Cognitron: A Self-organizing Multilayered Neural Network

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Abstract

A new hypothesis for the organization of synapses between neurons is proposed: "The synapse from neuron x to neuron y is reinforced when x fires provided that no neuron in the vicinity of y is firing stronger than y". By introducing this hypothesis, a new algorithm with which a multilayered neural network is effectively organized can be deduced. A self-organizing multilayered neural network, which is named "cognitron", is constructed following this algorithm, and is simulated on a digital computer. Unlike the organization of a usual brain models such as a three-layered perceptron, the self-organization of a cognitron progresses favorably without having a "teacher" which instructs in all particulars how the individual cells respond. After repetitive presentations of several stimulus patterns, the cognitron is self-organized in such a way that the receptive fields of the cells become relatively larger in a deeper layer. Each cell in the final layer integrates the information from whole parts of the first layer and selectively responds to a specific stimulus pattern or a feature.

1. Introduction

It is thought that the synaptic connections between neurons in the brain are not completely inherited, but are plastically modified by learning or experiences after birth. It is reported, for instance, that early experiences during maturation grossly modify the visual cortex of a cat. In the normal adult cat, neurons of the visual cortex are selectively sensitive to the orientation of the lines and edges in the visual field, and the preferred orientation of different neurons are uniformly distributed in all orientations (Hubel and Wiesel, 1959, 1962 and 1965). Blakemore and Cooper (1970) reared kittens in an abnormal environment consisting entirely of black-and-white stripes of one orientation. These animals had no cortical neurons responding to the orientation perpendicular to the stripes that they saw when they were young. It seems that the visual cortex adjusts itself during maturation to the nature of the visual experience. Perhaps the nervous systems are plastically modified to match the probability of occurrence of features in the visual inputs. Such kind of selforganization of neural networks would be more prominant in the higher center of the brain.

At present, however, the algorithm with which a neural network is self-organized is not known. Although several hypothesis for it have been proposed, none of them has been physiologically substantiated.

The three-layered perceptron proposed by Rosenblatt (1962) is one of the examples of the brain models based on such hypotheses. For a while after the perceptron was proposed, its capability for information processing was greatly expected, and many research works on it have been made. With the progress of the researches, however, it was gradually revealed that the capability of the perceptron is not so large as it had been expected at the beginning.

Although the perceptron consists of only three layers of neurons, it is known that the capability of a layered neural network is greatly enlarged if the number of the neural layers is increased. A model of the mechanism of feature extraction in the visual nervous system proposed by the author (Fukushima, 1970 and 1971) would be one of the examples which shows the capability of a multilayered neural network. In that model, however, the synaptic connections between neurons are fixed, and the plastic modification of the synapses has not been considered. It can be inferred that, even for a neural network with modifiable synapses, the multiplication of the neural layers would increase the capability of the network. Since the algorithm with which a multilayered neural network can be effectively organized has not been known, however, brain models with multilayered structure which have functions of memory or learning have little been reported. Consequently, the selforganizing system or a brain model hitherto reported did not go beyond the confine of a three-layered perceptron, in which only the synapses between the last two layers are modifiable.

In this paper, a new hypothesis for the organization of synapses between neurons is proposed. By introducing this hypothesis, a new algorithm with which a multilayered neural network is effectively organized can be deduced. A self-organizing multilayered neural

network is constructed following this algorithm, and is named a "cognitron". The performance of a cognitron has been simulated on a digital computer.

In a cognitron, similarly to the animal's brain, synaptic connections between neurons are plastically modified so as to match the nature of its experience. The neurons become selectively responsive to the features which have been frequently presented. Since wasteful functions which are utilized only for the detection of rarely appearing features are not formed, the capability of the neural network can be fully exhibited.

2. Hypothesis on the Synapse Modification

2.1. Hypotheses Hitherto Proposed

According to Marr (1970), the hitherto-proposed hypotheses on the synapse modification are classified into the following three categories as shown in Fig. 1.

In the hypothesis of Fig. 1a, a modifiable afferent synapse c_i is excitatory at the beginning. It becomes ineffective, if and only if the postsynaptic cell y firs without presynaptic activity x_i. This hypothesis is based on the idea that the irrelevant synapses become ineffective. Incidentally, the inhibitory afferent synapses shown in the figure control the threshold of the cell y at an appropriate level.

This hypothesis, however, has a fatal disadvantage: once an improper stimulus is given to the neural network, the network would suffer an irrecoverable damage, because the synapses are irreversibly modified only toward extinction.

In the hypothesis of Fig. 1b, a modifiable synapse c_i has a certain amount of excitatory component at the initial state. It will be reinforced if there is a presynaptic activity x_i simultaneously with the firing of the postsynaptic cell y. This hypothesis is based on the idea that only the synapses relevant to the firing of the postsynaptic cell are reinforced. Such synapses are called Brindley Synapses.

In a four-layered perception (Block et al., 1962), the synapses from A^{I}-cells to A^{II}-cells are of this type. Brindley synapses are also used in the model of visual cortex proposed by von der Malsburg (1973), in which orientation sensitive simple cells are self-organized. In these models, Brindley synapses are used only between particular two layers. It is not known whether a multilayered network with only Brindley synapses can be favorably organized or not. Probably, very sophisticated initial connections between neurons would be necessary, in order a multilayered network with only Brindley synapses be favorably organized. The information quantity for such sofisticated initial

$$\longrightarrow\!\square \quad : \text{modifiable}$$
$$\begin{cases} c_i > 0 \quad \text{at} \quad t=0 \\ c_i \quad \text{decreases} \quad (c_i \to 0) \\ \quad \text{if} \quad x_i = 0 \cap y > 0 \end{cases}$$

$$\longrightarrow \quad : \text{modifiable (Brindley synap}$$
$$\begin{cases} c_i > 0 \quad \text{at} \quad t=0 \\ c_i \quad \text{increases} \\ \quad \text{if} \quad x_i > 0 \cap y > 0 \end{cases}$$

$$\longrightarrow\!\triangleleft \quad : \text{modifiable (Hebb synapse)}$$
$$\begin{cases} c_i = 0 \quad \text{at} \quad t=0 \\ c_i \quad \text{increases} \\ \quad \text{if} \quad x_i > 0 \cap z > 0 \end{cases}$$
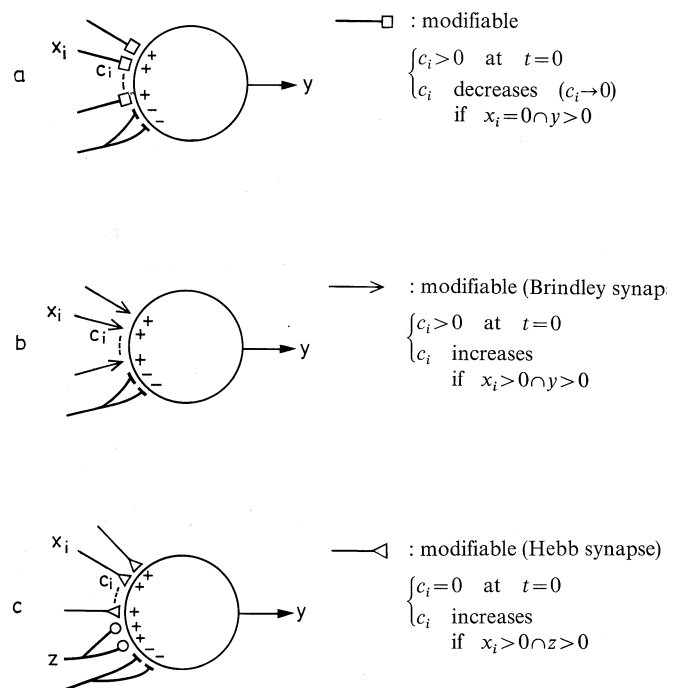
Fig. 1a–c. Hitherto-proposed three hypotheses on the modification of synapses

connections might be too much to be transmitted hereditarily, if they are to be determined by birth not only in the distal system but also in the higher center of the brain.

In the hypothesis of Fig. 1c, the postsynaptic cell y possesses another synaptic input z which controls the reinforcement of its ordinary afferent synapses. An ordinary synapse c_i, which is named a Hebb synapse, is initially ineffective, and is reinforced if there is a presynaptic activity x_i in conjunction with the control signal z. That is, the afferent synapses are reinforced following the state of the input signals at the moment when the control signal z comes. Marr (1969) proposes a hypothesis that the learning in the cerebellum is carried out by the synapses of this type, and that the afferent input from a climbing fiber corresponds to the control signal z. The control signal z is considered to be an instruction from a "teacher" for a "supervised learning". Following this concept, the modifiable synapses in a three-layered perceptron might be classified to this type.

In order to organize a multilayered network composed of Hebb synapses, a "teacher" should give instructions how each individual cell should respond whenever a stimulus is given to the network. These instructions must be given not only to the cells of the final layer, but also to the cells of the intermediate

layers. It is difficult to imagine that such a "teacher" exists in the brain.

Although above-mentioned hypotheses have been proposed, none of them has been physiologically substantiated, and they are still a matter of conjecture. Even if these hypotheses be accepted, it seems very difficult to deduce only from these hypotheses an algorithm for a successful organization of a multi-layered neural network.

If the synapses are modified following the new hypothesis proposed below, however, even a multi-layered neural network can be satisfactory organized neither with a special "teacher" nor with sofisticated initial connections.

2.2. A New Hypothesis

A new hypothesis on the modification of synapses is proposed here[1] (Fig. 2):

The synaptic connection from cell x to cell y is reinforced if and only if the following two conditions are simultaneously satisfied.

(i) Presynaptic cell x fires.

(ii) None of the postsynaptic cells situated near the cell y fires stronger (or brisker) than y.

It is physiologically believed that there are two kinds of neurons: excitatory ones and inhibitory ones. The former cells give excitatory effects, and the latter cells give inhibitory effects to the postsynaptic cells. It is assumed that the above hypothesis holds in case where the presynaptic cell x is an inhibitory one as well as an excitatory one. Where, the reinforcement of an inhibitory synapse means that the synapse is made more inhibitory (not less inhibitory).

It is assumed here that a cell does not always have a possibility to have afferent synapses from all the other cells. A cell can have afferent synapses only from a group of cells situated in a particular area predetermined for each cell. This area is named "connectable area" of the cell. The connectable area is determined by the spread of the dendrites of the postsynaptic cell and the spread of the axon terminals of the presynaptic cells.

Condition (ii) in the hypothesis means that, among a group of postsynaptic cells situated in a small area, only one cell has its afferent synapses reinforced. This small area is named a "vicinity area". The neighboring cells generally have approximately the same connectable area. Hence, if condition (ii) were neglected and only condition (i) were imposed, all the neighboring cells would become to have almost the same afferent synapses. As a matter of fact, however, since

[1] This hypothesis has been reported by the author in Japanese (Fukushima, 1974)
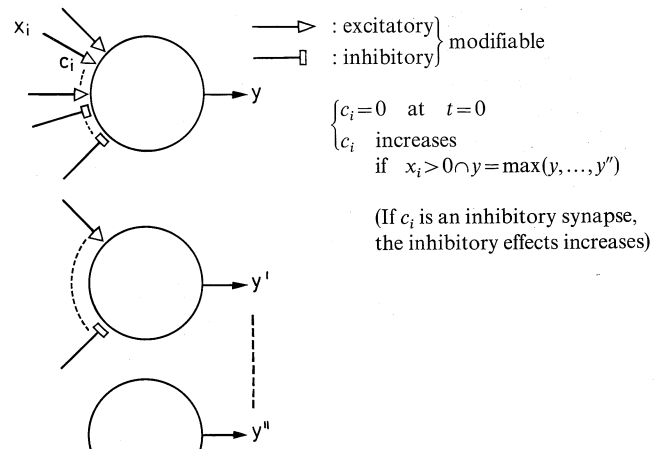

Fig. 2. A new hypothesis on the modification of synapses

condition (ii) is also imposed, only one cell which happens to have yielded a maximum output in the vicinity area is reinforced. The afferent synapses to other cells in the vicinity area, which have almost the same connectable areas, remains unchanged.

This is the case where there is at least one postsynaptic cell firing in the vicinity area. If no postsynaptic cell happens to fire in a vicinity area, however, all the postsynaptic cells in the area are to be reinforced under condition (i). Such a situation might occur, when the neural network is in an initial state where there are no connections between neurons, or when a stimulus unexperienced before is given to the network. Quantitatively speaking, however, as is discussed later, the amounts of the reinforcement of the afferent synapses are smaller when all the cells in the vicinity area are simultaneously reinforced than when only one cell is exclusively reinforced.

Although the connectable areas of the cells in a vicinity area overlap each other, they do not strictly coincide with each other but are slightly different. Therefore, even if all the cells in the vicinity area are once reinforced simultaneously, it does not mean that all of these cells are grown to have identical afferent synapses. Once even a slight difference in characteristics is generated between the cells, it will grow further and further because of condition (ii). Hence, each cell becomes to have its own individual characteristics.

If it is assumed that the synapses grow under these conditions, the neural network would also have a self-repairing function. That is, even if a certain cell is damaged, another cell will substitute for the damaged cell. When a cell which has responded strongly to a certain stimulus becomes nonresponsive

because of a damage, another cell which happens to respond stronger than the other cells to this stimulus will be grown so as to substitute for the damaged cell. Until the damage of the first cell, the second cell has been prevented from reinforcement of its afferent synapses.

Here, let us discuss whether the hypothesis is reasonable. Let us suppose, for instance, that the following situation takes place. For the reinforcement of the synapses, a certain kind of chemical substance must be supplied to the postsynaptic cells, and a kind of glia cells participate in the nourishment of this chemical substance. The spread of one glia cell coincides with a vicinity area. The glia cell supplies the nutrient concentratedly to a single cell which has yielded a maximum output within the vicinity area. In case where no cell is firing in the vicinity area, however, all the cells in the area are equally supplied with the nutrient. Since the total amount of the nutrient supplied at a time is limitted, the amount of nutrient given to each individual cell becomes smaller in this case than in case where only one cell is concentratedly nourished. If such a situation is supposed, the hypothesis proposed here would not be so ill-advised.

3. Neural Element

Before discussing the structure of the multilayered neural network "cognitron", let us discuss the characteristics of neural elements employed in a cognitron.

The neural element (which, in this paper, sometimes will be called merely a neuron or a cell) is of analog type with a mechanism of shunting inhibition. The inputs and the output of a neural element take non-negative analog values proportional to the pulse densities (or instantaneous mean frequencies) of the firing of the actual biological neurons. Let $u(1), \ldots, u(N)$ be the inputs from excitatory afferent synapses (that is, the the outputs of the presynaptic cells), and $v(1), \ldots, v(M)$ be the inputs from inhibitory afferent synapses. The output w of this cell is defined by:

$$w = \varphi \left[\frac{1 + \sum_{v=1}^{N} a(v) \cdot u(v)}{1 + \sum_{\mu=1}^{M} b(\mu) \cdot v(\mu)} - 1 \right],$$ (1)

where $\varphi[\ ]$ is a function defined by the following equation:

$$\varphi[x] = \begin{cases} x & (x \geq 0) \\ 0 & (x < 0). \end{cases}$$ (2)

The conductances of the excitatory and inhibitory synapses $a(v)$ and $b(\mu)$ take non-negative analog values.

The input-to-output characteristics of the cell could be interpreted as follows. The first term in [ ] of Eq. (1) stand for the membrane potential (short-term mean value), which is raised by the inputs from excitatory synapses, and, at the same time, is shunted by the effect of the inputs from inhibitory synapses. It is assumed that the cell fires with a pulse density proportional to the difference between the membrane potential determined in this way and the resting potential indicated by the second term in [ ] of Eq. (1).

Let e be the sum of all the excitatory effects, and h be the sum of all the inhibitory effects. That is,

$$e = \sum_{v=1}^{N} a(v) \cdot u(v),$$ (3)

$$h = \sum_{\mu=1}^{M} b(\mu) \cdot v(\mu).$$ (4)

With these symbols, Eq. (1) can also be written as

$$w = \varphi \left[\frac{1+e}{1+h} - 1 \right] = \varphi \left[\frac{e-h}{1+h} \right].$$ (5)

When the inhibitory input is small ($h \ll 1$), we have $w \doteqdot \varphi[e-h]$, which coincides with the characteristics of the usual analog-threshold-element (Fukushima, 1969). For a system like a cognitron where the synaptic conductances $a(v)$ and $b(\mu)$ increase further and further with the progress of learning, the employment of such elements like analog-threshold-elements is improper because their outputs increase boundlessly. In the cell proposed here, however, when the conductances of the input synapses increase and we have $e \gg 1$ and $h \gg 1$, Eq. (5) approximately becomes $w \doteqdot \varphi[e/h - 1]$ where the output is determined by the ratio e/h not by the difference of e and h. Therefore, even if the synaptic conductances increase with learning, the output of the cell converges to a certain value without divergence, so long as both the excitatory synaptic conductances $a(v)$ and the inhibitory ones $b(\mu)$ increases with the same rate.

Let us look at the input-to-output relation of the cell in case where the excitatory and the inhibitory input increase in proportion. If we write

$$e = \varepsilon x, \qquad h = \eta x$$

and if $\varepsilon > \eta$ holds, Eq. (5) can be transformed into

$$w = \frac{(\varepsilon - \eta)x}{1 + \eta x}$$

$$= \frac{\varepsilon - \eta}{2\eta} \left\{ 1 + \tanh \left(\frac{1}{2} \log \eta x \right) \right\}.$$ (6)

This input-to-output relation coincides with a logarithmic relation expressed by Wever-Fechner's law to which a S-shaped saturation expressed by tanh is

added. The same expression is often used as an empirical formula in neurophysiology and psychology to approximate the nonlinear input-to-output relations of the sensory receptors (for instance, cones) and the overall sensory systems of animals.

Since the neural element of this type resembles so well in characteristics to the biological neuron, it has a wide application not only for a cognitron but also for various kinds of visual and auditory information processing systems.

4. Structure of a Cognitron

4.1. The Basic Structure

According to the hypothesis discussed in Section 2.2, a self-organizing multilayered neural network, cognitron, is constructed (Fukushima, 1974). At first, the basic idea for the construction of a cognitron is discussed.

The cognitron has a multilayered structure. It consists of a number of neural layers of a similar structure cascaded one after another. The l-th layer U_l consists of excitatory neurons $u_l(n)$ and inhibitory neurons $v_l(n)$, where $n = (n_x, n_y)$ is a two-dimensional co-ordinates indicating the location of a cell.

An excitatory cell $u_l(n)$ receives modifiable synaptic connections from neurons $u_{l-1}(n+v)$ $[v \in S_l]$ and $v_{l-1}(n)$ in the preceding layer U_{l-1}. If we write the conductances of the synaptic connections as $a_l(v, n)$ and $b_l(n)$, the output of the cell $u_l(n)$ is given by

$$u_l(n) = \varphi \left[\frac{1 + \sum_{v \in S_l} a_l(v, n) \cdot u_{l-1}(n+v)}{1 + b_l(n) \cdot v_{l-1}(n)} - 1 \right] \quad (7)$$

where S_l indicates the connectable area of a cell.

Meanwhile, the inhibitory cell $v_{l-1}(n)$ receives fixed excitatory synaptic connections $c_{l-1}(v)[\geq 0]$ from the neighboring excitatory cells $u_{l-1}(n+v)$, and yields an output equal to the mean value of the outputs of the neighboring cells:

$$v_{l-1}(n) = \sum_{v \in S_l} c_{l-1}(v) \cdot u_{l-1}(n+v). \quad (8)$$

The values of the fixed synaptic connections are so determined as to satisfies

$$\sum_{v \in S_l} c_{l-1}(v) = 1. \quad (9)$$

As is seen from Eqs. (7) and (8), the connectable area of the cell $u_l(n)$ coincides with the connecting area of this inhibitory cell $v_{l-1}(n)$. Figure 3 shows how the cells of layers U_{l-1} and U_l are connected.

The reinforcement of the afferent synapses of cell $u_l(n)$ takes place only when none of the cells situated in the vicinity of $u_l(n)$ is firing stronger than $u_l(n)$. Let
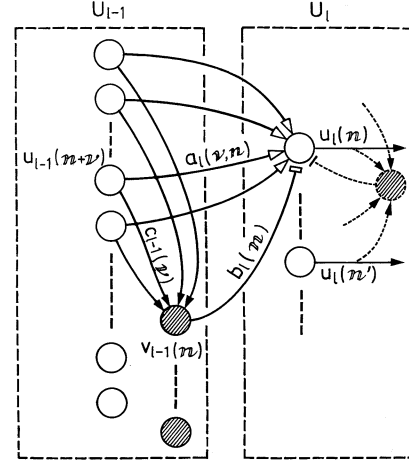

Fig. 3. The basic structure of the cognitron. The interconnections between two adjoining layers are shown

$\delta_l(n)$ be a function which takes a value 1 or 0 depending whether the synaptic reinforcement for cell $u_l(n)$ is performed or not:

$$\delta_l(n) = \begin{cases} 1 & \text{if } u_l(n) \geq u_l(n+v) \text{ for every } v \in \Omega_l \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where Ω_l stand for a vicinity area (for instance, the area in which $|v| < R$ holds).

When $\delta_l(n) = 1$ holds and the reinforcement is to be performed, the amounts of the synaptic reinforcement $\Delta a_l(v, n)$ and $\Delta b_l(n)$ change depending whether $u_l(n) = 0$ or $u_l(n) > 0$.

When $u_l(n) = 0$:

$$\Delta a_l(v, n) = q_0 \cdot c_{l-1}(v) \cdot u_{l-1}(n+v) \cdot \delta_l(n), \quad (11)$$

$$\Delta b_l(n) = q_0 \cdot v_{l-1}(n) \cdot \delta_l(n). \quad (12)$$

When $u_l(n) > 0$:

$$\Delta a_l(v, n) = q_1 \cdot c_{l-1}(v) \cdot u_{l-1}(n+v) \cdot \delta_l(n), \quad (13)$$

$$\Delta b_l(n) = \frac{\sum_{v \in S_l} a_l(v, n) \cdot u_{l-1}(n+v)}{2 v_{l-1}(n)} \cdot \delta_l(n)$$

$$= \frac{q_1 \sum_{v \in S_l} c_{l-1}(v) \cdot u_{l-1}^2(n+v)}{2 v_{l-1}(n)} \cdot \delta_l(n) \quad (14)$$

where q_0 and q_1 are positive constants which satisfies

$$q_1 > q_0 > 0. \quad (15)$$

4.2. Quantitative Analysis

Let us discuss the implication of this algorithm on reinforcement.

When both $\delta_l(n) = 1$ and $u_l(n) = 0$ hold, it is seen from Eq. (10) that there is no neuron firing in the

vicinity of $u_l(n)$. Consequently, also the other cells in its vicinity are reinforced following the algorithm of Eq. (11) and (12), if they are to be reinforced. As is seen from (15), the amounts of reinforcement are set smaller in this case than in case where $u_l(n)$ is the only cell reinforced in its vicinity. The latter case arises when both $\delta_l(n) = 1$ and $u_l(n) > 0$ hold.

As shown in Fig. 3, there are two paths of information flow from cell $u_{l-1}(n+v)$ in the preceding layer to cell $u_l(n)$: the excitatory information through the synapses of conductance $a_l(v, n)$, and the inhibitory information transmitted via inhibitory cell $v_{l-1}(n)$. As for the inhibitory information flow, the conductance of the synapse from $u_{l-1}(n+v)$ to $v_{l-1}(n)$ is $c_{l-1}(v)$ which is unmodifiable, and the conductance of the inhibitory synapse from $v_{l-1}(n)$ to $u_l(n)$ is $b_l(n)$ which is modifiable. The input-to-output characteristic of cell $v_{l-1}(n)$ is linear since it does not have inhibitory inputs. Hence, the overall conductance of the inhibitory path from $u_{l-1}(n+v)$ to $u_l(n)$ is $c_{l-1}(v) \cdot b_l(n)$.

Let $r_l(v, n)$ be the ratio of the amount of reinforcement of the excitatory conductance $\Delta a_l(v, n)$ to that of the over all inhibitory conductance $c_{l-1}(v) \cdot \Delta b_l(n)$:

$$r_l(v, n) = \frac{\Delta a_l(v, n)}{c_{l-1}(v) \cdot \Delta b_l(n)}. \tag{16}$$

That is, $r_l(v, n)$ takes a value greater than or less than 1 depending upon which of the excitatory or the inhibitory connection from cell $u_{l-1}(n+v)$ to $u_l(n)$ be reinforced stronger than the other.

It is reduced from Eqs. (11) and (12), or from Eqs. (13) and (14), that $r_l(v, n) > 1$ hods if and only if the following conditions are satisfied.

When $u_l(n) = 0$:

$$u_{l-1}(n+v) > v_{l-1}(n). \tag{17}$$

When $u_l(n) > 0$:

$$u_{l-1}(n+v) > \frac{\sum_{\mu \in S_l} c_{l-1}(\mu) \cdot u_{l-1}^2(n+\mu)}{2v_{l-1}(n)}. \tag{18}$$

As is seen from Eqs. (8) and (9), the output of cell $v_{l-1}(n)$ is equal to the (weighted) mean value of the outputs of the cells within the connectable area of $u_l(n)$. Accordingly, inequality (17) means that, when $u_l(n) = 0$, the excitatory connections from the cells responding stronger than the mean value are more reinforced than the inhibitory ones. As for the case where $u_l(n) > 0$, since the right side of inequality (18) is a little complicated, we will consider for a moment a simple case where all the outputs of the cells within the connectable area take value 0 or 1. In this special case, the right-hand side of inequality (18) is equal

to $1/2$. This means that, when $u_l(n) > 0$, the excitatory connections from the cells responding stronger than $1/2$ are more reinforced than the inhibitory ones.

In both cases, qualitatively speaking, the excitatory connection is more reinforced than the inhibitory one from a cell which is yielding a relatively large response $[r_l(v, n) > 1]$, and, inversely, the inhibitory connection is more reinforced than the excitatory one from a cell which is yielding a relatively small response $[r_l(v, n) < 1]$.

Generally, in a cognitron, the number of postsynaptic cells which are reinforced at one time tend to only one within a single vicinity area, after a certain degree of learning has taken place. Hence, at every instance, the distribution of strongly firing cells generally becomes sparse. Therefore, using Eqs. (16) and (11)–(14), we can conclude that the value of $r_l(v, n)$ is generally much smaller in case of $u_l(n) > 0$ than in case of $u_l(n) = 0$, if the inputs are the same for the two cases. That is, the relative amount of reinforcement of the inhibitory synapses to that of the excitatory ones is much larger in the former case. As the result of such a strong reinforcement of the inhibitory connections, the postsynaptic cells become reluctant to respond to other stimulus patterns than the one to which the cell has been reinforced, and the cognitron acquires the ability to differentiate a pattern from other similar patterns.

The amount of reinforcement for the case of $u_l(n) > 0$ is so determined that the increment of the total excitatory effect to the postsynaptic cell is just 2 times as large as that of the inhibitory one if the same stimulus pattern is given again. That is, *when $u_l(n) > 0$:*

$$\frac{\sum_{v \in S_l} \Delta a_l(v, n) \cdot u_{l-1}(n+v)}{\Delta b_l(n) \cdot v_{l-1}(n)} = 2. \tag{19}$$

Therefore, if the same stimulus patterns are given repeatedly, the output of cell $u_l(n)$ gradually increases and tend to 1. This conclusion can be deduced from Eqs. (7) and (19).

If the amount of reinforcement is shared in such a way between the excitatory and inhibitory synapses, however, the inhibitory synapses become too strong in case of $u_l(n) = 0$. Let us consider for a moment what would happen if the synapses were to be reinforced according to Eqs. (13) and (14) even for $u_l(n) = 0$. In the initial state where the synaptic connections from layer U_{l-1} to layer U_l are not completed, cell $u_l(n)$ might be presented with several kinds of different stimuli without yielding a response. If these stimulus patterns are random, the overall inhibitory connection from any of the cells $u_{l-1}(n+v)$ would become stronger

than that of the excitatory one. Hence, cell $u_l(n)$ would become nonresponsive to any of the stimulus patterns, and the organization of the cognitron would stop. Actually, in case of $u_l(n) = 0$, the amount of reinforcement of the excitatory synapse are kept small so as to satisfies the following equation.

When $u_l(n) = 0$:

$$\sum_{v \in S_l} \Delta a_l(v, n) = \sum_{v \in S_l} c_{l-1}(v) \cdot \Delta b_l(n) . \tag{20}$$

Equation (20) means that the synapses are reinforced under the condition that the cell responds neither in an excitatory nor in an inhibitory manner to a uniform pattern (or to a d.c. component of the spatial frequency).

4.3. Lateral Inhibition

In the last two sections, the principles of the construction of a cognitron has been discussed. In the actual construction of the network, however, a little modification is made.

An excitatory cell $u_l(n)$ receives lateral inhibition from the neighboring cells. That is, as shown in Fig. 3, there is a mechanism of backward lateral inhibition among the excitatory cells of the same layer.

In the computer simulation mentioned later, however, the backward lateral inhibition is substituted by a forward lateral inhibition in order to save the computation time.

That is, the right-hand side of Eq. (7) is regarded as a intermediate output $u_l'(n)$ instead of the final output of the cell $u_l(n)$. The fined output $u_l(n)$ is obtained by application of lateral inhibition to this intermediate output $u_l'(n)$. So, instead of Eq. (7), we have intermediate output $u_l'(n)$ by

$$u_l'(n) = \varphi \left[\frac{1 + \sum_{v \in S_l} a_l(v, n) \cdot u_{l-1}(n+v)}{1 + b_l(n) \cdot v_{l-1}(n)} - 1 \right] \tag{21}$$

and the final output of the cell is given by

$$u_l(n) = \varphi \left[\frac{1 + u_l'(n)}{1 + \sum_{\mu \in H_l} g_l(\mu) \cdot u_l'(n+\mu)} - 1 \right] . \tag{22}$$

In this equation, $g_l(\mu)$ represents the conductance of the equivalent forward lateral inhibition transformed from the backward one, and is determined so as to satisfy

$$\sum_{\mu \in H_l} g_l(\mu) = 1 \tag{23}$$

where H_l represents the spread of this lateral inhibition $g_l(\mu)$.

This kind of lateral inhibition is helpful for getting rid of an awkward situation mentioned below. Suppose that the spatial distribution pattern of the outputs of the excitatory cells of U_l happens to be of the shape like, say, Mt. Fuji, and have a single peak surrounded by a wide spread slope. In such a case, any of the cells in the slope is in the state that some other cells in its vicinity are yielding larger outputs than it. Hence, no cell in the slope would be reinforced. It is only the cell at the peak that can be reinforced, and a favorable progress of the self-organization could not be expected.

If the above-mentioned mechanism of lateral inhibition is added to the network, however, the wide spread slope vanishes, and a number of cells in the layer can be reinforced at a time. This results in a successful self-organization.

4.4. Connectable Areas and Branching of Axon Terminals

A cognitron consists of many neural layers of the above-mentioned fundamental structure cascaded one after another. The layers are named $U_0, U_1 \ldots$ from the headmost one. Layer U_0 is an input layer to which stimulus patterns are presented. The cells of layer U_0, however, are not necessarily the sensory receptor cells themselves. We suppose that another neural network like a feature extractor is placed in front of layer U_0, and the cells of layer U_0 receive the information already processed to some extent. Here we use the word "receptive field" in a wide sense: The area in layer U_0 (not necessarily the sensory receptor layer) which affects the response of a cell in a deeper layer will be called the receptive field of the cell.

In cascading layers, it is important how to determine the connectable area of each cell. Let us compare three possible methods shown in Fig. 4.

In the method of Fig. 4a, the size of the connectable area of each cell is determined to become equal independent of the layer to which the cell belongs. In this case, however, even if the number of layers are increased, the receptive field of a cell of the last layer does not increase its size so noticeably. In order the receptive field of a cell of the last layer covers the whole U_0 layer, a considerable number of layers should be cascaded.

On the other hand, in the method of Fig. 4b, the size of the connectable area of a cell increases with the depth of the layer in which the cell is situated. In this case, the receptive field of a cell in the last layer can be made to cover the whole U_0 layer with a less number of layers than for the method of Fig. 4a. If the sizes of the connectable areas are determined in such a way, however, all the cells in a deeper layer, especially in the last layer, would become to have almost identical connect-
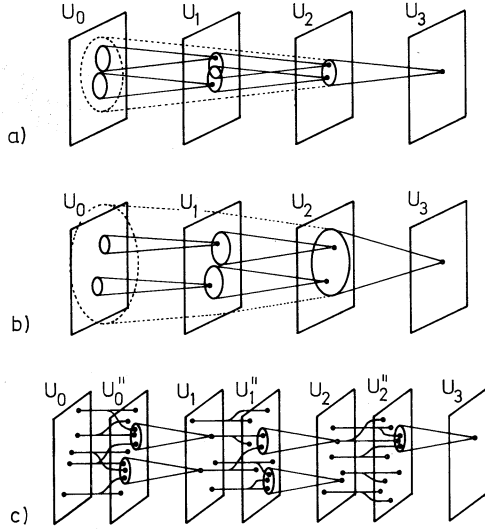
Fig. 4a–c. Three possible methods for interconnecting layers. The connectable area of each cell is differently chosen in these three methods. Method c is adopted for the cognitron discussed in this paper

able area because of too much overlapping. Hence, in order to make each cell have its own individual character, it is necessary to widen the size of the vicinity area Ω_l (which is the area in which the reinforcement of more than two cells is generally prevented). Consequently, we have a situation where only one or a few cell fire at a time in the last layer. This seems to contradict to the situation in the animals brain where it is supposed that many cells would fire for one stimulus pattern, and that the configuration of the firing pattern would correspond to a "concept". Furthermore, no more processing of information could be expected in this case, even if another layer is cascaded after the last layer, since the cells of the newly added layer would normally have only one firing cell at a time in their connectable areas. Judging from these, the method like Fig. 4b does not seem desirable either.

It is true that, however, for some applications, it would be desirable to have a network in which the firing of only one cell correspond to one stimulus. In such a case, it is good enough to design the network having a structure like Fig. 4b.

In Fig. 4c, the axons of the excitatory cells ramifies into a number of branches, and the destination of each branch is probabilistically distributed. The probabilistic distribution here does not mean, however, that the deviation of the destination from the starting position is completely random. The destinations are determined in such a way that branches with large deviation be less numerous.

With this method, the receptive field of each cell of the last layer will cover the whole U_0-layer without widening the connectable areas of postsynaptic cells so much nor increasing the number of layers so much. It is also possible to cascade another layers after the last one, since a number of cells would fire at a time even in the last layer.

In this paper, the method of Fig. 4c is adopted. Suppose that the axon of every excitatory cell $u_l(\mathbf{n})$ ramifies into $(K+1)$ branches. Let the spatial pattern representing the firing states of the terminals of these branches be $u_l''(\mathbf{n}, k)$ $[k=0, 1, 2, \ldots, K]$. Suppose the branches with $k=0$ are not deviated:

$$u_l''(\mathbf{n}, 0) = u_l(\mathbf{n}). \tag{24}$$

On the other hand, the destinations of the branches with $k \neq 0$ receive probabilistic permutation. Let $\mathscr{P}_{lk}$ be the operator representing the permutation on $\mathbf{n}$. Then we have

$$\{u_l''(\mathbf{n}, k)\} = \mathscr{P}_{lk}\{u_l(\mathbf{n})\} \qquad (k \neq 0). \tag{25}$$

Here the assignment of the permutation of each element is made in such a way that a permutation with small disparity between the positions before and after the permutation occurs more frequently.

In the computer simulation mentioned later, we discuss the case with $K=1$, that is, the case where each axon bifurcates into two branches. One of the two branches goes straight, but the other one receives a probabilistic permutation.

In case where every axons ramifies, Eq. (21) is to be replaced by

$$u_l'(\mathbf{n}) = \varphi$$
$$\cdot \left[\frac{1 + \sum_{k=0}^{K} \sum_{\mathbf{v} \in S_l} a_l(\mathbf{v}, \mathbf{n}, k) \cdot u_{l-1}''(\mathbf{n}+\mathbf{v}, k)}{1 + b_l(\mathbf{n}) \cdot v_{l-1}(\mathbf{n})} - 1 \right]. \tag{26}$$

Equations (8), (9), and (11)–(14) holds without change, if only the following replacements of the variables are carried out.

$$u_{l-1}(\mathbf{n}+\mathbf{v}) \rightarrow u_{l-1}''(\mathbf{n}+\mathbf{v}, k)$$
$$a_l(\mathbf{v}, \mathbf{n}) \rightarrow a_l(\mathbf{v}, \mathbf{n}, k)$$
$$c_{l-1}(\mathbf{v}) \rightarrow c_{l-1}(\mathbf{v}, k) \tag{27}$$
$$\sum_{\mathbf{v} \in S_l} \rightarrow \sum_{k=0}^{K} \sum_{\mathbf{v} \in S_l}.$$

5. Computer Simulation

5.1. The Parameters for the Simulation

In the computer simulation, the parameters are chosen in the following way.

The number of the layers are four, and the layers are named U_0, U_1, ..., U_4 from the front. In each layer, there are $12 \times 12 = 144$ excitatory cells $u_l(n)$ and the same number of inhibitory cells $v_l(n)$.

The connectable area S_l is a square of $5 \times 5 = 25$ in size for every l. The vicinity area Ω_l in which the reinforcement of more than two cells is generally prevented, is a little smaller and have a rhombic shape whose hight and width are both 5 (13 in area). The conductance $c_l(v, k)$ of the synaptic connection from an axon terminal $u_l''(n + v)$ to a cell $v_l(n)$ is actually a function of only v and independent of l and k. It is a two-dimensional Gaussian function of v.

The spread of the lateral inhibition H_l is a square of 7×7 in size for every l. The value of the interconnection $g_l(\mu)$ is independent of l and is a two-dimensional Gaussian function of μ.

The number of the branches of the ramified axon is 2 ($K = 1$). The permutation $\mathscr{P}_{lk}$ ($k = 1$) of the destinations of the axon terminals has been determined in the following way. At first, from a matrix which indicating the starting position of each axon, a pair of horizontally adjoining two elements have been chosen at random and have been permutated to each other. Next, from this new matrix, a pair of vertically adjoing two elements have been chosen at random and also have been permutated. Such an operation has been repeated 576 times each for the horizontal and vertical direction, and a matrix indicating the state of permutation $\mathscr{P}_{lk}$ has been obtained. Different random numbers have been used for $l = 0$, 1, and 2. The r.m.s. values of the disparities between the positions before and after the permutation determined in this way has been 3.28, 3.54, and 4.05 for $l = 0$, 1, and 2, respectively.

The parameters which determine the amount of reinforcement at a time are adjusted to $q_0 = 2.0$ and $q_1 = 16.0$. The initial conductances of all the modifiable synapses $a_l(v, n, k)$ and $b_l(n)$ are chosen to be 0.

Here, the method of boundary correction is discussed briefly. Since the size of the neural layers is limited in the computer simulation, the connectable area S_l and the spread of the inhibitory connection H_l of a cell which is situated near the boundary might exceed the boundary of the layer.

In Eqs. (9) and (23), if it is supposed that the summation is taken only within the part of S_l or H_l which is contained within the boundary of the layer, the left-hand sides of these equations would become less than 1 for such a chipped-off summation area.

Hence, in case of $u_l(n) = 0$, if the reinforcement is made following Eqs. (11) and (12), the inhibition would become too small for the cells near the boundary, and Eq. (20) would not be satisfied for such cells. In order to avoid such an effect, the amount of reinforcement given by the right-hand side of Eq. (12) is compensated by dividing it by the value of left-hand side of Eq. (9) calculated in the above-mentioned sense. As for the lateral inhibitions, the values of $g_l(\mu)$ themselves are compensated so as to satisfy the equation (23) in the sense mentioned above.

5.2. Responses of the Cells of Each Layer

Five stimulus patterns "0", "1", "2", "3", "4" have been presented repeatedly to layer U_0 in a cyclic manner. These patterns have been selected to become simple figures when directly watched, only for the sake of the convenience for examining the response. These patterns do not necessarily stand for the unprocessed retinal images themselves.

Figure 5 shows how the cells respond to each of the five stimulus patterns at the 20th cycle of presentation. The responses of the cells of each layer are indicated by the whiteness in the photographs. As is seen in Fig. 5, the cognitron has been organized in such a way that each stimulus pattern elicits its own response pattern to every layer. Most of the cells, especially in layer U_3, have become to respond selectively to one stimulus pattern.

In order to show how the permutation of axon branches is made, Fig. 6 exemplifies the responses at the terminals of the permutated axon-branches for the stimulus pattern "4".

5.3. Reverse Reproduction

In order to verify that the synapses have been satisfactorily organized, an experiment by means of reverse reproduction is made. Actually, the information flow through a synapse is unilateral, and, in case of a cognitron, it is always in the direction from the front to the last layer. In the reverse reproduction, however, it is supposed that the direction of information flow through synapses were to be reversed, and the responses of the cells under such condition are obtained by computer simulation. For example, if the reverse reproduction is made from a single cell of layer U_1 only the U_0-cells which have excitatory effect on this U_1-cell would respond. That is, the excitatory part of the receptive field of this U_1-cell can be seen.

To be more exact, in the reverse reproduction, it is assumed that the information flows in the following way. If a cell $u_l(n)$ responds with an intensity $u_l(n)$, the amount of excitatory effect transmitted to a branched axon $u_{l-1}''(n + v, k)$ of the preceding layer is $a_l(v, n, k) \cdot u_l(n)$, and the amount of inhibitory effect is $c_{l-1}(v, k) \cdot b_l(n) \cdot u_l(n)$. The inhibitory effect is transmitted via cell
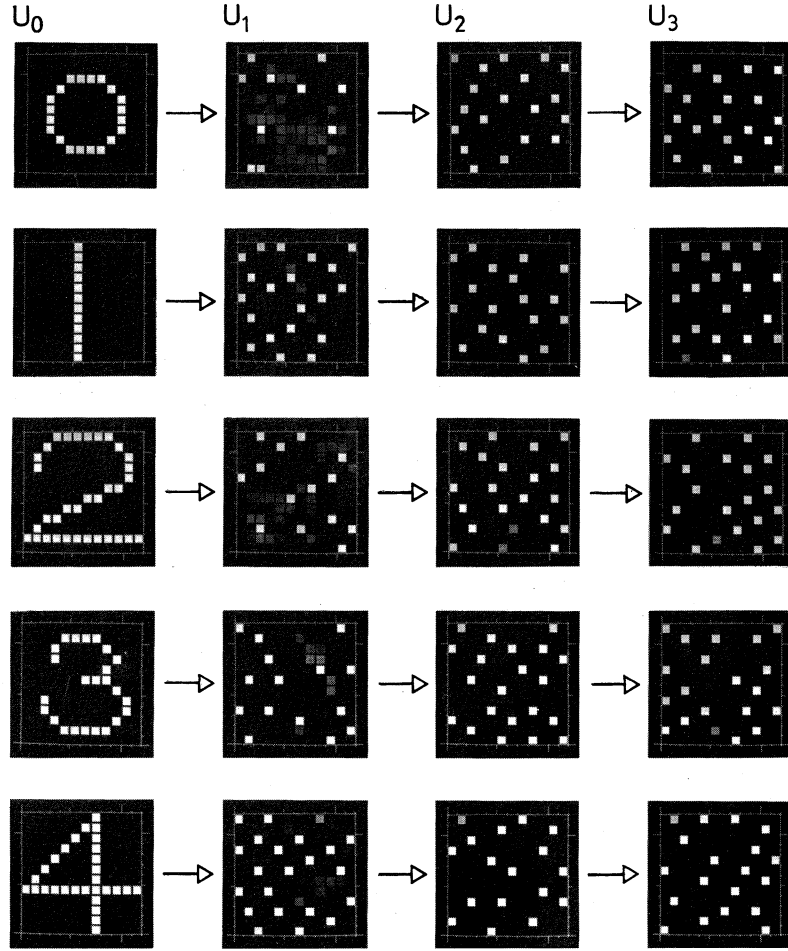
Fig. 5. The responses of the cognitron to five different stimulus patterns. These stimulus patterns have been presented to layer U_0 in a cyclic manner. The responses at the 20th cycle of stimulus presentation are shown
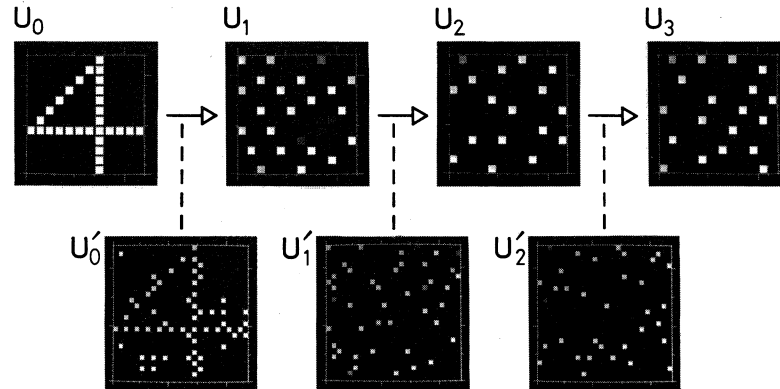

Fig. 6. An example of the responses at the terminals of the permutated axon-branches

$v_{l-1}(n)$. It is assumed that the excitatory cells of the preceding layer U_{l-1} has the input-to-output characteristic given by Eq. (5) also for the inputs in the reverse direction. The excitatory input e is assumed to be equal to the sum of the excitatory effects appeared at every branched axon terminals of the cell. The inhibitory input h is also calculated in the same manner. By substituting these values e and h to Eq. (5), the response to the reverse inputs is calculated. It is supposed that the lateral inhibition discussed in Sec-

tion 4.3 does not work in the process of reverse reproduction.

Figure 7 shows several results of reverse reproduction from the normal response patterns for stimulus "4" after the 20th cycle of learning. That first line of Fig. 7 shows the normal response of the cognitron to stimulus pattern "4" presented to layer U_0 and is identical with the fifth line of Fig. 5. The second line of Fig. 7 shows the reverse reproduction of the response of layer U_0 from the normal response pattern of layer U_1.

In the third line of Fig. 7, the response of layer U_1 is reversely reproduced from the normal response pattern of layer U_2 at first, and, again from this result, the response of layer U_0 is reversely reproduced. The fourth line shows the results of reverse reproduction from layer U_3. As is seen from these results, the input stimulus pattern is correctly reproduced by the reverse reproduction.

In contrast to Fig. 7, in which the reverse reproduction is made from the normal responses of the whole cells of a certain layer, Fig. 8 shows the results of reverse reproduction from single cells. The first line of Fig. 8 is the same as that of Fig. 7, and shows the response of the cognitron in the normal state. In the second line of Fig. 8, a U_1-cell which happened to respond strongly to stimulus "4" is chosen at first. (Here, it is not so important which cell is to be chosen, provided that the cell has yielded a large response to this stimulus. In Fig. 8, the cell whose normal response to this stimulus is maximum among the cells of layer U_1 has been chosen.) From this single cell, the response pattern of layer U_0 is reversely reproduced. Since the connectable area, hence the receptive field, of this cell is situated at the lower right part of layer U_0, only the lower right part of pattern "4" is reproduced. It can be considered that, in the reverse reproduction, excitatory responses are elicited only from the U_0-cells which, in the normal state, give excitatory effects to this U_1-cell. The third line of Fig. 8 shows the result of reverse reproduction from a single U_2-cell which has yielded a maximum output, and the fourth line shows the result of reverse reproduction from a single U_3-cell.

As is seen from these results, the cells in a deeper layer have relatively larger receptive fields, and the receptive field of the chosen U_3-cell covers the whole U_0-layer. That is, the deeper the layer is, the larger becomes the area from which a single cell of the layer integrates the information. In case of Fig. 8, the U_3-cell watches the whole U_0-layer and correctly grasps the information of pattern "4".

Figure 9 sums up the results of reverse reproduction for all the five stimulus patterns. It shows only the responses of U_0-layer and the firing patterns of U_3-layer from which the reverse reproduction are made. In the left half of Fig. 9, the results of reverse reproduction from the whole U_3-layer are shown. The right half of the figure shows the results of reverse reproduction from single U_3-cells whose outputs have been maximum in layer U_3. It is seen that the original stimulus patterns are correctly reproduced by the process of reverse reproduction, except for some errors for pattern "0". The imperfect reproduction of pattern "0" from single U_3-cell seems to be caused by the fact that this U_3-cell happens to be situated near the periphery of U_3-layer, and that the receptive field of this cell has been unable to cover the whole U_0-layer. We can find a U_3-cell, from which a better reproduction of pattern "0" is obtained. The reversely reproduced pattern from such single cell is almost the same as the pattern shown at the left and on the first line in Fig. 9. As is seen from these experiments, reverse reproduction is made correctly except a little error for pattern "0". Then we can conclude that the self-organization of the cognitron has been successfully performed.

5.4. The Time-Course of Synapse Organization

Figure 10 shows the time course of synapse organization observed by the reverse reproduction. That is, the U_3-cell which has yielded a maximum output to pattern "2" at the 20th cycle of presentation is chosen at first. This is the same cell as the one chosen in the experiment shown in the right side on the third line of Fig. 9. In order to observe how the synaptic connections to this cell have been organized, we start again from the initial state. We make the reverse reproduction from this cell after every cycle of presentation of the five stimulus patterns, and observe how the reversely reproduced pattern of U_0-layer varies with time. The numeral letter to the upper left of each pattern in Fig. 10 indicates the time from the initial state measured in cycles of pattern presentations.

From the 1st to the 3rd cycle, no pattern is reproduced by the process of reverse reproduction, since the paths from U_0-cells to this U_3-cell are not formed yet. At the 4th cycle, weak connections begin to be formed between the cells, and a faint pattern begins to appear. From the 4th to the 6th cycle, however, the reproduced pattern does not only contain the components of pattern "2" but also the components of patterns "0" and "1". These results show that, at this stage of development, this U_3-cell has not come to selectively detect pattern "2" yet, and responds also to the components of patterns "0" and "1",
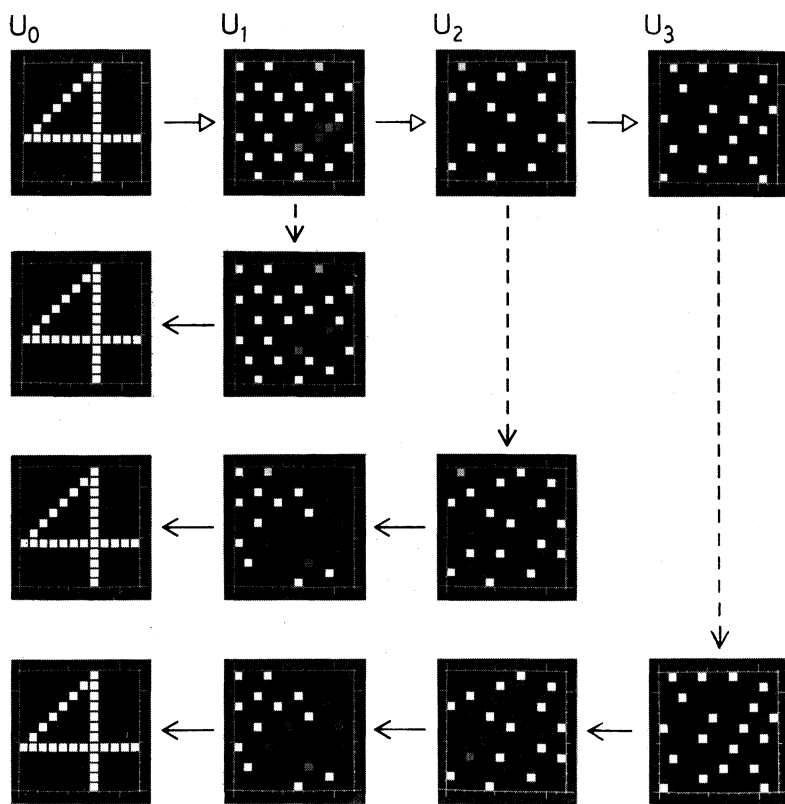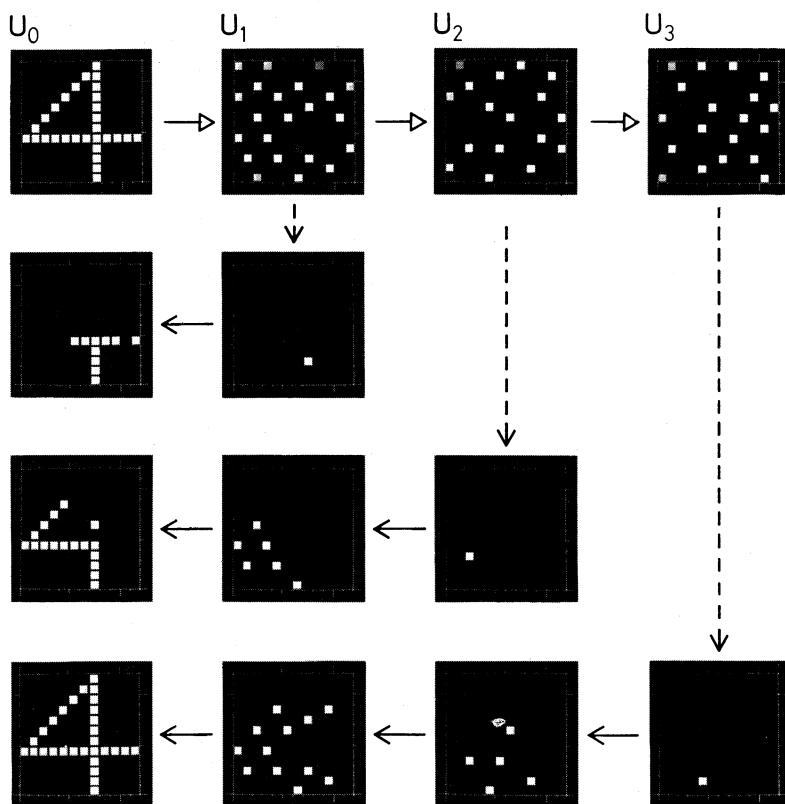
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Fig. 7. Reverse reproduction from the normal responses of the whole cells of single layers. The first line shows the normal response to stimulus "4" at the 20th cycle of pattern presentation. The second, the third and the fourth lines show the reverse reproduction from the normal response patterns of layers U_1, U_2, and U_3 respectively

Fig. 7

Fig. 8. Reverse reproduction from single cells. The first line shows the normal response to stimulus "4". The second, the third and the fourth lines show the reverse reproduction from the single cells whose normal responses have been maximum among the cells of layers U_1, U_2, and U_3 respectively
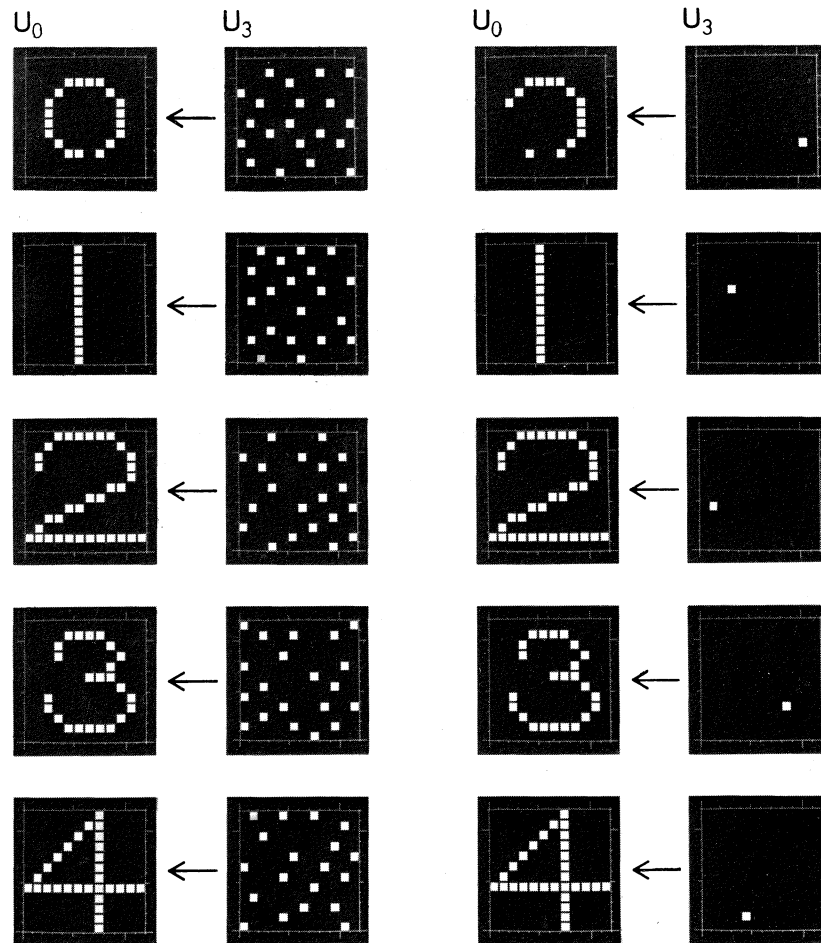
Fig. 8

Fig. 9. Summary of the results of reverse reproduction for five stimulus patterns. Left: the reverse reproduction of layer U_0 from the whole U_3 layer. Right: the reverse reproduction of layer U_0 from single U_3-cells whose responses to the stimuli have been maximum in layer U_3
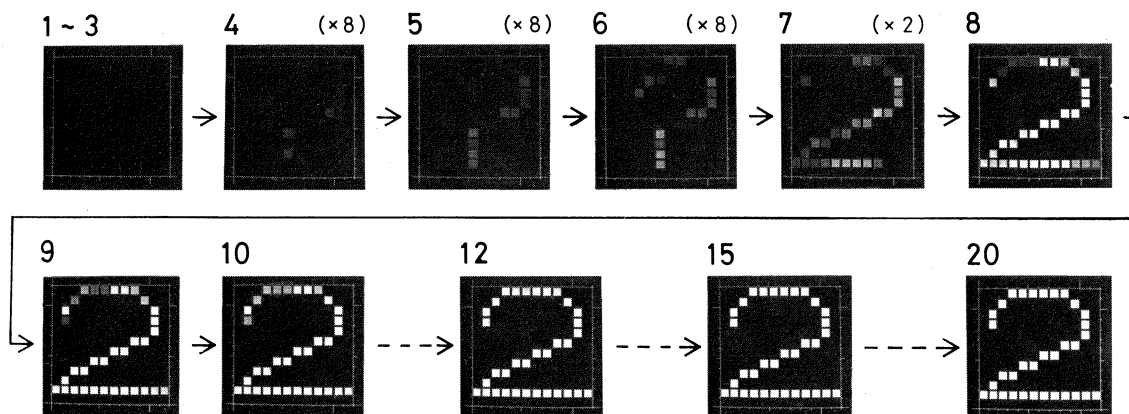

Fig. 10. The time course of synapse organization observed by the reverse reproduction

Since the magnitude of the reproduced patterns from the 4th to the 7th cycle are too small to be displayed with equal level to other patterns, in Fig. 10, the patterns from the 4th to the 6th cycle are displayed

with a level 8 times larger than actually is, and the one at the 7th cycle is displayed with a level 2 times larger.

After the 7th cycle, the reproduced patterns gradually become to bear a considerable resemblance
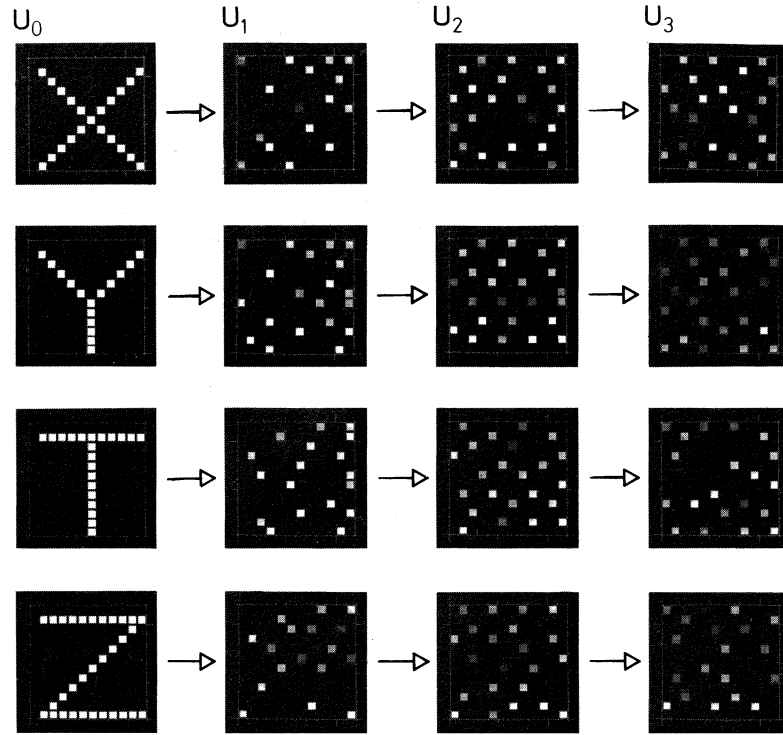
U_0 U_1 U_2 U_3

Fig. 11. The response of the cognitron to four stimulus patterns which resembles to one another. These stimulus patterns have been presented to layer U_0 in a cyclic manner. The responses at the 20th cycle of stimulus presentation are shown

to pattern "2", but contain some parts whose levels still remain low. This shows that some of the synapses have not been fully developed yet. After 15th cycle, however, the reproduced patterns reach a steady state, and it is seen that the synaptic connections have been completed.

5.5. Response to Resembling Patterns

Between the stimulus patterns used in the above experiments, there are not strong resemblances. In such a case, the response patterns of U_3-layer also bear little resemblance to each other. In this section, we discuss how the cognitron becomes to respond, if the stimulus patterns have considerable amounts of common components with one another.

The stimulus patterns presented to the cognitron are "X", "Y", "T", and "Z", and are shown in the left column of Fig. 11. There are considerable amounts of common components between "X" and "Y", "Y" and "T", "T" and "Z", "Z" and "X", and also between "Y" and "Z".

Figure 11 shows how the cells become to respond to these four stimulus patterns after 20 cycles of pattern presentation. In this case, even in layer U_3, there are many cells which respond to more than two different stimulus patterns. Figure 12 shows to which pattern

each U_3-cell responds. That is, Fig. 12 indicates, for instance, that the 3rd cell from the left on the 2nd line responds both "T" and "Z". In this figure, the magnitude of the response of each cell is neglected, and it is only checked whether the cell yields any output to the stimulus or not. In Fig. 12, we can find cells which respond to, for example, both "X" and "Y", which have several points of similarity to each other. We

Fig. 12. List of the names of the stimulus patterns to which each U_3-cell responds under the same condition as Fig. 11

U₀   U₁   U₂   U₃

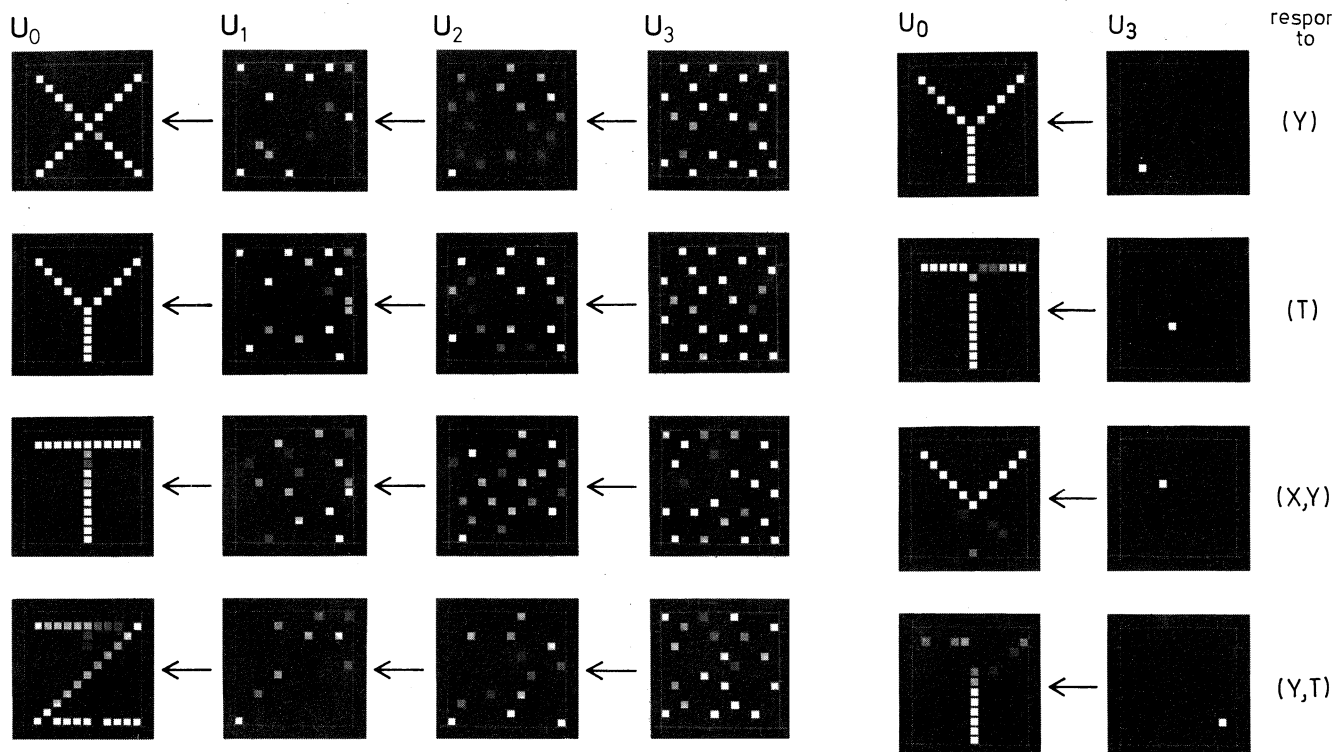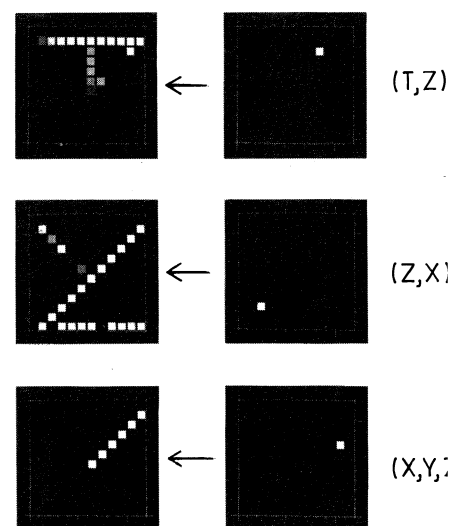U₀   U₃   respor
to

(Y)

(T)

(X,Y)

(Y,T)

(T,Z)

(Z,X)

Fig. 13. Reverse reproduction from the normal response patterns of the whole U_3-layer. The stimulus patterns presented to the cognitron have been "X", "Y", "T", and "Z", which are shown in Fig. 11

▶

Fig. 14. Typical examples of the reverse reproduction from single U_3-cells. The conditions are the same as Fig. 13

(X,Y,)

cannot find, however, cells which respond to both "X" and "T", between which there is little resemblance. These results show that resembling stimulus patterns elicit similar response patterns.

Figure 13 shows the results of reverse reproduction from the normal response patterns of the whole U_3-layer. It is seen that the original stimulus patterns are correctly reproduced except a little error for "Z".

Figure 14 shows some typical examples of the reverse reproduction from single U_3-cells. The left side pictures show the reversely reproduced patterns of

layer U_0. The right side pictures show the U_3-cells from which reverse reproduction is made. The letter drawn to the right of each of these pictures indicates the names of the stimulus patterns which elicit positive responses to these U_3 cells.

The first line of Fig. 14 shows the reverse reproduction from a single cell which responds only to stimulus "Y". It is seen that the pattern "Y" is correctly reproduced. Also, in the second line of Fig. 14, the stimulus pattern "T" is reproduced fairly well, although the reproduced pattern is missing at one cell. It is seen

that the reversely reproduced pattern from a single cell which selectively responds to one stimulus pattern generally coincide with the original stimulus pattern fairly well.

The third line of Fig. 14 shows the reverse reproduction from a cell which responds to both "X" and "Y". The reproduced pattern in this case is a mixture between "X" and "Y". The same situation is observed for the pictures in the following lines of Fig. 14. The U_3-cell shown in the bottom line of Fig. 14 responds to "X", "Y" and "Z". The pattern reversely reproduced from this cell consists of a line component which is the common component among these three stimulus patterns.

In some cases, a complete reproduction of the original pattern is impossible from only one U_3-cell. For example, the U_3-cell shown in the second line of Fig. 14 is the one which gives the best reproduction of pattern "T", but the reversely reproduced pattern contains some error. The reverse reproduction from other U_3-cells only give worse results. If the reverse reproduction is made from the whole cells of U_3-layer, however, a complete reproduction of the original stimulus pattern is performed as has been shown in the third line of Fig. 13. As is seen from these results, the response of a single cell by itself does not always serve for pointing out the presented stimulus pattern correctly, but the configuration of the spatial pattern representing the response of all the U_3-cells serves for the purpose. That is, in the cognitron, even the cells of the last layer generally divide the work among them, rather than only one of the cells works alone for the information processing of each stimulus pattern.

6. Conclusion

A self-organizing multilayered neural network "cognitron" has been constructed following a new hypothesis on the synapse organization. The computer simulation of the cognitron has shown that the cognitron has characteristics similar to that of the animal's brain in many points. Since the cognitron has a multilayered structure, it seems to have a larger capability for information processing than the usual brain models or learning machines proposed before.

The cognitron discussed in this paper is not intended to be a complete system for pattern recognition. If we want to make a pattern recognizer with a cognitron, some other functions must be added to it.

For instance, a feature extractor with a function of normalization of position, size, etc. would be necessary to be added in front of the cognitron, and a decision circuit should be cascaded after the last layer of the cognitron.

In the cognitron proposed here, the neural layers are merely cascaded one after another. It is expected that the neural network would acquire more ability if the structure of the network is modified. For instance, backward couplings between the cells of different layers, or cross couplings between the cells in the same layer would yield a better performance. Even for such cases, the algorithm used for the organization of the cognitron would be successfully applied.

The author conjectures that the hypothesis on the synapse organization proposed here holds not only in the higher center of the brain but also in the distal parts of the sensory systems. This does not mean, however, that this hypothesis is the only one rule which controls the organization of all kinds of synapses. Perhaps, the organization of some kinds of synapses would be controlled by some other rules.

References

Blakemore, C., Cooper, G. F.: Development of the brain depends on the visual environment. Nature (Lond.) **228**, 477–478 (1970)

Block, H. D., Knight, B. W., Rosenblatt, F.: Analysis of four-layer series-coupled perceptron. II. Rev. mod. Phys. **34**, 135–142 (1962)

Fukushima, K.: Visual feature extraction by a multilayered network of analog threshold elements. IEEE Trans. Syst. Sci. Cybernetics SSC-**5**, 322–333 (1969)

Fukushima, K.: A feature extractor for curvilinear patterns: A design suggested by the mammalian visual system. Kybernetik **7**, 153–160 (1970)

Fukushima, K.: A feature extractor for a pattern recognizer. A design suggested by the visual system (in Japanese). NHK Techn. J. **23**, 351–367 (1971)

Fukushima, K.: Self-organizing multilayered neuron network "Cognitron" (in Japanese), Paper of Technical Group on Pattern Recognition and Learning, Inst. Electronics Comm. Engrs. Japan, PRL74-25 (1974); and 1974 Nat. Conv. Rec. of Inst. Electronics Commun. Engrs. Japan, No. S9-8 (1974)

Hubel, D. H., Wiesel, T. N.: Receptive fields of single neurones in the cat's visual cortex. J. Physiol. (Lond.) **148**, 574–591 (1959)

Hubel, D. H., Wiesel, T. N.: Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. J. Physiol. (Lond.) **160**, 106–154 (1962)

Hubel, D. H., Wiesel, T. N.: Receptive fields and functional architecture in two nonstriate visual areas (18 and 19) of the cat. J. Neurophysiol. **28**, 229–289 (1965)

Malsburg, C. von der: Self-organization of orientation sensitive cells in the striate cortex. Kybernetik **14**, 85–100 (1973)

Marr, D.: A theory of cerebeller cortex. J. Physiol. (Lond.) **202**, 437–470 (1969)

Marr, D.: A theory of cerebral neocortex. Proc. roy. Soc. Lond. Ser. B, **176**, 161–234 (1970)

Rosenblatt, F.: Principles of Neurodynamics. Washington: Spartan Books 1962

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