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Local Gradient Dual Coding Book (LGDCB) Framework for Effective Texture Classification

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ABSTRACT

Local descriptors are popular in texture classification and they are robust and sustain and perform well in varying pose, lighting and illumination condition. The accuracy of these local descriptors depends up on the precision of local features derived on the local neighborhood. To achieve robustness this paper initially computes eight directional edge responses using kirsch masks for each sampling point of 3x3 overlapping window. This paper divides the 3x3 edge responses(E_r) windows into a dual matrix consist of four sampling pixels each. On each matrix this paper computes the edge response ranks and based on this a coding book sequence number is generated for each matrix and this process derives dual edge response sequence matrix (DE_rSM). The co-occurrence matrix and grey level co-occurrence matrix (GLCM) features derived on DE_rSM represent the feature vector. The proposed descriptor is tested with well-known texture databases with different categories. The experimental results of the proposed descriptor are compared with state-of-art local descriptors and the results demonstrate the efficacy of the proposed method over the other methods.

Key words: Edge response; dual matrix; sequence book; texture –databases; GLCM features.

1. INTRODUCTION

Texture analysis and texture classification are widely used in computer vision, image processing, and pattern recognition domains and it is one of the long standing problems of the research. The applications like object and sense recognition [2], pedestrian detection [3], sky extraction from fishy images [5], computer assisted diagnosis [6], motion and activity analysis and many more falls in the category of texture analysis. The texture feature extraction is to be carried out more precisely to extract significant texture features. In recent years the texture features are extracted locally and these methods focuses on extraction of pattern based features. The local binary pattern (LBP)[7] and its variants played a major role in extracting local features and LBP based methods are used in many applications like face detection [8,9], texture classification [9,10], content based image retrieval (CBIR)[11,12], age classification [13, 14], motion detection [15] and background subtraction [16]. The LBP based methods encode micro level information of edges, local features, spots around each pixel of the neighborhood based on intensity information. A great amount of information may be lost due to binary coding in most of the LBP based approaches. Further a small fluctuation or noise may change the LBP or binary code drastically. To address these factors the present paper initially derives directional edge information using kirsch masks for the sampling points of the neighborhood instead of intensity information as in the case of most of the LBP based methods. The directional edge information over comes the noise problem i.e. it is more noise resistant. This paper after computing, the directional edge responses (DE_r) using kirsch mask, divides the 3x3 DE_r window into cross and diagonal windows. This paper derives the ranks and sequence codes on these two windows. The derivation of a unique sequence code for the DE_r dual matrices by te proposed method inherits pertinent properties from both DE_r and contrast information. This paper derives GLCM features to extract more texture information on the edge response sequence coding.

This paper is organized as follows: the section 1 and 2 deals with introduction and proposed frame work. The section 3 and 4 represents the results and discussion and conclusion respectively.

2. PROPOSED DUAL EDGE RESPONSE SEQUENCE MATRIX (DE_rSM)

This paper proposes a new descriptor for texture classification and the proposed descriptor is motivated by the high edge responses of the boundaries of the texture. This paper extracts the edge directional patterns and extracts the texture features in the form of coding book indexes. This research extracts the eight edge directions over the sampling points of a 3x3 neighborhood. This paper adapted kirsch edge responses mask (Figure 1) as an edge operator. The kirsch edge operator is an efficient descriptor to estimate edge responses. The proposed descriptor uses the gradient direction instead of gradient magnitude for superior representation of texture features.

The basic image system in image processing and computer vision is usually formulated as

$$I(x, y) = A(x, y) + P(x, y) \quad (1)$$

Where x,y are x and y co-ordinates of the pixel location, I(x,y) represents the image pixel value, A(x,y) is the surface albedo and P(x,y) is the illumination at each point. In the literature gradient based methods have been used in many applications like texture classification, texture segmentation, face recognition, content based image retrieval (CBIR) etc., this is mainly because the gradient based methods are more robust to local variations, efficient in computation, simple, easy to understand and implement. The gradient operator enhances the edge responses. This research evaluated on each 3x3 window eight directional edge responses values, corresponding to a particular pixel using kirsch edge masks in eight different orientations (KM_0- KM_7) as shown in Fig.1. The advantage of this edge descriptor is it offers more reliability i) in the presence of noise, ii) in the presence of various conversion schemes such as color texture into gray level and illumination changes. The main reason for the above stable and reliable performance of kirsch mask is due to its significant edge responses in all eight directions and these are more stable than pixel brightness values. This paper initially divides the image into micro regions of size 3x3. The 3x3 window will have 8 sampling points over a center pixel. This paper computes the eight directional edge responses (DE_r) corresponding to each sampling point using kirsch masks (KM_0-KM_7) (Fig.1). This derives eight edge responses $|ER_0|$, $|ER_1|$… $|ER_7|$ and eight kirsch edge masks corresponding to pixels P_0, P_1..P_7 as shown in Figure 2.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

(KM_0) **(KM_1)** **(KM_2)**

$$\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}$$

(KM_3) (KM_4) (KM_5)

$$\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

(KM_6) (KM_7)

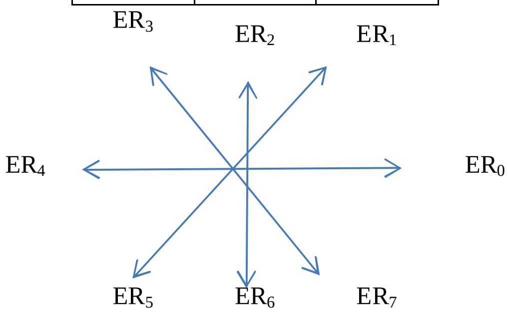
Figure 1: Kirsch edge response masks in eight directions.

65*5	36*5	29*-3
59*5	53*0	20*-3
40*-3	39*-3	41*-3

65*5	36*5	29*5
59*-3	53*0	20*-3
40*-3	39*-3	41*-3

65*-3	36*5	29*5
59*-3	53*0	20*5
40*-3	39*-3	41*-3

65*5	36*-3	29*-3
59*5	53*0	20*-3
40*5	39*-3	41*-3



65*-3	36*-3	29*5
59*-3	53*0	20*5
40*-3	39*-3	41*5

65*-3	36*-3	29*-3
59*5	53*0	20*-3
40*5	39*5	41*-3

65*-3	36*-3	29*-3
59*-3	53*0	20*-3
40*5	39*-5	41*5

65*-3	36*-3	29*-3
59*-3	53*0	20*5
40*-3	39*5	41*5

Figure 2: Directional Edge responses (DE_r) resulting from the convolution of 3x3 image patch and the eight kirsch masks (KM_0-KM_7).

In the next step this paper divides the 3 x 3 micro regions of DE_r in to cross DE_r (CDE_r) and Diagonal DE_r (DDE_r) s. The CDE_r and DDE_r consist of four DE_r i.e., namely {ER_1, ER_3, ER_5, ER_7} and {ER_0, ER_2, ER_4, ER_6} of the 3 x 3 micro region respectively. This paper derived ranks on each of the CDE_r and DDE_r matrices in the following way.

The rank vector is denoted as {R_1, R_2…R_d}, where d represents the number of elements in the set. The ranks can be initiated in ascending or descending order. After assigning ranks to individual elements this paper maps this to their per mutational sequence space (S). And based on the ranks and sequence of ranks a sequence matrix is constructed. The ranks are initially sorted in the ascending order. Then the above set is mapped to a corresponding d-dimensional vector, which will have d! Permutation sequences. The dimension of the sequence matrix will be d x d!, and d represents the number of elements in the rank vector, in our case it is d. Each column or position of the sequence matrix (SM) corresponds to a particular rank vector sequence which is unique. Each column represents one of the possible and unique rank vector sequences. The rank vector ‘V’ will be assigned a sequence corresponding to its column position of the coding book.

The rank vector of CDE_r and DDE_r consists of 4-elements each denoted as $\{R_1, R_2, R_3, R_4\}$. This research assigned ranks in the ascending order that is $R_1 <= R_2 <= R_3 <= R_4$. This paper computes the rank order of CDE_r and DDE_r elements individually and maps this to their permutational sequence space (S). The dimension of the sequence matrix (SM) of CDE_r and DDE_r 4 x 4!. Each column or position of the SM of CDEr and DDE_r corresponds to a particular rank vector sequence which is unique. The rank vector ‘V’ of CDE_r and DDE_r will be assigned a sequence corresponding to its column position of the coding book and this derives CDE_r Sequence (CDE_rS) and DDE_r sequence (DDE_rS). Using these relative sequences of CDE_rS and DDE_rS this paper derived dual Edge response sequence matrix (DE_rSM). The frame work of DE_rSM is shown in Figure.3. The ranks are assigned to Fig 3(a) and the rank associated with each value/code is displayed in Fig. 3(b). The rank vector of figure 3(a) is {3142}, since the ranking starts from top position in a clock wise direction in this paper. The rank vector {3142} corresponds to the column position number 14 of sequence matrix and the sequence number 14 is assigned as sequence code for the Figure. 3(a) of CDE_r. And CDE_r is replaced with CDE_rS code which is 14 in this case.

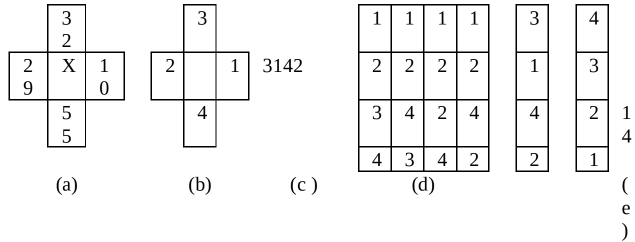


Figure 3: (a) cross matrix (b) allocation of ranks (c) ranks sequence (in clockwise direction) (d) sequence matrix (e) CDE_rS.

This paper derived DE_rSM based on the relative frequency occurrences of CDE_rS and DDE_rS as shown in Figure 4. Initially a 2-dimensional matrix DE_rSM of size d! and d! is created and it is initialized with zero values. The DE_rSM preserves the $DE_r$of cross and diagonal matrices rank sequence spatial information more effectively. The dimensions of DE_rSM will be d! xd!. In our case the size of DE_rSM is 24x24. This paper computed gray level co-occurrence matrix on DE_rSM and this derives DE_rS-CM.

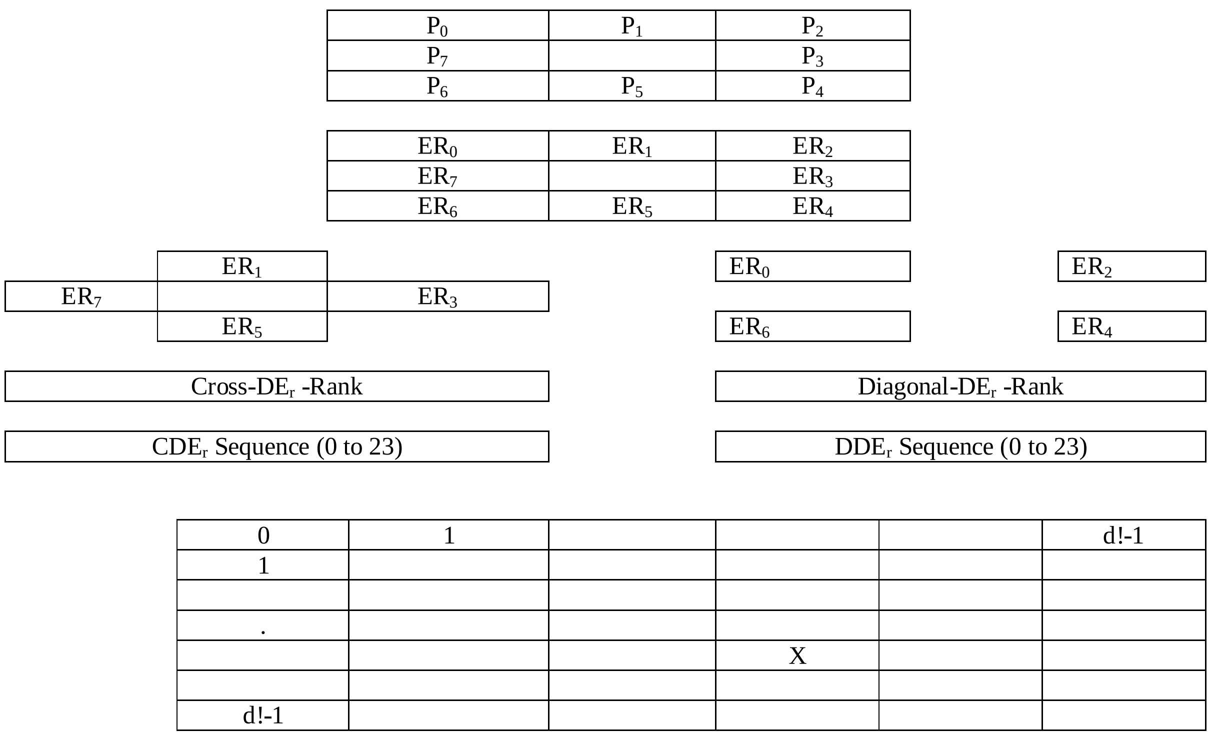


Figure 4: Framework of the proposed DE_rSM.

3. RESULTS AND DISCUSSIONS

This paper computed six GLCM features namely: Contrast, correlation, Entropy, Homogeneity, Inverse Difference Moment (IDM) and Prominence feature, on each rotation angle on the proposed DE_rS-CM. This paper derived DE_rS-CM for two distance values d=1 and 2 and with six degrees of rotations i.e. $\alpha = 0^o, 45^o, 90^o, 135^o, 180^o$ and 225^oon each d value. This results a total of 6x6= 36 features i.e. the feature vector size is 36 on each d value. To analyze the performance of the proposed method in terms of classification accuracy, this paper carried out investigation on most popular and most widely used texture databases namely: MIT Vision Texture database (Vistex) [17], Salzburg Texture database (Stex) [18], Colored Brodatz Texture database (CBT) [19], the USPtex [20], the Outex TC-00013 [21]. The classification accuracies of the proposed method on the above affordable databases are compared with recent state of art local based approaches. The sample images are displayed in the following figures and for the sake of clarity a brief description about the number of classes and images considered per each is given below. There are forty dissimilar color texture image classes with image dimension of 512 x 512 available in Vistex database [17]. This paper partitioned each image into non overlapping images of size 128 x 128. This result a total of 40 classes and 16 images are considered in each class. And it results a total of 640 images. The stex[18] database consists of 476 different images with a resolution of 512 x 512. This research divided each image into 16 non overlapping images of size 128 x 128 and this leads to a total database of 7616 images with 476 classes and 16 images per class. The CBT [19] is an extension of Brodtaz data base with images of dimension 640 x 640 with 112 images. This paper obtained 25 non overlapped images of size 128 x 128 by dividing each image in a non-overlapped manner. The USPtex [20] data base consists of 191 varieties of images with 12 images per class and with a dimension of 191 x 191. This paper considered 191 varieties of images with a resolution of 128 x 128 with 10 images per class and this leads to a database of size 191 x 10=1910. The Outex [21] database consists of sixty eight different classes of images with a dimension of 128 x 128 and twenty images per class. This paper considered all the images of Outex database.

Figure .5: The sample images of Vistex-640.

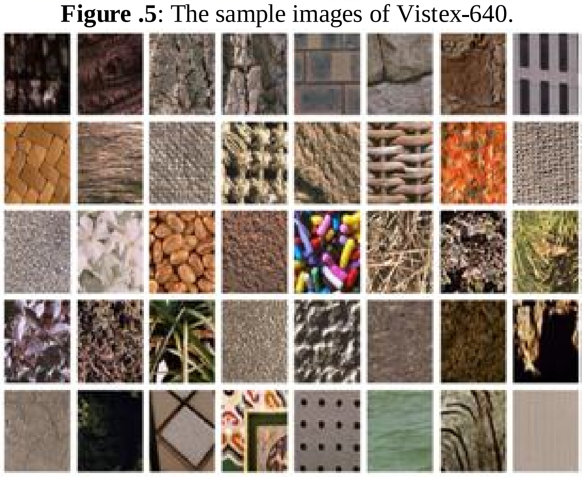


Figure.6: Stex-7616 database sample images

Figure. 7: The sample images of USPtex-2292.

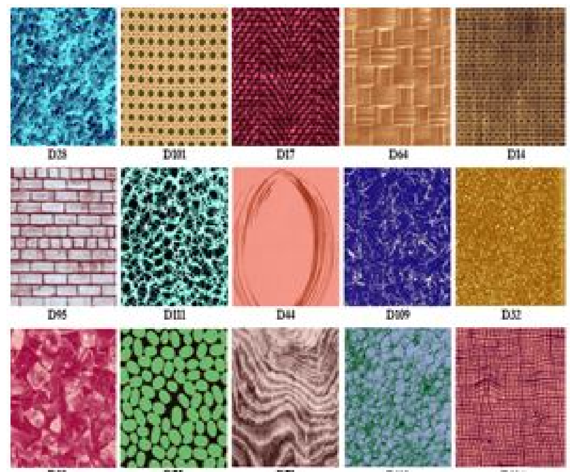


Figure.8: The sample images of CBT-2800.

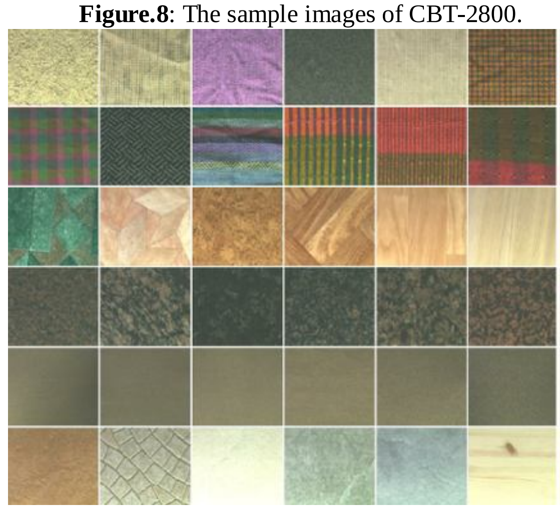


Figure .9: The sample images of Outex-1360.

The feature vector of the proposed descriptor DE_rS-CM is given as input to the multilayer perceptron, naïvebayes, Ibk and J48 classifiers and they have achieved a good classification rate on the above affordable databases and the classification rates are given in table 1 for ‘d’ value =2. In fact classification accuracies are computed for ‘d’ value =1 and 2 and high classification is resulted for ‘d’ value 2.Out of these four classifiers, multilayer perceptron achieved high classification rate followed by Ibk, naïvebayes and J48. The final row of the Table 1 displays the average classification rate on all databases considered for for 'd' value 2. This paper used the classification rate of multilayer perceptron in the remaining part of the paper. The classification rates of the proposed method are compared with other existing methods and classification rates are displayed in table 2 and also shown in Figure 10.

Table 1: classification rates of the proposed DE_rS-CM descriptor with different classifiers for d value 2.

Database	Multilayer Perceptron	Naivebayes	IBK	J48
MIT-VisTex	98.22	88.6	89.76	89.69
Stex	93.63	85.63	87.73	84.61
USPTex	99.72	90.79	91.54	88.51
CBT	98.38	89.61	90.85	87.42
Outex-13	98.98	89.49	89.86	90.07
Average	97.79	88.82	89.95	88.06

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

Database	LBP [22]	LTP [23]	CLBP-SMC[24]	CS-LBP [25]	MCM [26]	MMCM [27]	LMP-CM [28]	Proposed DE_rS-CM
MIT-VisTex	56.49	59.74	87.33	76.89	88.62	88.35	89.62	98.22
Stex	58.32	76.8	91.98	76.44	92.15	90.62	91.92	93.63
USPTex	58.4	78.12	92.4	76.97	93.06	92.2	93.11	99.72
CBT	65.07	69.4	89.74	76.57	90.29	90.06	91.31	98.38
Outex-13	66.37	68.42	91.24	74.47	92.06	91.12	92.31	98.98

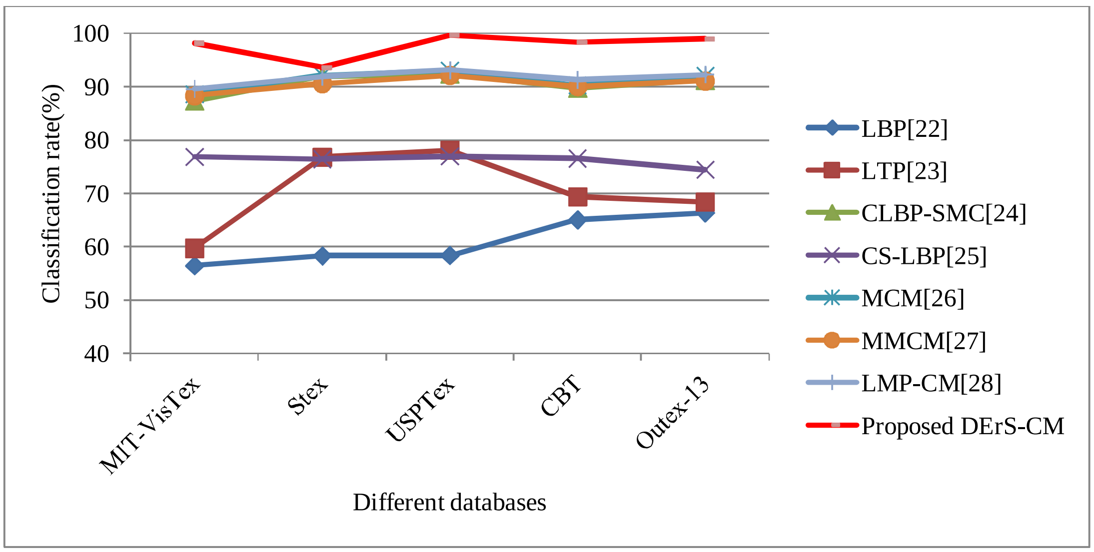


Figure 10: Comparison of proposed method performance with existing methods on different database.

This paper initially compared the classification results among the two existing popular local neighborhood descriptors based on 3x3 neighborhoods. The LBP and its variants LTP, CSLBP-SMC, CS-LBP are derived on 3x3 windows. The local patterns in LBP and LTP are derived by comparing center pixel value with sampling pixels gray level value. The LBP derived binary patterns and LTP derived ternary patterns. The CS-LBP derived binary patterns by comparing the grey level intensity relationships among symmetric sampling pixels over the center pixel. The CS-LBP produces relatively less number of bins when compared to LBP and LTP. The CS-LBP has attained high classification rate when compared to LBP and LTP. The motif based methods derived peano scan motif (PSM) on a 2 x 2 grid based on incremental difference rule from the current scan position. This paper compared the proposed descriptor with the recent motif based methods namely; MCM; MMCM; LMP-CM. The MCM is treated as static, since the initial scanning position is always fixed i.e., the left most pixel position of the 2 x 2 grid and it derives only six different scanning patterns. The MMCM is an improved version of MCM, in which two different PSM are extracted from two different initial positions of the 2 x2 grid. The LMP-CM further improves the MMCM. The motif based descriptors attained high classification rate than LBP, LTP and CS-LBP descriptors due to its compactness. Out of existing motif or PSM descriptors the new variants of motif namely MMCM and LMP-CM exhibited relatively improved classification rate than basic motif descriptors MCM on all the affordable databases. Out of the two recent motif descriptors the LMP-CM has attained relatively a narrow rate (0.2 to 1%) of high classification rate.

The proposed DE_rS-CM attained high classification rate when compared to local descriptors derived on a 3x3 neighborhood i.e. LBP, LTP, CS-LBP and CS-LBP. The proposed DE_rS-CM has exhibited relatively high classification rate than LMP-CM and MMCM and the proposed descriptor attained a 1% of high classification rate than these. Out of the five databases the proposed descriptors attained high classification rate on USPTex, Outex-13 and CBT databases followed by MIT-VisTex and Stex. The proposed descriptors DE_rS-CM attained a high classification rate due to the following integrated operations: derivation of edge responses derived in eight directions and division of this into dual edge response matrices, derivation of rank codes in clock wise direction and finally the derivation of DE_rS-CM. Thus the derived feature vector represents the edge responses with rank sequences. The GLCM features derived on DE_rS-CM represents the significant, precise and good amount of texture information than the frequency occurrence of co-occurrence pairs of dynamic motif indexes. That's why the DE_rS-CM attained high classification rate.

The main contribution of this paper is given below:

1. The edge responses derived in eight directions derives more discriminative information than intensity based methods.
2. The new descriptor called DE_rS-CM is more useful to understand local texture information than basic LBP and its variants and this descriptor conveys more valuable information regarding natural textures.
3. The division of edge response neighborhood into dual edge response matrices made the proposed descriptor as more compact and precise.
4. The derivation of rank codes in clock wise direction and derivation of unique sequence code for the dual matrices and derivation of DE_rS-CM provides a systematic and comprehensive approach in extraction of texture features.
5. The extensive experimental analysis on five natural databases and systematic and comprehensive comparison of classification rates between the proposed and the existing descriptors is the other significance by the proposed framework.

4. CONCLUSION

Most of the state-of-art methods come with limitations and weakness. In order to overcome this weakness and disadvantages and to keep simplicity, effectiveness of the texture classification framework, this paper extracted eight directional edge responses using kirsch mask on sampling points of 3x3 neighborhoods. This results the derivation of more discriminative information on local neighborhood in the form of directional edge responses than intensity information derived by most of the state-art-methods. The division of directional edge response neighborhood into dual matrix and derivation of rank sequence in the clock wise direction derives more significant information. The extraction of unique sequence code from each of the dual matrixes and the derivation of DE_rS-CM based on the relative frequency of the sequence codes of the cross and diagonal DE_r extracts the spatial relationships among the sequence codes of the both matrices. Thus the proposed DE_rS-CM is computationally simple and efficient texture descriptor for texture classification. The dimensions of the DE_rS-CM will be 24x24. The main advantage of the proposed descriptor over the existing ones is that, it combines the edge responses and derives rank sequence codes, with GLCM features of texture, in compact way and this provides more detailed and discriminative local information.

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