BI DIRECTIONAL ASSOCIATIVE MEMORY NEURAL NETWORK METHOD IN THE CHARACTER RECOGNITION

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ABSTRACT

Pattern recognition techniques are associated a symbolic identity with the image of the pattern. In this work we will analyze different neural network methods in pattern recognition. This problem of replication of patterns by machines (computers) involves the machine printed patterns. The pattern recognition is better known as optical pattern recognition. Since, it deals with recognition of optically processed patterns rather then magnetically processed ones. A neural network is a processing device, whose design was inspired by the design and functioning of human brain and their components. There is no idle memory containing data and programmed, but each neuron is programmed and continuously active. Neural network has many applications. The most likely applications for the neural networks are (1) Classification (2) Association and (3) Reasoning. One of the applications of neural networks is in the field of pattern recognition. The Bidirectional associative memory does heteroassociative processing in which, association between pattern pairs is stored. The Bidirectional Associative has capacity limitations. It can store and correctly recognize only six characters, with the condition that the characters should be slightly similar in shape.

Keywords: *Neural networks, bi-directional, machine printed patterns, pattern recognition*

1. INTRODUCTION

A neural network is a processing device, whose design was inspired by the design and functioning of human brain and their components. There is no idle memory containing data and programmed, but each neuron is programmed and continuously active.

Neural network has many applications. The most likely applications for the neural networks are (1) Classification (2) Association and (3) Reasoning. One of the applications of neural networks is in the field of pattern recognition. Pattern recognition is a branch of artificial intelligence concerned with the classification or description of observations. Its aim is to classify patterns based on either a priori knowledge or on the features extracted from the patterns.

Pattern recognition is the recognition or separation of one particular sequence of bits or pattern from other such patterns. Pattern recognition [PR] applications have been varied, and so also the associated data structures and processing paradigms. In the course of time, four significant approaches to PR have evolved. These are [1].

Statistical pattern recognition: Here, the problem is posed as one of composite hypothesis testing, each hypothesis pertaining to the premise, of the datum having originated from a particular class; or as one of regression from the space of measurements to the space of classes. The statistical methods for solving the same involve the computation other class conditional probability densities, which remains the main hurdle in this approach. The statistical approach is one of the oldest, and still widely used [2].

Syntactic pattern recognition: In syntactic pattern recognition, each pattern is assumed to be composed of sub-pattern or primitives strung together in accordance with the generation rules of a grammar characteristic of the associated class. Class identifications accomplished by way of parsing operations using automata corresponding to the various grammars [11, 12]. Parser design and grammatical inference are two difficult issues associated with this approach to PR and are responsible for its somewhat limited applicability.

Knowledge-based pattern recognition: This approach to PR [13] is evolved from advances in rule-based system in artificial intelligence (AI). Each rule is in form of a clause that reflects evidence about the presence of a particular class. The sub-problems spawned by the methodology are:-

1. How the rule-based may be constructed, and
2. What mechanism might be used to integrate the evidence yielded by the invoked rules?

Neural Pattern Recognition: Artificial Neural Network (ANN) provides an emerging paradigm in pattern recognition. The field of ANN encompasses a large variety of models [14], all of which have two important characteristics:

1. They are composed of a large number of structurally and functionally similar units called neurons usually connected various configurations by weighted links.
2. The Ann's model parameters are derived from supplied I/O paired data sets by an estimation process called training.

2. METHODOLOGY:

There are many neural network algorithms for the pattern recognition. Various algorithms differ in their learning mechanism. Learning can be either supervised or unsupervised. In supervised learning, the training set contains both inputs and required responses. After training the network we should get the response equal to target response. Unsupervised classification learning is based on clustering of input data. There is no prior information about input's membership in a particular class. The characteristics of the patterns and a history of training are used to assist the network in defining classes. This unsupervised classification is called clustering.

The characteristics of the neurons and initial weights are specified based upon the training method of the network. The pattern sets is applied to the network during the training. The pattern to be recognized are in the form of vector whose elements is obtained from a pattern grid. The elements are either 0 and 1 or -1 and 1. In some of the algorithms, weights are calculated from the pattern presented to the network and in some algorithms weights are initialized. The network acquires the knowledge from the environment. The network stores the patterns presented during the training in another way it extracts the features of pattern. As a result of this, the information can be retrieved later.

3. PROBLEM STATEMENT

The aim of the thesis is that neural network has demonstrated its capability for solving complex pattern recognition problems. Commonly solved problems of pattern have limited scope. Single neural network architecture can recognize only few patterns. Relative performance of various neural network algorithms has not been reported in the literature.

The thesis discusses on various neural network algorithms with their implementation details for solving pattern recognition problems. The relative performance evaluation of these algorithms has been carried out. The comparisons of algorithms have been performed based on following criteria:

(1) Noise in weights
(2) Noise in inputs
(3) Loss of connections
(4) Missing information and adding information.

4. BIDIRECTIONAL ASSOCIATIVE MEMORY (BAM):

The Bidirectional associative memory is heteroassociative, content-addressable memory. A BAM consists of neurons arranged in two layers say A and B. The neurons are bipolar binary. The neurons in one layer are fully interconnected to the neurons in the second layer. There is no interconnection among neurons in the same layer. The weight from layer A to layer B is same as the weights from layer B to layer A. dynamics involves two layers of interaction. Because the memory process information in time and involves Bidirectional data flow, it differs in principle from a linear association, although both networks are used to store association pairs. It also differs from the recurrent auto associative memory in its update mode.

4.1 Memory Architecture:

The basic diagram of the Bidirectional associative memory is shown in fig. 3.1. Let us assume that an initializing vector **b** is applied at the input to the layer A of neurons.

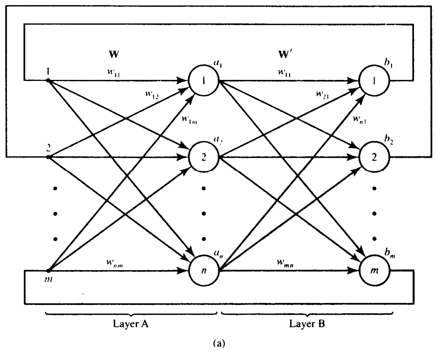

Fig.3.1: Bidirectional Associative Memory: General Diagram

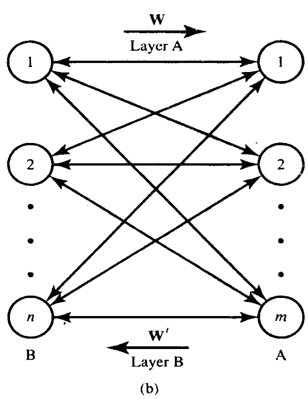

Fig 3.2: Bidirectional Associative Memory: Simplified Diagram

Fig (3.2) shows the simplified diagram of the Bidirectional associative memory often encountered in the literature. Layer A and B operate in an alternate fashion- first transferring the neuron's output signals towards the right by using matrix **W**, and then toward the left by using the matrix $\mathbf{W}^t$, respectively.

The Bidirectional associative memory maps bipolar binary vectors $\mathbf{a} = [a_1 a_2 \ldots a_n]^t$, $a_i = \pm 1$, $i = 1, 2, \ldots, n$, into vectors $\mathbf{b} = [b_1 b_2 \ldots b_m]^t$, $\mathbf{b}_i = \pm 1$, $i = 1, 2, \ldots, m$, or vise versa.

Where $\boldsymbol{a}^{(i)}$ ands $\boldsymbol{b}^{(i)}$ are bipolar binary vectors, which are members of the i'th pair.

4.2 Algorithm:

Step 1: The associations between pattern pairs are stored in the memory in the form of bipolar binary vectors with entries -1 and 1.

$$\{(\mathbf{a}^{(1)}, \mathbf{b}^{(1)}), (\mathbf{a}^{(2)}, \mathbf{b}^{(2)}), \ldots\ldots\ldots\ldots, (\mathbf{a}^{(p)}, \mathbf{b}^{(p)})\}$$

Vector **a** store pattern and is n-dimensional, **b** is m-dimensional which stores associated output.

Step 2: Weights are calculated by

$$W = \sum_{i=1}^{p} \mathbf{a}^{(i)} \mathbf{b}^{(i)t}$$

Step 3: Test vector pair **a** and **b** is given as input.

Step 4: In the forward pass, **b** is given as input and **a** is calculated as

$$\mathbf{a} = \Gamma[\mathbf{Wb}]$$

Each element of vector **a** is given by

$$a_i' = \operatorname{sgn}\left(\sum_{j=1}^{m} w_{ij} b_j\right), \qquad \text{for } i = 1, 2, \ldots, n$$

Step 5: Vector **a** is now given as input to the second layer during backward pass. Output of this layer is given by

$$\mathbf{b}' = \Gamma[\mathbf{Wa}]$$

Each element of vector **b** is given by

$$b_j' = \operatorname{sgn}\left(\sum_{i=1}^{n} w_{ij} a'_i\right), \qquad \text{for j} = 1, 2, \ldots, m$$

Step 6: If there is no further update then the process stops. Otherwise step 4 and 5 are repeated.

4.3 Storage Capacity:

Kosko (1988) has shown that the upper limit on the no. p of pattern pairs which can be stored and successfully retrieved is min (m, n). The substantiation for this estimate is rather heuristic. The memory storage capacity of BAM is

$$P \le \min(m, n)$$

A more conservative heuristic capacity measure is used in a literature,

$$p = \sqrt{\min(m, n)}$$

5. RESULTS

The network has 49 neurons in first layer and five neurons in the second layer. With this configuration the network is capable of storing six alphabets. The alphabets have been represented as a pattern grid of size 7×7. From the pattern grid each alphabet is obtained in the form of a vector with entries 1 and -1. All the alphabets in the form vector **a** and its associated output as vector **b** is stored. Weight matrix is obtained by taking inner product of **a** and **b**. The network has been tested for A, I, L, M, X, and P. The network gives the correct associated output when these characters are given at the time of testing. The result has been shown in table 3.1.

6. MERITS AND DEMERITS:

In BAM, a distorted input pattern may also cause correct heteroassociation at the output. The logical symmetry of interconnection severely hampers the efficiency of BAM in pattern storage and recall capability. It also limits their use for knowledge representation and inference [7]. There is limitation on number of pattern pairs, which can be stored and successfully retrieved.

7. CONCLUSION:

A bidirectional associative memory has been performed for the pattern recognition for the English alphabets (A-Z). The near optimal network architecture of this algorithm was found, so that it can correctly classify or recognize the stored pattern. .

When weighs were varied randomly for effect on noise, When Random numbers are added in the weight matrix only character A was recognized correctly. When Random numbers are added after divided by 10 in the weight matrix, than all the six characters are recognized correctly.

CHARACTER	INPUT	OUTPUT
A	**a** = [-1-1111-1-1-11-1-1-11-11-1-1-1-1-1111111111-1-1-1-1-111-1-1-1-1-111-1-1-1-1-11] **b** = [-1-1-1-11]	-1-1-1-11
I	**a** =[-111111-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-111111-1] **b** = [-11-1-11]	-11-1-11
L	**a** = [1-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-11-1-1-1-1-1-1111111] **b** = [-111-1-1]	-111-1-1
M	**a** = [1-1-1-1-1-1111-1-1-1111-11-11-111-1-11-1-111-1-1-1-1-11-1-1-1-1-111-1-1-1-1-11] **b** = [-111-11]	-111-11
P	**a** = [11111-1-11-1-1-1-11-11-1-1-1-1-111-1-1-1-11-111111-1-11-1-1-1-1-1-11-1-1-1-1-1-1] **b** = [1-1-1-1-1]	1-1-1-1-1
X	**a** = [1-1-1-1-1-11-11-1-1-11-1-1-11-11-1-1-1-1-11-1-1-1-1-11-11-1-1-11-1-1-11-11-1-1-1-1-11] **b** = [11-1-1-1]	11-1-1-1

Table 3.1: Given input and Obtained output in BAM

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