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INHERENCY THEORY BASED NEURON MODEL TO LEARN MOVEMENT DIRECTION SELECTION

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Abstract. *It is well-known that nerve cells have the reaction selectivity to react to certain special stimulus patterns. Focusing on the fact that neurons in the visual center are formed by the mechanism of chemical induction on the basis of the genetically determined program at birth, and the neurons repair the synapse by visual experience, we propose a model of neuron based on the inherency theory and use the model neuron to learn the movement direction selection in this paper. In simulations, we assume that the structure of dendrites of nerve cells in the visual center is initially arranged regularly rather than randomly, and train the model neuron to learn the motion direction detection. The proposed neuron model is capable of detecting the motion direction and determining the state of the synapse and neuronal dendrites. In addition, we show that the shape of the neuron with the selection function of motion direction obtained by learning has a regular structure, consistent with the shape of the motion direction selective neuron proposed by Koch. Furthermore, we also find that neurons with regularly arranged initialization learn the motion direction selection problem much more successfully than those with random initialization.*
Keywords: Neurons, Dendrites, Synapses, Inherency theory, Nonlinear interaction, Movement direction selection

1. **Introduction.** The functions of the dorsal stream, MT area and MST area behind mammals' visual area 2 are developed after birth. The functions of these areas are to detect the location of the objects and generate their action information for survive. These areas correspond to a high-order visual cortex of visual area 5, but in their response latency, they are faster than the visual area 2, suggesting that they are an important part of an individual for survival.

Analysis of shape of an object to be detected is considered to be done in TE area, and TEO area of ventral stream rather than in dorsal stream. The hypothesis of "grandmother cells" that recognize the features of an object has been known for a long time, and many researches on ventral stream have been carried out [1]. However, the reports about the dynamic analysis of the object detection are very few. Although nerve cells that make up the area MST have been found to have a reaction selectivity responding to the motion, but without being influenced by the shape color [3,4], these neuronal cells have no specific anatomical features, and their selective functions are said to be from their local structure details such as their dendrite structure, and synapses. A fact that indirectly supports the idea, was that an functional regular array structure of the nerve cell was identified [5].

Dendrite is a path of input signal to nerve cell body (soma). One possibility is that the regular array structure corresponds to the selection to a specific action. When considering living body materially, the feature is just a "case for purpose". Dendritic structures can be generated to meet the purpose of recognizing the moving object, and if the resulting functional structure of neurons does show some kind of regular array structure, it is possible to reinforce such kind of response. We believe that such reinforcement is helpful.

However, to know how living body builds such kind of structure for purpose is important. The large parts of information of living body are thought to function by the genetic system and the nervous system. The former is mainly the structural part, and the latter is primarily a functional part. The growth of the functional structure of the nervous system, also referred to as a learning process, is very limited and occurs only in a relatively short period of postnatal. There is a view that in order to make effective use of this limited period, the growth of the functional structure works in dendritic portion and synaptic portion but not in neuron body. This view is in good agreement with the properties of the nerve cells. Furthermore, it is quite unlikely that dendrite and synapses are generated from the state of chaos. Actually, computer simulations have shown that only very poor functions can be realized from the random initialization [5]. Therefore, it is very nature to think that the outline and dendrites of the nerve cells' structure in MST area are formed in a regular array by a gene, and then modified to realize the specific functions, for example the reaction selectivity, by the visual experience after birth. Based on these theoretical and experimental evidences, we propose a model of neuron based on the inherency theory and use the model neuron to learn the movement direction selection. In simulations, we assume that the structure of dendrites of nerve cells in the visual center is initially arranged regularly rather than randomly, and train the model neuron to learn the motion direction detection. Simulations show that the proposed neuron model is capable of detecting the motion direction and determining the state of the synapse and neuronal dendrites. In addition, we show that the shape of the neuron with the selection function of motion direction obtained by learning has a regular structure, consistent with the shape of the motion direction selective neuron proposed by Koch. Furthermore, we also find that neurons with regularly arranged initialization learn the motion direction selection problem much more successfully than those with random initialization.

2. **Congenital Theory and Acquired Theory of the Reaction Selectivity.** Cortex neurons in MST area have the reaction selectivity [4]. Hebb's blocking experiments have suggested that the reaction selectivity properties were acquired after birth [6], while Wiesel and Hubel believed that the reaction selectivity was assumed to be "nativism" [7]. It is well known that a part of neurons in the MST field already has the reaction selectivity at birth, while most of the rest lack such kind of properties. Those cells lacking the reaction selectivity can acquire the property in a limited period after birth, called "sensitive period". In the "sensitive period", nerve cells adapt to the reaction selectivity if an artificial visual experience is given, and do not show the reaction selectivity if no such visual experience is given. These findings support the acquired theory generally. However, neurons in mammalian's MST area grown under normal visual environment are regularly arranged in order. As an example, the order can be assumed to be the azimuth angle of moving objects. Furthermore, if the dendrites and the synapses of nerve cells have plasticity and are capable of learning to acquire the reaction selectivity after birth as the acquired theory suggested, it is very difficult to acquire the order of the reaction selectivity. Experiments also showed that only poor reaction selectivity could be acquired by Hebb's learning rule if the dendrites were initialized chaotically.

Of course, it is difficult to prove even with computer simulations that the inherency theory can explain the order of the reaction selectivity. According to the inherence theory, nerve cell structure with the reaction selectivity if exists [3], is realized by the genetic system rather than the neural learning process. It is natural to think that the layered structure of nerve cell group in MST area might be created by genetic information.

3. **Neuron Model.**

Koch et al. assumed the existence of a delay signal to detect motion. Motion detection is possible by the logical product (AND) of the current image and the delayed image. When signal is applied to a nerve cell, it is reasonable to assume that the signal is applied to part of the nerve cell without delay, and to other part of the nerve cell with a delay [8]. Therefore, we assume that a nerve cell receives two kinds of inputs, the "fast input", and the "slow input". It is the difference between the fast input and the slow input that makes a nerve cell detect different speeds. Figure 1 shows the neuron model with consideration to the inherency theory.

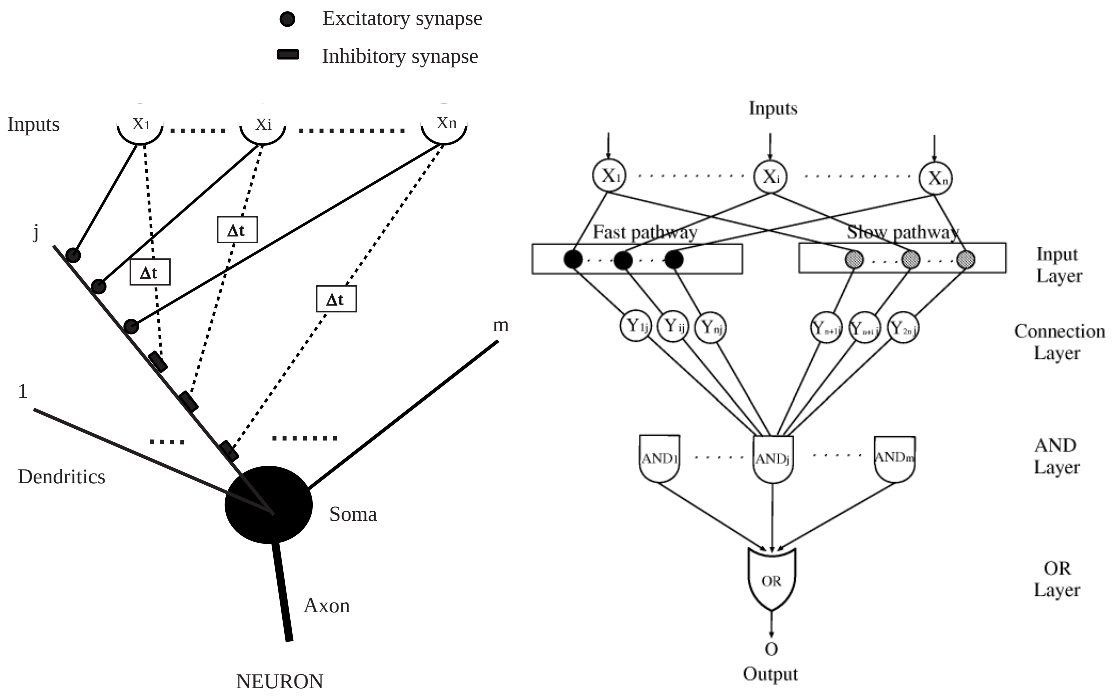

FIGURE 1. The neuron model with consideration to the inherency theory

The proposed neuron model has the structure as described below [9-11].

3.1. **Input layer.**

The first layer is called the input layer, conveying the input to dendrites through two paths, the fast path and the slow path. That is, when there are n external inputs, the input of $2n$ might be transmitted to dendrites. Thus, in the input layer, the input time difference occurs. If inputs are x_i $(i = 0, 1, \cdots, n)$, the inputs from the fast path are

$$X_i(t) = x_i(t) \tag{1}$$

And the inputs from the slow path are

$$X_{n+i}(t) = x_i(t - \Delta t) \tag{2}$$

where t represents the time variation of the input.

3.2. **Connection layer.** The second layer is called the connection layer, receiving input from the input layer, and transmitting to dendrites. It corresponds to a function of the coupling of neuronal synapse. The synapse coupling is assumed to have the following four possible states.

Excitatory Synapse: transmits the input signal to a dendrite directly.
Inhibitory Synapse: transmits the inverted input signal to a dendrite.
Constant 0 Connection: 0 is applied to a dendrite regardless of the input.
Constant 1 Connection: 1 is applied to a dendrite regardless of the input.

And because both input and output are either 0 or 1, the four connection states can be expressed by a differentiable sigmoid function as

$$Y_{ij} = f(u_{ij}) = \frac{1}{1 + e^{-ku_{ij}}} \tag{3}$$

where $u_{ij} = w_{ij}X_i - \theta_{ij}$, X_i $(i = 0, 1, \cdots, 2n)$ is the inputs and w_{ij}, θ_{ij} are the connection parameters. Y_{ij} is the synapse from i-th input to the j-th dendrite and k is a constant.

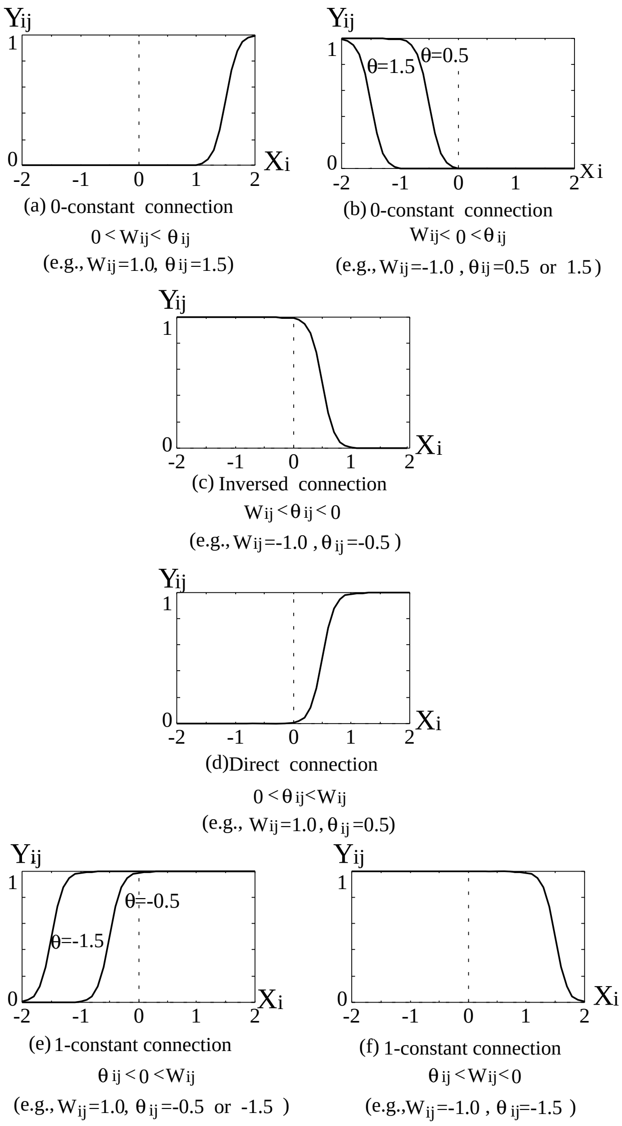

FIGURE 2. Sigmoid function output characteristics and its equivalent connection states

The connection states are determined by the connection parameters w_{ij} and θ_{ij} as shown in Figure 2. As can be seen from Figure 2, a desired connection can be obtained from the four connections by selecting appreciate connection parameters.

3.3. **AND layer.** The third layer is the AND layer, taking the logical AND of the output from the connection layer. This corresponds to a function of a dendritic branch of nerve cells. The logical AND operation can be approximated with a differentiable soft-minimum function as

$$f_{\min}(x_1, x_2) = \frac{x_1 e^{-ux_1} + x_2 e^{-ux_2}}{e^{-ux_1} + e^{-ux_2}} \tag{4}$$

where x_1, x_2 are the input variables, and u is a constant. In addition, this function is considered as an approximation of the AND logic function because it is very close to the logic AND function as the constant u reaches limit,

$$\lim_{u \to \infty} f_{\min}(x_1, x_2) = \min\{x_1, x_2\} \tag{5}$$

3.4. **OR layer.** The fourth layer is the logical OR layer, performing a logical OR operation on the inputs from the AND layer. It corresponds to the function of a branch point of nerve cells. The logical OR function can be approximated with a differentiable soft-maximum function,

$$f_{\max}(x_1, x_2) = \frac{x_1 e^{vx_1} + x_2 e^{vx_2}}{e^{vx_1} + e^{vx_2}} \tag{6}$$

where x_1, x_2 are the input variables, and v is a constant. In addition, this function is considered as an approximation of the OR logic function because it is very close to the logic AND function as the constant v reaches limit,

$$\lim_{v \to \infty} f_{\max}(x_1, x_2) = \max\{x_1, x_2\} \tag{7}$$

Therefore, a neuron can be modeled as a three-layer structure. Furthermore, the nodes are all differentiable. Thus, the neuron can be trained by traditional error back-propagation algorithm by modifying the connection parameters w_{ij} and θ_{ij}.

3.5. **Learning algorithm.** For an input pattern p, its teacher's signal is T_p. This input pattern p is applied to the model neuron through the fast path and the slow path, respectively. Assuming that output of a model neuron is O_p when a given input pattern p is applied to the model neuron, the mean square error between the actual output and the desired output can be defined as,

$$E_p = \frac{1}{2}(T_p - O_p)^2 \tag{8}$$

As the functions of all nodes are differentiable, the error function E_p can be reduced by adjusting the connection parameters of the connection functions of the model neuron, w_{ij} and θ_{ij} using the BP law as,

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} \tag{9}$$

$$\Delta \theta_{ij} = -\eta \frac{\partial E_p}{\partial \theta_{ij}} \tag{10}$$

where $\eta > 0$. Using the differential chain rule, we can obtain

$$\frac{\partial E_p}{\partial w_{ij}} = \frac{\partial E_p}{\partial O_p} \cdot \frac{\partial O_p}{\partial AND_j} \cdot \frac{\partial AND_j}{\partial Y_{ij}} \cdot \frac{\partial Y_{ij}}{\partial w_{ij}} \tag{11}$$

$$\frac{\partial E_p}{\partial \theta_{ij}} = \frac{\partial E_p}{\partial O_p} \cdot \frac{\partial O_p}{\partial AND_j} \cdot \frac{\partial AND_j}{\partial Y_{ij}} \cdot \frac{\partial Y_{ij}}{\partial \theta_{ij}} \tag{12}$$

where Y_{ij} and AND_j are the outputs of the connection layer and the AND layer, respectively. Thus, the connection parameters w_{ij}, θ_{ij} are updated as,

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \tag{13}$$

$$\theta_{ij}(t+1) = \theta_{ij}(t) + \Delta \theta_{ij}(t) \tag{14}$$

where $w_{ij}(t+1)$, $\theta_{ij}(t+1)$ are w_{ij}, θ_{ij} after updating, and $w_{ij}(t)$, $\theta_{ij}(t)$ are w_{ij}, θ_{ij} before updating.

4. **Simulations.** In this chapter, we examine the validity of that neuron model with a congenital structural element by training the model neuron to learn the movement direction selection function with computer simulations. We conducted simulations to learn the selectivity for stimulus that moves from side to side on one-dimension. Figure 3 shows the input pattern applied to the model neuron. When the input moves from the left to the right, the model neuron outputs $T = 1$, otherwise $T = 0$. In the first simulation, the initial structure of the connection layer of the model neuron was set to make the fast input with the connection state of excitatory synapse in range of $0 < \theta_{ij} < w_{ij}$, and the slow input with the inhibitory synapse in range of $w_{ij} < \theta_{ij} < 0$, randomly. Figure 4 shows the initial structure of the model neuron. Table 1 shows the learning parameters used in this simulation. In addition, the number of dendrites was set to 8 (i.e., the number of AND gates). One time learning was defined as that either left motion or right motion pattern was applied and update was performed. Learning was performed up to a maximum of 1000 times in all simulations. Figure 5 shows the change of the error function by learning. From the figure, we found that the error function converged to a small value for both the right direction stimulus (8 null direction) and the left direction stimulus (preferred direction). Especially, for the left direction input pattern that was the preferred direction and the teacher signal $T = 1$, the error function decreased greatly. Figure 6(a) shows a morphology of a model neuron that represents the connection status from the value of θ_{ij}

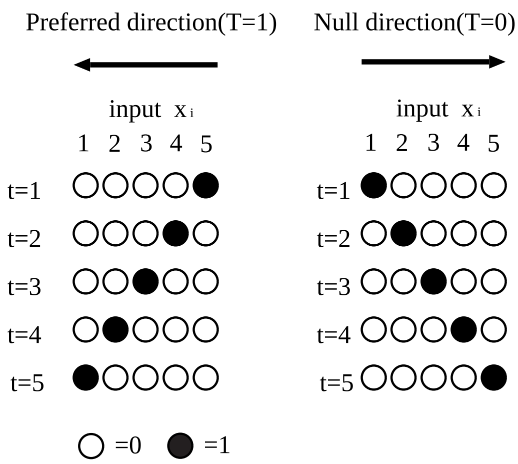

FIGURE 3. The model of movement detection

TABLE 1. The learning parameters

The learning constant η	0.5
The positive constant k of sigmoid function	5.0
The positive constant u of softmin function	5.0
The positive constant v of softmax function	5.0

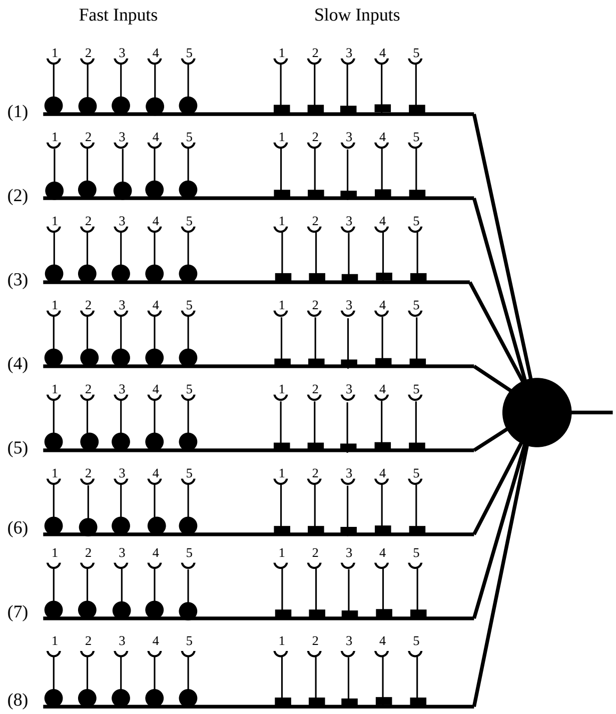

FIGURE 4. The morphology of the neuron on one-dimensional movement detection problem before learning

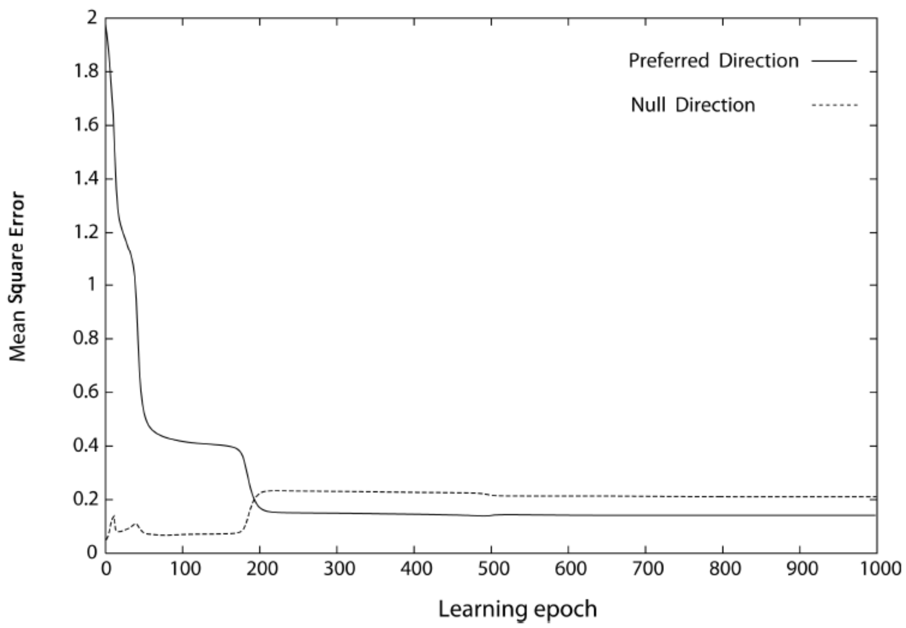

FIGURE 5. Learning to one-dimensional direction selectivity problem

and w_{ij} after learning. By removing the unnecessary synapses and branches, we can obtain idealized dendrites of the model neuron. For example, first, a branch (7) was always 0 because it had at least a 0-connection, and did not affect the nerve cells. Thus, the branch (7) could be eliminated through selection. The branches (1) and (5), and the branches (3) and (8) were the completely same. They can be incorporated into the branches (1) and (3). Thus, the morphology of the model neuron (Figure 6(a)) can be idealized into a dendritic branch as shown in Figure 6(b). As can be seen from Figure 6(b), if a stimulus

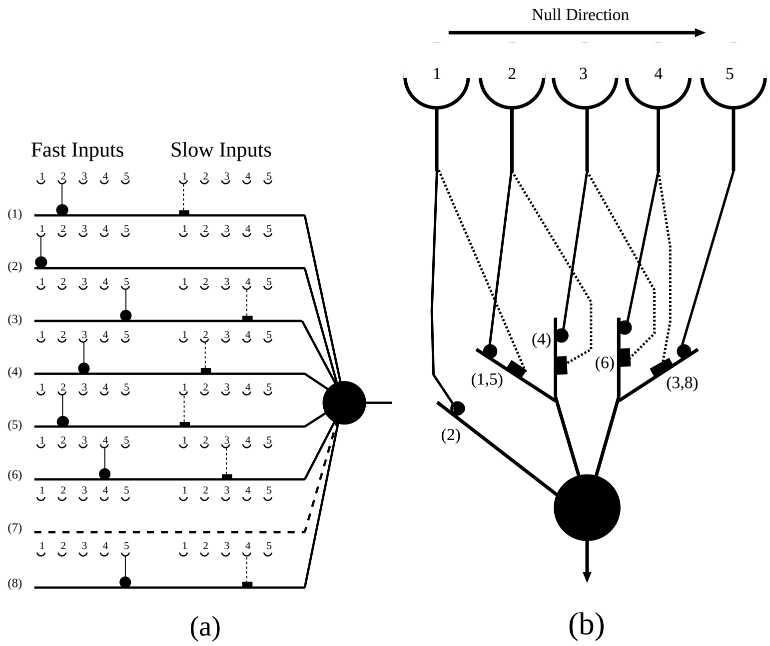

Figure 6. The morphology of the neuron on one-dimensional movement detection problem: after learning (a) and its corresponding dendritic branches (b)

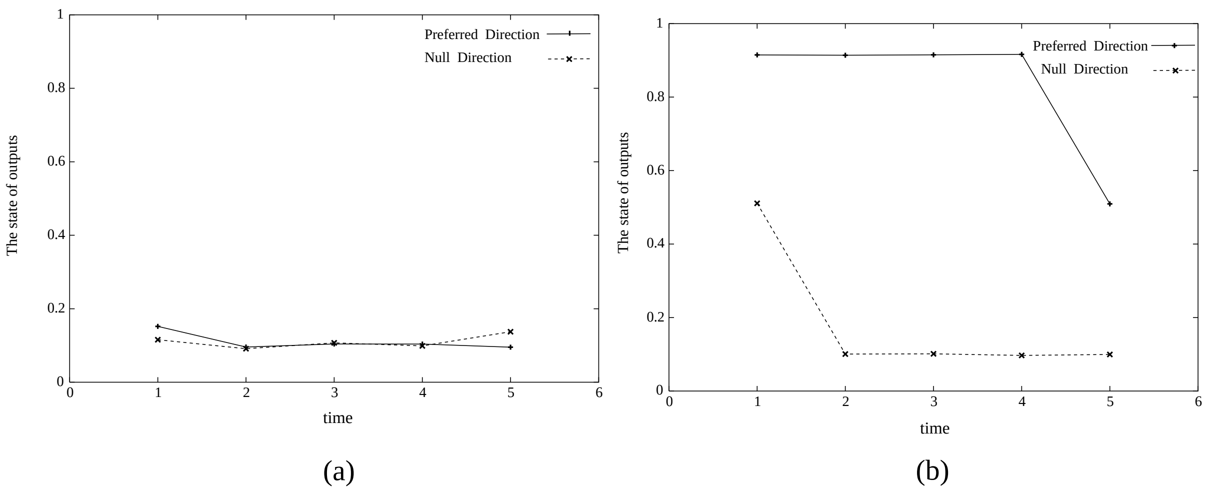

Figure 7. The state of output: (a) before and (b) after learning

moves from right to left, the model neuron would fire to output 1, and otherwise the neuron would be suppressed by slow input and output 0. In this way, the initial neuronal dendrite with the regularity (Figure 4) could learn to react selectively to the direction of movement and to form a functional neuronal dendrite with the regularity as shown in Figure 6(b). Furthermore, the dendrite obtained by learning, are consistent shape of the motion of a directional selection cell guessed by Koch [10]. In addition, the output states of the model neuron to the input pattern with the right direction movement stimulus and left direction movement stimulus before learning and after learning are shown in Figures 7(a) and 7(b), respectively. The model neuron almost did not react to both left and right input patterns before learning (Figure 7(a)). However, after learning, the neuron reacted strongly to and only to the left motion pattern (Figure 7(b)). From that, we can also say that the model neuron did learn to adjust the state of the synaptic coupling so as to react only to the left motion input pattern from the simulation. However, when there was only an input to the input 1, it could not receive the inhibitory signal from the slow input, thus resulting in the slow reaction.

Next, we will verify the validity of considering the inherency theory by comparing the simulation results of various initial structures. We varied parameters $k = u = v$ from 3 to 8 in increments of 1, used the different initial structures of $A \sim D$, and did learning simulations maximum to 1000 learning times with the learning parameter $\eta = 0.5$.

A: the initial structures θ_{ij} and W_{ij} were completely random;
B: the initial structures θ_{ij} and W_{ij} were set so that there was no selection of dendrites;
C: the initial structures θ_{ij} and W_{ij} were set so that there were only inhibitory synapses and excitatory synapses;
D: the initial structures θ_{ij} and W_{ij} were set so that the fast input had only excitatory synapses and no synaptic connection and the slow input had only inhibitory synapses and no synaptic connection.

Simulations were performed 100 times to each initial structure and their success rates are shown in Table 2. It was considered to be success if both errors to left motion input pattern and right motion input pattern are below to 0.5. As can be seen from Table 2, the proposed initial structure with regular structure had the highest success rate. In particular, parameters $k = u = v$ were 4, and the success rate got to 99%, achieving a very

TABLE 2. The states of success

$k = u = v$	3	4	5	6	7	8
A	11	48	44	29	7	3
B	25	42	29	21	12	15
C	28	74	66	33	25	27
D	27	66	37	30	17	17
Proposed method	62	99	91	85	67	63

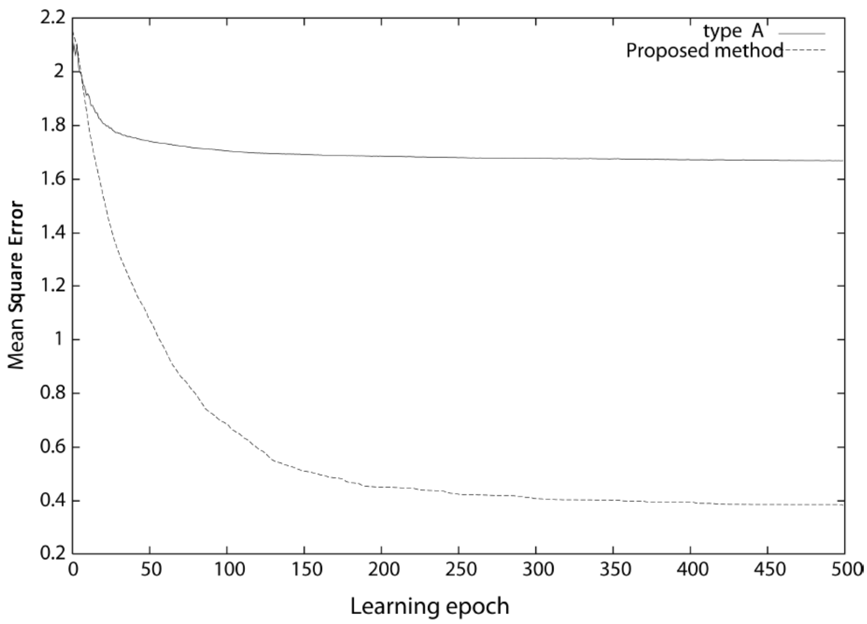

FIGURE 8. Learning performance for parameter ($k = u = v = 5$)

high success rate. Figure 8 shows the learning characteristic of A-type initial structure and the proposed regular structure at $k = u = v = 5$. It refers to the average error function of 100 simulations. Simulation results show that the proposed initial structure had converged to less than 0.5 at about 200 times of learning. From the above simulation results, we can conclude that the neuron with regular initial structure could learn much more efficiently than that with random initial structure.

5. **Conclusions.** In this paper, we proposed a model of neuron that takes the inherency theory into account and used the model neuron to learn the movement direction selection problem. In simulations, we performed the learning from different initial structure, trained the model neuron to learn the motion direction detection, and compared their learning performance. Simulation result showed that the proposed model neuron was capable of detecting the motion direction and determining the state of the synapse and neuronal dendrites. In addition, we demonstrated that the shape of the neuron with the selection function of motion direction obtained by learning had also a regular structure, consistent with the shape of the motion direction selective neuron proposed by Koch. Furthermore, we also found that neurons with regularly arranged initialization learned the motion direction selection problem much more successfully than those with random initialization, supporting the validity of the hypothesis that the structure of dendrites of nerve cells in the visual center was initially arranged regularly rather than randomly.

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