IMPROVED TRINARY ASSOCIATIVE MEMORY FOR CHARACTER RECOGNITION

Farid Ahmed , A. A. S. Awwal and C. L. Philip Chen
Wright State University
Computer Science & Engineering Department
Dayton, OH 45435.

Abstract

Character recognition by trinary associative memory (TAM) neural network model is investigated. Three different inner product thresholding schemes, namely, zero plus average thresholding, arithmetic mean thresholding and a novel adaptive thresholding are examined. It is shown that the novel threshold prescription with the permanent inhibition scheme enhances the convergence as well as storage capacity of the inner product associative memory.

1 Introduction

Retrieval of information from partial representation is an important task of pattern recognition which can be performed by associative memory [1]. Hopfield memory [2], inner product model [3] and their optical implementation [4-7] have been utilized for such task. Studies indicate that the convergence and storage capacity of such memory models depend heavily on input representation, memory retrieval scheme and storage prescription. Various methods [8-15] of neuron representation, storage structure have been proposed. Trinary associative memory has been shown to have better convergence and storage capacity than normal Hopfield implementation. However, when applied to character recognition, as the number of stored patterns is increased, the number of correct convergences reduces drastically using only the average thresholding. Usually the number of stored patterns for correct convergence is $S < .15L$, when L is the number of elements in the stored vector. In the present work, we show that, by incorporating a novel adaptive threshold scheme, storage capacity and convergence improves drammatically.

2 The Inner Product Model

The memory model consists of a collection of stored vectors in bipolar binary. The input vector V^{in} is represented in trinary: the known portion is represented in bipolar binary while the unknown part, by 0's.

The Retrieval Process : The input vector forms N inner products (IP) with all the N stored bipolar vectors. These inner products are thresholded and then a linear sum of the vectors weighted by inner products yeilds the retrieved vector. Mathematically, The estimated vector V^{es} is found from the stored vectors $V^{st,k}$ using the relationship,

$$V_i^{es} = \operatorname{sgn}[\sum_{k=1}^{M} V_i^{st,k} W^k] \tag{1}$$

where,

M is the number of stored patterns having inner products above a threshold.

W^k is the inner product of the input vector, V^{in}, to any stored vector $V^{st,k}$ and is given by

$$W^k = \sum_{j=1}^{n} V_j^{st,k} V_j^{in} \tag{2}$$

This estimated vector is fedback as new input, V^{in}, and the process is continued until a stable output is obtained. In arithmetic mean thresholding, the IP threshold value equals the mean of the IP's. In zero thresholding, the threshold is calculated after the negative IP's are disregarded.

CH3158-3/92/0000-0905 $1.00 © 1992 IEEE

3 Simulation

To test the new thresholding scheme, the model is utilized to recognize the English characters from their partial inputs. Each of the 26 english characters is stored in 9×12 matrix form in bipolar binary representation as illustrated in Fig. 1. In the previous trinary model [8] , the threshold used in the inner product domain was the average value of the inner products. In this work, average inner product, and adaptive thresholding scheme with/without permanent inhibition are compared and the superiority of the novel scheme is established.

The partial inputs in this simulation are formed by zeroing some of the rows of the character matrix. These are called missing rows. The inner product of the input with any of the stored vectors gives the degree of similarity between these two. Some of the inner products are positive and some are negative. Positive inner products give some degree of similarity. However, negative inner products indicate that they are highly dissimilar. To prohibit the contribution of these vectors in forming the final vector, average thresholding is used after the negative inner products are taken out.

Table I :Convergence with Average Thresholding

Number of Missing Rows	Number of Convergence		
	A	B	C
0	4	9	15
4(0-3)	3	4	15
6(0-5)	1	1	10
6(6-11)	1	5	8
10(0-9)	0	0	5

A- Averaging all inner products (no inhibition)
B- Averaging +ve inner products (no inhibition)
C- Averaging all inner products (Permanent inhibition)

The number of convergences, when the average is calculated taking all the inner products, positive and negative, is quite low as shown in Column A of the table. The negative inner product causes the threshold to be too small, bringing more characters into competition, and thus resulting in poor convergence. To overcome this, next the negative inner products are not considered in average calculation. As a result, average and thereby, threshold value is increased, with the resulting increase in the number of convergences, as evidenced in column B.

Now, in order to reduce number of competing vectors, inner products less than the threshold value are inhibited permanently. Thus, the corresponding characters are inhibited permanently in the following iterations and cannot be candidates for converged vector. Although the number of correct convergences increases, as is evidenved from Column C, still the number of stable states, even with 100% correct input is about half of the stored vectors.

It is noted that, during the first few iterations, the average is still very small. Thus not too many vectors are inhibited. This low threshold problem is overcome by considering only the positive inner products in the average calculation. At this stage, 22 out of 26 convergences were obtained for no missing element in the input, as is shown in Table II.

Table II :Convergence with Permanent Inhibition

Number of Missing Rows	Number of Convergence
0	22
4(0-3)	19
4(8-11)	18
6(0-5)	12
6(6-11)	15
10(0-9)	7
10(2-11)	7

In course of looking forward to further development, it was noticed that in all the previous cases, the threshold value was simply equal to the average. In a statistical distribution, the mean and median are usually very close to each other. Thus, approximately 50% of the inputs after the first iteration still come into competition as a probable candidate for convergence. This is confirmed by our simulation. Studying the threshold at each iteration and the consequent number of uninhibited inputs, it was inferred that if the threshold value could be increased, at the initial stage, then fewer stored patterns would have come into competition. Next, the convergence is estimated by randomly scaling the average and adding some dc component. Results with the threshold are listed in Table III.

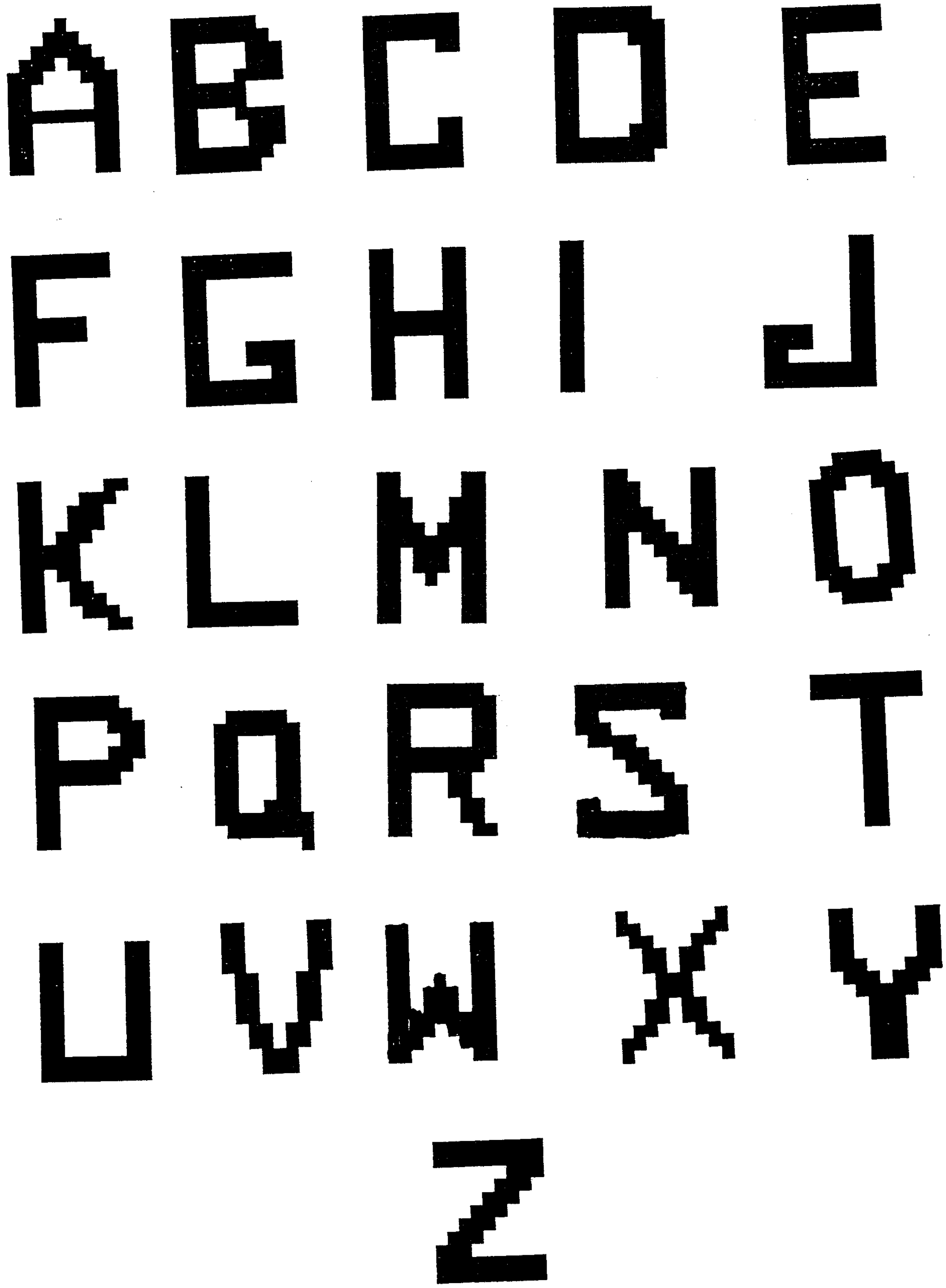

Fig. 1 Stored Characters

Table III : Development of the Threshold Scheme

Modification Scheme	Threshold Value	Number of Convergence
Adding a Constant offset	avg + 1	21
	avg + 5	23
	avg + 20	20
Scaling Only	1.2(avg)	22
	1.1(avg)	23
Scaling and Adding Offset	1.1(avg) + 1	23
	1.1(avg) + 2	24
	1.1(avg) + 3	24
	1.1(avg) + 4	24
	1.1(avg) + 5	24
	1.1(avg) + 7	21
	1.1(avg) + 15	13

This increment of the threshold value increased the number of convergence. It was observed that at the later stages of iterations, the number of competitors is less. Therefore, to improve the convergence, the threshold was kept at a higher value at the beginning of iteration, while at the end, it was set to a lower value. This was accomplished by setting Threshold=-0.6 $\times$avg + Number of Uncorrupted Elements . With this modification convergence is found to improve drammatically. The results are listed in Table IV. Note that the estimation of the percentage of missing elements is used directly to improve the convergences. This is analogous to signal-to-noise ratio estimate of the input, frequently used in signal processing.

Table IV : Convergence with Adaptive Threshold

Number of Missing Rows	Number of Convergence
0	26
4(0-3)	26
6(0-5)	25
6(6-11)	25
10(0-9)	9
10(2-11)	16

It is surprising to see that even with 50% missing rows, the number of correct converged vector is over 96%. Note the last row with 20% retained information is able to recognize 61% of the stored characters.

The 5th row shows that, with the bottom two rows preserved, the convergences are worse than when the top two rows are kept intact. This is logical, since the character contains more information on the top rows than on the bottom ones.

4 Optical Implementation

A ferroelectric liquid crystal spatial light modulator (SLM) can be used to realize the TAM. The SLM can rotate the direction of polarization of an incoming polarized light depending on the applied voltage. The bipolar coding can be performed using the SLM to encode the +1 and -1 by means of two states (rotation or no rotation) of the SLM. The SLM will be used to store both the bipolar vectors and the memory matrix. Input of 1 is represented by V light and a stored 1 , by the no-rotation operation. Thus when these two literals are multiplied, the output V light will denote a product of 1. Similarly an H light will denote -1, a rotation operation at the SLM will denote a stored -1, the product of the two is a V light, which denotes a +1. Note also that a V light multiplied by a rotation will become an H representing a -1. Thus with the FLC SLM could be used to perform bipolar multiplication. The bipolar results are collected in pair of detector arrays after a polarizing beam splitter. They are summed electronically to form the inner product value. After the inner product threshold, they are used to illuminate the SLM to form the output vector after thresholding. The gray level modulation required for representing the analog inner product can be achieved using SLM in gray mode or using additional LC TV.

5 Conclusion

A novel thresholding measure for the trinary inner product memory model is compared with other thresholding scheme. The proposed scheme is found to be very effective in increasing the storage capacity. The number of characters converged successfully was also increased with fewer iterations.

6 References

1. T. Kohonen, "Content Addressable memories," Springer-Verlag, NY, 1980.

2. J. J. Hopfield, "Neural networks and physical systems with emergent Collective computational abilities", Proc. Natl. Acad. Sci. USA, Vol. 79, p.2554, 1982.

3. S. Y. Kung and H. K. Liu, "An optical inner product Array Processor for Associative retrieval," Nonlinear optics and application, Proc. SPIE 613, p. 214, 1986.

4. J.S. Bayley and M. A. Fiddy, "On the use of the Hopfield Model for Optical Pattern Recognition," Opt. Commun. Vol. 64, p. 105, 1987.

5. N. H. Farhat, D. Psaltis, A. Prata, and E. Peak, "Optical implementation of the Hopfield Model", Appl. Opt., Vol. 24, p.1469, 1985.

6. K. M. Johnson, and G. Moddel, " Motivations for Using Ferroelectric Liquid Crystal Spatial Light Modulators in Neurocomputing," Applied Optics, pp. 4888-4899, 1989.

7. S. H. Song and S. S. Lee, "Properties of holographic associative memory prepared by the polarization encoding process," Appl. Opt., Vol. 24, p.1469, 1985.

8. A. A. S. Awwal, M. A. Karim, and H. K. Liu, "Recognition of Machine Objects Using Trinary Associative Memory," Opt. Engg., p. 537, 1989.

9. A. A. S. Awwal, M. A. Karim and H. K. Liu , "Associative Memory : An Optimum Binary Neuron Representations", Optical Pattern Recognition, H. K. Liu Ed., Proc. SPIE, Vol. 1053, pp. 17-29, June 1989.

10. M. A. Karim and A. A. S. Awwal, "Convergence Mechanism of Associative Memory", Proceedings of NAECON Conference, pp. 698-704, Dayton, Ohio, May, 1989.

11. B. Macukow, Henri H. Arsenault, "Modification of the threshold condition for a content addressable memory based on Hopfield Model," Appl. Opt., Vol 26(1),p. 34-36, 1986.

12. F. Ahmed, A.A.S. Awwal and C. L. Philip Chen, "Character Recognition using trinary associative memory neural network," presented at OSA 1991 annual meeting (San Jose, Calif. Nov. 1991), paper Thx6.

13. A.A.S. Awwal, M.A. Karim and H.K. Liu," Associative Memory: An optimum binary neuron representation", Optical Pattern Recognition, Proc. SPIE, 1989.

14. G.R. Gindi, A.F. Gmitro and K. Parthasarathy, "Hopfield model Associative memory with nonzero diagonal terms in memory matrix," Appl. Opt. 27,p. 129,1988.

15. A. K. Cherri, A. A. S. Awwal, and M. A. Karim, "Character Recognition using a Trinary Associative Memory", Technical Digest of the Annual Meeting of Optical Society of America, p. 190, Orlando, Florida, October 1989.

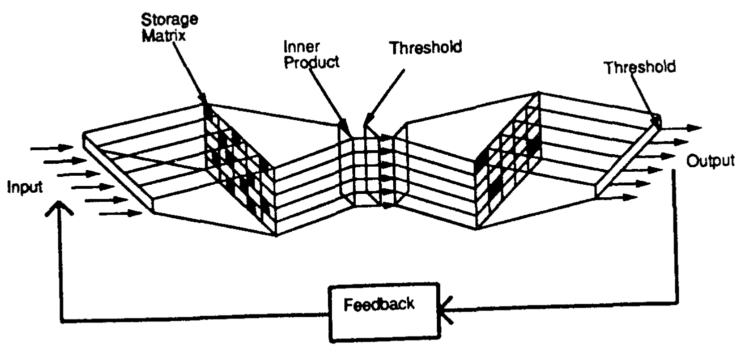

Fig 2 : Optical Implementation of Character Recognition