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An Approach for Classification of Preprocessed Textures Based On Boundary Moments

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Abstract*— Texture classification is one of the problems which have been paid much attention on by image processing scientists. Consequently, many different methods have been proposed to solve this problem. In most of these methods the researchers attempted to describe and discriminate textures based on linear and non-linear patterns. The present paper describes a novel and effective method of shape classification by combining innovative preprocessing techniques, morphological boundary method and Hu moments. To offer better classification rate, first innovative preprocessing methods are applied on various texture images. Preprocessing mechanisms describe various methods of converting a grey level image into binary image with minimal consideration of the noise model. Then shape features are evaluated using HM by suitable numerical characterization derived from moment invariant measures on the proposed Morphological Boundary(MB) method for a precise classification. This proposed MB derives a new shape descriptor to address the image classification problem by combining boundary extraction and Hu moment(HM) invariants information. A good comparison is made between these methods by combining preprocessing techniques, boundary extraction and Hu moments. This texture classification study using MB and HM has given a good performance. The experimental results clearly show the efficacy of the present method.

***Index Terms*— Image classification, shape representation, morphological operation, Hu moment invariants, boundary extraction, preprocessing techniques, structuring element.**

I. INTRODUCTION

Efficient shape classification 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. The classification problem is basically the problem of identifying an observed textured sample as one of several possible texture classes by a reliable but computationally attractive texture classifier. This implies that the choice of the textural features should be as compact as possible and yet as discriminating as possible. In other words, the extraction of texture features should efficiently embody information about the textural characteristics of the image. To design an effective algorithm for texture classification, it is essential to find a set of texture features with good discriminating power. A number of texture classification techniques have been reported in literature [4,5,13,14].

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Boundary based techniques represent the shape by its outline. In boundary based techniques, objects are represented in terms of their external characteristics (i.e. the pixels along the object boundary. 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.

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. To overcome this deficiency, a novel method is proposed which extracts the boundary of target image by applying preprocessing methods first, then Hu moments are applied on the extracted boundaries to achieve classification in efficient manner.

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.

II. METHODOLOGY

A. Preprocessing methods

The present section briefly outlines the various methods of converting grey level image into preprocessed image. The basic structure of this conversion is outlined in figure 1. A binary image can be obtained by various preprocessing methods[20,21]. The present paper taken into consideration the following preprocessing methods applied on local neighborhoods, which are listed as follows (a) local maximum, (b) local minimum, (c)mode, d)median , (e)mean and (f)((max-min)/2).

B. Classification of shape textures using MB Scheme on HM

The Hu moments which are evaluated on the proposed MB scheme are named as Boundary Moments (BM). The present paper evaluated seven BM's on five groups of shape pattern 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.

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- 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 are 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 MB 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.

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.

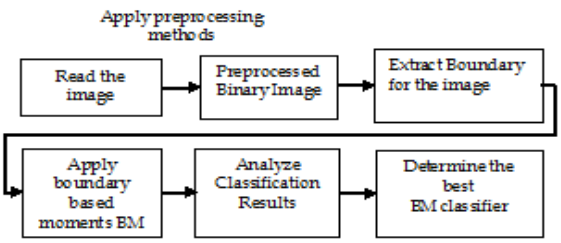

Figure.1 Proposed block diagram for Texture classification.

The MB obtains boundary of an image by simple morphological operations. Boundary extraction of the image (I) 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 3x3 matrix

C. 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-tippet 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 [12,15-19]. For a digital image with density distribution function f(x, y), the two dimensional (p + q) order moment is defined as follows:

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

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

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

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

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

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

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.

The seven boundary based moments are:

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

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

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

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

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

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

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

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D. Classification Algorithm for preprocessed texture images based on BM

A novel approach is proposed based on Morphological Boundary and Hu moments for classification purpose. The MB classification algorithm is given in Algorithm 1.

For an efficient classification problem the present paper considered five different groups of shape pattern textures as shown below from Fig. 2 to Fig. 6 namely brick, circle, curve, line and zigzag 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 MB scheme on HM.

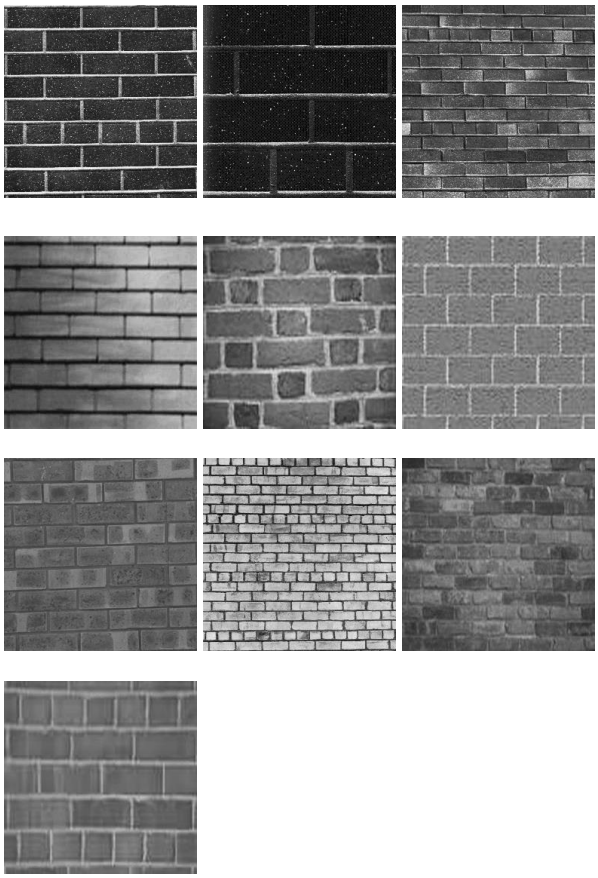
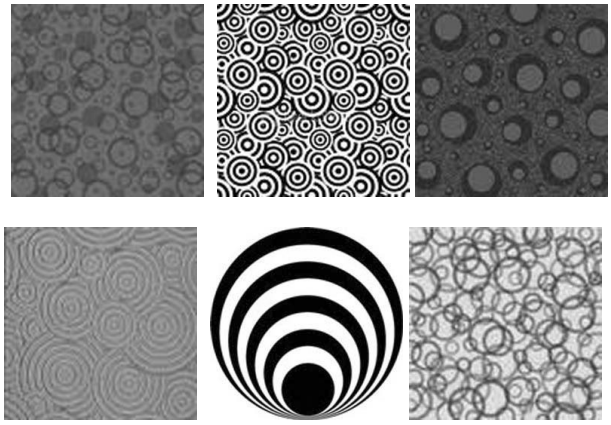


Fig. 2 Original images of brick textures.



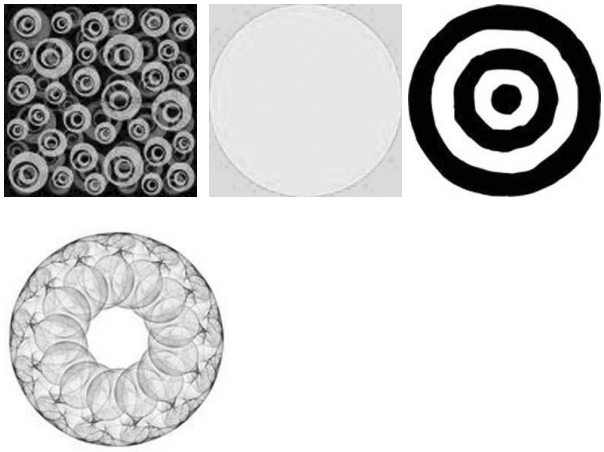
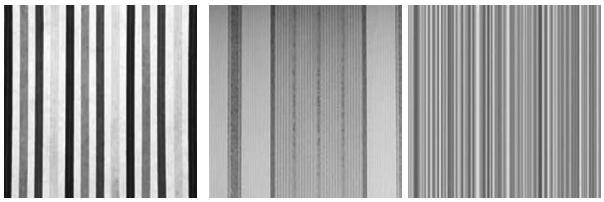


Fig. 3 Original images of Circles textures.

Fig. 4 Original images of Curves textures.



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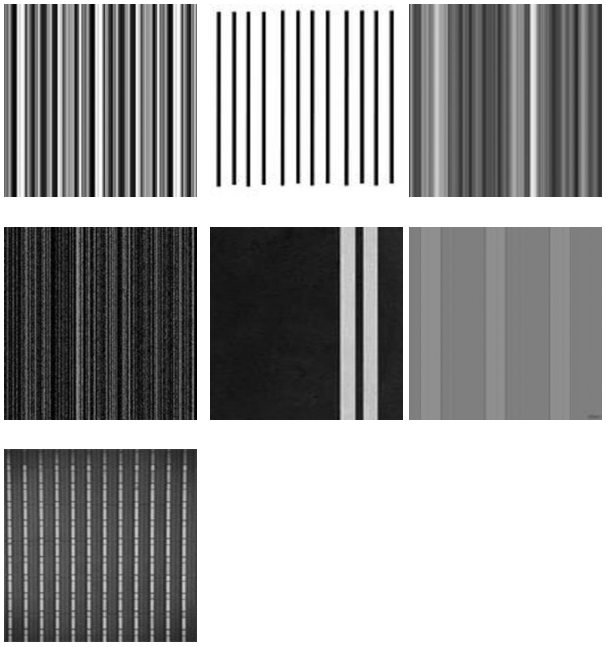

Fig. 5 Original images of Line textures.

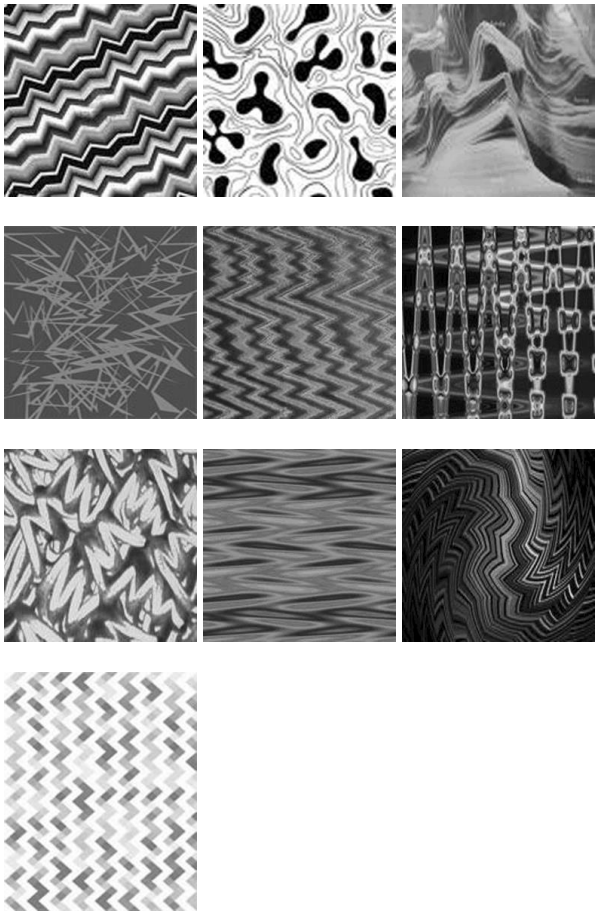

Fig. 6 Original images of Zigzag textures.

Algorithm 1: A Novel textures classification method using MB and BM

The proposed algorithm contains six steps. These steps are applied on five group of shape texture images.

Step 1: Convert the grey scale image into binary image.

Step 2: A binary image is obtained by applying preprocessing methods. The present paper taken into consideration the following preprocessing methods applied on local neighborhoods, which are listed below. a) local maximum, local minimum, local mode, local median, local mean and local maxmin i.e((max-min)/2).

Step 3: Apply the proposed MB 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 MB scheme.

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

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

III. RESULTS AND DISCUSSIONS

A. Classification by BM on preprocessed textures using local maximum

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

TABLE.1 AVERAGE BM'S AFTER PREPROCESSING THE IMAGE USING LOCAL MAXIMUM

Image Name	BM1	BM2	BM3	BM4	BM5	BM6	BM7
Brick	1.02471	0.02641	0.02545	0.00816	0.00034	0.00146	-0.0003
Circle	1.85206	0.00306	0.30035	0.4928	1.70147	0.05483	0.61966
Curve	1.4171	0.06822	0.2512	0.24083	-0.1146	-0.0096	0.08274
Line	2.50505	2.42625	0.11466	0.08907	0.05046	0.00673	0.00022
Zigzag	1.12301	0.03566	0.03325	0.0106	0.00044	0.00194	-0.0006

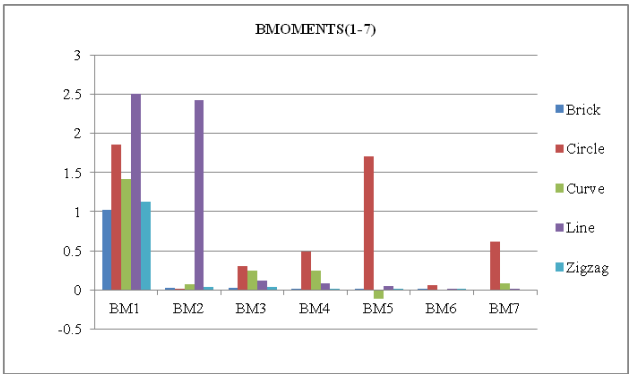

Figure 7. Classification graph on average BM's obtained after preprocessing texture images using local maximum.

B. Classification by BM on preprocessed textures using local minimum

The Algorithm 1 is applied on the same texture images after applying local minimum preprocessing method. The average value of the BM's are listed in Table 2 and the classification graph is plotted in the Figure 8.

TABLE.2 AVERAGE BM'S ON PREPROCESSED IMAGE USING LOCAL MINIMUM

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Image Name	BM1	BM2	BM3	BM4	BM5	BM6	BM7
Brick	1.1168	0.0340	0.0461	0.0118	0.0000	0.0005	0.0002
Circle	2.1545	0.0089	0.0550	0.0153	-0.0007	0.0006	0.0001
Curve	1.6956	0.1273	0.1850	0.4129	-0.2057	-0.2447	0.3311
Line	2.1543	2.8460	0.0226	0.0438	0.0053	-0.0104	-0.0135
Zigzag	1.3471	0.0260	0.0159	0.0160	0.0001	0.0008	-0.0010

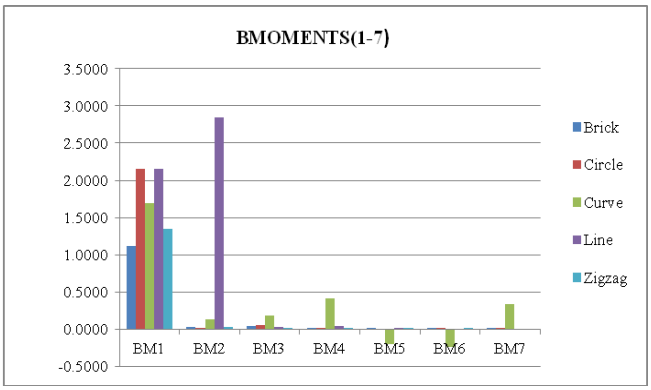

Figure 8. Classification graph on average BM's obtained after preprocessing texture images using local minimum.

C. Classification by BM on preprocessed textures using local MaxMin

The Algorithm 1 is applied on the same images after applying local MaxMin i.e ((max-min)/2) preprocessing method. The average value of the BM's are listed in Table 3 and the classification graph is plotted in the Figure 9.

TABLE.3 AVERAGE BM'S ON PREPROCESSED IMAGE USING LOCAL MAXMIN METHOD.

Image Name	BM1	BM2	BM3	BM4	BM5	BM6	BM7
Brick	0.7833	0.0011	0.0012	0.0008	0.0000	0.0000	0.0000
Circle	0.9886	0.0012	0.0026	0.0158	0.0007	0.0005	-0.0002
Curve	0.9904	0.0674	0.0683	0.0863	-0.0343	-0.0497	0.0311
Line	1.1731	0.0492	0.0825	0.4091	0.6951	-0.2734	-0.1584
Zigzag	0.5949	0.0050	0.0021	0.0007	0.0000	0.0000	0.0000

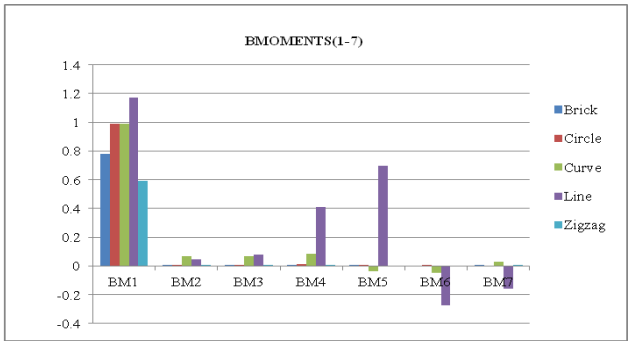

Figure 9. Classification graph on average BM's obtained after preprocessing texture images using local MaxMin.

D. Classification by BM on preprocessed textures using local mode

The Algorithm 1 is applied on the same texture images after applying local mode preprocessing method. The average value of the BM's are listed in Table 4 and the classification graph is plotted in the Figure 10.

Table.4 Average BM's on preprocessed image using local mode

Image Name	BM1	BM2	BM3	BM4	BM5	BM6	BM7
Brick	0.8576	0.0295	0.0228	0.0025	0.0012	0.0000	0.0000
Circle	1.7089	0.0057	0.2111	0.0872	-0.0338	0.0032	0.0760
Curve	1.2666	0.0808	0.1426	0.1922	0.0192	-0.0675	0.1328
Line	1.7574	1.4780	0.0910	0.0186	0.0008	0.0255	-0.0013
Zigzag	0.9738	0.0170	0.0070	0.0036	0.0000	0.0002	-0.0001

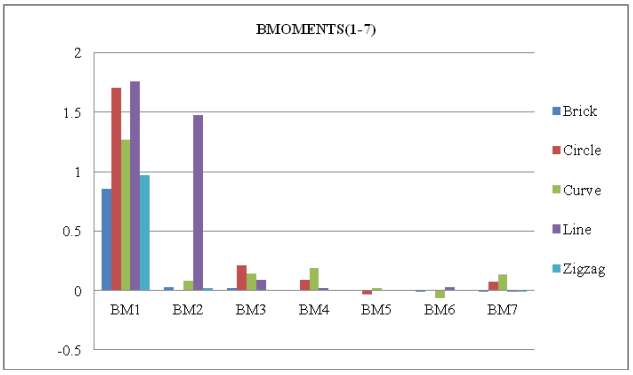

Figure 10. Classification graph on average BM's obtained after preprocessing texture images using local mode.

E. Classification by BM on preprocessed textures using local median.

The Algorithm 1 is applied on the same texture images after applying local median preprocessing method. The average value of the BM's are listed in Table 5 and the classification graph is plotted in the Figure 11.

Table.5 Average BM's on preprocessed image using local median

Image Name	BM1	BM2	BM3	BM4	BM5	BM6	BM7
Brick	1.1338	0.0486	0.0504	0.0060	0.0000	-0.0010	0.0000
Circle	1.7067	0.0034	0.1523	0.2245	0.2036	0.0354	0.3569
Curve	1.4338	0.1661	0.2787	0.4156	0.4654	-0.1581	0.7644
Line	2.2923	2.5494	0.0156	0.0166	-0.0005	0.0083	0.0006
Zigzag	1.1812	0.0304	0.0290	0.0093	0.0003	0.0008	-0.0007

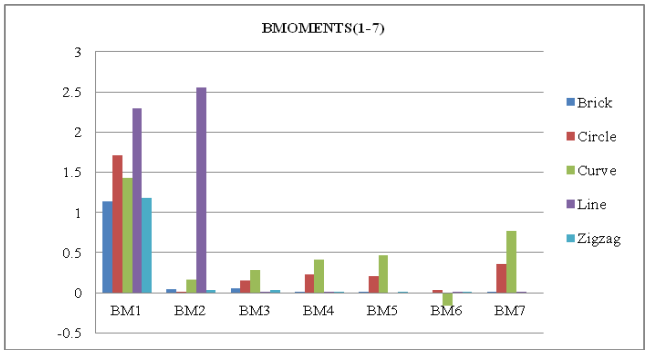

Figure 11. Classification graph on average BM's obtained after preprocessing texture images using local median.

F. Classification by BM on preprocessed textures using local mean.

The Algorithm 1 is applied on the same texture images after applying local mean preprocessing method. The average value of the BM's are listed in Table 6 and the classification graph is plotted in the Fig.12.

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Table.6 Average BM's on preprocessed image using local mean

Image Name	BM1	BM2	BM3	BM4	BM5	BM6	BM7
Brick	1.1921	0.0183	0.0107	0.0047	0.0001	0.0006	-0.0001
Circle	2.3948	0.0033	0.2125	0.1215	-0.0807	0.0120	0.1339
Curve	1.5862	0.1150	0.2333	0.3854	-0.1610	-0.2296	0.3270
Line	2.3709	2.5139	0.0234	0.0293	0.0018	0.0002	0.0006
Zigzag	1.2438	0.0237	0.0112	0.0113	0.0000	0.0010	-0.0003

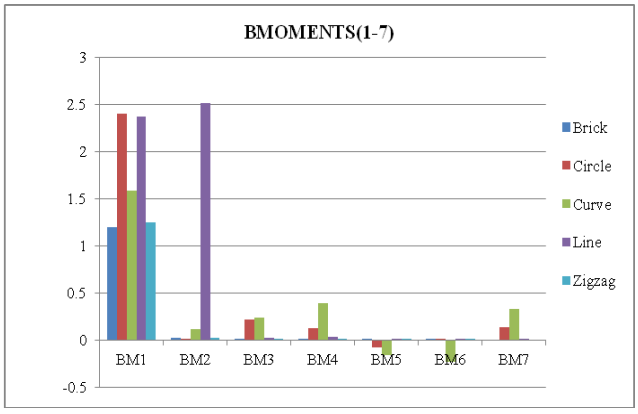

Figure 12. Classification graph on average BM's obtained after preprocessing texture images using local mean.

IV. CONCLUSION

The present paper proposes a novel Morphological Boundary representation method on Hu Moment for classification of textures with similar shape components. Classification has been carried out by applying preprocessing methods first followed by extracting the boundary of the target image on which Hu moments are computed to achieve precise classification of textures. The present paper taken into consideration the following preprocessing methods applied on local neighborhoods, which are listed below. a) local maximum, local minimum, mode, median , mean and maxmin i.e((max-min)/2). Based on the Tables and plotted graphs it is clearly evident that only BM1 classifies the given five groups of shape pattern textures. It is also clearly evident that BM2 to BM7 failed in classification of the texture images.

The present paper concludes that there are n numbers of preprocessing methods which can be further expanded. The final conclusion is "one cannot say which preprocessing method is superior; this depends upon the type of image, the way the grey levels are spread, and type of application. Therefore the present paper recommends it is better to choose one of the preprocessing methods by applying and comparing each instead of depending upon a constant method.

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