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Effects of Backpropagation Characteristics in a Hardware Active Dendrite Model

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1. Introduction

The human nervous system consists of billions of neurons of various types and lengths relevant to their location in the body. An oversimplified biological neuron consists of four major functional units - dendrites, synapses, cell-body and axon. The dendrites receive signals from other neurons through the synapses, and pass them over to the cell-body [1], [2].

The crude analogy between artificial neurons and biological neurons is that the connections between nodes are represented by the axons and the dendrites. And also, the connection weights are represented by the synapses, and the threshold is approximated by the activity in the cell-body.

Most neurons in the mammalian central nervous system encode and transmit information via action potentials. Knowledge of where these action potentials are initiated and how they propagate within neurons is therefore fundamental to an understanding of neuronal function [2]. Recent advances in physiology have shown that the dendrites of many neurons were not passive, and they contained some active conductances [3]. More experiments have shown that the action potentials were initiated at the cell-body, and then actively the action potentials propagated back into the dendrites [4].

Some neurons have backpropagating action potential, while others do not. The specific difference suggests that the backpropagation of action potentials into the dendrite is functionally important in those neurons [4]~[11].

Because the requisite experiments to trace information processing in living neural tissue are so difficult, model learning can be very helpful in bridging the gaps in our knowledge and developing insights. The traditional models for the dendritic processing have been represented by a passive, branched cable structure that is intended to emulate the behavior of biological neurons which have passive dendrites [12]~[14]. The hardware model of active dendrite has not yet been found.

We have attempted to produce hardware using analog circuits in the belief that the development of a new hardware neuron model is one of the most important problems in the study of neural networks [15]~[18].

We previously proposed a cell-body model, which was based on the pulse-type hardware chaotic neuron model [15], [16]. We also proposed an axon model based on the active line, which could exhibit chaotic phenomena [17].

We have been studying the backpropagation characteristics of the dendrites by using the model [18]. The traditional models for the dendritic processing have been represented by a passive, branched cable structure. Hitherto, we proposed the construction of the active dendrite models, and realized it by using hardware model. Furthermore, we used one branch in our model, and we showed that our hardware active dendrite model exhibited backpropagation characteristics [18].

In this paper, firstly we describe the hardware active dendrite model. Next we discuss the spike generation of our proposed model for periodic pulse train stimulation with particular reference to the backpropagation characteristics of the active dendrites. Furthermore, we discuss the response characteristics of our proposed model, with only two branches for the periodic pulse train stimulation.

2. Construction of the hardware active dendrite model

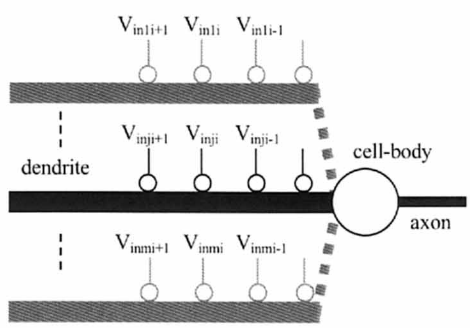

Fig. 1 Schematic diagram of the active dendrite model.

Figure 1 shows a schematic diagram of the tree-like active dendrite model. In the model, multi-branches and the active cable structure have been considered. The active dendrite has also been considered as an active line, having a structure distributed and cascaded active sections.

Figure 2 shows two sections of simplified equivalent circuit of the active dendrite model. In this figure, the active dendrite model is approximated by an active line, composed of voltage-controlled negative resistor, inductor, membrane capacitor, and membrane -leak resistor.

Figure 3 shows the hardware active dendrite model we propose in this paper. One branch of the hardware active dendrite model is constructed with cascading n active circuits through interstage coupling resistors R_{sji} (i=1,2...n). In each section, as the voltage-controlled negative resistor, we use a negative-resistance circuit composed of two complementary MOSFETs (M_{1ji}, M_{2ji}), MOS resistors (M_{3ji}, M_{5ji}, M_{6ji}), and capacitors (C_{gdji}, C_{gji}) as shown in Fig. 3. In this part, an equivalent inductor is included. And also, C_{mji} is used as the membrane capacitor, and M_{4ji} is used as the membrane-leak resistor as shown in Fig. 3. The pulse stimuli can be applied to V_{inji}. Considering the influence of stimuli commensurate with the distance from the cell-body, we apply the stimuli to the second section of the hardware active dendrite model.

Figure 4 shows the cell-body model. We used our proposed pulse-type hardware model as the cell-body model [15]. The pulse-type hardware model can be constructed from a negative resistance circuit composed of two complementary MOSFETs, resistors and capacitors. The pulse-type hardware model exhibits a negative resistance characteristic; it is changed with time and chaotic phenomena [16], resembling the properties of actual neurons.

Next, we discuss the spiking behavior in the hardware active dendrite model by injecting the pulse train stimulus into the second section of Fig. 3. Here, for simplicity, we consider only one branch with 20 sections in our model.

Figure 5 shows spiking behavior in each section by pulse train stimulus. This figure shows that trains of action potentials were elicited. The action potential could be evoked from both the cell-body section and the dendrite section. In this case, little attenuation of

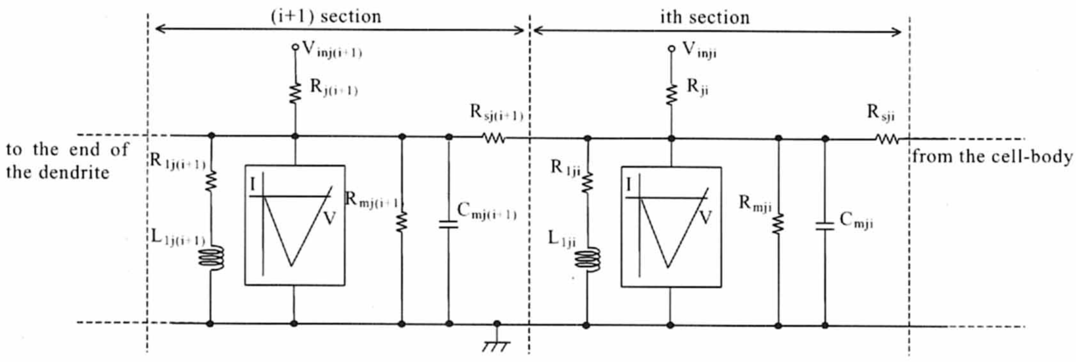

Fig. 2 The simplified equivalent circuit of the hardware dendrite model we proposed.

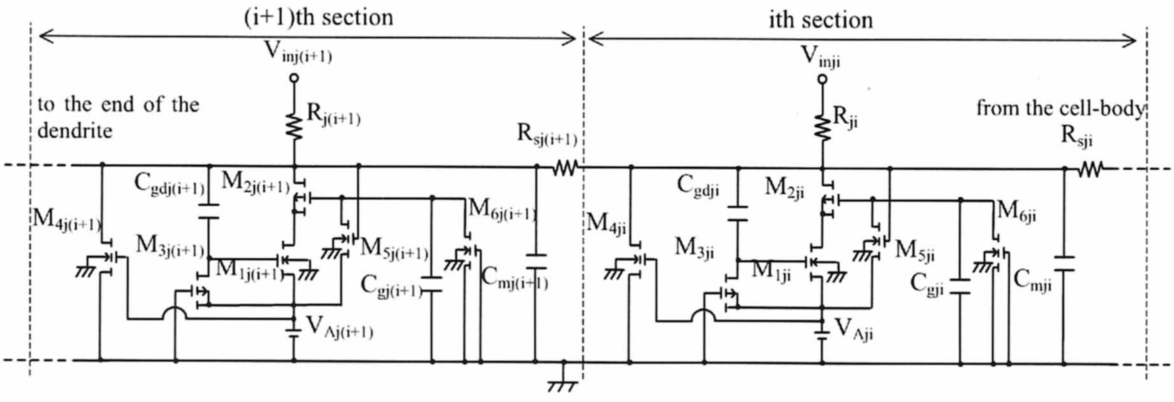

Fig. 3 The hardware active dendrite model.

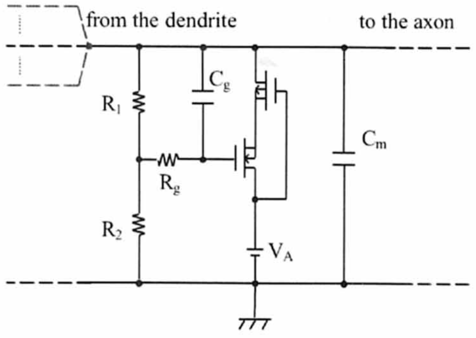

Fig. 4 The cell-body model.

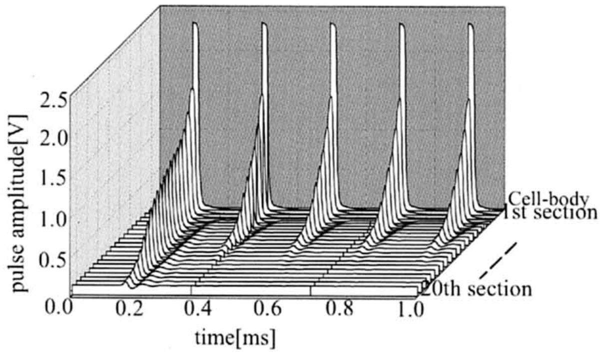

Fig. 5 Simulated spiking behavior in each section by pulse train stimulus.

somatic action potentials were observed. Attenuation of action potentials during the train was substantial in the dendrite model, with failure of action potential backpropagation in the distal region of the dendrite model. Fig. 5 also shows the backpropagation of action potentials into the hardware dendrite model. At the distal region of the hardware dendrite model, action potential amplitude decreased abruptly after the first action potential in pulse train. This indicated that the first action potential propagate actively throughout the entire hardware dendrite model, but induced a change such that later action potentials in the train failed to efficiently propagate into the distal region of the hardware dendrite model as present physiological experiments [5].

Figure 6 shows the involvement of back-propagating spikes in action potential amplification of the hardware active dendrite model. While this figure shows clearly that since the stimulus is put into the 2nd section the generation of action potential in the cell-body happens earlier than the generation of spikes in the dendrite. The potential change below the threshold value is looked at by the 2nd section earlier than the cell-body as present physiological experiments [5].

3. Effects of backpropagation characteristics in a hardware active dendrite model

Next, we discuss the response characteristics of our proposed model for the periodic pulse train stimulation.

When we input stimuli on one branch, and the action potentials are initiated at the cell-body, we consider that the action potentials are propagated back into all-branches. So, for simplicity, we next discuss the response characteristics for the periodic pulse train stimulation with only two branches.

Figure 7 shows an example of the response characteristics for the periodic pulse train stimulation. In case 1, we input stimuli on the same branch as shown in Fig 7(1). On the other hand, in case 2, we input stimuli on different branches as shown in Fig 7(2). Here, we assumed that a half period delay exists

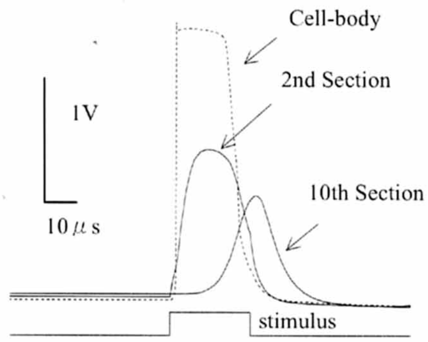

Fig. 6 Involvement of backpropagating spikes in action potential amplification.

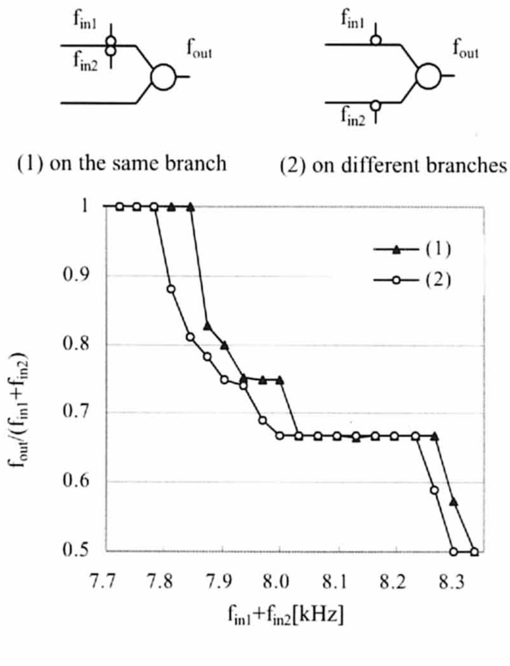

Fig. 7 Effects of backpropagation characteristics.

between the frequency of the stimuli (f_{in1} and f_{in2}). And f_{out} is the frequency of the cell-body's action potential. In both cases, the action potentials propagated back into the dendrites. In this figure, the abscissa is $f_{in1}+f_{in2}$, and the ordinate is the ratio of input-output frequency $f_{out}/(f_{in1}+f_{in2})$. This figure shows the differences of $f_{out}/(f_{in1}+f_{in2})$ between case 1 and 2, with the increase in the same input frequency ($f_{in1}+f_{in2}$). On the other hand, in the passive dendrite model which exhibits temporal summation of linear addition, $f_{out}/(f_{in1}+f_{in2})$ indicates the same value in both cases. It is suggested that, $f_{out}/(f_{in1}+f_{in2})$ at the cell-body is influenced by the backpropagation characteristics of the hardware active dendrite model.

4. Conclusions

In this paper, we described the hardware active dendrite model, in addition we discussed the spike generation in one branch and the response characteristics of our proposed model with two branches for periodic pulse train stimulation.

As a result, we firstly showed that the action potential could be evoked from both the cell-body section and the dendrite section. We also showed that the earliest action potential evoked from the dendrite's section was barely attenuated, and the subsequent spikes were attenuated propagating along the active dendrite. Finally, we showed that the ratio of input-output frequency at the cell-body was influenced by the backpropagation characteristics with two branches.

In future work, we will discuss temporal processing in our proposed hardware active dendrite model, and our model may use an approach to design pulse-type hardware neural networks.

Acknowledgments

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References

[1] F. Delcomyn, "Foundations of Neurobiology," W. H. Freeman and Company, 1998.

[2] G. M. Shepherd, "The synaptic Organization of the brain," Oxford University Press, 1998.

[3] D. Johnston, J. C. Magee, C. M. Colbert, B. R. Christie, "Active properties of neural dendrites," Annu. Rev. Neurosci., Vol.19, pp.165-186, 1996.

[4] G. J. Stuart, B. Sakamann, "Active propagation of somatic action potentials into neocortical pyramidal cell dendrites," Nature, Vol.367, pp.69-72, 1994.

[5] N. Spruston, Y. Schiller, G. Stuart, B. Sakamann, "Activity- Dependent Action Potential Invasion and Calcium Influx into Hippocampal CA1 Dendrites," Science, Vol.268, pp.297-300, 1995.

[6] J. C. Callaway, W. N. Ross, "Frequency- Dependent Propagation of Sodium Action Potentials in Dendrites of Hippocampal CA1 Pyramidal Neurons," Journal of Neurophysiology, Vol.74, No.4, pp.1395-1403, 1995.

[7] G. Stuart, N. Spruston, B. Sakamann, M. Hausser, "Action potential initiation and backpropagation in neuron of the mammalian CNS," Trend Neurosci., Vol.20, pp.125-131, 1997.

[8] P. Maršálek, F. Santamaría, "Investigating spike backpropagation induced Ca^{2+} influx in model of hippocampal and cortical pyramidal neurons," BioSystems, Vol.48, pp.147-156, 1998.

[9] M. Häusser, N. Spruston, G. J. Stuart, "Diversity and Dynamics of Dendritic Signaling," Science, Vol.290, pp.739-742, 2000.

[10] M. Megias, ZS. Emri, T. F. Freund, A. I. Gulyas, "Total Number And Distribution of Inhibitory And Excitatory Synapses On Hippocampal CA1 Pyramidal Cells," Neuronscience. Vol.102, No. 3, pp. 527-540, 2001.

[11] B. Doiron, A. Longtin, R. W. Turner, L. Maler, "Model of Gamma Frequency Burst Discharge Generated by Conditional Backpropagation." J Neurophysiol Vol.86, pp.1523-1545. 2001.

[12] W. Rall, "Cable Theory for Dendritic Neurons," in Methods in Neuronal Modeling: From Synapses to Networks, eds C. Koch and I. Segev, Chap 2, MIT Press, 1989.

[13] J. G. Elias, "Silicon dendritic trees," in Silicon Implementation of Pulse-Coded Neural Networks, eds. M. Zaghloul, J. Meador, and R. Newcomb Chap 3, Kluwer Academic Press, 1994.

[14] C. Rasche and R. Douglas, "Forward- and Backpropagation in a Silicon Dendrite," IEEE Transactions on Neural Networks, Vol 12, No 2, pp.386-393, 2001.

[15] Y. Sekine, "A pulse-type hardware neuron model," Computer Today. no. 90, pp.27-33. 1999.

[16] K. Someya, H. Shinozaki, Y. Sekine, "Pulse-type Hardware Chaotic Neuron Model and Its Bifurcation phenomena," International Neural Network Society (INNS), Neural Networks, Vol. 12, no. 1, pp.153-161, 1999.

[17] K. Someya, A. Fujita, Y. Sekine, K. Aihara, "Hardware Active Axon Model Simulating Chaotic Phenomena," Proc. 1999 International Conference on Neural Information Processing (ICONIP99), Vol. 3, Perth, Australia, pp. 1023-1027, 1999.

[18] Z.Y. Xue, M. Itagaki, K. Someya, K. Saeki, Y. Sekine, "A Hardware Active Dendrite Model," Proc. 8th International Conference on Neural Information Processing (ICONIP2001) , Shanghai, China, Vol. 3, pp.1219-1224, Nov.2001.