

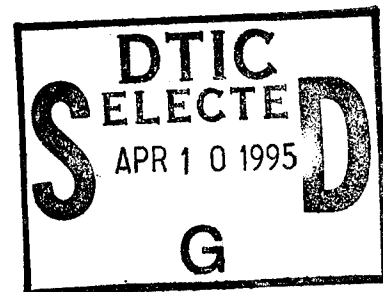
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## MULTI-VALUED NEURAL NETWORK MODIFIED MODEL AND ITS OPTICAL REALIZATION

by

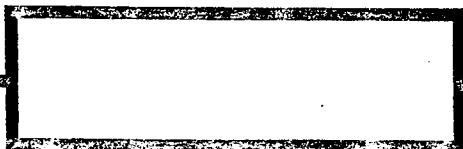
Zhu, Weili, Chen, Yansong



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MULTI-VALUED NEURAL NETWORK MODIFIED MODEL AND  
ITS OPTICAL REALIZATION<sup>1</sup>

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Zhu, Weili<sup>2</sup>, Chen, Yansong<sup>3</sup>

Abstract

This paper presents a modified optical neural network model, and the optical system, constructed with spatial light modulator PROM, can materialize the associative memory computation of such kinds of models. From the computer simulation and experimental results, it is clarified that the modified model improves cognitive ability of an optical neural network and also improves the storage capacity to a certain extent.

1. Introduction

Since at the early part of the '80s of this century Hopfield proposed his neural network physical model [1], research in such kind of computing models has become ever more widely spread and more in depth; it can be used to solve computation problems of immense amount of information [2], and also can be used to simulate the associative memory capability of the human neural network, and as long as the memory bank stays below 15 % of the total number of neurons [1], the results of searched memories have shown sufficient

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\* Numbers in margins indicate foreign pagination.  
Commas in numbers indicate decimals.

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accuracy. In 1985 Farhat and Psaltis first succeeded in applying optical methods to the realization of computation capability of the Hopfield neural network model [3], and initiated a new branch -- the optical neural network -- in the neural network computation science.

Because at present there is a limit in the direction of optical basic equipment capability, it is still rather difficult to realize multi-value or negative value of the Hopfield model. For this reason one cannot help to bring the mutually connected matrices of the model all into one (below it will be called the "return-to-one" model) in order to apply the binary characteristics of instruments, such as membrane, acoustic-optic, or electric-optic modulator, liquid crystal spatial light modulator, etc. and moreover by increasing the number of devices or sizes as a substitution for solving the negative value problems [3]. Some people use the internal storage computation method to replace the external storage computation method in order to avoid the appearance of negative values [4]. The above kind of modified model is difficult not to affect cognitive capability or convergence of the network.

This paper proposes a modified optical neural network model: the "Zheng-pu-tai" model, which has an advantage in improving the cognitive ability of the network and whose effect is clearly visible when the storage capacity is increased. This paper first explains the theory of this "Zheng-pu-tai" model, then continues on to carry out an analytic evaluation of the cognitive capability, followed by an introduction of the method to optically realize such model, and finally the paper presents the experimental results in order to carry out their analyses.

## 2. Presenting the "Zheng-pu-tai" model theory and evaluating its cognitive capability

Suppose there are M monopole 2-dimensional vectors  $V^m$  of N-unit length ( $m=1,2,\dots,M$ ), and let them be stored in a network of the external storage method, to construct the mutually connected matrices of the "Zheng-pu-tai" model as follows:

$$T_c(i, j) = \sum_{m=1}^M [V_i^m V_j^m + (1 - V_i^m)(1 - V_j^m)], \quad (i, j = 1, 2, \dots, N) \quad (1)$$

where the first term inside the square parenthesis is the external storage matrices of the stored vectors, while the 2nd term is the external storage matrices of their complimentary vectors. Obviously all the elements of matrix  $T_c$  are non-negative and multi-valued. By use of one N-dimensional 2-component vectors  $V^*$  as an input to the network to carry out the searching, one gets the output estimated value as follows:

$$V_i^* = \left[ \sum_{j=1}^N T_c(i, j) V_j^* \right]_{\alpha}, \quad (2)$$

where  $[ ]_{\alpha}$  stands for the threshold of neurons. After a repeated substitution, the output will stabilize onto vector  $V^{m_0}$ . Generally speaking,  $V^{m_0}$  must be the smallest Hamming distance stored vector of the input vector  $V^*$ ; that is, it is most similar to  $V^*$ .

As for the nature of the monopole 2-component vector adopted by this paper, one may refer to the analytic methods [5], suggested by Farhat and Psaltis, which can work out an evaluation on the cognitive capability of the "Zheng-pu-tai" model as follows:

For the sake of mathematical derivation simplicity, it is not forbidden:  $V^* = V^{m_0}$  so that by substituting Eqn. (1) into Eqn.(2), through derivation one can get

$$\hat{V}_i^{m_0} = \frac{N}{2} V_i^{m_0} + \sum_{m \neq m_0}^M a_m V_i^m + b_{i_0} \quad (3)$$

and thus the output signal-to-noise ratio becomes as follows:

$$S = \frac{N}{2 \sum_{m \neq m_0}^M a_m V_i^m} \cdot V_i^{m_0}, \quad (4)$$

among which

$$a_m = 2 \sum_{j=1}^N V_j^m V_j^{m_0} - \frac{N}{2}.$$

For a comparison, the results obtained with the Hopfield model under similar conditions are as follows:

$$\hat{V}_i^{m_0} = \left[ \sum_{j=1}^N T(i, j) V_j^{m_0} \right]_{th_0} \quad (5)$$

$$T(i, j) = \sum_{m=1}^M (2V_i^m - 1)(2V_j^m - 1) - M\delta_{ij}, \quad (6)$$

In these equations the terms of  $\delta_{ij}$  -- function can be satisfied by the condition of  $T_{ij} = 0$ , while the definition says that  $\delta_{ij} = 1$  (for  $i = j$ ) or 0 (for  $i \neq j$ ). With the precondition  $V^* = V^{m_0}$  and the substitution of Eqn. (6) into Eqn.(5), the derivation gets:

$$\hat{V}_i^{m_0} = (N - M) V_i^{m_0} + 2 \sum_{m \neq m_0}^M a_m V_i^m + c_{i_0} \quad (7)$$

One-time reiterative substitution leads to the output signal-to-noise ratio as follows:

$$S = \frac{N - M}{2 \sum_{m \neq m_0}^M a_m V_i^m} \cdot V_i^{m_0}. \quad (8)$$

By comparing Eqn. (4) with Eqn.(8), one can see that the convergence speed of the "Zheng-pu-tai" model is faster than that of the Hopfield model, and it receives very little

direct effect from  $M$ . This means that in the condition to satisfy  $M < (N/4)\ln N$  [5], these two differ only a little. However, when  $M$  increases, the signal-to-noise ratio of the Hopfield model declines drastically, to create the requirement of more iterative substitutions for computations, and also due to the decline in the cognitive capability, thus the stored vectors cannot all be recognized. Consequently, from this fact one can see that the allowable stored quantity of the "Zheng-pu-tai" model is relatively a little higher and this point will be substantiated in the following experiments.  $b_i$  and  $c_i$  in Eqn.(3) and Eqn.(7) are all constants, and their values are related to  $M$  and  $N$ , and thus they affect the selection of the threshold but do not affect the signal-to-noise ratio.

### 3. Optical realization of the "Zheng-pu-tai" model

By use of the optical system shown in Fig. 1, the optical neural network "Zheng-pu-tai" model was worked out for simulation computations, and its experimental setup is shown in the photo of Fig. 2; in Fig. 1, G and R are diode arrays to emit, respectively, green and red colors, and the former is a 2-dimensional array to be used as the external storage matrix of the input stored vector for the system; and "Zheng-pu-tai" mutually connected matrices  $T_{ci}$  were constructed step-by-step on a spatial light modulator PROM; the latter is a 1-dimensional array, to be used as the optical output of vector  $V^*$ , to search out the associative memory for the system; P and A are, respectively, the polarizer and analyzer; after the searched results have been received by utilizing CCD, the computer system helps realize the threshold computation. For the sake of simplicity, the optical photographic elements were omitted in the figure.

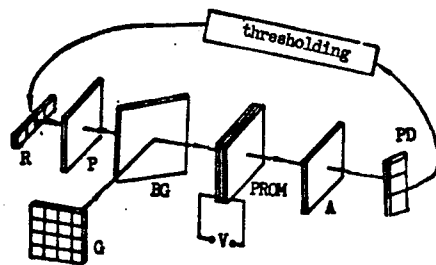


Fig. 1 A scheme of optical system for implementing neural network

R: red LED array, G: green LED array, P: polarizer, A: analyzer, BG: beam splitter, V: DC electrical power



Fig. 2 A photo of arrangement for optical neural network

Because the PROM instrument has a rather wide linear exposure region [6], thus it can pass repeatedly the exposure rays to implement the accumulated computations of the optical matrices. Every time the G-LED array is used to expose the light, there exists an external storage matrix of some stored vector (or its complimentary vector), and after 2M times of exposures, one gets their matrix-sum; that is, the "Zheng-pu-tai" mutually connected matrices  $T_{co}$  shown by Eqn. (1) use input vector  $V^*$  of the R-LED array to search out associative memories for the system, to realize the multiplication calculation of matrix  $T_c$  and vector  $V^*$  on PROM. With the optical information received by CCD, the input computer system carries out the threshold computation, then feeds back to the input terminal to carry out the next round of operations.

Because the external storage matrix of each stored vector (or the complimentary vector) are all monopole 2-dimensional matrices, thus by use of the switching on-and-off state of the G-LED one can conveniently express two value of 1-and-0 of the matrix elements, and the multi-valued characteristic of the mutually connected matrix  $T_c$  is to rely on the optical accumulative characteristics of the PROM instrument. Furthermore, the implementation of the

PROM instrument becomes an addition to the specified computational structure of the "Zheng-pu-tai" model to promote the vitality of the system, which is useful in constructing a dynamic optical neural network.

#### 4. Experimental results and analyses

By use of the "Zheng-pu-tai" model in the neural network of  $N = 35$  to carry out a computation simulation, the stored vector starts from  $M=6$  ( $M/N = 0.17$ ) to increase to  $M=12$  ( $M/N = 0.34$ ). According to the description given in the previous section, one can use the stored vector to carry out the searching job ( $V^* = V_{mo}$ ) for the network. The computed results show that when one uses a "Zheng-pu-tai" model PCM to compute, the stored vectors can be recognized in 100 times out of 100. However when the Hopfield model is being used, such rate drops down from 100% to 75%, and also the time of repetitions was obviously increased, in accordance with the previous theoretical estimations. When the return-to-one model is used in the computing, this rate also drops from 100 % for  $M = 6$  to 33% for  $M = 12$ .

By use of the optical system shown in Fig. 2 to carry out an optical simulation for the "Zheng-pu-tai" model, the magnitude of the network is  $N = 8$ , the number of stored vectors starts out at  $M = 2$  to increase to 4, and  $V^* (\neq V_{mo})$  is used to carry out the searching. As shown in Table 1, in the optical simulation results for  $M = 4$ , "0" means an accurate recognition while F stands for searching failure. For the sake of comparison, the computer simulation results carried out with the Hopfield model and the return-to-one model under similar conditions were also listed.

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Table 1 The searching results produced by computer simulation and by optical neural network ( $M=4$ )

stored vector $V^*$	input vector $V^*$	Hamming distance between $V^*$ and $V^{mo}$	expected value $V^{mo}$	result		
				POM	HM	OM
$V^1=11110000$	11110001	1, 5, 5, 8	$V^1$	0	F	F
	00101010	5, 5, 1, 5	$V^2$	0	0	0
	10110000	1, 5, 8, 5	$V^1$	0	F	F
	11000001	8, 8, 5, 1	$V^4$	0	F	F
$V^2=11001100$	11001101	5, 1, 5, 8	$V^2$	0	F	F
	10101000	8, 8, 1, 5	$V^2$	0	0	0
	11011100	8, 1, 5, 5	$V^2$	0	F	F
$V^3=10101010$	10111010	8, 5, 1, 5	$V^2$	0	F	F
	11111000	1, 8, 8, 5	$V^1$	0	F	F
$V^4=11000011$	01100000	2, 4, 4, 4	$V^1$	0	F	F
	10000100	4, 2, 4, 4	$V^2$	0	F	F
	00000111	7, 5, 5, 8	$V^1$	0	F	F
	00111000	8, 5, 8, 7	$V^4$	0	F	F
	00010011	5, 7, 5, 8	$V^2$	0	F	F

Computer simulations and the results of optical experiment all showed that :

- (1) The "Zheng-pu-tai" model improves cognitive ability of the network to a certain extent, and such improvement is clearly visible when the storage capacity is increased;
- (2) The "Zheng-pu-tai" mutually connected matrices choose non-negative elements, especially when they are applied to optical neural network computations;
- (3) Real-time spatial light modulators can be used as storage and computer parts, not only in realizing the storage capacity of multi-valued mutually connected matrices but also capable of increasing the vitality of the optical neural network system.

What is worth mentioning here is that this paper is concerned with computations by adopting stored vectors of fairly good orthogonality and ideal input vectors (that is to say, they are not different from the stored vectors or at least not too different). What has already been discovered in the simulation computations is that when the stored vectors of a little bit poorer orthogonality and the input vectors of rather deformed kinds are being used, the cognitive ability of the network declines accordingly. Furthermore, when the "Zheng-pu-tai" model is being used, the required threshold level for computing Eqn.(2) is much higher than those for other models.

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#### References

- [1] J. J. Hopfield; *Proc. Natl. Acad. Sci. (USA)*, 1982, 79 (Apr), 2554~2558.
- [2] M. Takeda, J. W. Goodman; *Appl. Opt.*, 1986, 25, No. 18 (Sep), 3033~3046.
- [3] N. H. Farhat *et al.*; *Appl. Opt.*, 1985, 24, No. 10 (May), 1469~1475.
- [4] B. A. Athale *et al.*; *Opt. Lett.*, 1986, 11, No. 7 (Jul), 432~434.
- [5] N. H. Farhat, D. Psaltis; in *Optical Signal Processing*, (J. L. Horner, Ed. Academic Press, San Diego, 1987), 131~135.
- [6] 朱伟利, 陈岩松, 《物理学报》, 1990, 39, No. 11 (Nov), 1791~1795.

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