COMPOSITE TEXTURE SHAPE CLASSIFICATION BASED ON MORPHOLOGICAL SKELETON AND REGIONAL MOMENTS

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ABSTRACT

After several decades of research, the development of an effective feature extraction method for texture classification is still an ongoing effort. Therefore , several techniques have been proposed to resolve such problems. In this paper a novel composite texture classification method based on innovative pre-processing techniques, skeletonization and Regional moments (RM) is proposed. This proposed texture classification approach, takes into account the ambiguity brought in by noise and the different caption and digitization processes. To offer better classification rate, innovative pre-processing methods are applied on various texture images first. Pre-processing 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 RM on the proposed Morphological Skeleton (MS) method by suitable numerical characterization measures for a precise classification. This texture classification study using MS and RM has given a good performance. Good classification result is achieved from a single region moment RM10 while others failed in classification.

KEYWORDS

Classification, Pre-processing, Morphological Skeleton, Hu Moments, Regional Moments

1. INTRODUCTION

Texture classification is an important step in many computer vision algorithms [1,2,3,4]. In texture classification, images of same group should be homogeneous with respect to some characteristics or features and different textures should have significant different features or characteristics.

We know a good shape representation should provide an accurate and complete description of a given object. One of the great advantages of shape representation is, only shape can be preserved instead of the whole image. By this, the storage size will be reduced and the original image can be reconstructed from the preserved shape. A simple and compact representation of a shape that preserves many topological characteristics like size, length of a shape, separation of the shapes, and other qualitative behavioral aspects of the shape can be provided by a skeleton representation. Such kind of shape representation schemes is useful for fast image retrieval and in image compression problems. By preserving intrinsic details of shape the original image can be reconstructed in skeletonization approach. Thus it plays an essential function in human visual perception in shape recognition and shape analysis problems.

It was Cayley and Sylvester who initially derived the theory of moment invariants based on analytical geometry. Using their study it was Hu who first introduced the concept of algebraic

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moment invariants. The set of Hu moments are invariant to any change in an object subjected to rotation, scale and translation change [5-9]. Most of the shape representation algorithms using moment invariants consider all pixels of a given image in classification taking a long time to compute and thus are relatively less inefficient. To overcome this deficiency, a novel method is proposed which extracts the skeleton of target image by applying preprocessing methods first, then Regional Moments (RM) derived from Hu moments are applied on the extracted skeleton to achieve classification in efficient manner.

The paper is organized as follows. Section 2 briefly described the methodology employed introducing preprocessing methods, skeletonization, Hu moments, regional moments and the classification algorithm, section 3 deals with results and discussions. Finally in section 4 conclusions are listed.

2. METHODOLOGY

The present section briefly outlines an effective method of shape classification by combining innovative pre-processing techniques, morphological skeletonization method and regional moments as shown in Figure 1. Pre-processing mechanism describes various methods of converting a grey level image into binary image. In this paper, six different pre-processing techniques are studied. They are mean, median, mode, maximum, minimum and max-min. The binary images obtained from those pre-processing techniques are then subjected to skeletonization using morphological methods. In other words, the most possible reduced image (skeleton) is obtained. Further, to the skeleton extracted binary images the paper evaluated ten regional moments on five groups of shape pattern images and derived an effective classifier.

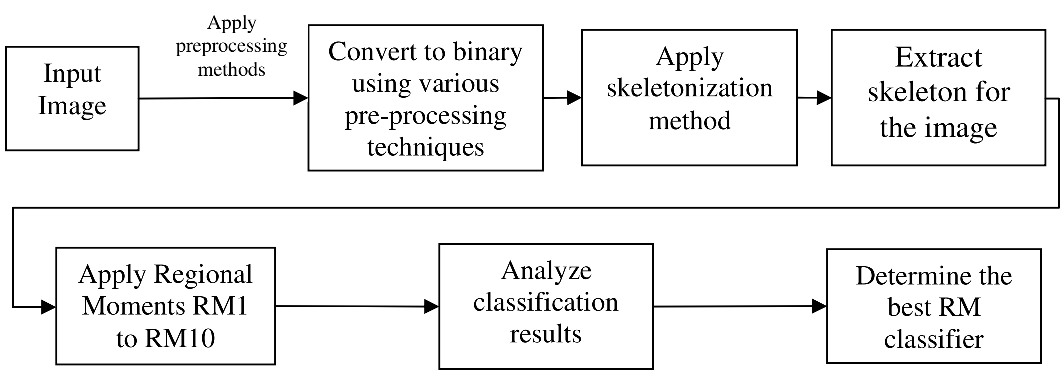

Figure 1. Proposed block diagram for Texture classification

2.1 Skeleton and shape

One key technique for shape representation is the skeletonization approach. It has been studied widely since skeletons have important properties which make them suitable for structural pattern recognition [10, 11]. Skeletonization methods are of two types: pixel-based and non-pixel-based. In a pixel-based method, all pixels in a shape are utilized in the skeletonization process. Pixel based methods often use thinning techniques [11, 12] or distance transforms [13,12]. Contour pixel of a shape is used for non-pixel-based skeletonization method. Hence, logically one can say the skeleton shape is represented by its contour [14, 15].

For this, the present section proposes a novel approach for skeletonization based on MS approach. One of the disadvantages of the existing skeletonization method is that it is not automatic and needs human interaction. The novelty of the paper is that it advocated an innovative approach for the extraction of skeleton based on MS scheme, which is completely based on morphology, for the classification purpose.

The MS scheme is a leading morphological shape representation algorithm [16, 26, 27]. In the MS scheme, a given shape is represented as a union of all maximal disks contained in the shape. The advantages of this basic algorithm include that they have simple and well-defined mathematical characterizations and they are easy and efficient to implement.

In MS scheme the skeleton of an image(I) is derived in terms of simple morphological operations erosions and openings. The morphological skeleton S_k of an image is defined by the Equation 1.

$$S_k(I) = (I \,\theta\, kB) - (I \,\theta\, kB)^\circ B \quad (1)$$

Where I, θ, -, $\circ$, B are

I	Denotes texture images
$-$	Denotes subtraction
θ	Denotes morphological erosion operation
$\circ$	Denotes morphological opening operation
B	Denotes structuring element.
K	Denotes successive erosions of I.

2.2 Hu Moment Invariants

An image classification problem involves sorting images based on their shape features. This is achieved by suitable characterization of the object shape. One can easily say whether a given image fall into the same set based on an important rule. That is ideally one can say dissimilar objects should have dissimilar categorization and similar objects should have similar description.

A group of algebraic moments based on the combination of general moments were proposed for the first time by Hu and were known as Hu moments. A greater part of image recognition experiments achieved good outcomes using those Hu moments[17-21]. These moments have achieved good results in the majority of 2D and 3D image recognition experiment. Let X and Y represent the horizontal and vertical axis in 2-Dimension, a point (x,y) represents the gray level value in the image and is given as f(x,y).

The (p + q)th two dimensional moment is defined as follows:

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

The (p+q)th two dimensional central moment is defined as follows

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

Where

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

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

The (p+q)th two dimensional normalized central moment is defined as follows

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

The HM includes invariants up to the third order. The HMs is given by HM1 to HM7 in equations 7 to 13.

The seven Hu moments are:

$$HM1 = \eta_{20} + \eta_{02} \quad (7)$$

$$HM2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (8)$$

$$HM3 = (\eta_{30} + \eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (9)$$

$$HM4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (10)$$

$$HM5 = (\eta_{30} + \eta_{12})(\eta_{30} - 3\eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + 3(\eta_{21} + \eta_{03})(\eta_{21} - \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (11)$$

$$HM_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (12)$$

$$HM7 = (\eta_{30} + \eta_{12})(3\eta_{21} - \eta_{03})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (\eta_{21} + \eta_{03})(3\eta_{12} - \eta_{30})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (13)$$

2.3 Regional Moments on MS

To illustrate shape of an object or to match it with patterns of similar shape and for classification problems based on shapes, moment invariants have been in use for a long time. A variety of texture classification methods are proposed in the literature for the past three decades. But so far no one has attempted classification of textures based on MS schemes especially using RM. The shape parameter derived from objects help in attaining it. Hence, the present study derived RM based on HM.

The RMs is given by RM1 to RM10 in equations 14 to 23.

$$RM1 = \frac{\sqrt{HM2}}{HM1} \quad (14) \qquad RM2 = \sqrt{\frac{HM1 + \sqrt{HM2}}{HM1 - \sqrt{HM2}}} \quad (15)$$

$$RM3 = \frac{\sqrt{HM3}}{\sqrt{HM4}} \quad (16) \qquad RM4 = \frac{HM3}{\sqrt{|HM5|}} \quad (17)$$

$$RM5 = \sqrt{\frac{HM4}{\sqrt{|HM5|}}} \quad (18) \qquad RM6 = \sqrt{\frac{|HM6|}{HM1 \times HM3}} \quad (19)$$

$$RM7 = \sqrt{\frac{|HM6|}{HM1 \times \sqrt{HM5}}} \quad (20) \qquad RM8 = \sqrt{\frac{|HM6|}{HM1 \times HM4}} \quad (21)$$

$$RM9 = \sqrt{\frac{|HM6|}{\sqrt{HM2 \times |HM5|}}} \quad (22) \qquad RM10 = \sqrt{\frac{|HM5|}{HM2 \times HM3}} \quad (23)$$

2.4 Classification of shape texture images based on RM

To demonstrate the classification process five sets of images with dissimilar shapes like brick, circle, curves, lines and zigzag are considered. Each set consists of ten images of similar shape. These texture images are displayed from Figure 2 to Figure 6. The classification process is given in Algorithm 1 below.

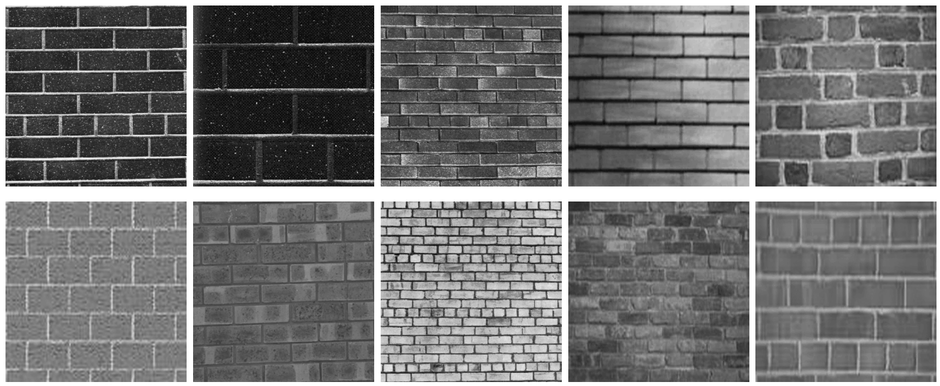

Figure 2. Original images of brick textures.

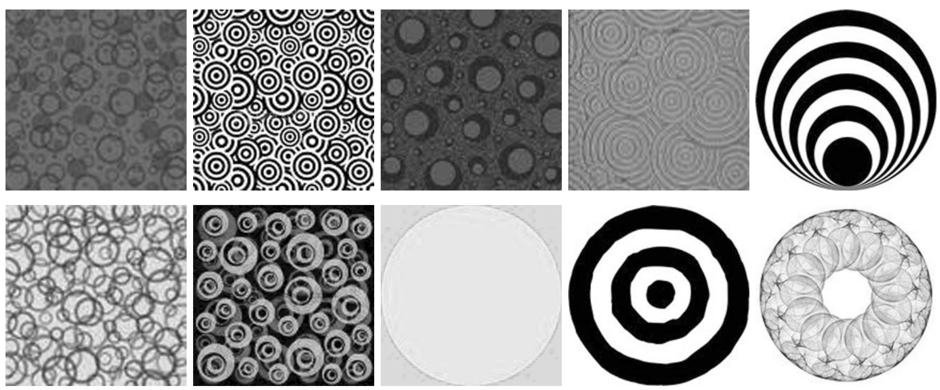

Figure 3. Original images of Circles textures.

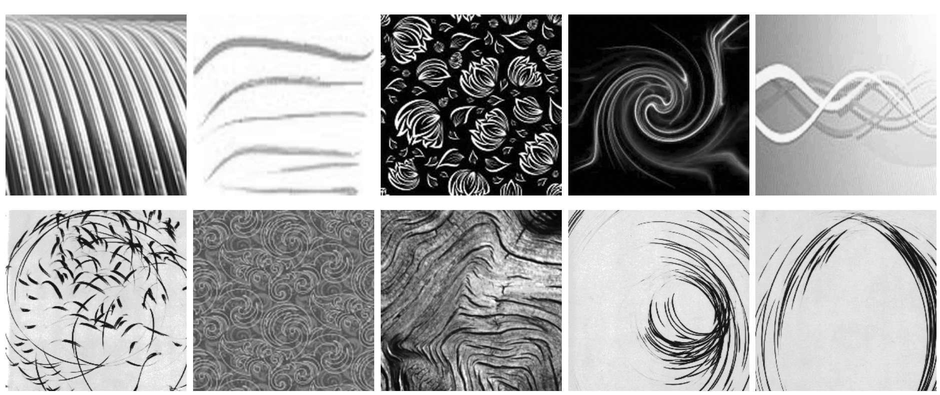

Figure 4. Original images of Curves textures.

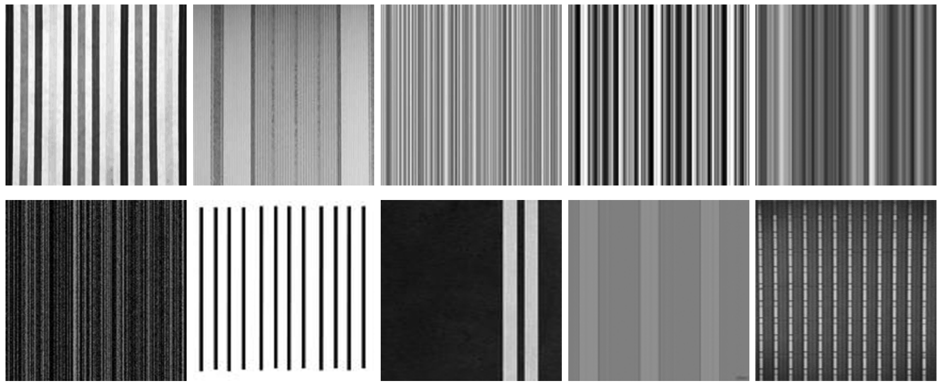

Figure 5. Original images of Line textures.

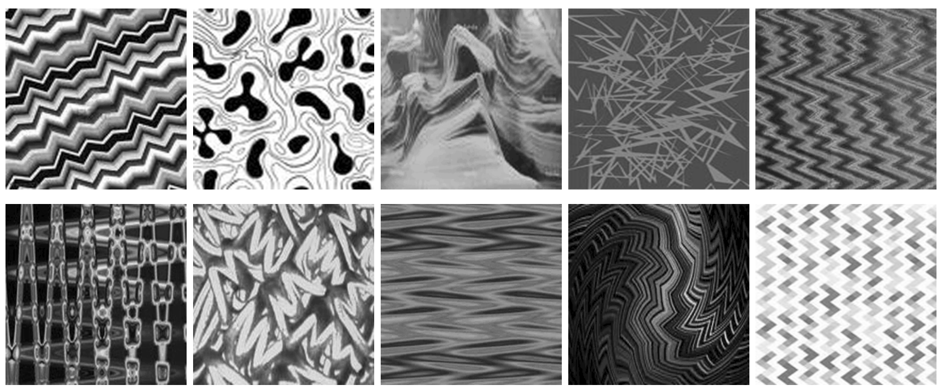

Figure 6. Original images of Zigzag textures.

Algorithm 1: A Novel textures classification method using MS and RM

Classification is performed on five groups of texture images by the following steps.

Step 1: Read the gray scale texture images and change it into a binary one.

Step 2: A binary images is obtained by applying six different pre-processing techniques like mean, median, mode, maximum, minimum and max-min.

Step 3: Each pre-processed binary image is then subjected to skeletonization using the MS scheme.

Step 4: Evaluate RM on the skeleton texture generated.

Step 5: On each set consisting of ten textures images, evaluate average values of each RM's and store them in a database.

Step 6: Plot the classification graph for all ten RM on MS scheme and determine the significant RM that classifies accurately and efficiently the given textures.

3. RESULTS AND DISCUSSIONS

3.1 Classification on shape texture by RM using local maximum pre-processing and MS method

In order to illustrate the classification problem five sets of different shape textures are taken. Each set comprises of ten images of similar shapes. For all set the average value of each regional moment from 1 to 10 is computed and given in the Table 1. A graph is also displayed based on these values as shown in Figure 7.

Table 1. Average RM on MS schemes obtained after pre-processing the image using local maximum.

Image	RM1	RM2	RM3	RM4	RM5	RM6	RM7	RM8	RM9	RM10
Brick	0.0898	1.1107	2.9135	2.3506	0.8937	0.1342	0.1860	0.2199	0.7803	59.2652
Circle	0.0308	1.0313	2.1898	3.3016	1.2229	0.1342	0.1739	0.1374	1.4000	133.2895
Curve	0.1234	1.1435	1.6063	1.7279	1.2570	0.3019	0.3401	0.2549	0.6254	83.0574
Line	0.1639	1.4251	1.3655	1.5130	1.0728	0.2716	0.3398	0.3208	0.9978	115.2402
Zigzag	0.0994	1.1127	2.3796	2.1447	1.0944	0.1921	0.2337	0.2120	0.8345	38.7425

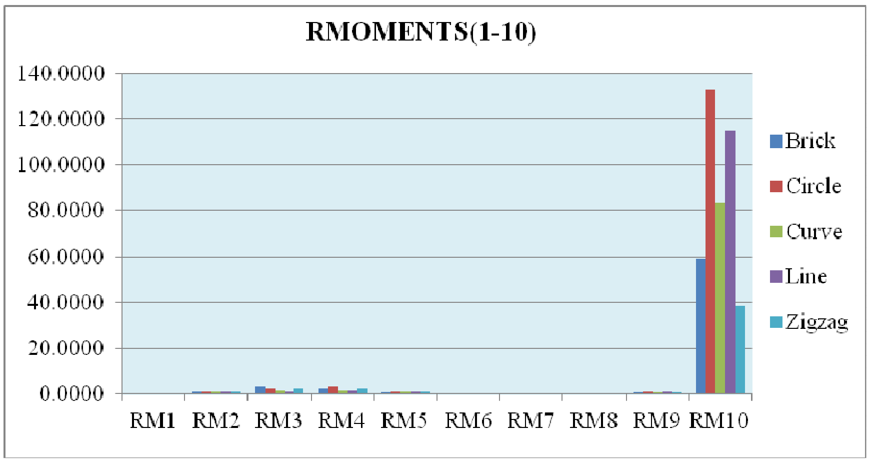

Figure 7. Classification graph on average RM's obtained after pre-processing texture images using local maximum

3.2 Classification on shape texture by RM using local minimum pre-processing and MS method

The Algorithm 1 is applied on the same texture images after applying local minimum pre-processing method. The computed values are given in Table 2. A graph is also displayed based on these values. Figure 8 gives a representation of it.

Table 2. Average RM on MS schemes obtained after preprocessing the image using local minimum.

Image	RM1	RM2	RM3	RM4	RM5	RM6	RM7	RM8	RM9	RM10
Brick	0.0756	1.0831	2.1575	1.9674	1.0595	0.1143	0.1863	0.1780	0.7368	56.1803
Circle	0.0436	1.0449	3.1076	2.2917	1.0493	0.1069	0.1400	0.1419	0.8891	47.2131
Curve	0.1746	1.2078	1.3197	1.4866	1.2078	0.2758	0.3816	0.2927	0.8514	43.0058
Line	0.1720	1.4639	1.2169	1.2872	1.0428	0.2842	0.3268	0.3241	0.9273	66.6750
Zigzag	0.1115	1.1221	2.3051	2.0425	1.0191	0.1370	0.2164	0.2183	0.6487	32.5595

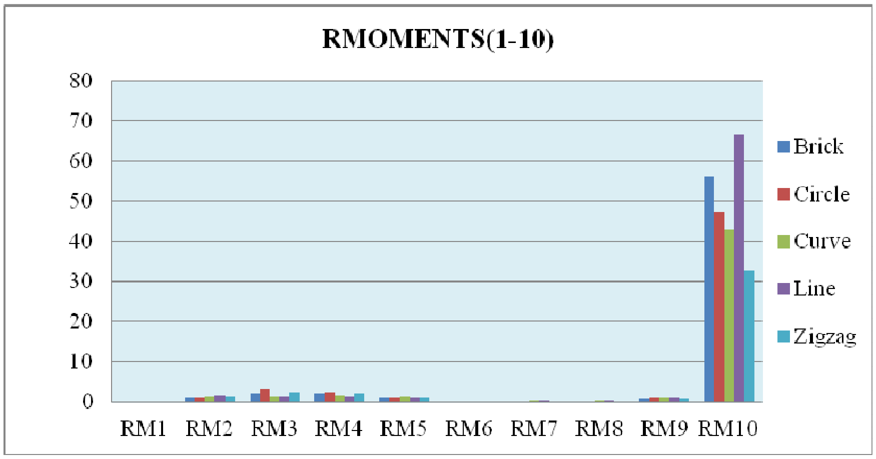

Figure 8. Classification graph on average RM's obtained after pre-processing texture images using local minimum

3.3 Classification on shape texture by RM using local max-min pre-processing and MS method

The Algorithm 1 is applied on the same texture images after applying local Max-Min pre-processing method. The computed values are given in Table 3. A graph is also displayed based on these values. Figure 9 gives a representation of it.

Table 3. Average RM on MS schemes obtained after pre-processing the image using local maxmin.

Image	RM1	RM2	RM3	RM4	RM5	RM6	RM7	RM8	RM9	RM10
Brick	0.0333	1.0340	2.0578	1.7756	1.3190	0.3052	0.1750	0.1297	0.8208	96.4573
Circle	0.0194	1.0198	1.4130	1.5529	1.2337	0.1710	0.1210	0.1023	0.9466	269.5946
Curve	0.1376	1.1544	4.8250	4.1798	1.0732	0.3138	0.3206	0.2890	0.9263	69.0026
Line	0.0689	1.0740	1.1491	1.1258	1.1157	0.3371	0.2675	0.2274	1.0667	231.0970
Zigzag	0.0792	1.0876	1.7605	1.7629	1.1150	0.1125	0.1780	0.1591	0.5890	89.6390

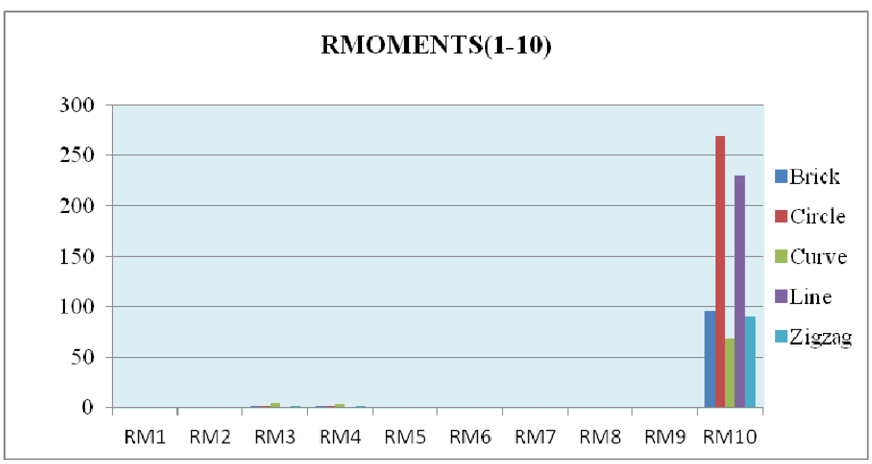

Figure 9. Classification graph on average RM's obtained after pre-processing texture images using local max-min

3.4 Classification on shape texture by RM using local mode pre-processing and MS method

The Algorithm 1 is applied on the same texture images after applying local mode pre-processing method. The computed values are given in Table 4. A graph is also displayed based on these values. Figure 10 gives a representation of it.

Table 4. Average RM on MS schemes obtained after pre-processing the image using local mode

Image	RM1	RM2	RM3	RM4	RM5	RM6	RM7	RM8	RM9	RM10
Brick	0.0754	1.0871	2.1417	1.7884	1.0626	0.1429	0.1811	0.1787	0.9167	86.4546
Circle	0.0276	1.0283	2.1994	2.0984	1.0566	0.0756	0.1259	0.1176	0.9296	1299.9533
Curve	0.1640	1.1880	1.2157	1.3007	1.1373	0.3213	0.3586	0.3181	0.9417	72.5362
Line	0.1443	1.4063	1.5700	1.5445	1.2058	0.3532	0.3068	0.2668	1.0231	74.9628
Zigzag	0.0849	1.0917	1.7182	1.8181	1.2964	0.1815	0.2437	0.1944	0.9972	43.5181

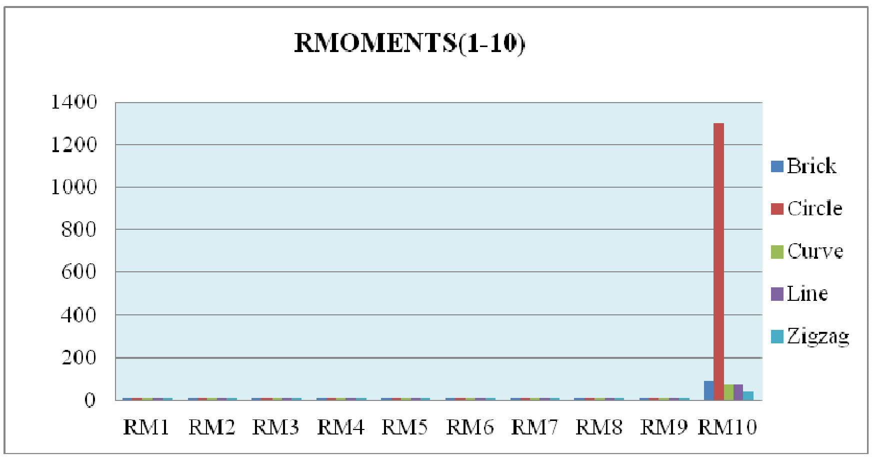

Figure 10. Classification graph on average RM's obtained after pre-processing texture images using local mode

3.5 Classification on shape texture by RM using local mean pre-processing and MS method

The Algorithm 1 is applied on the same texture images after applying local mean pre-processing method. The computed values are given in Table 5. A graph is also displayed based on these values. Figure 11 gives a representation of it.

Table 5. Average RM on MS schemes obtained after preprocessing the image using local mean

Image	RM1	RM2	RM3	RM4	RM5	RM6	RM7	RM8	RM9	RM10
Brick	0.0815	1.0960	2.4534	2.4520	1.1317	0.1576	0.2333	0.2083	1.1167	102.0747
Circle	0.0297	1.0303	3.8515	2.6614	0.8926	0.0761	0.1101	0.1294	0.6858	249.6272
Curve	0.1705	1.2024	2.8460	2.2374	1.1046	0.2557	0.3830	0.3262	0.8872	40.6571
Line	0.1637	1.4257	1.2451	1.2122	1.1184	0.3930	0.3555	0.3151	1.0295	118.1763
Zigzag	0.1087	1.1224	1.6402	1.5388	1.0120	0.1886	0.2285	0.2254	0.6376	40.9032

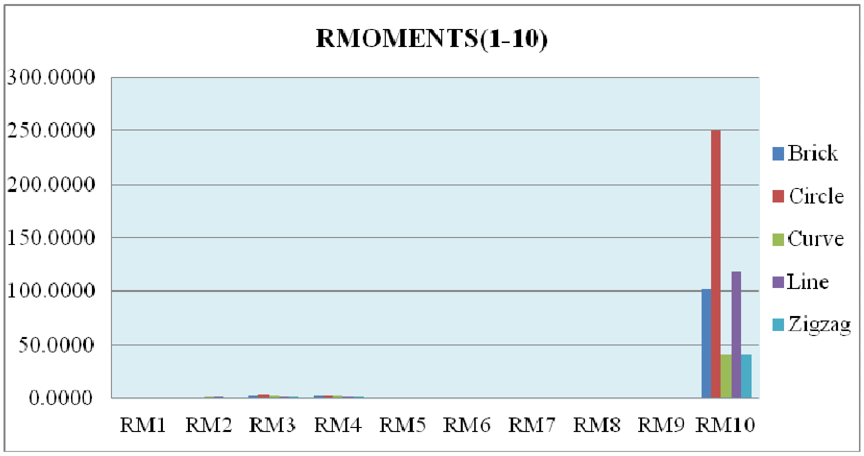

Figure 11. Classification graph on average RM's obtained after preprocessing texture images using local mean

3.6 Classification on shape texture by RM using local median pre-processing and MS method

The Algorithm 1 is applied on the same texture images after applying local median pre-processing method. The computed values are given in Table 6. A graph is also displayed based on these values. Figure 12 gives a representation of it.

TABLE 6. AVERAGE RM ON MS SCHEMES OBTAINED AFTER PRE-PROCESSING THE IMAGE USING LOCAL MEDIAN

Image	RM1	RM2	RM3	RM4	RM5	RM6	RM7	RM8	RM9	RM10
Brick	0.0830	1.0983	3.4013	2.8371	1.1507	0.1387	0.2040	0.1977	0.9983	90.6251
Circle	0.0257	1.0261	3.4835	2.6516	0.8904	0.0722	0.1082	0.1179	0.8420	105.3247
Curve	0.1805	1.2119	1.2130	1.2407	1.0669	0.3180	0.3543	0.3416	0.8720	66.5121
Line	0.1505	1.4473	6.3547	3.1408	1.0918	0.2799	0.2888	0.2452	1.0024	103.9337
Zigzag	0.0997	1.1100	2.3648	2.0695	1.2327	0.2775	0.2727	0.2137	0.8874	42.9339

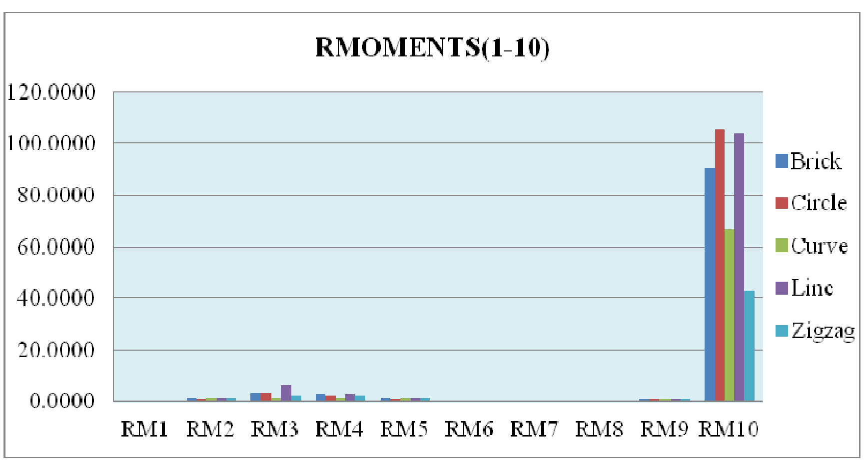

Figure 12. Classification graph on average RM's obtained after preprocessing texture images using local median.

From this proposed stratagem one can conclude that RM10 alone displays all five groups of textures in a unique manner while other RM's have failed. That is RM1 to RM9 show nearly same values and failed in classification of the textures. The classification obtained after applying local mode preprocessing method is poor when compared to other proposed methods. In all the Circle images are having maximum value than other shape textures after application of these proposed techniques.

4. CONCLUSIONS

The present paper proposes a novel Morphological Skeleton(MS) representation method on Regional Moments(RM) for classification of textures with similar shape components. A variety of texture classification methods are proposed in the literature for the past three decades. But so far no one has attempted classification of textures based on MS schemes especially using RM. The present paper evaluated RM on MS schemes to classify texture images of different shapes. Classification has been carried out by applying pre-processing methods first followed by extracting the skeleton of the target image on which regional 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) maximum, minimum, mode, median , mean and maxmin i.e((max-min)/2). Results generated prove that RM10 is sufficient to classify the given group of textures. One need not apply RM1 to RM9 for classification of any texture images as they have totally failed in classification even in the case of pre-processed texture images.

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