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Texture Classification based on Edge Descriptor texton Co-occurrence Matrix

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ABSTRACT

Texture classification is of great importance for image processing and pattern recognition. It has acknowledged a significant amount of attention over the last few decades as it creates the basis of most pattern recognition methods. The object of texture categorization is to match a query image with a allusion image or cluster such that the query has the same illustration texture as the allusion. In this manuscript, we proposed a new descriptor called EDTU for stone texture classification. The image edge information was extracts from texture images using ED. Independent charge of the skylight size, ED is a tiny 8-bit binary number, so it is suitable for real-time applications. Further, the combination of texton unit and ED called EDTU is proposed. In the present study considered seven statistical features based on EDTU matrix. The efficiency of the projected method is tested on two different texture datasets thereby significantly improving the performance in terms of stone texture classification.

Keywords: Edge Descriptors, Texture Analysis, Feature Fusion, Texture Matrix.

I. INTRODUCTION

Texture is a significant spatial characteristic, useful for classifying objects. Statistical procedures have broadly studied in the texture classification and analysis. The most popular structural methods are Texture edges (TE) and texton theory approach. The present chapter combined the features of Edge Descriptor (ED) and Texton Unit (TU) and derived a novel matrix called EDTU, it is for texture classification. In the proposed method, seven features are extracted from EDTU. This approach is processing extremely simple. We have conducted two experiments on five challenging texture databases (Brodatz, Vistex, CUReT, Mayang, and Paulbourke. The investigational outcome indicates the derived method classification performance is better than the other methods.

The rest of the paper is prepared as follows. In section 2, proposed methodology is described and results of standard classification and derived user defined algorithm are explained in section 3. In section 4 conclusions are given.

II. EDGE DESCRIPTOR TEXTON UNIT

The proposed approach is to classify four categories of stone textures with high rate of classification. Few developments of LBP were thereafter. On the other hand, a extraordinary processing was done on window size around the middle pixel cost called edge descriptor (ED). It was developed by Armanfard [20]. The texture unit approach [21] was proposed for classification of textures. In this paper, concentrated on rotation and gray-scale different stone texture classification, a novel generalized feature explanation called "edge descriptor texton unit" (EDTU) is proposed. EDTU can protect extra data to discriminate between dissimilar stone textures. ED aims to be additional robust and speed for texture analysis, furthermore, our approach is to select texton unit, they are primary rotation-invariant features of local image texture and their features is verified to be a very powerful texture features. The cost of the derived method is established on five stone texture databases in two datasets. The derived method is proved to be an outstanding rotation invariant stone texture classification. This paper presents a new descriptor, Edge Descriptor (ED), for texture analysis. ED proposes texture and edge data in order to provide. ED is a local descriptor because it is clear over a neighborhood. As shown in our investigation, ED performs LBP for texture classification in both complexity and precision.

2.1 Local Binary Pattern

The nearby descriptor to ED is local Binary Pattern (LBP), it is a common texture used in a variety of applications like fabric identification, stone texture classification. In this approach, texture characteristic assigned to a pixel, is narrow characteristic which prefer its nearby pixels. The general version of LBP is as follows.

$$LBP(Pc) = \sum_{n=0}^{p-1} s(g_n - g_c)\, 2^{n} \ , \ s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (1)$$

. The fundamental version of LBP considers a 3×3 nearby pixel as revealed in Figure 1 [12].

a

g_1	g_8	g_7
g_2	g_c	g_6
g_3	g_4	g_5

b

13	40	12
37	33	45
37	33	173

c

0	1	0
1	P_c	1
1	1	1

$LBP_{3\times3}$ (Pc) = 01111101

Figure 1. (a) A 3×3 nearby pixel of g_c b) intensity cost (c) binary number assigned to P_c; start from top left pixel anti-clockwise.

2.2 Edge description

The neighborhood of P_c for processing TED is well thought-out in such a way that it includes not only texture data but also vertical edge data. The idea proposed in [24], mull over a single-dimensional local binary model in the x-direction LBP^{x}_{i} , as shown in Fig. 2.

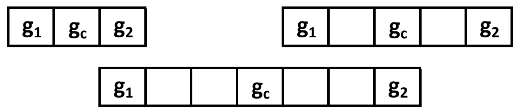

Figure 2. 1-D local binary pattern in the x-direction, LBP^{x}_{i} , for dissimilar nearby pixel size 3, 5 and 7

It can be provide that P_c is an best vertical edge, $LBP^{x}_{i}(P_c)$ for i = 3, 5, 7 forever returns 2-bit binary numbers 10 or 01. But outcome of LBP^{x}_{i} (Pc) on the vertical edges of stone textures that can be add to in the nearby pixel in x-direction, outcome in additional weight on the significant strength variations and low sensitivity to the different tiny-scale. As an outcome, extra pixels within E are measured as vertical edge. we use a horizontal rectangular neighborhood as exposed in Figure 3. Where g_c is the pixel value and g_n, n = 1, 2m . . ., 16. The nearby pixels separated into four regions. They are Upper Row (UR), Lower Row (LR), Right Column (RC), and Left Column, (LC). The information provided in following diagram.

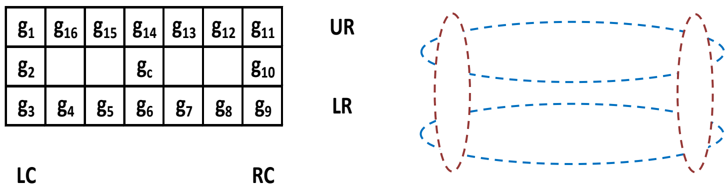

Figure 3. UR, LR, RC and LC regions in a 3×7 rectangular neighborhood.

2.3 ED Code Generations

The major drawback of LBP on rectangular nearby pixel is complexity that adds exponentially with the extra bits, P. A rectangular nearby pixel of size w×l, the total number of nearby pixels is P = 2(w+l) - 4. For these developments in a 3×7 nearby pixel, LBP returns a 16-bit binary number as display in Figure 4. In this paper an eminent descriptor called ED presented in Figure 5. ED is an 8-bit binary code clear on binary depiction of LBP.

a

151	143	143	143	152	153	146
135			143			146
155	142	142	138	147	153	142

b

1	1	1	1	1	1	1
0			**P_c**			1
1	0	0	0	1	1	0

$LBP_{3\times7}$ (Pc) = 1010001101111111

Figure 4. (a) Intensity cost of a sample 3×7 nearby pixels (b) The binary number assigned to Pc; starting from top left pixel anticlockwise.

b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7

Figure 5. 8-bit Edge Binary Code (ED code)

The rectangular nearby pixel where ED is processed over it is named ED window. b_0 and b_1 place for the texture of higher neighborhood of P_c and are clear in equation 2 and 3.

$$b_0 = \begin{cases} 1 & UR1s > (l-1)/2 \\ 0 & UR1s \le (l-1)/2 \end{cases} \quad (2)$$

$$b_1 = \begin{cases} 1 & URT \ge (l-1)/2 \\ 0 & URT < (l-1)/2 \end{cases} \quad (3)$$

$$b_3 = \begin{cases} 1 & LR1s > (l-1)/2 \\ 0 & LR1s \le (l-1)/2 \end{cases} \quad (4)$$

$$b_4 = \begin{cases} 1 & LRT \ge (l-1)/2 \\ 0 & LRT < (l-1)/2 \end{cases} \quad (5)$$

Where LR1s and LRT are defined in a same path as UR1s and URT. The last bits of ED to describing texture of Pc.

$$b_2 = \begin{cases} 1 & RCT = 0 \\ 0 & RCT \neq 0 \end{cases}$$

$$b_5 = \begin{cases} 1 & LCT = 0 \\ 0 & LCT \neq 0 \end{cases}$$

$$b_6 = \begin{cases} 1 & UR1s + LR1s + RC1s + LC1s = 0 \\ 0 & UR1s + LR1s + RC1s + LC1s \neq 0 \end{cases}$$

$$b_7 = \begin{cases} 1 & UR1s + LR1s + RC1s + LC1s = P \\ 0 & UR1s + LR1s + RC1s + LC1s \neq P \end{cases}$$

Where RCT and LCT transformations between 0 and 1 in the right column, RC, and left column, LC. The major benefit of ED is always eight bits self-governing of the ED. These bits contain implicitly texture and edge data. We reveal the efficiency of ED for stone texture analysis in a texton unit method in the next section.

2.4 Texton unit approach

The ED code method is applied to the input image with size 256×256, resultant 85×36 ED matrix is generated, this matrix contains the edge information but it is not enough for precise stone texture classification. To achieve precise stone texture classification, texton theory [25] is applied to the ED matrix.

The idea of texton was derived in [25] 20 years ago, and it is an awfully tool in texture analysis. The textons are clarified as a set of blobs or developing patterns distribution is a general property all over the image. A tiny element length, such as 2×2 block is used as textons for generating the texton unit matrix as present in Fig. 6 Denote every value in 2×2 block as V_1, V_2, V_3 and V_4.

V_1	V_2
V_4	V_3

Figure 6. 2×2 grid

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

Figure 7: 2×2 texton unit matrix

The following procedure is applied for generating texton unit matrix

For each 2×2 block do the following procedure

Step 1: Calculate the average of V_1, V_2, V_3 and V_4 of 2×2 block of ED matrix

Step 2: if average greater than or equal to V_i for i=1, 2, 3, and 4, value is 1 otherwise values zero and is generated 2×2 temp matrix

Step 3: Multiply every element with matrix shown in Fig. 6.7, and 2×2 matrix is stored in TEDTU

III. RESULTS AND DISCUSSIONS

In this research work, two dissimilar datasets of size 256×256 used for investigation. Dataset-1 consist of 80 stone surface images earned from VisTex, Brodatz textures, Mayang and every surface image is partition into sixteen 64×64, and four 128×128 non-extending image zones. Due to this, a total of 1600 (i.e., 80×20) image regions will be placed in the prescribed database. 240 stone contains texture images obtained from CUReT database (Dataset-2), Paulbourke and also from natural assets from digital camera; all texture image is fragmented into sixteen 64×64 and four 128×128 non-overlapping image regions.

The characteristic vector of first and second order arithmetical features are analysed from the EDTU. Feature vector F_1 include the first order statistical characteristics consider in the current method are kurtosis and skewness. The next order statistical characteristics such as contrast, correlation are given in Equations.(10)-(14). Another statistical characteristics analyzed from the matrix of co-occurrence is entropy. The equation of the entropy is given in equation 1.

$$\text{skewness} = \frac{\sum_{i=1}^{N}(Y_i - Y)^3}{(N-1)S^3} \qquad (5)$$

$$\text{kurtosis} = \frac{\sum_{i=1}^{N}(Y_i - Y)^4}{(N-1)S^{43}} - 3 \qquad (6)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (7)$$

$$\text{mean} = \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j) \qquad (8)$$

$$\text{Standard deviation} = \sqrt{\frac{1}{N^2}\sum_{i,j=1}^{N}[p(i,j) - \text{mean}]^2} \qquad (9)$$

where P_{ij} is the texton unit value in position (i,j) of the texton unit image, N is the number of texton unit values in the texton unit, μ is $\mu = \sum_{i,j=0}^{N-1} iP_{ij}$ mean of the texton unit and $\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}\,(i-\mu)^2$ variance of the texton unit.

The statistical characteristic process spatial distribution of texton unit cost is comparing local characteristics at all point in the image. In this level, an unidentified texture is used and extracted with the corresponding feature cost stored in feature library using a Euclidean distance vector formula given in Equation 15. The outcome of the dataset-1 and dataset-2 are programmed out in Tables 1 and 2.

$$D(i) = \sqrt{\sum_{j=0}^{n} \text{abs}[f_j(x) - f_j(i)]} \qquad (10)$$

Where n is the total number of features used, i = 1 to Q

Table 1. % classification rates of Dataset-1

S. No.	Texture Name	Classification (%)
1	concrete_bricks_170756	97.27
2	concrete_bricks_170757	98.62
3	concrete_bricks_170776	97.93
4	crazy_paving_5091370	98.19
5	crazy_paving_5091376	99.23
6	crazy_tiles_130356	97.83
7	crazy_tiles_5091369	96.8
8	dirty_floor_tiles_footprints_2564	94.75
9	dirty_tiles_200137	95.97
10	floor_tiles_030849	98.39
11	grubby_tiles_2565	95.77
12	kitchen_tiles_4270064	99.87
13	moroccan_tiles_030826	100
14	moroccan_tiles_030857	95.16
15	mosaic_tiles_8071010	98.33
16	mosaic_tiles_leaf_pattern_201005060	94.46
17	mosaic_tiles_roman_pattern_201005034	96.16
18	motif_tiles_6110065	99.46
19	ornate_tiles_030845	95.79
20	repeating_tiles_130359	97.3
	Average	**96.98**

Comparison with Proposed EDTU Method with Existing Methods

The proposed EDTU Method is compared with the recent classification methods CCR and ILBP [26], LQP [27] and LRTUM [28]. Table 3 shows the mean percentage categorization speed of the projected EDTU and presented methods. The graphical analysis of this is shown in Figure 9 from Table 3 and Figure 9 obviously shows that, the projected EDTU exhibits a high classification rate than the presented methods

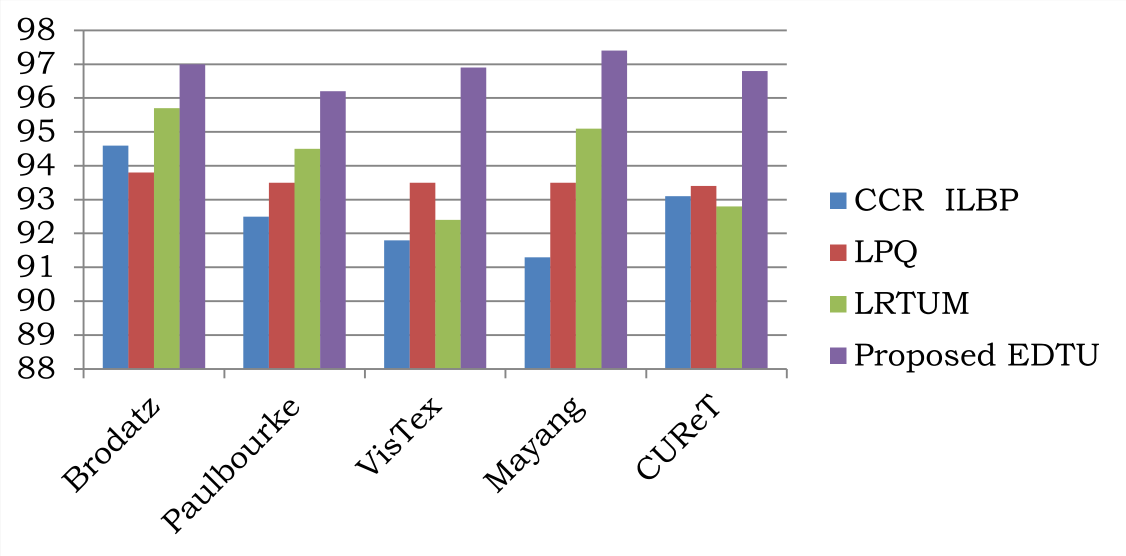

Figure 9. Comparative analysis of proposed TEDTU method with existing methods

Table 2. % classification rates of Dataset-2

S. No	Texture Name	% Classification
1	brick_tiles_1262639	95.64
2	ceramic_tiles_5091358	97.15
3	circular_tiles_6280660	94.72
4	clean_tiles_231067	98.17
5	concrete_250902	98.03
6	concrete_paving_170805	96.83
7	concrete_tiles_7040216	95.5
8	concrete_tiles_7040218	96.98
9	cracked_tiles_9280147	96.16
10	crack ed_tiles_9280148	93.96
11	crazy_paving_4142298	94.42
12	crazy_paving_5091370	93.55
13	dirty_floor_tiles_footprints_2564	96.34
14	dirty_tiles_200137	94.84
15	fine_square_tiles_4142311	97.12
16	floor_tiles_030849	96.62
17	flower_tiles_7040220	95.9
18	grubby_tiles_2565	99.44
19	images_015	97.41
20	images_031	97.11
21	images_052	95.88
22	, images_059	94.46
23	images_062	94.54
24	images_102	97.68

25	images_130	95.68
	Average	**96.67**

Table 4: EDTU method v/s Traditional methods

Texture Group	CCR ILBP	LPQ	LRTUM	Proposed EDTU
Brodatz	94.6	93.8	95.7	97.0
Paulbourke	92.5	93.5	94.5	96.2
VisTex	91.8	93.5	92.4	96.9
Mayang	91.3	93.5	95.1	97.4
CUReT	93.1	93.4	92.8	96.8
Average (%) of Classification	**92.66**	**93.54**	**94.1**	**96.9**

IV. CONCLUSION

In this manuscript, we proposed a new descriptor, EDTU for stone texture categorization. The image edge information was extracts from texture images using ED. ED was evaluated over a rectangular casement. Independent of the skylight size, ED is a small 8-bit binary number, so it is suitable for real-time applications. Further, the combination of texton unit and ED called EDTU is proposed. The present chapter considered seven statistical features based on EDTU matrix.. The efficiency of the projected method is proved on two different texture datasets thereby considerably improving the performance in terms of stone texture classification

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