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Texture Classification Based On Integrated Method

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ABSTRACT

The present paper proposes a novel way of extracting local texture features based on the Morphological Primitive Patterns with grain components (MPP-g) on texton based Local Directional Pattern (LDP) for effective stone texture classification. To reduce the dimensionality, the proposed research used Integrated Logical Compact LDP with OR operation on Textons (ILCLDP-T). Mathematical Morphology (MM) provides an efficient framework for analyzing object shape characteristics (such as size and connectivity) due to its geometry-oriented nature which are not easily accessed by linear approaches. A LDP feature is obtained by computing the edge response values in all eight directions at each pixel position of LBP and generating a code from the relative strength magnitude. The local descriptor LDP is more consistent in the presence of noise and illumination changes, since edge response magnitude is more stable than pixel intensity. The proposed Morphological Primitive Patterns with grain components (MPP-g) on ILCLDP-T are rotationally invariant due to Kirsch Edge Response. The present method experimented on the Dataset consists of various brick, granite, and marble and mosaic stone textures with resolution of 256×256 collected from Vistex, Mayang database and also from natural resources from digital camera. The experimental results and comparison with the other methods show the supremacy of the proposed method over the existing methods.

Key Words: LDP, Morphology, Textons, Morphological Primitive Patterns

I. Introduction

Texture is a surface property which gives combined information on the smoothness, coarseness, and regularity of objects (Gonzalez and Woods, 1992). On digital images, it reflects as local variations of the gray-scale content. The typical automatic texture classification system involves two steps: (1) a feature extraction step, where a set of texture features are extracted from the image under study and (2) a classification step, where a texture class membership is assigned to it according to the extracted texture features.

Texture classification plays an important role in computer vision and image processing. In the past decades, numerous algorithms for texture feature extraction have been proposed, many of which focus on extracting texture features that are robust to noises, rotation and illumination variants [1]. Goyal et al. [2] proposed a method by using texel property histogram. Cohen et al. [3] characterized texture as Gaussian Markov random fields and used the maximum likelihood to estimate rotation angles. Chen and Kundu [4] addressed rotation invariant by using multichannel sub-bands decomposition and hidden Markov model (HMM). Recently, Varma and Zisserman [5,6,7] proposed to cluster a rotation invariant texton dictionary from a training set, and then form the textural histogram based on these textons. Later, Xu et al. [8,9,10] presented scale invariant texture classification methods by using a multi-fractal spectrum (MFS).

In [11], Ojala et.al. proposed to use the Local Binary Pattern(LBP) for rotation invariant texture classification. LBP is a simple yet efficient operator to describe local texture, and has been proven to be invariant to monotonic grayscale transformations.Since Ojala's work, a lot of variants of LBP have been proposed. Although LBP and its variants have achieved impressive classification results on representative texture databases, there still remain some potential flaws of LBP. For example, LBP is sensitive to noise, and often classifies many different patterns in to same class.

Taskeed Jabid et al [12] proposed new local descriptor LDP considers the edge response values in all different directions instead of surrounding neighboring pixel intensities like LBP.This provides more consistency in the presence of noise; since edge response magnitude is more stable than pixel intensity.

The primitives and their spatial arrangements are used to characterize textures. For example, morphological operations are used to characterize textures [13]. Song's method [14] decomposes textures into a set of scale images, finds square texels of the same size at each scale, and uses the histogram of the texels as texture features. The method proposed by Gui et al. [15] extracts the size, position, periodicity, and spatial organization of texels to analyze textures. Khellah's method [16] uses the similarity between pixels and their surrounding neighbors within a predefined window and generates a global map called the "Dominant Neighborhood Structure".This paper attempts to classify Textures by evaluating Morphological primitive patterns on Logical ORing of LDP and Textons.

The paper is outlined as follows. The details about the proposed method given in section2, section 3 show the results and discussions and conclusions are mentioned in section 4.

II. METHODOLOGY

The pattern analysis of an image plays an important and crucial role in classification and characterization of textures. That's why the present paper investigates how the frequency occurrences of various texture grain patterns vary on stone textures. So far, no study has attempted to classify the stone textures based on the frequency occurrences of MPP on ILCLDP-T. The proposed method consists of six steps. The block diagram of the proposed Method is shown in Fig.1.

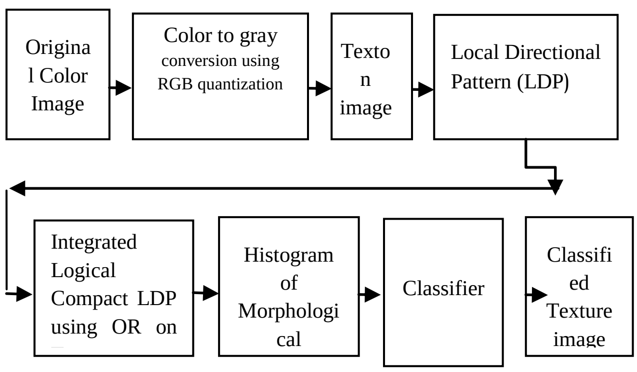

Fig.1: Integrated framework for texture classification using MPP-g on ILCLDP-T.

A. Colour Quantization and Texton Evaluation

To convert colour images into gray level image, the proposed MPP on ILCLDP-T approach utilized RGB colour quantization method. In order to extract colour information, the RGB colour space which quantizes the colour space into 8-bins to obtain 256 gray levels, then the statistical information of textons is calculated to describe image features.

B. Disadvantages of LBP and Need of LDP

The present research uses a Local Directional Pattern concept [12], which overcomes the drawbacks of LBP and is more robust for classification. The local descriptor LDP considers the edge response values in all different directions instead of surrounding neighboring pixel intensities like LBP. This provides more consistency in the presence of noise, and illumination changes, since edge response magnitude is more stable than pixel intensity. The LDP is based on LBP. In the LBP operator, a gray-scale invariant texture primitive, has gained significant popularity for describing texture of an image [17].

Ojala et al. [17] also observed that in significant image area certain local binary patterns appear frequently. These patterns are named as "uniform LBP" as they contain very few transitions from 0 to 1 or 1 to 0 in circular bit sequence. Ahonen et al. [18] used this variant of LBP patterns which have at most two transitions (LBPu2) for their face recognition. This variant of LBP is still sensitive to random noise and non-monotonic to illumination variation. To overcome this, the present paper used LDP technique with Kirsch edge response, as explained below.

C. Derivation Local Directional Pattern (LDP) with Kirsch Edge Response

The LDP is an eight bit binary code assigned to each pixel of an input image. This pattern is calculated by comparing the relative edge response value of a pixel in different directions. For this purpose, the present paper evaluates on LDP eight directional edge response value of a particular pixel using Kirsch masks in eight different orientations (M_0~M_7) centered on its own position. These masks are shown in the Fig.2.

$$\underset{(M_0)}{\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}}\underset{(M_1)}{\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}}\underset{(M_2)}{\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}\underset{(M_3)}{\begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}$$

$$\underset{(M_4)}{\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}}\underset{(M_5)}{\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}}\underset{(M_6)}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}}\underset{(M_7)}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}}$$

Fig.2: Kirsch edge response masks in eight directions.

By applying eight masks, eight edge response values m_0, m_1, …, m_7 are obtained, each representing the edge significance in its respective direction. The response values are not equally important in all directions. The presence of corner or edge show high response values in particular direction.

The LDP code produces more stable pattern in the presence of noise, illumination changes and various conversion schemes of color textures into gray textures. For instance, Fig.3 shows an original image and the corresponding image with illumination changes. After illumination change, 5^{th} bit of LBP changed from 1 to 0, thus LBP pattern changed from uniform to a non-uniform code. Since gradients are more stable than gray value, LDP pattern provides the same pattern value even in the presence of noise and non-monotonic illumination changes.

85	32	26
53	50	10
60	38	48

LBP=00111000

LDP=00010011

85	32	26
49	50	10
60	38	48

LBP=00101000

LDP=0001001

Fig.3: Stability of LDP vs. LBP (a) Original image (b) Image with noise.

D. Evaluation of Morphological Primitive Patterns with Grain Components (MPP-g) on ILCLDP-T

On the binary Integrated Logical Compact LDP with OR operation on Textons (ILCLDP-T) texture images of the previous step, the present paper evaluated the frequency occurrence of MPP-g on a 3×3 mask. The novel classification approach of the present paper is based on the number of grain components that occur in any order instead of calculating the frequency occurrences of various patterns on a 3×3 mask. These make the present method as rotational shape invariant. Frequency occurrences of MPP-g in the present paper are counted if and only if the central pixel of the window is a grain. If the central pixel is not a grain then the window is treated as a zero grain component. In the following figures '0' indicates no grain and '1' indicates a grain. There will be 8 combinations of MPP-g, which are shown in the Fig.4.

1	0	0
0	1	0
0	0	0

(a)

0	1	0
0	1	0
0	0	0

(b)

0	0	1
0	1	0
0	0	0

(c)

0	0	0
0	1	1
0	0	0

(d)

0	0	0
0	1	0
0	0	1

(e)

0	0	0
0	1	0
0	1	0

(f)

0	0	0
0	1	0
1	0	0

(g)

0	0	0
1	1	0
0	0	0

(h)

Fig.4: Representation of MPP-1g.

There will be 7 different formations of MPP's with two grain components (MPP-2g) by fixing one of the grains at pixel location (0,0) on a 3×3 mask as shown in Fig.5. In the similar way there will be 6 formations of MPP-2g by positioning one of the grains at the pixel location (0, 1) as shown in Fig. Thus there will be 7! ways of forming MPP-2g for a 3×3 window. In the same way, there will be 6!, 5!, 4!, 3!, 2! and 1! ways of forming MPP with 3, 4, 5, 6, 7 and 8 grains respectively, on a 3×3 mask.

1	1	0
0	1	0
0	0	0

(a)

1	0	1
0	1	0
0	0	0

(b)

1	0	0
0	1	1
0	0	0

(c)

1	0	0
0	1	0
0	0	1

(d)

1	0	0
0	1	0
0	1	0

(e)

1	0	0
0	1	0
1	0	0

(f)

1	0	0
1	1	0
0	0	0

(g)

Fig.5: Representation of MPP-2g by fixing one of the grain component at (0,0).

0	0	0
0	1	0
0	0	1

(a)

0	0	0
0	1	0
0	1	0

(b)

0	0	0
0	1	0
1	0	0

(c)

0	0	0
1	1	0
0	0	0

(d)

0	1	0
0	1	0
1	0	0

(e)

0	1	0
1	1	0
0	0	0

(f)

Fig.6: Representation of MPP-2g by fixing one of the grain Component at (0, 1).

III. Results and Discussions

Experiments are carried out to demonstrate the effectiveness of the proposed method for stone texture classification. The present paper carried out the experiments on original color textures. The Dataset consists of various brick, granite, and marble and mosaic stone textures with resolution of 256×256 collected from Vistex, Mayang database and also from natural resources from digital camera are shown in Fig.7. Dataset contains 80 original color texture images. The sum of frequency of occurrence of all MPP-g on ILCLDP-T of marble, brick, granite and mosaic input texture images are listed out in Tables 1, 2, 3 and 4 respectively. The classification graph is shown in Fig.8.

Fig.7. Input texture group of 8 samples of Mosaic, Granite, Brick and Marble.

Sno	Texture Name	MPP-g1	MPP-g2	MPP-g3	MPP-g4	MPP-g5	MPP-g6	MPP-g7	Total
1	Apollo	2	6	149	133	598	321	183	1392
2	Canyon_blue	3	7	137	127	613	325	159	1371
3	Cotto	1	3	88	82	354	282	155	965
4	Curry_stratos	1	1	97	139	729	361	174	1502
5	Flinders_blue	0	5	109	75	621	577	266	1653
6	Flinders_green	0	3	133	185	681	374	183	1559
7	Forest_boa	1	3	44	102	699	269	127	1245
8	Forest_stone	0	0	8	19	110	165	77	379
9	Goldmarble1	15	14	74	100	402	375	194	1174
10	Green_granite	0	0	4	3	27	44	15	93
11	Grey_stone	0	0	25	19	156	384	180	764
12	Greymarble1	2	0	69	37	356	450	289	1203
13	Greymarble3	1	4	644	168	445	98	26	1386
14	Marble01	0	0	55	54	304	486	207	1106
15	Marble18	0	0	4	3	27	42	12	88
16	Marble34	0	0	34	41	238	276	155	744
17	Marble33	3	3	207	86	457	504	245	1505
18	Marble12	0	0	4	13	96	236	83	432
19	Marble14	0	0	4	3	27	42	12	88
20	Marble20	0	0	4	4	30	58	15	111

Table 1: Frequency occurrences of MPP-g on ILCLDP-T on Marble Texture.

Table 2: Frequency occurrences of MPP-g on ILCLDP-T on Brick Texture.

Sno	Texture Name	MPP-g1	MPP-g2	MPP-g3	MPP-g4	MPP-g5	MPP-g6	MPP-g7	Total
1	Brick.0001	1	18	246	292	1258	975	429	3219
2	Brick.0002	6	17	285	298	962	1061	563	3192
3	Brick.0003	1	15	322	382	1240	972	421	3353
4	Brick.0004	4	13	288	361	1431	913	383	3393
5	Brick.0005	6	32	372	427	1265	992	352	3446
6	Brick.0006	2	37	326	495	1543	1194	369	3966
7	Brick.0007	9	61	383	461	1412	1217	348	3891
8	Brick.0008	23	63	415	395	1704	868	321	3789
9	Brick.0009	16	55	358	401	1364	1228	461	3883
10	Brick.0010	41	69	431	469	1168	1052	370	3600
11	Brick.0011	30	61	468	474	1319	900	315	3567
12	Brick.0012	6	32	371	400	1500	858	350	3517
13	Brick.0013	24	63	434	457	1397	1149	364	3888
14	Brick.0014	0	5	219	249	955	1034	694	3156
15	Brick.0015	41	83	403	428	1273	1049	409	3686
16	Brick.0016	16	45	422	509	1540	1184	351	4067
17	Brick.0017	9	26	522	367	924	881	403	3132
18	Brick.0018	16	43	528	432	963	979	448	3409
19	Brick.0019	11	28	526	366	999	902	410	3242
20	Brick.0020	7	25	411	353	845	1107	546	3294

Table 3: Frequency occurrences of MPP-g on ILCLDP-T on Granite Texture.

Sno	Texture Name	MPP-g1	MPP-g2	MPP-g3	MPP-g4	MPP-g5	MPP-g6	MPP-g7	Total
1	Blue_granite	2	4	130	150	849	431	195	1761
2	Blue_pearl	2	18	139	147	994	651	271	2222
3	Blue_topaz	6	32	308	241	737	552	292	2168
4	Brick_erosion	1	4	86	119	616	714	422	1962
5	Canyon_black	0	8	141	131	724	730	283	2017
6	Dapple_green	11	32	198	255	621	794	336	2247
7	Ebony_oxide	3	1	225	94	622	741	404	2090
8	Giallo_granite	8	21	274	102	625	529	331	1890
9	Gosford_stone	1	3	182	67	627	707	402	1989
10	Greenstone	7	7	230	79	599	661	348	1931
11	Interlude_haze	4	10	741	301	685	214	62	2017
12	Kalahari	6	17	656	153	575	239	120	1766
13	Mesa_twilight	6	10	752	284	702	215	51	2020
14	Mesa_verte	1	2	682	248	724	412	185	2254
15	Monza	0	1	126	76	507	773	416	1899
16	Pietro_nero	0	4	194	72	536	657	336	1799
17	Russet_granite	2	4	268	189	718	741	338	2260
18	Granite10	10	30	443	262	680	559	263	2247
19	Granite13	17	32	313	247	649	570	179	2007
20	Granite20	0	3	291	118	480	534	240	1666

Table 4: Frequency occurrences of MPP-g on ILCLDP-T on Mosaic Texture.

S.No	Texture Name	MPP-g1	MPP-g2	MPP-g3	MPP-g4	MPP-g5	MPP-g6	MPP-g7	Total
1	Concrete_bricks_170756	3	10	125	175	1018	860	373	2564
2	Concrete_bricks_170757	0	8	202	140	1344	741	278	2713
3	Concrete_bricks_170776	3	9	180	141	966	755	393	2447
4	Cragy_paving_5091370	2	15	337	301	1287	695	336	2973
5	Cragy_paving_5091376	0	9	160	340	1130	885	349	2873
6	Crazy_tiles_130356	0	2	39	103	540	985	811	2480
7	Crazy_title_5091369	5	25	151	306	884	1143	537	3051
8	Dirty_floor_tiles_foot_256	6	11	180	258	1183	770	263	2671
9	Dirty_tiles_200137	0	2	521	225	916	631	324	2619
10	Floor_tiles_030849	0	1	336	177	769	827	348	2458
11	Grubby_tiles_2565	0	8	584	275	888	497	239	2491
12	Kitchen_tiles_4270064	0	5	715	319	775	344	125	2283
13	Moroccan_tiles_030826	1	2	677	387	1060	581	182	2890
14	Moroccan_tiles_030857	0	1	261	178	911	1148	556	3055
15	Mosaic_tiles_8071010	0	3	626	342	923	479	181	2554
16	Mosaic_tiles_leaf201005	0	4	653	310	936	568	253	2724
17	Mosaic_tiles_leaf20100 5034	2	25	334	259	1143	922	421	3106
18	Motif_tiles_6110065	0	3	626	342	923	479	181	2554
19	Ornate_tiles_030845	7	26	658	277	809	467	190	2434
20	Repeating_tiles_130359	4	11	279	229	718	815	393	2449

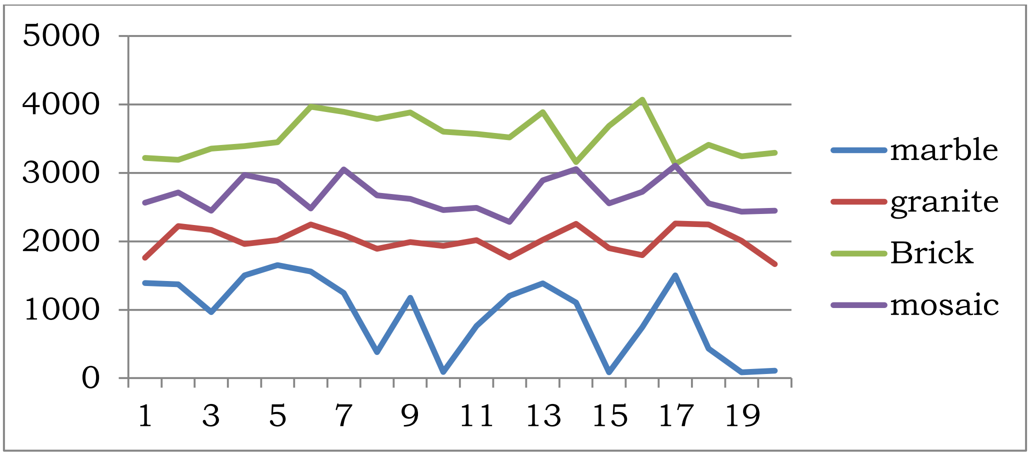

Fig.8: Classification graph of the stone textures based on MPP-g on ILCLDP-T.

The Tables 1 to 4 and the classification graphs of Fig.8 indicate a precise and accurate classification on stone textures using frequency occurrences of MPP-g on ILCLDP-T. Based on the above Tables the present paper derived an algorithm for classification and recognition among these four i.e. Brick, Granite, Marble and Mosaic group of textures. The frequency occurrences of MPP-g on ILCLDP-T are dependent on the dimension of the textures. To address this problem the present research derived a recognition algorithm which is a ratio dependent with the original dimension of the textures considered i.e 256×256 with the dimension of the test image K×K. The basic classification algorithm for local grey to grey level pre processing based on maximum is given below.

Algorithm 1: Recognition of Stone textures based on frequency occurrences of MPP-g on ILCLDP-T.

Let TMPP is the total frequency of occurrences of Morphological primitive patterns on ILCLDP-T test image with dimension K×K.

Begin

if TMPP <= $\left(\frac{K \times K}{256X256} \times 1653\right)$

print (" texture is marble class")

else if TMPP <= $\left(\frac{K \times K}{256X256} \times 2260\right)$

print (texture is granite class")

else if TMPP <= $\left(\frac{K \times K}{256X256} \times 3106\right)$

print(" texture is mosiac class")

else if TMPP <= $\left(\frac{K \times K}{256X256} \times 4067\right)$

print ("texture is brick class")

else

print(" Unknown class ")

End

The proposed MPP-g on ILCLDP-T method is compared with Syntactic Pattern on 3D method [19] Primitive Pattern Unit approach [20] and texton feature evolution method [21]. The above two methods [19,20]] classified stone textures into two groups only. This indicates that the existing methods [19,20] failed in classifying all stone textures. The percentage of classification rates of the proposed method and other existing methods [19,20,21] are listed in Table 5. The Table 5 clearly indicates that the proposed MPP-g on ILCLDP-T method outperforms the other existing methods. Fig.9 shows the comparison chart of the proposed MPP-g on ILCLDP-T method with the other existing methods of Table 5.

IV. Conclusion

The present paper evaluated a new method of classification of stone textures based on frequency of occurrences of MPP-g on ILCLDP-T method on a 3×3 mask. The proposed study attempted classification of four similar groups of stone textures namely brick, marble, granite and mosaic. Classification is carried out on finding the trends of MPP-g of stone textures. The graphs plotted based on trends of Proposed MPP-g on ILCLDP-T method clearly indicates that a precise and accurate classification of stone textures. The experimental results on 256×256 textures clearly indicates a high recognition rate for all stone textures on MPP with seven grain components on a 3×3 mask.

Table 5: Mean % classification rate of the proposed and existing methods.

Image Dataset	Syntactic Pattern on 3D method [19]	Primitive Pattern Unit approach [20]	Texton Feature Detection [21]	Proposed MPP-g on ILCLDP-T method
Mayang	93.29	92.19	95.56	96.15
VisTex	92.53	92.56	94.15	96.05
Akarmarble	93.30	91.29	95.27	97.12
Brodatz	93.59	92.16	94.97	95.85

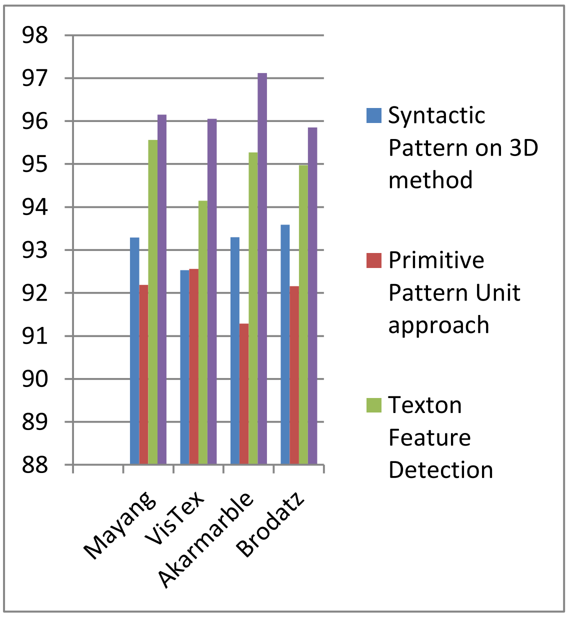

Fig.9: Comparison graph of proposed method and existing methods.

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