Human Visual Aging Effect Simulation by Computer Neural Network

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Abstract

The MTF properties of the human visual spatial neural system are deteriorating in the high spatial frequency region for aged persons.

When the MTF properties were transformed by the Fourier Transformation, the lateral inhibited visual field averaged around the visual retinal area was obtained. An aged person's visual field is wider than a younger person's. One of the reasons for this visual field spread as a result of aging seems to depend on the death of neurons in the visual neural system. Incidentally, after using a back propagation algorithm, the distribution of connection co-efficient among neurons with similar lateral inhibited properties was present. Therefore, using this computer simulation and destroying some neurons in the network, the wider lateral inhibited distribution of the connection co-efficient was obtained. This distribution of the co-efficient seems to be similar to the human aged visual field.

1. Introduction

The spatial neural properties in the retinal and the neural network from the retina to the cortex are known to have lateral inhibited properties. In the biological lateral inhibition, there are two types of properties, one is on-type, and the other is off-type. In this paper, on-type lateral inhibition is considered. When the visual MTF properties is transformed by the Fourier Transformation, a similar lateral inhibition function was obtained. This function should be averaged around the visual retinal area. The visual MTF properties from the retina to the cortex according to ages, were measured by Ohzu and Nameda in 1987 [1]. From these properties, lateral inhibition functions were obtained. Also, the three layered neural network as shown in Fig. 1 has been used as a computer procedure [2].

On one occasion, after this network learned some inputs, the connection coefficients among neurons show lateral inhibited distribution [3]. This distribution seems to be similar to the lateral inhibition properties of the human visual properties.

This paper shows the similarities of the lateral inhibited distribution of the connection coefficients among neurons.

2. Principle of back propagation

In Fig. 1, the j th neuron accepts the output of the i th neuron : y_i connection with the co-efficient w_{ji}. If the summation of the outputs about i is expressd as u_j, u_j is shown as follows,

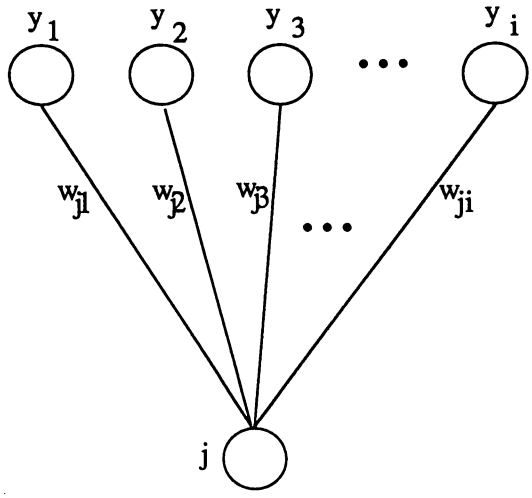

Fig. 1 Connection coefficients between *j*-neuron and each *i*-neuron.

$$u_j = \sum_i w_{ji} y_i$$

Output of j-neuron is Sigmoid Function

$$y_j = f(u_j)$$

If y_0 is a desirable output (teaching function), the output of y_j, has the deviation from the y_0 as follows,

$$E = \frac{1}{2} \sum_j (y_j - y_0)^2$$

Making E to less values, w_{ji} is subtracted by Δw_{ji}. This subtracting value is expressed as follows,

$$\Delta w_{ji} = -\Sigma \frac{\partial E}{\partial y_i} f'(u_j) y_i$$

3. Method

A three layered network was constructed by 20 neurons on each layer, and an each side neuron was connected with its opposite neuron to build up like a cylinder (Fig. 2). Input values presented step like functions or pulse like functions. A desirable output function (a teaching function) was a line function. In calculation procedure, the initial connection coefficients were intially set at random numerical values. Calculation was carried out according to above-mentioned back propagation procedure. After 30,000 and more trials were carried out, the output function became the same as the teachng function. At the state, the neurons had the lateral inhibited connection coefficients with the adjacent layer neurons as shown in Fig. 3. The computer used in this experiment was NEC PC-9821, and the computer language used in the procedure was "C".

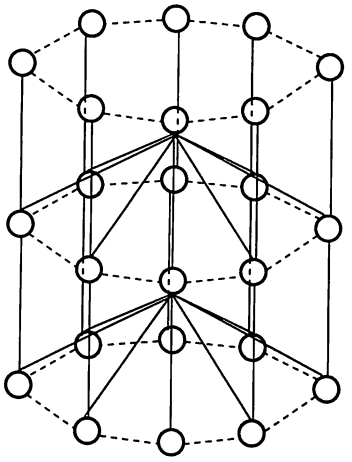

Fig. 2 Cylinderical connection.

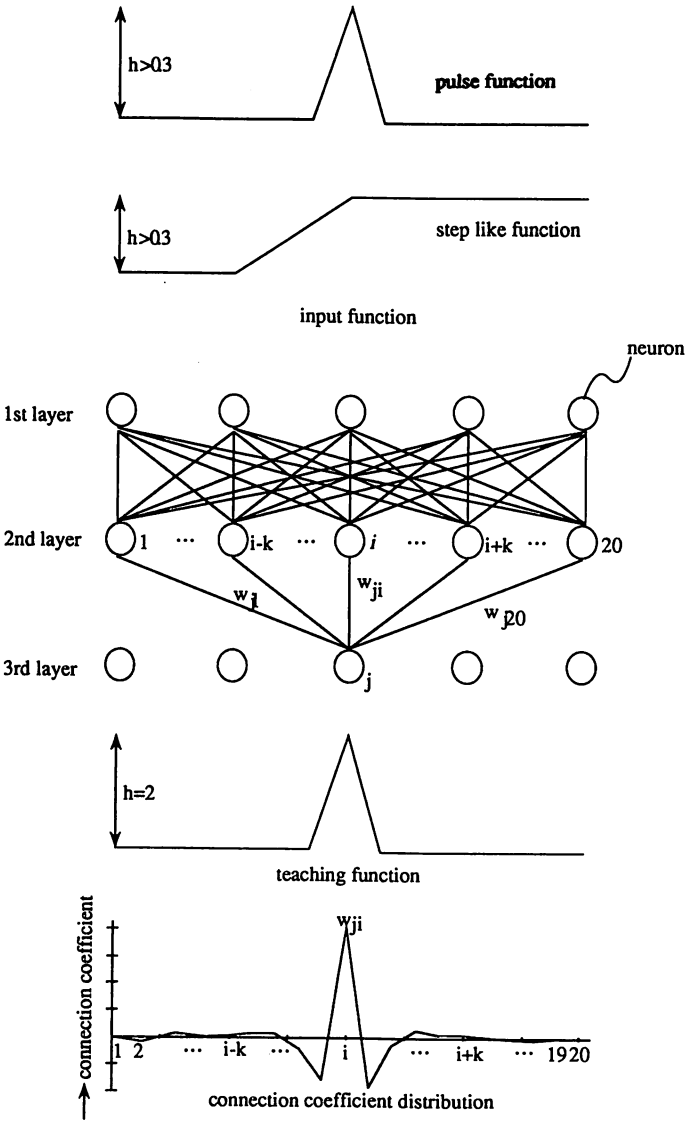

Fig. 3 The lateral inhibited connection coefficient distribution.
Upper figure shows input functions.
From up to down, a pulse function, and a step like function.
Middle figure shows a neural network.
Lower figure shows a teaching function.
The lowest figure shows the lateral inhibited connection coefficient distribution.

4. Calculation and discussion

First, initial connection coefficients were set as random values. However, the connection coefficients did not show the lateral inhibited distribution, after the network had learned the

teaching function. Next, when coefficients faced to face between the 1st layer neurons and the 2nd layer neurons were set 10 and more numeral values and the coefficient distribution at the neuron which was taught, had the lateral inhibited distribution.

Figure 4 shows the resulting coefficient distribution. As the reference, the initial coefficients values are shown in the upper figure in Fig. 3.

Figure 5 shows the coefficient distribution twice width of non-killed distribution.

These phenomena seem to be similar to the lateral inhibition of the aged visual properties changing from the young visual properties to the aged properties.

In real neural network system, the neural network seems to be estimated to have the similar learning procedure.

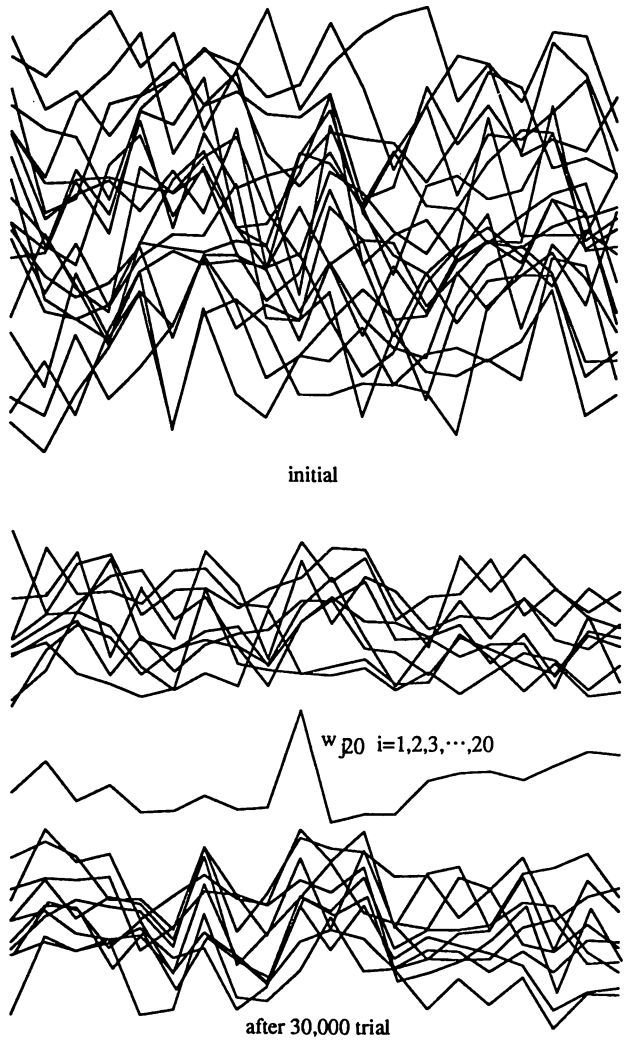

Fig. 4 Connection coefficient distribution.
Upper figure shows the initial coefficient distribution.
Lower figure shows the resulting coefficient distribution.

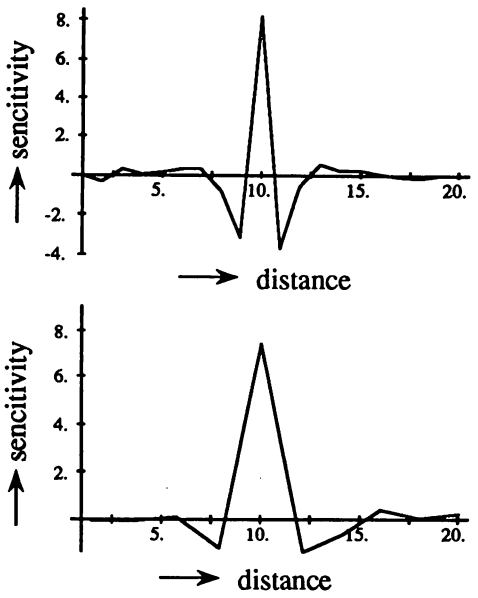

Fig. 5 Coefficient distribution, when half of the 2nd layer neurons were killed.
Upper figure shows the non-killed neurons coefficient distribution.
Lower figure shows the killed neurons coefficient distribution.

Acknowledgement

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References

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