改良型 IPA 神經網路模式
The Enhanced Inter Pattern Associative Neural Network

沈林弘 楊昌彪
Lin-Hung Shen Chang-Biau Yang
Department of Applied Mathematics
National Sun Yat-Sen University

汪啓茂
Chii-Maw Uang
Department of Electronic Engineering
Chinese Air Force Academy

摘要

IPA 類神經網路是一個有效的網路模式. 它的互聯巨陣是經由激勵及抑制機制的邏輯運算而得. 此文將探討此邏輯運算所造成的應用限制. 和改善的方法. 電腦模擬結果證明這些改善的方法確實有效.
關鍵字: IPA 類神經網路, 圖像識別, 聯想記憶體.

Abstract

The Inter Pattern Associative neural network is an efficient model for both pattern recognition and associative memory. In this paper, we will discuss the limitation (storage capacity) of the original IPA model caused by the logic operations, and propose some modified IPA models for improving the performance. The computer simulation results show that the modified models have greatly improved the network performance.
Keywords: *Inter Pattern Associative (IPA) neural network, pattern recognition, associative memory.*

1. Introduction

The Inter Pattern Associative (IPA) neural network model[1,2], proposed by T. W. Lu and F. T. S. Yu, is based on the association between reference patterns. The association of this model not only considers the common but also emphasizes the special features among the reference patterns by applying a series of logic operations. Where the reference patterns are similar to each other (e.g., human faces, fingerprints, handwritten characters), the special features of each pattern become very important in pattern recognition. The model has been proved as an efficient model for both pattern recognition and associative memory[3-10].

In IPA model, the weight is constructed by using logic operations[1,2] based on excitation and inhibition relations. However, the contribution to the network performance of the excitatory and inhibitory links are not equal. It is the logic operation that causes the storage capacity of the original IPA model been greatly limited. We will discuss its limitation in section 2. Actually, the performance of the original IPA model is limited by the inhibit logic operation. To avoid these limitations, we propose some modified IPA models, which are the variation of the original IPA model. These models include:

(1) Enhanced IPA (EIPA) model: In the original IPA model, a logic "0" is only provided for inhibition reference. We will show that both logic "1", and "0" are needed to consider separately to get better performance.

(2) Unipolar Enhanced IPA (UEIPA) model: Two interconnection weight matrix (IWM) are constructed, one is based on excitatory signal, while another is based on inhibitory signal.

(3) Auto threshold IPA model: Naturally, each neuron should has its own unique threshold. The threshold is determined by the network architecture and also the whole memorized patterns.

They will be discussed in section 3, 4, 5, respectively.

2. The Limitation of the IPA Model

Generally speaking, the storage capacity of an associative memory should be increased as the number of neurons are increased. However, we found that the storage capacity of the IPA model is not so good as they discussed in [1,2]. The main reason is that the contribution to the network performance of the excitatory links is not the same as the inhibitory links. The other reason is that after a series of logic operations a side-effect of exclusion will be produced, which will reduce the number of excitatory links in the interconnection weight matrix (IWM), as the number of stored pattern are increased. The upper bond of the storage capacity of IPA model can be easily decided by the condition of the number of "1" existed in the IWM. If the elements "1" in the IWM are reduced to only those included along the main diagonal line (in IPA model, the elements in the diagonal line should be 1) then upper bond is reached. Based on this definition, we have a computer simulation result shown in Fig. 1. The x-axis denotes the number of neurons in nxn form, for example, 4 means 4x4, and 7 means 7x7. The y-axis represents the upper bond of the storage capacity. The five curves denote the percentage of the number of 1 presented in each test pattern, which are 30%, 40%, 50%, 60% and 70%, respectively.

Looking inside the figure 1, we found that n more than 30, on the x-axis, the number of neurons are increased rapidly, while the upper bond of the storage capacity, on the y-axis, increased very few, almost no increased. This result shows that the memorizing ability of the IPA model is limited. To improve this draw back, we will provide some modified model as discussed in the following sections.

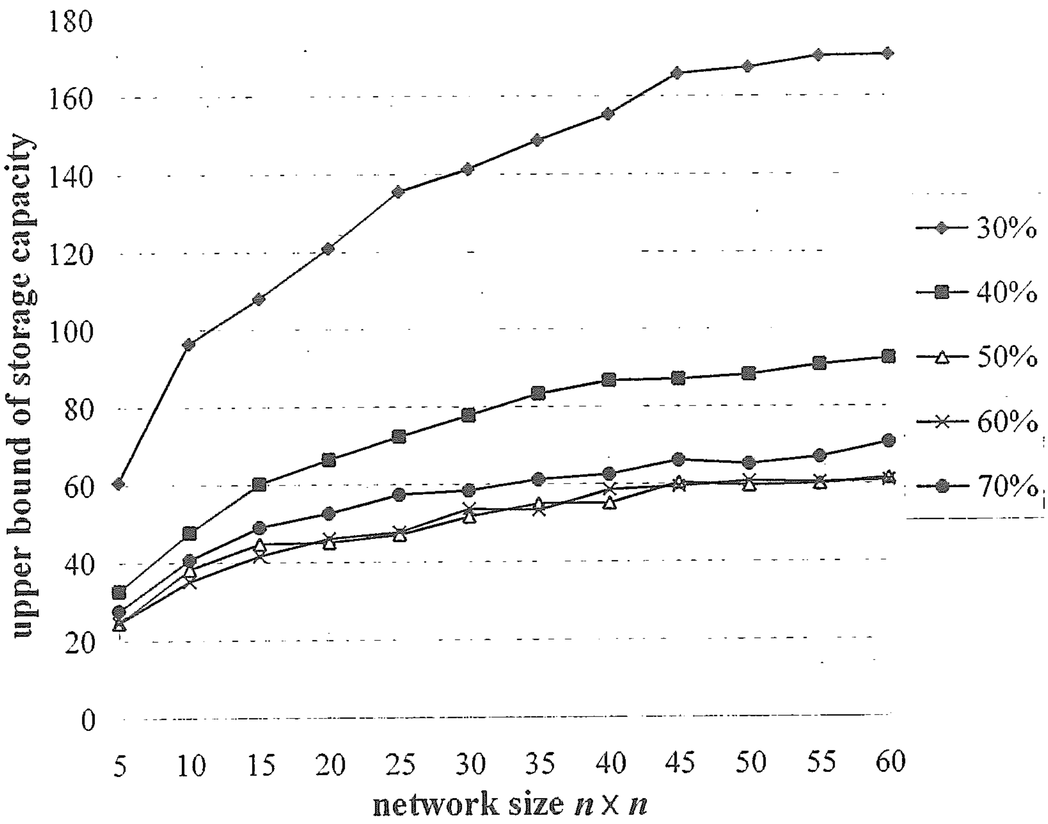

Fig.1. The upper bound of the IPA network storage capacity.

3. EIPA Model

The logic operation defined by Lu, et. al.[1-3], produces a negative bias on the inhibitory links, and reduces the network performance. To avoid this problem, we propose the EIPA model[11]. The learning steps of this model are as follows:

1. Use the original IPA algorithm to construct the IWM, named IWM_P.
2. Invert the bit of each pattern in the training set; i.e., each bit changes 1 to 0, and 0 to 1.
3. Use the inverted pattern and the original IPA algorithm to construct the IWM, named IWM_N.

The constructed IWMs, IWM_P, and IWM_N are used to memorize the stored patterns. By them, the retrieval steps of this model are as follows:

1. Use the original test pattern and IWM_P to recall the memorized pattern, named R_P.
2. Use the inverted pattern and IWM_N to recall the memorized pattern, named R_N.
3. The correct result can be obtained from R_P and R_N, that is; Output, $O = R_P - R_N$.

For easy understand, here, we give an example: Assume that we have three patterns;

$A=(1,1,0,0,1,0)$; $B=(0,1,1,0,1,1)$; $C=(1,0,1,1,0,0)$. The inverted patterns are $\bar{A}=(0,0,1,1,0,1)$; $\bar{B}=(1,0,0,1,0,0)$; $\bar{C}=(0,1,0,0,1,1)$. By EIPA algorithm, we obtain the weight matrix IWM_P and IWM_N as:

$$IWM_P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & -1 & 1 & 1 & -1 & -1 \\ 0 & 1 & 0 & -1 & 1 & 0 \\ -1 & 1 & 1 & -1 & 1 & 1 \end{bmatrix} \text{ and}$$

$$IWM_N = \begin{bmatrix} 1 & -1 & -1 & 1 & -1 & -1 \\ -1 & 1 & -1 & -1 & 1 & 1 \\ -1 & -1 & 1 & 1 & -1 & 1 \\ 0 & -1 & 0 & 1 & -1 & 0 \\ -1 & 1 & -1 & -1 & 1 & 1 \\ -1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

If test pattern A will be recalled, then $R_P = A(IWM_P) = (1,2,0,-2,2,-1)$, and $R_N = \bar{A}\,(IWM_N) = (-2,-2,1,2,-2,2)$. The correct result is $O = R_P - R_N = (3,4,-1,-4,4,-3)$. After thresholding we obtain recalled pattern A = (1,1,0,0,1,0). This is what we stored in the EIPA memory.

4. UEIPA Model

Uang et. al.[7,8], have proposed a unipolar IPA model, which eliminates all the inhibitory links, and showed only slightly effect on the network performance. As we mention above, the logic operations of the IPA model intend to make discrimination between excitatory and inhibitory links. Consider in the test patterns, if we only pick element 1 as the excitation requirement to construct the unipolr IWM (named $UIWM_P$), and also only pick element 0 as the excitation requirement to construct the another unipolr IWM (named $UIWM_N$), then both of them have the same contribution to the network performance. Hence, we can use this ideal to propose Unipolar Enhanced IPA (UIPA) model[11]. Again, the learning steps of this model are as follows:

1. Use the training patterns and unipolar IPA algorithm to construct the IWM, named $UIWM_P$.
2. Invert the training patterns; i.e., changes 1 to 0, and 0 to 1.
3. Use the inverted pattern and the unipolar IPA algorithm to construct the IWM, named $UIWM_N$.

The retrieval steps of this model are as follows:

1. Use the test pattern and $UIWM_P$ to recall the memorized pattern, named U_P.
2. Use the inverted pattern and $UIWM_N$ to recall the memorized pattern, named U_N.
3. The correct result can be obtained from R_P and R_N, that is; Output, $O = U_P - U_N$.

For easy understand, we again use the previous example, then we construct $UIWM_P$ and $UIWM_N$ as:

$$UIWM_P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 & 1 \end{bmatrix} \text{ and}$$

$$UIWM_N = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

If test pattern A will be recalled, then $U_P = A(UIWM_P) = (1,2,0,0,2,0)$, and $U_N = \bar{A}\,(UIWM_N) = (0,0,1,2,0,2)$. The correct result is $O = U_P - U_N = (1,2,-1,-2,2,-2)$. After thresholding we obtain recalled pattern A = (1,1,0,0,1,0). This is what we stored in the UEIPA memory.

5. Adaptive Threshold Algorithm for IPA Model

The threshold value plays a main role before output neuron been set. Naturally, each neuron should has its unique threshold value which depends on the pattern structure of the whole memorized patterns. Mu et. al., propose an adaptive threshold technique on the Hopfield model[5]. Slightly modified, the concept can also be adapted for using in the IPA model. Because the IPA model using excitatory and inhibitory links to associate the neuron relationships among the other patterns, which will produce a different bias on each neuron. This bias causes a shift of threshold value. Thus, setting a fixed threshold at 0 for all neurons is not suitable, and causes to increase the error rate. We have proposed a procedure for the IPA models to decide the threshold value of each neuron, the detail procedure was discussed in [11].

6. Computer Simulation

In our simulation, we let the size of test pattern is 10x10 (100 neurons). Each pattern contains almost 50% of the elements of 1, and 0, which are generated randomly. Each item of data is averaged from the result of 1000 times. The noise bits are additive, and are randomly added to the pattern. For all tables, because the number of neuron is 100, the number of percentage is also the number of error bits, as well as the number of recalled error bits. Where the recalled error bits over the noise bits can be seen as the storage capacity of the model. From table 1, we can see that if the number of neuron is 100, then the storage capacity of the IPA model is 8. While in table 6, the capacity is much more over than 10. Table 1-3 show the network performance of IPA, EIPA, and UEIPA model, respectively, without adaptive threshold. While table 4-6 are with adaptive threshold[11].

Stored patterns	The number of error bits in each pattern												
	Noise ratio												
	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	12%	15%
2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0.13	0.15	0.23	0.98	1.00	1.25	3.23	3.93	5.90	8.63
6	0	0.53	1.03	1.82	2.75	3.58	4.43	5.87	6.48	7.33	8.08	10.1	14.1
8	0	1.39	2.60	4.11	5.20	6.84	7.75	8.85	9.84	10.7	11.6	13.5	17.7
10	0	2.71	3.45	5.13	6.08	8.85	9.46	10.6	12.0	12.0	13.0	16.0	19.9

Table 1. The results of the original IPA model.

Stored patterns	The number of error bits in each pattern												
	Noise ratio												
	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	12%	15%
2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0.15	0.15	0.53	1.90	2.45	6.40	11.3
6	0	0.08	0.42	1.22	1.77	2.68	3.40	4.95	5.00	6.75	7.27	9.72	14.2
8	0	0.69	1.78	3.35	4.19	5.54	6.83	7.98	9.13	9.86	10.9	12.7	16.8
10	0	1.35	2.67	4.29	5.31	68.1	8.27	9.88	10.7	11.4	12.5	15.2	19.2

Table 2. The results of the EIPA model.

Stored patterns	The number of error bits in each pattern												
	Noise ratio												
	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	12%	15%
2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0.08	0.08	0.63	0.97	1.00	2.25	3.05	3.10	5.73	9.23
6	0	0.15	0.67	1.32	2.10	3.03	4.03	4.75	5.77	6.47	6.82	9.10	12.9
8	0	0.86	1.60	2.79	3.64	4.74	6.34	7.63	8.29	9.23	10.4	12.6	15.7
10	0	1.05	2.04	3.34	4.33	5.34	7.25	8.49	8.99	10.4	11.1	13.9	17.3

Table 3. The results of the UEIPA model.

Stored patterns	The number of error bits in each pattern												
	Noise ratio												
	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	12%	15%
2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0.02	0.03	0.03	0.05	0.05	0.18	0.28	2.33
8	0	0.05	0.16	0.16	0.39	0.71	0.82	1.12	1.75	1.85	2.41	3.74	7.46
10	0	0.80	0.97	1.19	1.59	3.30	3.38	4.15	5.20	5.38	6.04	8.56	13.6

Table 4 The original IPA model with adaptive thresholds.

Stored patterns	The number of error bits in each pattern												
	Noise ratio												
	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	12%	15%
2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0.12
8	0	0	0	0.01	0.04	0.08	0.10	0.13	0.15	0.16	0.26	0.49	2.39
10	0	0.02	0.11	0.14	0.33	0.52	0.76	0.95	1.32	1.48	1.74	2.76	6.58

Table 5 The EIPA model with adaptive thresholds.

Stored patterns	The number of error bits in each pattern												
	Noise ratio												
	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	12%	15%
2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0.13
6	0	0	0	0.02	0.02	0.03	0.07	0.07	0.08	0.18	0.35	0.47	1.87
8	0	0.08	0.11	0.19	0.24	0.50	0.78	1.05	1.08	1.44	2.01	2.64	5.41
10	0	0.29	0.56	1.08	1.30	1.86	2.44	3.00	3.55	4.01	4.56	6.40	9.58

Table 6 The UEIPA model with adaptive thresholds.

A real world application simulation also carried out in our experiments. We have used a set of eight 32x32 pixel patterns shown in Fig.2 as the training set to construct the IWM for the E-IPA model and UE-IPA model. A series of input exemplars which are embedded in 10% additive noise are presented in Fig. 3 for testing. The corresponding exemplars retrieved by the original IPA model, the E-IPA model and the UE-IPA model which are without adaptive threshold, are shown in Fig. 4, Fig. 5, and Fig. 6 respectively. While which are with adaptive threshold, are shown in Fig. 7, Fig. 8, and Fig. 9 respectively[11].

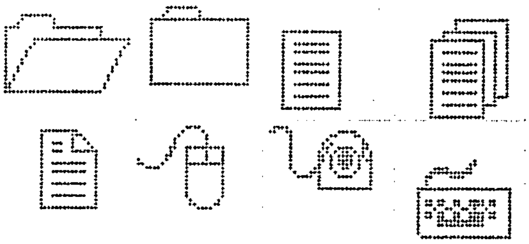

Fig. 2. The original patterns for learning.

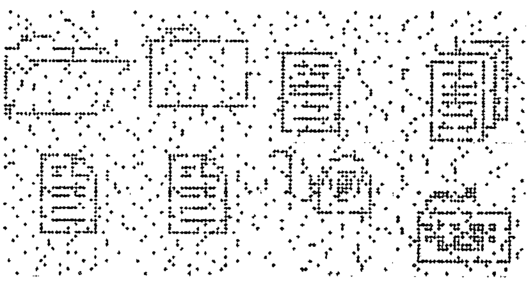

Fig. 3. 10% additive noise for testing.

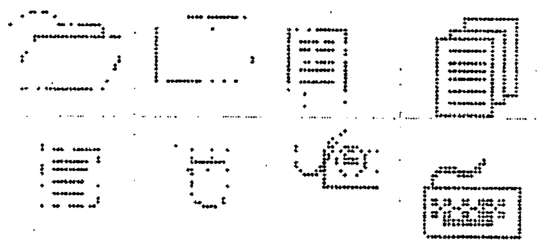

Fig. 4 The patterns retrieved by the original IPA without adaptive thresholds.

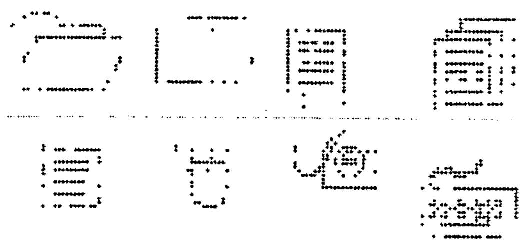

Figure 5 The patterns retrieved by the EIPA without adaptive thresholds.

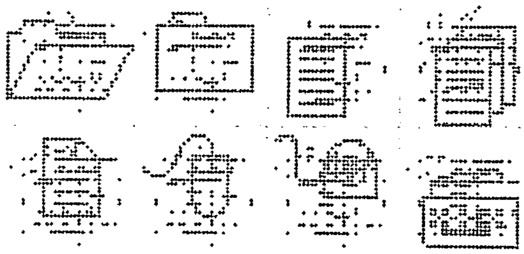

Fig. 6. The patterns retrieved by the UEIPA without adaptive thresholds.

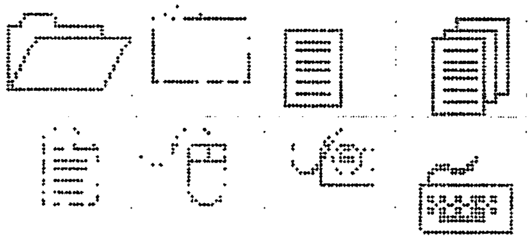

Fig. 7. The patterns retrieved by the original IPA with adaptive thresholds.

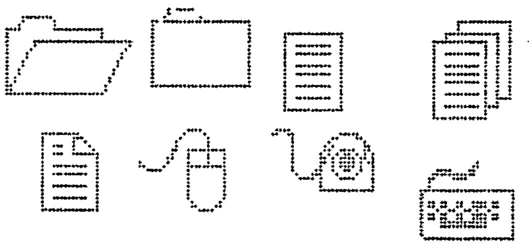

Fig. 8. The patterns retrieved by the EIPA with adaptive thresholds.

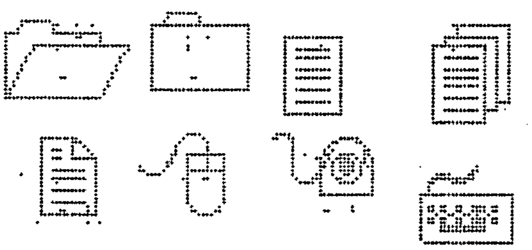

Fig. 9. The patterns retrieved by the UEIPA with adaptive thresholds.

Comparing these figures, we can see that our modified IPA models and adaptive threshold procedure have improved the network performance, including the storage capacity and noise immunity.

7. Summary

We have presented two modified IPA models; EIPA and UEIPA models, and also proposed an adaptive thresholding procedure for the IPA models. Computer simulation results show that the network performance was greatly improved. We also tested the practical application of using IPA model as associative memory for recognize some patterns, which shows that the modified IPA models indeed can meet the real world requirements.

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