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OCR for Script Identification of Hindi (Devnagari) Numerals using Feature Sub Selection by Means of End-Point with Neuro-Memetic Model

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***Abstract*—**Recognition of Indian languages scripts is challenging problems. In Optical Character Recognition [OCR], a character or symbol to be recognized can be machine printed or handwritten characters/numerals. There are several approaches that deal with problem of recognition of numerals/character depending on the type 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. global based approach using end-points information, which is extracted from images of isolated numerals. These feature vectors are fed to neuro-memetic model [18] that has been trained to recognize a Hindi numeral. The archetype of system has been tested on varieties of image of numerals. . In proposed scheme data sets are fed to neuro-memetic algorithm, which identifies the rule with highest fitness value of nearly 100 % & template associates with this rule is nothing but identified numerals. Experimentation result shows that recognition rate is 92-97 % compared to other models.

***Keywords*—**OCR, Global Feature, End-Points, Neuro-Memetic model.

I. Introduction

IN Optical Character Recognition [OCR],a character or symbol to be recognized can be machine printed or handwritten characters/numerals [1].Handwritten numeral recognition is an exigent task due to the restricted shape variation, different script style & different kind of noise that breaks the strokes in number or changes their topology [1]. As handwriting varies when person write a 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 are presented in [14]. Off-line recognition and online recognition is reviewed in [**7**, 10, 12, 15] and [16, 17] respectively. Some development can be observed for isolated digit recognition because many research scholars [8, 9**,** 11, and 13] across the global have chosen their field in handwritten numeral/character recognition.

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II. Overview of Recognition System in Our Proposed Work

The recognition system consists of three parts each dealing with feature extractor, Learning stage & recognition stage. In feature extractor, global based approach using end-points information is extracted from binary image and fed to Neuro-Memetic model [18] that has been trained to recognize a numeral.

Block diagram of recognition model are portray in Fig. 1.

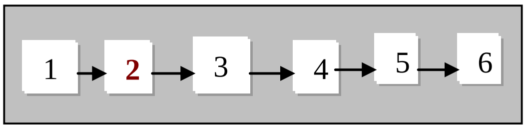

Fig. 1 Block diagram of recognition model

1-> Binary Image
2->Draw the directed graph
3->Extract the feature from the End point Approach
4->Memetic algorithm (MA)
5->Neural network
6->Recognition Result

A. Feature Extraction

Feature extractor is a vital part of any recognition system. The main intend of feature extraction is to depict the pattern by means of bare minimum number of attributes. One significant job in design of pattern recognition system is to develop as algorithm to extort characteristics of pattern from initial measurement. Some features that have been carried for numeral recognition are geometric feature, topological, directional, mathematical & structural features. [1].The derived features are then used as input to numeral classifier.

1. The feature extraction by Global Based Technique Using End-Points Information

End point information can easily extract from each numeral. In this technique of feature extraction binary image of numerals is partitioned into fixed number of sub-slices called A, B, C, & D as shown in Fig. 2. If end –points of numerals lies in any of these slice then assign 1 else 0. If image touch the partition line 1, 2, 3 & 4 then assign 1. In Fig. 3 the sample image of Hindi six numeral has endpoints in the region B& C and the image touches the line 1, 3 & 4.

Hence taking all above consideration the feature vector for this image in Fig. 3 is as follows:

Feature vector F2=[0 1 1 0 1 0 1 1]

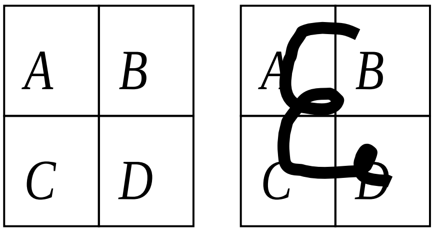

Fig. 2 Sub Slice Fig. 3 Sample image

Algorithm

Step1: Start

Step2: Binary image of numerals is partitioned into fixed number of sub-slices called A, B, C, & D

Step3: If end –points of numerals lies in any of these slice then assign 1 else 0.

Step4: If image touch the partition line 1, 2, 3 & 4 then assign 1

Step5: Combining step 3, 4 we are getting the feature vector (F2) for the image.

Step 6: End

B. Neuro-Memetic Model

In our previous work Neuro-memetic model [18] was implemented to predict the sub circuit from circuit with minimum interconnections between them pertaining to VLSI design. We attempted to make use of Neuro-memetic model to recognize the handwritten number in pattern recognition area.

1. Training Procedure

The MAPE (Mean Absolute Percentage Error) is minimized by adjusting input/output parameter which is the main aim for training neural network by using Back propagation learning algorithms. In learning phase of neural network, termination at a local minimum is a major setback faced. In other words, such a neural network is not completely trained [3]. A neural network is a dominant data modeling paraphernalia that is able to confine and signify complex input/output relationship [18]. It is a natural proof that some problem that beyond the scope of current computer are indeed solvable by small energy efficient package [2]. Nevertheless, memetic algorithms offer proficient search method for complicated (i.e., possessing many local optima) spaces to find almost local optima. Thus, its capacity to search a superior suboptimal solution or have a privileged probability to obtain the local optimal solution makes it one of the ideal candidates to decipher the learning problem.

2. Training with MA

Memetic algorithm with operator like arithmetic crossover and non uniform mutation are used to refrain the parameters of neural network [18]. A population (P) with 135 genotypes is considered for this said application. They are arbitrarily initialized, with utmost number of iterations fixed at 100. MA executes for 100 generations with the similar population size. The preeminent model was found after 53 generations. In this work, the probability of crossover is 0.6 and the probability of mutation is 0.2 are taken. These probabilities are chosen by trial and error through experiments for excellent performance. The new offspring which share some features takes forms each parent are replaced by new population. The above procedures are repetitive until a certain execution condition is contented. The figure of the iterations essential to train the anticipated MA-based neural network is 1250. The range of the fitness function of neural network is [0, 1].

3. Evaluate Individuals Using the Fitness Function

The aim of the fitness function is to minimize the forecast error. In order to avert over-fitting and looking at the system, we have changed the fitness evaluation scaffold. The fitness of a chromosome for the normal class is evaluated as depict in [18] as in shown example.

Take testing samples

01	10	10	11

Now take the one of data set (d1)

00	01	10	10
↓	↓	↓	↓
+1	-2	+2	+1

For dataset d2

01	00	11	1 0
↓	↓	↓	↓
+2	+1	+1	+1

Calculate the sum of (+) credit & (-) debit for each sample data d1 & d2.

For d1=-1-2+2+1=0 and d2=+2+1+1+1=5 so it has found that sample fitness of data d2 is best sample.

C. Design of Proposed System to Recognize the Numerals

The present work on numeral recognition involves the development of neural network [18],

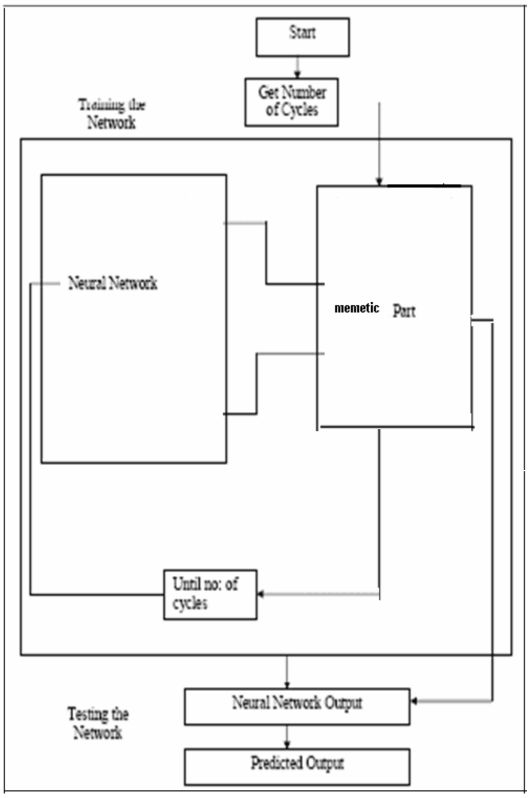

Fig. 4 Block Diagram of Neuro-memetic

which can train to recognize the numeral presented to it. Following are the steps involved in design the system.

1. Create a input data file which consists of training pairs
2. Extracting the features of binary image by using Global based technique using end-points information
3. Design the neural network based upon the requirement and Availability
4. Simulate the software for network
5. Initialize count=O, fitness=O, number of cycles
6. Generation of Initial Population. The chromosome of an individual is formulated as a sequence of consecutive genes, each one coding an input parameter [18] .
7. Initialize the weight for network. Each weight should be set to a random value between –0.1 to 1.
8. Calculates activation of hidden nodes

$$xJh = \frac{1}{1+e^{-(\sum wjk_{h} * xpn)}}$$

9. Calculate the output from output layers

$$xio = \frac{1}{1+e^{-(\sum wij_{o} * xjh)}}$$

10. Compares the actual output with desire outputs and finds a measure of error. The genotypes are evaluated on the basis of the fitness function.
11. If (previous fitness < current fitness value) Then store current weights
12. Count = count + 1
13. Selection: Two parents are selected by using the roulette wheel mechanism [14].
14. Genetic Operations: Crossover, Mutation and Reproduction to generate new weights (Apply new weights to each link)
15. If (number of cycles> count) Go to Step 7
16. Training set is reduce to an acceptable values
17. Verify the capability of neural network in recognition of test data
18. End

In the perspective of handwriting recognition, the 3-layer neural network is available to learn the input-output relationship by making use the MA. In our proposed work, Neural network contains 8 input nodes, 20 neurons in the first hidden layer, 14 neurons in the second hidden layer and the output layer has 10 neurons. It outcome in a 8-14-10 back propagation neural network. Memetic Algorithm is employed for learning [4]. For the back-propagation, the learning rate is 0.2 and the momentum constant used is 0.65.

III. RESULTS AND OBSERVATION

The given dataset is the numeric dataset. In feature extractor we have used global based approach using end-points information. Extracted features from images of isolated numerals i.e. feature vectors are fed into generalized delta rule algorithm and memetic algorithm combined and train the network to recognize the unconstraint numerals.

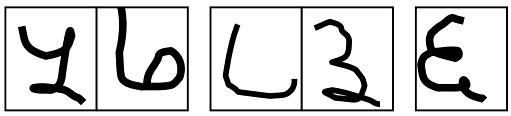

Image1 Image2 Image3 Image4 Image5

TABLE I
RECOGNITION RATE OF NEURAL NETWORK

Numerals	Correct	Error
0	85.34	15.7
1	80.05	19.05
2	81.0	19.0
3	85.34	15.6
4	90.4	9.6
5	75.4	24.6
6	84.0	16.0
7	85.63	14.6
8	83.7	13.3
9	81.0	19.0

TABLE II
RECOGNITION RATE OF NEURO-MEMETIC APPROACH

Data sets Numerals	Correct recognition rate	False rate
0	93.34	6.7
1	94.05	5.05
2	92.0	8.0
3	93.42	6.58
4	93.4	7.6
5	92.0	08.0
6	97.0	3.0
7	94.63	5.4
8	91.7	8.3
9	92.5	8.0

Fig. 5 shows the curves of the BP neural network and the Neuro-memetic ensemble by plotting pairs of error rate and correct detection rate. Since the curve of the Neuro-memetic is nearer to the upper-left area than the curve of the BP neural network test, the Neuro-memetic model performs well again than the BP neural network method in detection of numerals with respect to both false rate and detection rate. These scheme shows that BP neural network performs with recognition rate 80-90 % & whereas in Neuro-memetic approach (we observe detection rate up to 92-97%.

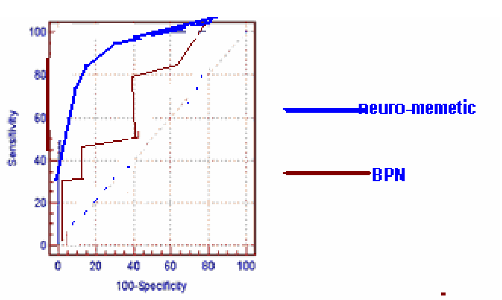

Fig. 5 Comparison of Back Propagation and Neuro-Memetic in Recognizing Numerals

A. Test Parameters

The performance of BP neural network and the Neuro-memetic the proposed scheme for handwritten Hindi numerals was compared. The performance assessment of these algorithms are based on completion time and CPU utilization time captivating into account the number of iterations and number of generation. .

1) Changing Number of Iterations

The number of iterations were varied from 35-200 to achieve the optimal probability and the consequence of these on total completion time and CPU Utilization time.BP neural network takes more completion time as number of iteration increase compared to Neuro-memetic.BP neural network takes less CPU utilization as number of iteration increase compared to Neuro-memetic

2) Changing Momentum Constant

The numbers of momentum were varied from 0.1-0.65 to achieve the optimal probability and the effects of these on average recognition rate are given below. Average Recognition rate depends on the momentum. A graph depicts average recognition rate increases proportionately with respect of number of momentum. Average Recognition rate is less in BP neural network compared to Neuro-memetic as the momentum constant varied linearly.

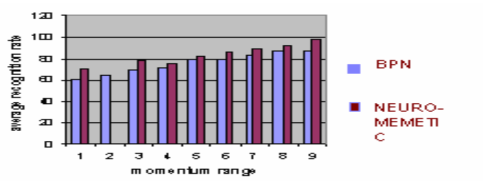

Fig. 6 Momentum range v/s recognition rate

3) Changing the Probability of Cross Over in Neuro-Memetic Approach

In this work, the probability of crossover is 0.6 and the probability of mutation is 0.2. These probabilities are chosen by trial and error through experiments for good performance. The probability of cross over were varied from 0.1-0.6 to achieve the optimal probability and the effect of these on average recognition rate are given below. Average Recognition rate depends on the probability of crossover in neuro-memetic approach. A graph depicts average recognition rate increases proportionately with respect probability of crossover.

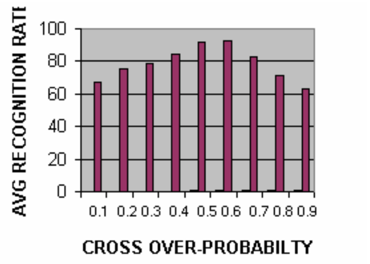

Fig. 7 Crossover probability v/s recognition rate

IV. Conclusion

In this paper, prediction system has been implemented in order to detect handwritten numerals. A Recognition system is constructed using BP neural network and Neuro-memetic ensemble networks, and tested their performance on a set of raw data collected by author data. The simulation results seem quite promising and outperforming than the Back Propagation neural network technique in the benchmark test. Classification is done by a Neuro-memetic at the rate of about 200 digits per seconds where as the BP neural network at rate of 200 digits per 2.5 seconds. From this we are concluding that the model which we are proposed i.e neuro-memetic model with Global Based Technique Using End-Points Information as a feature extraction.

- Simple in theory
- Recognition rate 92-97 %
- Easy for implementation
- Computationally less expensive
- Efficiency comparable to other models
- Effect of presence of noise, performance is better

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