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# Texture Classification with Motif Shape Patterns on Local Directional Pattern

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***Abstract: The present paper evaluates motif shape patterns on Local Directional Pattern for texture classification. In this method Local Directional Pattern is computed on the image and then motif shape parameters are evaluated. These shape patterns are used as features for classification. The present method extensively tested on the Dataset consists of various brick, granite, and marble and mosaic stone textures collected from Vistex, Mayang database and also from natural resources from digital camera. The experimental results demonstrate that it is simple and much more effective than the other methods for texture classification.***

***Keywords: Texture classification, LDP, Motif shape patterns***

## 1. Introduction

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, 12], Ojala et.al. proposed to use the Local Binary Pattern(LBP) for rotation invariant texture classification.

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. Face recognition with the Local Directional Pattern [16]. This LDP is better way of representing textures compared to LBP. So, the present paper uses motif shape patterns on LDP of images. This paper is organized as follows. In section II, proposed methodology is described, section III includes results and discussions and conclusions are drawn in section IV.

## II. Methodology

**Step -1: Color image to gray image conversion**

The given colour image is converted into a grey level image using RGB color quantization method.

**Step2: Local Directional Pattern**

The present research uses a Local Directional Pattern concept [16], 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. 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 LDP as eight directional edge response value of a particular pixel using Kirsch masks in eight different orientations (M0-M7) centered on its own position. These masks are shown in the Fig.2. 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 LDP is formed considering only first three values of sorted edge responses in descending order.

| | | |
|---|---|---|
| -3 | -3 | 5 |
| -3 | 0 | 5 |
| -3 | -3 | 5 |

M0

| | | |
|---|---|---|
| -3 | 5 | 5 |
| -3 | 0 | 5 |
| -3 | -3 | -3 |

M1

| | | |
|---|---|---|
| 5 | 5 | 5 |
| -3 | 0 | -3 |
| -3 | -3 | -3 |

M2

| | | |
|---|---|---|
| 5 | 5 | -3 |
| 5 | 0 | -3 |
| -3 | -3 | -3 |

M3

| | | |
|---|---|---|
| 5 | -3 | -3 |
| 5 | 0 | -3 |
| 5 | -3 | -3 |

M4

| | | |
|---|---|---|
| -3 | -3 | -3 |
| 5 | 0 | -3 |
| 5 | 5 | -3 |

M5

| | | |
|---|---|---|
| -3 | -3 | -3 |
| -3 | 0 | -3 |
| 5 | 5 | 5 |

M6

| | | |
|---|---|---|
| -3 | -3 | -3 |
| -3 | 0 | 5 |
| -3 | 5 | 5 |

M7

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

**Step-3 : Motif Shape patterns**

The LDP image is divided into 2 x 2 grids. These grids are then replaced by a particular Peano scan motif which would traverse the grid in the optimal sense. Here, the optimality of the Peano scan is with respect to the incremental difference in LDP values along the scan line minimizing the variation in the LDP values in a local neighborhood. In general, 24 different Peano scans (motifs) could traverse a 2x2 grid. But we consider only the Peano scans (motifs) which start from the top left a corner of the grid because they represent a complete family of space filling curve, reducing the number of motifs to only six [17]. The motif shape patterns are defined over a 2×2 grid, each depicting a distinct sequence of pixels starting from the top left corner as shown in figure 3 for age group classification and are denoted as Z, N, U, C, Gamma, and Alpha respectively. The present paper considers motif shape patterns on LDP of the texture image. The frequency occurrences of all these shape patterns are evaluated on LDP of the image with a 2 x2 grid from left to right and top to bottom in non-overlapped fashion. The process of finding motif shape patterns on LDP is shown in figure 4.

## III. Results and Discussions

In this paper presented the results of the experiments on the dataset, which consists of various brick, granite, marble and mosaic stone textures collected from Vistex, Mayang, Akarmarble, Brodatz databases and also from natural resources from digital camera. Sample of Granite, Mosaic, Marble, Brick textures are shown in Fig.7.

Texture images are classified based on frequency occurrences of the shape patterns Z, N, C, U, GAMMA, and ALPHA and Sum of Frequency Occurrences of the Motif Shape Patterns (SFMSP). The frequency occurrences of Z, N, C, U, GAMMA and ALPHA are represented with FZ, FN, FC, FU, FGAMMA, and FALPHA respectively. The proposed method is investigated on considered dataset and the results are shown in Table 1. From the results, frequency occurrences motif shape patterns N, U, GAMMA and ALPHA and also sum of frequency occurrences of the motif shape patterns are considered as features for texture classification. The classification algorithm is proposed with these features, has given 96% correct classification rate.

,

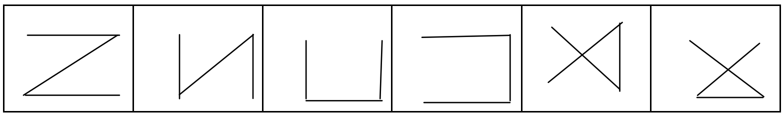
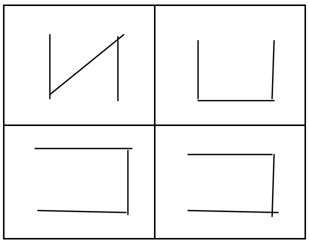


Fig 3: Motif Shape Patterns Z, N, U, C, Gamma and Alpha

| | | | |
|---|---|---|---|
| 205 | 56 | 79 | 65 |
| 110 | 48 | 78 | 90 |
| 54 | 111 | 219 | 99 |
| 210 | 203 | 65 | 90 |



(a) LDP image

(b) Motif shape patterns on 2x2 grid of LDP

Fig 4: Computation of Motif Shape Patterns on LDP images

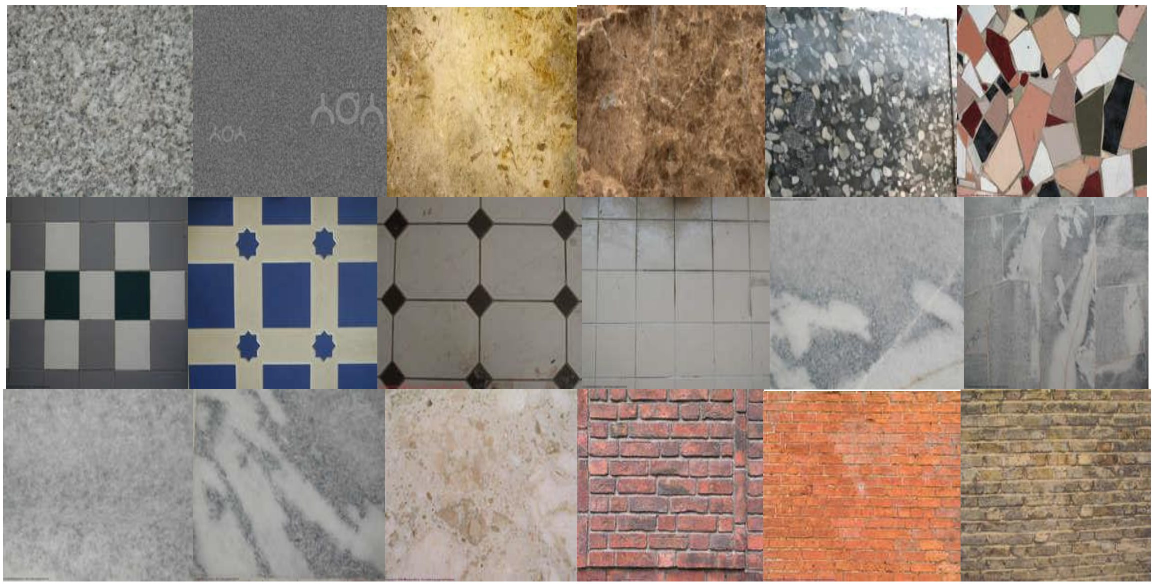


Fig 5: Sample images of Granite, Mosaic, Marble, Brick Textures

Table 1: The Frequency Occurrences of Motif Shape Patterns on LDP of Images

| IMAGE | FZ | FN | FC | FU | FGAMMA | FALPHA | SFMSP |
|---|---|---|---|---|---|---|---|
| Granite1 | 1771 | 1212 | 1832 | 1420 | 1070 | 967 | 8272 |
| Granite2 | 1711 | 1358 | 1758 | 1502 | 972 | 947 | 8248 |
| Granite3 | 1735 | 1455 | 1603 | 1634 | 957 | 932 | 8316 |
| Granite4 | 1625 | 1426 | 1777 | 1621 | 906 | 901 | 8256 |
| Granite5 | 1626 | 1441 | 1654 | 1620 | 926 | 961 | 8228 |
| Granite6 | 1580 | 1369 | 1683 | 1541 | 948 | 964 | 8085 |
| Granite7 | 1416 | 1541 | 1504 | 1696 | 986 | 1071 | 8214 |
| Marble1 | 1428 | 1317 | 1520 | 1372 | 1086 | 1135 | 7858 |
| Marble2 | 1430 | 1339 | 1564 | 1424 | 1112 | 1084 | 7953 |
| Marble3 | 1400 | 1254 | 1536 | 1406 | 1137 | 1102 | 7835 |
| Marble4 | 1459 | 1273 | 1519 | 1461 | 1049 | 1149 | 7910 |
| Marble5 | 1444 | 1245 | 1516 | 1349 | 1143 | 1145 | 7842 |
| Marble6 | 1374 | 1213 | 1423 | 1385 | 1187 | 1146 | 7728 |
| Marble7 | 1504 | 1306 | 1586 | 1405 | 1064 | 988 | 7853 |
| Brick1 | 2613 | 1011 | 2700 | 1496 | 794 | 745 | 9359 |
| Brick2 | 2521 | 716 | 2560 | 1227 | 885 | 817 | 8726 |
| Brick3 | 2578 | 1121 | 2622 | 1538 | 883 | 744 | 9486 |
| Brick4 | 2480 | 1150 | 2639 | 1580 | 849 | 746 | 9444 |
| Brick5 | 2407 | 1272 | 2533 | 1555 | 834 | 716 | 9317 |
| Brick6 | 2442 | 920 | 2519 | 1401 | 870 | 809 | 8961 |
| Brick7 | 2267 | 1266 | 2385 | 1607 | 813 | 805 | 9143 |
| Mosaic1 | 2481 | 2074 | 2610 | 2349 | 1069 | 998 | 11581 |
| Mosaic2 | 2137 | 2135 | 2242 | 2345 | 1369 | 1362 | 11590 |
| Mosaic3 | 2097 | 2211 | 2256 | 2417 | 1413 | 1387 | 11781 |
| Mosaic4 | 3619 | 4193 | 3754 | 4313 | 2111 | 2108 | 20098 |
| Mosaic5 | 3726 | 3191 | 3810 | 3387 | 1905 | 1917 | 17936 |
| Mosaic6 | 3167 | 3000 | 3243 | 3177 | 1663 | 1614 | 15864 |
| Mosaic7 | 3774 | 3237 | 3870 | 3511 | 1938 | 1944 | 18274 |

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**Algorithm 1**: Texture classification using frequency occurrences of Motif Shape Patterns on LDP images

BEGIN

IF (SFMSP > 8085 & SFMSP < 8316)
WRITE (“GRANITE IMAGE”)
ELSE IF (SFMSP > 7728 & SFMSP L < 7953)
WRITE (“MARBLE IMAGE”)
ELSE IF ((FGAMMA > 784 & FGAMMA < 885) & (FALPHA > 716 & FALPHA < 817) & (SFMSP > 8726 & SFMSP < 9486))
WRITE(“BRICK IMAGE”)
ELSE IF ((FN > 2074 & FN < 4193) & (FU > 2345 & FU < 4313) & (SFMSP > 11581 & SFMSP < 20098))
WRITE(“MOSAIC IMAGE”)
ELSE
WRITE(“OTHER IMAGE”)

END

The proposed method for texture classification is compared with existing methods syntactic pattern on 3D method [18], primitive pattern unit approach [19] and texton feature evolution method [20]. The comparison chart of the proposed method with the other existing methods is shown in Fig.6. From the graph, it clearly indicates that the proposed LDP based motif shape patterns method outperforms the other existing methods.

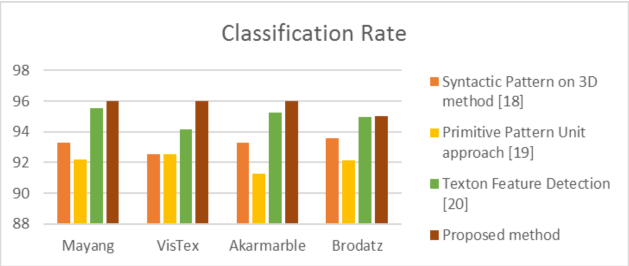


Fig.6: Classification rates of proposed and existing methods

## IV. Conclusion

The proposed method for texture classification uses features motif shape patterns on LDP of images. In this method edge responsiveness of each pixel in eight directions are evaluated and only prominent edge directions are considered for LDP. The motif shape patterns on this LDP are evaluated as features for classification. The algorithm1 with these new set of features classified texture images with a good classification rate compared to other existing methods. This method is very simple, effective and efficient for texture classification.

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