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Boundary and Region based Moments Analysis for Image Pattern Recognition

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Abstract. In a number of pattern recognition application, moments have been used to recognize image patterns. The recognition process involves effective shape representation method. So, the present paper analyzes the recognition rate in two different shape representation methods called external and internal representation. With the proper shape representation of the given image pattern, the present paper has computed 7 boundary (external) based and 10 region (internal) based Hu moments. The experimental results on five different pattern image groups (Brick, Circle, Curve, Line and Zigzag) are precisely recognized by both boundary based and region based moments of order 1 and 10 respectively.

Keywords: Skeleton, Hu Moment, recognition

1. Introduction

Image retrieval is becoming a more important problem with the rapid increase of media information. Users want to provide query images and obtain a set of similar images. In content-based image retrieval systems, several low-level image features, such as color, texture, shape or the combination of these features, describe images. Shape is an important low-level image feature.

There are generally two types of shape descriptors: external representation based shape descriptors and internal representation based shape descriptors. External representation based shape descriptors use only the boundary of the objects shape, while the internal representation based shape descriptors use the internal region details in addition to the boundary [1].

Moments due to its ability to represent global features have found extensive applications in the field of image processing [2]–[10]. In 1961, Hu [2] introduced moment invariants. Based on the theory of algebraic invariants he derived a set of moment invariants, which are position, size and orientation independent. Dudani et al. [4] used Hu’s moment invariants up to the third order in the recognition of images of aircraft. The same invariants were also used for recognition of ships [5]. Markandey et al. [10] developed techniques for robot sensing based on high dimensional moment invariants and tensors. Gang Xu et al. [11] has proposed a new image recognition algorithm by using region based shape representation. They proposed new region based moments based on skeletons. Zhihu Huang et al. [12] has performed an analysis of boundary based Hu’s Moment invariants on image scaling and rotation. Hongbo Mu [13] used boundary and region based Hu moments for recognizing different types of defects in wood pattern images. Cecila Di Ruberto et al. [14] has combined morphological image features with the moment invariants for classification.

The organization of the paper is as follows. Section 2 deals with the methodology of boundary and region based moment computation, the results and discussions are presented in section 3 and last section deals with conclusions.

2. Methodology

Shape representation is an important issue in image processing and computer vision, because it provides the foundation for developing algorithms for shape-related processing such as image coding, shape matching and object/pattern recognition, content-based video processing and image data retrieval.

The present paper uses two types of shape representation namely external representation and internal representation. In external representation, the shape of the given object is represented by the boundary while in the internal representation, the entire region is represented by skeleton.

From the second- and third-order normalized central moments, a set of seven invariant moments, which are invariant to translation, scale change and rotation, has been derived by Hu as given in Equations (1)-(7). The present paper has computed the 7 Hu moments on the boundary of the given image pattern.

$$BM_1 = \eta_{20} + \eta_{02} \tag{1}$$

$$BM_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{2}$$

$$BM_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{3}$$

$$BM_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{4}$$

$$\begin{aligned} BM_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ &+ 3(\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \tag{5}$$

$$BM_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{11})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{11})(\eta_{21} + \eta_{03}) \tag{6}$$

$$\begin{aligned} BM_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ &+ (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \tag{7}$$

Where the normalized central moment of order (p+q) is given in the Equation (8)

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\frac{p+q+2}{2}}} \tag{8}$$

The central moment of order (p+q) is given by the Equations (9)-(11).

$$\mu_{pq} = \int_{x,y\in c}\int (x-\bar{x})^p (y-\bar{y})^q f(x,y)dxdy \tag{9}$$

$$\bar{x} = \frac{m_{10}}{m_{00}} = \frac{\iint_{x,y\in c} xf(x,y)dxdy}{\iint_{x,y\in c} f(x,y)dxdy} \tag{10}$$

$$\bar{y} = \frac{m_{01}}{m_{00}} = \frac{\iint_{x,y\in c} yf(x,y)dxdy}{\iint_{x,y\in c} f(x,y)dxdy} \tag{11}$$

The 10 extended Hu moments given in the Equations (12)-(21) are computed on the skeleton of the given image.

$$RM1 = \frac{\sqrt{BM2}}{BM1} \tag{12}$$

$$RM2 = \sqrt{\frac{BM1 + \sqrt{BM2}}{BM1 - \sqrt{BM2}}} \tag{13}$$

$$RM3 = \frac{\sqrt{BM3}}{\sqrt{BM4}} \tag{14}$$

$$RM4 = \sqrt{\frac{BM3}{\sqrt{|BM5|}}} \tag{15}$$

$$RM5 = \sqrt{\frac{BM4}{\sqrt{|BM5|}}} \tag{16}$$

$$RM6 = \sqrt{\frac{|BM6|}{BM1 \times BM3}} \tag{17}$$

$$RM7 = \sqrt{\frac{|BM6|}{BM1 \times \sqrt{BM5}}} \tag{18}$$

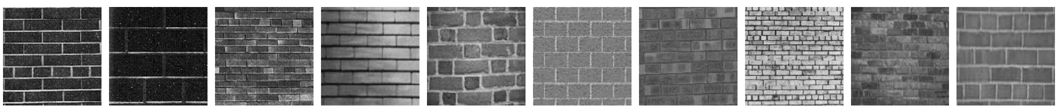
$$RM8 = \sqrt{\frac{|BM6|}{BM1 \times BM4}} \tag{19}$$

$$RM9 = \sqrt{\frac{|BM6|}{\sqrt{BM2 \times |BM5|}}} \tag{20}$$

$$RM10 = \sqrt{\frac{|BM5|}{BM2 \times BM3}} \tag{21}$$

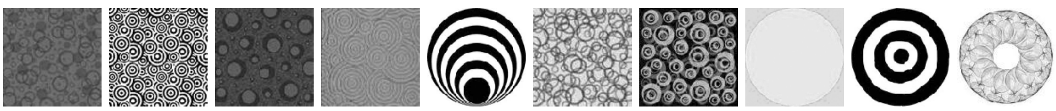
3. Results and Discussions

The experiments are conducted with 5 different image pattern groups namely Brick, Circle, Curve, Line and Zigzag patterns, 10 images per group of each size 256×256, collected as shown in Figure (1)-(5). In the first method, the 7 boundary based Hu moments are calculated and with in each group, the average of all 10 images is computed and are represented in Table 1. In the second method, the 10 region based extended Hu moments are calculates and within each group, the average of all 10 images is computed and are represented in Table 2.



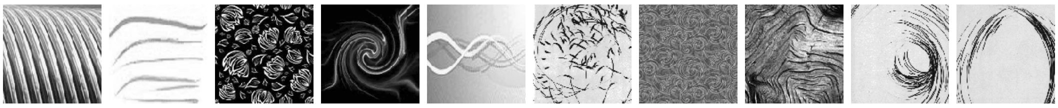
(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 1. Input Images of Brick Pattern Images (a) Brick1 (b) Brick2 (c) Brick3 (d) Brick4 (e) Brick5 (f) Brick6 (g) Brick7 (h) Brick8 (i) Brick9 (j) Brick10.



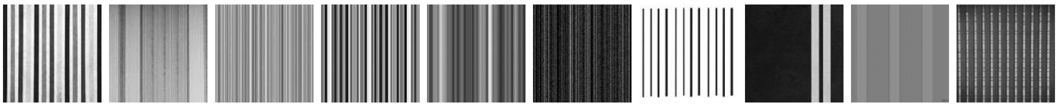
(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 2. Input Images of Circle Pattern Images (a) Circle1 (b) Circle2 (c) Circle3 (d) Circle4 (e) Circle5 (f) Circle6 (g) Circle7 (h) Circle8 (i) Circle9 (j) Circle10.



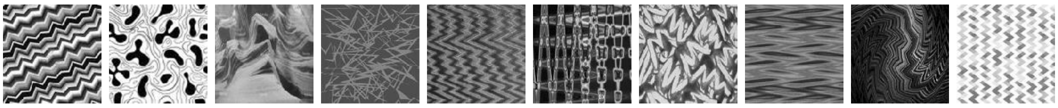
(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 3. Input Images of Curve Pattern Images (a) Curve1 (b) Curve2 (c) Curve3 (d) Curve4 (e) Curve5 (f) Curve6 (g) Curve7 (h) Curve8 (i) Curve9 (j) Curve10.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 4. Input Images of Line Pattern Images (a) Line1 (b) Line2 (c) Line3 (d) Line4 (e) Line5 (f) Line6 (g) Line7 (h) Line8 (i) Line9 (j) Line10.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 5. Input Images of Zigzag Pattern Images (a) Zigzag1 (b) Zigzag2 (c) Zigzag3 (d) Zigzag4 (e) Zigzag5 (f) Zigzag6 (g) Zigzag7 (h) Zigzag8 (i) Zigzag9 (j) Zigzag10.

Table 1. Average Boundary based Hu moment values of Image Pattern Groups.

Image Name	**BM1**	**BM2**	**BM3**	**BM4**	**BM5**	**BM6**	**BM7**
Brick	0.8873	0.0397	0.0393	0.0035	0.0000	-0.0007	0.0000
Circle	1.4598	0.0005	0.0324	0.1274	0.0639	0.0002	-0.0057
Curve	1.2604	0.0787	0.2987	0.2461	-0.0557	-0.0940	0.3726
Line	2.1213	2.4965	0.1688	0.1627	0.2216	0.0214	0.0099
Zigzag	0.9981	0.0206	0.0203	0.0057	0.0000	-0.0003	-0.0004

Table 2. Average Region based Extended Hu moment values of Image Pattern Groups.

Image Name	**RM1**	**RM2**	**RM3**	**RM4**	**RM5**	**RM6**	**RM7**	**RM8**	**RM9**	**RM10**
Brick	0.0739	1.0873	2.2204	2.0890	1.1205	0.1411	0.1657	0.1613	0.9113	191.3938
Circle	0.0240	1.0244	2.2818	4.1238	1.6135	0.1508	0.1746	0.1079	1.4050	316.7487
Curve	0.1688	1.1959	1.2629	1.6468	1.3142	0.2768	0.3598	0.2828	1.0213	55.8664
Line	0.1457	1.4402	1.2398	1.3584	1.2829	0.3139	0.3283	0.2385	1.1754	535.7405
Zigzag	0.0821	1.0888	3.6058	2.7394	0.9756	0.2596	0.2132	0.2035	0.8462	60.8954

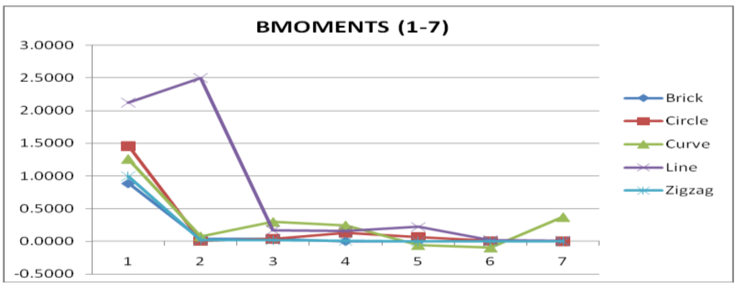


Figure 6. Recognition graph for Image Pattern Groups by Boundary based Moments.

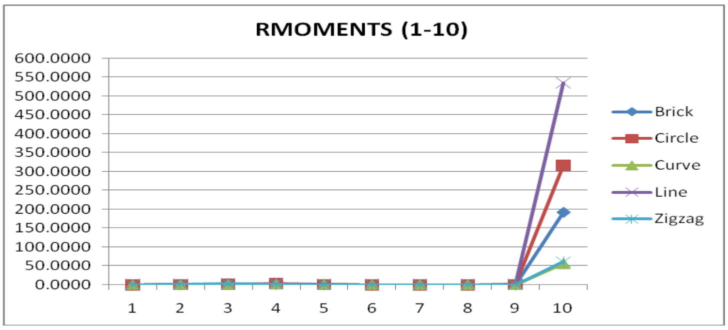


Figure 7. Recognition graph for Image Pattern Groups by Region based Moments.

The graphs of Figure 6 and 7 show the recognition rate of all five different image pattern groups. All five groups are precisely recognized by using boundary based moments of order 1 and region based moments of order 10. The Table 3 shows the average computation time (in second) used by the boundary based and region based moments per each group of image pattern.

Table 3. Computation Time (in seconds) used by Boundary based and Region based Moments.

Input Image Pattern Group	Boundary based Moment	Region based Moment
Brick	2.21466	1.49968
Circle	2.20549	2.16217
Curve	2.22533	2.38623
Line	2.22407	1.63937
Zigzag	2.20469	1.66281

4. Conclusions

All the five types of images are clearly classified by using boundary and region based Moments. The images are precisely classified by using Boundary Moment of order 1 and by using Region Moment of order 10. In boundary and region moments, Line shape images are having maximum values. Though the images are precisely classified by boundary and region moments, the region moments are efficient because the average computation time is less compared to boundary moments.

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