Invariant and Zernike Based Offline Handwritten Character Recognition

S.Sangeetha Devi
P.G. Scholar, Dept. of CSE-PG,
Dhanalakshmi College of Engineering, Manimangalam,
Tambaram, Tamilnadu, India.

Dr.T.Amitha,
Prof. & Head, Dept. of CSE-PG,
Dhanalakshmi College of Engineering, Manimangalam,
Tambaram, Tamilnadu, India.

***Abstract*—Character recognition is one of the tough method processes attributable to the nice variations of writing styles, fully totally different size and orientation angle of the characters. Many researchers are specializing in recognizing written digits and characters in many languages. To the foremost effective of our data, little work has been done in the realm of Tamil written character recognition which they experimented with their own data. The invariant written character recognition is tougher. This paper introduced and evaluated utterly completely different shape-based image invariants from the perspective of their invariability property to image transformations in addition as scaling, translation, rotation and completely different image spatial resolutions. To appreciate these ideas, we've got an inclination to use Hu's and Zernike moment as feature. The proposing system analysis the features in the character and trains itself to identify and recognize the invariant characters using the previously learned data.**

Keywords—Optical Character Recognition, Online Handwritten Recognition, Offline Handwritten Recognition, Hu's Moment, Zernike Moment, Artificial Neural Network.

I. INTRODUCTION

One of the foremost necessary analysis areas in today's world is pattern analysis and machine intelligence. Hand written Tamil Character recognition refers to the method of conversion of written Tamil character into Unicode Tamil character. Handwriting recognition is historically divided into on-line and offline recognition [5]. Typical knowledge acquisition devices for off-line and on-line recognition are unit scanners and digitizing tablets, respectively. In on-line recognition, a series of coordinates, representing the movement of the pen tip is captured, whereas within the offline case, only an image of the text is obtainable. If the input may be a scanned document from a sheet of paper is referred as offline, while in the on-line recognition it captures the temporal and dynamic information of pen mechanical phenomenon. Due to less quantity of information, off-line handwriting recognition is taken into account harder than on-line handwriting recognition.

Optical character recognition (OCR) is the process of translating scanned images of typewritten text into machine-editable information. OCR is one of the most fascinating and challenging areas of pattern recognition with various practical applications. In a typical OCR systems input characters are digitized by an optical scanner.There are four completely different steps concerned in OCR techniques they're Pre-processing, Segmentation, Feature extraction, Classification and Recognition. Tamil written character recognition has perpetually been a difficult task in pattern recognition because of the quality within the letter structure [1]. These days such a lot of researchers have targeted on Tamil written character recognition. Tamil character recognition system has achieved recognition of 90%, but for the invariant characters little amount of work has been done, they also achieve an 85%recognition rate.

II. RELATED WORKS

In Early years, several researchers have targeted in written recognition for normal words. Despite more than 30 years of handwriting recognition research [2-5] developing a reliable general purpose system for invariant character recognition remains an open problem. Krishnamoorthy, 1980 started an initial approach for hand printed Tamil character, subsequent to 1990 work focus towards on handwritten words, but some little amount of work was done for invariant characters. Initially pre-processing is performed then the features are extracted. Chao Kan et al [10] proposed a new method of combining Orthogonal Fourier Mellin moments (OFMMs) with centroid bounding circle scaling. Ramteke et al [15] presents associate experimental assessment of the potency of assorted methods based on Invariant Moments for written Devanagari vowels recognition. Bhaskara Rao et al [9] proposed the evaluation of Zernike moments for various patterns of objects that are cursive in nature. Mustapha Oujaoura et al [9] present a system for recognizing isolated Arabic printed characters by using the feature as Zernike moments, invariant moments and Walsh transformation. Sridevi et al [11] propose a new method to combine the statistical and regional features from handwritten Ancient Tamil script. Alirezaee et al [7] use several moment invariant features combined with various classification methods for the recognition of middle age Persian manuscripts.

Ali Broumandnia et al [6] proposed a novel approach of fast Farsi character recognition based on fast Zernike wavelet moments.Hidden Markov Models is used for the ultimate section of recognition [3,7and15]. Peyarajan et al [14] used Kohonen's Neural Network that is additionally called Self Organizing Map. Mustapha et al [12] used the designed multi-layer neural network classifier. The designed multi-layer back propagation neural network (BPNN) classifier [6, 11]

ISSN: 2278 – 1323

consisting of 3 layers- the input, hidden, and output. Alirezaee et al [7] used a special classifier for recognizing the middle Age Persian Characters by means K-NN (K- Nearest Neighbour) is functioned for the learning and also the testing phases.

III. Frame for Invariant Characters

This study focuses on the recognition of invariant characters. Figure. 1 illustrates that the scanned character is feed as the input to the system. It involves three different process, they are preprocessing, feature extraction and classification. These methods are to be carried out with the input image to obtain the correct character.

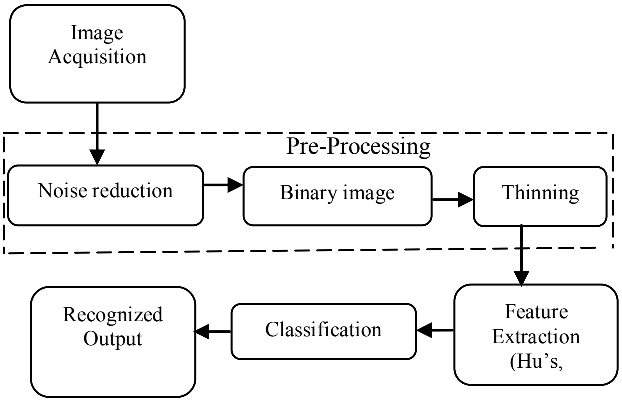


Fig.1. Frame work of the proposed system

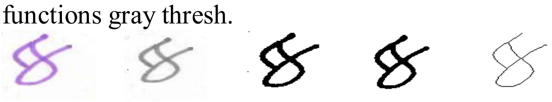
A. *Image Accquistion*

Image Acquisition is generally outlined because the action of retrieving an image from some source, typically a hardware-based source. Without a picture, no process is feasible.

B. *Pre-Processing*

The scanning method might contain an exact form of noises is shown in Figure.2a. Consequently those noises are to be eliminated by employing a many preprocessing techniques and to smooth the written characters are as follows: Binarization, Noise removal and thinning. Binarization is a technique in which the grey scale images (Figure.2b) are converted to binary images (see Figure. 2c).

The threshold value worth ought to be within the nominal range of [0, 1]. To compute the level argument by use the functions gray thresh.



(a) (b) (c) (d) (e)

Fig. 2.Pre-Processing example. (a) Original image. (b) Grayscale image. (c) Binary image. (d) Cleaned image. (e) Skeleton image.

The main objective of noise removal is to get rid of the unwanted pixel present within the binary image. The median filter is employed to preserve the edges of the character. Figure.2d. shows the input image when applying the filter.

Thinning may be a morphological operation, used to take away designated foreground pixels from binary pictures. Thinning is generally applied to binary images and produces another binary image as output. The image with single pixel is bestowed in Figure.2e. It needs solely les memory space to store the image and less processing time.

C. *Feature Extraction*

Image invariant features will have about the same values for samples of the same image that are instance, translated, scaled, rotated, skewed, blurred, or noise affected. This can be the reason that justifies the use of Zernike moments and Hu's invariant moments as[10] within the system. They're measures of the pixel distribution around the centre of gravity of the character and permit capturing the global character form information.

1. *Regular moments and central moments*

Regular moments (also be referred to as geometric moments) are defined as:

$$m_{pq} = \iint_R x^p y^q f(x,y)\,dxdy \qquad (1)$$

Where m_{pq} is the (p + q)th order moment of the continuous image function f(x, y).

The central moments of f(x, y) are defined as:

$$\mu_{pq} = \iint (x-\bar{x})^p (y-\bar{y})^q f(x,y)\,dxdy \qquad (2)$$

Where $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$, which are the centroid of the image.

For digital images the integrals are replaced by summations and m_{pq} becomes:

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y), \text{ p,q=0,1,2,.} \qquad (3)$$

Then the central moments are changed to:

$$\mu_{pq} = \sum_x \sum_y (x-x)^p (y-y)^q \text{ f(x,y),p,q=0,1,2,3...} \qquad (4)$$

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.

2. *HU's Moments*

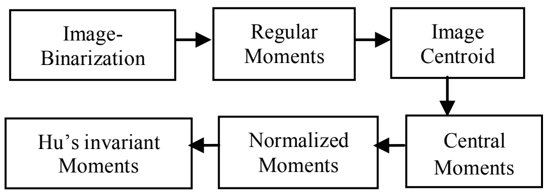


Fig.3 Block diagram of computing Hu's seven moment invariants.

Figure.3 shows the computing process of Hu's seven moment invariants. The input image is first converted to binary format. The function to compute the regular moments is in the format: [*m*] = moment (fig, p, and q). Fig is the input binary image, and *p*, *q* are predefined moment's order. The

ISSN: 2278 – 1323

summations are performed with the available parameters, the regular moment's eqn (3) by going through all of the pixels in the image. For a binary image, m_{00} is the total number of white pixels of the image. The centroid of the binary image is computed according to $\bar{x} = m_{10} / m_{00}$ and $\bar{y} = m_{01} / m_{00}$.

Based on the centroid of the image, similar to the regular moments, the central moments function is in the format: [μ] = central moment (fig, p, and q). This is computed according to the eq.4: Based on normalized central moments, Hu's introduced seven nonlinear functions which are translation, scale, and rotation invariant. The seven moment invariants are defined as [10] paper as

$$\phi_1 = \alpha_{20} - \alpha_{02} \tag{5}$$

$$\phi_2 = (\alpha_{20} - \alpha_{02})^2 + 4\alpha_{11}^2 \tag{6}$$

$$\phi_3 = (\alpha_{20} - \alpha_{02})^2 + (3\alpha_{12} - \alpha_{03})^2 \tag{7}$$

$$\phi_4 = (\alpha_{30} + \alpha_{12})^2 + (\alpha_{21} + \alpha_{03})^2 \tag{8}$$

$$\begin{aligned} \phi_5 &= (\alpha_{30} - 3\alpha_{12})(\alpha_{30} + \alpha_{12})[(\alpha_{30} + \alpha_{12})^2 \\ & 3(\alpha_{21} + \alpha_{03})^2] + (3\alpha_{21} + \alpha_{03})^2(\alpha_{21} + \alpha_{03})) \\ & [3\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] \end{aligned} \tag{9}$$

$$\begin{aligned} \phi_6 &= (\alpha_{20} - \alpha_{02})[(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] \\ & + 4\alpha_{11}(\alpha_{30} + \alpha_{12})(\alpha_{21} + \alpha_{03}) \end{aligned} \tag{10}$$

$$\begin{aligned} \phi_7 &= (3\alpha_{21} - \alpha_{30})(\alpha_{30} + \alpha_{12})[(\alpha_{30} + \alpha_{12})^2 - \\ & 3(\alpha_{21} + \alpha_{03})^2] + (3\alpha_{12} - \alpha_{03})(\alpha_{21} + \alpha_{03})) \\ & [3(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] \end{aligned} \tag{11}$$

Hu's has shown that these quantities $\O_i$, ($1 \le i \le 7$) are invariant under scaling, translation and rotation.

3. Zernike Moments

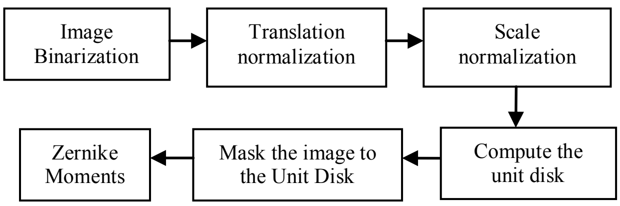


Fig .4. Block diagram of computing Zernike moments.

Figure.4 shows the block diagram of Zernike moment's computation. Compared with Hu's, the computation of Zernike moments is more complicated. The reason for this is the image normalization process. In Hu's, 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.

Zernike introduced a set of complex polynomials $V_{mn}(x,y)$ which form a complete orthogonal set over the unit disk of $(x^2 + y^2) = 1$ in polar coordinates. The form of the polynomials is:

$$V_{mn}(r,\theta) = R_{mn}(r)e^{-jn\theta} \tag{12}$$

where n is positive integer or zero; m is integers subject to constraints n-|m| is even, and $|m| \le n$; 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; $R_{nm}(\rho)$ is Radial polynomial defined as:

$$R_{mn}(r) = \sum_{s=0}^{\frac{m-|n|}{2}})(-1)^s \frac{(m-s)!}{s!(\frac{m+|n|}{2} - s)!(\frac{m-|n|}{2} - s)!} r^{m-2s} \tag{13}$$

The Zernike moment of order n with repetition m for function f (x, y) is defined a

$$z_{mn} = \frac{m+1}{n} \int_x \int_y I(x,y)[V_{nm}(x,y)]dxdy \tag{14}$$

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. Zernike moments themselves are not invariant to translation and scale change. The images need to be preprocessed first to achieve the property of translation and scaling invariance. The advantage of Zernike moments lays in the image reconstruction priority.

4. Classification and Recognition

The classification stage is the deciding a part of a recognition system and it uses the features extracted within the previous stage. A ANN (Artificial Neural Network) classifier is used to classify the unknown character into a known character. Artificial neural networks are models inspired by animal central nervous systems (in particular the brain) that are capable of machine learning and pattern recognition. They are usually presented as systems of interconnected "neurons" that can compute values from inputs by feeding information through the network. For handwriting recognition, a set of input neurons may be activated by the pixels of an input image representing a letter or digit. The activations of these neurons are then passed on, weighted and transformed by some function determined by the network's designer, to other neurons, etc., until finally an output neuron is activated that determines which character was read. System has three layers. The first layer has input neurons, which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons. More complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The most commonly used family of neural networks for pattern classification task is the feed-forward network, which includes multilayer perceptron and Radial-Basis Function (RBF) networks.

ISSN: 2278 – 1323

An ANN is typically defined by three types of parameters:

1. The interconnection pattern between different layers of neurons

2. The learning process for updating the weights of the interconnections

3. The activation function that converts a neuron's weighted input to its output activation.

.

D. Experimental Results

All experiments reported in this paper are conducted on handwritten text lines from variety of users. This database includes over 40 scanned forms of handwritten text from more than 35 different writers, a total of more than 500 fully transcribed handwritten characters, without restrictions on the writing style or the writing instrument used. In this totally six hidden layers are used to recognize the invariant characters.

TABLE I. FEATURES EXTRACTED USING HU'S MOMENTS FOR THE CHARACTER "க"

Instane	Moment 1	Moment 2	Moment 3
1	0.2950	0.0054	9.5603e-06
2	0.2982	7.3007e-04	1.1522e-04
3	0.314	0.0028	3.5452e-04
4	0.3272	0.011	0.0012
5	0.3340	0.0016	0.0012

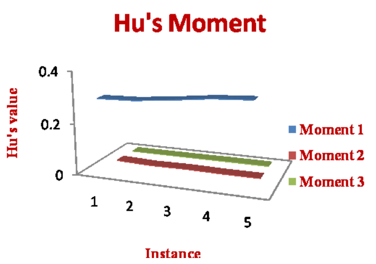


Fig . 5 Distribution of Hu's moment

From Table I and Fig. 5. the values of the computed moment value for 3 invariants the values from forth to seventh moment invariants are close or equal to zero. Based on this point, we can conclude that Hu's seven moment invariants can meet the recognition requirements.

TABLE II. FEATURES EXTRACTED USING ZERNIKE MOMENTS FOR THE CHARACTER "க"

Instane	Moment 1	Moment 2	Moment 3
1	0.2950	0.0054	9.5603e-06
2	0.2982	7.3007e-04	1.1522e-04
3	0.314	0.0028	3.5452e-04
4	0.3272	0.011	0.0012
5	0.3340	0.0016	0.0012

Instane	Moment 1	Moment 2	Moment 3
1	0.2950	0.0054	9.5603e-06
2	0.2982	7.3007e-04	1.1522e-04
3	0.314	0.0028	3.5452e-04
4	0.3272	0.011	0.0012
5	0.3340	0.0016	0.0012

From the below Table II and Fig. 6. Zernike moments up to order 15 can catch the gross shapes of the images. When the order reaches to 20, the reconstructed images can be recognized by human eyes without confusions.

The reconstructed images are more and more clear and include most of the details of the original images when the order gets to 35. Based on the reconstruction result, we recommend using Zernike moments up to order 20 to compose the feature vectors so that good recognition result can be achieved.

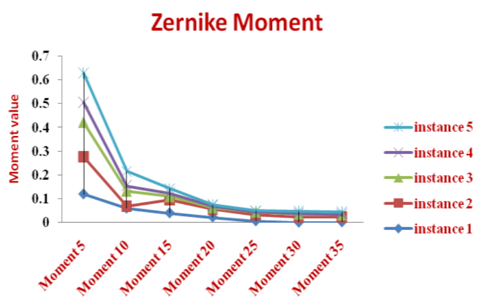


Fig . 6 Distribution of Zernike moment

TABLE III. RESULT OBTAINED

Character	Recognition %	Mis-Recognition %
1	100	0
2	98	2
3	99	1
4	98	2

From Table III illustrates that the detailed recognition results for 200 samples. The recognition rate of 100%, 98%, 99%, and 98% was achieved for the Sample1, Sample2, Sample3 and sample 4. The error rate of 0%, 2%, 1%, 2% was occurred for sample 1, sample2, sample3 and sample4.

The Fig.7. emphasizes very clearly that the proposed system performance is better with respect to all the features. The comparative study is made with the Zone based and Gradient features. The same set of data is used with the Hu's and Zernike moments. The system is experimental through 50

ISSN: 2278 – 1323

samples for each character out of which 45 characters are correct, the main reason is by combining the hu's and Zernike moments.

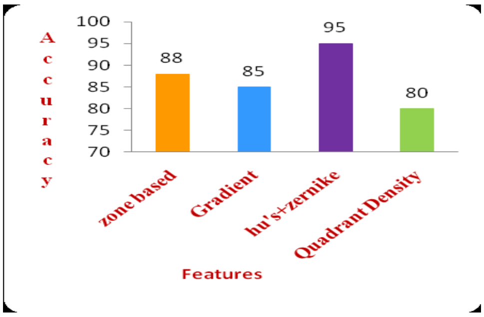


Fig. 7. Comparitive study of various features

IV. Conclusion

Digital recognitions are taking part in wide role and providing nice scope to perform analysis in written character recognition. Still there are several challenges and problems. Therefore it's obvious have to be compelled to strengthen the present one. Several researchers have contributed many solutions for partitioning the problems. The projected work has the novel resolution for activity the character. This work is especially used to recognize the invariant characters. The feature values are used to determine the varied angles of the character. Based on the feature extraction only the accuracy may get multiplied.

From the test results it's known that the directional data of feature extraction yields the very best recognition accuracy of 98 the concerns. This work has sure to important enhancement than the present work. In future additional improvement within the performance from the projected approaches is typically recommended on the large-scale invariant image databases.

References

[1] P.Chinnuswamy and S.G.Krishnamoorthy, "Recognition of Hand printed Tamil Characters," Pattern Recognition Vol. 12, pp141-152, 1980.

[2] C. Tappert, C. Suen, and T. Wakahara, "The State of the Art in Online Handwriting Recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. 8, pp. 787-808, Aug. 1990.

[3] R. Plamondon and S.N. Srihari, "On-Line and Off-Line Handwriting Recognition: A Comprehensive Survey," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 1, pp. 63-84, Jan. 2000.

[4] A.Vinciarelli, "A Survey on Off-Line Cursive Script Recognition," Pattern Recognition, vol. 35, no. 7, pp. 1433-1446, 2002.

[5] H. Bunke, "Recognition of Cursive Roman Handwriting-Past Present and Future," Proc. Seventh Int'l Conf. Document Analysis and Recognition, vol. 1, pp. 448-459, 2003.

[6] Ali Broumandnia and Jamshid Shanbehzadeh "Fast Zernike Wavelet Moments for Farsi Character Recognition," Elsevier Image and Vision Computing 25 2007.

[7] Alirezaee, H. Aghaeinia K. Faez and M. Ahmadi "Off-Line Recognition of Handwritten Middle Age Persian Characters Using Moment," Pattern Recognition and Image Analysis, Vol. 16, No. 4 2007.

[8] Bharath A and Sriganesh Madhavanath "HMM-Based Lexicon- Driven & Lexicon Free Word Recognition For Offline Handwritten Indic Scripts," IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 34, No. 4 2012.

[9] Bhaskara Roa. P, Vara Prasad .D and Pavan Kumar. Ch "Feature Extraction Using Zernike Moments," International Journal of Latest Trends In Engineering and Technology Vol2 Issue2 2013.

[10] Chao Kan and Mandyam D.Srinath "Invariant Character Recognition with Zernike and Orthogonal Fourier-Mellin Moments," Pattern Recognition 25 2002.

[11] Dr Subhashini , N.sridevi, "Moment based feature extraction for classification of Handwritten Ancient Tamil Script," International Journal of Emerging trends in Engineering and Development, Vol 7, Issue 2, 2012.

[12] Mustapha Oujaoura, Rachid El Ayachi1, Mohamed Fakir1, Belaid Bouikhalene and Brahim Minaoui "Zernike Moments and Neural Networks for Recognition of Isolated Arabic Characters," International Journal of Computer Engineering and applications, Vol2 Isssue3 2012.

[13] Nirase Fathima Abubacker and Indra Gandhi Raman "An Approach for Structural Feature Extraction for Distorted Tamil Character Recognition," International Journal of Computer Applications (0975 – 8887) Volume 22– No.4 2011.

[14] Peyarajan and R. Indra Gandhi "Off-Line Tamil Hand Written Character Recognition Using Kohonen Neural Network," Research Journal of Computer Systems Engineering- An International Journal of Computer Applications, Vol 02, Issue 02 2011.

[15] Ramteke "Invariant Moments Based Feature Extraction for Handwritten Devanagari Vowels Recognition," International Journal of Computer Applications (0975 - 8887) Volume 1 – No. 1 .2010.

ISSN: 2278 – 1323