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Reconstruction of Oriya Alphabets Using Zernike Moments

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ABSTRACT
There has been a significant amount of research in pattern recognition in different aspects of printed character based user interfaces including interactive design tools, ink beautification and printed character recognition. Optical Character recognition (OCR) systems have been effectively developed for the recognition of printed characters of non-Indian languages. Efforts are on the way for the development of efficient OCR system for Indian language especially for ORIYA. I present in this paper the reconstruction of the basic characters (vowels and consonants) in Oriya text, which can handle different font sizes and font types. Hu's seven moments and Zernike moments have been progressively used to extract the features of ORIYA characters. When I reconstruct by taking the extracted features, due to certain difficulties in the Hu's moments I can use the Zernike moments. The methodology can be extended for recognition of the ORIYA conjuncts too.

General Terms
Zernike moment, Hu moment

Keywords
Orthogonal function, Polynomial, feature extraction, Image reconstruction, Invariant moment, Optical character recognition

1. INTRODUCTION
Optical character recognition (OCR) is an important research area under pattern recognition [8]. The objective of an OCR system is to recognize alphabetic letters, numbers, or other special characters like conjuncts, which are in the form of digital images, without any human intervention [9]. Optical Character Recognition (OCR) is one of the oldest sub fields of pattern recognition with a rich contribution for the recognition of printed documents OCR systems scan the documents printed on a paper as an image and recognize the characters present in the document image to form a separate digital text document, which can be edited or processed. 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 Indian OCR context, most of the works have been carried out for the OCR for Devanagari, Bangla and Telugu Scripts and not many works are reported for Oriya language. Oriya, an Indo-Aryan language spoken by about 40 million people mainly in Orissa a State in the eastern part of India, and also in West Bengal and Jharkhand. The alphabet of the modern Oriya script consists of 13 vowels and 36 consonants symbols. These characters are called basic characters. The basic characters of Oriya 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 Oriya script.

Figure 1. Set of Oriya Vowels and Consonants

Moment based features are a traditional and widely used tool for character recognition. 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 character recognition nowadays. In this paper we have presented the scheme of reconstruction by using Zernike moments for basic ORIYA characters.

The outline of these papers is as follows. I discuss the related development in this area of Zernike moment in section2. In section3 I introduce the theory of recognition. In section4 I have presented my experimental analysis and result. In section5 I have concluded my research paper

2. RELATED DEVELOPMENT IN THIS AREA
Zernike moments are used to recognize printed digits in grayscale images. 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.

Some author presents overview of feature extraction methods for offline recognition of segmented characters .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.

Some researchers are used colour spatial and zernike moment to present an integrated colour and shape featured for content based trade mark retrival.Combining the colour spatial feature and zernike moments feature can indeed enhance the recognition capability.

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 Indian OCR context, most of the works have been carried out for the OCR for Devanagari, Bangla and Telugu Scripts and not many works are reported for Oriya language. Some researchers has been developed their work on different Indian languages numerals also. So here by using the zernike moment I reconstruct the oriya alphabets.

3. THEORY OF RECOGNITION

In the Oriya OCR system the scanned Oriya text can be used as in. Then in the preprocessing 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. In future I have a plan to work towards the development of an OCR system which can match the extracted text image of Oriya characters with the image model library and then classifying the characters towards recognition. The model library will consists of different samples of ORIYA character with different fonts and font sizes.

3.1. Hu Moments

Hu (1962) introduced seven nonlinear functions which are translation, scale, and rotation invariant. The seven moment invariants are defined as [6]

$$\emptyset_1 = \eta_{20} + \eta_{02}$$

$$\emptyset_2 = \left(\eta_{20} - \eta_{02}\right)^2 + 4\eta_{11}^2$$

$$\emptyset_3 = \left(\eta_{30} + 3\eta_{12}\right)^2 + \left(3\eta_{21} + \eta_{03}\right)^2$$

$$\emptyset_4 = \left(\eta_{30} + \eta_{12}\right)^2 + \left(\eta_{21} + \eta_{03}\right)^2$$

$$\emptyset_5 = \left(\eta_{30} + 3\eta_{12}\right)\left(\eta_{30} + \eta_{12}\right) - \left[\left(\eta_{30} + \eta_{12}\right)^2 - \right.$$

3η21+η032+3η21+η03η21+η03+

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

$$\emptyset_6 = \left(\eta_{20} + \eta_{02}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right] + 4\eta_{11}\left(\eta_{30} + \eta_{12}\right)\left(\eta_{21} + \eta_{03}\right)$$

$$\emptyset_7 = \left(3\eta_{21} - \eta_{03}\right)\left(\eta_{30} + \eta_{12}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - \right.$$

3η21+η032+3η21−η30η21+η03+

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

Hu's seven moment invariants have been widely used in pattern recognition, and their performance has been evaluated under various deformation situation including blurring[10], spatial degradations[3], random noise[1], skew and perspective transformations[7]. 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.

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

HU	1	2	3	4	5	6	7
ଅ	0.2112	0	0.0229	0.0421	-0.0000	-0.0002	-0.0000
ଆ	0.2184	0.0855	0.0513	0.0751	-0.0000	0.0005	-0.0000
ଇ	0. 2171	0	0.0442	0.0639	0.0000	0.0002	0.0000
ଈ	0.2216	0.1027	0.0272	0.0754	0.0000	0. 0002	0.0000
ଉ	0.2101	0	0.0375	0.0279	0.0000	0.0000	0.0000
ଊ	0.2111	0.0248	0.0495	0.0437	0.0000	-0.0000	0.0000
ଏ	0.2002	0.0401	0	0.0874	0.0000	0.0001	-0.0000
ଐ	0.2148	0.1796	0	0.1241	0.0000	0.0000	-0.0000
ଓ	0.2072	0.0627	0	0.0351	-0.0000	0.0001	-0.0000
ଔ	0.2198	0.2257	0.0197	0.0798	0.0000	-0.0004	-0.0000

3.2. Zernike Moments

Moments are pure statistical measure of pixel distribution around center of gravity of characters and allow capturing global character shapes information .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:

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

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.

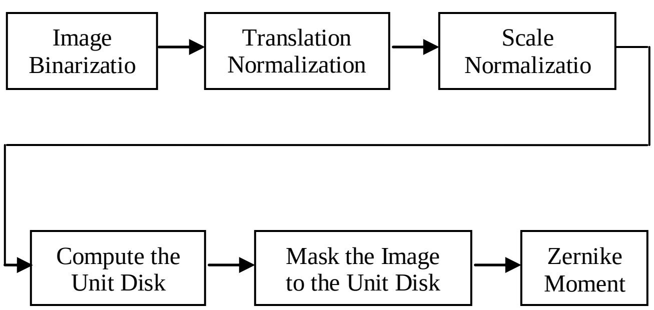


Fig 2: Block diagram of computing zernike moments

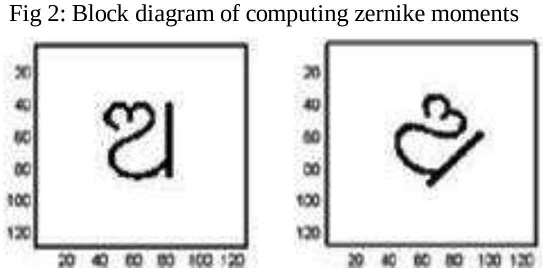
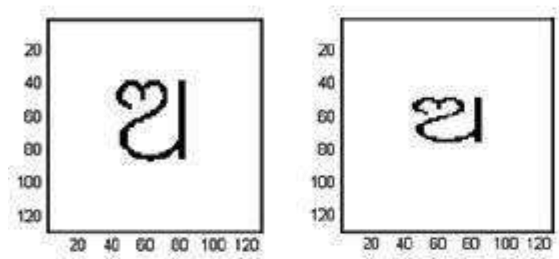


Fig 3: Comparision between the original image and the translation normalization image

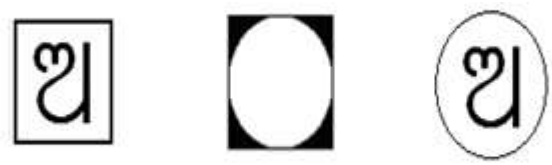
The scale normalization is achieved by set the image's 0th order regular moment *m00* to a predetermined value. Figure 3 given below compared the original image and the scale normalized image. Because *m00* is the total number of white pixels for binary image, we use interpolation to set *m00* to the predetermined value. Different from the regular moments which employ the summation within a square range of pixels, Zernike polynomials take the unit disk *x2+y2≤1* 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 Image | Unit circle with fixed radius of 32 pixels | Computational range

Fig 5: The computation process of the unit disk mapping for Zernike moment shown for Oriya Alphabet 

To reconstruct any printed character image computation of Zernike moments is used in the reconstruction process. So following steps are necessary to implement over any character image to compute the 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 polor coordinate

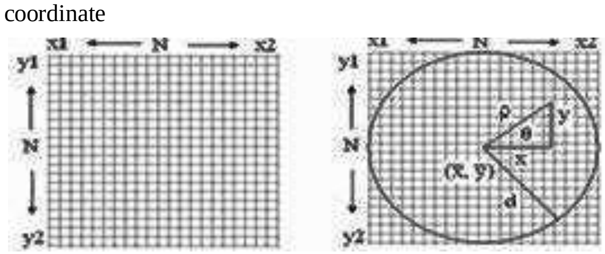


Fig 6(a) NxN pixels image bitmap | Fig. 6(b) Unit Circle Mapped onto NxN pixel size image

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, ρ is polar value and θ 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 ρ and angle θ for any (x,y) pixel in f(x,y) in polar coordinates as

$$\rho = \sqrt{(x-\bar{x})^2 + (y-\bar{y})^2/d}$$

$$\theta = \tan^{-1}\left[\frac{x-\bar{x}}{y-\bar{y}}\right]$$

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+y2≤1 in polar coordinates[1]. The form of the polynomials is:

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)e^{im\theta}$$

Where $j = \sqrt{-1}$,$\theta = \tan^{-1}\frac{y}{x}$, ρ is the length of the vector from the origin to the pixel (x, y); θ is the angle between the vector ρ and x axis in counterclockwise direction; Rnm(ρ) is Radial polynomial defined as:

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

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. Here fitting of unit disc is required because the orthogonality principle of the Zernike polynomials holds good only within the unit disc. When the image is mapped into unit disc computes real and imaginary parts by using radial polynomials.

(4)Then compute Zernike moment of order n and repetition m for function f(x,y) is defined as :

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

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

Table 2: Total no of moments upto 10th order

Order(n)	**Zernike moment of order n with repetation m(Anm)**	**Total number of moments up to order 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	

(5)Then reconstruct the image by taking the Zernike moments

$$f'(x,y) = \sum_{n=0}^{N}\sum_{m}^{M} A_{nm}\,V_{nm}(x,y)$$

where all n>=0, |m|<=n and n-|m| is even Here computational cost is low because we can consider only the pixels which are within the unit circle. While fitting of the unit disc we can shift the Cartesian co-ordinates system to the polar co-ordinate system[2]. Since the basis is orthogonal, Zernike moments have minimum information redundancy (Teague 1980).

4. EXPERIMENTAL ANALYSIS AND RESULT

In the first stage the document image is binarized. Next compute the geometric (regular) moment which is pure statistical measure of pixel distribution around center of gravity. It capturing global character shape information

$m_{pq} = \sum_x\sum_y x^p y^q f(x,y)$ where p,q = 0,1,2 ………

Where |q|<=p and p-|q|=even

Table 3. Geometric moment Calculated for Oriya Alphabet for size 32x32 up to order 5 and repetition 5

Fig.(32x32)	**Order**	**Repetition**	**Geometric Moment Value**
	1	1	2554
	2	0	13722
	2	2	13722
	3	1	80224
	3	3	80224
	4	0	491910
	4	2	491910
	4	4	491910
	5	1	3108544
	5	3	3108544
	5	5	3108544

Table 4: Geometric moment Calculated for Oriya Alphabet for size 32x32 up to order 5 and repetition 5

Fig.(32x32)	**Order**	**Repetition**	**Geometric Moment Value**
	1	1	2566
	2	0	13758
	2	2	13758

	3	1	80332
	3	3	80332
	4	0	492234
	4	2	492234
	4	4	492234
	5	1	3109516
	5	3	3109516
	5	5	3109516

Here in the above table 3 and 4 it is shown that geometric moment values for the sample Oriya alphabets taken produces exactly same values when the order is kept constant even if the repetition values are changed.

Table 5. Centroid Values for the Binary Images of Oriya Alphabets as per different size

Fig	Centroid Location as per size given below		
	16x16	32x32	64x64
ଅ	|X,Y|= (8.5750, 8.7400	|X,Y|= (16.5036, 16.6908)	|X,Y|= (32.3992, 32.8124)
ଆ	|X,Y|= (8.3571, 8.7473)	|X,Y|= (15.9554, 16.7244)	|X,Y|= (31.9894, 32.8319)
ଇ	|X,Y|= (8.6497, 8.3858)	|X,Y|= (16.7924 ,16.3842)	|X,Y|= (32.8836 ,31.8365)
ଈ	|X,Y|= (8.6119, 8.3333)	|X,Y|= (16.7432, 16.1093)	|X,Y|= (32.8836, 31.8365)
ଉ	|X,Y|= (8.5250, 8.4550)	|X,Y|= (16.4590, 16.4257)	|X,Y|= (32.4860 ,32.3414)
ଊ	|X,Y|= (8.5000, 8.4235)	|X,Y|= (16.5423, 16.3802)	|X,Y|= (32.5848, 32.2636)
ଏ	|X,Y|= (8.2297, 8.5856)	|X,Y|= (15.6968, 16.6350)	|X,Y|= (31.4147, 32.7264)
ଐ	|X,Y|= (7.9086, 8.7208)	|X,Y|= (15.6580, 16.8202)	|X,Y|= (30.8963, 33.0985)
ଓ	|X,Y|= (8.5263, 8.4641)	|X,Y|= (16.6114, 16.5029)	|X,Y|= (32.6649, 32.4628)
ଔ	|X,Y|= (8.2000, 8.3684)	|X,Y|= (31.3080, 31.7543)	|X,Y|= (15.5088, 15.9213)

Then the central moments are changed to

$\mu = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y)$ where p,q= 0,1,2 ……….

The central moments are computed using the centroid of the image, which is equivalent to the regular moments of an image whose center has been shifted to coincide with its centroid; therefore the central moments are invariant to image translations.

Then the centroid of an image is calculated by using the moment values

$$\bar{x} = m_{10}/m_{00} \quad \bar{y} = m_{01}/m_{00}$$

Here $\bar{x}$ and $\bar{y}$ are the centroid of the image.

Table 6: Central moment Calculated for Oriya Alphabet for size 32x32 up to order 5 and repetition 5

Figure (32x32)	Order	Repetition	Central Moment Value
ଅ	1	1	-2.0103e+004
	2	0	2.0103e+004
	2	2	6.8515e+005
	3	1	-5.1548e+005
	3	3	-2.5802e+007
	4	0	5.1548e+005
	4	2	1.7568e+007
	4	4	1.0229e+009
	5	1	-1.3218e+007
	5	3	-6.6162e+008
	5	5	-4.1820e+010

Table 7: Central moment Calculated for Oriya Alphabet for size 32x32 up to order 5 and repetition 5

Figure (32x32)	Order	Repetition	Central Moment Value
ଇ	1	1	-2.0203e+004
	2	0	2.0203e+004
	2	2	6.8763e+005
	3	1	-5.1798e+005
	3	3	-2.5862e+007
	4	0	5.1798e+005
	4	2	1.7630e+007
	4	4	1.0243e+009
	5	1	-1.3280e+007

	5	3	-6.6307e+008
	5	5	-4.1848e+010

It has been observed that the central moment values obtained for the sample Oriya alphabets taken are all distinct with respect to the change either in Order or repetition values. Unlike the geometric moments the central moment values for all the Orders and repetitions under consideration are different not only for different alphabets but also for the same alphabet but of different font size .This shows that the contribution of the central moment values in comparison to geometric moment values for the alphabet recognition is more as there are no redundant instances found in the central moment vectors retrieved.

Then we can compute the unit disk with (x, y) as the center of the unit disc and ρ is the polar value and θ is the polar co-ordinate as shown in fig 7. Then mask the pixels lying inside or on unit circle.

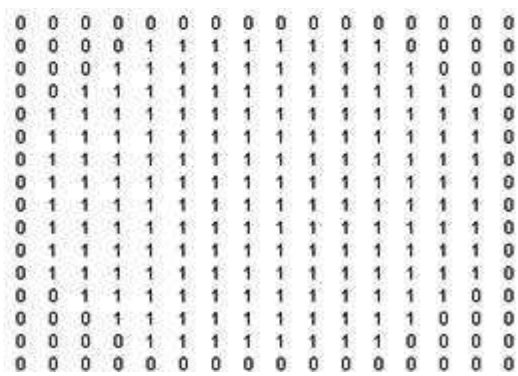


Fig 7: unit circle or unit disc in which image is mapped

Then the image is mapped on to unit disc compute real and imaginary parts of Zernike moments by using radial polynomials

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

Then compute Zernike moment of order n and repetition m are expressed as:

$$Z_{nm} = \frac{n+1}{\pi} \sum_{x} \sum_{y} f(x,y)\, V^{*}_{nm}(x,y)$$

Where n>=0, |m|<=n, n-|m|=even and * is the complex conjugate operator. Then reconstruct the image by taking the Zernike moments.

$$f'(x,y) = \sum_{n=0}^{N} \sum_{m}^{M} A_{nm}\, V_{nm}(x,y)$$

Table 8. Zernike moment calculated for ORIYA alphabet given below

	n	m	Zernike moment values
	0	0	1.7921
	1	1	0.0047 - 0.0614i
	2	0	1.7921
	2	2	0.0047 - 0.0614i
	3	1	-0.1530
	3	3	0.1353 + 0.0910i
	4	0	0.0502 + 0.0188i
	4	2	-0.0569 - 0.0075i
	4	4	0.4190
	5	1	-0.0213 + 0.0618i
	5	3	0.2043 - 0.0558i
	5	5	0.0337 - 0.2409i

Table 9: Zernike moment calculated for ORIYA alphabet given below

	n	m	Zernike moment values
	0	0	1.7634
	1	1	0.1006 + 0.0398i
	2	0	0.1776
	2	2	0.1144 + 0.0419i
	3	1	0.0103 - 0.2965i
	3	3	-0.0381 + 0.0435i
	4	0	0.2947
	4	2	-0.0039 + 0.1297i
	4	4	-0.0329 - 0.0169i
	5	1	-0.2021 + 0.4116i
	5	3	-0.0694 - 0.0075i
	5	5	0.0277 - 0.0957i

It is observed that the zernike moment values obtained for the sample of Oriya Alphabets experimented with contain both a real part and an imaginary part .The real and the imaginary parts together form the magnitudes of the zernike moments obtained for the Oriya Alphabets that can be later used for the reconstruction purposes. It is observed that when the Repetition is '0' the imaginary part does not exist i.e there is only real part and not any imaginary part. Hence the Zernike moments with their reconstruction ability can be used to recognize the alphabets at the later stage

Next the reconstructions for the set of characters are done with order up to 30.The results are shown in Figure 8.The reconstruction property shown that after a particular order the image is converge. It is observed that after order 25 the images converge.

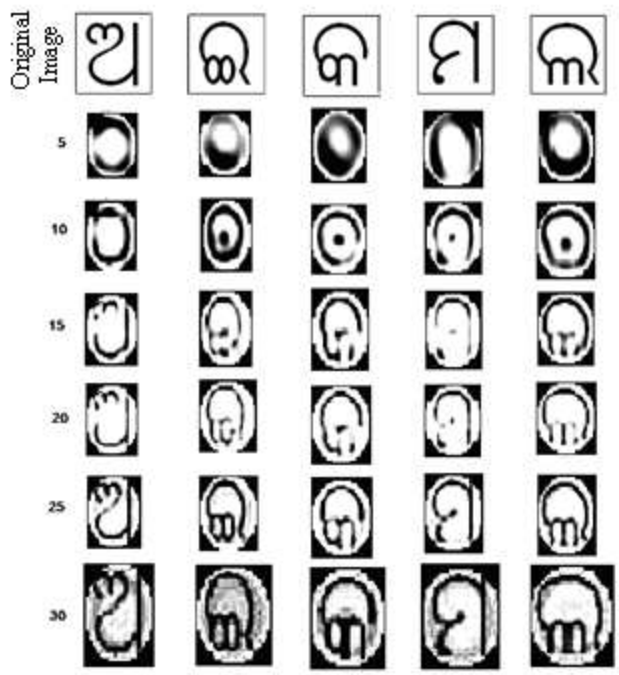


Figure 8: Reconstruction Property Evaluation results with Zernike moments of order 5, 10, 15, 20, 25, 30 of Oriya Alphabets (32x32).

5. CONCLUSION AND FUTURE WORK

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 recognition of basic characters (vowels and consonants) in ORIYA 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 ORIYA characters. Zernike moments themselves are only invariant to image rotations. The invariance to different spatial resolutions can be achieved by enlarging or reducing each image so that the image's 0th regular moment $m'00$ equals to a predetermined value, Zernike moments possess the priority of easy image reconstruction ability. It can also help to find out the accuracy of the reconstructed Oriya alphabets of different sizes. So we have focused the research on extracting features of Oriya Alphabets by using Zernike moments can be later used for cognition purposes .Based on the analysis of reconstructed images with Zernike moments of different orders, using the first twenty-five orders of the series to compose the feature vectors to achieve good image recognition result. In this piece of work I have mainly focused our effort on the extraction of the features and then reconstruction of the lain ORIYA characters. The slant and distorted characters is my next work. In future I have a plan to work towards the development of an OCR system which can match the extracted text image of Oriya characters with the image model library and then classifying the characters towards recognition. The model library, which will consist of different samples of ORIYA characters with different fonts and font sizes to a total of about 1000 characters, will be used for the purpose.

6. ACKNOWLEDGMENTS

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