Abstract

One of the important ability in human brain is making associations among patterns. Associative Memory (AM) is the process by which learning is apparent through stimuli and environment. This paper discuss three different models of Associative Memories (AM), Linear Associator, Hopfield Associative model, and Bidirectional Associative Memory with the Autoassociative an Hetroassociative memory pattern mapping.

Keywords: Associative Memory (AM), Linear AM, Hopfield AM, and Bidirectional AM.
1 INTRODUCTION

Neural networks got additional computing power because of its massively parallel distributed structure and capability to learn. Now a days artificial neural networks getting more attention in research because of its (i) adaptive nature: synaptic weights of the neurons are adapted and subsequently surrounding environment is changed, (ii) self organizing to learn and organize information without being given correct answers to the input pattern, (iii) real-time operation and fault tolerance, means able to robust computation and its performance reduces elegantly under different working conditions. Associative memory is distributed memory, like brain that learns by association. Nature of every neuron in human body is always oscillates in one mode or another, just to survive. Aristotle (Anderson, 1995) observed that human brain connects items like images, sensation, etc. Association is taken place based on comparison (similarity), contrary (dissimilar), spatial and temporal characteristics. The function of an associative memory is, to generate the associated output pattern from memory whenever the one of its input pattern is applied to the neural networks [19]. Associative memory can be implemented using either by feedforward neural networks or recurring neural networks. An associative memory having a content addressable structure to recall the data based on similarity between input pattern and stored pattern. The remaining parts of the paper is structured as follows: in II session introduction to Associative memory, III session Gives Associative Memory models, and conclusion in IV session.

2 ASSOCIATIVE MEMORIES

An associative memory (AM) arrangement serves as a highly disentangled model of human memory, the associated patterns are recall or output when the related input pattern is incited. Associations are stored in memory, when the memory is spark for given input pattern for incidence then the memory retrieves the associated pattern. Associative Memory (AM) works in two phases, first phase for storing all the patterns in memory and in second phase is recall phase; retrieve the stored pattern from
2.1 Notation and structure

Where $X^k = [x_1, x_2, x_3, \ldots, x_n]$ and $Y^k = [y_1, y_2, y_3, \ldots, y_m]$ and output $Y = M[X]$ in fig 1.a.

Output pattern $= M(\text{Input pattern})$

In fig 1.b output pattern $\square = M(\pm)$

Where $M$ is memory vector/matrix

$\square$ Output pattern

+ input pattern

Memory vector $(M)$ is computed using input patterns. Input and output neuron connection is characterized with $(W)$. Correlation weight matrix $(W)$, $W = [w_{jk}] \epsilon \mathbb{R}^{n \times m}$, where $w_{jk}$ represents the synaptic weight of the $j$th input neuron in input layer to the $k$th output neuron in output layer and vice versa. This correlation weight matrix stores $m$ different pattern pairs $(X_p, Y_p) | p = 1, 2, \ldots, m$, where $X_p$ and $Y_p$ are bipolar.
representations,

\[ X_p = \{-1, +1\}^n \quad \text{and} \quad Y_p = \{-1, +1\}^p \]  

[10, 11].

Construction of correlation weight matrix \( W \) called storage or encoding, and it is constructed based on the neuron connections. Computation of weight matrix is obtained by using method sum of outer products mentioned in equation (2) and (3). Storage of pattern pairs (associated) in memory is done by single and multiple manner, respectively [10, 11].

\[
(W_{jk})_p = (X_j)(Y_k) \quad (2)
\]

\[
W = \sum w_p \quad (3)
\]

After the storage stage, network has to retrieve or recall the stored pattern from memory. Recalling of stored pattern from memory for a specified an input pattern is called decoding. For given input pattern stimuli \( X \), decoding is obtained by computing the net output units using input units as [12].

\[
Y_k = W.X_j \quad (4)
\]

Based on the structure of neural network associative memory (AM) is classified into two types, first one is static and second one is dynamic. In static model input pattern is applied and associated pattern is retrieved in single step (feedforward) so that it can be called as one step processor single step process, where as in dynamic model input is applied iteratively to get the exact output pattern by using feedback connections. Two types of associations are identified based on the nature of the associations those are autoassociative and heteroassociative memories in neural networks.

Neural associative memory performance is usually measured by, the amount of patterns stored in memory (memory capacity), and the facts content that may be discovered and retrieved (retrieval), divided via the variety of synapses required. If the input patterns are mutually orthogonal perfect retrieval is possible, otherwise perfect retrieval not possible due to crosstalk among the patterns.
Construction of the connection weight matrix using Hebb’s learning rule of associative memory yields a significantly low memory capability, because of the limitation of Hebb’s learning rule, several modifications and variations are projected to maximize the memory capability.

3 ASSOCIATIVE MEMORY MODELS

Numerous associative memories are available in literature, among which linear associative memories, the brain-states-in-a box, Hopfield associative memories, and bidirectional associative memories.

3.1 Linear Associator Model

The linear associator is a traditional and primary associative memory model. It is a feedforward network type and output is produced in single feedforward pass or phase. In this model associations are performed within p pattern pairs X(p), Y(p) by simply performing the matrix multiplication operation 

\[ Y = WX, X \in \mathbb{R}^n, Y \in \mathbb{R}^m, W \in \mathbb{R}^{n \times m}. \]

Figure 2: Structure of Linear Associator model

For given P associations \((X_i, Y_j)\) if \(X_i = Y_j\) then the network is called autoassociative memory neural network, otherwise network
is hetroassociative memory neural network. This structure supports both autoassociative and hetroassociative memory models. \( X_i = [x_1, x_2, x_3, \ldots, x_m] \) input patterns and \( Y_j = [y_1, y_2, y_3, y_n] \) are output patterns. This model is an unsupervised learning i.e. Hebb's learning rule applied to compute cross correlation matrix: \( W_{ij} = W_0 + X_i Y_j / W_0 \) with initial weight vector assigned to zero before training takes place done during encoding process. Input pattern is represented as column matrix and output/target pattern is represented as row matrix. \( X = (x_1, x_2, \ldots, x_n) \) and \( Y = (y_1, y_2, \ldots, y_n) \). Weight matrix \( W = X^T Y \). According to Hebb's learning rule pattern pairs of input and outputs are represented by either binary or bipolar pattern. During decoding process using equation (4), activation function of the output units are given. Threshold function for binary units is

\[
y_j = \begin{cases} 
1, & x > 0 \\
0, & x < 0 
\end{cases} \tag{5}
\]

Bipolar units threshold function

\[
y_j = \begin{cases} 
1, & x > 0 \\
0, & x = 0 \\
-1, & x < 0 
\end{cases} \tag{6}
\]

Correlation weight matrix is increased if cross product of input and output is positive, otherwise weight vector is decreases. This model has a very low memory capacity and if noisy input pattern is applied to the network, then the network retrieves the pattern which one is close to the given input pattern. Due to this feature linear associative model is vigorous and fault tolerant, this one degrades the network performance.

### 3.2 Hopfield Associative Memory model

Predecessor of Hopfield associative memory is BrainState-in-aBox (BSB) [13, 14], which was developed by J.A. Anderson, J.W. Siwersten, S.A. Ritz; R.S. Jones [21] in 1977. BSB is first dynamic model with discrete or continuous time intervals. BSB neural associative network model similar to
Hopfield Associative Memory model, and extends the Linear Associator model, but having feedback connections with single layer. Usage of linear threshold signals function in BSB model it stands different from all other models. Applications of BSB are restricted to clustering of data soon after it is also used in many other applications. Later in year 1982, John Hopfield developed a model that has wide range of applications. Hopfield model structure is given in fig 3

Figure 3: Hopfield Associative Memory model for 3 units in two ways

Every unit in the Hopfield network is connected to other units with recurrent connections but not connected to itself, and all units in this model behave like input and as well as output units with single layer of neurons. In this model network send the feedback signals to each unit until network reaches to stable state.

Storage of input patterns in memory is same as linear associator model except external input is applied to every unit and keeping 0s at diagonal position in weight matrix. $W_{jk} = W_{kj} \neq 0 \text{ and } W_{jj} = 0$ where weights are symmetric.

Hopfield associative model is autoassociative type-it cannot associate with different memory but it can retrieve noisy or incomplete patterns. Storage patterns in memory by Hopfield model is summing $m$ outer products as
W = \sum = 1[X]^T[X]x \epsilon (-1, 1)

In this model retrieval of stored pattern is obtained by nonlinear threshold and matrix multiplication function

\[ X^\text{new}_j = f(x_iw_{ij}, x^\text{old}_j) \text{here } j = 1, 2, ..., P \text{ patterns and bipolar threshold function is} \]

\[ f(s, t) = \begin{cases} 
1, & s > 0 \\
q, & s = 0 \\
-1, & s < 0 
\end{cases} \quad (7) \]

3.3 Bidirectional Associative Memory (BAM) Model

Bart Kosko in year 1988 developed Bidirectional Associative Memory (BAM), which is expansion of Hopfield network model. The BAM structure is similar to the Linear Associator Model structure (LAM) because both have two layers but while Hopfield model has only one layer. Bidirectional Associative Memory (BAM) has bidirectional connections between two layers.

BAM model works as hetroassociative model and its bidirectional connections between two layers iterates until all units reach stable state. Due to its bidirectionality feature weight matrix can be calculated in any direction, for feedforward connections weight matrix is represented as W (input layer to output layer) as in feedback connections WT (Output layer to
BAM has a higher capability of error correction compared to Hopfield network because it has two layers while Hopfield model has only one layer. Encoding of BAM is similar to the Linear Associative model, weight matrix

\[ W = \sum_{i=1}^{n} X_i (Y_i)^T \]  

(8)

where \( X \) is input vector and \( Y \) is output vector. Activation function

\[ y_j(f) = \begin{cases} 
1, & J_j > T_{Y_j} \\
-1, & J_j < T_{Y_j} \\
y_j(t - 1), & J_j = T_{Y_j} 
\end{cases} \]  

(9)

where \( J_j = \sum_{i=1}^{m} W_{ij} X_i \), Binary threshold is used as an activation function in bidirectional associative memory network. Due its high error correction capability Bam can be used in many other applications like authentication of passwords, recognition of characters and fabric defect identification.

4 CONCLUSION

This paper gives overview on Associative memory models with their applications. All the models are storing input patterns using bipolar and binary representation, bipolar representation gives accurate retrieval. Both Linear Associator and Bidirectional associative memory models retrieves the closed pattern even though noisy or corrupted patterns are applied to the network where as Hopfield model does not retrieves other patterns.

References


**BIOGRAPHY**

S. Shoba Rani received B.Tech degree in Computer Science and Engineering from Swami Ramananda Tirtha Institute of Science & Technology, in 2003 and M.Tech degree in Software Engineering from JNTUH, Hyderabad, India in 2008. Pursuing Ph.D from JNTU Hyderabad. At present working as Associate Professor in the department of Computer Science and Engineering at Vardhaman College of Engineering, Hyderabad, India. I have totally teaching experience 12 years. I have Three international Publications.