HETERO ASSOCIATIVE NEURAL NETWORK FOR PATTERN RECOGNITION

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ABSTRACT

We present an Inter-Pattern Association (IPA) neural network model, in which basic logical operations are used to determine the association among common and special features of reference patterns (i.e., inter-pattern association). Hetero- and auto-associative memory are synthesized by applying a generalized logical rule. Computer simulations for pattern recognition by using the IPA model have shown a better performance and a higher storage capacity than Hopfield model. A 2-D adaptive optical neural network is used to perform parallel neurocomputations. Since the Interconnection Weight Matrix (IWM) for IPA model has a tri-state structure, the dynamic range imposed on a Spatial Light Modulator (SLM) is rather relaxed, and the interconnections are much simpler than the Hopfield model.

I. INTRODUCTION

The superior capability of human perception in pattern recognition has stimulated a great enthusiasm among neural network researchers. Mathematical modeling of various neural networks has been developed during the past several decades [1-4]. However, for recognition of a given set of reference patterns, many neural network algorithms construct the Interconnection Weight Matrix (IWM) by emphasizing on the association of the elements within each reference pattern (i.e., the intra-pattern association), while paying little attention to the association between patterns (i.e., inter-pattern association). For example, in Hopfield type neural networks[5], the outer-products of the reference patterns are added to form the IWM. This type of approach is based on the assumption that reference patterns are significantly different. However, in practice, the reference patterns are usually not independent, and the differences among the patterns are often very small (e.g. human faces, finger prints, handwritten characters, etc.). Thus it may create an unstable or ill-conditioned network. Under these circumstances, the special features of the patterns play an important role in pattern recognition. Therefore it is necessary to consider the relationships between the common and the special features among the reference patterns in constructing the IWM.

In this paper, we shall present a neural network model based on the association between reference patterns. First, this model determines the common and special features among patterns by applying logical operations on the pixels in the pattern space. Based on the relationship between the special and common features, two equivalent logical rules are presented in Sec. II to construct the excitatory and inhibitory interconnections in the network. In Sec. III, the Inter-Pattern Association (IPA) model is compared with the Hopfield model in the performance versus number of reference patterns in a noisy environment. Computer simulations of IPA model are conducted for recognizing tools of different orientations. In Sec. IV, a 2-D hybrid parallel optical neural network is used for the implementation of IPA and Hopfield models. The experimental results show that IPA model performs more effectively than Hopfield model.

II. IPA MODEL AND ASSOCIATIVE MEMORY

The information obtained from pixels in the special areas of a reference pattern is generally more important than that from the common areas (i.e. areas shared by more than one pattern) in terms of constructing the associative memory matrix for a neural network. The basic concept of IPA model is to determine whether the pixels in the pattern space belong to special or common spaces of the reference patterns, and then set the excitatory or inhibitory interconnections according to a logical relationship.

Figure 1 shows an example of a training set that consists of three overlapping patterns A, B and C in space S_1 (see Fig.1(a)), and their corresponding desired output patterns A', B' and C' in space S_2 (see Fig.1(b)). These patterns can be divide into 7 subspaces; For instance, in space S_1, subspaces I, II and III are the special areas of patterns A, B and C, respectively. IV, V and VI are the common areas of A and B, B and C, C and A, respectively, while VII is the common area of A, B and C. And the rest can be defined as an empty space Φ. Similarly, for the subspaces in S_2, as illustrated in Fig.1(b). The subspaces of S_1 and S_2 can be expressed by the following logical functions:

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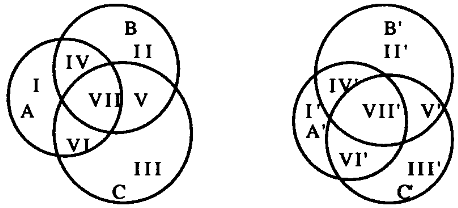


S1 S2

(a) (b)

Fig.1: (a) Common and special areas of three reference patterns, (b) corresponding desired output patterns.

$$
\begin{aligned}
&\mathrm{I} = A \wedge \overline{(B \vee C)}, && \mathrm{I}' = A' \wedge \overline{(B' \vee C')},\\
&\mathrm{II} = B \wedge \overline{(A \vee C)}, && \mathrm{II}' = B' \wedge \overline{(A' \vee C')},\\
&\mathrm{III} = C \wedge \overline{(A \vee B)}, && \mathrm{III}' = C' \wedge \overline{(A' \vee B')},\\
&\mathrm{IV} = (A \wedge B) \wedge \overline{C}, && \mathrm{IV}' = (A' \wedge B') \wedge \overline{C'}, \qquad (1)\\
&\mathrm{V} = (B \wedge C) \wedge \overline{A}, && \mathrm{V}' = (B' \wedge C') \wedge \overline{A'},\\
&\mathrm{VI} = (C \wedge A) \wedge \overline{B}, && \mathrm{VI}' = (C' \wedge A') \wedge \overline{B'},\\
&\mathrm{VII} = (A \wedge B \wedge C) \wedge \overline{\Phi}, && \mathrm{VII}' = (A' \wedge B' \wedge C') \wedge \overline{\Phi},
\end{aligned}
$$

where ' $\wedge$ ', ' $\vee$ ' and ' $\overline{\ \ }$ ' stand for the logic "AND" , "OR" and "NOT" operations, respectively.

When a pixel in area VII is on (i.e. the pixel has a value '1'), it implies that there is an input, but we can not judge whether it belongs to any of the A, B, and C patterns. Thus this pixel can only excite the pixels within area VII', for which it has no connection with the pixels in other areas belong to space S_2.

When a pixel in area V is on, it implies that the input pattern is not A, but we can not tell whether it belongs to pattern B or C. Thus this pixel should excite the pixels in areas V' and VII', but inhibit the pixels in area I'. Similarly, logical operations can also be applied to pixels in area IV or VI.

For the case when a pixel is on in area I, it implies that pattern A is appeared at the input end. Therefore, this pixel can excite all the pixels in pattern A' (i.e. areas I', IV', VI' and VII'), but inhibit the pixels in areas ($B' \vee C'$) $\wedge \overline{A'}$ (i.e. areas II', III' and V'). Similarly, for the pixels in area II or III , they must excite area B' or C', and inhibit areas I', III' and VI', or areas I', II' and IV', respectively.

In view of eq.(1), the descriptive logic can be summarized in the following rule, which is extented for any number of reference patterns:

<u>Rule A:</u>

An arbitrary subspace X in input space S_1 can always be represented by the following expression:

$$X = P \wedge \overline{Q}, \qquad (2)$$

where $P = p_1 \wedge p_2 \wedge \ldots \wedge p_n$, (3)

$$Q = q_1 \vee q_2 \vee \ldots \vee q_m \ . \qquad (4)$$

$p_1, p_2, \ldots, p_n$, are input reference patterns that occupy the subspace X , $q_1, q_2, \ldots q_m$ are input reference patterns that do not belong to X, *n* and *m* are two positive integers, and $n+m = M$ the total number of reference patterns. Similarly, the logical operation in subspace X' in S_2 can also be written in the same form, such as:

$$X' = P' \wedge \overline{Q'}, \qquad (2')$$

where $P' = p'_1 \wedge p'_2 \wedge \ldots \wedge p'_n$, (3')

$$Q' = q'_1 \vee q'_2 \vee \ldots \vee q'_m \ . \qquad (4')$$

The pixels in area *X* must excite (i.e. having positive connections with) all the pixels in area P', inhibit (i.e. having negative connections with) all the pixels in area $Q' \wedge \overline{P''}$, where P'' is defined by

$$P'' = p'_1 \vee p'_2 \vee \ldots \vee p'_n, \qquad (5)$$

and have no connection with the remaining areas in S_2. For simplicity, the connection strengths (i.e. weights) are defined as '1' for positive connections; '-1' for negative connections; and '0' for no connection. Thus the IPA neural network can be constructed in a simple tri-state structure.

If patterns in S2 are the same as the patterns in S1, then Rule A can be used to construct the auto-associative memory.

To illustrate further the construction of the IPA model, we shall synthesize an auto-associative memory for A, B and C, three 2x2 array patterns as shown in Figs. 2(a), (b) and (c), respectively. The pixel-pattern relationship is given in Table I. It is apparent that pixel 1 represents the common feature of A, B and C, pixel 2 is the common feature of A and B, pixel 3 the common feature of A and C, and pixel 4 represents the special feature of C.

By applying Rule A to the three reference patterns A, B and C, a tri-state neural network can be constructed, as illustrated in Fig. 2(d). This is a single layer neural network with 4 neurons at the input end and 4 neurons at the output end. Each neuron is matched to one pixel of the input/output patterns. For example, the 1st input neuron corresponds to pixel 1 of the input pattern, and excites only the 1st output neuron. The 2nd input neuron (the corresponding pixel belongs to patterns A anb B) excites both the 1st and the 2nd output neurons, while inhibiting the 4th output neuron, which belongs to the special area of pattern C.

It is interesting to analyze the structure of the IWM. Since the reference patterns are in 2-D form, the weight matrix becomes a 4-D matrix. We can partition the 4-D IWM into a 2-D submatrix array [6], as illustrated in Fig.2(e). The IWM can be divided into 4 blocks. Each block corresponds to one output neuron. The 4 elements in one block represent the 4 neurons in the input end. For example, since all the 4 elements in the upper-left block have value 1, it indicates that either one of the 4 input neurons can excite the 1st ouput neuron. In the upper-right block, as another example, the 1st and 3rd elememts are 0, the 2nd element has value 1, and the 4th element is -1. From this example we can determine that the 1st and 3rd input neurons have no connection to the 2nd output neuron, the 2nd input neuron excites the 2nd output neuron, and the 4th input neuron inhibits the 2nd output neuron.

In order to simplify the algebraic operations, an equivalent rule, Rule B, is developed as follows, which can be used to construct the IWM by examining the pixel-pattern relationships.

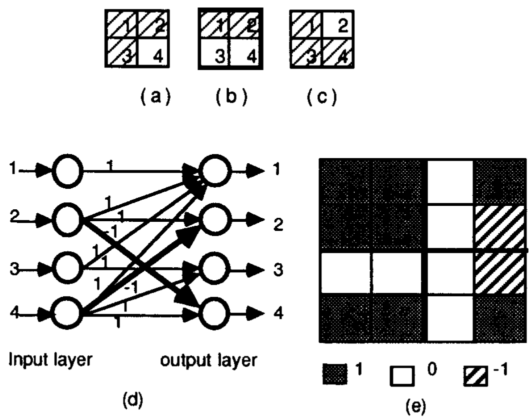


Fig.2: Constructing an auto-associative memory matrix using IPA model: (a), (b), and (c) represent three 2x2 reference patterns, (d) a tri-state neural network, (e) interconnection weight matrix.

Pixel / Pattern	1	2	3	4
A	1	1	1	0
B	1	1	0	0
C	1	0	1	1

Table I: Pixel-pattern relationship of the three reference patterns in Fig.2.

Rule B:

Let us define $D_{l,i}$ as a 2-D matrix that corresponds to the 2-D pixel-pattern array in table I, where l and i denote the row and column number, and $D'_{l,i}$ as the corresponding pixel-pattern matrix for desired output patterns. Let d_i be the number of patterns that are bright (i.e. in state '1') at the ith pixel, then it can be determined by summing the elements in the ith column of table I, i.e.,

$$d_i = \sum_{l=1}^{M} D_{l,i} \,, \tag{6}$$

$$d'_j = \sum_{l=1}^{M} D'_{l,j} \,. \tag{7}$$

Let us also define

$$K_{ij} = \sum_{l=1}^{M} D_{l,i} D'_{l,j} \,. \tag{8}$$

Then we shall now construct an IPA neural network by applying the following logical rules:

(1) If $K_{ij} = d_i$, this means that the patterns sharing the *ith* pixel in S_1 are included by patterns of which the corresponding patterns in S_2 share the *jth* pixel. thus pixel i in S_1 should excite pixel j in S_2;

(2) If $0 < K_{ij} < d_i$, this implies that some patterns sharing the *ith* pixel do not share the *jth* pixel, thus the *ith* pixel in S_1 can not excite the *jth* pixel in S_2.

(3) If $K_{ij} = 0$,

when $d_i \neq 0$, and $d'_j \neq 0$, which means that no common pattern shares pixels i and j, then pixel i in S_1 must inhibit pixel j in S_2;

when $d_i = 0$ and/or $d'_j = 0$, then pixel i must have no connection to pixel j.

We stress that, these logical rules for constructing the IWMs are rather straight forward, which are suitable for computer implementations. Notice that, the IWMs computed by Rule B are equivalent to those obtained by Rule A.

III. COMPARISON WITH THE HOPFIELD MODEL

It is the differences, rather than the similarities among patterns, used for pattern recognition. For example, the outline of the eyes, nose and mouth are common features in all human faces. People distinguish different persons by the differences, rather than the detail of faces.

Similar to many other neural network algorithms, Hopfield model constructs the IWM by correlating the elements within each pattern, however, ignoring the relationships among the reference patterns. The IWM of Hopfield model for three reference patterns A, B and C can generally be expressed as

$$T = AA^T + BB^T + CC^T - 3I \tag{9}$$

where ' T ' stands for the transpose of the vectors and I is the unit matrix, which makes the weight matrix zero-diagonal.

If input pattern A is applied to the neural system, then the output would be

$$V = TA$$
$$= A(A^T A) + B(B^T A) + C(C^T A) - 3A \tag{10}$$

where $A^T A$ represents the autocorrelation of pattern A, while $B^T A$ and $C^T A$ are the respective cross-correlation between A and B, A and C. If the differences between A, B and C are sufficiently large, the autocorrelation of A, B or C would be much larger than the cross-correlation between them, i.e.,

$$A^T A \gg B^T A, \quad A^T A \gg C^T A \,. \tag{11}$$

Notice that, from eq. (10), pattern A has a larger weighting factor than patterns B and C, for which patterns B and C can thus be considered as noise. By choosing the proper threshold value, pattern A can be reconstructed at the output end of the neural network.

On the other hand, if A, B and C are closely similar, the inequalities of Eq. (11) are no longer held, since the weights of patterns B and C are comparable with those of pattern A. Patterns B and C can no longer be treated as noise. Thus the threshold value for Hopfield model can not be easily defined, and the neural network would become unstable.

Computer simulations of a 2-D neural network, with an 8 x 8 array neurons at the input and output ends have been conducted for both Hopfield and IPA models. The reference patterns considered are the 26 capital English letters, lined up in sequence based on the similarities of the letters, ' B ', ' P ', ' R ', ' F ', . . . , and each letter occupies with an 8 x 8 array pixels.

Figure 3 shows the output error rates as a function of reference patterns for Hopfield and IPA models under noisy conditions. The input noise levels are set at about 0%, 5% and 10%, respectively. We notice that, Hopfield model becomes unstable when four patterns ' B ', ' P ', ' R ' and 'F' are stored in the IWM, wheras IPA model is quite stable with 12 stored letters. Under the condition of noiseless input, the IPA model can produce correct results for all 26 stored letters in the IWM, wheras Hopfield model starts making significant errors when the number of reference patterns is increased to 6. From Fig. 3 we see that the IPA model is more robust and it has a larger storage capacity as compared with the Hopfield model.

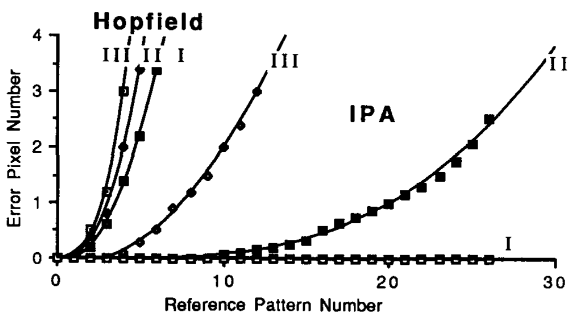
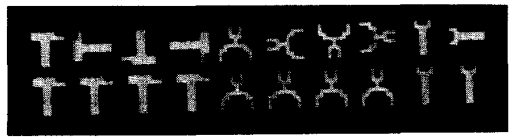


Fig.3: Comparison of IPA and Hopfield models; input noise levels: I: 0%, II: 5%, and III: 10%.

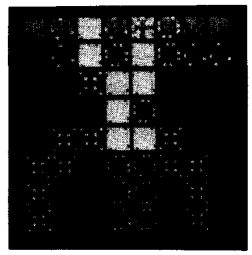
The neural network is trained to recognize tools with different orientation, as shown in Fig.4. IPA model is used to construct an Hetero-associative memory of these tools. The first row in Fig.4(a) consists of 10 training patterns. The desired output must be the correct tool, and always aligned in the up right direction, as shown in the second row of Fig.4(a). The interconnection weight matrix, built by Rule B, are rather simple, as shown in Fig.4(b), the dark parts are inhibitory weights (i.e., -1), the bright parts are exitatory weights (i.e., +1), and the medium gray level represents no connection (i.e., 0).

Figure 4(c) shows some simulated results performed by the IPA neural network. The patterns in the first and third columns are input patterns, either incomplete or with noise. After parallel processing by IPA neural network, the output patterns (i.e., the patterns in the 2nd and 4th columns) become complete patterns with correct orientation.

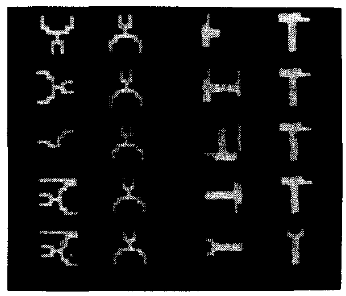
Due to limited size (eg., 64 neurons), the neural network can only be trained to recognize simple patterns with limited orientation. However, if we build a neural network with about100x100 neurans, IPA model can be used to train neural networks to perform shift and rotation invariant pattern recognition, since the IPA neural network has large storge capacity and high robustness.



(a)



(b)



(c)

Fig.4: Computer simulated results for recognizing tools of different orientations: (a) a set of training patterns, (b) an IWM generated with IPA model, (c) input/output results of the neural network.

IV. OPTICAL IMPLEMENTATION

One of the important properties of neural networks is the massive interconnection among large number of simple processing elements (i.e., neurans). The 2-D and 3-D parallel processing capabilities of optical systems make it an important candidate in solving the complex interconnection problems in neural networks [8,9,10].

An adaptive optical neural network[8] is used to implement IPA model. The optical architecture is illustrated in Fig.5. In this system a high resolution video monitor is used to display the weight matrix which was constructed with the IPA model. This proposed system differs from the matrix-vector processor of Farhat and Psaltis[9], for which the position of the input SLM and the IWM have been exchanged. We note that this arrangement makes it possible to use a video monitor for associative memory matrix generation, instead of a low

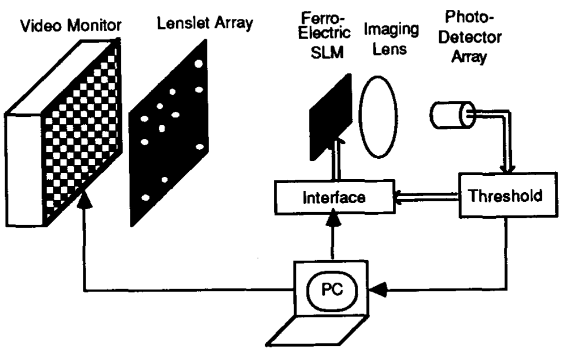


Fig.5: A 2-D hybrid optical neural network.

resolution and low contrast SLM. A lenslet array consisting of NxN small lenses is used to establish the optical interconnections between the IWM and the input pattern, where a moderate sized SLM with NxN binary pixels is served as the input device. As depicted in Fig.6, the light beam emitted for each submatrix from the video screen would be imaged by a specific lens of the lenslet array onto the input SLM. Thus an NxN number of submatrices would be added onto the input SLM. The overall transmitted light through SLM can be imaged at the ouput plane to form an NxN output array distribution, which represents the product of the 4-D matrix T and the 2-D input pattern. The output pattern can be picked up by an NxN photo-detector array for thresholding and feedback iterations.

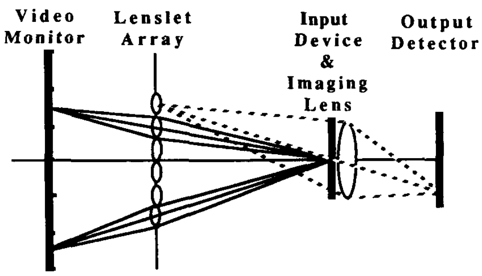


Fig.6: Illustration of optical interconnections of the neural network.

To form a closed loop neural network operation, the output signals from the detector array are fed back to the input SLM via a thresholding circuit. It is apparent, by the intervention of a computer, the proposed optical neural network can be made adaptive.

We propose that a ferroelectric liquid crystal SLM would be used as the input device of the system. Accordingly, its contrast ratio can be as high as 125:1 [11]. Since the SLM can be addressed in parallel, the detector and the input arrays can communicate in parallel. Thus the electro-optical feedback loop can be performed in a completely parallel manner. This arrangement would allow the system to operate at high-speed asynchronous mode. Thus the sequencial electronic bottleneck can be alleviated to some extend with the feedback loop. Although displaying the memory matrices using a video monitor is relatively slow, however, the programming speed of IWM is not required to match the iteration speed in the feedback loop. With reference to a 1024x1024 pixels video monitors (which are available commercially), it is possible to build a parallel hybrid optical neural network with 32x32 (i.e. 1024) neurons.

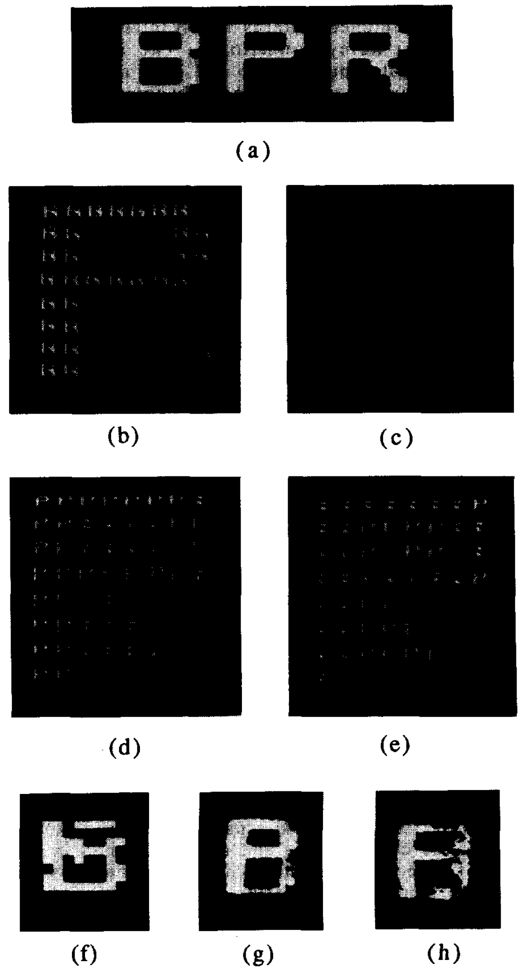


Fig.7: Experimental demonstrations obtained with the proposed optical neural network of Fig. 5, using an LCTV as an input SLM: (a) three similar English letters as reference patterns, (b & c) positive and negative parts of the IWMs of the IPA model, (d & e) positive and negative parts of the Hopfield model, (f) Input pattern , SNR = 7dB, (g) pattern reconstruction using IPA model, (h) pattern reconstruction obtained with Hopfield model.

Since the resolution requirement of the lenslet array is rather relaxing. An array of 32x32 lenses with 2.5 mm in diameter can provide at least 10 times the resolution of a commercially the TV monitor, which has a resolution of about 3 lines/mm.

However the alignment of the optical system is critical for the matrix-vector operations. The submatricies on TV screen have to be precisely imaged onto the input SLM by the lenslet array in superimposing position. Since the proposed optical neural network is essencially a close-loop feedback system, the precise alignment can be corrected by adjusting the position of each submatrix on TV screen by computer intervention, and the intensity of the TV screen can also be adjusted. Thus the proposed optical system can indeed perform in adaptive mode.

In experiments, Hopfield and IPA models are chosen to perform pattern recognition using noisy input patterns. ' B ' , ' P ' and ' R ' are three letters stored in the weight matrix as shown in Fig. 7(a). The positive and negative parts of IWMs for IPA model are shown in Figs. 7(b) and (c), while those for Hopfield model are displayed in Figs. 7(d) and (e). In comparison between these two sets of IWMs it can be seen that the IPA model has two major advantages over the Hopfield model, namely:

1. less interconnections;

and 2. fewer gray levels.

The later is significant because the IPA model requires only 3 gray levels to represent the IWM, whereas the Hopfield model needs 2M+1 gray levels, where M denotes the number of stored reference patterns.

The experimental results of these two models are obtained based on an input pattern ' B ' embedded in 30% random noise (SNR = 7 dB), as shown in Fig.7(f). The output patterns of the IPA model and the Hopfield model are shown in Figs.7(g) and (h) respectively. Because of the curvature of the video monitor screen, the output results are somewhat distorted. Nevertheless, the results obtained from the IPA model have been shown better than those obtained from the Hopfield model.

V. CONCLUSIONS

We have illustrated IPA neural network model for pattern recognition. By using a simple logical rule, the common features and the special features of the reference patterns can be obtained, and the positive, negative or no interconnections can be assigned to each neuron. The IWM can be easily formulated, which requires merely 3 gray levels. An adaptive optical neural network is used to carry out the parallel processing. Computer simulations and experimental results have shown that the IPA model can perform more effectively in terms of pattern recognition (among similar patterns) than the Hopfield model. The basic reason is that the IPA model puts more emphasis on the inter-pattern relationships, while the Hopfield model deals only the intra-pattern association.

.ACKNOWLEDGEMENT

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