IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-5, May 2018 E-ISSN: 2347-2693

A Combinational Approach of Feature Extraction for Offline Handwritten Hindi Numeral Recognition

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Available online at: www.ijcseonline.org

Accepted: 21/May/2018, Published: 31/May/2018

Abstract- Offline Handwritten Character Recognition is a very challenging field to work upon, as the handwriting of an individual differs very much from another individual, even the handwriting of an individual may differ on different times. Studies have shown that recognition efficiency of characters depends on the ways the features are extracted and formulated as the feature vector. A lot of techniques have been proposed by the various research scholars for feature extraction. In this paper, a combinational approach of feature extraction is proposed as combinational feature vectors (Gradient features, Zernike complex moment features, and Wave based features) may contribute to improved recognition rate. For training and testing purpose, samples of Hindi numerals from 0 to 9 are taken. A feature vector of directional gradient histogram (DGH), a feature vector of Zernike complex moments (ZCM) and a feature vector of Wave features (WF) are feed to the Back-propagation based Neural Network classifiers for training and recognition rate of approx. 79.7%, 92.7% and 73% are attained respectively. By combining the feature vectors DGH, CZM, and WF, a higher recognition rate of 96.4% is obtained for isolated Hindi Numerals.

Keywords: Character Recognition, Gradient features, Zernike Moments, Wave features, Backpropagation Neural Network.

I. INTRODUCTION

Offline Character Recognition means to recognize either printed or a handwritten character. In our study character set includes all the numerals from 0 to 9. The problem of recognizing the printed character is still an easier task as the font styles and their families are limited in number while in case of handwritten character recognition becomes very complex as there is no control on the way of writing the text by an individual. Recognition of characters may be performed at the time of writing or maybe afterwards. If the process of recognizing characters and writing the text is performed simultaneously then it is known as Online Character Recognition otherwise if recognition is performed after writing the text is known as Offline Character Recognition.

Character recognition process itself includes a number of phases- sample collection from different people of different age group, pre-processing on collected samples in order to make the samples prepared to mine the features, an efficient and effective technique is required to extract features and to form feature vector, once the feature vector is formed, a classification algorithm is used to classify the character samples. A number of algorithms are available for classification like BPNN, Decision Trees, K-NN, SVM, Naive Baye's Classifier and Fuzzy Classification etc. [1, 2, 3, 4].

A lot of feature extraction techniques have been suggested by the different researchers for feature extraction. These feature extraction techniques for handwritten character recognition are based on either statistical features or structural features of an image. Statistical features include the average pixel density, pixel distribution, Mathematical transformation etc. Structural features include contour, strokes, number of bifurcation points, and number of circles, number of crossover point, number of horizontal and vertical lines etc.

As per the studies done so far, statistical features may be computed quickly using simple methods and may produce high-quality recognition results, especially in closed testing data, but statistical features may also be simply get affected by the distortion of symbols/ objects, thus may not be applied to other applications.

Structural features are very much close to the intuitive thinking of human brain, thus structural features are more robust with respect to the distortion of symbols/ objects. But, typically these features depend on human concise rules for the recognition of the object. When new symbols/ objects are brought in into the application, it needs lots of costs to adjust the algorithm [5]. Figure.1 depicts the various phases, which are in general, performed for character recognition.

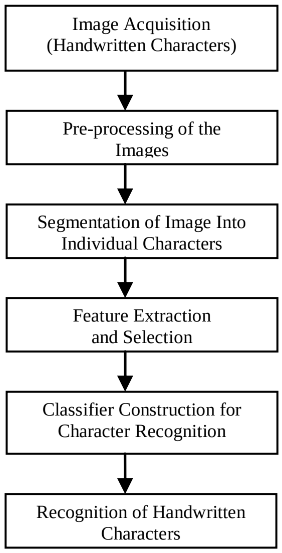


Figure 1. Steps Involved in Handwritten Character Recognition System

Rest of the paper is organized as follows, Section I contains the introduction of Offline Character Recognition, Section II contains the related research work of Offline Character Recognition, Section III presents the motivation and objectives behind the current study, Section IV explains in detail the proposed methodology through various steps involved, section V gives the implementation detail of proposed methodology, Section VI gives a brief discussion on results, Section VII concludes research work with future directions.

II. RELATED WORK

Offline character recognition belongs to the domain of pattern recognition; the prime objective of this research area is to develop character recognition system with higher recognition rate. Using an efficient and effective technique for feature extraction and a precisely taken feature vector may achieve improved accuracy in recognition with less time complexity. As the process of character recognition involves a number of steps and each step have the scope of improvement in order to enhance the overall recognition rate of the system.

The following section gives a brief of work done in the area of offline character recognition-

U. Pal and Kimura [6] performed a comparative analysis of Devanagari handwritten character recognition using 12 classifiers with 4 set of features.

Sandhya Arora et al. [7] developed a technique based on weighted-majority voting, by using three Multilayer Perceptron (MLP) classifiers as a combination and based upon the outcomes of these classifiers, a decision for classification was taken for the recognition of Handwritten Devanagari characters.

Xianjing et al. [8] proposed a technique using circular grid zoning on Polar transformation and attained 92.3% accuracy.

Ashutosh Agarwal et al. [9] proposed the feature vector by considering only 8-directional gradients by normalizing and dividing the image into small blocks and achieved the recognition rate 97% approximately with SVM classifier equipped with RBF kernel for Gurmukhi characters.

Karbhari V. Kale et al. [10] presented a technique for extraction of features to recognize handwritten offline Marathi compound characters using Zernike moments as features of the character image, k-NN and SVM were adopted as a classifier. On the whole, recognition accuracy achieved with SVM and k-NN classifiers were 98.37% and 95.82% respectively.

Kulkarni Sadanand A. et al. [11] discussed the competency of Zernike moments for offline recognition of handwritten characters of Marathi Language.

Dayashankar et al. [12, 13] proposed a technique that computes the directional gradient feature and then these features were normalized to 8-directions and a recognition rate of 90% was claimed.

Ajay Indian et al.[14] proposed a new technique ‘TARANG’, feature extraction method based on natural wave movement, for feature extraction to recognize offline handwritten vowels of Hindi script using Backpropagation learning algorithm and a recognition rate of 96.2% was attained.

K. Radha Revathi et al. [15] presented an approach of hand-written character recognition using a Backpropagation neural network classifier, which can work well in presence of noise. The approach tested with various level of noise present in the character image.

Siddhartha Banerjee et al. [16] introduced the graph matching technique to estimate the similarity between the characters extracted from bank-cheques with the samples of characters stored in the database for the recognition of characters written on the bank-cheques.

Combinational Approach for Feature Extraction

Nowadays, a combination of different feature vectors extracted using various feature extraction techniques, from the same character, is used to represent the character, instead of focusing only on the feature vector based upon a single feature extraction technique. The benefits of combining these feature set obtained from various techniques for the same character that it may offer a wider range of classification clues to improve the accuracy of the recognition.

Shen Wei Lee et al. [17] used a combinational technique for extracting the features and obtained a recognition rate of 98% with an SVM classifier.

G. Raju et al. [18] created a feature vector using both statistical and structural elements from the sample set and incorporated run length code (RLC), image centroid, gradient features and aspect ratio to figure out the feature vector having 147 features. Using this combinational feature vector 99% accuracy achieved for handwritten Malayalam characters and concluded that combinational feature vectors may result in higher accuracy.

In Heutte et al. [19] a combinational feature vector consisting of statistical as well as structural features is proposed to recognize hand-written characters. A feature vector of 124-variable was constructed comprising seven different types of features.
Aroa et al. [20] presented an approach based on the fusion of various feature extraction methods like-shadow features, intersection features, curve fitting features and chain code features for handwritten Devanagari character recognition.

Kimura et al. [21] proposed an approach using the Genetic algorithm for selecting a suitable combination of features from a large set of features in order to improve the accuracy of the recognition.

III. MOTIVATION AND OBJECTIVE

It has been revealed through the extensive literature review that a combination of multiple feature sets obtained from various statistical and structural feature extraction techniques may enhance the overall recognition rate, as the different existing feature extraction techniques may have their own pros and cons, in order to recognize the handwritten characters. So, precisely selected feature sets from the existing feature extraction techniques may contribute to improved recognition rate. In this paper main objective is to study the performances of Directional gradient features, complex Zernike moment features, and Wave based features individually and with different combinational of feature sets, in order to find the best combinational feature set from the various feature sets under study.

IV. PROPOSED METHODOLOGY

The prime objective of this study is to find out an efficient method for the feature extraction with precise length of the feature vector in order to enhance the efficiency of recognizing Hindi numerals. For human beings, it is almost effortless task to recognize printed as well as handwritten characters, as human beings have a natural potential to extract the common patterns from the images very quickly by using their natural intelligence. And natural intelligence does not work on exact matching rather it works upon fuzzy/ approximate matching. But, writing computer programs with such intelligence to exhibit characteristic like humans is a very difficult task. Because computers work upon the exact matching of two entities, if the two entities are exactly same, the computer may recognize or else it may not.

To make such intelligent computer program, it is necessary to first analyze and study the ways by which human beings became able to learn or recognize things. The main task in designing such programs is to create the feature vector (feature extraction) which may describe the shape of different characters/objects uniquely when required to recognize. So, in the proposed combinational approach three different feature extraction techniques- Gradient direction features, Zernike moments as features and Wave-based features are used to form the feature vector. When used individually, these techniques have already been proved as a better descriptor of an object.

Hence the combinational feature vector of these three techniques may enhance the overall recognition rate of the system. The next significant task i.e. classification is to develop the classifier using the above-mentioned feature vectors. With the help of this classifier, the computer will be able to recognize the different characters in an efficient manner comparable to human beings.

The proposed approach may be illustrated by the following steps-

Image Acquisition Phase
Step 1- Collect samples of handwritten Hindi Numerals on A4 white paper sheets from different peoples of varying age groups including left handed and right handed persons.
Step 2- Convert all the samples in digital image form by scanning all paper sheets with samples.

Pre-processing Phase
Step 3- Pass the image through the 2-D filter in order to reduce the noise from the image.

Segmentation Phase
Step 4- Segment the pre-processed image having the sample of numerals using bounding box method, in order to isolate individual numerals and resized each isolated numeral into an image of 40x40 pixels.

Feature Extraction and Selection Phase

Step 5- Gradient direction, Zernike complex moment features and Wave-based features of individual numerals are computed as given below-

A) Compute the Directional Gradient features Histogram (DGH) of individual numerals

- Compute the Gradient direction features using Sobel operator.
- Round off the directional gradient features. Normalize the Gradient direction features using Directional Gradient Histogram (DGH) by considering the nine classes for directions as shown in Table. 1.
- A feature vector DGH= {C1, C2, C3..., C9} of length 9 is be obtained [9].

Table 1. Directional Gradient Classes

Gradient Direction (DGHir)	Class
45 > = DGHir > 0	1
90 > = DGHir > 45	2
135 > = DGHir > 90	3
180 >= DGHir > 135	4
225 >= DGHir > 180	5
270 >= DGHir > 225	6
315 >= DGHir > 270	7
360 >= DGHir > 315	8
DGHir = 0	0

B) Compute the Zernike complex moment features of individual numerals (ZCM)-

- Zernike moments, from 3rd up to 10th order, $ZC_{n,m}$ (n=3,2,4..10, m=3,4,5,..10) of each sample image of numerals are calculated and a feature vector ZCM= {$ZC_{3,1}$, $ZC_{3,3}$, ..$ZC_{10,6}$,$ZC_{10,8}$, $ZC_{10,10}$} of length 32 is obtained as discussed in [10, 11] and shown in Table.2.

Table 2. List of Selected Zernike Complex Moments from 3rd up to 10th order

Zernike Complex Moments of Order (n)	Zernike Complex Moments (ZC_{nm}) of Order n with Repetition (m)	No. Of Zernike Moment Features
3	$ZC_{3,1}$, $ZC_{3,3}$	2
4	$ZC_{4,0}$, $ZC_{4,2}$,$ZC_{4,4}$	3
5	$ZC_{5,1}$,$ZC_{5,3}$,$ZC_{5,5}$	3
6	$ZC_{6,0}$,$ZC_{6,2}$,$ZC_{6,4}$,$ZC_{6,6}$	4
7	$ZC_{7,1}$,$ZC_{7,3}$,$ZC_{7,5}$,$ZC_{7,7}$	4
8	$ZC_{8,0}$,$ZC_{8,2}$,$ZC_{8,4}$,$ZC_{8,6}$,$ZC_{8,8}$	5
9	$ZC_{9,1}$, $ZC_{9,3}$, $ZC_{9,5,}$ $ZC_{9,7}$,$ZC_{9,9}$	5
10	$ZC_{10,0}$,$ZC_{10,2}$,$ZC_{10,4}$,$ZC_{10,6}$,$ZC_{10,8}$,$ZC_{10,10}$	6
	Total No. Of Zernike Moments	32

Zernike Complex Moments of Order (n)	Zernike Complex Moments (ZC_{nm}) of Order n with Repetition (m)	No. Of Zernike Moment Features
3	$ZC_{3,1}$, $ZC_{3,3}$	2
4	$ZC_{4,0}$, $ZC_{4,2}$,$ZC_{4,4}$	3
5	$ZC_{5,1}$,$ZC_{5,3}$,$ZC_{5,5}$	3
6	$ZC_{6,0}$,$ZC_{6,2}$,$ZC_{6,4}$,$ZC_{6,6}$	4
7	$ZC_{7,1}$,$ZC_{7,3}$,$ZC_{7,5}$,$ZC_{7,7}$	4
8	$ZC_{8,0}$,$ZC_{8,2}$,$ZC_{8,4}$,$ZC_{8,6}$,$ZC_{8,8}$	5
9	$ZC_{9,1}$, $ZC_{9,3}$, $ZC_{9,5,}$ $ZC_{9,7}$,$ZC_{9,9}$	5
10	$ZC_{10,0}$,$ZC_{10,2}$,$ZC_{10,4}$,$ZC_{10,6}$,$ZC_{10,8}$,$ZC_{10,10}$	6
	Total No. Of Zernike Moments	32

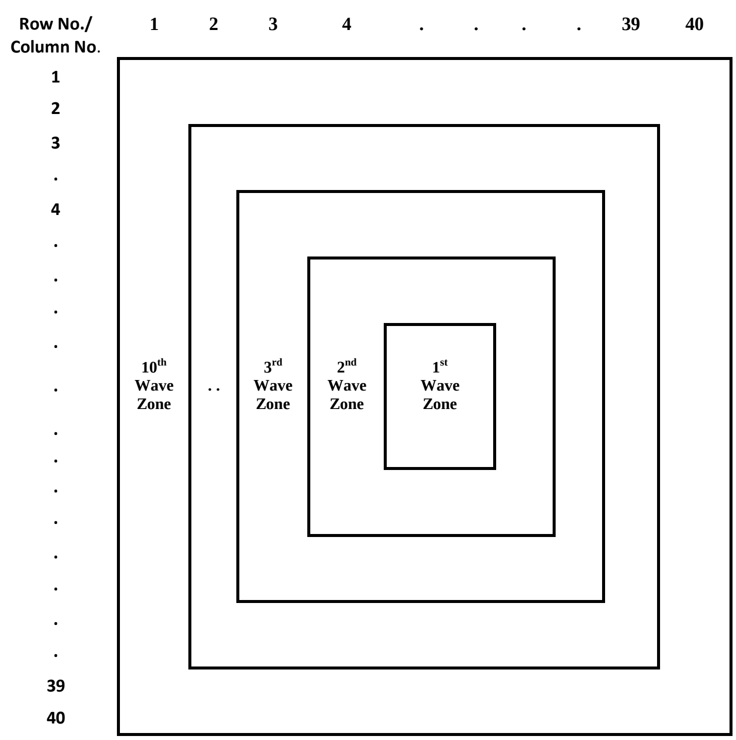


Figure 2. Division of an Image into 10 Wave Zones

C) Compute the Wave Features (WF) of individual numerals

- Each image of the individual numeral is decomposed into 10 wave zones as shown in Figure.2.
- The average intensity A_i (i = 1, 2, 3..., 10) of each wave zone is computed as discussed in [14] in order to obtain the wave feature vector WF = {D_1, D_2, D_3..., D_{10}}.

Classification and Recognition Phase

Step 6- Resilient Backpropagation Neural Network is trained with various feature vectors individually, created in the last step, as well as the different combinations of these feature vectors.

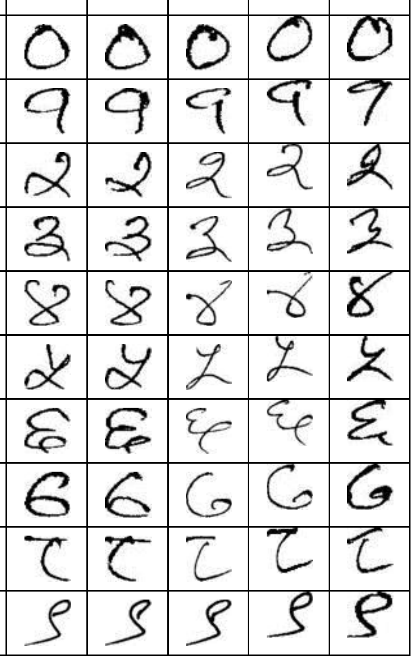
Step7-The trained neural networks are used for classification and recognition of numerals and their efficacy is tested.

IV. IMPLEMENTATION

Samples of all Hindi numerals, ranging from 0 to 9, are collected on the white paper sheet of A4 size from 200 persons of various age groups to form a dataset of 2000 samples. All experiments were performed on this dataset of numeral samples using the MATLAB 2013a. Samples of Hindi numerals collected from five different persons are shown in Table.3.

Table 3. Samples of Handwritten Numerals of Hindi Script Collected from Five Persons

S. No.	The Sample of Handwritten Numerals in Hindi Script				
	1	2	3	4	5
1					
2					
3					
4					
5					
6					
7					
8					
9					
10					



To study the efficiency of the computed feature vectors and their combinations for offline handwritten Hindi numeral recognition, following strategies have been adopted:

Strategy I- Having a feature vector of Gradient direction (DG) of length 9 for training the network.

Strategy II- Having a feature vector of Zernike complex moments (ZCM) of length 32 for training the network.

Strategy III- Having Wave feature vector (WF) of length 10 for training the network.

Strategy IV- Combined feature vector of Directional gradient histogram (DG) of length 9 with Wave feature vector (WF) of length 10, and obtained a feature vector C1= {DG} U {WF} of length 19.

Strategy V- Combined feature vector of Gradient Directional gradient histogram (DG) of length 9 with the feature vector of Zernike complex moments (ZCM) of length 32, and obtained a feature vector C2= {DG} U {ZCM} of length 41.

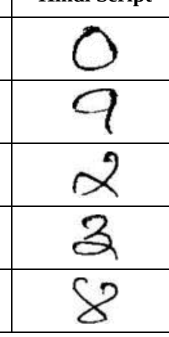
Strategy VI- Combined feature vector of Zernike complex moments (ZCM) of length 32 with Wave feature vector (WF) of length, and obtained a feature vector C3= {ZCM} U {WF} of length 42.

Strategy VII- Combined feature vector of Gradient direction (DG) of length 9, Zernike complex moments (ZCM) of length 32 with Wave feature vector (WF) of length 10 and obtained a feature vector C4= {DG} U {ZCM} U {WF} of length 51.

Taking into consideration the complexity of character recognition problem, Resilient Back-propagation Neural Network (RBPNN) with two hidden layers (H1, and H2) are adopted as a classifier. The output layer (O) of the neural network topology used four neurons for representing the ten different classes of Hindi numerals as shown in the Table.4, whereas the number of neurons in the input layers (I) reflect the length of feature vectors.

Table 4. Representing the Ten Different Classes of Numerals in Hindi Script with Assigned Class Labels

Numerals in English Script	Corresponding Numerals in Hindi Script	Assigned Class Labels
0		0000
1		0001
2		0010
3		0011
4		0100



5		0101
6		0110
7		0111
8		1000
9		1001

Once the neural networks are trained using all stated strategies (I to VII), these networks became ready as classifier to classify the handwritten numerals of Hindi script.

V. EXPERIMENTAL RESULTS

The performance of different strategies, as stated in section 4, in terms of training time (in seconds) and recognition rate (in %) is presented in Table.5. It is obvious from the results shown in the table that Directional gradient features set (the strategy I) and Wave feature set (strategy II) individually achieved lower recognition rate 79.7% and 73%, respectively. Whereas Zernike complex moments feature set (strategy III) individually achieved a higher recognition 92.7%. But, when Directional gradient features are combined with Wave features to form strategy IV, a higher recognition rate 91.8% is achieved. Further, when Zernike moment features are combined with Wave features to form strategy V, a higher recognition rate 94.5% is achieved. Combination of Directional gradient features and Zernike complex moment features i.e. strategy IV, achieved second highest recognition rate 96%. At last, the highest recognition rate of the present study 96.4% is achieved, when Directional gradient features, Zernike moment features, and Wave features are combined to form strategy VII. It is clearly observed from the results that strategies based on combinational feature vectors performed better than the individual feature vectors.

Table 5. Recognition Rate (in %) of Individual Numerals with Different Strategies

S.No.	Hindi Numerals	Recognition Rate of Different Strategies (%)						
		I	**II**	**III**	**IV**	**V**	**VI**	**VII**
1		76.5	91	93.5	97.5	96.5	96	96.5
2		92.5	94	71.5	95.5	98	96.5	97.5
3		53.5	81	36.5	56.5	92	83	90.5
4		88.5	94	79.5	98	95	91	96
5		89.5	89	74	96	97.5	95	97.5
6		67	96	88	97.5	95.5	97.5	96.5
7		74	94	55.5	87	90	95.5	95.5
8		68.5	95.2	83	96.5	98	97	97
9		94.5	98.5	92	97.5	100	100	98.5
10		92.5	94	56.5	95.5	98	94	98
Overall Recognition Rate		**79.7**	**92.7**	**73**	**91.8**	**96**	**94.5**	**96.4**

It is clearly shown in the table that there is a trade-off between the training time and recognition rate. The more complex neural network architecture is required to accommodate the large combinational feature vector; hence these combinational feature vector approaches require more time to get trained for the classification of characters.

Table.6 gives the description about the length of feature vectors, the architecture of neural networks, corresponding training time and their performances in percentage strategy wise.

Table 6. Length of Feature Vectors, Architecture of Neural Networks, Training Time and Performances of Various Strategies in Percentage.

Strategy	Length of Feature Vector	Neural Network Architecture (I-H1-H2-O)	Training Time (in secs)	Recognition Rate (in %)
I	9	9-10-10-4	22	79.7
II	32	32-26-10-4	88	92.7
III	10	10-10-10-4	40	73.0
IV	19	19-10-10-4	28	91.8
V	41	41-26-10-4	272	96.0
VI	42	42-26-10-4	203	94.5
VII	51	51-26-10-4	238	96.4

VI. CONCLUSION AND FUTURE WORK

It has been observed and concluded that recognition rate of combinational feature set (Directional gradient features, Complex Zernike moment features, and Wave based features) is highest as compared with individual feature set as well as the combination of any two feature sets. But, for combinational approaches, more complex neural network architecture with high computing capabilities are required, because combinational feature set became very large as compared to the individual feature set as shown in Table.6. Although, benefits of individual feature extraction techniques may be derived in combinational approach with a trade-off of the speed of learning as the combinational feature set became very large.

Overall recognition rate by combining all feature sets (understudy) is 96.4%. The proposed approach was only tested on numerals of Hindi script, in the future entire character set of Hindi script and as well as character set of other scripts may be tested with different classification algorithm. In the proposed approach, only statistical features were considered to develop the combinational approach for feature extraction, further, a blend of statistical features, as well as the structural features, may be combined even to get better performance. As the combinational feature sets became very large, a feature selection technique may be employed in future work, in order to reduce the length of combinational feature sets.

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