OFFLINE HANDWRITING RECOGNITION USING GENETIC ALGORITHM

Shashank Mathur, Vaibhav Aggarwal, Himanshu Joshi, Anil Ahlawat

Abstract: In this paper, a new method for offline handwriting recognition is presented. A robust algorithm for handwriting segmentation has been described here with the help of which individual characters can be segmented from a word selected from a paragraph of handwritten text image which is given as input to the module. Then each of the segmented characters are converted into column vectors of 625 values that are later fed into the advanced neural network setup that has been designed in the form of text files. The networks has been designed with quadruple layered neural network with 625 input and 26 output neurons each corresponding to a character from a-z, the outputs of all the four networks is fed into the genetic algorithm which has been developed using the concepts of correlation, with the help of this the overall network is optimized with the help of genetic algorithm thus providing us with recognized outputs with great efficiency of 71%.

Keywords: Handwriting Recognition, Segementation, Artificial Neural Networks, Genetic Algorithm.

ACM Classification Keywords: I.2 Artificial Intelligence, I.4 Image processing and Computer Vision, I.5 Pattern Recognition.

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Introduction

Over the years, computerization has taken over large number of operations that had been taken care of manually, one such example is of offline cursive handwriting recognition, which is the ability of a computer to receive and interpret intelligible handwriting input present in the form of scanned images [I]. The various methods for character recognition have already been published[II] but the method presented here is advanced than those methods since cursive handwriting can be recognized with the help of a combination of artificial neural networks and genetic algorithm, this becomes the primary advantage of the method over other existing methods. The methodology here has been developed with four multilayer artificial neural networks with Levenberg-Marquardt back propagation algorithm along with genetic algorithm unlike few published methods that use a multilayer feed-forward neural network[III] thus providing an efficient output as compared to the previously published works.

The recent spurt in the advancement in handwriting recognition has provided publications one of which discussed here is recognition of text written in ‘Oriya’, a traditional south-eastern Indian language [IV] but do not involve any combinations of artificial neural networks and optimization techniques such as genetic algorithms which lead to lower efficiency in recognition as compared to the ones that our approach here presents. Several areas have seen application of neural networks such as the Processing of Verbs and Nouns [V], Face Detection [VI] and Real-time Face Detection [VII]. The application of genetic algorithms in various areas like initial population generation methods [VIII], mooring pattern optimization [IX], substitution ciphers [X] and designing of reverse logistic networks [XI] has proved its advancement over its predecessors. The handwriting recognition model described here works at three stages, segmentation of the handwritten text, recognition of segmented characters with the help of artificial neural networks and lastly selecting the best solution from the four artificial neural network outputs with the help of genetic algorithm.

The cursive handwriting recognition is carried out with the help of artificial neural networks, which is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach to computation and which has the capability of being adaptive and thus can change its structure based on the information provided to it. The artificial neural networks made in this case contain 625 input neurons, 3 hidden layers and 26 output neurons. The recognition model involves the usage of artificial neural networks which form the basis of recognition after the network has been exhaustively trained to recognize different types of handwritings. This is achieved by training the four artificial neural networks using a highly efficient supervised learning algorithm, Levenberg-Marquardt back propagation algorithm [XII,XIII] unlike other published methods like fast learning method for neural networks based on sensitivity analysis [XIV].

In general, a single neural network is used for recognition purposes.

The method described does not have any limitations on the type of font or text that is being taken in as input [XV], any handwritten information can be converted into editable textual information. Plethora of the character recognition methods have been published previously [XVI] but they do not incorporate advanced optimization techniques such as the ones provided by the genetic algorithms which have provided high efficiency in the method described here. Only a few handwritten character recognition papers for applications like form registration [XVII] have been published till date with optimization with the help of genetic algorithms but we advance by application of both artificial neural networks and genetic algorithm to cursive handwriting.

The purpose of this paper is to present a new methodology for cursive handwriting recognition using artificial neural networks and genetic algorithm. Handwriting segmentation is carried out with the help of a novel algorithm which is capable of extracting handwriting words from the handwritten text given as input in the form of an image and carries out segmentation of the selected word to generate vectors for individual characters of a word. These vectors are given as an input to four neural networks. The four neural networks generate four sets of final outputs, each out of which the genetic algorithm chooses the fittest set of values to provide the user with a highly efficient handwriting recognition model. The usage of Levenberg-Marquardt algorithm along with genetic algorithm assures highly efficient results.

Handwriting Segmentation Algorithm

The handwritten document is scanned and taken as an input to obtain individual characters which are written in a text file and are later read back and are passed as inputs to the four Artificial Neural Networks. In the algorithm, the scanned gray scale image is read into an image matrix which is converted into a monochromatic image matrix which pixel values of 0 for black points and 255 for white points. Then row wise searching is started from the point (0,0) to find out the first black point. This is the assumed top point of the first word of the handwritten text that has been inputted. This point is referred to the “Upper Point”. After the upper point is found, all the black pixels that are connected to this pixel are given a value of 999.

a. b. c.

Fig.1(a-c). Different stages of handwriting segmentation.

Once this step is complete, then all the characters linked to that word have a value of 999 in the matrix under consideration. After finding all the connected points, a row wise search starts from the bottom to the top to find the first 999 value. This value corresponds to the “Lowest Point”. After this point is obtained, the area between the top and bottom point is searched on the left to check if any word has been missed on the left. In case another word is present on the left, then the new top point is obtained and the bottom point is found again else the procedure continues. After this is carried out, the left and right points of the word are found out by column wise searches. After the four points, the Upper, Lower, Right and Left point are found out, the word can be extracted and stored in a different matrix. This step is followed by marking of intersection points between various characters in the cursive handwriting. The word is searched for the number of cuts in a column wise manner. All the cases in which number of cuts is one and has an edge on either left or its right are marked and then all the successive markings are averaged to provide one optimum point through which a cut is marked with gray value of 0.5. After all the cuts are marked, in a loop all the characters are written into a file which is later read by the neural network to recognize the character.

Architecture of Artificial Neural Network used

The four artificial neural networks used consist of an input layer, three hidden layers and an output layer for each of the individual networks. The input layers takes the input from the image segmentation algorithm thus has 625 input neurons. The number of hidden layer neurons is as shown in the Table 1. The output layer consists of 26 neurons; this is due to the fact that there are 26 characters to be identified. Thus each output neuron corresponds to every character. Four artificial neural networks have been employed for the character recognition. The properties of each of the four artificial neural networks are designed using different parameters as shown in Table 1. The outputs of these four artificial neural networks are fed into the genetic algorithm with chooses the fittest and the best solution and provides us with the recognized alphabet. Thus providing us with an overall high efficiency for the offline handwriting recognition using artificial neural networks and genetic algorithm.

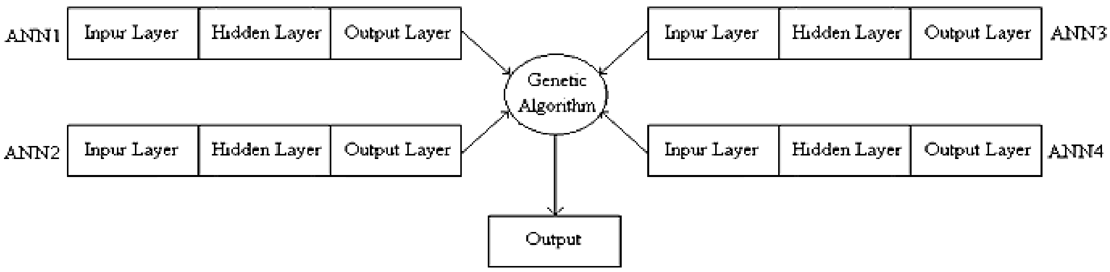

Fig.2. Architecture of neural networks used.

Table 1. List of parameters used for the four artificial neural networks.

Name of Parameter		Artificial Neural Network 1	Artificial Neural Network 2	Artificial Neural Network 3	Artificial Neural Network 4
Number of neurons	Input Layer	625	625	625	625
	Hidden Layer1	8	8	6	8
	Hidden Layer2	16	14	16	12
	Hidden Layer3	8	8	6	8
	Output Layer	26	26	26	26
Training function(Algorithm)		trainlm (Levenberg-Marquardt algorithm)			
Number of Epochs		5000	4000	3000	2500
Performance Function		Mse (Mean square error)		Sse (Sum squared error)	
Training Goal		0.01	0.05		0.012
Memory Reduction Parameter		50			
Transfer Function		Purelin (Pure Linear)			

Segmented handwritten character recognition method

A column vector is generated by the Image Segmentation consisting of 625 elements, which is saved in a ".txt" file. This ".txt" file is read and the elements are fed as an input to each of the four neural networks. These neural networks read all the weights and biases values that were saved in another files during the training process. Corresponding to the input, output is generated at the output layer. A "1" is set at the index of the characters that has been recognized. There can be more than one character that could be recognized based on the noise in the input of the neural network.

Methodology used for segemented handwriting recognition

The following method is applied for handwriting recognition:

1. Provide initial inputs of sample handwritten letters to train the four artificial neural networks with different parameters (Table 1.).
2. Start the process of training the networks with different sets of letters.
3. Store the weight matrices and bias values obtained after training as files.
4. Read the file containing the input matrix.
5. Feed this as the input to all the four neural networks.
6. Send the outputs of the neural networks to the Genetic Algorithm.

As we have developed four artificial neural networks we need to select the best and fittest solution from the set of outputs obtained. This is carried out with the help of Genetic Algorithm which is applied such that it accepts the outputs of the four artificial neural networks. There are cases when the neural networks recognize more than one character. For that case we have created four neural networks, which have different training parameters and also trained differently from each other. We pass the input column matrix in all the four neural networks and get the output. The outputs are sent to the Genetic Algorithm and hence making the initial population for the Algorithm. We then calculate the number of "1's" at the output for each neural network.

The one with the minimum number of "1's" is selected. The characters corresponding to the index of those ones are shortlisted. These shortlisted indexes are sent to the fitness function where the correlation coefficients of the indexes are calculated. We specify the threshold value. Below this value of the correlation coefficients the indexes are discarded. The correlation coefficients above this value are selected and this forms the new generation of the indexes. The steps are repeated again and again for different training sets. These results are taken and the character which has the maximum correlation with the input set is selected and shown as the output. With the combination of four artificial neural networks and their optimization using genetic algorithm, the efficiency of the offline handwriting recognition model increases to a great extent delivering accurate results of recognition.

The following method is applied for applying genetic algorithm to the outputs of the four artificial neural networks:

1. Initialization: Select the output of the neural network with the indexes comprising of "1's". This corresponds to the initial population for the Genetic Algorithm.
2. Selection: Select the indexes from the neural network that has minimum number of "1's".
3. Fitness function: Compute the correlation coefficients of the selected indexes.
4. Mutation & Crossover: For the correlation coefficients less than the threshold value 0.50 repeat the step of the fitness function for a different training set. Discard the indexes that have coefficient values less than 0.3.
5. Evaluation: Select the index which has the maximum correlation coefficient with the input matrix.
6. Output the selected character.

Results and Discussions

In order to check the accuracy of the individual modules of the approach discussed here, handwriting samples were collected from various people and segmentation was carried out after which the four neural networks were trained and various characters were subjected to the neural networks and genetic algorithm to see how well the recognition process is carried out for the various different handwritten scanned input characters.

The testing phase was to check the efficiency of recognition and the recognition rates of the individual four neural networks. Once the network weights and biases are initialized, the network is ready for training. The network can be trained for function approximation (nonlinear regression), pattern association, or pattern classification. The training process requires a set of examples of proper network behavior — network inputs p and target outputs t.

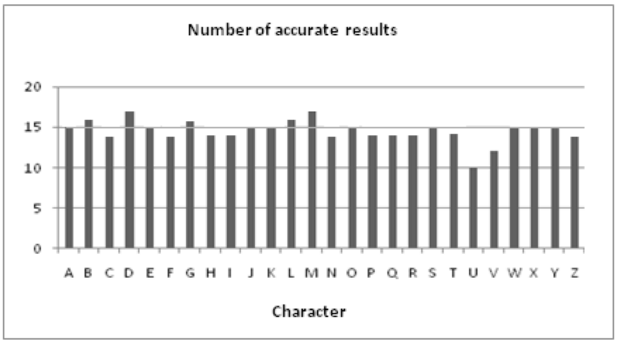

Fig.4. handwriting segmentation testing.

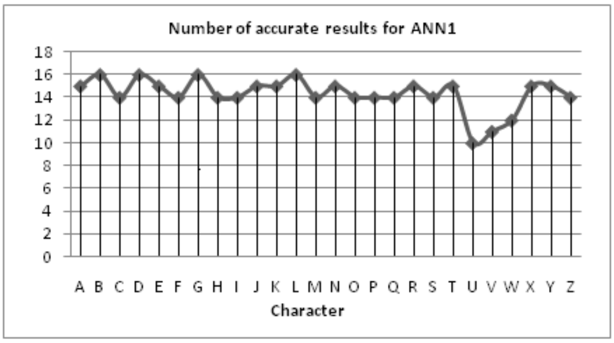

Fig.5. Graph obtained for testing of artificial neural network 1.

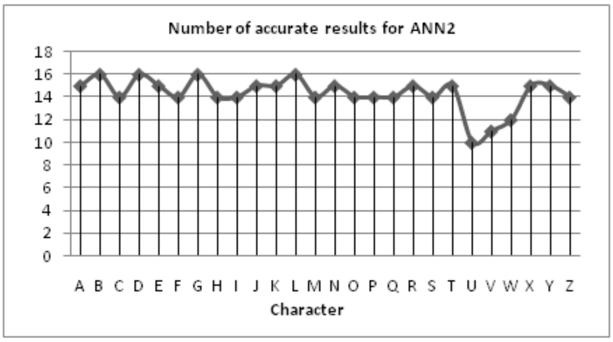

Fig.6. Graph obtained for testing of artificial neural network 2.

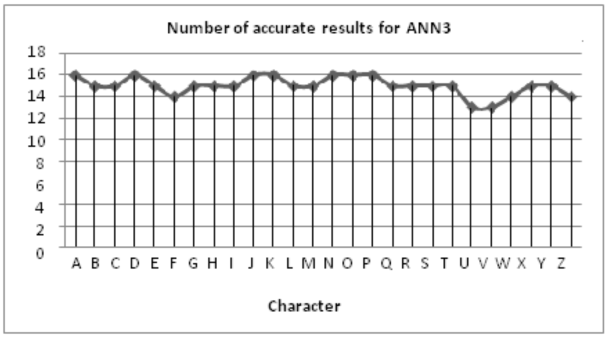

Fig.7. Graph obtained for testing of artificial neural network 3.

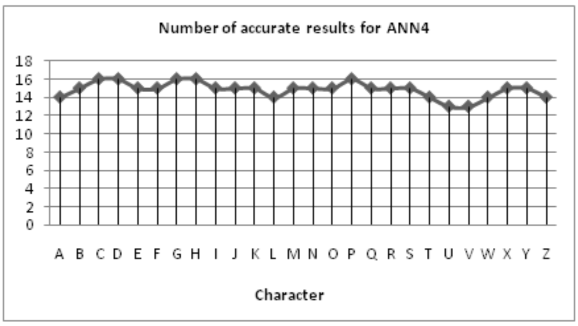

Fig.8. Graph obtained for testing of artificial neural network 4.

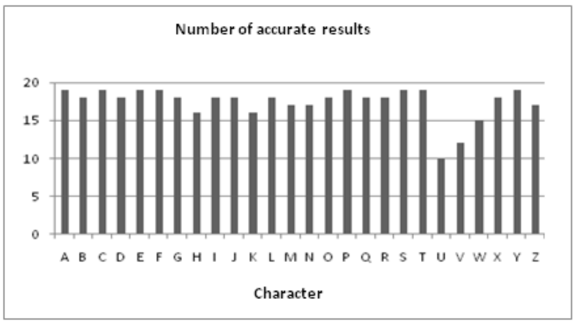

Fig.9. Artificial neural network and genetic algorithm testing.

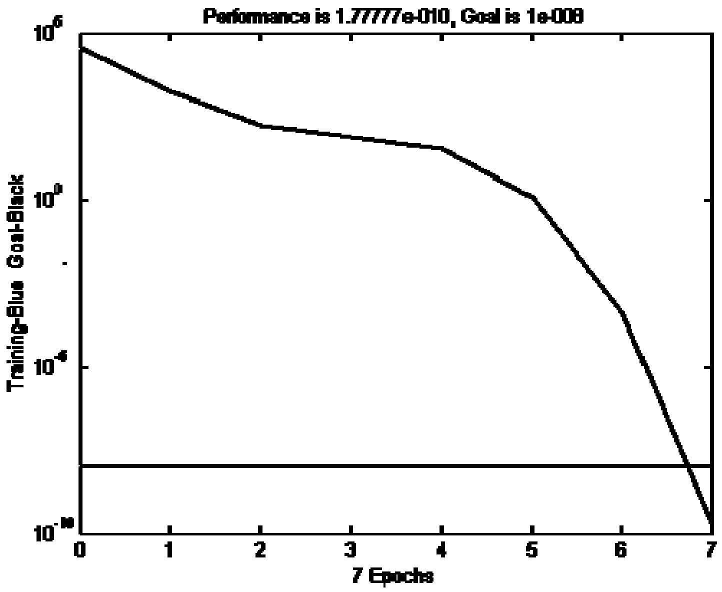

Fig. 10. Error graph

During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. The gradient is determined using a technique called back propagation, which involves performing computations backward through the network. When the networks are trained the weights and the biases of each neural networks are saved into ".txt" files. The following error graph was obtained after training the neural network with trainlm. The algorithms have been specially designed for handwriting recognition using the various mathematical logics for image segmentation and neural networks for recognition.

The three above mentioned algorithms for handwriting segmentation, neural networks and optimization using genetic algorithms were programmed and trained with the help of 260 handwritten character samples, 10 samples per letter on a Pentium 4 (3.4 GHz), 2GB RAM and MATLAB 7.0 and tested individually and then the integration of the three algorithms after exhaustive testing has provided us with a highly efficient handwriting recognition with the help of which a human handwritten text can be converted into a textual format on a computer thus providing the user flexibility to edit the text. The algorithms were tested with 200 handwritten samples out of which 142 samples were correctly recognized providing us with an overall efficiency of 71.0%.

Conclusion

The paper has presented a new method of handwriting recognition using a unique and robust combination of artificial neural networks and genetic algorithms. On programming and testing the modules a very high efficiency has been noted. The handwriting recognition is indeed a tough task which can be easily done with the help of the methodology described here. A high efficiency reflects the accuracy of segmentation as well as the recognition using the neural network that has been optimized by genetic algorithms. The concept here has abridged handwriting recognition completely with artificial intelligence after the application of both artificial neural networks and genetic algorithms.

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