The Effect of Synaptic Disconnection on Bi-directional Associative Recall

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Abstract

The effects of synaptic disconnection ("damage") on associative recall in Bi-directional Associative Memories are reported. The degradation of recall under various types of damage are described. the extent of failure is seen to be significantly dependent on the nature as well as extent of damage caused to the BAM.

A BAM is a two-level non-linear neural network that recalls associative pairs of bit patterns. Particularly in the presence of noise. Like other neural networks, BAM's are fault tolerant, since they are distributed parallel processing elements, with each node contributing to the final output response.

The paper describes the basic coding and decoding strategies as well as the strategies followed for "damaging" the BAM.

In the experiments reported, graceful degradation, rather than catastrophic failure was observed. While this is expected in most neural networks, it was observed that the extent of failure is significantly dependent on the nature of damage caused to the BAM.

The results show that recall is most sensitive to clustered synaptic disconnection and least sensitive to random synaptic disconnection. Some similarities to biological systems are mentioned in the paper.

1. INTRODUCTION

A Bidirectional Associative Memory (BAM) is a two level non-linear neural network [1] - [4]. BAM's recall associative pairs of bit patterns. Particularly in the presence of noise. Subsequent to Kosko and others original work on BAMs. Wang and others [5] have introduced more efficient coding strategies, enabling better quality recall for a large number of stored pairs of a BAM. BAM's, like other neural networks, are fault tolerant [6] since they are distributed parallel processing elements, with each node contributing to the final output response. In this paper, the degradation of a BAM's recall under various types of synaptic disconnection ("damage") are described. While graceful degradation, rather than catastrophic failure was observed, the extent of failure was significantly dependent on the nature of damage caused to the BAM.

The basic coding and decoding strategies as well as methods of augmented coding are described in the next section. This is followed by a description of the experiments performed. Finally, the results are presented and certain interesting, if speculative, extrapolation to biological systems are discussed.

2. CODING AND DECODING STRATEGIES

BAM's store and recall using the following basic schemes introduced by Kosko:

Let there be N training pairs

$$\{(A_1,B_1),\ (A_2,B_2)\ \ldots\ (A_i,B_i)\ \ldots\ (A_n,B_n)\}$$

where

$$A_1 = (a_{i1}, a_{i2}, \ldots, ain) \quad (1)$$

and

$$B_1 = (b_{i1},\ b_{i2}, \ldots, bin) \quad (2)$$

Each a_{ij} or b_{ij} are either ON or OFF (i.e., 1 or 0)

In the bipolar mode the corresponding values are 1 or -1.

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A BAM is defined as the correlation matrix

$$M = \sum_{i=1}^{n} X_i^T Y_i \tag{3}$$

Where X_i (Y_i) is the bipolar mode of A_i (B_i). When an arbitrary vector α_0 is presented to the network matrix M. We wish to retrieve the nearest (A_i, B_i) association.

To do so we apply α_0 to M to produce an associative vector β_1 . ie.

$$\beta_1 = \phi(\alpha_0 M) \tag{4}$$

where ϕ (F) = G = $(g_1, g_2, g_3, \ldots, g_n)$ (5)

$$F = (f_1, f_2, f_3, \ldots, f_n) \tag{6}$$

$$g_i = 1, f_i > 0 \tag{7}$$

$$g_i = 0, f_i < 0 \tag{8}$$

and is unchanged if $f_i = 0$ (9)

Now we determine a new α by applying β_1 to M.

$$\alpha_1 = \phi(\beta_1 M^T) \tag{10}$$

and

$$\beta_2 = \phi(\alpha_1 M) \tag{11}$$

$$\alpha_2 = \phi(\beta_2 M^T) \tag{12}$$

We repeat (11) and (12) until

$$\alpha_n = \alpha_{n-1} = \alpha_F \tag{13}$$

and

$$\beta_n = \beta_{n-1} = \beta_F \tag{14}$$

At this stage we should find

$$A_i = \alpha_F \tag{15}$$

and

$$B_i = \beta_F \tag{16}$$

Kosko has shown that (α_F, β_F) will always be obtained after a finite number of iterations. However, this scheme does not guarantee that A_i will always recall B_i and vice versa.

In practice, A_i (or B_i) can produce a pair (A_F, B_F) which was not stored at all (Deja Vu) or a pair (A_i, B_i) which was stored but is not the correct solution (A_i, B_i). Wang *etal* [5] have developed multiple training and dummy augmentation strategies by which the correct trained pair can always be recalled,

3. REDUNDANCY AND RECALL

To use a BAM for pattern recognition, each vector of n bits can be represented as a grid of x by y such that

$$n = xy \tag{17}$$

Within this grid a 1 bit can be represented by a Dark rectangle and a 0 bit by a Light rectangle to represent a pattern (Fig. 1).

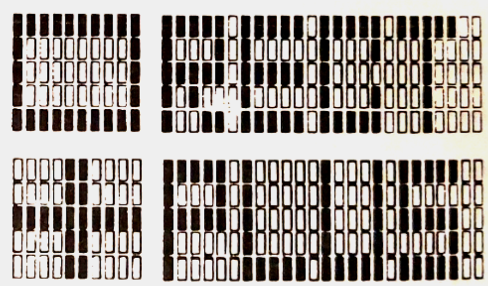

Fig. 1 *The associations stored in the experimental BAM*

If such a vector is associated to another vector of m bits represented by a x' by y' grid, the resultant BAM is an nxm matrix. if several such vector pairs are coded into the BAM and rows and columns of the resulting matrix are displayed as (x,y) or (x',y') grids it is immediately apparent that the input patterns are overlayed and stored repeatedly in the BAM (Fig.2). Thus if the pattern is disturbed in one area of the BAM it is usually recoverable from another region. It is this characteristic which enables fault tolerant recall in BAMs.

Fig. 2 Visual representation of a column in the experimental BAM

4. EXPERIMENTAL DESIGN

To measure degradation in recall under synaptic damage, a 50x125 BAM was created by encoding A and B vectors of 50 and 125 elements each. The A vectors were represented as 5x10 grids while the B vector were 5x25 grids. two patterns were stored as shown in Fig. 1. The BAM recalled both patterns (A_1,B_1) and (A_2,B_2) correctly when presented with any one of the vectors. A_1 when visualized, was a rectangle while the corresponding vector B_1 spelled the word "RECT". A_2 was a cross and B_2 represents the word "PLUS" . Recall was also good for partial inputs. For instance, a corner of the rectangle presented to the BAM produced . (A_1,B_1) while the central section of the cross recalled (A_2, B_2) . It is interesting to note that when presented with an ambiguous input consisting of two ON pixels in the middle of the first row in the A gird (i.e. one of the areas where the cross and rectangle intersect), the BAM produced a new (A,B) pair with A showing all four places where the rectangle and cross intersect and B spelling the word "PLUT" as though it had invented a new word to describe the new shape (Fig. 3).

Synaptic disconnection in a BAM is equivalent to changing a non-zero element in the matrix to zero. We defined "damage" as the percent ratio of the number of such disconnections to the total number of originally connected (i.e. non-zero) synapses.

Fig. 3 A spurious association on the experimental BAM

In order to measure the effect of synaptic disconnection, we designed the following types of "damage".

(a) Sequential Disconnection of Neurons: Here entire neurons were disconnected form the BAM by changing all elements of the corresponding row or column to zero. Neurons were disconnected in sequence from A or B or both until a desired level of damage (specified as a percentage of synapses disconnected to the total number of synapses connected originally) was achieved.

(b) Random Disconnection of Neurons: Here neurons were disconnected at random until the desired level of damage was achieved.

(c) Random Disconnection of Synapses: Here synapses (i.e. non-zero matrix elements) were disconnected (changed to zero) at random until the desired level of damage was achieved.

(d) Clustered Disconnection of Synapses: Here "lesions" were created in the matrix by disconnecting all connected synapses in a randomly chosen region of the matrix. The size of the region was isotropically increased until the desired level of damage was achieved.

5. RESULTS

The four types of disconnection damage described above was applied to the BAM described at the beginning of this section. Between 10 and 90% disconnection was studied in steps for each type of damage.

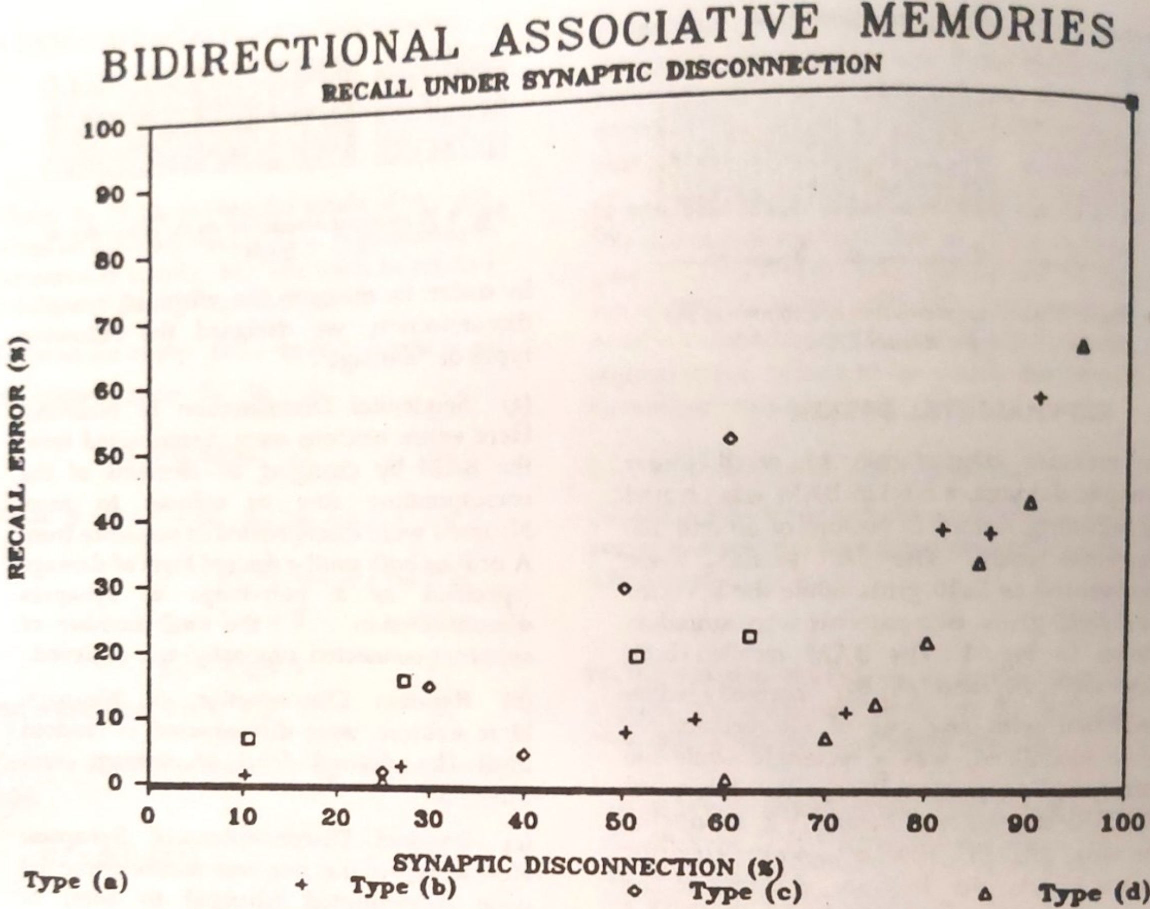

Fig. 4 : *Recall errors plotted against percent damage for each of the four types of damage discussed in the text.*

Each damaged BAM was made to recall the two stored associations and the error in recall was calculated by counting the number of pixels in erroneous states (i.e. 0 instead of 1 or vice versa) in the recalled association. This was then converted to a percentage error in recall by dividing by the total number of pixels to be recalled. Finally each experiment was repeated three times and a mean of the percent error in recall was calculated for that degree and type of damage. The results are displayed as a graph of the percent synapses disconnected against the percent error in recall (Fig.4).

The results show that recall was most sensitive to clustered synaptic disconnection and least sensitive to random synaptic disconnection. For example, a 50% clustered synaptic disconnection resulted in a 30% error in recall while the same percent disconnection when carried out randomly on synapses caused virtually no error in recall.

Damage types (b), (c) and (d) were seem to follow graceful degradation curves while this was not so evident for damage type (a). i.e. sequential disconnection of neurons.

this experiment, it was observed that when the error in recall exceeded about 30%, the patterns were no longer meaningful or discernible to the human eye (Fig. 5). If one were to assign an arbitrary value of 30% as the maximum possible error allowed in recall for an imaginary application, the experimental results show that the BAM would survive

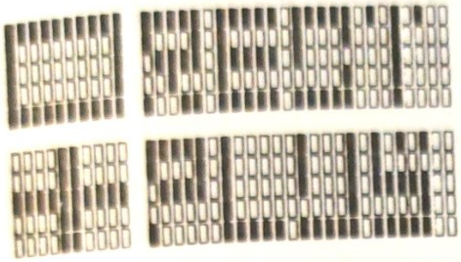

Fig. 5 *Typical recall at 75% random synaptic disconnection*

upto 50% clustered damage and upto 75% of the other kinds of damage. In other words, a BAM subjected to gradual random damage will continue to produce meaningful results until 75% of its synapses are distributed, while for localised ("traumatic") damage it will be disabled at about 50% disturbance onwards. It is tempting, though speculative, to extrapolate this to biological neural networks where also gradual synaptic damage, which takes place throughout its lifetime, causes observable memory errors only after about 75% of the life of the network is over while accidental lesions in the network, which effect much smaller sections of it, cause disproportionately larger disorders of recall.

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