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Handwritten Numeral Pattern Recognition Using Neural Network

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***Abstract*– Unconstrained handwritten numeral recognition has been a recent research area from last few decades. Handwritten numeral recognition approach is used in many fields like bank checks, car plates, ZIP code recognition, mail sorting, reading of commercial forms etc. This paper presents a technique to recognize handwritten numerals, taken from different pupils of different ages including male, female, right and left handed persons. 340 numerals were collected from 34 people for sample creation. Conjugate gradient descent back-propagation algorithm (CGD-BP) is used for training purpose. CGD-BP differs from primary back-propagation algorithm in the sense that conjugate algorithms perform line search along different directions which produce faster convergence than primary back-propagation. Percentage Recognition Accuracy (PRA) and Mean Square Error (MSE) have been taken to estimate the efficiency of neural network to recognize the numerals.**

***Index Terms*– Numeral Recognition, Conjugate Gradient Descent Back-Propagation Algorithm (CGD-BP), PRA and MSE**

I. INTRODUCTION

RECOGNIZING the objects and the surrounding environment is a trivial task for human beings. But if the point of implementing it artificially came, then it becomes a very complex task. Pattern Recognition provides the solution to various problems from speech recognition, face recognition to classification of handwritten characters and medical diagnosis [1]. Handwritten Character Recognition involves recognition of handwritten numerals alphabets, symbol etc. This phenomenon is used for the processing of many practical applications such as ZIP code recognition [2], mail sorting, reading of commercial forms, automatic reading of bank checks [3], and recognition of numbers on car plates [4].In last few years, lots of work has been done by the researchers in the field of handwritten character recognition leading to formulation of efficient least time consuming classifiers [5, 6]. Most of the times, we easily recognize characters despite the presence of inherent variability in size, slant and styles. But when it comes to implement an unconstrained handwritten character recognition system artificially it is not that much easy. By unconstrained we mean that there are inherent variations in style, thickness and size of the written character. No size, style and slant boundations are imposed on characters. Several approaches had been proposed in the past for feature extraction [7]. These approaches can be classified as: Global Analysis and Structural Analysis and moment based features. Global analysis comprises techniques which extract features from every point which lies within a frame surrounding the character. Techniques such as template matching, measurements of density of points, characteristic loci and mathematical transforms like Fourier, Walsh, Hadamard comes under global analysis. Global features are characterized by their low sensitivity to noise. In structural analysis essential shape features of characters from their skeletons or contours are captured to extract features. These include strokes, endpoints, loops, arcs, junctions, concavities and convexities. Legendre or Zernike moments are moment based features which form a compact representation of the original features that makes the process of recognition independent of scale, transformation and rotation.

Yangie Wang et al. [8] worked on handwritten numeral string segmentation. A distribution of Gaussian mixture model (GMM) is taken as the feature vector. Corresponding posterior pseudo-probability measure function separates correctly segmented numerals from incorrectly segmented numerals. Foremost criterion of segmentation is contour and profile analysis. Experiments of segmentation of off-line handwritten strings are conducted on NIST SD19 database, in the length-free test where the number of digits in the string is not present, 97.45% and 94.6% correct rates of segmentation were achieved for 2-digit and 3-digit strings, respectively. The corresponding results were 97.95% and 95.4% in length – fixed test where number of digits in strings are preset.

El-Sayed M, El-Alfy [9] designed a hierarchical classifier to improve recognition of handwritten numerals. Each numeral is described by a feature vector consisting of 16 non-Gaussian topological features. The optimal threshold is determined based on the balance between specificity and sensitivity for each classifier using ROC analysis. Then hierarchical model is tested for 1500 instances in the dataset. The overall classification accuracy has been improved to 91.8%.

Amit choudhary et al. [10] proposed an approach for recognition of hand numeral digits in which performance analysis of network models using different activation functions at hidden layer and output layer had been observed. An optimum performance of recognition accuracy 99.1%, with

MSE 0.000216485 is achieved utilizing 'tansig'-'tansig' combination at hidden layer and output layer.

J.Pradeep et al. [11] proposed a three layer classifier. The hidden layers use log sigmoid activation function and output layer is a competitive layer as one of the characters is required to be identified. Seven different neural network architectures were chosen by varying number of hidden layers and number of hidden layer neurons, and each was trained with 50 data sets for a target MSE of 10e-8. The neural network having two hidden layers each with 100 neurons is found to yield the highest recognition accuracy of 90.19%.

In this paper the proposed technique recognizes isolated numerals using Multilayer Perceptron (MLP) network having single hidden layer .This MLP network is trained by conjugate gradient descent back-propagation algorithm (CGD-BP).The performance of the system is quantified on the basis of PRA and MSE.

Rest of the paper is organized as: Section II describes various sub-blocks of recognition system and training algorithm. Discussion of results and conclusion is made in section III.

II. System Design

A hand-numeral recognition system is composed of various system subcomponents, which include image preprocessing sub-block, training system and post-processing the output, which simplifies classification results (Fig. 1).

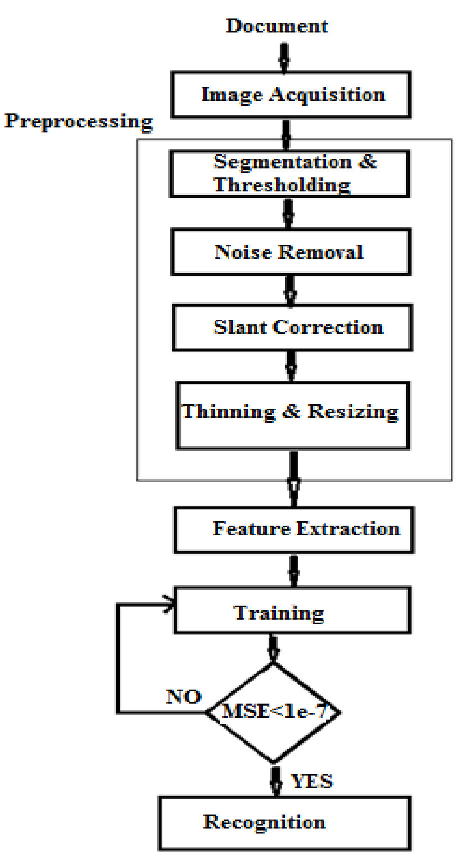

Fig. 1: Handwritten Numeral Recognition System

A. Image Acquisition

Digital format of sample can be acquired either through scanning or using a digital camera. Samples collected from 34 people were scanned using laser printer. In this way digital file of acquired samples is obtained as given below in Fig. 2.

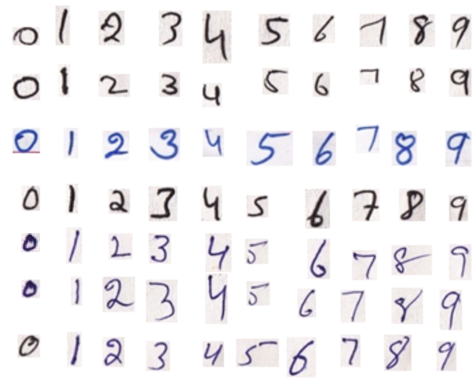

Fig. 2: Samples from different people

B. Image Preprocessing

The aim of preprocessing as shown in Fig. 3 is to remove the variability among numerals due to difference in size, slant and style. Preprocessing operations are based on mathematical morphological techniques. Preprocessing techniques used in the system are:

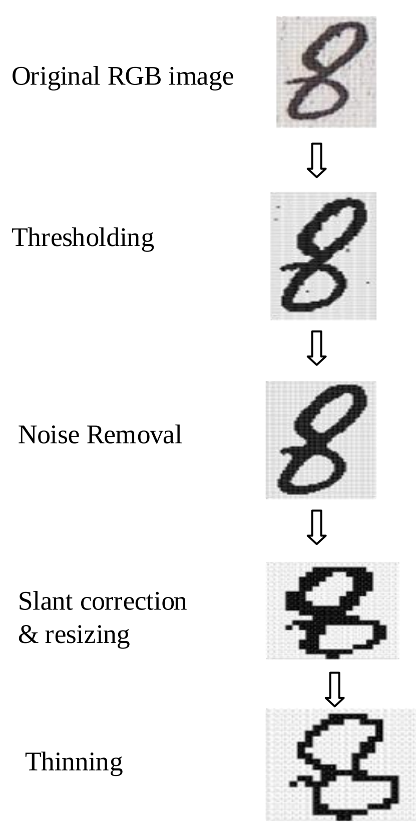

Fig. 3: Image preprocessing Steps

Segmentation

Segmentation operation is performed to isolate the desired characters. There are various types of segmentation methods present in image processing like threshold techniques, edge-based methods, region based techniques, and connectivity preserving relaxation methods [12]. Here the edge detection based segmentation is used due to isolated nature of sample digits.

Thresholding

Thresholding is applied to the patterns to separate the patterns from their backgrounds. Segmented numerals are in RGB format. For feature extraction these are converted into binary format using 0.7 threshold.

Noise Removal

Scanning devices and transmission media may introduce noise in the off-line handwritten character recognition system. Various gray scale transformation methods like mean filter, median filter, adaptive mean filter can be utilized to remove noise [13]. In our proposed system noise has been removed using mean filter.

Slant Correction

As slants can be different as samples are taken from different people; slant correction is done by rotating the image through various angles in clockwise or counter-clockwise direction depending upon the alignment of numeral.

Resizing

Image is resized to 20 by 20 pixels using nearest neighbor interpolation method [14]. There are various other methods for resizing like bipolar interpolation and bi-cubic interpolation. But in the case of numerals, nearest neighbor interpolation gives best results.

Thinning

Thinning operation is performed to remove the meaningless line width variations. This reduces storage size, transmission time and complexity of handwritten numeral recognition system [15].

C. Feature Extraction

For training purpose a set of features are taken. These can be a set of pixel arrangement or some structural features like number of loops, curves, area occupied in different directions [5].

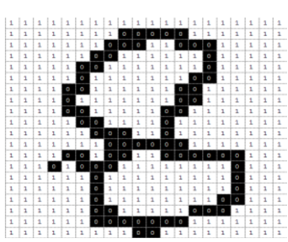

Fig. 4: Pixel arrangement of digit '8'

In proposed system we have taken pixel arrangement of digits as input vector to differentiate different digits, as different digits have different pixel arrangements. Processed digital image of a numeral is a 20 by 20 arrangement of pixel as shown in Fig. 4. This 20 by 20 Matrix is converted into a column vector, and this column vector is fed to the input neurons.

D. Classification/Training

After performing all preprocessing operations all 340 binary formats are joined together to form training data set.204 samples are used for training purpose, 68 samples are used for validation purposes and 68 samples are used for testing purpose.

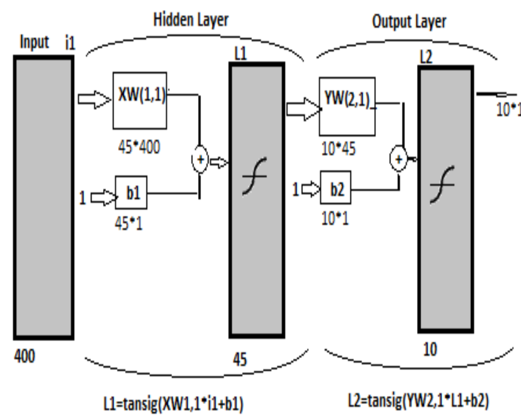

Fig. 5: Neural Network System

Training samples are presented to the neural network during training as shown in Fig. 5, and networks parameters are adjusted towards minimizing the MSE. Validation samples are used to measure network generalization. Network stops learning when generalization stops improving. Testing samples provide an independent measure of network performance during and after training. A feed forward network is used for training in which activation travels from input layer to output layer [16]. Input layer has 400 neurons corresponding to 400 pixel values representing each digit. Output layer has 10 neurons representing 10 numeral classes 0, 1….9.hidden layer has 45 neurons. Network is trained with back-propagation algorithm. Data set was presented to the proposed system repeatedly until target error rate is achieved. 'tansig' activation function [17] is used in hidden layer and output layer.

$$\text{Tansig}(x) = \frac{2}{1+e^{-x}} - 1$$

Output of the network is presented on a "COMPET" transfer function. COMPET is a competitive transfer function which puts '1' for the output neuron which has maximum weight age. The difference between actual output and desired output is calculated for each iteration and network weights are adjusted until network achieves optimum performance.

Training Algorithm

A multilayer perceptron (MLP) network with one hidden layer trained with conjugate gradient descent back-propagation algorithm (CGD-BP) is used for training purpose. Processing nodes of the input layer neurons used linear activation function, hidden layer and output layer neurons used hyperbolic tangent transfer activation function. Back-propagation algorithm performs in two directions. In forward direction; inputs from input layer are presented on output layer through hidden layer to provide outputs. Error is calculated and propagated back from output layer to input layer, then adjustment of weights is done [18]. Back-propagation algorithm works in following manner [17].

1. Initialize weights to zero.
2. While e>=1e-7 iterate steps 3-9.
3. Assign a pattern of bits a 200 by 10 vector to the input layer
4. For hidden layer's processing unit output:

$$Y_i = f\left(\sum_{j=1}^{n} X_j W_{ij}\right)$$

Where X_j: Output of input layer

W_{ij}: Weight between input and hidden layer

5. Output f the network can be determined as:

$$Z_k = f\left(\sum_{i=1}^{n} Y_i W_{ik}\right)$$

Where Y_i: Output of hidden layer

W_{ik}: Weight between hidden and output layer.

6. For each output unit calculate its error as;

$$E = 0.5\sum_k [t_k - z_k]^2$$

Where t_k: desired output

7. The error minimization can be shown as:

$$E/\ \ W_{ik} = [t_k - z_k]\dot{f}\ (z_k) Y_i$$

8. Weights are modified as

$$\Delta V_{ij} = \sum_k \ \ k * W_{ik}\dot{f}\ \ (Y_i)$$

9. In this way updated weights for output units can be defined as:

$W_{ik}(n+1) = W_{ik}(n) + \eta\ \Delta W_{ik}(n) + \alpha\ \Delta W_{ik}(n-1)$

Where $W_{ik}(n)$: state of weight matrix at iteration n

$W_{ik}(n-1)$: state of weight matrix at previous iteration

$W_{ik}(n+1)$: state of weight matrix at next iteration

$\Delta W_{ik}(n)$: modification in weight matrix

α :Momentum constant

η: Learning Rate

III. Results And Conclusion

We presented a hand-numeral recognition system trained using conjugate descent back-propagation algorithm. Different image preprocessing operations like thresholding, noise removal, and slant correction, resizing and thinning are applied on numeral patterns before presenting them to training network. After preprocessing operations feature extraction is done, by converting image into bit patterns. We presented our data set repeatedly to the network until we achieved the desired efficiency level, and it has been observed that as we repeatedly presented data set to the network, network performance increases. An optimum selection of number of neurons in hidden layer guarantees a good performance. Excessive number of hidden layer neurons leads to overtraining, and an optimum amount helps in better generalization capability of neural network. Fig. 6 shows the training window.

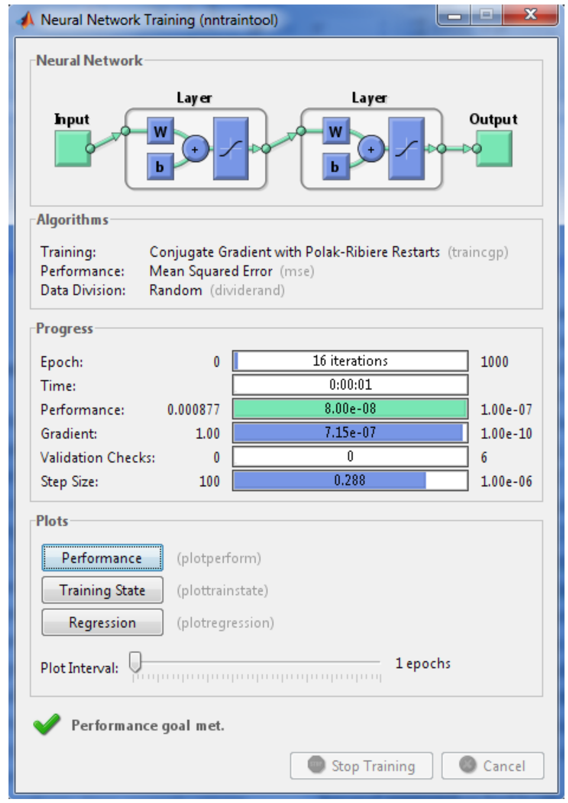

Fig. 6: Training Window

In Table 3.1 network parameters adjusted for the training purpose have been shown. Fig. 7 is a plot between performance parameter MSE and its improvement with increased iterations. Different curves show recognition behavior of training, testing and validation data sets. 99.4% recognition accuracy with mean square error of 8.00e-08is achieved as shown in Table 3.2.

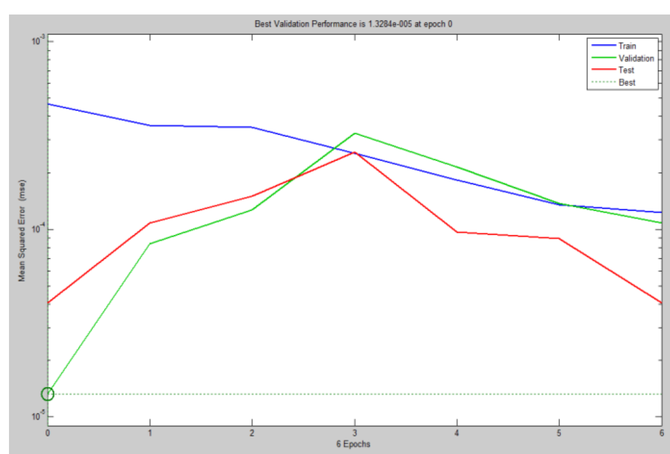

Fig. 7: Performance Plot of Training Network

Table 3.1: Network Parameters

Parameters	Value
Input Layer	
Input Vector	400
Hidden layer	
No. of hidden layer neurons	45
Activation Function	'tansig'
Learning Rule	Gradient Descent with Momentum
Training Function	Conjugate Gradient Descent
Output Layer	
Output vector	10
Activation Function	'Tansig'
Performance function	MSE
Learning Rate	0.05
Momentum Constant	0.9

Table 3.2: Network Performance

Parameter	Value
Recognition Accuracy	99.4%
MSE	8.00e-8

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