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Texture Classification using Texton Co-Occurrence Matrix Derived from Texture Orientation

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Abstract*— The present paper derived a new co-occurrence matrix based on textons and texture orientation for rotation invariant texture classification of 2D images. The new co-occurrence matrix is called as Texton and Texture Orientation Co-occurrence Matrix (T&TO-CM). The Co-occurrence Matrix (CM) characterizes the relationship between the values of neighboring pixels, while the histogram based techniques have high indexing performance. If the CM is used to represent image features directly, then the dimension will be high and the performance is decreased. On the other hand, if histogram is used to represent image features, the spatial information will be lost. Texture Classification based on T&TO-CM, integrates color, texture and edge features of an image. The proposed T&TO-CM is used to describe the spatial correlation of textons and texture orientation for texture classification. T&TO-CM can capture the spatial distribution of edges, and it is an efficient texture descriptor for images with heavy textural presence. The proposed method is computationally attractive as it computes different features with limited number of selected pixels. The experimental results indicate the efficacy of the present method over the various other methods.

***Index Terms*— Co-occurrence Matrix;Texton, Texture Orientation**

I. INTRODUCTION

Texture analysis plays an important role in many tasks, such as object recognition, remote sensing, medical imaging and content-based image retrieval. Texture is described as a pattern with some kind of regularity. The approaches of mathematical modeling are grouped into structural, statistical and signal theoretic methods [1]. Structural methods are based on a more or less deterministic arrangement of textural elements (texels). They are mainly used in industrial quality control, where artificial patterns are regular and differences between model and reality indicate failures [2,3]. Statistical methods define textures as stochastic processes and characterize them by a few statistical features. Most relevant statistical approaches are Co-occurrence matrices [4], Markov random fields [5] and autocorrelation methods [6]. Signal theoretic approaches focus on periodic pattern resulting in peaks in the spatial frequency domain, e.g. Gabor filtering [7,8] and wavelet decomposition [9]. Most of these algorithms make an implicit assumption that all images are captured under the same orientation. In many practical applications this assumption is not valid. Therefore rotation and scale invariant texture classification becomes necessary in such applications.

Beside texture, color is an important issue not only in human vision but in digital image processing where its impact is still rising. In contrast to intensity, coded as scalar gray values, color is a vectorial feature assigned to each pixel in a color image. The mathematical difference between scalars and vectors for gray and color values, respectively, demands a careful transfer of methods from the gray-scale to the color domain. Although the use of color for texture analysis is shown to be advantageous, the integration of color and texture is still exceptional.

The main contributions in this paper are (i) novel rotation invariant features for texture classification, (ii) performance of these features for the choice of, texture orientation from sobel and canny edge detectors, Texton co-occurrence matrix.

This paper is organized as follows. In Section 2, novel rotation invariant texture features are proposed. Section 3 discusses results and discussions. Conclusion and discussion is given in Section 4.

II. ROTATIONAL INVARIANT TEXTURE CLASSIFICATION BASED ON T&TO-CM

The proposed rotation invariant texture classification method consists of three stages as shown in Figure 1. In the first stage, texton image is evaluated and from this a Texton Matrix (TM) of the image is obtained. In the second stage, gradient map is obtained with magnitude and orientation and it results a Texture Orientation Matrix (TOM) of the image. In the third stage, the proposed T&TO-CM of the image is evaluated by using TM and TOM. Texture features are evaluated on the new T&TO-CM for classification of textures.

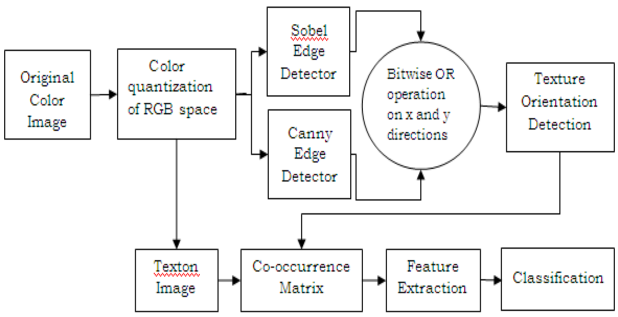

Figure 1. Rotational invariant texture classification based on T&TO-CM

During the course of feature extraction, the original images are quantized into 128 colors of RGB color space and the color gradient is computed from the RGB color space and then the statistical information of textons is calculated to describe image features.

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- ***Color Quantization of 7-bit Binary Code***

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In order to extract gray level features from color information, the proposed T&TO-CM utilized the RGB color space which quantizes the color space into 7-bins to obtain 128 gray levels. The index matrix of 128 color image is denoted as C(x, y). The RGB quantization process is done by using 7-bit binary code of 128 colors as given in Eqn.(1).

$$C(x,y)= 16*I(R)+2*I(G)+I(B) \quad (1)$$

where

$$I(R)= 0,\ 0\leq R\leq 16,\quad I(R)= i,\ ((16*i)+1) \leq R \leq (16*(i+1)) \quad i = [1, 2, \ldots,7] \quad (2)$$

$$I(G)= 0,\ 0\leq G\leq 16,\quad I(G)= i,\ ((16*i)+1) \leq G \leq (16*(i+1)) \quad i = [1, 2,\ldots,6] \quad (3)$$

$$I(B)= 0,\ 0\leq B\leq 32,\quad I(B)= i,\ ((32*i)+1) \leq B \leq (32*(i+1)) \quad i =[1, 2, 3] \quad (4)$$

Therefore, each value of C(x, y) is a 7 bit binary code ranging from 0 to 127.

- ***Texton Detection***

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Various algorithms are proposed by many researchers to extract color, texture and shape features. Color is the most distinguishing important and dominant visual feature. That's why color histogram techniques remain popular in the literature. The main drawback of this is, it lacks spatial information. Texture patterns can provide significant and abundance of texture and shape information [10]. One of the features proposed by Julesz [11] called texton, represents the various patterns of image which is useful in texture analysis. Textons [12] are considered as texture primitives which are located with certain placement rules. Textons show a close relationship with image features and local distribution. The textons are defined as a set of blobs or emergent patterns sharing a common property all over the image [11, 12].

The different textons may form various image features. If the textons in the image are small and the tonal difference between neighbouring textons is large, a fine texture may result. If the textons are larger and concise of several pixels, a coarse texture may result. If the textons in image are large and consists of few texton categories, an obvious shape may result. If the textons are greatly expanded in one orientation, pre-attentive discrimination is somewhat reduced. If elongated elements are not jittered in orientation, the texton gradients at the texture boundaries are increased. To address this, the proposed TM utilized four texton types on a 2×2 grid as shown in Figure 2. In Figure 2, the four pixels of a 2×2 grid are denoted as V_1, V_2, V_3 and V_4. If two pixels are highlighted in gray color of same value then the grid will form a texton. The four texton types denoted as T_1, T_2, T_3 and T_4 respectively are shown in Figure 2. The construction mechanism of texton matrix for the proposed method is illustrated in Figure 3. Here the texton image itself is called as TM.

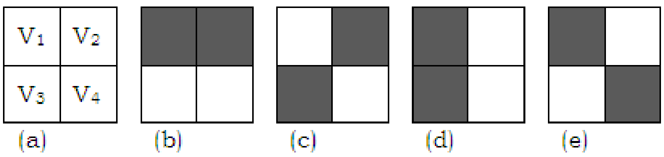

Figure 2. Four special types of textons a) 2×2 grid b)T_1 c) T_2 d) T_3 and e) T_4

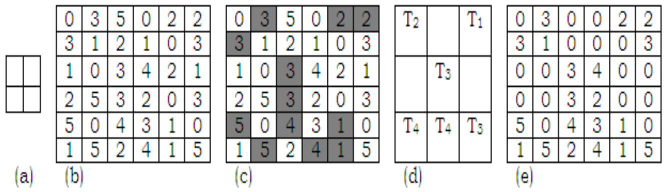

Figure 3. Illustration of the Texton detection process: (a) 2×2 grid (b) Original image (c) & (d) Texton location and texton types (e) Texton Matrix (TM)

Recently Texton Co-occurrence matrix (TCM) is proposed in the literature [13] for higher retrieval and precession rate. TCM is defined to be the distribution of co-occurring textons with a given offset over the texton index image. The disadvantage of TCM is that the orientations are performed on texton image only.

The TCM fails in representing or detecting the saltation of color, color edge stripe and acuity problems of an image. More over TCM is a computationally expensive procedure. To overcome this, the present paper considered only Texton Matrix (TM), which is directly obtained from a texton image. To extract precise texture features, the present study computes texture edge orientation separately. This overcomes the disadvantages of TCM.

- ***Texture Orientation Detection***

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Texture orientation analysis plays an important role in computer vision and pattern recognition. For instance, orientation is used in pre-attentive vision to characterize textons. Texture orientation can also be used to estimate the shape of the textured images. The orientation map in an image represents the object boundaries and texture structures, and provides most of the semantic information of the image. The image edge has a close relationship with contour and texture pattern. It can provide abundance of texture information and shape information. Based on this assumption, the present paper used a computationally efficient algorithm for texture orientation.

To achieve this, Sobel and Canny edge detection is applied on the image to segment the enhanced borders from the background image. The Sobel edge detector applies Sobel approximation to the derivative of the image and detects edges. The canny edge detector finds edges by looking for local maximum of the gradient of unprocessed input image. In each edge detection algorithm, the gradient is calculated. A gradient map g(x,y) can be obtained with the gradient magnitude and orientation defined in Eqn.(5), and the output is a binary image, where 1 represents edges and 0 represents background. The outputs of Sobel and canny edge operators are logically oRed together by horizontally and vertically to produce a new image as shown in Figure 1.

$$|g(x,y)| = \sqrt{G_x^2 + G_y^2} \quad \text{and} \quad \theta = \arctan\left(g_y/g_x\right. \quad (5)$$

There are two masks associated with the Sobel and canny filters: one mask corresponds to the gradients in the X-direction and the other to the gradients in the Y-direction. The response function for the Sobel and canny filter are given Eqs.(6) &(7):

$$G_x = |(R_{sx}|R_{cx})| \quad (6)$$

$$G_y = |(R_{sy}|R_{cy})| \quad (7)$$

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where R_{sx}, R_{sy}, R_{cx} and R_{cy} are given in Eqs.(8)-(11):

$$R_{sx} = m_1^1 I_1 + m_2^1 I_2 + m_3^1 I_3 + \cdots \quad (8)$$

$$R_{sy} = m_1^2 I_1 + m_2^2 I_2 + m_3^2 I_3 + \cdots \quad (9)$$

$$R_{cx} = n_1^1 I_1 + n_2^1 I_2 + n_3^1 I_3 + \cdots \quad (10)$$

$$R_{cy} = n_1^2 I_1 + n_2^2 I_2 + n_3^2 I_3 + \cdots \quad (11)$$

where m_i^1, m_i^2 corresponds to the first and second mask of sobel operator and n_i^1, n_i^2 are canny operators.

The texture orientation is computed based on the above equations. Then texture orientation of each pixel is quantized into 18 orientations with 10^0 as the step length. From this texture orientation matrix is formed. The proposed TOM can detect the saltation of color, color edge stripe and acuity problems of an image which is not possible by TCM.

- ***Derivation of T&TO-CM from TM and TOM***

One of the powerful visual cues about the contents of an image is the orientation. Strong orientation usually indicates a definite pattern. The natural images show various contents which may have some common fundamental elements. The different combinations and spatial distributions of those basic elements of a texture is not possible to represent using textons completely. That's why the present paper represented orientations separately by Texture orientation Matrix (TOM) and spatial distribution with patterns of texton by TM. By combining TM&TOM based on co-occurrence method, the present paper derived T&TO-CM in the following way.

Let the values of a texton image (TM) denoted as w {0, 1,…,W-1} as shown in Figure 4(a). Denote P1=(x1,y1) and P2=(x2,y2) as the two neighboring pixels, and their values are T(P1)=w1 and T(P2)=w2 as shown in Figure 4(b). In the texture orientation image θ(x,y), the angles at P1 and P2 are denoted by θ(P1)=v1 and θ(P2)=v2. In texton image TM(Pi,Pj) and the two neighboring pixels may have the same value with different texture orientations. In the same way, in texture orientation image TOM(Pi,Pj), the two neighboring pixels may have the same value with different texture orientations. Based on this, T&TO-CM with different orientations 0^0, 45^0, 90^0, and 135^0 are formed as shown in Figure 4(c)-(f) respectively.

The co-occurring number of two values v1 and v2 are denoted by N, and the co-occurring number of two values w1 and w2 are denoted by $\overline{N}$. The distance between two neighboring pixels is denoted by D and the T&TO-CM is defined by Eqs.(12)&(13) as follows:

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$$H(T(P_1)) = \begin{cases} N\{\theta(P_1) = v_1 \wedge \theta(P_2) = v_2 \| P_1 - P_2 = D\} \\ \text{where } \theta(P_1) = \theta(P_2) = v_1 = v_2 \end{cases} \quad (12)$$

$$H(\theta(P_1)) = \begin{cases} \overline{N}\{\theta(P_1) = w_1 \wedge \theta(P_2) = w_2 \| P_1 - P_2 = D\} \\ \text{where } \theta(P_1) = \theta(P_2) = w_1 = w_2 \end{cases} \quad (13)$$

The Figure 4 illustrates the above definitions of a T&TO-CM (d=1, θ= 0^0). A problem with the proposed T&TO-CM is that, a majority of the cells in the matrix will be zero, which implies the behavior of a sparse matrix. The sparse matrix requires excessive computation to generate the co-occurrence texture features. To overcome the problems of sparse matrix and high dimensionality Statistical Dimension Reduction Technique (SDRT) is used on the derived T&TOM-CM. Reduction of sparse matrix, stores only the nonzero elements of the matrix, together with their index. This represents a way to obtain similar or even better classification accuracy with a reduced number of texture elements. The reduction of sparse matrix is shown in Figure 5.

0	3	0	0	2	2
3	1	0	0	0	3
0	0	3	4	0	0
0	0	3	2	0	0
5	0	4	3	1	0
1	5	2	4	1	5

(a)

14	14	12	12	7	7
4	2	14	14	5	5
3	4	6	6	12	10
4	3	6	7	16	14
4	5	12	15	2	1
1	4	11	12	2	16

(b)

0°	0	1	2	3	4	5
0	2	0	2	0	0	0
1	0	0	0	0	0	0
2	0	0	1	0	0	0
3	0	0	0	0	1	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0

(c)

45°	0	1	2	3	4	5
0	1	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	1	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0

(d)

90°	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	1	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	1	0	0
4	0	0	0	0	0	0
5	1	0	0	0	0	0

(e)

135°	0	1	2	3	4	5
0	1	0	0	2	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	1	0
5	0	0	0	0	0	1

(f)

Figure 4: a) Texton matrix (b) Texture orientation matrix (c) Fig.4:(c), (d), (e)and (f) represents the number of occurrences on T&TO of 0^0, 45^0, 90^0 and 135^0.

0°	0	1	2	3	4	5
0	2	0	2	0	0	0
1	0	0	0	0	0	0
2	0	0	1	0	0	0
3	0	0	0	0	1	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0

(a)

A	2	2	1	1	values
i	0	0	2	3	rows
j	0	2	2	4	columns
	0	1	2	3	

Co-ordinate Format

(b)

Figure 5. a) Co-occurrence matrix b) Reduction of sparse matrix

where Fig.5(a) is the sample co-occurrence matrix and Fig.5(b) is the T&TOM-CM after applying SDRT, where row-1 indicates co-occurrence matrix values, row-2 and row-3 indicate the indexes of these values.

Co-occurrence matrix can measure the texture of the image because co-occurrence matrices are typically large and sparse. The various metrics of the matrix are often considered to get a more useful set of features. Classification is performed with the k-NN classifier.

III. RESULTS AND DISCUSSIONS

The proposed method is experimented with Vistex and Google color image databases, of size 512×512 as shown in Fig.6 and Fig.7 respectively. Dataset-1 and Dataset-2 contains 50 original color texture images each. Every texture image is subdivided into 4 sub images of non-overlapped image regions of size (256×256), 16 (128×128) and 64 (64×64). This results into a total of 4200 (50×84) sub image regions. The classification is done for all 84 (4+16+64) sub image regions derived from each texture image in Dataset-1 and Dataset-2.

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The proposed T&TO-CM combines the features of first and second order statistics into an entity for texton analysis. The first order statistical features considered in the present approach are skewness and kurtosis are used. The second order statistical features considered are energy, entropy, contrast, local homogeneity, correlation, cluster shade and cluster prominence calculated. In order to improve the classification gain, the proposed T&TO-CM combines the features of first and second order statistics, instead of using them separately. The combination of all the feature vectors F_1 and F_2 are named as feature vector F_3. Feature set leads to representation of the training and testing images. The absolute difference of the feature vector values of the query image and database images are also calculated. After that, inorder to identify the relevant images, fixed threshold, *K-NN* classifier is used to measure the similarity between query image and the database images. In case of fixed threshold, the threshold values are computed for different query images. The best threshold value is chosen as the threshold of that particular texture feature. The Euclidean distance between these FVs helps in classifying the images into correct clusters.

The results from two datasets are obtained in Table 1 & 2 which shows the average classification rates of the proposed T&TO-CM method.

IV. COMPARISON WITH OTHER METHOD

The proposed T&TO-CM is compared with Steerable Pyramid Decomposition [15] and Gabor Wavelets [14] methods. Mean classification rates for the proposed T&TO-CM and the other existing methods using K-NN classifier is shown in Table 3 which clearly indicates that the proposed T&TO-CM outperforms the other existing methods with different scales(S) and orientations (k). Fig.8 shows the comparison chart of the proposed T&TO-CM with the other existing methods of Table 3.

The proposed T&TO-CM method is also compared with the proposed ILCLBP-T, Logical transform [16], SGLDM [17], Wavelet algorithm [18], Laws [19], and Gabor algorithms [20]. The results are shown in Table 4 which clearly indicates that the proposed T&TO-CM method outperforms the existing methods. Fig.9 shows the comparison chart of the proposed T&TO-CM with the other existing methods of Table 4.

To have a more clarification between the proposed methods T&TO-CM and ILCLBP-T, the average correct classification rates of all textures like bark, brick, leaves, fabric and stone of VisTex database and bark, granite, leaves, marble and stone textures of Google database are observed using the feature vectors F3 and listed in Table 5 which clearly indicates that the ILCLBP-T shows a little bit higher classification rate than the proposed T&TO-CM. The same is also shown in terms of bar-graph in Fig.10. However, the proposed T&TO-CM is more suitable with orientations. The proposed method is experimented with Vistex and Google color image databases.

Table 1: VisTex Database: (%) mean classification rate of each group of textures

Sl.No	Images	%
1	Bark.0001	94.62
2	Bark.0002	90.43
3	Bark.0003	90.81
4	Bark.0004	92.86
5	Bark.0005	96.43
6	Bark.0006	98.81
7	Bark.0007	95.24
8	Bark.0008	95.25
9	Bark.0009	98.35
10	Bark.0010	97.62
	Average	95.04

Sl.No	Images	%
1	Brick.0000	96.43
2	Brick.0001	92.86
3	Brick.0002	91.67
4	Brick.0003	95.24
5	Brick.0004	98.75
6	Brick.0005	97.81
7	Brick.0006	91.86
8	Brick.0007	94.43
9	Brick.0008	94.05
10	Brick.0009	91.24
	Average	94.43

Sl.No	Images	%
1	Leaves.0001	93.43
2	Leaves.0002	92.86
3	Leaves.0003	92.67
4	Leaves.0004	92.86
5	Leaves.0005	91.67
6	Leaves.0006	95.67
7	Leaves.0007	95.24
8	Leaves.0008	91.67
9	Leaves.0009	97.62
10	Leaves.0010	97.62
	Average	94.13

Sl.No	Images	%
1	Fabric.0001	96.81
2	Fabric.0002	95.24
3	Fabric.0003	97.56
4	Fabric.0004	97.45
5	Fabric.0005	97.62
6	Fabric.0006	92.81
7	Fabric.0007	98.81
8	Fabric.0008	95.45
9	Fabric.0009	94.56
10	Fabric.0010	90.48
	Average	95.68

Sl.No	Images	%
1	Stone.0001	93.2
2	Stone.0002	98.81
3	Stone.0003	92.86
4	Stone.0004	94.05
5	Stone.0005	94.24
6	Stone.0006	91.67
7	Stone.0007	98.81
8	Stone.0008	93.25
9	Stone.0009	93.45
10	Stone.0010	93.81
	Average	94.42

Table 2: Google Database: (%) mean classification rate of each group of textures

Sl.No	Images	%
1	Bark.0001	91.67
2	Bark.0002	95.24
3	Bark.0003	98.75
4	Bark.0004	97.62
5	Bark.0005	92.81
6	Bark.0006	98.81
7	Bark.0007	95.45
8	Bark.0008	92.86
9	Bark.0009	91.67
10	Bark.0010	97.62
	Average	95.25

Sl.No	Images	%
1	Granite.0001	92.86
2	Granite.0002	92.67
3	Granite.0003	92.86
4	Granite.0004	91.67
5	Granite.0005	95.67
6	Granite.0006	95.24
7	Granite.0007	98.81
8	Granite.0008	95.45
9	Granite.0009	94.56
10	Granite.0010	91.24
	Average	94.10

Sl.No	Images	%
1	Leaves.0001	98.81
2	Leaves.0002	92.86
3	Leaves.0003	94.05
4	Leaves.0004	94.24
5	Leaves.0005	91.67
6	Leaves.0006	98.81
7	Leaves.0007	93.25
8	Leaves.0008	91.86
9	Leaves.0009	94.43
10	Leaves.0010	94.05
	Average	94.40

Sl.No	Images	%
1	Marble.0001	93.45
2	Marble.0002	98.81
3	Marble.0003	97.45
4	Marble.0004	97.62
5	Marble.0005	92.81
6	Marble.0006	98.81
7	Marble.0007	93.25
8	Marble.0008	93.45
9	Marble.0009	93.81
10	Marble.0010	94.24
	Average	95.37

Sl.No	Images	%
1	Stone.0001	97.45
2	Stone.0002	97.62
3	Stone.0003	92.81
4	Stone.0004	98.81
5	Stone.0005	94.56
6	Stone.0006	90.48
7	Stone.0007	98.81
8	Stone.0008	92.86
9	Stone.0009	91.67
10	Stone.0010	95.67
	Average	95.07

Table 3: Mean classification rates for the two different texture image datasets using k-NN classifier

Image Dataset	Feature vectors with different scales(S) and orientations (k)	Steerable Pyramid Decomposition	Gabor Wavelets	Proposed Method T&TO-CM
Brodatz	(s=2;k=4,5,6,7,8)	93.19%	93.19%	94.50%
VisTex	(s=2;k=4,5,6,7,8)	92.3%	93.56%	94.58%
Google	(s=2;k=4,5,6,7,8)	85.30%	91.29%	95.10%

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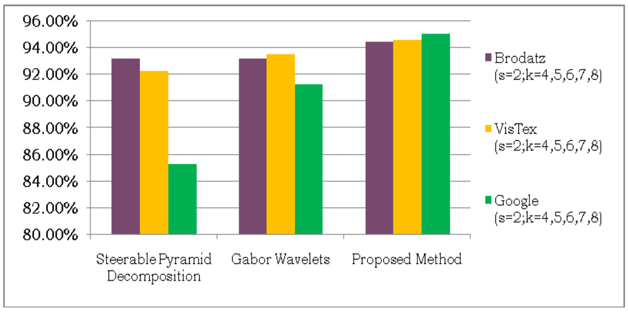

Figure 8. Classification accuracy comparison of K-NN classifier obtained in Brodatz dataset using (S = 2) scale with (K = 4, 5, 6, 7, 8) orientations for Gabor wavelets, conventional steerable pyramid decomposition and proposed method

Table 4: Comparison of other methods with the proposed T&TO-CM method

Texture Name	% Correct Classification (PCC) results						
Brodatz Textures with Texture ID's	Logical Transform	SGLDM	Wavelet Algorithm	Laws	Gabor Algorithm	Proposed Methods	
						ILCLBP-T	T&TO-CM
D94	93	67	63	52	62	93.75	94.25
D28	96	84	62	84	70	96.88	97.5
D90	88	64	62	47	67	97.5	96.5
D105	89	59	53	46	55	95.67	96.25
D28-1	99	67	65	77	63	89.13	93.5
D103	90	77	58	58	59	92.86	94.25
Average % of Classification	93	70	61	61	63	94.3	95.5

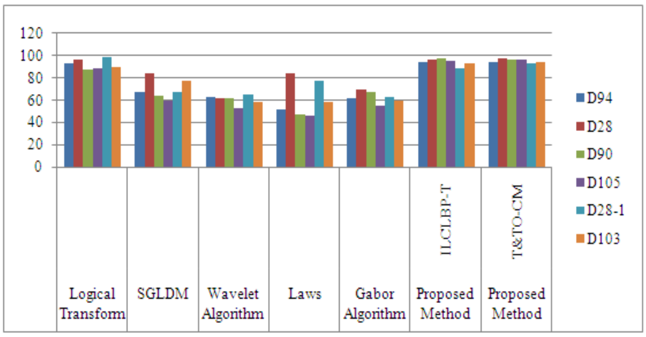

Figure 9. The comparison chart of the proposed T&TO-CM with the other existing methods of Table 4

Table 5: Comparison of ILCLBP-T with the proposed T&TO-CM method

VisTex database			Google database		
Texture Group	ILCLBP-T	T&TO-CM	Texture Group	ILCLBP-T	T&TO-CM
Bark	94.46	95.04	Bark	95.43	95.25
Brick	95.97	94.43	Granite	97.97	94.1
Leaves	94.78	94.13	Leaves	94.95	94.4
Fabric	95.81	95.68	Marble	96.42	95.37
Stone	95.74	94.42	Stone	96.77	95.07
Average	95.35	94.74	Average	96.31	94.84

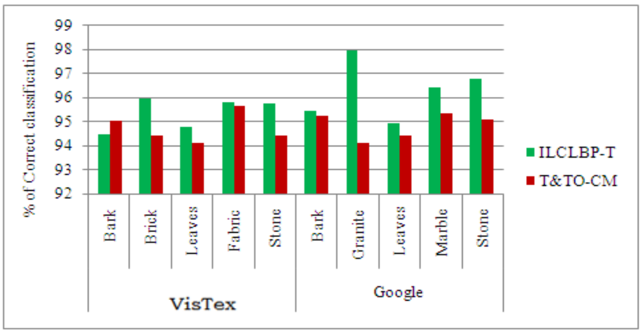

Figure 10. Bar graph--Comparison of proposed T&TO-CM with ILCLBP-T

V. CONCLUSIONS

The present paper derived a new co-occurrence matrix called as Texton and Texture Orientation Co-occurrence Matrix (T&TO-CM) for rotation invariant texture classification. Julesz [12] proposed texton which represents the patterns of image which is useful in texture analysis. The disadvantage of TCM is that, the orientations are performed on texton image only and it is computationally expensive. To overcome this problem, the present paper considered only the Texton Matrix (TM), which is directly obtained from a texton image and to extract a precise texture features, the present study computed texture edge orientation separately.

The proposed T&TO-CM is used to describe the spatial correlation of textons and texture orientation which captures the spatial distribution of edges. The orientation map of TOM represents the object boundaries and texture structures and provides most of the semantic information of the image. A problem with the proposed T&TO-CM is that a majority of the cells in the matrix will be zero due to sparse data problem. The sparse requires excessive computation to generate the co-occurrence texture features. To overcome these problems, Statistical Dimension Reduction Technique (SDRT) is used on TM&TOM. This gives better classification accuracy with a reduced number of texture elements. The experimental results clearly indicate the efficacy of the proposed T&TO-CM over the various existing methods.

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The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression, “One of us (R. B. G.) thanks . . .” Instead, try “R. B. G. thanks”. Put sponsor acknowledgments in the unnum-bered footnote on the first page.

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