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Texture Classification Using Complex Pattern Derived On Micro and Macro Regions

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Abstract: *The local based methods are very popular in the texture classification methods. The local based methods are mostly derived on circular regions or on isotropic structures. In the literature few researchers carried out research based on elliptical neighborhoods or anisotropic structures. The main drawback in the derivation of anisotropic structural information is they derive huge histogram bin size i.e. twice of local binary pattern (LBP). This paper derived complex patterns on a 5x5 micro region and the complex pattern derives the complete structural information of isotropic, anisotropic and hyperbolic shapes. The disadvantages of local based methods are they fail in representing the macro structures. To address this paper initially divides the texture image into macro regions of size 15x15 and each macro region is divided into a micro region of size 5x5 and complex patterns are derived. The complex patterns derive a very huge histogram bin size which is the 64 times of LBP code. This paper derived region based Dual weighted symmetric complex patterns (RWDSCP) to reduce the bin size to a huge extended by preserving macro and micro features of complex structure. The proposed RWDSCP is experimented on popular texture databases and compared with state of art local based methods. The results indicate the high classification rate of the proposed method over the exiting methods.*

Keywords: *isotropic; anisotropic; hyperbolic; structures; macro; micro; feature.*

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I. Introduction

Texture is an important and crucial visual cue and it is treated as ubiquitous in natural images. Texture classification (TC) is an important area of research in image processing over several decades from 1962 of Julesz's initial research [1]. The texture classification is a two-step process: in the first step the features are extracted and in the second step the classification task is performed most research in TC is focused on the extraction of texture features [2]. A good and extensive survey on the feature extractions are carried out in the literature [3-4]. The early methods of TC includes the methods based on statistical measures of gray levels : gray level co-occurrence matrix (GLCM)[5], gray level difference histograms (GLDH) [6] gray level run length histograms [6], simultaneous autoregressive models [7], Markov random fields [8-9], fractal models [10]. The research on TC has changed dramatically in 1980 by the introduction of new methods based on Gabor filters [11-12], pyramid filters [13] and wavelets [14]. Further advances in TC are recorded in the literature by replacing the simple statistics with multi dimension histograms such as gray level auro histograms [15] , local binary patterns [16] and the variants of local binary pattern (LBP). These methods extracted texture features from local image patches. One of the recent surveys on TC conducted a comparative study and concluded that there is no single best approach that is suited for all types' images of different environments [2]. The feature extraction methods on local patches focus on the extraction of texture features using the gray level patterns surrounding a given pixel mainly the central pixel. The critical parameter in a patch-based classification is the size of the patch. Small patch sizes cannot capture the large scale structures and they are not robust to local changes, sensitive to noise and illumination. The large patch increases the dimension of the patch space and also the complexity of finding textons or small variations.

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 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 [24-26], texture recognition [27-29], age classification [30, 31], texture classification [32-33], bio medical image analysis [34, 35], environmental modeling [36, 37].Many variants are proposed to LBP in the literature to improve its performance and the popular LBP variants include [38-40]. The advantages of these local descriptors are [39, 40, 41], they are handcrafted methods and they can easily incorporate with other complex methods [42, 43]. 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 [41, 42, 43, 44]. 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 [44, 45].

A texture contains repetitive patterns/patches. The patch based classification methods also played a vital role in texture classification [46-48]. 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 [46-48].

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 [49, 50]. 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)[51], multi texton histogram (MTH) [52], complete texton matrix (CTM) [53]. 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. Proposed method

The local based methods played a crucial role in various applications of computer vision and image processing. One of the popular and successful local based approaches is the local binary pattern (LBP) and its variants. The LBP and its variants extracted significant local features of isotropic nature. The other important local features are extracted from anisotropic structures, however only few researchers have shown interest in elliptical neighborhood (EN) [54-56]. The elliptical patterns or EN represent anisotropic structures. To derive complete anisotropic features one has to derive features from two types of elliptical neighborhoods namely horizontal and vertical. Thus the elliptical patterns (horizontal and vertical) derive huge histograms and that's why they haven't become popular in the literature.

This paper identified the basic disadvantages of local based approaches is they fail in representing macro structures. The macro features also plays a major role, however the combinations of macro and micro features derives more meaningful information. To derive and to integrate macro and micro features this paper derived region based methods. The local based approaches like LBP and its variant and ELBP are only capable in deriving significant features on a small spatial neighborhood of 3x3 or 3x5 or 5x3 or at most 5x5.

This paper aims to derive "region based symmetric texture matrix (RSTM) on 5x5 neighborhood that represents circular, elliptical and hyperbola structures. This paper initially divides the image into non-overlapped macro regions (NMR) of size 15x15. This paper divides each NMR into a local micro sub region (LMSR) of size 5x5. For this, the present research divides each NMR of size 15x15 by sub regions of size 3x3. This step derives a total of 25 LSRs (15x15/3x3) i.e. five sub regions of each size of 3x3 on each row and column. This process of division of LMSR from a NMR is shown in Fig.1.

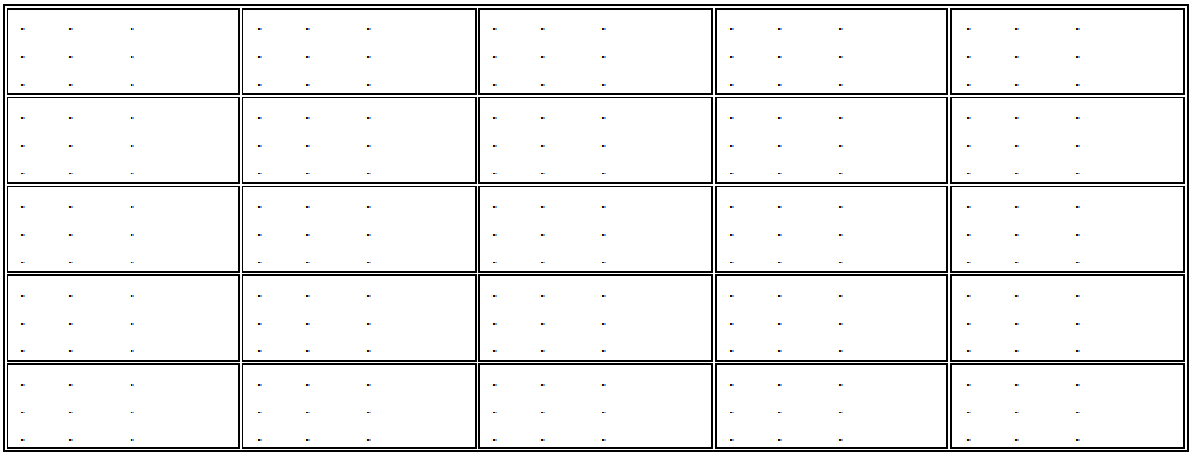

Fig.1: Division of LSR from a NMR.

This paper computes the average value of each LMSR and the average gray level value replaces the LMSR. The average value of each LMSR is computed efficiently by using integral image, and this makes the process of this computation very fast. Thus this paper initially divided the image into NMR of size 15x15 and later divides each NMR into 25 LMSRs of size 3x3. By replacing each LMSR with its average value the macro region of size 15x15 is optimized into a micro region of size 5x5. In figure 1 each sampling point represents the average gray level intensity of a 3x3 LMSR.

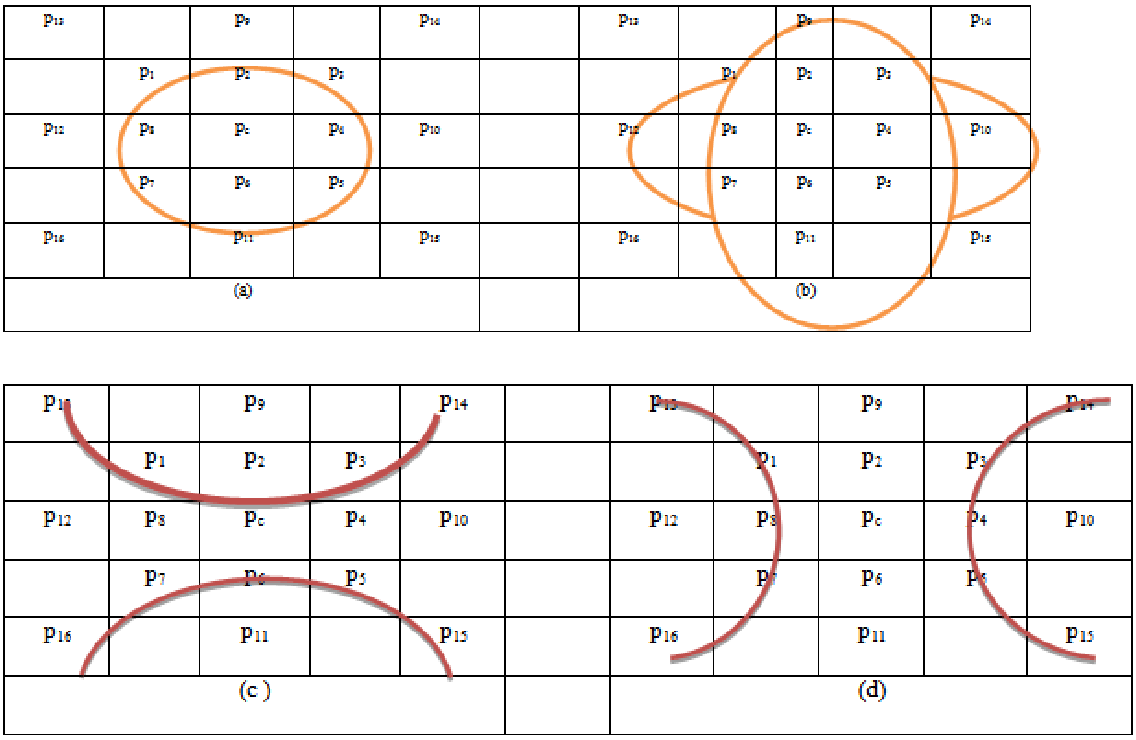

Fig. 2: (a) The 5x5 circular, (b) symmetric (c) Horizontal parabolic (d) Vertical hyperbolic neighborhoods (CEN).

In the above figure the pixels (p_1,p_2,p_3..p_8) represents the gray level values of a circular neighborhood over central pixel pc. The pixels p_1,p_2,p_3,p_{10},p_5,p_6,p_7,p_{12} represents the sampling point gray levels of horizontal elliptical neighborhood (HEN).The pixels p_9,p_1,p_8,p_7,p_{11},p_5,p_4 and p_3 represents the gray level values of sampling points of vertical elliptical neighborhood.The pixels p_{13}, p_1, p_8, p_7 and p_{15} ; and p_{14}, p_3, p_4, p_5 and p_{15}represent the grey level values of sampling pointsof horizontal hyperbola structures over center pixel p_c. The vertical hyperbola structure represents the sampling points: p_{13},p_1,p_2,p_3 and p_{14}; and p_6,p_7,p_6,p_5 and p_{15}.This derives a total of 16 sampling points over $p_c$that represents the circular elliptical and hyperbolic neighborhood (CEHN) the sampling points are p_1,p_2…..p_{15} and p_{16}. Each of these sampling points represents average value of a LSMR of size 3 x 3. Thus the circular elliptical and hyperbola neighborhood (CEHN) of this 5x5 in fact represents a NMR of size 15x15.

The combination of the binary pattern that represents circular, elliptical and hyperbola structuresare named as complex binary patterns (LCBP) over a 5x5 neighborhood. A 5 x 5 neighborhoods will have 24 sampling points over the central pixel pc. From the above it is evident that one requires only 16 sampling points out of 24 sampling points of 5 x 5 neighborhood, to represent the complete isotropic or circular; complete elliptical or anisotropic ; complete hyperbolic structures. This paper derived local region based complex binary patterns(RCBP) and also derived the RCBP code in the following way as given in equations 1 and 2.

$$RCBP_c = \sum_{i=1}^{16} 2^{i-1} * f(I(p_i) - I(p_c) \quad (1)$$

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

The proposed RCBP derives a code of 2^{16} patterns ranging from 0 to 2^{16}-1 unique patterns. The $RCBP_c$replaces the center pixel. Thus the macro region of size 15x15 is replaced with RCBPc. This becomes very huge, however it represents all significant structures of a 5 x 5 neighborhood. This paper listed outthe histogram sizes of all complex patterns and placed in Table 1.

Table 1: different patterns over 5 x 5 neighborhoodsand their bin -size.

S.No	Type of pattern	No. of samplings	Histograms size	Type of information
1	LBP over 3x3	8	256	Only isotropic
2	H-ELBP 3x5	8	256	Only partial anisotropic
3	V-ELBP 5x3	8	256	Only partial anisotropic
4	Complete ELBP	12	2^{12}	Complete anisotropic
5	Complete CELBP	12	2^{12}	Complete isotropic and anisotropic
6	Horizontal-Hyperbola	10	2^{10}	Partial Hyperbolic
7	vertical-Hyperbola	10	2^{10}	Partial Hyperbolic
8	Complete Hyperbola	12	2^{12}	Complete Hyperbolic
9	Complete circular hyperbola	12	2^{12}	Complete isotropic and Hyperbolic
10	Complete complex pattern	16	2^{16}	Complete isotropic, anisotropic and Hyperbolic

The table 1 clearly indicates the histogram bin sizes of all individual sets of patterns. These bin sizes are huge. To overcome this in the literature center symmetric local binary patterns (CS-LBP) are proposed. The CS-LBP measures the relationship between gray levels of symmetric sampling points of the central pixel of p_c. The CS-LBP_c is derived based on the equation 3 and 4.

$$CS - LBP_c = \sum_{i=1}^{4} 2^{i-1} * f(I(p_i) - I(p_{i+4}) (3)$$

$$f(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & Otherwise \end{cases} \quad (4)$$

This paper summarized the following CS-LBP properties:

1) The CS-LBP derivation measured symmetric relationship by not considering the central pixel, which is a vital one in the LBP.
2) The CS-LBP derives a code of range 2^4 i.e. 0 to 15.
3) The CS-LBP derives only symmetric relationship of circular neighborhood.
4) The coder range of CS-LBP is small and ignores some significant relationship.

From the Table 1 it is evident that to represent complete complex set of patterns (circular, complete elliptical and complete hyperbolic) one requires a huge and huge histogram of size 2^{16}. The complete set may derive good number of wide features; however it is not possible to use them in any application due to its high complexity and dimension.

The center symmetric-complex binary pattern (CS-CBP) measures the relationship between the sampling points i. p_1 vs. p_5 ii. p_2 vs. p_6 iii. p_3 vs.$p_{7;}$ iv. p_4 vs. $p_{8;}$ v. p_9 vs.p_{13}; vi. p_{10} vs. p_{14}; vii. p_{11} vs. p_{15}; viii. p_{12} vs. p_{16}. This derives an eight bit CS-CBP code i.e. The range of CS-CBP code will be 0 to 255 which is a huge however it has the reduced the CBP_c from 2^{16} to 2^8. The proposed weighted center symmetric complex binary pattern (WCS-CP) code measures the symmetric relationship among the complex structure sampling points with respect to twice of the center pixel. The dimensionality of the proposed WCS-CBP_c is huge and it derives a histogram of size 256. To reduce this dimensionality and to extract significant features from the complex structure, this paper partitioned, the complex structure that holds the complete circular, elliptical and hyperbolic structures of 16 sampling points into two different sets that consists of internal and external units i.e. 8 sampling points.

The inner and external units of complex neighborhood represent the pixel p_1 to p_8 and p_9 to p_{16} respectively. This research derived WS-C_EBP (weighted symmetric complex external binary pattern) by measuring the symmetric relationship among external points with respect to central pixel as given the following equation

$$WS - C_E BP_c = \sum_{i=1}^{4} 2^{i-1} * f(I(p_{i+8}) + I(p_{i+12}) - 2 * I(p_c))(4)$$

$$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & Otherwise \end{cases} \quad (5)$$

The WS-C_IBP (weighed symmetric complex internal binary pattern) code is derived in the following way

$$WS - C_I BP_c = \sum_{i=1}^{4} 2^{i-1} * f(I(p_i) + I(p_{i+4}) - 2 * I(p_c)) \quad (4)$$

$$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & Otherwise \end{cases} \quad (5)$$

The WS-$C_E BP_c$ and WS-$C_I BP_c$ ranges from 0 to 15. This paper derived region based dual weighted symmetric-complex pattern matrix (RDWSCPM) based on the relative frequencies relationship between WS-$C_E BP_c$ and WS-$C_I BP_c$. This derives a 2 dimensional matrix for RDWSCPM of size 16x16. This research computed co-occurrence matrix on RDWSCPM and the following six GLCM features are derived for efficient texture classification as given in the following equations 6 to 11.

This paper derives five GLCM features as given below:

1. Contrast :

$$\text{Contrast} = \sum_{n=0}^{M-1} n^2 \left\{\sum_{i=1}^{M} \sum_{j=1}^{N} X(i,j)\right\}, |i-j| = n \quad (6)$$

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

2. Correlation :

$$\text{Correlation} = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \frac{\{iXj\}XX(i,j) - \{\square_x X \square_y\}}{\sigma_x X \sigma_y} \quad (7)$$

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

3. Entropy :

$$\text{Entropy} = \sum_{i,j} \log(X(i,j)).\ X(i,j) \quad (8)$$

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

4. Homogeniety, Angular Second Moment (ASM):

$$\text{ASM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{X(i,j)\}^2 \quad (9)$$

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)

$$\text{IDM} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \quad (10)$$

This paper performed classification of ages by using the four machine learning classifiers namely Ibk, Naviey bayes and multi-layer perceptron.

6. Prominence feature

$$Prominence = sgn\ (B)|B|^{1/4} \quad (11)$$

$$where\ B = \sum_{i,j=0}^{N-1} (i + j - 2\mu)^4 P_{ij} \Big/ 4\sigma^4(1 + C)^2$$

III. Results And Discussions

To evaluate the performance, this paper compared the classification rates of the proposed RDWSCPMdescriptor with LBP based descriptors i.e. LBP[16], LTP[38], CS-LBP[57] , CLBP-SMC[58] and texton based descriptors TCM[51] and MTH[52].The experiments are conducted on five different popular data bases namely, Brodatz [59], UIUC [60], Outex-TC-10[61], Outex-TC-12[61], KTH-TIPS [62] and ALOT[63]. The summary of these databases are given in table 2. The sample images of these databases are shown from figures 7 to 12.

Table 2: 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

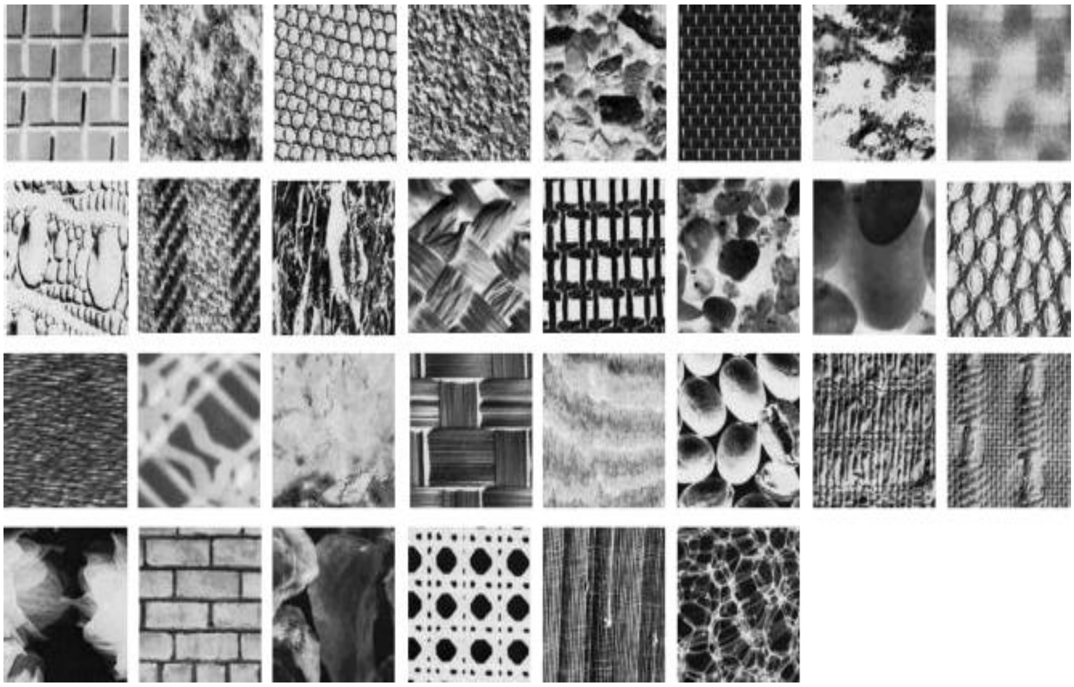

Fig. 7: Samples of the 30 classes randomly selected from the Brodatz database.

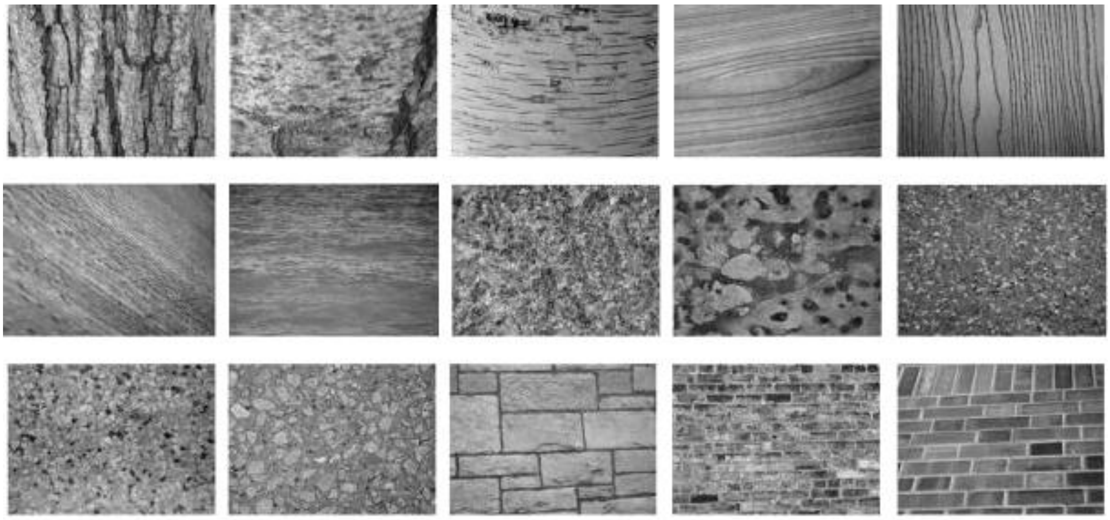

Fig. 8: Sample images from the UIUC database.

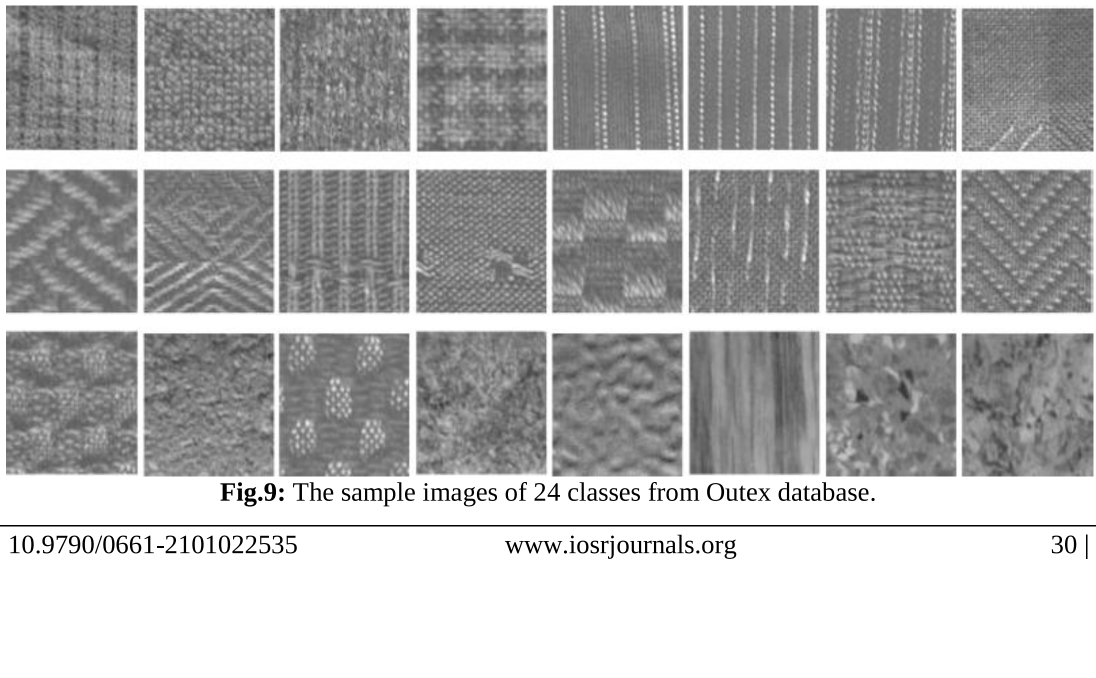

Fig.9: The sample images of 24 classes from Outex database.

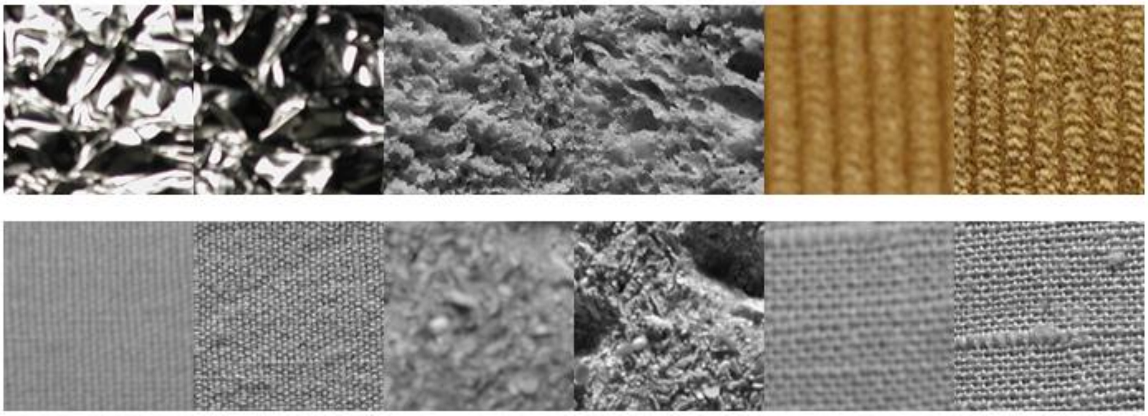

Fig. 10: Sample images of KTU-TIPS texture database.

Fig. 11: ALOT texture database.

The proposed RDWSCPM descriptors have shown high classification rate for 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 3). For comparison purpose with the other existing descriptors, now onwards the classification rates of multilayer perceptron is quoted for the proposed RDWSCPM descriptor.

Table 3: Average classification rate of the proposed RWSCPM with s=1 on different databases using different classifiers for d=2

Proposed Method	Databases	Naviebayes	Multilayer-perceptron	Ibk	J48
Proposed RDWSCPM	Brodtaz [59]	80.84	86.69	85.01	84.1
	UIUC[60]	77.34	82.9	81.26	80.6
	Outex-TC-10[61]	87.83	92.6	91.26	90.26
	Outex- TC-12[61]	77.84	84.56	82.8	81.3
	KTH[62]	73.7	82.72	79.49	77.26
	A LOT[63]	72.46	81.49	78.86	76.06
	AVERAGE	78.34	85.16	83.11	81.60

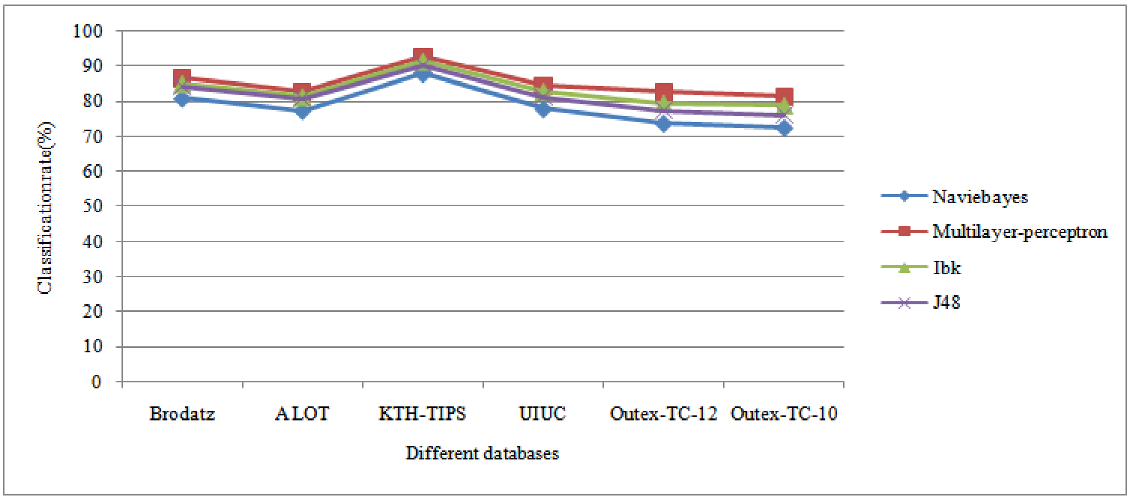

Fig. 12: Classification rate (%) of proposed RDWSCPM method on different databases.
The classification rate of proposed and existing methods is given in table 4.

Table 4: Classification rate of proposed and existing methods.

Database	LBP[16]	LTP[38]	CLBP-SMC[58]	CS-LBP[57]	MTH[52]	TCM[51]	Proposed RDWSCPM
Brodatz	54.28	57.50	85.23	74.56	87.25	86.57	89.12
UIUC	62.86	67.16	87.64	74.24	87.83	85.7	87.21
Outex-TC-10	55.62	74.12	89.85	73.47	90.12	91.14	92.32
Outex-Tc-12	56.19	75.88	90.30	74.64	91.87	92.65	93.21
KTH-TIPS	64.16	66.18	89.14	72.14	87.89	87.51	91.21
ALOT	52.26	56.24	80.46	70.14	85.65	86.10	89.32

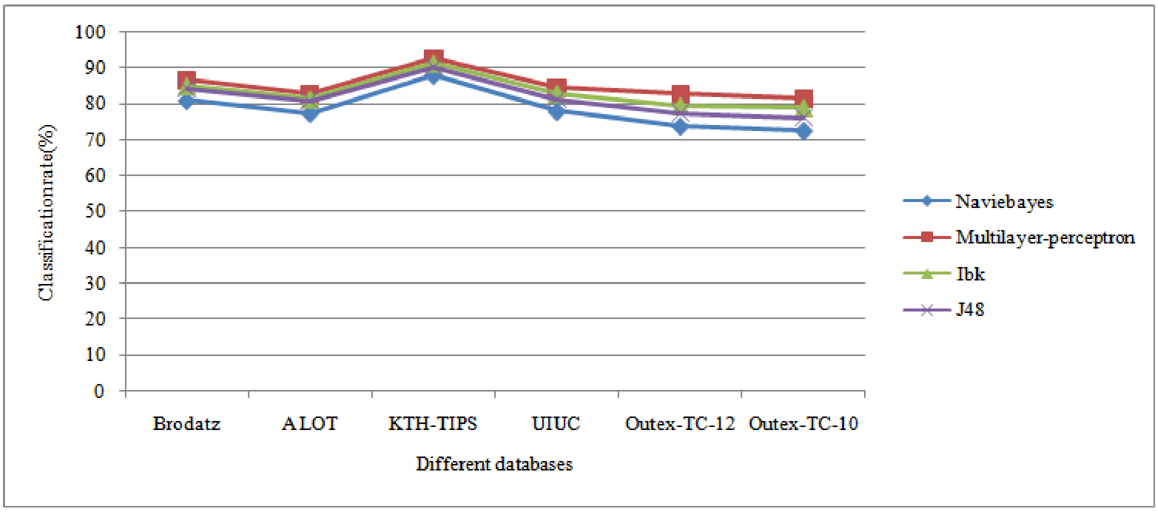

Fig.13: Comparison graph of proposed method with existing methods.

The major contribution of this paper

1. Derivation of complex binary patterns (CBP) on 5x5 neighborhoods in a précised manner that represents both macro and micro structure information.
2. The derivation of CBP that represents the complete isotropic, anisotropic and hyperbolic structure information on macro regions.
3. The derivation ofdual weightedcenter symmetric relationship by dividing the neighborhood into two parts.
4. The derivation of a new matrix based on the relative frequencies of inner and external WCS complex binary patterns.
5. The major contribution is the great reduction of histogram size of 2^{16} to a GLCM of size 16x16 with more precise information about complex patterns of macro and micro regions.

The proposed RDWSCPM 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 derivation of complete set of complex patterns that represent both micro and macro structures with low dimensionality. Further the derivation of GLCM features Dual symmetric patterns represented both statistical and structural features. 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, uniform LBP (ULBP), centre symmetric LBP (CS-LBP) and local ternary patterns (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 RDWSCPMis proposed by carefully analyzing the weakness of existing methods.

IV. Conclusions

This paper derived macro and micro features from three types of structures namely isotropic, anisotropic and hyperbolic. To reduce the dimensionality and to retain all the features of the above complex structure this paper divided the given 5x5 micro neighborhoods, that represents the macro region of size 15x15, into two units and derived dual weighted symmetric relationship between sampling points. The advantage of the proposed method is it integrated the complex structural information of micro and macro regions with statistical features. This has achieved high classification rate than the existing state art of methods on the popular databases. The proposed method can also be used in other applications like content based image retrieval (CBIR), face recognition rate (FR) etc.

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