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Feature Extraction Using Zernike Moments for Symbols

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Abstract – *Shape identification and feature extraction are the main concern of any pattern recognition system. Object parameters are mostly dependent on spatio-temporal relationships among the pixels. However feature extraction is a complex phenomenon which needs to be addressed from the invariance property, irrespective of position and orientation. Zernike moments are used as shape descriptors and identified as rotation invariant due to Orthogonality property. However the computational complexity is high. Script as a basis for evaluation of patterns and cursive nature of script language SYMBOL. The present work is aimed at evaluation of Zernike moments for various patterns of objects that are cursive in nature. Therefore feature extraction of patterns like vowels and consonants in cursive script SYMBOL using Zernike moments is considered in comparison with Hu's seven moments.*

Keywords – Cursive script, Hu's moment, Gujarti , Zernike moment.

I.INTRODUCTION

Optical character recognition (OCR) is an important research area under pattern recognition [7]. An experimental approach needs to be developed to compare and evaluate the performance of different invariant features of different shape-based SYMBOL alphabets. The investigations of the feature extraction of the region-based SYMBOL alphabets image are a major motivation for this thesis. The Zernike moment algorithms may perform well for the ideal clean SYMBOL alphabets. Feature extraction of SYMBOL alphabets and patterns that are of various shapes is being a goal of recent research. Evaluating the accuracy of Feature extraction of SYMBOL alphabets using Zernike moment is of the thesis's interest.

In the Indian OCR context, most of the works have been carried out for the OCR for Devanagari and Bangla and not many works are reported for SYMBOL language. SYMBOL, an Indo-Aryan language spoken by about 80 million people mainly in Andhra Pradesh a State in the southern part of India. The alphabet of the modern SYMBOL script consists of

16 vowels and 36 consonants symbols. These characters are called basic characters. The basic characters of SYMBOL script are shown in Figure 1. Writing style in the script is from left to right. The concept of upper/lower case is absent in SYMBOL script.

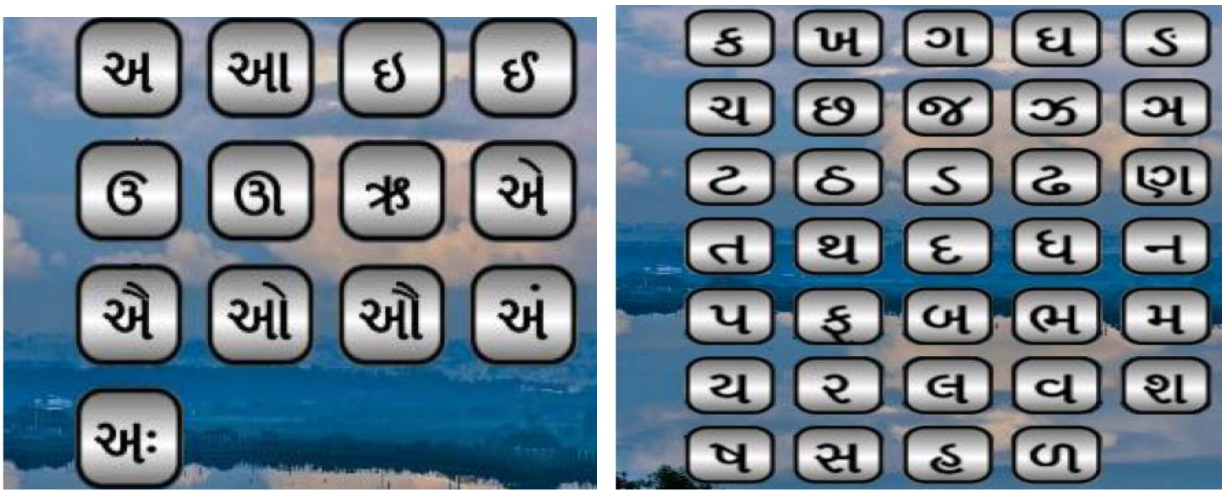


Figure 1. SetofGujarativvowelsandConsonants.

Moment based features are a traditional and widely used tool for feature extraction. There are basically two types of moment based methods are used. One is the Hu' seven moments introduced by Hu (1962) are not derived from family of orthogonal function and so contain much redundant information about a character shape due to which reconstruction is not possible. To overcome the problem Fruits Zernike introduced Zernike moments based on the theory of Orthogonal Polynomials [5] are becoming popular in feature extraction nowadays. In this paper we have presented the scheme of feature extraction by using Zernike moments for basic SYMBOL characters. The rest of the paper is organized as follows. Explained the theory of feature extraction in section II. Experimental results are presented in section III. Concluding remarks are given in section IV.

II. THEORY OF FEATURE EXTRACTION

Zernike moments are used to extracting the features of printed digits in grayscale images [1]. The Zernike moments uniquely describe functions on the unit disk, and can be extended to images. There invariance properties make them attractive as descriptors for optical character recognition. Different feature extraction methods are designed for different representation of the characters such as solid binary character and gray level sub image of each individual character. Due to the impact and the advancements in the Information Technology, nowadays more emphasis is given in regional languages. Currently there are many OCR systems available or handling printed English documents with reasonable levels of accuracy. Such systems are also available for many European languages as well as some of the Asian languages such as Japanese, Chinese, etc. However, there are not many reported efforts at developing OCR systems for Indian languages.
In the SYMBOL OCR system the scanned SYMBOL text can be used as in. Then in the pre-processing stage the scanned image is to be binarized. Binarization is the process of converting the input gray scale scanned image into a binary image with foreground as white and background as black. After Binarization we can extract the feature by using Zernike moments technique. Then we can reconstruct the image [4].

2.1. Hu's Seven Moments-

Hu (1962) introduced seven nonlinear functions which are translation, scale, and rotation invariant. The seven moment invariants are defined as [6], Hu's seven moment invariants have been widely used in pattern recognition, and their performance has been evaluated under various deformation situations. As Hu's seven moment invariants take every image pixel into account the computation cost will be much higher than boundary-based invariants. As stated before, image's spatial resolution decides the total amount of pixels, and to reduce the computation cost. Hu's moment can show the redundant properties due to which reconstruction is very difficult. So here by using the Zernike moment I extract the features of SYMBOL (vowels and consonants) alphabets.
The Hu's seven moment invariants are defined as:

$$\phi_1 = \eta_{20} + \eta_{02}$$
$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$
$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$
$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$
$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} - \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$
$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$
$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} - \eta_{30})(\eta_{21} - \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

Table 1: Hu,s seven moment invariants for the SYMBOL Alphabets

HU	1	2	3	4	5	6	7
ક	1.0441	0.61145	0.48121	0.71147	1.0638	1.0399	0.012835
ખ	0.96663	0.53294	0.39058	0.61904	0.67361	0.76752	0.012749
ગ	1.0831	0.64034	0.49177	0.76391	1.2371	1.1683	0.0096101
ઘ	0.88049	0.44542	0.30017	0.57262	0.3892	0.53136	-0.0067741

ઙ	0.89958	0.44669	0.29573	0.56262	0.43232	0.57357	0.0063938
ચ	1.0612	0.618	0.48387	0.7329	1.1624	1.107	-0.0007857
છ	0.97493	0.53906	0.39705	0.60804	0.72568	0.80666	0.014937
જ	1.2513	1.0476	1.1434	1.2684	3.7349	2.3566	0.079046
ઝ	0.84433	0.40552	0.26102	0.53503	0.30909	0.45552	0.0018944
ઞ	0.89356	0.46234	0.32259	0.53963	0.43827	0.57222	0.014001
ટ	0.99699	0.55564	0.41744	0.65701	0.81633	0.87124	0.011131
ઠ	1.0198	0.56935	0.4046	0.6364	0.85096	0.91604	0.02428
ડ	0.86412	0.42345	0.27329	0.54365	0.3402	0.48867	0.002531
ઢ	0.86412	0.42345	0.27329	0.54365	0.3402	0.48867	0.002531
ણ	0.93225	0.50172	0.35793	0.61794	0.53844	0.66042	-0.014814
ત	0.971767	0.548198	0.419596	0.660821	0.870167	0.853579	0.011304
થ	0.966944	0.543981	0.415488	0.657444	0.857258	0.841158	0.011202
દ	0.966965	0.544717	0.417149	0.660004	0.869501	0.846067	0.011099
ધ	0.959223	0.538342	0.412174	0.653077	0.844994	0.824585	0.011198
ન	0.964472	0.544537	0.419641	0.658441	0.875381	0.844133	0.012397
પ	0.968798	0.55106	0.427902	0.664829	0.904918	0.862171	0.012797
ફ	0.962638	0.546598	0.424171	0.660291	0.887753	0.845849	0.013702
બ	0.961819	0.5471	0.425979	0.663775	0.898557	0.848461	0.01362

ભ	0.94252	0.513734	0.378151	0.623466	0.709468	0.747919	0.009258
મ	0.949066	0.520948	0.385959	0.629362	0.73616	0.767412	0.009749
ય	0.952766	0.524855	0.390184	0.635344	0.756019	0.780425	0.009466
ર	0.949818	0.522803	0.388367	0.6339	0.751998	0.774371	0.009355
લ	0.945152	0.5197	0.387285	0.633733	0.745401	0.764926	0.00836
વ	0.950555	0.526116	0.394884	0.639738	0.772414	0.783343	0.008748
શ	0.956317	0.532961	0.402991	0.646144	0.801229	0.802988	0.009163
ષ	0.957921	0.535043	0.405995	0.648025	0.818748	0.812493	0.010761
સ	0.956998	0.534166	0.405088	0.647172	0.81532	0.809753	0.010725
હ	0.956335	0.533512	0.404395	0.646487	0.812524	0.80766	0.010693
ળ	0.955627	0.532765	0.403544	0.645586	0.808726	0.805099	0.010666
ક્ષ	0.955387	0.532393	0.402969	0.645086	0.806308	0.8038	0.010631
જ્ઞ	0.954781	0.531584	0.401858	0.644196	0.801703	0.801111	0.010513

2.2 Zernike Moments-

Moments are pure statistical measure of pixel distribution around center of gravity of characters and allow capturing global character shapes information[1]. They are designed to capture both global and geometric information about the image. Moment-based invariants explore information across an entire image rather than providing information just at single boundary point, they can capture some of the global properties missing from the pure boundary-based representations like the overall image orientation. In the discrete case the integral in the moment definition must be replaced by summation. In discrete form of an image can be consider as a 2D Cartesian density distribution function f(x,y) with this assumption the general form of a moment of order n with repetition m evaluating over the complete image is as follows:

$$m_{pq} = \sum_{x} \sum_{y} x^{p} y^{q} f(x,y)$$

Where N is the size of the character image and f(x,y) is the gray levels of individual pixels. m_{pq} is the moment of any discrete image. Zernike polynomials are one of infinite set of polynomials that are orthogonal over the unit circle Figure given below is the block diagram of Zernike moment's computation. Compared with Hu's seven moment invariants, the computation of Zernike moments is more complicated. The major reason for this is the image normalization process. In Hu's moment invariants, the whole concept is based on the central moments which have integrated the translation and scale normalization in the definitions. The Zernike moments, however, are only invariant to image rotation for themselves. To achieve translation and scale invariance, extra normalization processes are required. The translation normalization is achieved by moving the image center to the image centroid. Figure:3 given below compared the translation-normalized image with the original image.

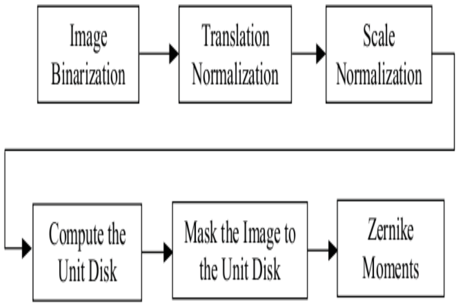


Fig 2: Block diagram of computing Zernike moments.

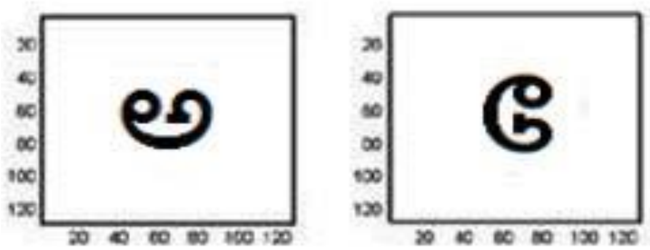
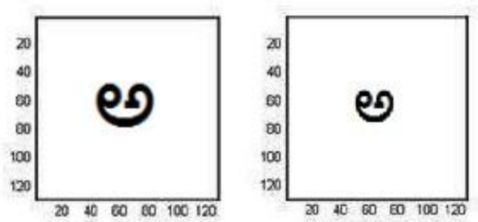


Fig 3: Comparison between the original image and the translation normalization image.

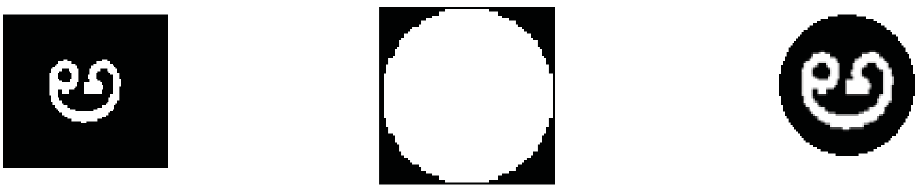
The scale normalization is achieved by set the image's 0th order regular moment m00 to a predetermined value. Figure 3 given below compared the original image and the scale normalized image. Because m00 is the total number of white pixels for binary image, we use interpolation to set m00 to the predetermined value. Different from the regular moments which employ the summation within a square range of pixels, Zernike polynomials take the unit disk x2+y2Ç1 as their computation domain.



(Original) (Scale Normalized)

Fig 4: Comparisons between the original image and the scale normalized image.

To compute the Zernike moments of a digital image, the range of the image should be mapped to the unit circle first with its origin at the image's center. The pixels falling outside the unit circle are discarded in the computation process. In our implementation of Zernike moments, we use binary images with spatial resolution of 64×64. All of these binary images are normalized into a unit circle with fixed radius of 32 pixels.



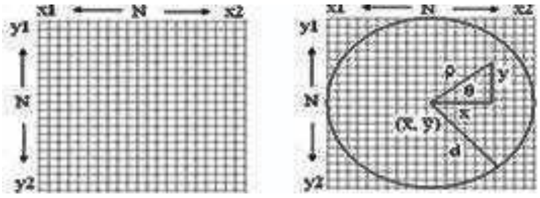
Original binary image | Compute the Unit Disk | Computational range

Figure 5: The computation process of the unit disk mapping for Zernike moments

So following steps are necessary to extract features of any character image using Zernike moments. (1)

First of all converts gray-scale image into the binary numeral image

(2) To map over a unit disc image be convert into polar coordinate



(a) (b)

Fig 6(a) NxN pixels Fig. 6(b) Unit Circle Mapped image bitmap onto NxN pixel size image.

In the above figure 6 the center of the image and disk is same. Where x1x2 are X-axis dimensions and y1y2 are Y- axis dimensions of the pixel rectangle. $(\bar{x},\bar{y})$ is the center of the unit disk, q is polar value and 8 is polar angle. Now the image is mapped into polar co-ordinates and onto unit circle as:Compute the distance d in fig6(b) above as

$$d = \sqrt{(x2-\bar{x})^2\frac{1}{2} + (y2-\bar{y})^2\frac{1}{2}}$$

Compute the distance vector q and angle 8 for any (x,y) pixel in f(x,y) in polar coordinates as

$$\rho = \sqrt{(x-\bar{x})^2 + (y-\bar{y})^2/d} \qquad \theta = \tan^{-1}\left[\frac{x-\bar{x}}{y-\bar{y}}\right]$$

This step maps pixel coordinate (x1,x2) to (-1,+1) and (y1,y2) to (-1,+1) in polar. In this way almost all the pixels in image bound box as given in fig above are inside unit circle except some foreground pixels.

(3) Fruits Zernike(1934) introduced a set of complex polynomials {Vnm(x, y)} which form a complete orthogonal set over the unit disk of x2+y2Ç1 in polar coordinates[2]. The form of the polynomials is:

$$V_{nm}(x, y) = V_{nm}(q,8)= R_{nm}(q)=e^{jm8}$$

Where j=N−1,8=tan^{-1}y/x, q is the length of the vector from the origin to the pixel (x, y); 8 is the angle between the vector q and x axis in counter clockwise direction. R_{nm}(q) is Radial polynomial defined as:

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!(\frac{n+|m|}{2}-s)!(\frac{n-|m|}{2}-s)!}\rho^{n-2s}$$

Where n>=0, |m|<=n , n-|m|=even. When the image is mapped onto unit disc, take desired value of order of moment , i.e. n and compute real and imaginary parts of the Zernike moment using Radial polynomials. (4)
Then compute Zernike moment of order n and repetition m for function f(x,y) is defined as :

$$A_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x,y)V^*_{nm}(x,y), \quad x^2+y^2 \le 1$$

Where n>=0, |m|<=n and * is the complex conjugate operator .The first 36 moments of up to order 10 can be tabled as follows:

Table2: Total no of moment's upto 10th order

Order (n)	Zernike moment of order n with repetition m (Anm)	Total number of moments up to 10
0	A0,0	
1	A1,1	
2	A2,0 A2,2	
3	A3,1 A3,3	
4	A4,0 A4,2 A4,4	

5	A5,1 A5,3 A5,5	36
6	A6,0 A6,2 A6,4 A6,6	
7	A7,1 A7,3 A7,5 A7,7	
8	A8,0 A8,2 A8,4 A8,6 A8,8	
9	A9,1 A9,3 A9,5 A9,7 A9,9	
10	A10,0 A10,2 A10,4 A10,6 A10,8 A10,10	

III. EXPERIMENTAL ANALYSIS AND RESULT

Table 3: Zernike moment calculated for SYMBOL given below

	n	m	Zernike moment
అ	0	0	28.966
	1	1	0.49656+2.5592i
	2	0	-8.6967
	2	2	-5.2529+0.22689i
	3	1	-0.25528-5.3013i
	3	3	0.87071-4.3525i
	4	0	-17.969
	4	2	6.9765-1.2463i
	4	4	-5.975+0.24356i
	5	1	-0.51687+0.10042i
	5	3	-1.745+7.6192i
	5	5	0.622-0.60109i

Table 4: Zernike moment calculated for SYMBOL alphabet given below

	n	m	Zernike moment values
క	0	0	38.834
	1	1	0.99313+2.139i
	2	0	-19.062
	2	2	7.563-1.6226i
	3	1	-2.4049+4.4798i
	3	3	0.52034-1.0979i
	4	0	-31.023
	4	2	-8.8801-1.9249i
	4	4	-4.2944+1.9544i
	5	1	2.1901-12.253i
	5	3	-1.8083-1.2957i
	5	5	-0.69732-0.18187i

The experiment results are mainly based on the feature extraction of SYMBOL alphabets. The results of feature extraction include the calculation of Hu's seven moment invariants of the loaded images of 16x16 spatial resolutions. For Zernike moments, the experiment focused on the feature extraction of SYMBOL alphabets. Several image examples based on Zernike moments of different orders are given and analyzed.

IV. CONCLUSION

OCR systems scan the documents printed on a paper as an image and recognize the characters present in the document image. Many OCR systems have been developed for different languages I have made an effort towards the development of an OCR system for the feature extraction of basic characters (vowels and consonants) in SYMBOL text, which can handle different font size and font types. The input to the system is a binarized image. Then the moment features are extracted. Here we are using Zernike moments to extract features of SYMBOL characters. Zernike moments themselves are only invariant to image rotations. So we have focused the research on extracting features of SYMBOL Alphabets by using Zernike moments.

In this piece of work I have mainly focused our effort on the extraction of the features of the lain SYMBOL characters. . In future I have a plan to work towards the development of an OCR system which can match the extracted text image of SYMBOL characters with the image model library and then classifying the characters towards recognition. The model library will consists of different samples of SYMBOL character with different fonts and font sizes.

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