Texture discrimination by structuring elements using shape index

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Abstract - ***This paper extends the concept of Binary Cross Diagonal Shape Descriptor Texture Matrix (BCDSDTM) by using structuring elements known as textons with the help of two separate texton images. The first one is Texton based Cross Shape Descriptor Index (TCSDI) image and second one is Texton based Diagonal Shape Descriptor Index (TDSDI) image. The proposed images are formed based on the shape descriptors on Cross Texture Unit Element (CTUE) and Diogonal Texture Unit Element (DTUE). By deriving Grey Level Co-Occurrence Matrix (GLCM) features on TCSDI and TDSDI, TCSDI Co-occurrence Matrix (TCSDI-CM) and TDSDI Co-occurrence Matrix (TDSDI-CM) are formed which are used for effective discrimination of the texture.***

Key Words: *Textons, GLCM features, Shape Descriptor, Shape Index, Co-occurrence Matrix.*

1. INTRODUCTION

The basic idea of textons was first introduced by Julesz as the elements of texture perception [1]. Textons refer to fundamental micro-structures in generic natural images and the basic elements in early visual perception. In practice, the study of textons has important implications on a series of problems[6,8]. Firstly, decomposing an image into its constituent components reduces information redundancy and thus leads to better image coding algorithms [16,17]. Secondly, the decomposed image representation often has much reduced dimensions and less dependence between variables therefore it facilitates image modelings which are necessary for image segmentation and recognition [18,19]. Thirdly, in biologic vision the micro-structures in natural images provide an ecologic cue for understanding the functions of neurons in the early stage of biologic vision system [20]. The main features of textons are that a significant relationship can be obtained by textons using attributes of images like spatial allocation, orientation of shape, local allocation, [14,15] etc.

The present paper extends the concept of Binary Cross Diagonal Shape Descriptor Texture Matrix (BCDSDTM) [4] by deriving two separate texton images. First one, Texton Based Cross Shape Descriptor Index (TCSDI) image and second one, Texton based Diagonal Shape Descriptor Index (TDSDI) image. The proposed TCSDI and TDSDI are formed based on the shape descriptors on Cross Texture Unit Elements (CTUE) and Diagonal Texture Unit Elements (DTUE) [5]. By the derivation of GLCM features [10,11] on TCSDI and TDSDI, TCSDI Co-occurrence Matrix (TCSDI-CM) and TDSDI Co-occurrence Matrix (TDSDI-CM) [7,9] are formed and used for effective discrimination [4].

2. FORMATION OF TEXTON IMAGE

One of the important primitive that is situated and described by certain placement rule is the texton [2]. The textons are a set of evolving patterns to form various image features [12,13] sharing a universal property of the image. The present paper considers texton pattern with 2×2 grid where the pixels are referred by P_1, P_2, P_3 and P_4. This 2×2 texton patterns are represented by five texton patterns (T_1, T_2, T_3, T_4 and T_5) where three or more pixels having same intensity levels as shown in Fig 1.

The proposed method derived textons on each 2×2 grid of input image by shifting one column to the right until it reaches the last column. similarly, one row down until it reaches the last row of the entire image for deriving textons. The process of finding textons will be completed when it reaches the last row and the last column. Whenever a desired texton is found on a 2 × 2 grid of the image the grey levels of texton pixels remains unchanged and the pixels which are not part of any textons will be made as zeros. As an example the entire process of texton formation on 4 × 4 image is shown in Fig 2.

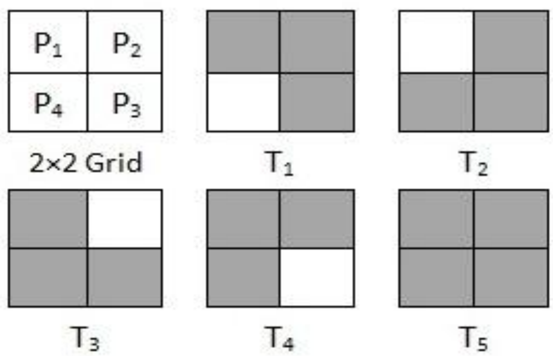


Fig -1: 2×2 grid textons

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

(a) Grey image

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

(b)Texton detection

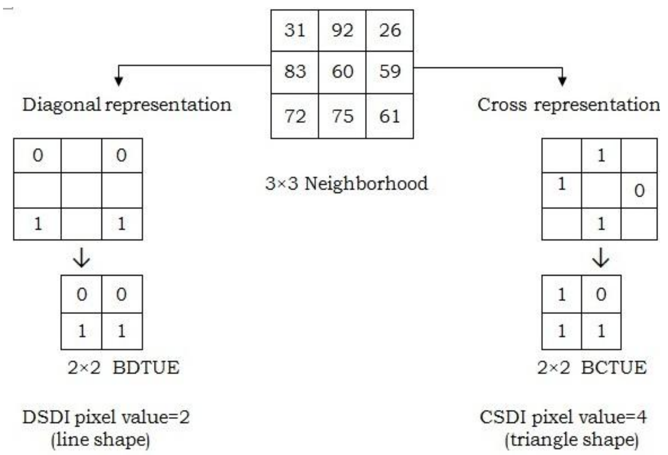
3	0	1	1
3	3	0	1
0	5	5	0
0	5	5	0

(c) Formation of Texton image

Fig -2: Texton image formation process: (a) Grey level image (b) Texton detection (c)Texton image

3. TEXTON BASED CROSS AND DIAGONAL SHAPE INDEXED IMAGES

In the present paper the Texture Unit Element (TUE) of a 3×3 neighborhood are divided into two 2×2 separate elements of 4 pixels named as Binary Cross Texture Unit Elements (BCTUE) and Binary Diagonal Texture Unit Elements (BDTUE). For these elements shape descriptor indexes(SDI) ranging from 0 to 5 are assigned. The present method derived two separate texture images called Cross Shape Descriptor Index (CSDI) image and Diagonal Shape Descriptor Index (DSDI) image derived from shape descriptor indexes of BCTUE and BDTUE respectively. The two separate CSDI and DSDI texture images are formed replacing the center pixel of the 3×3 neighborhood with shape descriptor index of BCTUE and BDTUE as shown in Fig 3. This process is repeated for entire image in an overlapped manner.



. **Fig -3**: Formation of Shape index on BDTUE and BCTUE

(a) Elephant b) DSDI image of (a) c) CSDI image of (a)

. **Fig -4**: Different shape descriptor images of an elephant

a) Car image b) DSDI image of (a) c) CSDI image of (a)

Fig -5: Different shape descriptor images of a car

The CSDI and DSDI of Elephant and Car images are obtained with good border images as shown in Fig 4 and Fig 5 respectively. TCSDI and TDSDI images are derived by evaluating textons on CSDI and DSDI images respectively. The grey level of CSDI and DSDI images range from 0 to 5, because the rotational invariant shape descriptor indexes of the 2×2 grid ranges from 0 to 5 only. Finally, GLCM features i.e contrast, correlation, energy and homogeneity are evaluated separately on TCSDI and TDSDI and that leads to TCSDI Co-occurrence Matrix (TCSDI-CM) and TDSDI Co-occurrence Matrix (TDSDI-CM).

4. RESULTS AND DISCUSSION

The GLCM features of TCSDI-CM and TDSDI-CM are derived on Car and Elephant images collected from Google & FGNET databases shown in Fig 6 and Fig 7. The average of GLCM features are evaluated with 0^o, 45^o, 90^o & 135^o with a distance of 1 on TCSDI-CM & TDSDI-CM image textures and the results are tabulated. The Tables 1, Table 2 indicates the average of GLCM feature values for Car and Elephant images of TCSDI-CM and TDSDI-CM texture images respectively. Algorithms 1 and 2 are derived based on the GLCM feature vector values for TCSDI-CM and TDSDI-CM texture images respectively to obtain effective discrimination rates. Table 3 and Chart 1 represent discrimination rates of proposed methods.

Fig -6: Images of Car textures

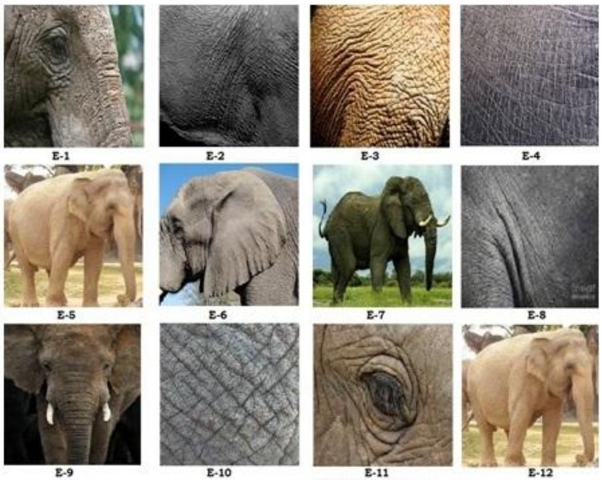


Fig -7: Images of Elephant textures

Table -1: GLCM values with 0^0, 45^0, 90^0, 135^0 for TCSDI-CM of Car and Elephant images change values

Texture	Car				Elephant			
	Contrast	Correlation	Energy	Homogeneity	Contrast	Correlation	Energy	Homogeneity
1	4.67	0.51	0.28	0.77	5.75	0.33	0.12	0.65
2	5.04	0.49	0.24	0.75	5.59	0.30	0.13	0.65
3	4.61	0.53	0.26	0.77	4.72	0.32	0.15	0.67
4	4.32	0.53	0.28	0.78	4.80	0.33	0.14	0.67
5	5.28	0.46	0.23	0.74	4.66	0.32	0.14	0.66
6	5.57	0.46	0.19	0.72	4.86	0.31	0.15	0.67
7	5.18	0.49	0.23	0.74	4.03	0.27	0.16	0.67
8	5.18	0.51	0.22	0.75	6.24	0.31	0.12	0.64
9	5.23	0.47	0.24	0.75	5.43	0.35	0.12	0.65
10	3.86	0.56	0.35	0.81	3.35	0.28	0.16	0.69

5. ALGORITHMS

5.1. Texture discrimination by GLCM features on TCSDI images

```
Begin
        if energy>= 0.19 && energy<= 0.35
          print("The texture image is car ")
        else
          print ("The texture image is Elephant")
End
```

Table -2: GLCM values with 0^0, 45^0, 90^0, 135^0 for TDSDI-CM of Car and Elephant images change values

Texture	Car				Elephant			
	Contrast	Correlation	Energy	Homogeneity	Contrast	Correlation	Energy	Homogeneity
1	5.20	0.48	0.17	0.72	3.24	0.26	0.17	0.69
2	5.18	0.47	0.15	0.70	3.93	0.46	0.14	0.68
3	4.90	0.50	0.18	0.73	3.97	0.42	0.14	0.68
4	4.73	0.52	0.18	0.74	2.75	0.22	0.18	0.70
5	4.99	0.49	0.18	0.73	3.41	0.24	0.17	0.69
6	4.08	0.56	0.29	0.79	3.54	0.33	0.14	0.68
7	2.75	0.59	0.30	0.80	3.69	0.32	0.14	0.69
8	4.25	0.56	0.22	0.76	3.95	0.33	0.16	0.68
9	5.08	0.48	0.19	0.73	3.15	0.24	0.19	0.70
10	4.46	0.53	0.22	0.76	3.93	0.41	0.14	0.68

5.2. Texture discrimination by GLCM features on TDSDI images

```
Begin
        if contrast>= 2.75 && contrast< 3.97
          print ("The texture image is Elephant")
        else
            print ("The texture image is Car")
End
```

Table -3: Discrimination rates of proposed methods

Texture Database	Proposed Methods	
	TCSDI-CM	TDSDI-CM
Elephant	80 %	100 %
Car	100 %	93 %
Average discrimination rate	90 %	96.5 %

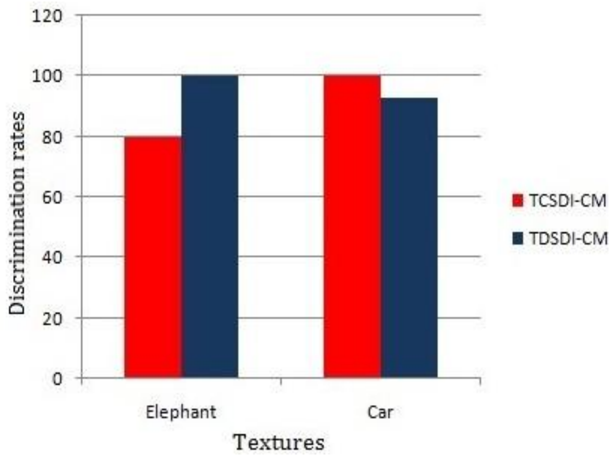


Chart -1: Discrimination rates of proposed methods

6. CONCLUSIONS

The present paper effectively utilized the concept of structuring elements i.e textons for texture discrimination. The textons are applied on the DSDI and CSDI images which shows a good boundary with good shape features and leads for deriving two separate texture images for the input texture. Here formation of textons become simpler because the rotational invariant SDI ranges from 0 to 5 only. The proposed TCSDI-CM and TDSDI-CM methods shows high discrimination rates and also they are rotational invariant.

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BIOGRAPHIES

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