PULSE-TYPE NEURO DEVICES WITH SPIKE TIMING DEPENDENT SYNAPTIC PLASTICITY

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Keywords: Neural Network, Pulse-Type, STDP, Synaptic Weight, Neuro Device, Noise Tolerance.

Abstract: Even though the neurons in the human brain are sensitive to noises, human central nervous systems can operate correctly under a noisy environment. Since neural networks have superior information processing functions, many investigators have attemptted to model biological neurons and neural networks. A number of recent studies of neural networks have been conducted with the purpose of applying engineering to the brain. Especially, neuro devices have been created that focus on how to have a learning function. Here, we focus on spike timing dependent synaptic plasticity (STDP) and construct pulse-type neuro devices with STDP using analog VLSI technology. We show that it is possible to extract phase differences representing the reinforcement part of the synaptic weight by using pulse-type neuro devices with STDP. Moreover, we investigate noise tolerance for thermal noise and fluctuation of time.

1 INTRODUCTION

An artificial neural network that performs similarly to the human brain would be required to construct a brain-type information processing system. Our human central nervous systems can operate correctly in noisy environments even though the neurons in the brain are sensitive to noise. On the other hand, it would be necessary to use neuro devices as components in an environment without noise. To focus on this superior function, investigators are studying the noise tolerance of artificial neural networks. Because it is not possible to learn correctly when influenced by noise, an information processing system cannot be constructed. The classical Hebbian learning rule is proposed as the learning rule. (Hebb, 1949). This rule is thought to play an important role in the synaptic plasticity of neural networks in the brain. This rule uses mean spike firing correlations between pre- and postsynaptic neurons to drive learning. Recently, the form of synaptic plasticity was seen to be dependent on the order and time intervals of pre- and postsynaptic spikes (STDP: spike timing dependent synaptic plasticity (Bi and Poo, 1998, Nishiyama, Hong, Mikoshiba, Poo, and Kato, 2000)), as was observed in the hippocampus and cerebral cortex. (Patrick and Curtis, 2002, Sakai and Yoshizawa, 2003, Tsukada, Aihara, Kobayashi and Shimazaki, 2005). STDP manifests itself as the potentiation of a synapse if the presynaptic spike precedes the postsynaptic spike, and as depression if the presynaptic spike follows the postsynaptic spike. Potentiation and depression were determined from the results of experiments on rat hippocampal neurons (Patrick and Curtis, 2002) and frog tectal neurons. (Zhang, Tao, Holt, Harris and Poo, 1998). The timing based learning rule enhances the excitatory postsynaptic potentials induced by coincident input spikes, since the synaptic connections already contributing to postsynaptic firing are further strengthened. (Gerstner, Kempter, van Hemmen and Wagner, 1996). It is reported these characteristics are useful and effective for the extraction of synchronous firing so that STDP is buried in the noise. (Fukai and Kanemura, 2001, Saeki, Hayashi and Sekine, 2006). In addition, the hardware model with STDP (Bofill-i-Petit and Murray, 2004) has been proposed based on the physiological experiment results. However these

Saeki K., Hayashi Y. and Sekine Y. (2008).
PULSE-TYPE NEURO DEVICES WITH SPIKE TIMING DEPENDENT SYNAPTIC PLASTICITY.
In *Proceedings of the First International Conference on Biomedical Electronics and Devices*, pages 264-268
DOI: 10.5220/0001051702640268

models are complex circuits and don't study the noise tolerance.

On the other hand, we proposed a pulse-type neuro device that approximately simulates pulse signals as an information transmission means in the brain. (Sekine 1999, Saeki, Sekine, and Aihara, 1999, Sekine, Sumiyama, Saeki and Aihara, 2001).

In this paper, we discuss the construction of neural networks from pulse-type neuro devices with STDP. We show that it is possible to extract the phase difference representing the reinforcement part of synaptic weight. Moreover, we investigate the noise tolerance of thermal noise and the fluctuation of time.

2 CIRCUIT OF NEURO DEVICES WITH STDP

An STDP block diagram is shown in Fig. 1. This block diagram has cell body blocks and an STDP block. When pulses are inputted to each temporal summation block, output pulses from each temporal summation block have first-order delays and are transmitted to the subsequent blocks. When the post-synaptic cell generates the pulses, the synaptic weight W_p between pre- and post-synaptic cells is reinforced based on the output amplitude of the temporal summation block with the pre-synaptic cell. On the other hand, when the pre-synaptic cell generates the pulses, W_p is suppressed based on the output amplitude of the temporal summation block with the post-synaptic cell.

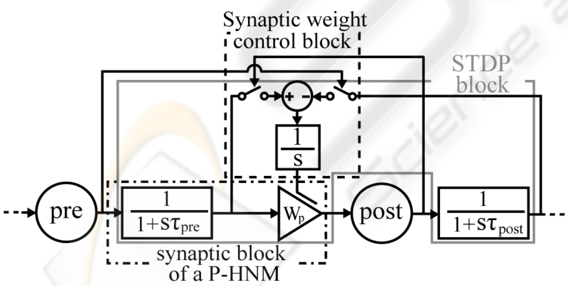
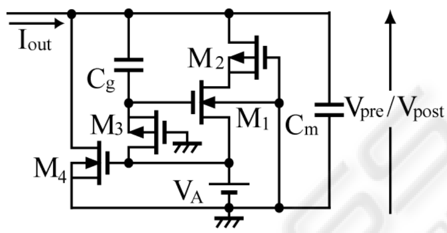
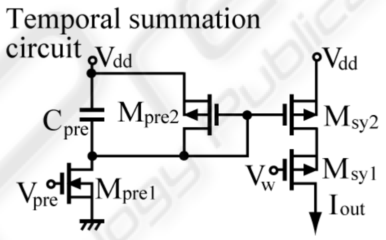


Figure 1: STDP block diagram.

A pulse-type neuro device is shown in Fig. 2. The pulse-type neuro device consists of a cell body circuit and a synaptic circuit. Figure (a) shows the cell body circuit. When I_{out} is inputted to the cell body circuit, output pulses are generated. This circuit has a threshold and a refractory period characteristic. Figure (b) shows the synaptic circuit. When pulses are inputted to the input terminal V_{pre} of the synaptic circuit from the pre-synaptic cell, I_{out} is generated. The current I_{out} changes according to V_w. Therefore, the synaptic weight between the pre- and post-synaptic cells can be controlled by V_w. Spatial summation circuits can also be constructed when a series circuit of M_{sy1} and M_{sy2} is connected in parallel.



(a) Cell body circuit.



(b) Synaptic circuit.

Figure 2: Pulse-type neuro device.

The synaptic weight generation circuit is shown in Fig. 3. This circuit consists in part of three blocks; two temporal summation circuits and a synaptic weight control circuit. The voltage V_w is the output voltage of this circuit and is the parameter that controls the synaptic weight between the pre- and post-synaptic cells.

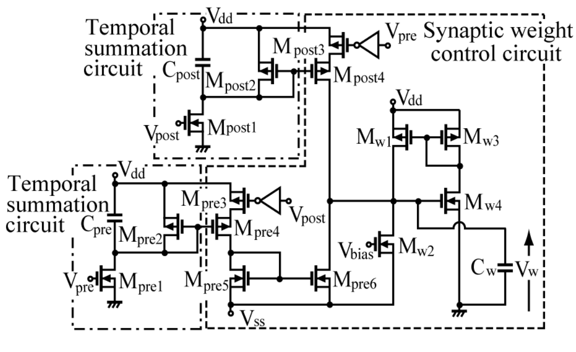


Figure 3: Synaptic weight generation circuit.

A function of V_w in the synaptic weight generation circuit is shown in Fig. 4. The horizontal axis is the time interval Δt', which is the time of the pre-synaptic pulse minus the time of the post-synaptic pulse, and the vertical axis is the amount of voltage change ΔV_w of V_w after generating pulses in pre- and post-synaptic cells. This figure shows that V_w increases when a pulse generated in the post-synaptic cell after a pulse is generated in the pre-synaptic cell, but decreases when the pulse generated in the pre-synaptic cell follows the pulse generated in the post-synaptic cell. Furthermore, as $\Delta t'$ becomes shorter, ΔV_w increases exponentially.

From these results, we clarify principles of the operation of the proposed circuits when the circuit in

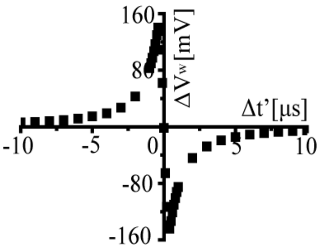


Figure 4: Characteristic of V_w in the synaptic weight.

Fig. 2 is controlled with V_w in Fig. 3. Therefore, controlling the circuit depicted in Fig. 2 with V_w, as depicted in Fig. 3, generates the STDP function.

3 EXTRACTION OF PHASE DIFFERENCE INFORMATION

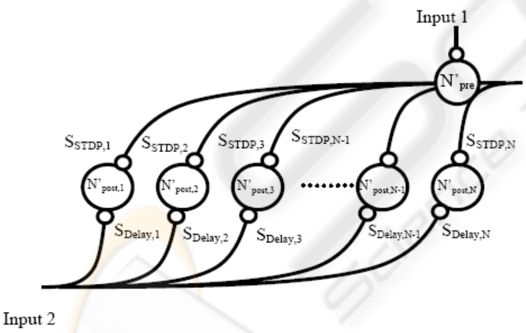


Figure 5 : A neural network that extracts phase.

Figure 5 shows an example of a neural network composed of $S_{Delay,(1\sim k\sim L)}$ that represents the synaptic circuits of each difference in the propagation delay time, $S_{STDP,(1\sim k\sim L)}$ that represents the synaptic circuits, with synaptic weight control circuits, N'_{pre} and parallel $N'_{post,(1\sim k\sim L)}$. Moreover, inputs 1 and 2 are made in the same cycle. The synaptic weight control voltage of $S_{STDP,(1\sim k\sim L)}$ is $V_{W,STDP(1\sim k\sim L)}$, and the synaptic weight control voltage of $S_{Delay,(1\sim k\sim L)}$ is a constant value $V_{W,STDP(1\sim k\sim L)} = 0.0$ V. The propagation delay time of $S_{Delay,k}$ is assumed to be the next equation. $\tau_k = \Delta\tau \cdot (k-1)$ (1)

In equation, τ_k is the propagation delay time. $\Delta\tau$ is the sampling time of the propagation delay time.

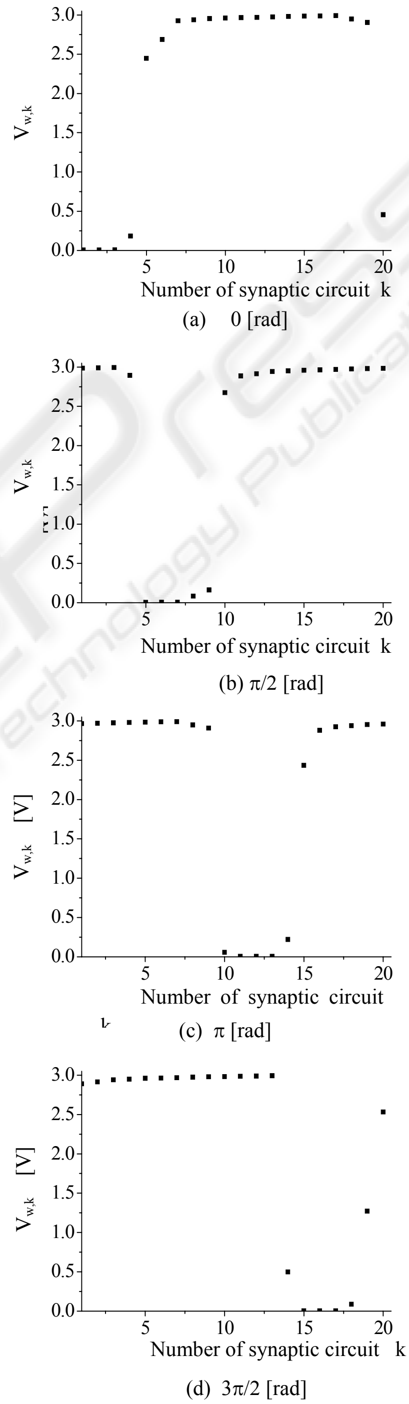


Figure 6: Synaptic weight control voltage.

Input 2 is transmitted $N'_{post,(1\sim k\sim L)}$ through the $S_{STDP,(1\sim k\sim L)}$, and $N'_{post,(1\sim k\sim L)}$ outputs pulses at each different time. The synaptic weigh control voltage of the synaptic circuit, which connects the cell body circuit and input 1 corresponds to the phase difference between inputs 1 and 2, decreases because the cycles of inputs 1 and 2 are the same. As a result, the phase difference can be learned as the number of the synaptic circuit which it reinforces. Moreover, the cell body circuit connected with the reinforced synaptic circuit can output a pulse when input 1 is inputted again after the learning finished, and the phase difference between inputs 1 and 2 can be extracted.

Figure 6 shows the characteristics of each synaptic weight control voltage $V_{w,k}$ to the phase difference of input 2 based on input 1. In this case, we use the parameters, T=10μs, L=20 and Δτ=0.5μs. The horizontal axis is the number of the synaptic circuits, and the vertical axis is $V_{W,STDP(1\sim k\sim L)}$. This figure shows that $V_{w,k}$ with the minimum value neighbourhood appear to be 1~4, 5~9, 12~16 and 17~20 for phase differences between inputs 1 and 2 of 0, π/2, π and 3π/2, respectively. That is to say, the minimum neighbourhood depends on the phase difference between inputs 1 and 2. Therefore, it is possible to extract the phase difference from pulse-type neuro devices with STDP.

4 NOISE TOLERANCE

4.1 Thermal Noise

In this section, thermal noise is assumed, and tolerance to white noise is investigated.

The signal of the next equations is used as a train of pulses that adds white noise to a periodic train of pulses of the cell body circuit.

$$S'_{pre} = \sum_{i=1}^{m} v_{pre,i}(T \cdot i) + v_{white}(\sigma') \quad (2)$$

$$S'_{post} = \sum_{j=1}^{n} v_{post,j}(T \cdot j + dt) + v_{white}(\sigma') \quad (3)$$

In these equations, v_{white} shows white noise that generates random numbers. σ' is the standard deviation of distribution, shows noise tolerance. In this case, we use these parameters, T=10μs and dt=1μs.

Figure 7 shows a characteristic of the synaptic weight control voltage to the strength of the white noise. The horizontal axis is the strength of the white noise and the vertical axes are the average of V_w (■) and the ratio that becomes V_w less than 1V (○), respectively. We assume that it is transmitted to the pulses from N_{pre} to N_{post}, when V_w less than 1V. This figure shows that not more than σ' =1.0V is displayed below V_w=1.5V, and σ' =1.05V is displayed above V_w=1.5V. Noise strength shows that if the influence of the reinforcement displays below σ' =1.0V, the influence of the suppression appears as σ' =1.05V. As well, the rate that V_w becomes not more than 1V is 100% within the range of σ' =0.8V or less. This suggests a neural network with STDP that has a learning function with tolerance for white noise of 0.8V or less.

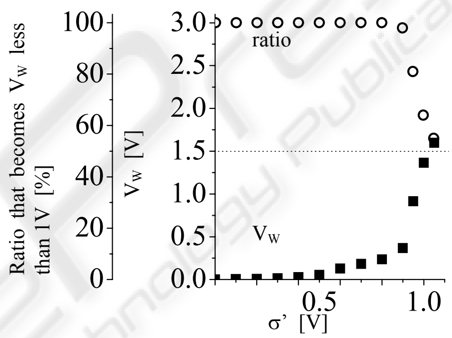


Figure 7: Synaptic weight control voltage to the strength of white noise.

4.2 Fluctuation of Time

Next, the difference of the pulse timing caused by the wiring capacity etc. is investigated. The signal of the next equations is used as a train of pulses that adds the fluctuation of the timing of the cell body circuit.

$$S''_{pre} = \sum_{i=1}^{m} v_{pre,i}\left(T \cdot i + t_{Nrand,i}(\sigma'')\right) \quad (4)$$

$$S''_{post} = \sum_{j=1}^{n} v_{post,j}\left(T \cdot j + dt + t_{Nrand,j}(\sigma'')\right) \quad (5)$$

In these equations, $t_{Nrand,i}$ $t_{Nrand,j}$ show the fluctuation of time. σ'' is the standard deviation of the distribution, showing the noise tolerance. In this case, we use the parameter, T=10μs.

Figure 8 shows a characteristic of the synaptic weight control voltage to the fluctuation of the time. The horizontal axis is σ'' and the vertical axes are the average of V_w (■) and the ratio that becomes V_w

less than 1V (○), respectively. This figure shows that not more than σ'' =1.8μs is displayed below V_w=1.5V, and σ'' =2.0μs is displayed above V_w=1.5V. The fluctuation of time shows that the influence of reinforcement is displayed below σ'' =1.8μs, and the influence of suppression appears at σ'' =2.0μs. As well, the rate at which V_w becomes not more than 1V is 100% within the range of σ'' =0.6μs or less. This suggests a neural network with STDP that has a learning function with tolerance for the fluctuation of time of 0.6μs or less.

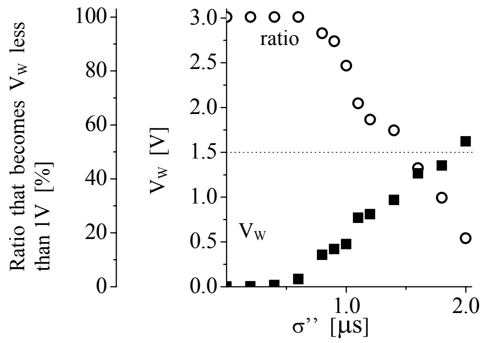


Figure 8: Synaptic weight control voltage to fluctuation of the time.

5 CONCLUSIONS

In this paper, we focus on STDP and we construct neuro devices with STDP to study the effect of STDP on the ability to extract phase differences. Using these devices, we construct a neural network that extracts phase difference information. As a result, it is possible to extract the phase differences of pulse-type neuro devices with STDP, representing the reinforcement component of synaptic weight. Moreover, we investigated the noise tolerance of the proposed model. As a result, we demonstrated pulse-type neuro devices with STDP that have a learning function with tolerance for white noise of 0.8V or less, and for fluctuation of time of 0.6μs or less. That is to say, we showed that pulse-type neuro devices with STDP had a learning function with noise tolerance for the thermal noise and the fluctuation of the time.
In our future work, we will construct an integrated circuit with pulse-type neuro devices with STDP.

ACKNOWLEDGEMENTS

This work was supported in part by Amano Institute of Technology.

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