

Novel Architecture for Cellular Neural Network Suitable for High-Density Integration of Electron Devices-Learning of Multiple Logics

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Abstract. We will propose a novel architecture for a cellular neural network suitable for high-density integration of electron devices. A neuron consists of only eight transistors, and a synapse consists of just only one transistor. We fabricated a cellular neural network using thin-film devices. Particularly in this time, we confirmed that our neural network can learn multiple logics even in a small-scale neural network. We think that this result indicates that our proposal has a big potential for future electronics using neural networks.

Keywords: Cellular neural network · High-density integration · Electron device · Learning · Multiple logics

1 Introduction

Cellular neural networks are neural networks where a neuron is connected to only neighboring neurons [1], hence suitable for integration of electron devices, and promising for image processing [2], pattern recognition [3], etc. Until now, fundamental theory, working principle, and application potential have been actively investigated using formal models and numerical simulation. However, there exist few reports on actual hardware of cellular neural networks [4], although they are suitable for integration of electron devices as aforementioned. We imagine that this is because the conventional circuits of the neurons and synapses are still complicated, even though the structure of the network is simple.

We are developing neural networks from the viewpoint of device hardware [5, 6]. In this presentation, we will propose a novel architecture for a cellular neural network suitable for high-density integration of electron devices. The main advantage is that the circuits of the neurons and synapses are excellently simple. A neuron consists of only eight transistors, and a synapse surprisingly consists of just only one transistor. As a result, the structure of the cellular neural network and learning principle must be modified. We will explain the device architecture, learning principle, fabrication process, experimental

method and result in detail. It should be also noted that we fabricated a cellular neural network using thin-film devices, which are expected as key technologies for micro-giant electronics. Although there will be some repetition of the prior publications, we will explain them again because it is available for the readers in research areas of information technologies who have not yet known our research. Particularly in this time, we confirmed that our neural network can learn multiple logics of AND and OR even in a small-scale neural network of 5×5 . Although this result is primitive, we think that it indicates that our proposal has a big potential for future electronics using neural networks.

2 Device Architecture

2.1 Neuron

Figure 1 shows the neuron. We limited the necessary functions of the neuron to that a binary state is maintained by itself and altered by the input signals. In order to realize this simple function, we adopted a latch circuit that circularly connects two inverters with two switches. The firing or non-firing state is maintained using the latch circuit when the switches are turned on, namely, we defined the firing state as a situation when the voltages at node α and node β are high and complementarily low, respectively, whereas we defined the non-firing state as the opposite situation. Although the latch circuit is a well-known circuit for maintaining a binary state, it should be noted that its characteristic is similar to a sigmoid function, a typical function used to provide a favorable soft threshold in neural network models. The binary state is altered after the switches are turned off, the input signals are applied to nodes α and β , and the switches are turned on again. In any case, by employing complementary inverters and switches, we succeeded in making a neuron consist of only eight transistors.

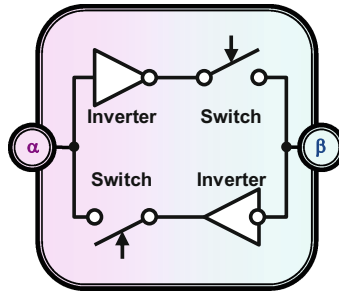


Fig. 1. Neuron.

2.2 Synapse

Figure 2 shows the synapse. We limited the necessary functions of the synapse to that an input signal from a neuron is weighted by its synaptic connection strength and

transferred to another neuron, and the synaptic connection strength is adjusted. In order to realize this simple function, we adopted a variable resistor, which will be replaced by a transistor in practical electron devices. An input voltage from a neuron is weighted by the conductance of the variable resistor and transferred to another neuron. The synaptic connection strength corresponds to the conductance of the variable resistor, which is adjusted obeying a modified Hebbian learning as below mentioned. In any case, we succeeded in making a synapse consist of just only one resistor.

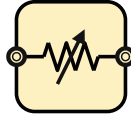


Fig. 2. Synapse.

2.3 Network

Figure 3 shows the network. Since the neuron and synapse were dramatically simplified, the structure of the cellular neural network must be modified. We arrayed multiple neurons and connected each neuron to only four up, down, left, and right neighboring neurons through the synapses. In order to compensate the small number of the synapses, we connected a pair of neurons through a pair of synapses, namely, concordant and discordant synapses. The concordant synapse is connected between the same nodes in the two neurons, nodes α and α or nodes β and β , and tends to make the states of the two neurons the same. On the other hand, the discordant synapse is connected between different nodes, nodes α and β , and the discordant synapse tends to make the states of the two neurons different. The eight input voltages from the four neighboring neurons are weighted by the conductances of the four concordant synapses and four discordant synapses and transferred to the target neuron. The target neuron becomes the firing or non-firing state, namely, is subject to the majority rule of multiple signals with weighted strengths. Moreover, it should be noted that this network is a kind of interconnective networks, where a synapse transfer a signal from a neuron to another neuron and simultaneously from the latter neuron to the former neuron vice-versa, which may correspond to the function of two synapses and also compensate the small number of the synapses. In any case, we succeeded in making an interconnective network where we connected each neuron to only four neighboring neurons, which is exceedingly suitable for integration of electron devices. The detailed information on the structures, sizes, circuits, and characteristics of the neuron, synapse, and networks were also explained in the prior reports [5, 6].

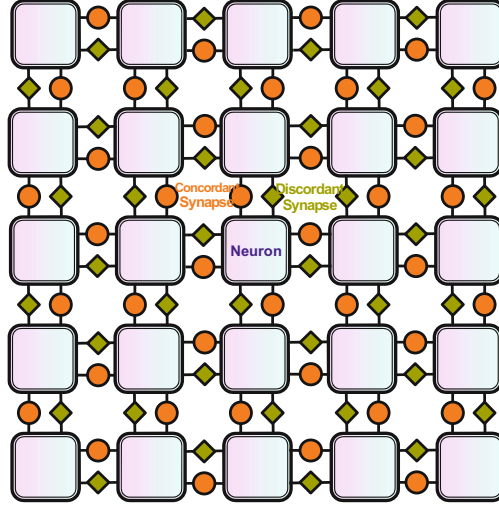


Fig. 3. Network.

3 Learning Principle

Hebbian learning is a typical learning procedure in biological and artificial neural networks [7]. The synaptic connection strength is enhanced when both neurons connected to the synapse are in firing states and impaired otherwise. Since the neuron and synapse were dramatically simplified, the leaning principle must be also modified. Figure 4 shows the modified Hebbian learning. Here, we assume NOT logic as an example. The left and right neurons are assigned to input and output elements, respectively. Initially, at the initial recalling stage, a non-firing state is applied to the input element, and a non-firing state arises from the output elements, and vice versa because the synaptic connection strength of the concordant synapse is accidentally slightly stronger than that of the discordant synapse, which is not NOT logic. Next, at the first learning stage, a non-firing state is applied to the input element, and a firing state is applied to the output element. Since the concordant synapse is connected between the same nodes in the two neurons, and the states at both nodes in two neurons are different, electric current flows through the concordant synapse because of the voltage difference, whereas electric current does not flow through the discordant synapse. Consequently, the characteristic degradation gradually occurs, which is a necessary property of our synapses [8], the conductivity has gradually higher impedance, and only the synaptic connection strength of the concordant synapse becomes gradually weakened. At the second learning stage, a firing state is applied to the input element, and a non-firing state is applied to the output element. Similarly, only the synaptic connection strength of the concordant synapse becomes gradually weakened. Finally, at the final recalling stage, a non-firing state is applied to the input element, and a firing state arises from the output elements, and vice versa because the synaptic connection strength of the concordant

synapse becomes slightly weaker than that of the discordant synapse, which is NOT logic. It should be noted that although the absolute values of the synaptic connection strengths cannot be enhanced even if both neurons connected to the synapse are in the firing state because we employed the characteristic degradations of the synapses, the relative values of the synaptic connection strengths can be enhanced, which is a reason that we called it modified Hebbian learning. In any case, by employing the modified Hebbian learning and characteristic degradations of synapses, we succeeded in making a synapse consist of just only one resistor.

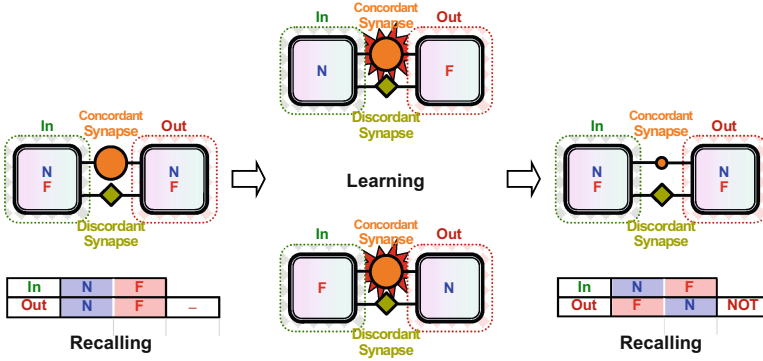


Fig. 4. Modified Hebbian learning.

4 Fabrication Process

We fabricated a cellular neural network using thin-film devices, which are expected as key technologies for micro-giant electronics. Micro-size electron devices can be fabricated on large and inexpensive substrates. Although the device size is in the order of μm in this research, it can be in the order of nm in the most advanced researches [9]. Although they are fabricated on a glass substrate in our research, they can be fabricated on plastic films [10], which can be folded down to compact size as human brains do. Therefore, we believe that thin-film devices are most promising electron devices for cellular neural networks.

We fabricated thin-film devices as follows. First, an amorphous-Si film was deposited using LPCVD of Si_2H_6 , crystallized using XeCl excimer pulse laser, and patterned to form poly-Si films [11], whose thickness is 50 nm, which are used as channels for transistors. Next, a SiO_2 film was deposited using PECVD of TEOS to form an insulator film, whose thickness is 75 nm, which is used as gate-insulator films for transistors. Afterward, the first metal film was deposited and patterned, which is used as gate terminals for transistors and simultaneously the first electrode wires. Subsequently, phosphorous and boron were implanted into the poly-Si films and thermally activated to form doping regions, which are used as source and drain regions for transistors. Next, a SiO_2 film was deposited to form an insulator film, which is used as an interlayer-insulator film. After that, and the second metal film was deposited and patterned, which is used

as source and drain terminals for transistors and simultaneously the second electrode wires. Finally, water-vapor heat treatment was performed to improve the poly-Si films, the SiO_2 film and their interfaces. Consequently, the field effect mobility and threshold voltage of the n-type transistors are $93 \text{ cm}^2 \text{ V}^{-1} \text{ s}^{-1}$ and 3.6 V , respectively, while those of the p-type transistors are $47 \text{ cm}^2 \text{ V}^{-1} \text{ s}^{-1}$ and -2.9 V , respectively. These parameters are sufficient for the circuits in the cellular neural network.

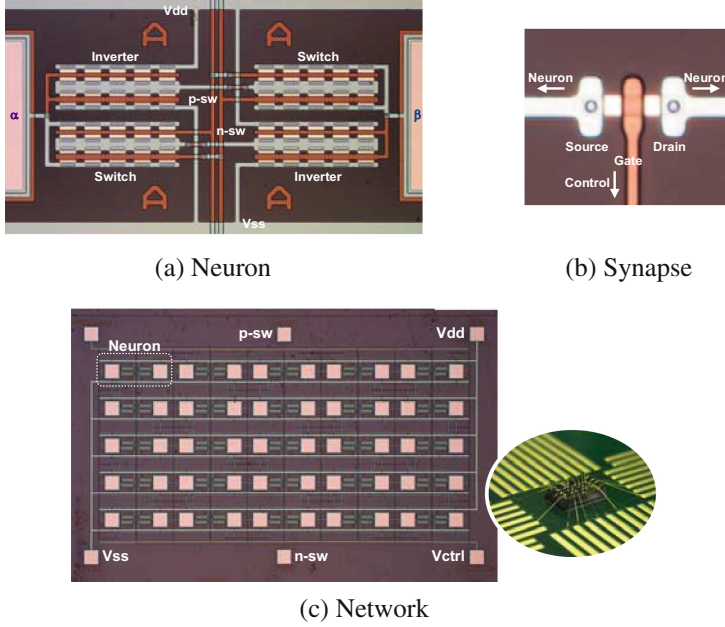


Fig. 5. Actual devices.

Figure 5 shows the actual devices. We arrayed 5×5 neurons and utilized transistors as synapses. The actual chip is die bonded on a printed circuit board and wire bonded to metal contacts.

5 Experimental Result

We tried to make the cellular neural network learn multiple logics. Figure 6 shows the input and output pattern. Four neurons at the corners were assigned to In1 and In2, and two neurons at the inside were assigned to Out1 and Out2, although they can be assigned freely to some extent. The non-firing or firing states were applied to In1 and In2 for each logic pair. At the recalling stage, output voltages generated from the network were measured at Out1 and Out2, whereas at the learning stage, corresponding outputs of AND and OR were applied to Out1 and Out2. Switching pulses were periodically applied to repeat the switch on and off of the switches in the neuron. At the recalling stage, a lower control voltage of 10 V was applied to the gate terminal of the transistor to avoid

the characteristic degradations of the synapses, whereas at the learning stage, a higher control voltage of 15 V was applied to induce the characteristic degradations. The recalling and learning stages were repeated several ten times.

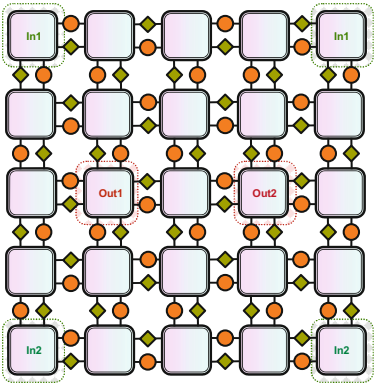


Fig. 6. Input and output pattern.

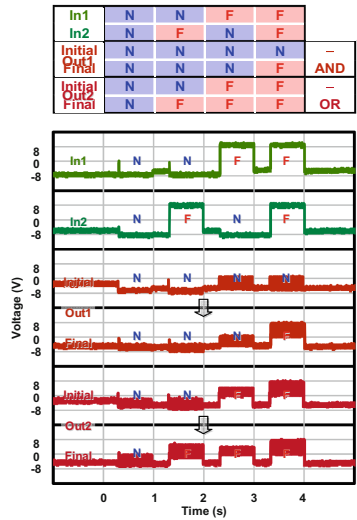


Fig. 7. Input and output pattern.

Figure 7 shows the learning result. It is found that at the first recalling stage, wrong output voltages were generated from Out1 and Out2. On the other hand, at the final recalling stage, correct output voltages corresponding outputs of AND and OR were generated from Out1 and Out2, respectively. Although this is an example, it was checked that the learning was successful in most cases in spite that the number of the times until

the correct output voltages were generated was widely distributed. In conclusion, we confirmed that our neural network can learn multiple logics of AND and OR even in a small-scale neural network of 5×5 .

6 Conclusion

We proposed a novel architecture for a cellular neural network suitable for high-density integration of electron devices. A neuron consists of only eight transistors, and a synapse consists of just only one transistor. We fabricated a cellular neural network using thin-film devices. Particularly in this time, we confirmed that our neural network can learn multiple logics even in a small-scale neural network. We think that this result indicates that our proposal has a big potential for future electronics using neural networks.

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