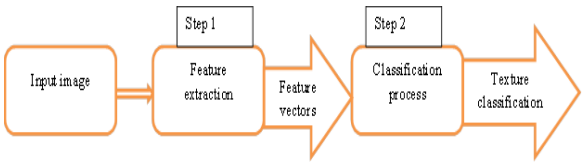

Fig.1: Frame work of texture classification.

Out of these two steps, the texture feature extraction is the most vital and crucial step. The extracted features of the first step should have more distinguishable features with rich contents. If the extracted features are poor in content then even a best classifier may not produce satisfactory results. The texture features are extracted locally, globally or region wise based on the type of application and input image dataset. A lot of research is being carried out and new descriptors are derived time to time to meet the requirements of the distinguishable features. The texture features can also be extracted more precisely based on structural, statistical, geometric and mode based descriptors. The basic and most vital features of any image texture are color, structure and texture. The color is the most crucial and easily distinguishable feature; however, if the dataset images are of same color, then one has to extract the feature from the other two sets. The statistical and structural approaches are the two most important approaches of texture analysis. The gray level co-occurrence matrix (GLCM) [1] is one of the popular and well known statistical methods for extraction of texture features. The main disadvantage of GLCM is it may not yield good results if the training and test images are of different orientations. The other disadvantage of GLCM is, it is a 2D array and the dimension of the array is directly proportional to the number of gray level or codes in the image. To address the rotational invariance various methods are developed in the literature: i) geometrical and photometrical representation [2 - 7] ii) Circular auto-regressive dense approach [8] iii) Gaussian Markov random model [9] iv) Multi resolution model [10] v) hidden Markov model [11]. The structural methods are one of the oldest and popular methods. The Julesz [12] proposed a structural model called textons 20 years back. The textons represents different structures on a local grid of size 2x2. The textons played crucial role in many image processing applications like texture classification [13-15], Content based image retrieval [16-19], face recognition [20-22] etc. The textons are formed if and only, if two or more pixels exhibits the same intensity levels. The complex structures are defined by textons using simple patterns. The extractions of texture features based on local approaches are more popular than global approaches. The local approaches can sustain too many variations than global approaches. One of the popular, well known and simple descriptor that extracts more meaningful and discriminant texture information from the local neighborhood is the local binary pattern (LBP) [23]. The researchers shown tremendous interest on LBP and derived various variants to LBP to improve its performance

in various applications i.e. in texture classification [13-15] , CBIR [16-19] , face recognition [20-22], medical image processing [24, 25], age classification [26, 27] etc. The variants of LBP are dominant LBP (DLBP) [28], completed LBP (CLBP) [29], LBP variance (LBPv) [30], to resist noise local directional pattern (LDP) [31] is proposed. The local ternary pattern (LTP) [32] is also proposed an extension to LBP to overcome the noise problems. The model based and learning based methods are also proposed for texture classification.

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The model based methods [33, 34] are not popular due to its high dimensionality. The learning based methods attained a high classification rate, however they require two steps for extraction of texture features i.e. representation and learning stages. Thus this process also becomes costly. The popular learning based methods are texton dictionary [34, 35, 36, 37, 38] and Bag-of-features (BoF) [36] frame work. The proposed LTCSTM descriptor derives spatial correlation of textons with center symmetric nature and thus produces the image content with high discrimination power of texture, color and shape features. The present paper is organized as follows. The section one presents the brief introduction. The section two gives the proposed frame work in a detailed manner. The section 3 represents the results and discussion with a brief notes on the description of the database. The section four describes the conclusions.

II. DERIVATION OF THE PROPOSED LTCSTM

The frame work of the proposed LTCSTM is shown in Fig.2.

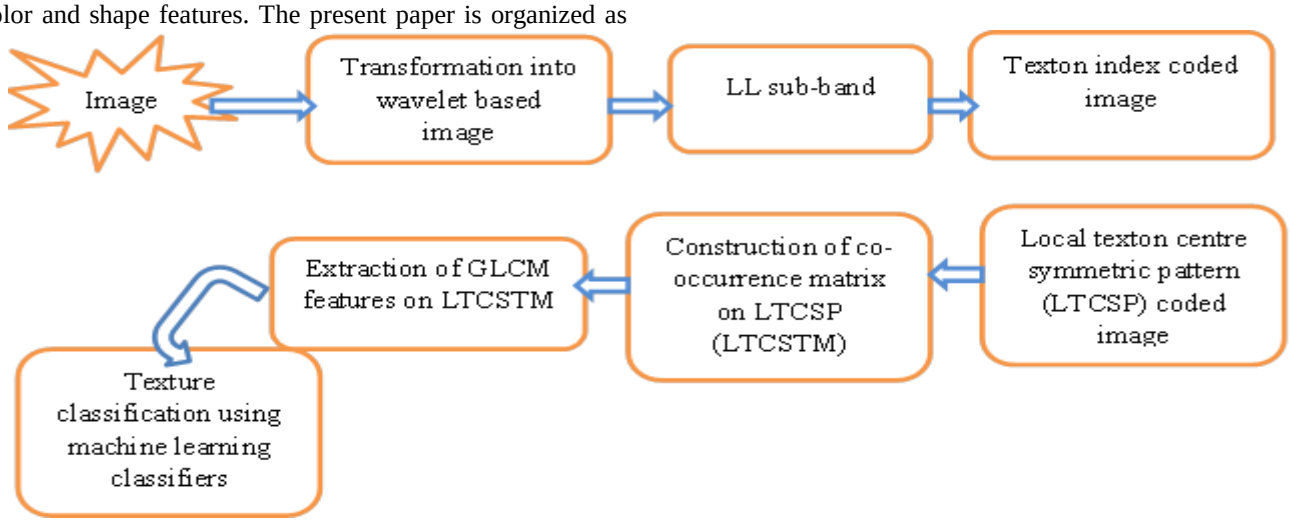

Fig.2: The framework of the proposed LTCSTM approach.

The proposed wavelet based LTCSTM initially transforms the texture image into discrete wavelet transformed (DWT) image. The DWT image divides the original texture image into four bands denoted by low-low (LL), high-low (HL), low-high (LH) and high-high (HH) after one-level decomposition. This paper derives the features on the LL sub band image. This paper initially divides the LL sub band image into small local grids of size 2x2. The identification of textons is performed on each local grid and the local grid is replaced with texton indexes. This paper derived the following micro structures as textons on a local 2x2 grid. This paper considered a texton if and only if two pixels exhibit the same intensity levels. The texton represents a pattern or micro structure of the local gird. A 2x2 local grid is represented with gray level values V, W, X, Y as shown is Fig.2. The proposed LTCSTM defined the following eleven different texton shapes with indexes ranging from 0 to 10 as shown in Fig. 3.The local textons defined in this paper are completely different from TCM, MTH and CTM approaches.

V	W
X	Y

Fig.2: representation of a 2x2 grid.

V	W
X	Y

0

V	V
X	Y

1

V	X
Y	V

2

V	X
V	Y

3

X	V
Y	V

4

X	V
V	Y

5

X	Y
V	V

6

V	V
W	W

7

V	W
W	V

8

V	W
V	W

9

V	V
V	V

10

Fig.3: The texton definitions of the proposed LTCSP.

The proposed local texton indexes are completely different from MTH, TCM and CTM. The TCM only defined structural patterns or textons if and only if all three or four pixels of the 2 x 2 grid exhibit exactly the similar grey level values. That is the TCM has completely ignored a texton type if two pixels have similar grey level values. The MTH only defined few textons with two identical pixels. The CTM has defined textons with two or three or four identical pixels, however it has ignored the identification of multiple

textons of two identical pixels as shown in the figure 5. The drawback of MTH and CTM indexing is they creates ambiguity when two different pairs of pixels have same intensity levels. The MTH has not defined all possible texton shapes with two identical pixels on the local 2x2 grid. The following Fig.4 shows the texton shapes defined by the MTH. The MTH defined only four possible texton shapes.

V	W
X	Y

(a)2x2 grid

V	V

MT_1

	V
V	

MT_2

V	
V	

MT_3

V	
	V

MT_4

Fig.4: Frame work of MTH.

This paper identified the following incapability of MTH and CTM indexing and the following Fig.5 shows one of them. For the 2x2 grid with gray level values of Fig.5, the MTH and CTM assigns multiple texton indexes for Fig. 5 and this has overcome by the proposed local texton indexing method.

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75	75
90	90

(a)2x2 grid

75	75

(b) MT_1

90	90

(c)MTH does not recognize this structure. CTM creates ambiguity

Fig.5: Ambiguity in MTH and CTM.

In Fig.5 there are two texton structures with two different pixel patterns. The MTH only recognized the top one i.e. the pixels with intensity levels 75 & 75 (fig.5(b)). The proposed local texton model recognizes the multiple local texton structure with a unique index of 7.

The proposed LTCSTM initially replaces the local LL-1 sub band 2 x 2 grid with texton shape indexes, i.e. the local grid is replaced with an index value ranging from 0 to 10. After this transformation, this paper derived center symmetric relationship on a 3 x 3 neighborhood and replaced the center value with LTCSPc. The Center symmetric relationship is extracted by deriving the relation between sums of the symmetric texton structure indexes with two times of center texton structure index value as given in equation 1 and shown in Fig 6.

$$LTCSP_{3,8} = \sum_{i=1}^{4} 2^{i-1} * f(T_i + T_{i+4}) - 2 * T_c \quad (1)$$

$$f(x) = \begin{cases} -1, & x \geq 0 \\ 0, & Otherwise \end{cases} \quad (2)$$

Where Ti and Tc represent the local shape index of texton for the local pixel i and center pixel c. The derivation of the LTCSP3,8 on a 3x3 local texton index image is shown in Fig.6. Each Ti and Tc represents a texton index derived on a wavelet based local grid of size 2 x 2.

T_1	T_2	T_3
T_8	T_c	T_4
T_7	T_6	T_5

(a) 3x3 local texton index window

$(T_1+T_5-2*T_c)$	$(T_2+T_6-2*T_c)$
$(T_3+T_7-2*T_c)$	$(T_4+T_8-2*T_c)$

(b) CS-texton relation

2^0	2^1
2^3	2^2

(c) binary weight

$LTCSP_c$

(d) code

Fig.6: Generation of LTCSPc from the texton index image.

The LTCSPc ranges from 0 to 15. This paper replaces the local texton shape index of the center pixel with LTCSP code. This process is repeated on entire LL-1 sub band image with a step length of one. This process transforms the LL-1 sub band image into an image with code ranging from 0 to 15. This paper constructed the co-occurrence matrix on LTCSP coded LL-1 sub band image. Eventually, the given wavelet image is transformed to LTCSTM, that maps the texton indexes with values ranging from 0 to 10, to 16x16 after constructing a co-occurrence matrix on center symmetric texton pattern coded image. This paper derived six GLCM features on LTCSTM as given in equation from 3 to 8. This paper computed three different LTCSTM with distance values ranging from 1 to 3. On each d value, this paper computed the six GLCM features on each rotation of 0o, 45o, 90o and 135o. The average value of GLCM features on each distance value is considered as feature vector. The LTCSTM derives the spatial relationship of center symmetric texton structures. This paper integrated color, texture, shape primitives with GLCM features by integrating center symmetric structural relationship of textons with co-occurrence matrix for a precise texture classification.

III. RESULTS AND DISCUSSION

To test the performance of the proposed wavelet based LTCSTM descriptor, this paper compared the classification results with the other popular and stat-of-art methods of texture classification: LBP[23], LTP[32], CLBP-SMC [29], CS-LBP [37] , MTH[40], TCM[39] and CTM[38] , To analyze the performance and to have proper conclusions this paper conducted experiments on five representative popular texture databases: Brodatz [41], Outex [42], UIUC [43], KTH-TIPS [44] and ALOT [45]. And brief description about these databases is given below. The Brodatz database consists of several different categories of texture images and on each category there will be several images. This paper selected 30 different categories of Brodatz textures of size 512x512 and each category texture image is divided into texture image of size 64x64 in a non-overlapped manner. These results a total 64 texture images under each category. The sample sub set of Brodatz database is shown in Fig.7.

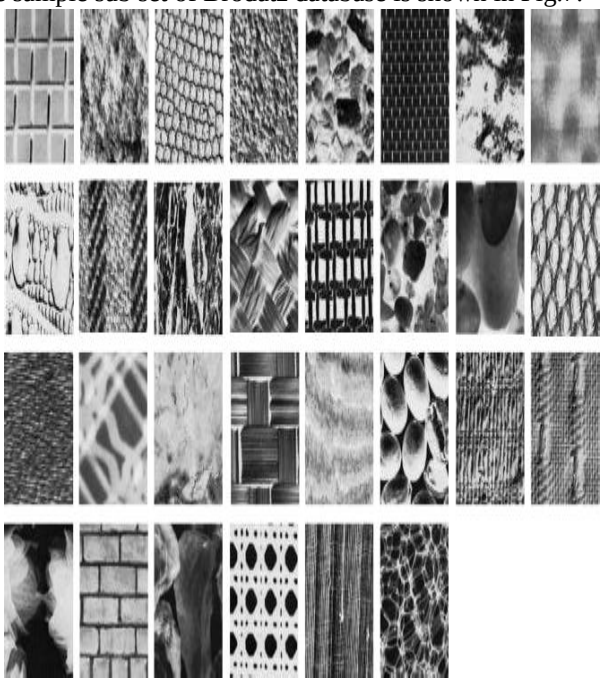

Fig.7. Sample images of Brodatz database.

There are two different sets of texture image in Outex-TC database i.e. Outex-TC-10 and Outex-TC-12 (Fig.8). The images of Outex are captured under different conditions with nine rotation angle 0 to 90o (0o, 5o, 10o, 15o, 30o, 45o, 60o, 75o, 90o). The texture image sizes are 128 x128. And there will be 20 different images under each rotation.

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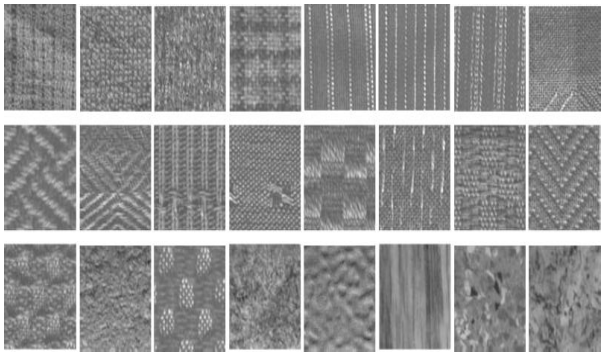


Fig.8. sample images of Outex database.

The UIUC texture database image consists of 1000 images with 25 categories and there will be 40 texture images under each category and the size of each image is 640 x 480. This paper divided each image into 70 non-overlapped images of size 64x64. This process has made a total of 1750 images under each category with a size of 64x64. The sample images of UIUC are shown in Fig.9.

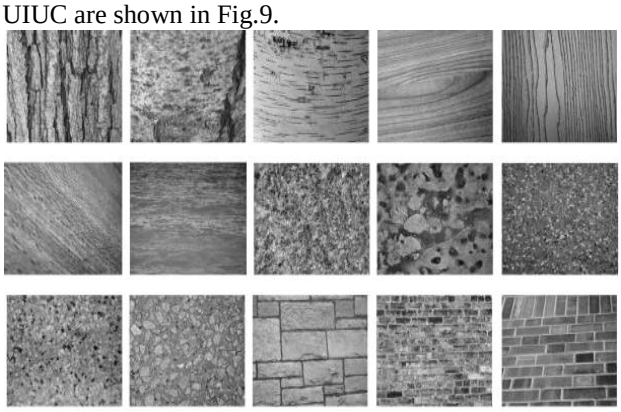
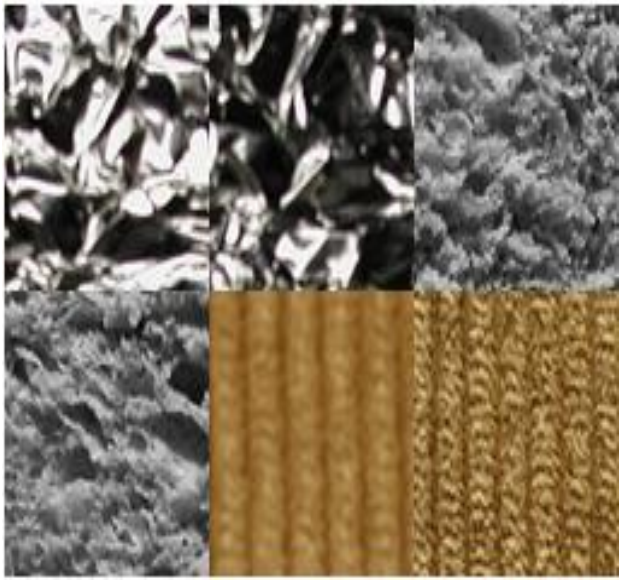


Fig. 9: Sample images of UIUC database.

The KTH-TIPS textures under varying illumination, pose and scale database was an extension to CURET database. The KTH-TIPS considered as extensions into two directions and provides variation in scale as well as pose and illumination. There are only 10 categories of texture image and 81 images under each category. The sample images of this database are shown in Fig. 10.



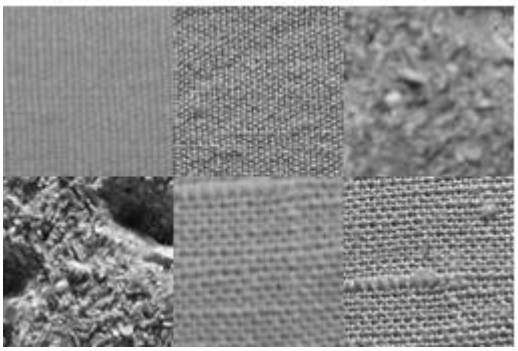


Fig. 10: Sample images of KTU-TIPS texture database.

The ALOT texture database images are collected under varying illumination conditions and angles (Fig.11). This database consists of 250 categories of texture image with a resolution of size 250x100 under each category there are 100 images. This paper divided each image with a size of 64x64, and this has leaded a total of 300 images under each category.

Fig.11. Sample images of ALOT database.

The average classification rate of the proposed descriptor on Haar, Daubechies, Coiflet and Symlet wavelet transformed images using multilayer perceptron (MLP), Naivebayes, Ibk and J48 classifiers are computed and found that the proposed LTCSTM descriptor on Haar wavelet exhibited a little high classification rate than other wavelet transforms. The classification results of Haar wavelet on proposed LTCSTM descriptor on the five databases using the four machine learning classifiers are listed in table 1.

Table 1: classification rates of the proposed LTCSTM descriptor on Haar wavelet image.

Database	Multilayer Perceptron	Naivebayes	IBK	J48
Brodatz	95.76	88.23	89.46	89.42
ALOT	91.17	85.26	87.43	84.34
KTH-TIPS	97.26	90.42	91.24	88.24
UIUC	95.92	89.24	90.55	87.15
Outex-TC-10	96.52	89.12	89.56	89.80
Outex-TC-12	98.02	89.46	91.25	85.24
Average	95.78	88.62	89.92	87.37

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1 has given the average classification rate of the proposed descriptor on Haar wavelet on all databases using four different machine leaning classifiers. The multilayer perceptron has resulted on average 4 to 5% of high classification rate when compared to the rest of the classifiers. The multilayer perceptron has exhibited high classification rate on the proposed LTCSTM descriptor on Haar wavelet transformed images. In the remainder of this paper, we have used this results when compared with the other existing methods.

The major contribution of this paper

The derivation of texton structure with two identical pixels on a local micro grid of a wavelet based image.

The assignment of texton indexes by considering the multiple texton formation on a 2x2 grid.

The extraction of center symmetric texton relationship and transformation of the wavelet image into a local texton center symmetric pattern coded image.

The integration of local textons with center symmetric structures and with gray level features for a precise classification with a low dimension of 16x16.

The proposed local textons describes the spatial correlation of textons and derives rotational invariant local patterns with complete set of structures with two identical pixels.

This paper proposed an efficient mechanism for generation of local textons to overcome the ambiguity issues of MTH, CTM and the derivation of center symmetric relationship on these local structures transform the image into an image with rich and powerful image contents.

Table 2: Classification rate (%) of proposed and state-of-art-methods on various databases.

Database	LBP[23]	LTP[32]	CLBP-SMC[29]	CS-LBP [37]	MTH [40]	TCM [39]	CTM [38]	Propose LTCSTM
Brodatz	54.28	57.50	85.23	74.56	86.21	87.14	87.52	88.95
Outex-Tc-10	56.11	74.56	89.88	74.11	89.74	89.41	89.82	90.42
Outex-Tc-12	56.19	75.88	90.30	74.64	90.65	90.99	91.01	91.21
UIUC	62.86	67.16	87.64	74.24	87.88	88.85	89.21	89.84
KTH-TIPS	64.16	66.18	89.14	72.14	89.65	89.91	90.21	90.84
ALOT	52.26	56.24	80.46	70.14	81.11	91.88	91.89	92.11

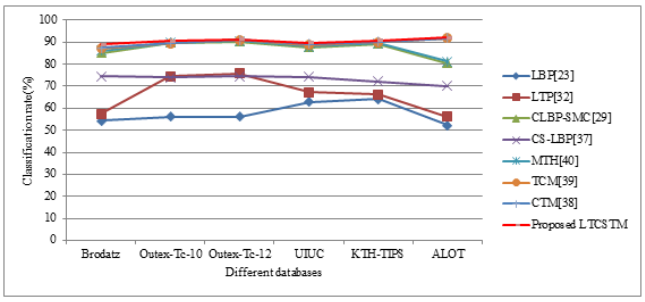

Fig.12: Comparison graph of the proposed and existing methods in terms of classification rate (%).

The table 2 shows the classification rates of the proposed method versus the existing methods. The ALOT database has shown a little low classification rate when compared to other databases. The main reason is due to the few images under each category. The Outex-TC-10 also shown low classification rate, due to the large variations in between images. The Brodatz and UIUC database has shown almost similar classification rate. The KTH-TIPS and Outex-TC-12 have shown high classification rate.

IV. CONCLUSIONS

This paper proposed a novel descriptor LTCSTM for efficient texture classification. The novelty of the LTCSTM, it derived center symmetric relationship among the texton shape features and thus has extracted significant local structural and texture features and the computation of GLCM features on these enhanced the classification accurately of the proposed method. The derivation of the proposed LTCSTM on different wavelet domains clearly indicates the fact that Haar wavelet has narrow edge on other wavelets. The proposed derivation of textons with two identical pixels is completely different from multi texton matrix (MTH), TCM and CTM and it has overcome the ambiguity in assigning unique indexes for the texton shapes. The experimental results on popular databases clearly reveal the efficiency of the proposed methods over the state of art texton and local based methods.

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