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Texture Unit Pattern Approach For Stone Texture Classification

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Abstract

Texture classification is widely used to understand the patterns on the textures and it has wide range of application domains like classification of satellite images, pulmonary disease, industrial surface inspection etc. Gray Level Co-occurrence Matrix (GLCM), Texture Pattern Unit (TPU) and Texton Unit approaches are the popular statistical methods used to measure the textural information of images. The present paper proposes a model "Pattern based Dimension Reducing Binary" (PDRB) over texture images, by decreasing the 5×5 gray-level image into a 2×2 binary image. The novelty of the approach is it integrates TU and GLCM features using the Pattern based Dimension Reducing Binary (PDRB) approach for a better classification. The proposed PDRB image model reduces the overall dimensionality while preserving the important features of the texture. On the proposed PDRB image, the Texture Unit (TU) is derived and TU value of PDRB image contains 16 values which range from 0 to 15. Texture unit characterizes local texture aspects and these local texture aspects contain information regarding texture behavior. On the TU of PDRB image model the present research evaluated GLCM features for classifying stone texture images into four groups.

Keywords: Texture, Classification, Texture Unit, GLCM, Dimensionality Reduction

INTRODUCTION

The Texture is considered as a neighborhood property and it is an important characteristic. Analysis and characterization of texture are important for interpreting the patterns and understanding the same. The analysis of texture includes identification of patterns on texture, segmentation and classification of textures [1]. Texture analysis is considered to be an important technique to analyze and interpret images containing repetition or partial repetition of fundamental image elements. The analysis and classification of textures can be achieved using structural or statistical approaches. For portraying the attributes of the neighborhood the surface descriptors like Local Binary Pattern (LBP) [2, 3], Gray Level Co-occurrence Matrix (GLCM), Texture Unit (TU) and Textons [4] are used. The GLCM is widely used in characterizing the texture [5, 6]. Several rotationally invariant texture classification methods are introduced by authors based on Markov Random Fields [7,8], filter bank responses[9,10] and autoregressive models[11]. Several approaches in the literature which are experimented on TU, considered the TU range from 0 to 3561 [12, 13], 0 to 2020 [14, 15, 16], 0 to 255 [17] and 0 to 79 [18]. The GLCM features are more suitable for those images whose texture unit range is minimal. To address this in the proposed PDRB image model, the TU ranges from 0 to 15 and they have derived by compressing 5×5 local gray level windows into a 2×2 binary window. The GLCM features on the proposed PDRB image model experiments on stone texture images for a precise stone texture classification.

PROPOSED METHODOLOGY

After comprehensive understanding of the various approaches and their shortfalls the present paper proposes an approach for stone texture classification using GLCM, TUs after reducing the image both in terms of dimensionality and pixel range. The block diagram of proposed TU-PDRB model is shown in Figure 1 consisting of 8 steps:

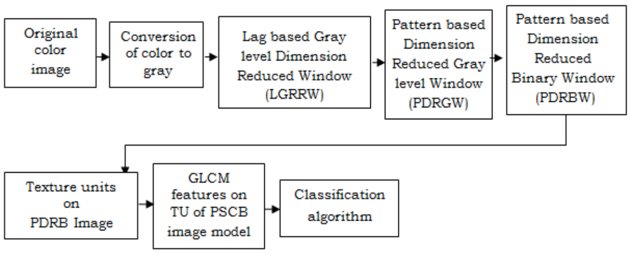

Figure 1: Block diagram of the proposed TU-PDRB image model

Step1: In this step the input Stone Texture is converted to gray picture by utilizing shading quantization of 7-bit two fold code, using step 1 to 4

Keeping in mind the end goal to concentrate dark level elements from shading data, the proposed strategy used the

RGB shading space which quantizes the shading space into 7-canisters to get 128 dim levels represented by C(x, y). The RGB quantization process is performed by utilizing 7-bit paired code of 128 hues as given in Eqn. 1 to 4 so that, each estimation of C(x, y) is a 7-bit parallel code running from 0 to 127.

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

where

$I(R)= 0$ if $0 \le R \le 16$ and $I(R)= i$

$$\text{if } ((16 * i) + 1) \le R \le (16*(i+1)) \text{ for } i = [1, 2, \dots ,7] \quad (2)$$

$I(G) = 0$ if $0 \le G \le 16$, $I(G)= i$

$$\text{if } ((16 * i) + 1) \le G \le (16 * (i + 1)) \text{ for } i=[1, 2,\dots ,6] \quad (3)$$

$I(B) = 0$ if $0 \le B \le 2$, $I(B) = i$

$$\text{if } ((32 * i) + 1) \le B \le (32 * (i + 1)) \text{ for } i=[1, 2, 3] \quad (4)$$

Step 2: Generation of "Lag based Gray level Range Reduced Window (LGRRW).

In the considered 5×5 sub window, each pixel value is compared with centre pixel. If the pixel value is same as that of centre pixel then its value is replaced with 2. If the pixel value is less than the centre pixel it is replaced with 1. If the pixel value is more than centre pixel it is replaced with 0. Apply this on the whole image by the non-covering way. By this, the pixel estimations of the whole picture will have values either 0 or 1 or 2. This structures the Lag based Gray level Range Reduced Window (LGRRW).

Step 3: Derivation of "Example based Dimension Reduced Gray level Window (PDRGW)".

For diminishing dimensionality for each 5×5 window the proposed technique embraced restrictive example based approach. The 5×5 LGRRW of the progression 2 is appeared in Fig. 2 (a). The pixel estimations of 5×5 LGRRW ranges from 0 to 2. The Fig. 2 (b) represents the Pattern based Dimension Reduced Gray level window (PDRGW). The g1, g2, …, g9 pixel estimations of PDRGW speaks to the examples of five level, two diagonals, focus vertical line and internal 3×3 window of LGRRW, which are gotten from the Equations 5 to 13.

v_1	v_2	v_3	v_4	v_5
v_6	v_7	v_8	v_9	v_{10}
v_{11}	v_{12}	v_{13}	v_{14}	v_{15}
v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
v_{21}	v_{22}	v_{23}	v_{24}	v_{25}

(a)

g_1	g_2	g_3
g_4	g_5	g_6
g_7	g_8	g_9

(b)

b_1	b_2	b_3
b_4	b_5	b_6
b_7	b_8	b_9

(c)

Figure 2: (a) Local 5x5 LGRRW (b) generated 3x3 PDRGW (c) Generated 3x3 PDRBW.

$$g_1 = v_1 + v_2 + v_3 + v_4 + v_5 \quad (5)$$

$$g_2 = v_6 + v_7 + v_8 + v_9 + v_{10} \quad (6)$$

$$g3 = v_{11} + v_{12} + v_{13} + v_{14} + v_{15} \quad (7)$$

$$g_4 = v_{16} + v_{17,} +v_{18} + v_{19} + v_{20} \quad (8)$$

$$g5 = v_7 + v_8 + v_9 + v_{12} +v_{13} + v_{14} + v_{17} + v_{18} + v_{19} \quad (9)$$

$$g_6 = v_{21} + v_{22} +v_{23} + v_{24} + v_{25} \quad (10)$$

$$g_7 = v_1 + v_7 + v_{13} + v_{19} + v_{25} \quad (11)$$

$$g_8 = v_5 + v_9 + v_{13} + v_{17} + v_{21} \quad (12)$$

$$g_9 = v_3+ v_8 + v_{13} + v_{18} + v_{23} \quad (13)$$

By watching the conditions of g1, g2, g3, g4, g6, g7, g8 and g9 it is clear that that each of these pixel esteems can have a most extreme estimation of 10. Promote the condition for g5 plainly demonstrates that g5 can have a most extreme estimation of 18. To change over them into Pattern based Dimension Reduced Binary window (PDRBW) a condition is connected as given in Equations 14 and 15. By this the 3×3 "PDRGW" is changed over into double window "PDRBW" as appeared in Fig 2(c).

On the off chance that $gi >= 5$ then $bi = 1$ generally

$$bi = 0 \text{ for } \quad i=1, 2,3,4,6,7,8,9 \quad (14)$$

On the off chance that $g5>= 9$ then $b5 = 1$ generally

$$b5 = 0 \quad (15)$$

Step 4: Generation of PDRBW of 2×2 from PDRBW of 3×3.

The PDRBW of 3×3 produced in the past stride comprise pixel esteems just either 0 or 1. This progression decreases each of the 3×3 sub picture of (PDRBW) into "Pattern based Dimension Reduced Binary Window (PDRBW)" of 2×2 utilizing the accompanying restrictive equations as represented from (16) to (20) as appeared in Fig..3.

b_1	b_2	b_3
b_4	b_5	b_6
b_7	b_8	b_9

(a)

q_1	q_2
q_3	q_4

(b)

Figure : (a) 3x3 PDRBW (b) 2x2 PDRBW

$$q_1 = b_1 + b_5 + b_9 \quad (16)$$

$$q_2 = b_3 + b_5 + b_7 \quad (17)$$

$$q_3 = b_2 + b_5 + b_8 \quad (18)$$

$$q_4 = b_4 + b_5 +b_6 \quad (19)$$

By observing the conditions of q1, q2, q3 and q4 it is obvious that each of these pixel esteems can have a greatest estimation of 4. Again to change over those into Pattern based Dimension

Reduced Binary Window (PDRBW) of size 2×2 a condition is connected as given in Equation 20.

On the off chance that qi >= 2 then qi = 1 generally

$$qi = 0 \text{ for } i = 1 \text{ to } 4 \qquad (20)$$

By this, the 3 x 3 PDRBW is diminishing the dimensionality two-fold window of size 2×2 without losing and significant components. By applying steps 2,3 and 4 on whole picture on a 5×5 non-overlapped window basis, the whole surface picture is changed over into PDRB picture model.

Step 5: Generation of TU on PDRB image model.

The proposed technique extricated nearby picture data as surface unit on each of the PDRBW. The proposed TU-PDRBW is unique in relation to normal surface unit represented in literature, which is determined just on 3×3 windows. The proposed strategy shrewdly packed a 5×5 window into a 2×2 window and inferred TU on them. In this way the determined TU additionally tells about a TU of a 5×5 window. From each 2×2 PDRBW, TU esteem is computed by utilizing the Eqn.6.21. This procedure is connected on whole picture, at that point the picture tells about TU of PDRB image Model.

$$\sum_{k=0}^{3} \mathrm{power}(2,k) * q_i \text{ for } i = 1,2,3,4 \qquad (21)$$

TU of PDRBW consist the values ranging from o to 15 (totally 16) only. There is no unique way to label and order the texture units.

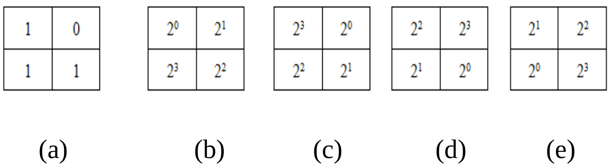

Figure 4: Different ways of 2x2 neighborhoods.

The value of the TU modifies by the illustration of the weights as shown in Fig 4. The TU can be designed in 4 dissimilar ways for a 2×2 window as exposed in Fig 4. That is for any 2×2 neighborhood one can produce four TU values. The TU value for the Fig. 4(a) in all four directions are represented in Fig. 4(b), 4(c), 4(d) and 4(e) is given as 13, 14, 7 and 11 respectively.

To attain sole and rotating invariant possessions the future TU on PDRBW measured the smallest amount value. That is the proposed model considers 7 as TU in the above case.

The picture procedure of produces the TU from innovative image of size 5×5 is shown in Fig.5.

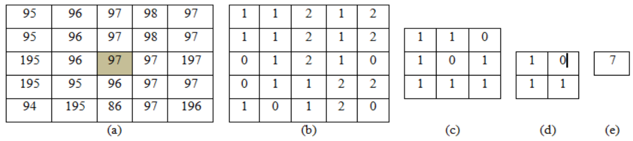

Figure 5: (a) Original 5 x 5 gray level window (b) a 5 x 5 LGRRW (c) a 3 x 3 PDRBW (d) 2×2 PDRBW (e) TU-PDRBW value.

Step 6: Generation of GLCM elements on the determined TU of PDRBW model (PDRBW-TU).

GLCM acquainted by Haralick endeavor with depict surface by factually inspecting how certain dim levels happen in connection to other dim levels. Co-occurrence Matrix (CM) is the expansive scope of its conceivable esteems (256 dim esteems) which additionally requires more calculation time. When all is said in done, the span of CM relies on upon dark level scope of estimations of the picture. To diminish dark esteems extend in picture and furthermore to decrease general measurement of the picture, the present research derived TU on PDRB picture image. The PDRB approach diminishes the dimensionality of original image to [2M/5×2N/5], where picture size is (M×N)) and also the gray level of each TU of PDRB model is decreased to 0-15. A set of GLCM features i.e, Homogeneity, contrast and correlation are extracted on the TU of PDRB stone texture images. They are represented from Eqn. 22 to 24. The proposed TU of PDRB image model combines the merits of both statistical and structural information of images and thus represents complete information of the texture image.

$$\text{Contrast} = \sum_{i,j=0}^{N-1} -\ln\,(P_{ij})^2 \qquad (22)$$

$$\text{Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \qquad (23)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (24)$$

Where P_{ij} is the pixel value in position (i,j) of the PDRBW-TU image, N is the number of gray levels in the image.

$\mu = \sum_{i,j=0}^{N-1} iP_{ij}$ mean of the image and

$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}\,(i-\mu)^2$ variance of the image.

RESULTS AND DISCUSSIONS

The proposed GLCM include on TU of PDRB picture model is tried different things with a database of 612 stone images gathered from Mayang database, 678 stone images gathered from VisTex database, 832 images gathered from Paul Bourke database, 400 stone images gathered from Google database.

This leads an aggregate of 2522 specimen stone textures. In the proposed technique the example images are assembled into four pre-characterized gatherings: Bricks, Marble, Granite and Mosaic. Some of the stone texture images covering each of the groups are shown in the figure 6. The GLCM components are extricated on TU of PDRB facial pictures of various Image gatherings and the outcomes are put away in the element database. The GLCM highlights on TU of PDRB picture demonstrate for four stone gatherings of stone surface pictures are appeared in Tables 1, 2, 3, and 4 individually. In light of this data the proposed strategy infers a calculation called "Stone Texture characterization in light of TU of PDRB model" to effectively order the stone texture into four groups which is represented in Algorithm 1.

Figure 6: Sample stone textures from various databases.

Table 1: GLCM feature set values on the derived TU of PDRB Bricks texture images.

S. No	Image	Contrast	Homogeneity	Correlation
1	Brick.001	44.88	0.643	0.313
2	Brick.002	45.42	0.633	0.364
3	Brick.003	47.71	0.632	0.223
4	Brick.004	45.88	0.62	0.301
5	Brick.005	45.68	0.621	0.287
6	Brick.006	46.18	0.617	0.277
7	Brick.007	45.4	0.626	0.243
8	Brick.008	46.82	0.615	0.356
9	Brick.009	47.06	0.641	0.318
10	Brick.010	45.58	0.67	0.287
11	Brick.011	46.18	0.64	0.371
12	Brick.012	48.06	0.62	0.364
13	Brick.013	47.76	0.652	0.287
14	Brick.014	45.88	0.641	0.24
15	Brick.015	46.51	0.625	0.223
16	Brick.016	46.26	0.616	0.236
17	Brick.017	48.27	0.624	0.246
18	Brick.018	45.26	0.633	0.21
19	Brick.019	44.86	0.643	0.265
20	Brick.020	45.25	0.655	0.249

Table 2: GLCM feature set values on the derived TU of PDRB Marble texture images.

S. No	Image	Contrast	Homogeneity	Correlation
1	Marble001	47.3	0.565	0.237
2	Marble002	48.16	0.588	0.229
3	Marble003	48.06	0.597	0.25
4	Marble004	47.02	0.575	0.252
5	Marble005	47.78	0.596	0.265
6	Marble006	46.84	0.6	0.262
7	Marble007	47.94	0.582	0.249
8	Marble008	45.73	0.599	0.263
9	Marble009	48.46	0.563	0.277
10	Marble010	46.85	0.557	0.249
11	Marble011	47.84	0.55	0.261
12	Marble012	46.04	0.575	0.231
13	Marble013	46.29	0.549	0.263
14	Marble014	47.96	0.593	0.24
15	Marble015	46.98	0.545	0.263
16	Marble016	45.24	0.565	0.225
17	Marble017	46.26	0.55	0.265
18	Marble018	47.24	0.565	0.251
19	Marble019	47.65	0.599	0.243
20	Marble020	46.26	0.549	0.238

Table 3: GLCM feature set values on the derived TU of PDRB Granite images.

S. No	Image	Contrast	Homogeneity	Correlation
1	Granite.001	54.72	0.545	0.198
2	Granite.002	56.05	0.564	0.245
3	Granite.003	55.62	0.573	0.217
4	Granite.004	58.02	0.565	0.206
5	Granite.005	62.29	0.54	0.273
6	Granite.006	57.95	0.55	0.267
7	Granite.007	56.82	0.554	0.239
8	Granite.008	57.51	0.583	0.271
9	Granite.009	55.73	0.562	0.263
10	Granite.010	59.71	0.52	0.181
11	Granite.011	56	0.56	0.2
12	Granite.012	53.23	0.583	0.204
13	Granite.013	57.48	0.591	0.181
14	Granite.014	60.96	0.548	0.181
15	Granite.015	62.72	0.602	0.195
16	Granite.016	63.52	0.61	0.218
17	Granite.017	59.66	0.55	0.258
18	Granite.018	62.86	0.583	0.249
19	Granite.019	63.04	0.581	0.24
20	Granite.020	59.63	0.576	0.265

Table 4: GLCM feature set values on the derived TU of PDRB Mosaic images

S. No	Image	Contrast	Homogeneity	Correlation
1	Mosaic001	55.43	0.56	0.147
2	Mosaic002	57.3	0.543	0.177
3	Mosaic003	59.91	0.489	0.165
4	Mosaic004	56.83	0.55	0.158
5	Mosaic005	54.63	0.573	0.178
6	Mosaic006	56.25	0.572	0.158
7	Mosaic007	63.52	0.565	0.149
8	Mosaic008	59.68	0.554	0.157
9	Mosaic009	62.71	0.591	0.136
10	Mosaic010	63.47	0.56	0.148
11	Mosaic011	57.47	0.563	0.118
12	Mosaic012	55.63	0.587	0.126
13	Mosaic013	56.32	0.573	0.133
14	Mosaic014	57.26	0.496	0.145
15	Mosaic015	61.23	0.486	0.135
16	Mosaic016	53.36	0.515	0.111
17	Mosaic017	58.66	0.503	0.124
18	Mosaic018	59.65	0.526	0.126
19	Mosaic019	61.24	0.496	0.157
20	Mosaic020	64.33	0.486	0.179

Algorithm 1: Stone Texture classification algorithm based TU of PDRB image model.

```
Begin
If ((Contrast >48.5) and (Homogeneity > 0.61))
Print ("Stone image is treated as bricks image");
Else If ((Contrast < 48.5) and (Homogeneity < 0.6))
Print ("Stone image is treated as Marble image");
Else If ((Contrast >48.5) and (Correlation >= 0.18))
Print ("Stone images are treated Granite image");
Else If ((Contrast >48.5) and (Correlation < 0.18))
Print ("Stone image is treated as Mosaic image");
Else
        Print ("unknown class");
End
```

Table 6: % mean classifiction rates of the proposed PDRB image model and other existing methods.

Image Dataset	5-bit 'T' Pattern Approach	Syntactic Pattern on 3D method	Texton Feature Detection	Wavelet based Histogram on Texton Patterns	Proposed TU of PDRB Method
VisTex	95.95	93.15	95.46	92.87	96.5
Texture Images Taken by Camera	96.35	92.87	95.12	91.7	96.08
Google	96.76	93.32	94.86	93.56	96.59
Mayang	95.85	92.83	94.39	92.95	97.71
Paul Bourke	95.93	93.05	95.23	93.05	96.5

To assess the exactness and essentiality of the present technique probe or test images taken from considered databases. The test was done on a PC machine with i5 processor 2.6 GHz CPU and 4 GB RAM memory under MATLAB 10.1a stage. For training the model 40% of texture images covering different textures from each of the datasets are utilized for and remaining 60 % of the texture images are utilized for testing reason On test picture, GLCM components are assessed on TU of PDRB model of stone picture. The components extricated on the stone pictures with their fruitful arrangement comes about utilizing present plan is given in Table 5 and classification of textures w.r.to different datasets are represented in Figure 7.

Table 5: % of Stone texture classification on considered datasets by the proposed PDRB images model

Stone Dataset/ Class	Mayang	Paul Bourke	Google	VisTex	Scanned Photos
Bricks	98.54%	95.50%	96.00%	96.15%	95.85%
Granite	98.50%	97.00%	96.85%	96.85%	96.15%
Marble	98.25%	97.50%	96.50%	96.76%	96.35%
Mosaic	95.50%	96.00%	97.00%	96.26%	95.95%
Average	97.70%	96.50%	96.59%	96.50%	96.08%

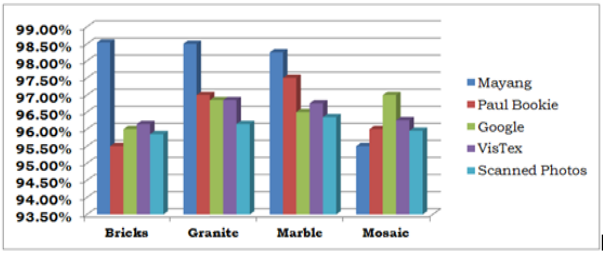

Figure 7: % of correct classification of stone texture image graph of considered datasets based on Algorithm

COMPARISON WITH OTHER EXISTING METHODS

In spite of the fact that the proposed characterization calculation in light of GLCM highlight on TU of PDRB model of stone pictures is effective in order of stone surfaces gathered into four. Still, it is contrasted and different existing calculations. The present strategy is looked at among 5-bit T designs approach [19]. The method is utilized to characterize the stone surfaces into 4 bunches in view of the 5bit 'T designs framed on 3×3 sub picture, Wavelet construct Histogram in light of Texton Patterns (WHTP) [20], in the technique [21] is utilized to order the stone surface pictures into four classifications by utilizing wavelet based texton design histogram and texton include development strategy, this strategy likewise used to arrange the pictures into four gatherings in view of rate of occurrence of texton patterns. The proposed strategy is additionally contrasted with the technique Syntactic Pattern on 3D strategy [22] in which stone surfaces is characterized into four classifications in light of the event of precise examples. It is plainly evident that, the proposed technique hint at a high grouping rate than the current strategies. The percent mean grouping rate for the proposed technique and other existing strategies are spoken to in Table 6. The graphical portrayal of the rate mean arrangement rate for the proposed strategy and other existing techniques appear in Figure 8.

CONCLUSION

This paper presents a novel approach for stone texture grouping which includes Bricks, Marble, Granite and Mosaic textures. In this approach GLCM features on the inferred Texture units of the PDRB model are extracted after decreasing the image dimensionality from MXN to [2M/5×2N/5]. The proposed TU-PDRBW shrewdly packed a 5X5 window into a 3×3 window and further into a 2×2 window and inferred TU on them. Accordingly the determined TU likewise speaks to a TU of a 5×5 window. The proposed model of TU of PDRB picture diminished the range of TU's to 0-15. For an exact and precise grouping, the present paper assessed three GLCM highlights on the inferred TU of PDRB stone pictures. The present method is implemented using four databases like Google, VisTex, Mayang and Paul bourke and Scanned pictures. The classification of the present framework has shown better results with Mayang database in contrast with other considered stone texture databases. The average classification rate of proposed approach is 96.67%.

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