OCR for Script Identification of Hindi (Devnagari) Numerals using Error Diffusion Halftoning Algorithm with Neural Classifier

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Abstract—The applications on numbers are across-the-board that there is much scope for study. The chic of writing numbers is diverse and comes in a variety of form, size and fonts. Identification of Indian languages scripts is challenging problems. In Optical Character Recognition [OCR], machine printed or handwritten characters/numerals are recognized. There are plentiful approaches that deal with problem of detection of numerals/character depending on the sort of feature extracted and different way of extracting them. This paper proposes a recognition scheme for handwritten Hindi (devnagiri) numerals; most admired one in Indian subcontinent our work focused on a technique in feature extraction i.e. Local-based approach, a method using 16-segment display concept, which is extracted from halftoned images & Binary images of isolated numerals. These feature vectors are fed to neural classifier model that has been trained to recognize a Hindi numeral. The archetype of system has been tested on varieties of image of numerals. Experimentation result shows that recognition rate of halftoned images is 98 % compared to binary images (95%).

Keywords—OCR, Halftoning, Neural classifier, 16-segment display concept.

I. Introduction

IN Optical Character Recognition [OCR], a character numerals which has to recognized can be machine printed or handwritten characters/numerals [1]. There is extensive work in the field of handwriting recognition, and a number of reviews exist. Handwritten numeral recognition is an exigent task due to the restricted shape variant, unusual script style & different kind of noise that breaks the strokes in number or changes their topology [1]. Recognize of is gaining wider importance today & is one of the benchmark problem in document analysis. As handwriting varies when person write a

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same character twice, one can expect enormous dissimilarity among people. These are the reason that made researchers to find techniques that will improve the knack of computers to characterize and recognize handwritten numerals. General methodologies in pattern recognition & image analysis are presented in [14].character recognition is reviewed in [**7**, 10, 12, 15] for off-line recognition, and in [16, 17] for online recognition. Most of researchers have chosen numeric characters for their experiment [8, 9**,** 11, 13] so, some maturity can be observed for isolated digit recognition.

A. Halftoning

Halftone imagery is bi-level imagery, which appears to have multiple grey-levels due to the microstructure [2]. Active and passive color liquid-crystal displays (LCD's) (already used in notebook personal computers, and also proposed in wall-mounted displays for HDTV), & other display devices such as light-emitting diodes (LED's), electro-luminescent displays, and plasma displays, which are additive color systems using a mosaic of red, green, and blue "dots" to produce color are foremost applications of Halftone imagery.

B. Artificial Neural Network

ANN is physical cellular system that can acquire stores and make use of investigational facts/data. To fine-tune the input and output parameters of the Neural network model, we have to train the process so that the MAPE (Mean Absolute Percentage Error) measure is minimized. The feed-forward neural network model is train by using Back propagation learning algorithms [6]. A neural network is a foremost data modeling equipment that is able to confine and signify complex input/output relationship. It is a natural proof that some problem that beyond the scope of current computer are indeed solvable by small energy efficient package [1].

II. Implementation

The recognition system consists of three parts, each dealing with preprocessing stage, feature extractor, Learning stage & recognition stage. In feature extractor, local based approach

using 16 segment display concept information is extracted from binary image & halftoned images. Extracted features from binary & halftoned images i.e. feature vectors are fed to Neural network model that has been trained to recognize a numeral.Block diagram of recognition model are portray in Fig. 1.
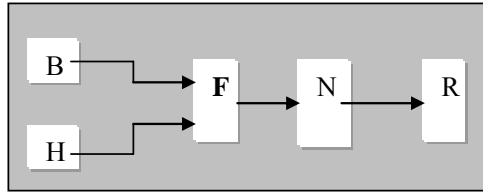

Fig. 1 Recognition Model

B-> Binary Image
H-> halftoned images
F->Extract the feature from the local approach
N->Neural network
R->Recognition Result

A. Preprocessing Stage

We made use of Separable Error Diffusion Halftoning algorithm to generate a halftone image.

1. Separable Error Diffusion Halftoning

This algorithm designs digital color halftones by Separable Error Diffusion. This is equivalent to applying grayscale error diffusion halftoning methods separable to each of the 3 color planes. There are Floyd-Steinberg, Jarvis and Stucki error filters. Here the best error diffusion halftoning filter used is that of Floyd-Steinberg. There are two major dithering approaches: ordered and error diffusion. Ordered dithering uses carefully chosen square grids of binary pixels to represent different gray scale ranges. A particular square grid is chosen so that its pattern corresponds to the appropriate gray level. The correspondence is established by its proximity to the average grayscale level. This technique can be parallelized, since each grid is calculated independently of the surrounding ones.
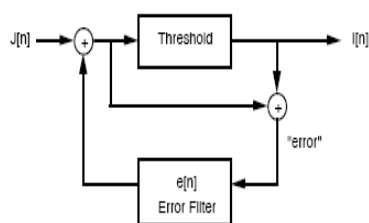

Fig. 2 Floyd-Steinberg process

The final outcome is likely to contain some characteristic diagonal artifacts which reduce the quality of the final dithered image. Error-diffusion is an alternative dithering technique that has emerged as the standard because of its simplicity and quality of output.   The error-diffusion algorithm, first proposed by Floyd and Steinberg [3], is schematically shown in Fig. 2 and works as follows. Pixels J[n] of the continuous-tone digital image are processes in a linear fashion, left-to-right and top-to-bottom. At every step, the algorithm compares the grayscale value of the current pixel, represented by an integer between 0 and 255, to some threshold value (typically 128). If the grayscale value is greater than the threshold, the pixel is considered black and its output value I[n] is set to 1, else it is considered white and I[n] is set to 0. The difference between the pixel's original grayscale value and the threshold is considered as error. To achieve the effect of continuous-tone illusion without the diagonal visual artifacts, this error is distributed to four neighboring pixels that have not been processed yet, according to the matrix shown graphically in Fig. 3, proposed by Floyd and Steinberg [3]. The following pseudo code implements the [4] error-diffusion dithering of an n by m grayscale image. The boundary conditions are ignored. The notation (J[i,j] < 128)? 0: 1 is the Clike if-then-else shortcut notation.

```
for i = 1 to n
for j = 1 to m
I[i,j] = (J[i,j] < 128)? 0 : 1
err = J[i,j] - I[i,j]*255
J[i+1,j] += err*(7/16)
J[i-1,j+1] += err*(3/16)
J[i,j+1] += err*(5/16)
J[i+1,j+1] += err*(1/16)
end for
end for
```
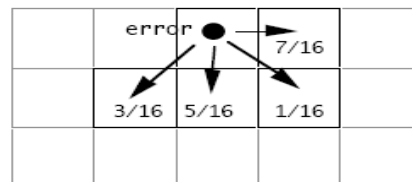

Fig. 3 Diffusion matrix of distributing error fractions to four neighboring pixels

B. Feature Extractor

1. Local-based approach, a method using 16-segment display concept

We have attempted to extend the seven segment display concept into sixteen segment display concept. [5] for recognizing handwritten Hindi numerals. In 16-segment display concept, input handwritten Hindi numerals are encoded into seven line segments arranged in a template as shown in Fig. 4
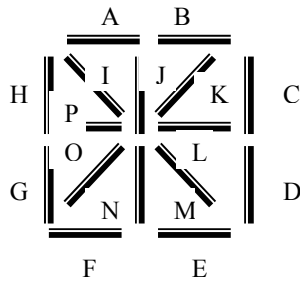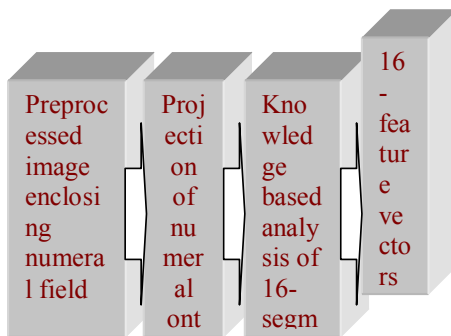
Fig. 4 16-segment display

Fig. 5 Sixteen-segment display concept to extract the features from image

Stages involved in this method are depicted in Fig. 5. The encoding takes the form of shadow projection. A shadow projection operation is defined as simultaneously projecting a numeral into closest vertical & horizontal segments. After all point is projected, shaded encoded segments are obtained. Fixed the threshold for every segments based on pixel size of number [5].These thresholds are being used to find whether sufficiently large numbers of pixels are projected onto the corresponding segments. Identify the segment whose projected pixels count above the respectively threshold & assign it 1 & remaining 0. A string of such shaded segment in sequence of 0's & 1's we get as a feature vector.
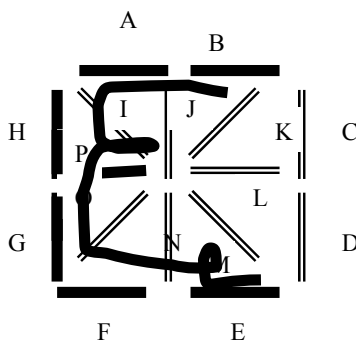
Feature vectorF1=[110011110000001]

Algorithm:

Step1: start
Step2: divide the logical box vertically into two halves.
Step3: Horizontally projects all pixels of the left halve onto segment 'h' & 'g'
Step4: Horizontally projects all pixels of the right halve onto segment 'c' & 'd'
Step5: Horizontally projects all pixels of the center halve onto segment 'j' & 'n'
Step6: Divide the logical box horizontally into three parts. First part is top ¼ of the height of number. Second part is bottom ¼ of height of number. The remaining middle portion constitutes second part.
Step7: Vertically projects all pixels of the first part onto segment 'a & b'.
Step8: Vertically projects all pixels of the first part onto segment 'p'& 'l'.
Step9: Vertically projects all pixels of the first part onto segment 'f'& 'e'.
Step10: diagonally projects all pixels of the first part left halve onto segment i'& 'o'.
Step11: diagonally projects all pixels of the first part right halve onto segment k'& 'm'.
Step12: Determine threshold for every segment based on pixel size of number.
Step 13: Identify the segment whose projected pixels count above the respectively threshold & assign it 1 & remaining 0.
Step 14: A string of such shaded segment in sequence of 0's & 1's, we get as a feature vector (F1).
Step 15:End

C. Recognition Stage

In the perspective of handwriting recognition, the 3-layer neural network is available to learn the input-output relationship. The layers of input neuron are responsible for inputting a feature vectors i.e, Feature vectors F1 from global based technique given to the input layer separately .The amount of neurons in this output layer is determined by range of set of desired output, with each possible output being represented by separate neuron. In our proposed work, neural network contains 16 input nodes, 20 neurons in the first hidden layer, 14 neurons in the second hidden layer and the output layer has 10 neurons. It outcomes in a 16-14-10 back propagation neural network. Sigmoid function is used as the activation function. For the back-propagation, the learning rate is 0.2 and the momentum constant used is 0.9. During the training process the performance is 0.00126123 at 14400 epochs.

The present work on numeral recognition involves the development of neural network, which can train to recognize the numeral presented to it.

Following are the steps involved in design the system

- Create an input data file which consists of training pairs consist of halftoned images & binary images
- Extracting the features from local approach technique

- Design the neural network based upon the requirement and Availability
- Simulate the software for network
- Train the network using input data files until error falls below the tolerance level
- Verify the capability of neural network in recognition of test data

III. RESULTS AND OBSERVATION

TABLE I
RECOGNITION RATE OF BINARY IMAGE

Numerals	Correct	Error
0	93.62	6.47
1	80.32	18.05
2	85.02	14.42
3	92.5	7.5
4	80.4	19.6
5	89.5	11.5
6	74.0	26.0
7	92.34	7.6
8	91.7	8.3
9	74.5	25.5

The given dataset is the numeric dataset. In feature extractor we have used local based approach using16-segment display concept. Extracted features from halftoned images & binary images of isolated numerals i.e. feature vectors are fed into generalized delta rule algorithm and train the network to recognize the unconstraint numerals.
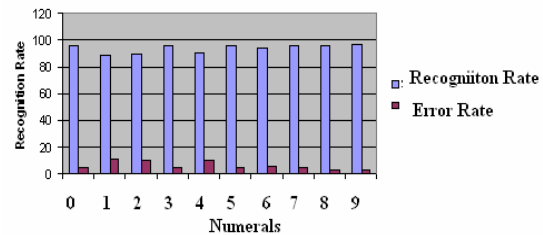
TABLE II
RECOGNITION RATE OF HALF TONED IMAGE

Numerals	Correct	Error
0	95.34	4.7
1	89.05	11.05
2	90.0	10
3	95.34	4.6
4	90.4	9.6
5	95.4	4.6
6	94.0	6.0
7	95.63	4.6
8	95.7	3.3
9	97.5	3.0
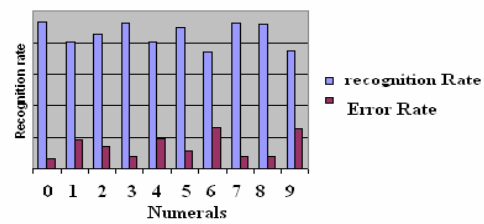
The graphs above show the comparison of two techniques.

IV. CONCLUSION

The strength of the halftoned image in recognition of handwritten Hindi numeral detailed above In this paper we had used two different types of images-(binary & halftoned image), by using local (sixteen segment –display concepts) for feature extraction which is mentioned in section 2.2 in detail with example and then given to neural network to recognize the numerals. In feature extraction (sixteen segment –display concepts) we have fixed threshold for every segment (bar) which has to follow. These thresholds are being used to find whether sufficiently large numbers of pixels are projected onto the corresponding segments .It is found that for halftoned image the recognition rate (98%) is better than simple binary image (95%). The below fig gives original image, which is a three dimension array of size 109x121x3 & total amount of bits utilized is 39,567.
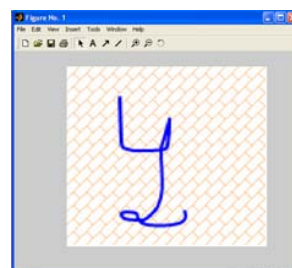

Fig. 6 Screen shot for original image

TABLE III
COMPARISON OF BINARY & HALFTONED IMAGES

Parameter	Binary Image	Halftoned Image (using random modulation)
Eg. Images		
size in pixels	109x121	109x121
Bits per pixel	1	1
size in Bits	13189	26378
Visual quality	Low	medium
Example pixels (1:3,1:5) in Fig. 2.2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 1 0 0 1 0 0 0
Accuracy	Low	Medium
% Recognition	80-90	90-95
Error rate	High	Low
Effect of presence of noise	Performance very poor	Performance good

The Table III above shows percentage of recognition of binary & halftoned image. The data rate of an uncompressed Halftoned image is 1 bit per pixel, which is very much reduced relative to the rate of the original grayscale image (8 bits per pixel) as shown in Table III. However, large Halftoned images still require several megabytes of data to be transmitted. Data compression can be used to reduce this further. The simulation results seem quite capable and outperforming than the Binary image using Back Propagation neural network technique in the benchmark test comparable to halftoned image. Classification is done by a Neural network for binary image at the rate of about 250 digits per 2.5 seconds whereas for half toned image 250 digits per seconds.

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