Journal of Information Hiding and Multimedia Signal Processing ©2011 ISSN 2073-4212
Ubiquitous International Volume **2**, Number **1**, January **2011**

Complementary Features Combined in a MLP-based System to Recognize Handwritten Devnagari Character

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Received March 2010; revised September 2010

Abstract. *In this paper a scheme for offline Handwritten Devnagari Character Recognition is proposed, which uses different feature extraction and recognition algorithms. The proposed system assumes no constraints in writing style, size or variations.First the character is preprocessed and features namely : Chain code histogram , four side views , shadow based are extracted and fed to Multilayer Perceptrons as a preliminary recognition step. Finally the results of all MLPs are combined using weighted majority scheme. The proposed system is tested on 1500 handwritten devnagari character database collected from different people. It is observed that the proposed system achieves 98.16% recognition rates as top 5 results and 89.58% as top 1 results.*

Keywords: Classification, Multilayer Perceptron, Feature Extraction, Weighted majority Scheme.

1. **Introduction.** Although first research report on handwritten Devnagari characters was published in 1977 [4] but not much research work is done after that. At present researchers have started working on handwritten Devnagari characters and few research reports are published recently. Hanmandlu and Murthy [5, 14] proposed a Fuzzy model based recognition of handwritten Hindi numerals and characters and they obtained 92.67% accuracy for Handwritten Devnagari numerals and 90.65% accuracy for Handwritten Devnagari characters. Bajaj et al [6] employed three different kinds of features namely, density features, moment features and descriptive component features for classification of Devnagari Numerals. They proposed multi-classifier connectionist architecture for increasing the recognition reliability and they obtained 89.60% accuracy for handwritten Devnagari numerals. Kumar and Singh [7] proposed a Zernike moment feature based approach for Devnagari handwritten character recognition. They used an artificial neural network for classification. Sethi and Chatterjee [8] proposed a decision tree based approach for recognition of constrained hand printed Devnagari characters using primitive features. Bhattacharya et al [9] proposed a Multi-Layer Perceptron (MLP) neural network based classification approach for the recognition of Devnagari handwritten numerals and obtained 91.28% results. N. Sharma and U. Pal [1] proposed a directional chain code features based quadratic classifier and obtained 80.36% accuracy for handwritten Devnagari characters and 98.86% accuracy for handwritten Devnagari numerals. In most of the works reported above, multiple classifier combination has not been reported for handwritten Devnagari characters. Most of them are based on single classifier or reported for handwritten Devnagari numerals. In this paper we are presenting the results of various feature extraction techniques experimented on handwritten Devnagari characters. Different features are experimented individually using MLP classifiers and their combined results are also experimented. The results of all MLPs are combined using weighted majority scheme.

Our feature set is obtained from chain code histogram, shadow and view based. Chain codes histogram features are extracted from scaled contour of the image. Shadow features and view based features are extracted from scaled character image. These features are then fed to the multi layer perceptron for recognition.
Rest of the paper is organized as follows. In section 2, peculiarities of Devnagari script are discussed. Feature extraction techniques are reported in section 4. Section 5, deals with the classifiers used for the recognition purpose. The experimental results are discussed in section 6.

2. **Peculiarities of Devnagari Script.** Devnagari script is different from Roman script in several ways. This script has two-dimensional compositions of symbols: core characters in the middle strip, optional modifiers above and/or below core characters. Two characters may be in shadow of each other. While line segments (strokes) are the predominant features for English, most of the characters in Devnagari script is formed by curves, holes, and also strokes. In Devnagari language scripts, the concept of upper-case, the lower-case characters is absent. However the alphabet itself contains more number of symbols than that of English.
Devnagari script have around 13 vowels and 37 consonants resulting in a total of 50 or even more basic characters. Vowels occur either in isolation or in combination with consonants. Apart from vowels and consonants characters called basic characters, there are compound characters in Devnagari script alphabet system, which are formed by combining two or more basic characters. The shape of compound character is usually more complex than the constituent basic characters. Coupled to this in Devnagari script there is a practice of having more than twelve forms each for 37 consonants , giving rise to modified shapes which, depending on whether the vowel is placed to the left, right, top or bottom of the character. They are called modified characters. The net result is that there are several thousand different shapes or patterns, which may, in addition be connected with each other without any visible separation. This makes Devnagari OCR more difficult to develop.

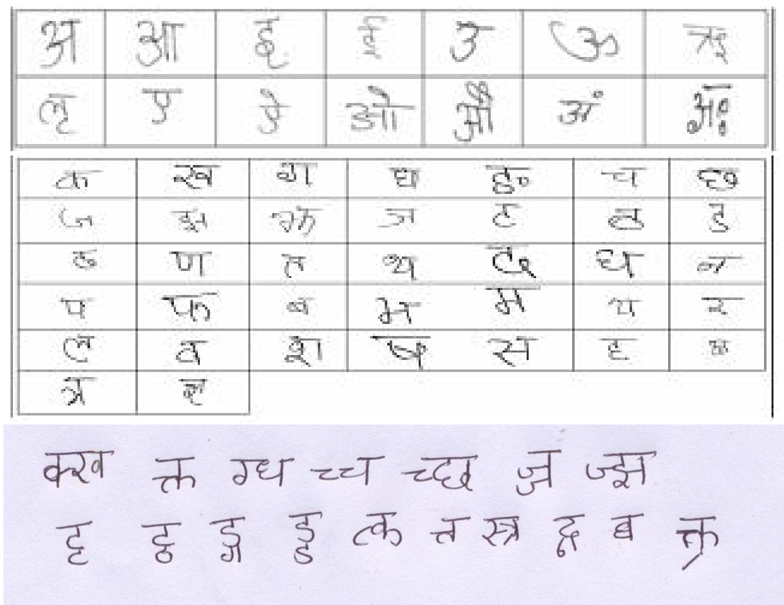

FIGURE 1. Sample of Handwritten Devnagari a) vowel b) consonants c) compound characters

3. **Proposed Method.** In our proposed method, we are first performing thresholding [16], scaling of character bitmap and after that we are extracting three different features. First, 24 shadow features are extracted from eight octants of the character image. Second, 200 chain code histogram features are obtained by first detecting the contour points of character image, and dividing the contour image into 25 segments. For each segment chain code histogram features are obtained. Third, from contour detected image, set of 11 points that plot one of four projections of the image side views (top, bottom, left, right) are extracted. So 44 view based feature vector is constructed. These features are then fed to MLP for recognition.

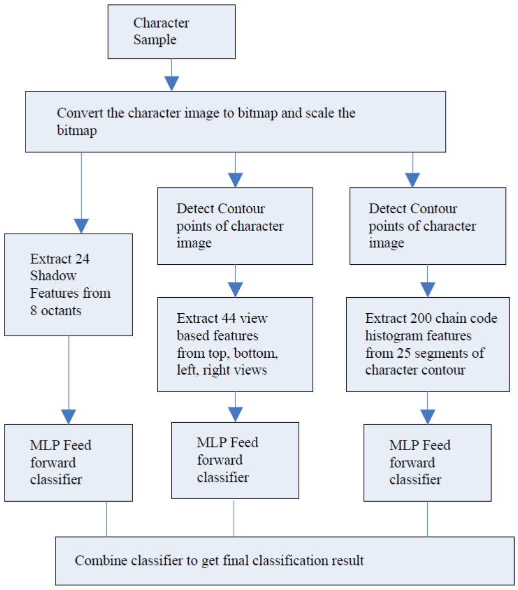

FIGURE 2. Block diagram to represent the proposed technique

4. **Feature Extraction.** In the following, we give a brief description of the feature sets used in our proposed system. Chain code histogram features are extracted by chain coding the contour points of the scaled character bitmapped image. View based features are extracted from scaled, contour of character image. Shadow features are extracted from scaled character image.

4.1. **Shadow Features of character.** For computing shadow features [13], the rectangular boundary enclosing the character image is divided into eight octants, for each octant shadow of character segment is computed on two perpendicular sides so a total of 24 shadow features are obtained. Shadow is basically the length of the projection on the sides as shown in figure 3. These features are computed on scaled image.

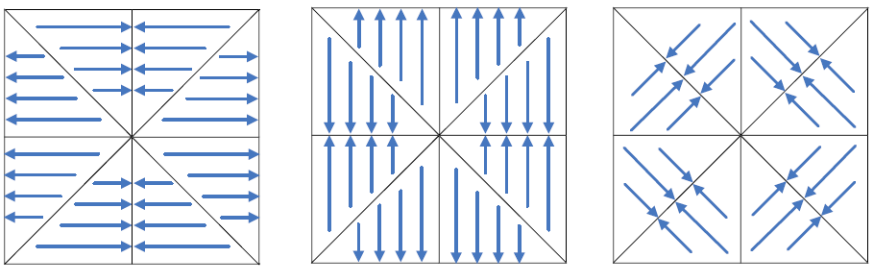

FIGURE 3. Shadow features

4.2. **Chain Code Histogram of Character Contour.** Given a scaled binary image, we first find the contour points of the character image. We consider a 3 X 3 window surrounded by the object points of the image. If any of the 4-connected neighbor points is a background point then the object point (P), as shown in figure 4 is considered as contour point.

The contour following procedure uses a contour representation called chain coding that is used for contour following proposed by Freeman [15], shown in figure 5a. Each pixel of the contour is assigned a different code that indicates the direction of the next pixel that belongs to the contour in some given direction. Chain code provides the points in relative position to one another, independent of the coordinate system. In this methodology of using a chain coding of connecting neighboring contour pixels, the points and the outline coding are captured. Contour following procedure may proceed in clockwise or in counter clockwise direction. Here, we have chosen to proceed in a clockwise direction.

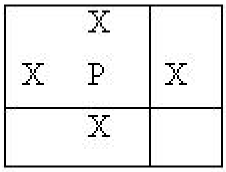

FIGURE 4. Contour point detection

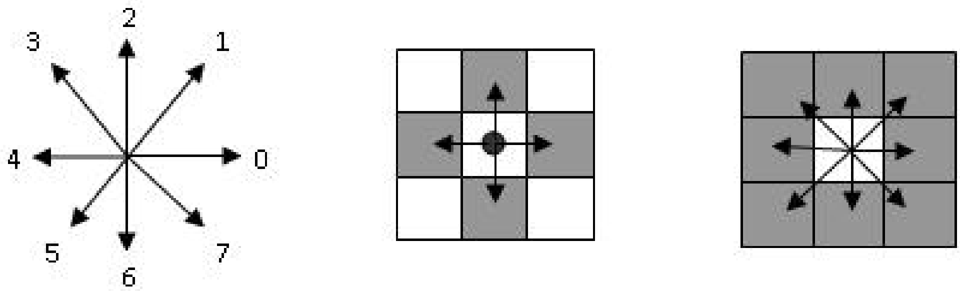

FIGURE 5. Chain Coding: (a) direction of connectivity, (b) 4-connectivity, (c) 8-connectivity. Generate the chain code by detecting the direction of the next-in-line pixel

The chain code for the character contour will yield a smooth, unbroken curve as it grows along the perimeter of the character and completely encompasses the character. When there is multiple connectivity in the character, then there can be multiple chain codes to represent the contour of the character. We chose to move with minimum chain code number first.
We divide the contour image in 5 X 5 blocks. In each of these blocks, the frequency of the direction code is computed and a histogram of chain code is prepared for each block. Thus for 5 X 5 blocks we get 5 X 5 X 8 = 200 features for recognition.

4.3. **View based features.** This method is based on the fact, that for correct character-recognition a human usually needs only partial information about it its shape and contour. This feature extraction method examines four views of each character and extracting from them a characteristic vector, which describes the given character. The view is a set of points that plot one of four projections of the object (top, bottom, left and right) it consists of pixels belonging to the contour of the character and having extreme values of one of its coordinates. For example, the top view of a letter is a set of points having maximal y coordinate for a given x coordinate. Next, characteristic points are marked out on the surface of each view to describe the shape of that view (Figure 6) The method of selecting these points and their number may vary from letter to another. In the considered examples, eleven uniformly distributed characteristic points are taken for each view.

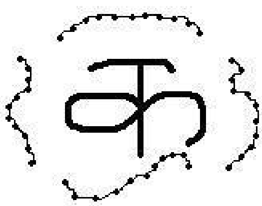

FIGURE 6. Selecting characteristic points for four views

The next step is calculating the y coordinates for the points on the top and down views, and x coordinates for the points on left and right views. These quantities are normalized so that their values are in the range [0, 1]. Now, from 44 obtained values the characteristic vector is created to describe the given character, and which is the base for further analysis and classification.

5. **Character Recognition.** We used different MLP with 3 layers including one hidden layer for three different feature sets consisting of 200 chain code histogram features 24 shadow features and 44 view based features. The experimental results obtained while using these features for recognition of handwritten Devnagari characters is presented in section 6. At this stage all characters are non-compound, single characters so no segmentation is required.
Each MLP is trained with Backpropagation learning algorithm with momentum [9]. It minimizes the sum of squared errors for the training samples by conducting a gradient descent search in the weight space. Learning rate and momentum term are set to 0.8 and 0.7 respectively. As activation function we used the sigmoid function. Numbers of neurons in input layer of MLPs are 200, 24 and 44 for chain code histogram, shadow and view based features respectively. Number of neurons in Hidden layer is not fixed, we experimented on the values between 20-50 to get optimal result and finally it was set to 50, 30 and 40 for chain code histogram, shadow and view based features respectively. The output layer contained one node for each class, so the number of neurons in output layer is 20.

5.1. **Classifier Combination.** The ultimate goal of designing pattern recognition system is to achieve the best possible classification performance. This objective traditionally led to the development of different classification scheme for any pattern recognition problem to be solved. The result of an experimental assessment to the different design would then be the basis for choosing one of the classifiers as the final solution to the problem. It had been observed in such design studies, that although one of the designs would yield the best performance, the sets of patterns misclassified by the different classifiers would not necessarily overlap. This suggested that different classifier designs potentially offered complementary information about the pattern to be classified which could be harnessed to improve the performance of the selected classifier. So instead of relying on a single decision making scheme we can combine classifiers. We have three Neural networks classifiers as discussed above, which are trained on 200 chain code, 24 shadow and 44 view based features respectively. The outputs are confidences associated with each class. As these outputs cannot be compared directly, we used an aggregation function for combining the results of all three classifiers. Our strategy is based on weighted majority voting scheme as described below.
So if k^{th} classifier decision to assign the unknown pattern to the i^{th} class is denoted by O_{ik} with $1 \leq i \leq m$, m being the number of classes, then the final combined decision d_i^{cm} supporting assignment to the i^{th} class takes the form of :-

$$d_i^{com} = \sum_{k=1,2,3} \omega_k * O_{ik} \cdots\cdots\cdot 1 \leq i \leq m$$

The final decision d^{com} is therefore :-

$$d^{com} = \max_{1 \leq i \leq m} d_i^{com}$$

$$\omega_k = \frac{d_k}{\sum_{k=1}^{3} d_k}$$

where $m = 20$ and $\omega 1$, $\omega 2$ and $\omega 3$ are 0.384 ,0.354 and 0.262 respectively as $d1 \geq d2 \geq d3$
d1=88.19% result of classifier trained with chaincode histogram features.
d2=81.25% result of classifier trained with shadow features.
d3=60.07% result of classifier trained with view based features.

6. **Results.** The experiment evaluation of the above technique was carried out using isolated devnagari characters collected different people. A total of 1500 samples of Devnagari basic characters (vowels as well as consonants) are used for our experiment out of which 65% characters are used for the training and rest is used for testing purpose. The recognition accuracy obtained from our above discussed classifiers separately are shown in table I. Three MLPs are designed for features namely Chain code Histogram based, four side views based and Shadow based features. There are certain characters, given in figure 7, which are misclassified because of their similar shapes. Some characters not classified by one classifier may be classified by another classifier so results of three MLPs are combined using weighted majority scheme discussed above. Combined MLP is giving 98.61% accuracy as we considered top 5 choices results.

We applied 3-fold cross validation testing. We divided the whole dataset into three parts. In first fold, first two parts are used for training and third part is used for testing. In second fold, first and third part is used for training and second part is used for testing. In fold three, second and third part is used for training and first part is used for testing. The average error across all three trials is computed. The advantage of this method is that it matters less how the data gets divided. Every data point gets to be in test set exactly once, and gets to be in training set remaining times. We compared our current results with those existing pieces of work. Details comparative results are given in table III.

Table 1. Results of three different MLP

MLP	Input Layer Neuron	Hidden Layer Neuron	Output Layer Neuron	Results
Chain code histogram feature based	200	50	20	88.19%
Shadow feature based	32	15	20	81.25%
View feature based	44	30	20	60.07%

Table 2. Top Choices Results

S.No.	Proposed method result	Accuracy obtained
1	Top 1 choice	89.58%
2	Top 2 choice	94.79%
3	Top 3 choice	97.57%
4	Top 4 choice	98.26%
5	Top 5 choice	98.61%

Table 3. Comparison of Results

S.N.	Method proposed by	Technique	Data set	Accuracy
1	Kumar and Singh [7]	Zernike moment based approach	200	80%
2	N.Sharma, U. Pal, F. Kimura, and S. Pal [1]	Directional chain code features using quadratic classifier	11270	80.36%
3	M.Hanmandlu, O.V.R Murthy, V.K. Madasu [14]	Fuzzy model based recognition, using exponential membership function estimated by entropy and error function	4750	90.65%
4	Proposed method	Shadow, ,view based, Chain code histogram features with MLP neural network combination	1500	98.61%

7. **Conclusion.** India is a multi-lingual and multi-script country comprising of eleven different scripts. Devnagari is third most widely used script, used for several major languages such as Hindi, Sanskrit, Marathi and Nepali, and is used by more than 551 million people. But not much work has been done towards off-line handwriting recognition of Devnagari script. In this paper we present a technique of recognition of offline handwritten Devnagari characters using MLP In future, we plan to experiment on other feature extraction methods to get higher recognition accuracy from our system.

Acknowledgment. Authors are thankful to the Centre for Microprocessor Application for Training Education and Research and Project on Storage Retrieval and Understanding of Video for Multimedia, at the Department of Computer Science and Engineering, Jadavpur University, Kolkata-700032 for providing the necessary facilities for carrying out this work. First author gratefully acknowledge the support of the Meghnad Saha Institute of Technology for carrying out this research work.

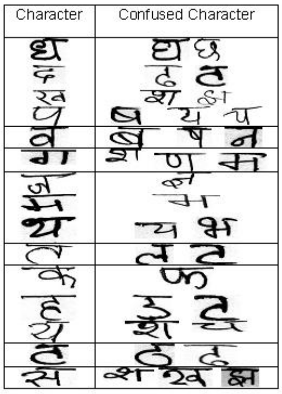

FIGURE 7. Confused character set

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