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Simulating Biological Neural Network Structure in Computers with help of MATLAB for Handwriting Recognition Tasks

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Abstract : This report presented here describes the basic human neural structure and its artificial competent. The human neurological structure is analyzed in detail to get the techniques of its learning and determination of results. The processing of this structure is tried to simulate using a feed-forward artificial neural network in which the error term is propagated to back -layer for corrections. This artificial neural network is designed and trained for recognition of 500 handwritten letters. The co-relation between the artificial neural network and biological natural neural network is also investigated and explained.

Key words : Biological and Artificial Neural Network, Character Recognition, Feed forward Neural Network, Segmentation, Back propagation.

Introduction :

Human has always been very keen to know about the processing mechanisms of brain. How does brain trains itself has always been very fascinating. Making a competent of the brain is greatest challenge in-front of computer-scientists. The modern computer easily out-performs the human in pre-programmable, repetitive computations. However, real-time speech understanding and visual perception, which a human being implements effortlessly, are still beyond the reach of serial digital computers even the speed of these computers is increased by several magnitude. Good amount of research is being done in this area to make use of computers for automatic processing of text and speech. Handwritten text recognition attains big area in this field as there is significant demand of automated processing of different application forms, bank checks, postal envelopes, medical prescriptions etc in current industry. If achieved, this may save human processing time and leads to accuracy. This way the throughput is increased thousands of times in terms of more data is processed in less time as compared to human processing.

Artificial neural networks try to solve the problems by mimicking the deep thought mechanisms of human beings. In the human brain, there are billions of neuron cells in the human cortex working together to accomplish highly complicated mental activities. However, for individual neuron cells, the function mechanism is quite simple. Similarly, a complex structure of simple functioning bodies called Artificial Neurons has been tried to build as a simulation of Brain. This ANN (Artificial Neural Network) is made to learn English characters and then asked to recognize other samples.

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Brain - A Biological Neural Network :

The reason why brain is superior to even most sophisticated AI computer system for pattern recognition is because of the following features of brain :

(1) Flexibility : Without any pre made instructions the network adjusts itself to a new environment.

(2) Fault Tolerant and Robust : Any harm to nerve cells does not affect the performance of the brain significantly.

(3) Can handle a variety of data situations without extra effort.

(4) Continuous Learning : The network can learn in an infinite loop.

The Structure of Biological Neural Network : The fundamental unit of the network is called a neuron or nerve cell. Figure 2.1 shows a schematic of the structure of the neuron. The main body of cell is called "soma" where nucleus is located. It has tree like fine fibers attached called dendrites. These dendrites receive signals from other neurons. 'Axon' is the single long fiber which extends from soma, which branches into strands and sub-strands connecting to many other neurons at the synaptic junction.

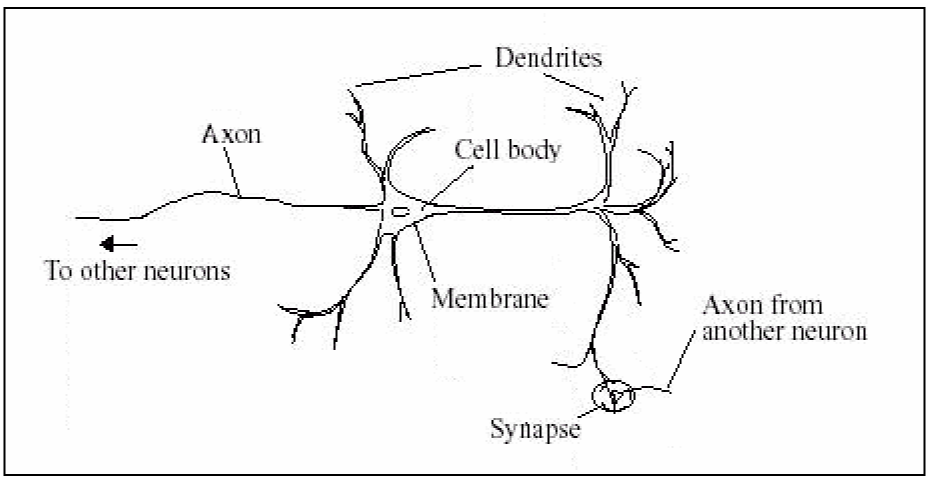

Figure 1 : Biological Neuron and its different components. Also depicts the connection between two Neurons.

Each neuron accepts stimuli from other neighbor neurons and produces output as soon as overall effect of the input stimulus exceeds the threshold limit that a neuron can bear. The connection and connection strength among neurons reflect the knowledge pattern of human beings. A neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use; it resembles the brain in two respects:

- Knowledge is acquired by the network through a learning process.
- Interneuron connection strengths known as synaptic weights are used to store the knowledge.

Building Blocks of Artificial Neural Network : The artificial neural network (ANN) can be considered as highly simplified model of biological neural network. The behavior of a neuron can be captured by a simple model as shown in Figure 2.2 below. Every component of the model bears a direct analogy to the actual constituents of a biological neuron that's why termed as artificial neuron.

Processing Unit : The processing unit of an artificial neuron is the summation unit. This receives inputs (x1,x2,….,xn) through dendrites on synapse from other neurons it is connected to, weights them and computes a weighted sum. These weights are multiplicative factors of the inputs to account for the strength of the synapse.

Synaptic Link Weights : The amount of the output of one unit received by another unit depends on the strength of the connection between the units, and it is reflected in the weight value associated with the connection link.

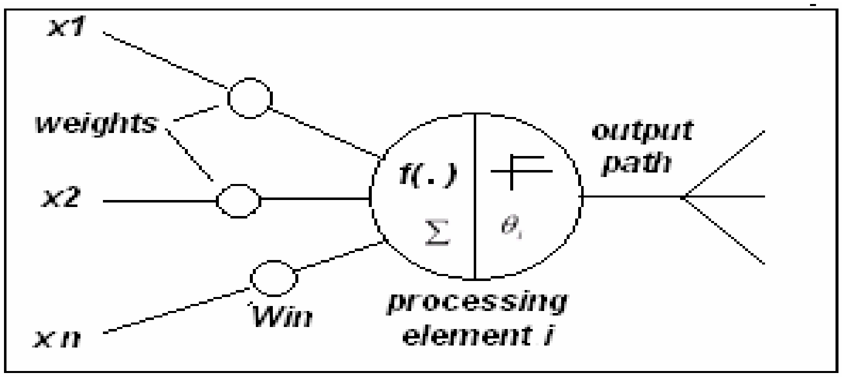

Figure 2: The architecture of Artificial Neuron. The functions used depicted by mathematical symbols and the input weights are adjustable according to the particular need.

Threshold : Every Artificial Neuron has a threshold value associated with it. If the total amount of weighted input is greater than threshold then the neuron will output 1 else 0.

The total input *I* received by the soma (Summation/Processing Unit) of the artificial neuron is :

$$I = w_1 x_1 + w_2 x_2 + ... + w_n x_n$$

$$I = \sum_{i=1}^{n} (w_i x_i) ....(2.2.1)$$

To generate the final output y, the sum is compared with threshold. Hence y is :

$$y_k = f(\sum_{i=1}^{n} Z_i W_{ik}) ....(2.2.3)$$

Update : The ANN is in layered structure of neurons. Output of each neuron layer is passed as input to next layer. The network is trained by correcting the error in network output. This error is propagated back in to the first layer and the weights are updated correspondingly.

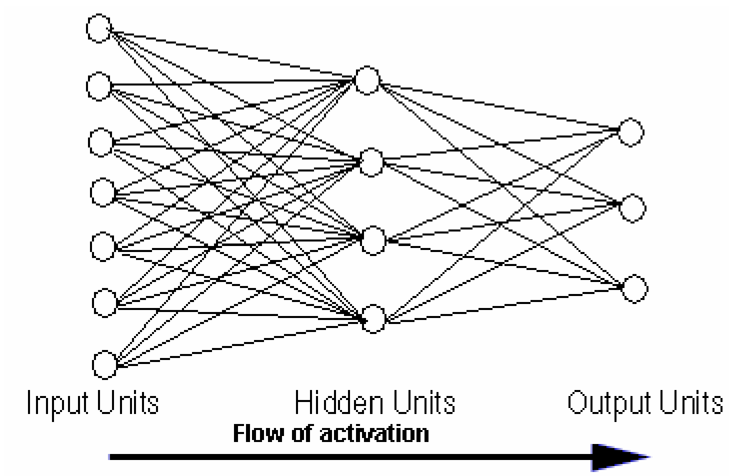

Figure 3 : Architecture of Artificial Feed Forward Neural Network. First layer is made up of input units and second layer is of Hidden Units. The final layer consists of 26 output neuron units.

Handwriting Recognition using ANN :

The domain of hand written text recognition has two completely different problems: Online text recognition [3] and Offline text recognition [4, 5]. Online recognition is the interpretation of human handwriting "Real-Time", when it is created using media like - light pen, digital writers, touch panel etc. The applications of online handwriting recognition are very much evident in day-today life as PDA, digital writers and tablet-PCs are very commonly used.

On the contrary offline recognition is the reading of handwritten text in the form of binary/gray scale image [1, 2]. The documents which are written sometime back are considered as offline data for handwriting recognition. In this big domain of handwriting recognition both online case (which pertains to the availability of trajectory data during writing) and the offline case (which pertains to scanned image) are considered. A wide variety of research has been done in offline hand written text segmentation and recognition using neural networks.

Here in this paper we propose a system that works on segmented words into characters. These English letters are first changed into binary format as shown below:

Overall System Design and Experiments : The complete functioning of the system can be best explained by following block diagram :

The system is simulated using a feed forward neural network system consist of 150 neurons in input layer , 10 neurons in hidden layer and 26 output neurons. The network has 150 input neurons that are equivalent to the input character's size as we have resized every character into a binary matrix of size 15 X 10. The 26 output neurons correspond to 26 letters of English alphabet. The 600 samples are gathered form 10 subjects of different ages including male and female for the input patterns.

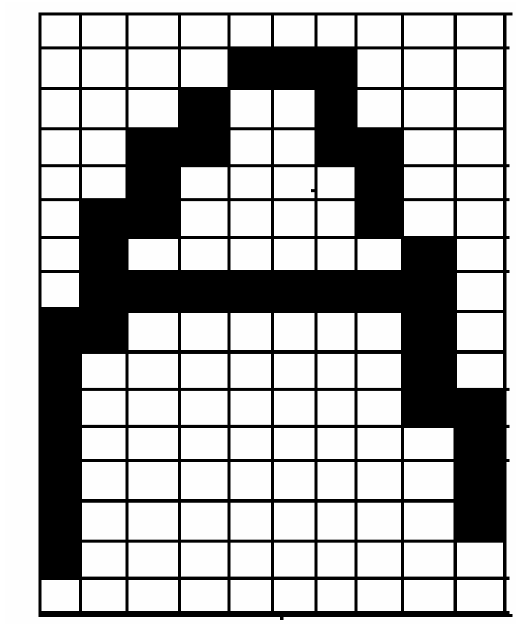

Figure 4: Binary image of letter "A"

1	1	1	1	1	1	1	1	1	1
1	1	1	1	0	0	0	1	1	1
1	1	1	0	1	1	0	1	1	1
1	1	0	0	1	1	0	0	1	1
1	1	0	1	1	1	1	0	1	1
1	0	0	1	1	1	1	0	1	1
1	0	1	1	1	1	1	1	0	1
1	0	0	0	0	0	0	0	0	1
0	0	1	1	1	1	1	1	0	1
0	1	1	1	1	1	1	1	0	1
0	1	1	1	1	1	1	1	0	0
0	1	1	1	1	1	1	1	1	0
0	1	1	1	1	1	1	1	1	0
0	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1

1
1
1
1
1
1
1
1
1
1
1
1
1
0
…. .
150*1 Matrix
1
1

Figure 5(a) Binary matrix representation of character "A" 5(b) Reshaped matrix for letter "A"

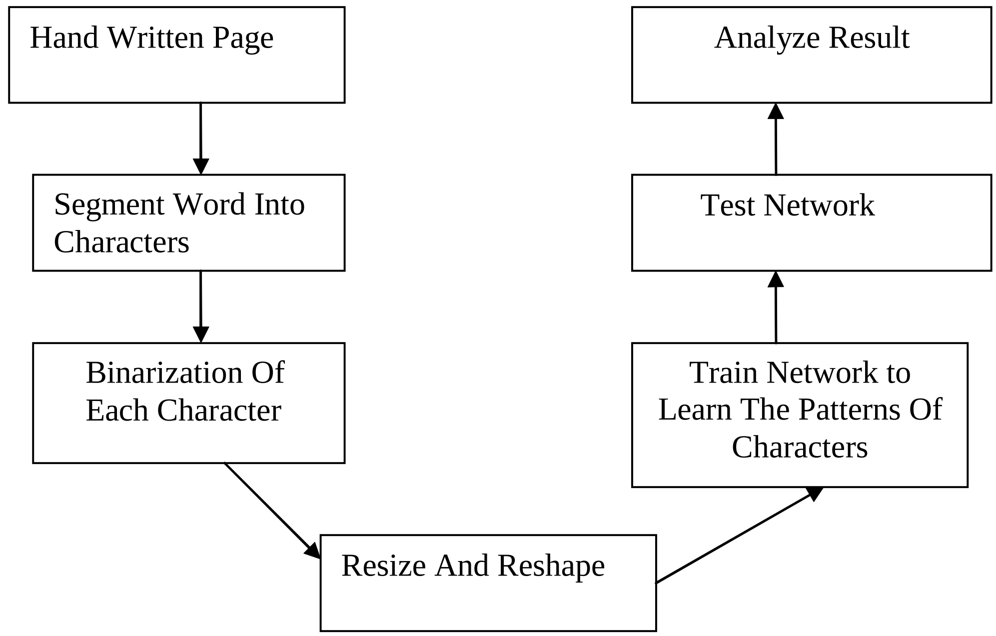

Figure 6: Steps involved in the artificial character recognition system.

500 experiments have been conducted. The same neural network is used for all learning and testing experiments.

The binarization is done using logical operation on gray intensity level as :

If ....(3.1.1)

Else

$I = 1$ where $0 < level <= 1$

Where *level* is the threshold parameter.

This threshold parameter is based on the gray-scale intensity of the text in document. More intensity leads to the more threshold value. This parameter is decided based on the following table :

The first column of Table-1 represents the intensity of text present in the document. This intensity is a gray-scale value when the document is saved in gray scale image format after scanning and the second column of this table represents the corresponding value of threshold level for binarization process.

Actual output of the network is obtained by "COMPET" function. This is a competitive transfer function which puts 1 at the output neuron in which the maximum trust is shown and rest neuron's result into '0' status. The out put matrix is a binary matrix of size (26, 26). The difference between the desired and actual output is calculated for each cycle and the weights are adjusted. This process continues till the network converges to the allowable or acceptable error. The architecture of the neural network used in these experiments is shown below in figure . The desired output in matrix format is shown below in table-:

Gray-Scale Intensiti of the Text	Value of Threshold level
0 – 0.25	0.20
0.26 – 0.50	0.45
0.51 – 0.75	0.65
0.76 – 1.0	0.85

Table 1 : Intensity / Threshold Comparison Table used for the process of Converting bitmap image into binary form

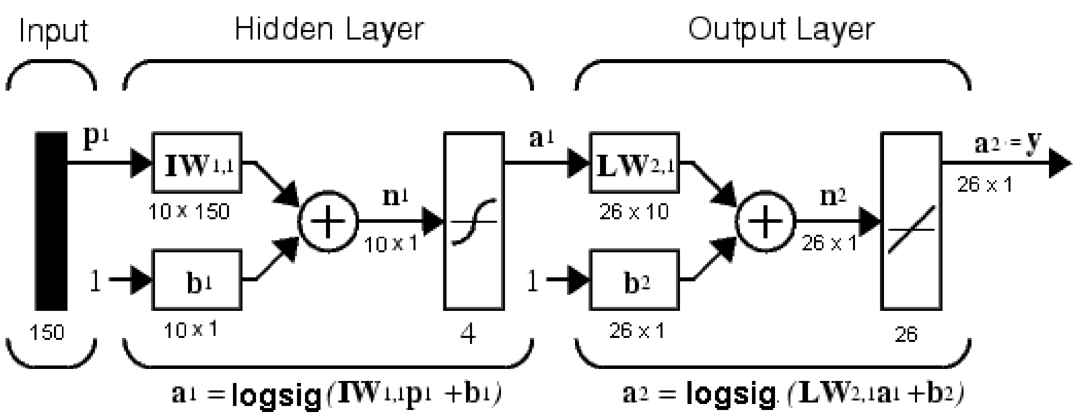

Figure 7 : Architecture of the Neural Network used in the Three Word English Character Recognition System.

1	0	0	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0	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	0
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
0	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	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Figure 8 : In this table presence of 1 indicates the corresponding character. Like 1 in first column means the character is "A" second place 1 means character "B" and so on.

Results :

The following parameters are used in all the experiments:

Sr. No.	Parameter	Value
1	Allowed Maximum Error For Learning	0.001
2	Performance Function	Sum Square Error
3	Maximum Training Iterations	50000
4	Initial Weights values	Randomly generated values between 0 and 1

Table : 2 Parameters v/s their values used in all learning processes.

The segmentation technique yields the following results with applied two constraints:

Segmentation Constraint	Correctly Segmented Words (Out of 600)	Incorrect Segmented Words (Out of 600)	Success Percentage
Height / 2	427	173	71.16 %
2 * Height / 3	498	102	83 %

Table 3 : Results of Vertical Segmentation Technique with two Constraints.

The first column of table represents the constraints applied on the segmentation process based on the height of the word the second and third columns represent the number of correctly and incorrectly segmented words respectively with applied two constraints. The last column shows the percentage of correctly segmented words. It is clearly evident that the $\frac{2}{3} * H_{avg}$ constraint leads to better results for proposed vertical segmentation technique.

The learning process results of the network in terms of the number of training iterations depicted as Epoch are represented in the following table :

Learning Iterations for different samples				
Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
247	351	486	312	365
654	837	1173	1980	1426
7852	19286	32459	24290	38031
48024	50000	50000	50000	50000
50000	50000	50000	50000	50000

Table 4: Comparison of Network Learning Iterations for 500 trails, each samples being trained 50 times

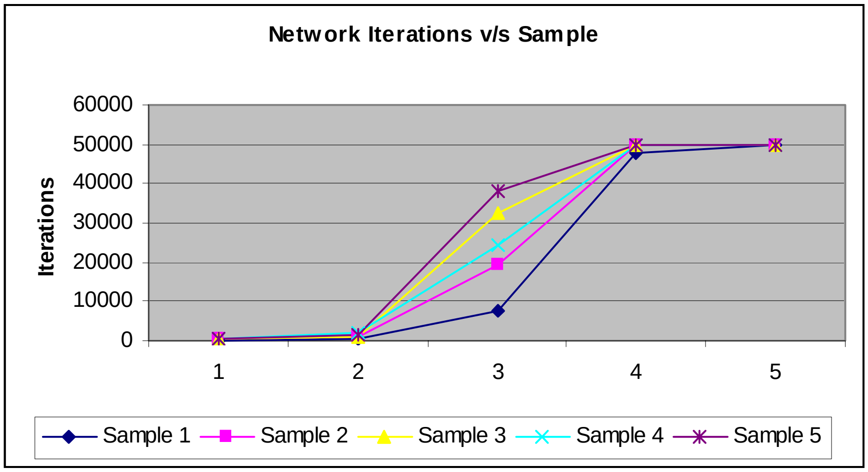

Figure 9 : Network learning iterations for different samples.

In the table above specified; Sample 1, Sample 2, Sample 3… represents the handwriting samples made input the ANN for learning. Each figure represents the average of number of network iterations for a particular sample when presented to the neural network 50 times for learning.

Conclusion :

The proposed method for the handwritten words recognition using the segmentation and back propagation approach, showed the remarkable enhancement in the performance. The results as shown in table 4, for the different sample of the three characters words, represent the number of iteration as epochs that a sample has considered for the learning of input patterns.

Here we have introduced an additional momentum term in the weight-age modification, this additional momentum term accelerates the process of convergence and the network shows better performance. The second derivative of errors gradient has been computed. This represents the local minima points on the error surface for the presented training patterns. The performance can be observed for the modified technique as represented above in figure-9. The success in the recognition also depends upon the segmentation criterion. It means that if we change the segmentation or methods for separating the characters, the success of performance will also change.

The proposed segmentation technique has been quite successful in segmenting all types of characters (cursive and non cursive). The segmentation technique is yielding better results when the 2/3* height constraint applied.

This constraint gives 83% correct segmentation success whereas 71% success rate is achieved in case of ½ * height constraint. The used second momentum term is useful for the knowledge of rate of convergence and also to identify the present error in the training of a sample.

Nevertheless, more work needs to be

done especially on the test for large complex handwritten characters. Some future works should also be explored. The proposed work can be carried out to recognize English words of different character lengths. The segmentation technique suggested in this paper is also useful to segment words of all lengths. Making the network more trained can yield to better results of recognition.

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