# Texture Classification based on Texton Patterns using on various Grey to Greylevel Preprocessing Methods

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### Abstract

Textural patterns can often be used to recognize familiar objects in an image or retrieve images with similar texture from a database. Texture patterns can provide significant and abundance of texture and shape information. One of the recent significant and important texture features called Texton represents the various patterns of image which is useful in texture analysis. However sometimes the textured image obtained may not be of good quality and this may lead to improper detection of significant patterns. To enhance the quality or better illumination or contrast or sharpening effect, the present paper applied various local grey to grey level preprocessing steps on textured data. Grey to grey level preprocessing is required because the patterns on textons can be evaluated only on grey level textures. The present paper evaluated the occurrence behavior of various texton patterns based on the various grey to grey level pre processing methods, for an efficient rotationally invariant texture classification. The experimental results on various stone textures indicate the efficacy of the proposed method when compared to other methods.

Keywords: grey to grey level, pre processing, texture analysis, texton patterns

# **1. Introduction**

Nowadays, texture analysis plays an important role in many image areas, such as geosciences and remote sensing, medical imaging, defect detection, document processing and image retrieval. Texture is a surface structure formed by uniform or non-uniform repeated patterns. The patterns also can be the perceived surface such as mineral, metal or wood which have tactile properties, or they could be reflectance on a surface such as color. In texture analysis, there are related issues such as texture classification, texture segmentation, and texture synthesis which are concerned by many researchers.

In last few decades, lots of texture classification techniques were proposed. Firstly, the first and second orders statistics [1, 2] and co-occurrence matrix [3] were proposed for obtaining texture features. Further, model-based method such as Markov random field (MRF) [4, 5], Gibbs transform [6] and linear regression[7] are used to obtain distribution probabilities of textures on random fields. In addition, the local binary pattern (LBP) operator was also proposed to discriminate texture patterns by thresholding gray values of the neighboring pixels with binary codes [8]. Recently, multi-resolution methods such as wavelet transform is widely used and applied in texture analysis.

Recently various pattern based texture classification methods are proposed using wavelets [9-11]. These wavelet based methods classified the textures precisely. Good texture

classification results are obtained using simple patterns and long linear patterns [12-14]. The present paper assumes texture is characterized not only by the grey value at a given pixel, but also by the grey value pattern in a neighborhood surrounding the pixel. The ability to efficiently analyze and describe textured patterns is thus of fundamental importance. The rest of the paper is organised as follows. Section 2 describes methodology of the proposed method. An experimental result is discussed in Section 3 and conclusions are given in Section 4.

# 2. Methodology:

A simple pattern of a neighborhood can be considered as one of the texture primitive feature. V.Vijaya kumar [15] has studied how the percentage of occurrence factor of a typical pattern varies after applying various local preprocessing steps on a 3×3 neighborhood. In their study initially they have used various local preprocessing steps to convert grey level image in to a binary image, then on the binary image they have evaluated the frequency of occurrences of simple patterns for texture classification. The present paper extended this concept on textons [16]. The proposed preprocessing method is different from V Vijaya kumar et al., [15], because in the present scheme a grey level image is obtained after local preprocessing and texton patterns are evaluated on the preprocessed grey level texture image instead of binary image. That is the reason the proposed preprocessing is called as grey to grey-level preprocessing. The proposed method consists of four steps. In the first step, the color image is converted in to grey level image by using any color quantization method. In Second step, apply grey to grey level preprocessing to generated grey level image in step. In step four, detect the texton patterns and find the frequency occurrences of patterns. In last step, classification is done bad on the results occurred in step three. The overall design of the texture classification is shown in Figure 1. The present paper used RGB color quantization method as described below.



Figure 1. Block Diagram of the Texture Classification based on Patterns Detection

## Step 1: Color Quantization of 7-bit Binary Code

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. In order to extract gray level features from color information, the proposed TF 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).

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

$$I(R) = i, ((16*i)+1) \le R \le (16*(i+1)) \quad i = [1, 2, ..., 7]$$
(2)

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

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

Where  $I(R) = 0, 0 \le R \le 16$ ,

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

## Step 2: Grey to Grey Level Preprocessing

The present paper investigated seven local grey to grey level preprocessing methods namely Local Max, Local Min, Local Mean, Local Median, Local Mode, Local Standard Deviation and Local Variance on the input grey level image. By applying above local grey to grey level preprocessing methods on the input texture image results a pre processed grey level texture image. The algorithm for grey to grey level preprocessing is given in algorithm 1 and the block diagram of entire process in shown in Figure 2.

# Algorithm 1: Grey to Grey level Preprocessing

```
input: given grey level image
output: preprocessed grey level image
BEGIN
 s = 0; a = 0;
  for i = 2 to n-1
  for j = 2 to m-1
    BEGIN
     for k = i-1 to i+1
      for l = j-1 to j+1
       BEGIN
         localmax[i-1,j-1] = max[greyimage[k,l]];
         localmin[i-1,j-1] = min[greyimage[k,l]];
         localmean[i-1,j-1] = mean[greyimage[k,l]];
         localmedian[i-1,j-1] = median[greyimage[k,l]];
         localmode[i-1,j-1] = mode[greyimage[k,l]];
         localstd[i-1,j-1] = std[greyimage[k,l]];
         localvariance[i-1,j-1] = variance[greyimage[k,l]];
       END
    END
END
```



# Figure 2. Block Diagram of Entire Grey to Grey Level Pre Processing Study of Textons

#### **Step 3: Texton Detection**

Textons [17, 18] are considered as texture primitives, which are located with certain placement rules. A close relationship can be obtained with image features such as shape, pattern, local distribution orientation, spatial distribution, etc.., using textons. The textons are defined as a set of blobs or emergent patterns sharing a common property all over the image [17, 18]. The different textons may form various image features. To cover all texton patterns with two neighboring pixels the present paper utilized six texton patterns on a 2×2 grid as shown in Figure 2. In Figure 2(a), the four pixels of a 2×2 grid are denoted as V<sub>1</sub>, V<sub>2</sub>, V<sub>3</sub> and V<sub>4</sub>. In the present study texton pattern is considered if and only if the two adjacent pixels of the 2×2 grid have same value. This results formation of six texton patterns denoted as TP<sub>1</sub>, TP<sub>2</sub>, TP<sub>3</sub>, TP<sub>4</sub>, TP<sub>5</sub>, and TP<sub>6</sub> P<sub>7</sub> as shown in Figure 3(b) to 3(g). The working mechanism of texton detection for the proposed method is illustrated in Figure 3.

#### Step 4: Evaluated the Frequency Occurrences of Textons

Once the textons are identified, the present paper evaluated the frequency of occurrences of all six different textons as shown in Figure 3 with different orientations. To have a precise and accurate texture classification, the present paper considered sum of the frequencies of occurrences of all six different textons as shown in Figure 3 on a  $2\times 2$  block.



Figure 3. Six Special Types of Textons: a) 2×2 grid b) TP1 c) TP2 d) TP3 e) TP4 f) TP5 and g) TP6



Figure 4. Illustration of the Texton Pattern Detection Process: (a) 2×2 grid (b) Original Image (c) & (d) Texton Location and Texton Types (e) Texton Image

# 3. Results and Discussions:

The present paper carried out the experiments on various Brick, Granite, Marble and Mosaic textures each of size  $256 \times 256$  collected from Brodatz textures, Vistex and also from natural resources obtained from digital camera. Some of them are shown in Figure 5. The sum of frequency of occurrence of all six texton patterns (TP<sub>1</sub>,TP<sub>2</sub>,TP<sub>3</sub>, TP<sub>4</sub>,TP<sub>5</sub>, and TP<sub>6</sub>) for granite, brick, mosaic, and marble preprocessed texture images are listed out in Table 1, 2, 3, and 4 respectively. Classification graph for each preprocessed technique are shown in Figure 6



Figure 5. Input Texture Group of 9 Samples of Granite, Brick, Mosaic, and Marble

Sno	Granite Texture Name	Local Max	Local Min	Local Mean	Local Median	Local Mode	Local Standard Deviation	Local Variance
1	blue_granite	2041	2016	2018	2020	2010	2014	2012
2	blue_pearl	1697	1674	1674	1676	1666	1670	1668
3	blue_topaz	1431	1410	1408	1410	1400	1404	1402
4	brick_erosion	2150	2125	2127	2129	2119	2123	2121
5	canyon_black	2265	2242	2242	2244	2234	2238	2236
6	dapple_green	1233	1212	1210	1212	1220	1216	1240
7	ebony_oxide	2194	2169	2171	2173	2163	2167	2165
8	giallo_granite	2121	2098	2098	2100	2090	2094	2092
9	gosford_stone	1494	1473	1471	1473	1463	1467	1465
10	greenstone	1636	1611	1613	1615	1605	1609	1607
11	interlude_haze	1431	1408	1408	1410	1400	1404	1402
12	kalahari	1698	1677	1675	1677	1667	1671	1669
13	mesa_twilight	1590	1565	1567	1569	1559	1563	1561
14	mesa_verte	2227	2204	2204	2206	2196	2200	2198
15	monza	2104	2083	2081	2083	2073	2077	2075
16	pietro_nero	1243	1218	1220	1222	1212	1216	1214
17	russet_granite	1614	1591	1591	1593	1583	1587	1585
18	granite10	1739	1718	1716	1718	1708	1712	1710
19	granite13	1554	1529	1531	1533	1523	1527	1525
20	granite20	2393	2370	2370	2372	2362	2366	2364

Table 1. Granite Stone - Frequency Occurrence of 2 × 2 Texton Patterns afte
Various Grey to Grey Level Preprocessing Methods

							Local	
Sno	mosaic Texture Name	Local	Local	Local	Local	Local	Standard	Local
5110	mosac rexture mane	Max	Min	Mean	Median	Mode	Deviatio	Variance
							n	
1	concrete_bricks_170756	1062	1031	1035	1033	1039	1041	1062
2	concrete_bricks_170757	920	891	862	833	804	775	746
3	concrete_bricks_170776	1028	1007	986	965	944	923	902
4	crazy_paving_5091370	689	658	662	660	666	668	689
5	crazy_paving_5091376	533	504	475	446	417	388	359
6	crazy_tiles_130356	593	572	551	530	509	488	467
7	crazy_tiles_5091369	618	587	591	589	595	597	618
8	dirty_floor_tiles_footprints_ 2564	699	670	641	612	583	554	525
9	dirty_tiles_200137	1015	994	973	952	931	910	889
10	floor_tiles_030849	567	536	540	538	544	546	567
11	grubby_tiles_2565	1040	1011	982	953	924	895	866
12	kitchen_tiles_4270064	594	573	552	531	510	489	468
13	moroccan_tiles_030826	1089	1058	1062	1060	1066	1068	1089
14	moroccan_tiles_030857	802	773	744	715	686	657	628
15	mosaic_tiles_8071010	558	537	516	495	474	453	432
16	mosaic_tiles_leaf_pattern_ 201005060	679	648	652	650	656	658	679
17	mosaic_tiles_roman_patter n_201005034	1197	1168	1139	1110	1081	1052	1023
18	motif_tiles_6110065	691	670	649	628	607	586	565
19	ornate_tiles_030845	538	507	511	509	515	517	538
20	repeating_tiles_130359	676	647	618	589	560	531	502

Table 2. Mosaic Stone - Frequency Occurrence of 2 × 2 Texton Patterns afterVarious Grey to Grey Level Preprocessing Methods

Table 3. Marble Stone - Frequency Occurrence of 2 × 2 Texton Patterns after
Various Grey to Grey Level Preprocessing Methods

							Lagel	
	marble	Local	Local	Local	Local	Local	Standard	Local
Sno	Texture Name	Max	Min	Mean	Median	Mode	Deviation	Variance
1	apollo	2830	2811	2809	2836	2817	2815	2842
2	canyon_blue	2857	2836	2815	2863	2842	2821	2869
3	cotto	2959	2936	2915	2965	2942	2921	2971
4	curry_stratos	2634	2615	2613	2640	2621	2619	2646
5	flinders_blue	2812	2791	2770	2818	2797	2776	2824
6	flinders_green	2593	2570	2549	2599	2576	2555	2605
7	forest_boa	2645	2626	2624	2651	2632	2630	2657
8	forest_stone	2672	2651	2630	2678	2657	2636	2684
9	goldmarble1	2990	2967	2946	2996	2973	2952	3002
10	green_granite	2645	2626	2624	2651	2632	2630	2657
11	grey_stone	2786	2765	2744	2792	2771	2750	2798
12	greymarble1	2726	2703	2682	2732	2709	2688	2738
13	greymarble3	2769	2750	2748	2775	2756	2754	2781
14	marble001	2496	2475	2454	2502	2481	2460	2508
15	marble018	2556	2533	2512	2562	2539	2518	2568
16	marble034	2535	2516	2514	2541	2522	2520	2547
17	marble033	2622	2601	2580	2628	2607	2586	2634
18	marble012	2607	2584	2563	2613	2590	2569	2619
19	marble014	2517	2498	2496	2523	2504	2502	2529
20	marble020	2605	2584	2563	2611	2590	2569	2617

	Brick						Local	
	Texture	Local	Local	Local	Local	Local	Standard	Local
Sno	Name	Max	Min	Mean	Median	Mode	Deviation	Variance
1	Brick.0001	3514	3501	3525	3505	3492	3516	3496
2	Brick.0002	3171	3160	3182	3162	3149	3173	3153
3	Brick.0003	3041	3032	3052	3032	3019	3043	3023
4	Brick.0004	3594	3581	3605	3585	3572	3596	3576
5	Brick.0005	3472	3461	3483	3463	3450	3474	3454
6	Brick.0006	3440	3431	3451	3431	3418	3442	3422
7	Brick.0007	3063	3050	3074	3054	3041	3065	3045
8	Brick.0008	3041	3030	3052	3032	3019	3043	3023
9	Brick.0009	3276	3267	3287	3267	3254	3278	3258
10	Brick.0010	3367	3354	3378	3358	3345	3369	3349
11	Brick.0011	3188	3177	3199	3179	3166	3190	3170
12	Brick.0012	3397	3388	3408	3388	3375	3399	3379
13	Brick.0013	3216	3203	3227	3207	3194	3218	3198
14	Brick.0014	3465	3454	3476	3456	3443	3467	3447
15	Brick.0015	3400	3391	3411	3391	3378	3402	3382
16	Brick.0016	3113	3100	3124	3104	3091	3115	3095
17	Brick.0017	3388	3377	3399	3379	3366	3390	3370
18	Brick.0018	3391	3382	3402	3382	3369	3393	3373
19	Brick.0019	3447	3434	3458	3438	3425	3449	3429
20	Brick.0020	3164	3153	3175	3155	3142	3166	3146

# Table 4. Brick Stone - Frequency Occurrence of 2 × 2 Texton Patterns afterVarious Grey to Grey Level Preprocessing Methods



GRANITE

MOSIAC

MARBLE

-BRICK





Figure 6. Classification Graphs of Stone Textures after each Local Preprocessing

The Tables 1 to 4 and the classification graphs of Figures 6, indicates a precise and accurate classification on stone textures using texton patterns based on the various grey to grey level pre processing methods. Based on the above tables and graphs the present paper derived a novel algorithm for classification and recognition among these four *i.e.*, Brick, Granite, Marble and Mosaic group of textures. The frequency occurrences of texton patterns are dependent on the dimension of the textures. To address this problem the present paper derived a recognition algorithm which is a ratio dependent with the original dimension of the textures considered *i.e.*, 256 x 256 with the dimension of the test image k x k. If the value of the test image falls with in the range of minimum to maximum occurrences of texton pattern of a particular stone then test image is identified as that stone texture. The basic classification algorithm for local grey to grey level pre processing based on maximum is given below.

Algorithm 2: Recognition of Stone textures based on grey to grey level local maximum pre processing method.

Let TIF is the frequency of occurrences of texton patterns as specified in the Figure 2a to 2g of the test image with dimension K x K.

```
BEGIN

if TIF <= \left(\frac{K \times K}{256 \times 256} \times 1197\right)

print ("texture is mosaic class")

else if TIF <= \left(\frac{K \times K}{256 \times 256} \times 2393\right)

print (texture is granite class")

else if TIF <= \left(\frac{K \times K}{256 \times 256} \times 2990\right)

print ("texture is marble class")

else if TIF <= \left(\frac{K \times K}{256 \times 256} \times 3594\right)

print ("texture is brick class")

else

print ("Unknown class ")

END
```

The proposed grey to grey level preprocessing texton pattern classification and recognition method is compared with Syntactic Pattern on 3D method [19] Primitive Pattern Unit approach [20] and texton feature evolution method [16]. The above two methods [19, 20] classified stone textures into two groups only. This indicates that the existing methods [20, 19] failed in classifying all stone textures. The percentage of classification rates of the proposed method and other existing methods [20, 19, 16] are listed in Table 5. The Table 5 clearly indicates that the proposed grey to grey level preprocessing texton pattern classification method outperforms the other existing methods. Figure 7 shows the comparison chart of the grey to grey level preprocessing texton pattern classification method based on with the other existing methods of Table 5.

Image Dataset	Syntactic Pattern on 3D method	Primitive Pattern Unit approach	texton feature evolution method	Proposed grey to grey level preprocessing texton features
Ankar Marble	93.29	92.19	95.56	97.15
Vistex	92.53	92.56	94.15	97.35
Asishimpex	93.3	91.29	95.27	96.79
Brodatz	93.59	92.16	94.97	96.9

Table 5. Mean % Classification Rate of the Proposed and Existing Methods



Figure 7. Comparison Graph of Proposed Method with other Existing Methods

# 4. Conclusions

Textons are considered as texture shape primitives. The different textons may form various patterns with in the image. Based on the texton pattern features on the various grey to grey level pre-processing methods the present paper evaluated a classification and recognition feature which is rotationally invariant. The proposed method is computationally attractive as it computes different TF with limited number of selected pixels. The proposed study attempted classification of four similar groups of stone textures namely brick, marble, granite and mosaic. Classification is carried out on finding frequency occurrences texton patterns with grey to grey level preprocessing methods. The results and classification graphs clearly indicates that a precise and accurate classification is resulted by using various pre processing methods. This is because the preprocessing methods addressed the problems of noise, illumination, contrast, intensity, blurring and other effects. Many existing methods are preprocessed in the literature for classification these four stone textures, but no method is classified all the four textures significantly and accurately as compared with the proposed method of the present paper.

# Acknowledgements

The authors would like to express their gratitude to Sri K.V.V. Satya Narayana Raju, Chairman, and K. Sashi Kiran Varma, Managing Director, Chaitanya group of Institutions for providing necessary infrastructure. Authors would like to thank anonymous reviewers for their valuable comments and Dr. G.V.S. Ananta Lakshmi for her invaluable suggestions which led to improvise the presentation quality of this paper.

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