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Parameter β(m) Dependence in TA Model Optical Associative Memory

Abstract

By the computer simulations, we give the parameter $\beta^{(m)}$ dependence in TA model optical associative memory. When $\beta^{(m)} < 1$ the associations are failed and the good results are obtained when $\beta^{(m)}$ is 1.

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In order to obviate the spurious state and small basins of attractions in the Hopfield neural network, the concept of the terminal attractor (TA) has been introduced.[1] Consider a discrete time type of neural networks consisting of *N* neurons with bipolar outputs. The neural dynamics of the TA model for associative memory are given by

$$x_i(t+1) = \sum_{j=1}^{N} W_{ij} f\left[x_j(t)\right] - \sum_{m=1}^{M} \alpha^{(m)} \left\{ f\left[x_i(t)\right] - x_i^{(m)} \right\}^{\frac{1}{3}} \times \exp\left\{ -\beta^{(m)} \left\{ f\left[x_i(t)\right] - x_i^{(m)} \right\}^2 \right\}, \quad (1)$$

$$f\left[x_i(t)\right] = \tanh\left[x_i(t)\right], \quad (2)$$

where M is the number of memorized patterns. $\alpha^{(m)}$ and $\beta^{(m)}$ are positive control constants and W_{ij} is a connection weight. $f(x)$ is a output threshold function.

For the feasibility of the optical implementation of the TA network, we make some approximations to Eqs. (1) and (2) without loosing the essence of the TA model.[2] By using those assumption, the Eqs. (1) and (2) are written by

$$x_i(t) = \sum_{j=1}^{N} W_{ij} f\left[x_j(t)\right] - \sum_{m=1}^{M} \left\{ f\left[x_i(t)\right] - x_i^{(m)} \right\} \times \exp\left\{ -\beta^{(m)} \left| f\left[x_i(t)\right] - x_i^{(m)} \right| \right\}, \quad (3)$$

$$f\left[x_j(t)\right] = 1\left[x_i(t)\right], \quad (4)$$

where $1[u] = 1$ when $u > 0$ and -1 when $u < 0$. The optical neural network system based on the TA model architecture described by Eqs. (3) and (4) is shown in Fig. 1.

In the exponential term of the Eq.(3), the parameter $\beta^{(m)}$ is significant. In practice, the values of $\beta^{(m)}$ controls the influence of the exponential term at the neighborhood of the stored patterns. A small $\beta^{(m)}$ (for instance, $\beta^{(m)} \le 0.5$) causes stronger cross talk among stored patterns, and the spurious states caused by cross talks are generated near the boundary of a basin of a stored pattern. Whereas, a large $\beta^{(m)}$ reduces the cross talks. In other words, the value of $\beta^{(m)}$ decides the behavior of neighbors of a terminal attractor. However, the optimal value of $\beta^{(m)}$ is not theoretically obtained. In this paper, we will give a intuitive explanation by a numerical simulation to choose values of $\beta^{(m)}$.

The numerical simulation have been performed by using a 10×10 neuron network model. Three characters “Y”, “A”, and “O” are embedded in the network as the memorized patterns. The Hamming distances of four initial imperfect inputs from stored pattern "Y" are 3, 5, 7, and 9, respectively. We tested for four $\beta^{(m)}$ values of 0.2, 0.5, 1, and 3. The results indicate that the associations are successful when $\beta^{(m)}$ is 1 and 3. Figures 2 and 3 are examples of the test results. From Figs. 2 (c) and (d), the associations are failed for case

$\beta^{(m)} = 0.2$. On the other hand, when $\beta^{(m)} = 1$, the networks correctly converged to "Y". In practice, the good experimental results have been obtained by using the optical system of $\beta^{(m)} = 1$ (Fig. 1).[2,3]

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Figure Captions

Fig. 1 Optical TA neural network system. P1-P6: polarizers.

Fig. 2 Computer simulations for the recalling property with N=100, $\beta^{(m)}$=0.2. Hamming distances of the inputs from the pattern “Y” are H=3 (a), H=5 (b), H=7(c), and H=9 (d).

Fig. 3 Computer simulations for the recalling property with N=100, $\beta^{(m)}$=1. Hamming distances of the inputs from the pattern “Y” are H=3 (a), H=5 (b), H=7(c), and H=9 (d).

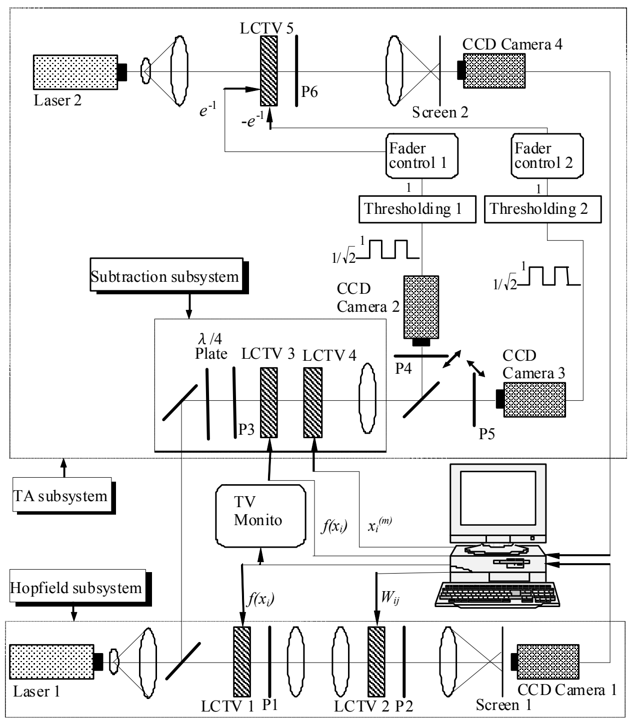

Fig.1

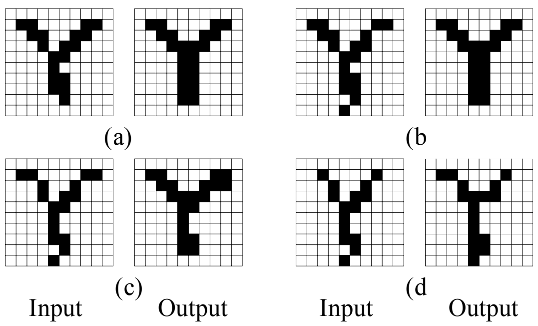

Fig.2

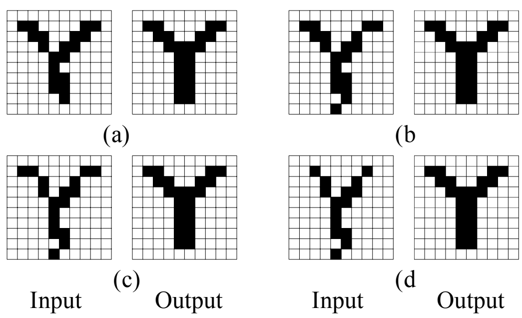

Fig.3