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MORPHOLOGICAL BOUNDARY BASED SHAPE REPRESENTATION SCHEMES ON MOMENT INVARIANTS FOR CLASSIFICATION OF TEXTURES

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ABSTRACT

Efficient shape representation and recognition is an important issue in image processing and computer vision. It provides the foundation for the development of efficient algorithms for many shape related processing tasks. One of the disadvantages of these shape representation schemes is that they yield a poor classification and recognition rate. The classification requires a human intervention, thus the shape representation and classification methods are not automatic. To address these problems the present paper presents a novel and effective methods of shape representation by morphological boundary based methods. The shape features are evaluated by the proposed morphological boundary based methods by suitable numerical characterization derived from moment invariant measures for a precise classification. The proposed Morphological Boundary based Shape Representation scheme (MBSR) derives a new shape descriptor to address the image classification problem by combining boundary extraction and Hu moment (HM) invariants information. The proposed novel schemes of shape representation are applied on original, noisy, rotated and scaled images. The experimental results clearly show the efficacy of the present method.

Keywords: Shape representation and classification, morphological operation, Hu moment invariants, boundary extraction, erosion residue edge detector, structuring element.

1. INTRODUCTION

Efficient shape representation provides the foundation for the development of efficient algorithms for many shape related processing tasks, such as image coding [1], shape matching and object recognition [2, 3], content-based video processing and image data retrieval. Mathematical morphology is a natural processing approach for image object identification since it is a technique based directly on shape [4]. Shape recognition using morphology demands systematical methods of selecting features from a given set of shapes to be classified. There are many shape representation and description techniques in the literature. Zhang et al. in [5] classified shape representations and description methods into two categories: boundary based (also called contour-based) and region based, these methods are performed by using defined image-coding schemes to represent image contents.

Boundary based techniques represent the shape by its outline. In boundary based, objects are represented in terms of their external characteristics (i.e. the pixels along the object boundary), while in region based shape features are extracted from the whole shape region (i.e. the pixels contained in the region). Shape parameters can be extracted from objects in order to describe their shape, to compare it to the shape of template objects, or to partition objects into classes of different shapes. In this respect the important question arises how shape parameters can be made invariant on certain transformations. Objects can be viewed from different distances and from different points of view. Thus it is of interest to find shape parameters that are scale and rotation invariant or that are even invariant under affine or perspective projection.

The theory of moment invariants is derived from the analytic geometry and was proposed by Cayley and Sylvester first. Based on their mathematical study, Hu in 1961 published his first paper about a two dimensional image pattern recognition using moments [6]. In it Hu proposed the concept of algebraic moment invariants for the first time, and gave a group of algebraic moments based on the combination of general moments. The set of moments known as Hu moments are invariant in the scale, translation and rotational change of the objects. The image recognition method based on these moments has achieved good results in the majority of 2D and 3D image recognition experiment, which caused researchers' widespread attention [7, 8, 6, 9, 10]. However, the approach needs to deal with all pixels of the target image region, taking a long time, so has relatively low efficiency. A fundamental criterion for characterizing shape representation techniques is boundary. For this reason the present paper evaluated moment invariants on boundaries that represent the shape. The present paper is organized as follows. The section 2 describes the methodology, the results and discussions are given in section 3 and conclusions are listed in section 4.

2. METHODOLOGY

2.1 Classification of Textures Using MBSR Scheme on HM

The Hu moments which are evaluated on the proposed MBSR scheme are named as Boundary moments (BM). The present paper evaluated seven BM's on five groups of texture images and derived an effective classifier. After a careful study on the existing literature on boundary based methods the paper listed out some of the disadvantages.

- The existing boundary based methods are sensitive to the starting point of the shape boundary, i.e if the starting point changes, the whole boundary sequence is changed.
- The existing methods suffer from digitization noise so these methods are not desirable to be used directly for shape description and matching.
- Most of the boundary based methods are not rotationally invariant by nature.

To overcome this, the paper proposes a novel Morphological Boundary based Shape Representation (MBSR) approach for shape representation that looks for effective ways to capture the essence of the shape features that make it easier for a shape to be stored, transmitted, compared against and recognized. The proposed MBSR is also independent of translation, rotation and scaling of the shape.

Boundary based moments derived from HM use erosion residue edge detector for boundary extraction, since the morphological edge detector is a basic tool for shape detection. Based on this thought, the paper proposes a method for image classification based on boundary as in Figure 1.

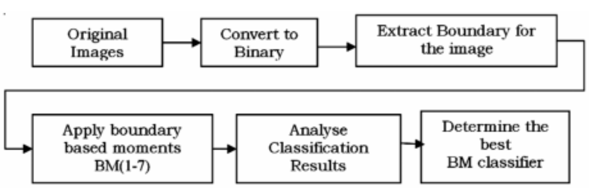

Figure 1: Texture Classification Algorithm based on the Combination of Boundary and HM Invariants

The MBSR obtains boundary of an image by simple morphological operations. Boundary extraction of the image (I) of MBSR is obtained by first eroding I by Structuring Element (SE) and then performing the set difference between I and its erosion as in equation 1.

$$A(I) = I - (I \Theta SE) \qquad (1)$$

Where I, Θ, – and SE are

I Denotes texture images

– Denotes subtraction

Θ Denotes morphological erosion operation

SE Denotes structuring element consisting of all ones in a 3 × 3 matrix

2.2 Hu Moment Invariants

A typical image recognition and classification task involves grouping images based on the shape features. This is accomplished by suitable numerical characterization of the shape of the given objects. The given image falls into same group if the numerical characterization of the shape of the images falls into the closest difference value. Ideally, two important properties of a shape characterization are (1) visually distinct objects should have distinct characterizations and (2) numerical similarity of the characterization of two objects should correspond to a visual similarity between them.

For a given object in an image, Hu [11] defined a characterization consisting of an ordered seven-tuplet of real numbers listing seven moment invariants derived from the first three central moments. This characterization is invariant to object scale, position and rotation. HM invariants are derived from normalized central moments, the details of deriving moment invariants can be found in [12]. For a digital image with density distribution function $f(x, y)$, the two dimensional $(p + q)$ order moment is defined as follows:

$$m_{pq} = \int_{x,y \in c}\int x^p y^q f(x,y)\,dx\,dy \qquad \text{Where } p, q = 0, 1, 2 \ldots\ldots \qquad (2)$$

The double integrals are to be considered over the whole area of the object including its boundary. The density distribution function $f(x, y)$ gives the intensity color of the point (x, y) in image space. In practical pattern recognition applications the image space is reduced to a binary version, and in such a case $f(x, y)$ takes the value of 1 when the pixel (x, y) represents objects or even noise and it is 0 when it is part of the background.

When the geometrical moments m_{pq} in equation 2 is referred to the object centroid $(\bar{x}, \bar{y})$ they become the Central Moments, and is given by equation 3.

$$\mu_{pq} = \int_{x,y \in c}\int (x-\bar{x})^p (y-\bar{y})^q f(x,y)\,dx\,dy \qquad (3)$$

Where

$$\bar{x} = \frac{m_{10}}{m_{00}} = \frac{\int_{x,y \in c}\int x f(x,y)\,dx\,dy}{\int_{x,y \in c}\int f(x,y)\,dx\,dy} \qquad (4)$$

$$\bar{y} = \frac{m_{01}}{m_{00}} = \frac{\int_{x,y \in c}\int x f(x,y)\,dx\,dy}{\int_{x,y \in c}\int f(x,y)\,dx\,dy} \qquad (5)$$

In the binary case, m_{00} represents the region area. Scale invariant features can also be found in scaled central moments η_{pq}. The normalized central moment of order $(p + q)$ is given by equation 6.

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\frac{p+q+2}{2}}} \quad (6)$$

The set of seven lowest order rotation, translation and scale invariant function of HM include invariants upto the third order. The HMs applied on the extracted boundary of the image is termed as Boundary Moments (BM). They are given by BM1 to BM7 in equations 7 to 13.

$$BM1 = \eta_{20} + \eta_{02} \quad (7)$$

$$BM2 = (\eta_{20} - \eta_{02})^2 + 4\,\eta_{11}^2 \quad (8)$$

$$BM3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (9)$$

$$BM4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (10)$$

$$BM5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + 3\,(\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (11)$$

$$BM6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (12)$$

$$BM7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (13)$$

2.3 Classification Algorithm of MBSR on BM

The paper developed a novel approach called Morphological Boundary based Shape Representation scheme on Hu moments for classification purpose. The MBSR classification algorithm is given in Algorithm 1.

For an efficient classification problem the present paper considered five different groups of textures as shown below from Figure 2 to Figure 6 namely brick, granite, fabric, mosaic and marble respectively, where each group contains ten textures each. These textures are of similar shape. That is the reason the present study has chosen this texture group, and applied the proposed MBSR scheme on HM.

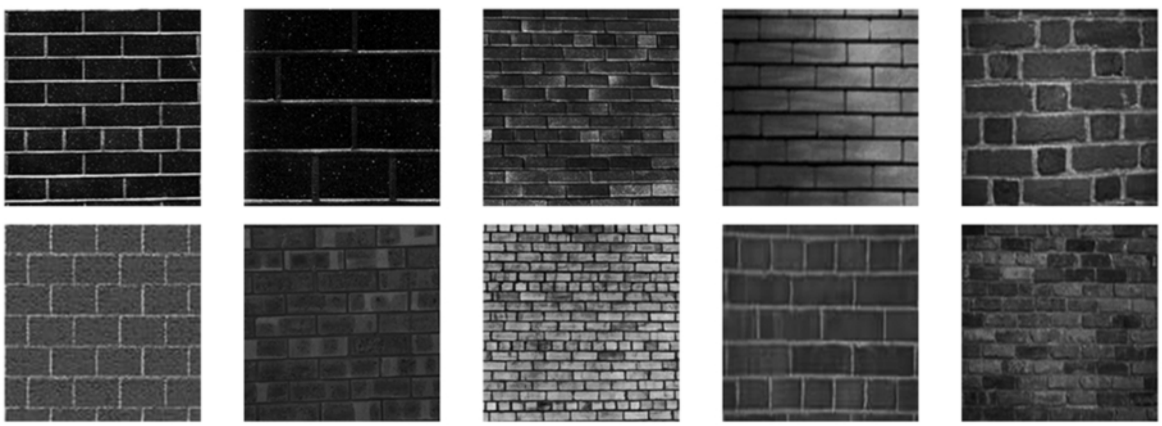

Figure 2: Original Images of Brick Textures

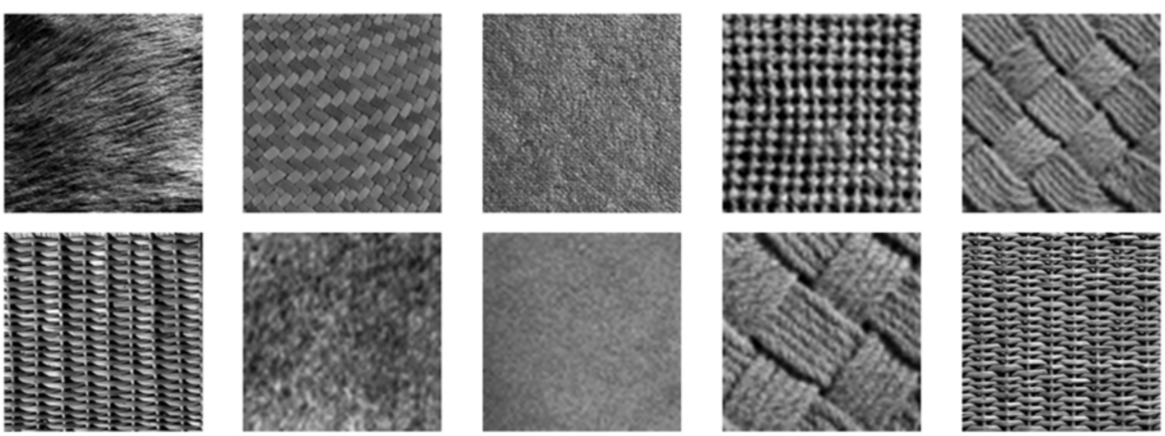

Figure 3: Original Images of Fabric Textures

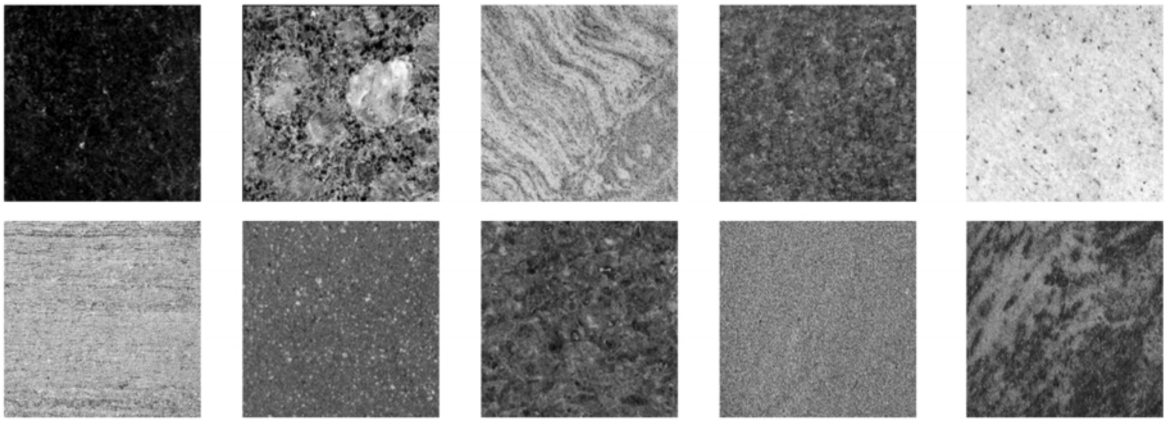

Figure 4: Original Images of Granite Textures

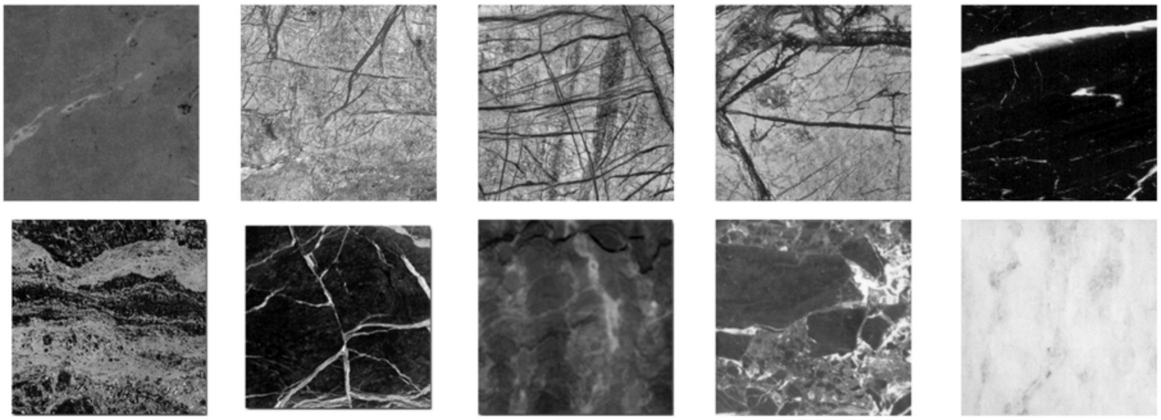

Figure 5: Original Images of Marble Textures

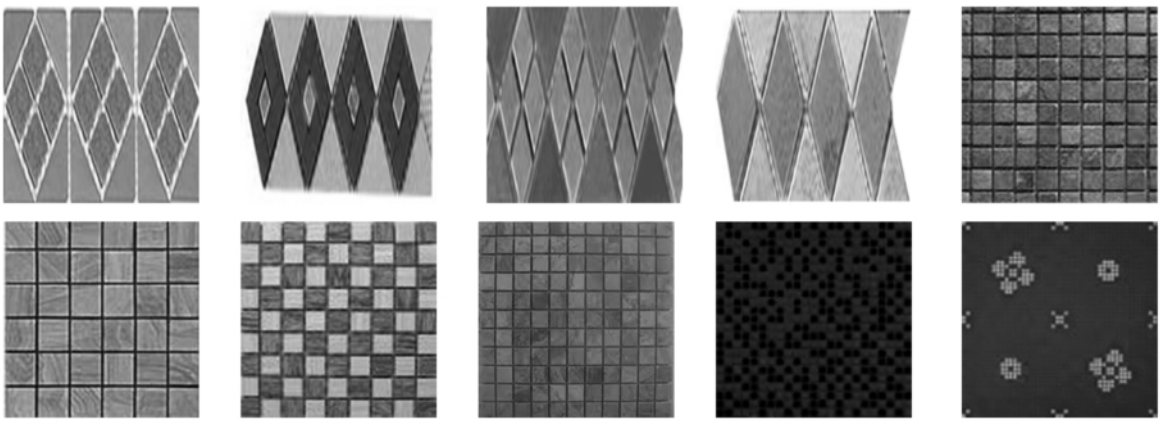

Figure 6: Original Images of Mosaic Textures

Algorithm 1: A Novel MBSR scheme on BM.

The proposed algorithm contains six steps. These steps are applied on original, noisy, rotated and scaled images.

Step 1: Convert the given color image into grey scale image.

Step 2: Convert the grey scale image into binary image.

Step 3: Apply the proposed MBSR scheme on the generated image of step 2 to obtain boundary that represents the shape of the texture in an efficient way.

Step 4: Evaluate BM on MBSR scheme.

Step 5: Calculate the average BM value for each group of ten textures and place them in database.

Step 6: Plot the classification graph for all seven BM on MBSR scheme and determine the significant BM that classifies accurately and efficiently the given textures.

3. RESULTS AND DISCUSSIONS

3.1 Classification of Original Texture Images on MBSR Scheme Using BM

The algorithm 1 is applied on the five groups of textures, where each group consists of ten textures each, which results a total of 50 textures. The average BM values for each group of texture is listed in Table 1 and based on this a classification graph is plotted in Figure 7.

Table 1
Average BM's on MBSR Schemes Obtained from Original images

Images	*BM1*	*BM2*	*BM3*	*BM4*	*BM5*	*BM6*	*BM7*
Brick	0.8857	0.0396	0.0391	0.0035	0.0000	–0.0007	0.0000
Fabric	0.5636	0.0860	0.0003	0.0002	0.0000	0.0000	0.0000
Granite	0.4788	0.0009	0.0009	0.0006	0.0000	0.0000	0.0000
Marble	0.9258	0.0121	0.0587	0.0142	–0.0007	–0.0025	–0.0021
Mosaic	1.2093	0.0202	0.0189	0.0261	0.0010	0.0024	–0.0006

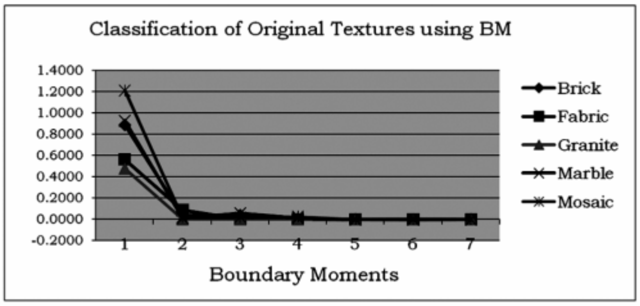

Figure 7: Classification Graph on Average BM's of MBSR Scheme Obtained from Original Images

3.2 Classification of Noisy Texture Images on MBSR Schemes using BM

The Algorithm 1 is applied on the same texture images by adding salt and pepper noise. The average value of the BM's are listed in Table 2 and the classification graph is plotted in the Figure 8.

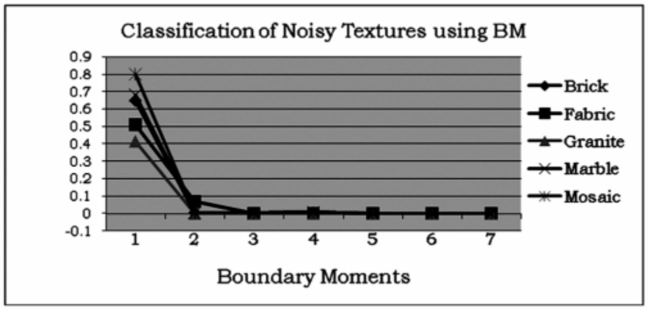

Figure 8: Classification Graph on BM's of MBSR Scheme Obtained from Noisy Images

Table 2
Average BM's on MBSR Schemes Obtained from Original images

Images	*BM1*	*BM2*	*BM3*	*BM4*	*BM5*	*BM6*	*BM7*
Brick	1.2818	0.0917	0.1476	0.0142	0.0007	–0.0059	0.0001
Fabric	0.7117	0.0009	0.0003	0.0002	0.0000	0.0000	0.0000
Granite	0.6940	0.0011	0.0017	0.0011	0.0000	0.0000	0.0000
Marble	1.3072	0.0134	0.0920	0.0283	–0.0021	–0.0046	–0.0049
Mosaic	1.8497	0.0499	0.0669	0.0745	0.0060	0.0079	–0.0026

3.3 Classification of Texture Images on MBSR Scheme with Rotations using BM

To test the transformation property of the BM on the proposed MBSR scheme, the original images are rotated from 00 to 1800 with an incremental rotation of 450. The Algorithm 1 is applied on the rotated texture images. The average value's of the BM's is listed in Table 3 and the classification graph is plotted in the Figure 9.

Table 3
Average BM's on MBSR Schemes Obtained from Rotated Images

Images	*BM1*	*BM2*	*BM3*	*BM4*	*BM5*	*BM6*	*BM7*
Brick	0.7939	0.0277	0.0196	0.0016	0.0000	–0.0001	0.0000
Fabric	0.4839	0.0008	0.0003	0.0002	0.0000	0.0000	0.0000
Granite	0.4730	0.0008	0.0011	0.0005	0.0000	0.0000	0.0000
Marble	0.9007	0.0107	0.0306	0.0125	0.0000	–0.0014	–0.0012
Mosaic	1.0838	0.0150	0.0141	0.0205	0.0008	0.0022	–0.0005

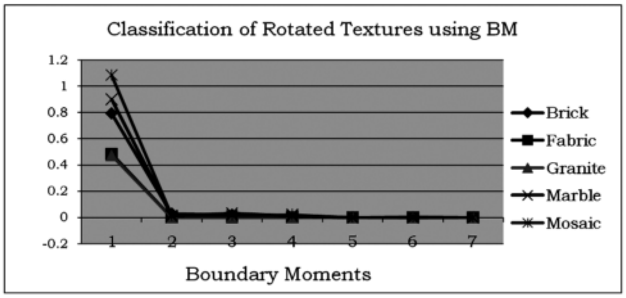

Figure 9: Classification Graph on BM's of MBSR Scheme Obtained from Rotated Images

3.4 Classification of Texture Images on MBSR Scheme with Scaling Transformation Using BM

To test the transformation property of the BM on MBSR scheme with scaling transformation, the original images are scaled to double and half size and the Algorithm 1 is applied on the scaled image textures. The average BM's of MBSR scheme is listed in Table 4 and classification graph is plotted in Figure 10.

Table 4
Average BM's on MBSR Schemes Obtained from Rotated Images

Image	*BM1*	*BM2*	*BM3*	*BM4*	*BM5*	*BM6*	*BM7*
Brick	1.2818	0.0917	0.1476	0.0142	0.0007	–0.0059	0.0001
Fabric	0.7117	0.0009	0.0003	0.0002	0.0000	0.0000	0.0000
Granite	0.6940	0.0011	0.0017	0.0011	0.0000	0.0000	0.0000
Marble	1.3072	0.0134	0.0920	0.0283	–0.0021	–0.0046	–0.0049
Mosaic	1.8497	0.0499	0.0669	0.0745	0.0060	0.0079	–0.0026

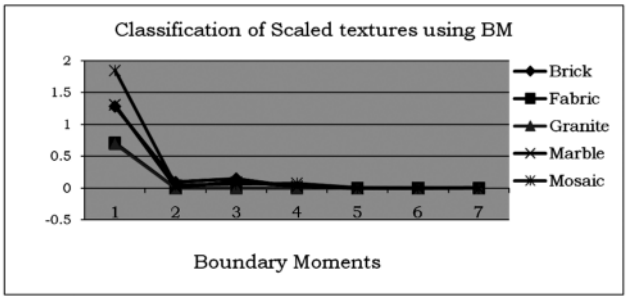

Figure 10: Classification Graph on BM's of MBSR Scheme Obtained from Scaled Images

Based on the Tables 1, 2, 3 and 4 and plotted graphs of Figures 7, 8, 9, and 10 it is clearly evident that only BM1 on boundary of original, noisy, rotated and scaled images obtained from MBSR scheme classifies the given five groups of textures and all other six BM's from BM2 to BM7 shows more or less same value and plotted in the same region of the graph. That is BM2 to BM7 on boundary of MBSR scheme failed in classification of the textures. In all the above representations the mosaic textures are having high average BM1 value on MBSR scheme. The classification by scaled textures is poor when compared to other methods.

4. CONCLUSION

The present paper proposed a novel and effective methods of classification by morphological boundary based methods. The proposed novel schemes of shape representation are applied on original, noisy, rotated and scaled images.

The proposed MBSR, capture the essence of the shape features that make it easier for a shape to be stored, transmitted, compared against and recognized. The proposed MBSR is also independent of translation, rotation and scaling of the shape. The Boundary moments derived from Hu moments, which are invariant in the scale, translation and rotational change of the objects, are applied on MBSR for effective precise texture classification.

Based on the Tables and plotted graphs it is clearly evident that only BM1 on boundary of original, noisy, rotated and scaled images obtained from MBSR scheme classifies the given five groups of textures. And BM2 to BM7 on boundary of MBSR scheme failed in classification of the textures. The classification by scaled textures is poor when compared to other methods.

REFERENCES

[1] Kresch R. and Malah D., "Skeleton-based Morphological Coding of Binary Images", *IEEE Trans. Image Processing*, **7**, pp. 1387-1399, Oct. 1998.

[2] Belongie S., Malik J. and Puzicha J., "Shape Matching and Object Recognition Using Shape Contexts", *IEEE Trans. Pattern Anal. Mach. Intell.*, **24(4)**, pp. 509-522, Apr. 2002.

[3] Ei-Kwae E.A. and Kabuka M.R., "Binary Object Representation and Recognition Using the Hilbert Morphological Skeleton Transform", *Pattern Recognition*, **33**, pp. 1621-1636, 2000.

[4] Haralick R.M., Sternberg S.R. and Zhuang X, "Image Analysis Using Mathematical Morphology", *IEEE Trans. PAMI*, PAMI-0, pp. 532-550, May1986.

[5] Zhang D.S. and Lu G., "Review of Shape Representation and Description Techniques", *Pattern Recognition*, **37(1)**, 1-19, 2004.

[6] Ming-Kuei Hu, "Visual Pattern Recognition by Moment Invariants", *Information Theory, IRE Transactions*, **8**, pp. 179-187, Feb. 1962.

[7] Boyce J.F. and Hossack W.J., "Moment Invariants for Pattern recognition", *Pattern Recognition Letters*, **1**, pp. 451-456.

[8] Chen C.C., Tung-I T Sai, "Improved Moment Invariants for Shape Discrimination", *Pattern Recognition*, **26(5)**, pp. 683-686, 1993.

[9] Sluzek A, "Identification and Inspection of 2-D Objects using New Moment-based Shape Descriptors", *Pattern Recog.*, **16**, pp. 687-697, 1995.

[10] Teaque M.R., "Image Analysis via the General Theory of Moments", *Journal of the Optical Society of America*, **70**, pp. 920-930, 1980.

[11] Hu M.K., "Visual Pattern Recognition by Moment Invariants", *IRE 2lan.s. Inform. Theory*, IT-8, 1962, pp. 179-187.

[12] Jia-Guu Leu, "Computing a Shape's Moments from Its Boundary", *Pattern Recognition*, **24(10)**, pp. 949-957, 1991.