8th International Conference on Information Science and Technology
June 30-July 6, 2018; Granada, Cordoba, and Seville, Spain

Memristor-based Neuron Circuit with Adaptive Firing Rate

Xinming Shi
School of Automation
Huazhong University of Science and Technology
Wuhan, China
Email: M201672506@hust.edu.cn

Zhigang Zeng
School of Automation
Huazhong University of Science and Technology
Wuhan, China
Email: zgzeng@hust.edu.cn

***Abstract*—Adaptive firing rate of neuron plays an indispensable role in stabilizing the neural system, which means that the firing rate of neuron could be adjusted adaptively within an inherent range. In this paper, two aspects of implementing the adaptive firing rate are proposed at the circuit level. First, a memristor model is used in the neuron circuit to represent membrane sensitivity. Second, the threshold voltage of neuron circuit can be adjusted adaptively to change the firing rate. Combined these two methods, the adaptive firing rate of neuron circuit is realized effectively, which is in accordance with its biological counterpart. Furthermore, the proposed neuron circuit is applied in the spiking neural network to verify its functionality, where pattern recognition could be realized. All the simulations are carried out on PSPICE.**

***Keywords*—adaptive firing rate; neuron circuit; spiking neural network; PSPICE**

I. Introduction

Considering the special abilities of memristors such as nonvolatility, programmable resistance and nanoscale dimensions, memristors are always applied to implementing neuromorphic architectures with synchronous regulation [1]. These emerging neuromorphic devices can well emulate biological features including synaptic plasticity characteristics such as Pair Spike Timing Dependent Plasticity (PSTDP) [2], Spike Rate Dependent Plasticity (SRDP) [3] and Triplet Spike Timing Dependent Plasticity (TSTDP) [1], [4], as well as the some neuron characteristics such as the phospholipid bilayer [5] and "all-or-noting" firing [6].However, there is another characteristic playing an indispensable role in neural system [7]. It can stabilize the disorders that derive from the long-term potentiation (LTP) and long-term depression(LTD) [8], which is the adaptive firing rater of neuron and also called homeostasis. In the real application, this plasticity performed negative feedback behavior also have attracted attention for realizing pattern recognition of spiking neural network. Querlioz and Sheridan have induced the homeostatic plasticity into the spiking neural network by changing the different threshold voltages of neurons in software level [9], [10]. Their results confirmed the superiority of the neuron with adaptive firing rate in pattern recognition.

However, this type of plasticity is seldom implemented by memristor-based architecture, while there have been some researches to realize it by CMOS circuits or very large-scale integration (VLSI). Chiara proposed VLSI networks of spiking neurons with adaptive firing rate [11]. Liu presented the silicon synaptic adaptation mechanisms to implement the adaptive firing rate by VLSI [12]. The results also accounted for the mechanism observed in cortical simple cells and further extended the circuit applications. Considering the various features of memristor, it has great potential to apply the memristor to implementing the adaptive firing rate of neuron in a more compact and efficient way.

In order to implement the adaptive firing rate of the neuron, two aspects are taken into consideration in this paper, membrane sensitivity and firing rate of neuron circuit. A memristor model is used in the establishment of neuron circuit, as a result, its memristance can be varied according to the differences between firing rate and inherent firing rate, which mimics the variation of membrane sensitivity in the biological neuron. Due to the slow pace of the membrane sensitivity variation, the memristance is also varied slowly. On the other hand, adaptive regulation on firing rate also depends on the neuron threshold. Taking these two aspects into consideration, a memristor-based neuron circuit is implemented. Furthermore, based on this neuron, a spiking neural network is designed, where the pattern recognition is realized.

The rest of paper is organized as follows. Section II proposes the implementing of adaptive firing rate. Section III designs a spiking neural network based on the adaptive firing rate. Section IV draw a conclusion.

II. Implementing of Adaptive Firing Rate

The adaptive firing rate can be adjusted by two ways in biological neuron, which are the regulation of membrane sensitivity and neuron threshold. In order to keep consistent with the biological counterpart, the circuit implementation of adaptive firing rate is also divided into two aspects, which are performed as the usage of memristor in neuron circuit and the regulation of neuron threshold voltage, respectively.

A. Regulation on Membrane Sensitivity

Due to the high efficiency of leaky integrate-and-fire (LIF) model [13], it is used as original neuron circuit model in this paper. Based on the original LIF model, the resistor that receives the input stimuli from other neurons is substituted as a

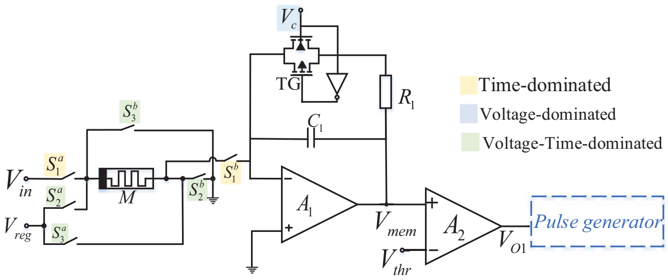
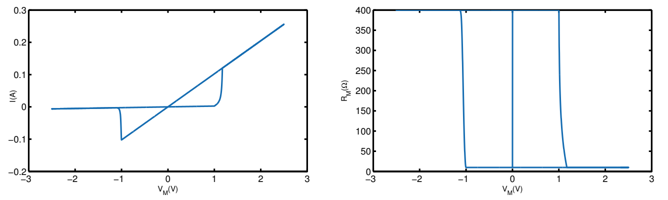


Fig. 1. Memristor-based LIF neuron model and pulse generator.



(a) (b)

Fig. 2. (a) The current-voltage characteristics of the utilized memristor. (b) Memristance characteristics of the utilized memristor.

memristor model, which is shown in Fig. 1. And its integration constant τ could be revised as follows

$$\tau = R_M \cdot C_1. \tag{1}$$

In order to realize the adaptive firing rate, the memristance of this memristor that represents membrane sensitivity should be varied, when the applied voltage on the two terminals of memristor exceeds its threshold voltage. Therefore, a memristor model that derives from Ag/AgInSbTe/Ta (AIST) memristive device with threshold voltage is used in this paper, which can be described as follows

$$I(t) = G(w) \cdot V_M(t) \tag{2}$$

$$\frac{dw}{dt} = \begin{cases} k_{tr} \cdot (V_M(t) - V_{tr}) \cdot e^{a_{tr} \cdot w} \cdot f(w, V_M(t)) & \text{if } 0 < V_{tr} < V_M(t) \\ 0 & \text{if } V_{tl} \leq V_M(t) \leq V_{tr} \\ k_{tl} \cdot (V_M(t) - V_{tl}) \cdot e^{a_{tl} \cdot w} \cdot f(w, V_M(t)) & \text{if } V_M(t) < V_{tl} < 0, \end{cases} \tag{3}$$

where $f(w, V_M(t))$ is a window function, which has been used in [14]. V_{tl} and V_{tr} are the reset voltage and set voltage respectively. k_{tr}, k_{tl}, a_{tr} and a_{tl} are fitting parameters of modeling. In order to obtain the characteristic of the memristor model, a sinusoidal voltage is applied to two terminals of the memristor. The current and voltage characteristic of the proposed model is shown in Fig. 2.

As shown in Fig. 1, V_{in} is the input stimuli, whose amplitude is less than the threshold voltage of memristor. V_{reg} is a positive voltage, whose amplitude is higher than the threshold voltage of memristor model. In addition, there are three pairs of switches, which are S_1^a, S_1^b, S_2^a, S_2^b, S_3^a and S_3^a, to control the memristance variation. The time-dominated switches S_1^a and S_1^b can control the circuit states. When these two switches turn on, the circuit will work in the integration or firing period, where the input stimuli V_{in} could inject the neuron successfully. When these two switches turn off, the input stimuli V_{in} will be cut off. S_2^a, S_2^b, S_3^a and S_3^a are voltage-dominated switches. When the present firing rate of neuron is higher than the inherent firing rate, S_3^a and S_3^b will turn on while S_2^a and S_2^b will turn off. Therefore, V_{reg} will apply on the top electrode of memristor resulting in the increasing memristance. On the contrary, when the present firing rate of neuron is higher than the inherent firing rate, S_2^a and S_2^b will turn on while S_3^a and S_3^a will turn off. In this way, V_{reg} will apply on the bottom electrode of the memristor causing the decreasing memristance. Due to the memristance variation, the integration constant of the neuron circuit could be regulated. Hence the firing rate could be adjusted adaptively. The more detailed procedure will be discussed in Section II-B.

B. Regulation on Neuron Threshold

Besides the regulation on membrane sensitivity, there is another way to realize the adaptive firing rate of neuron circuit, which is the regulation on neuron threshold. In order to fire a spike, the input stimuli will charge across the membrane structure to increase the membrane potential, once the membrane potential exceeds the neuron threshold, the neuron will fire. Therefore, adjusting the neuron threshold results in the different firing timings and further influences the firing rate of neuron.

It is hard to compare different frequencies directly at the circuit level. Therefore, in this paper, the firing frequency of neuron circuit is transferred as different voltage values. The specific mathematic relationship between them depends on a transistor pump frequency discriminator, which has been mentioned in [15]. The diagram of implementing the regulation on neuron threshold is shown in Fig. 3. According to the charge conservation upon the transistor Q_1, the relationship between the firing frequency of neuron circuit and the output voltage of the transistor pump frequency discriminator V_{c3} can be described as follows

$$V_{c3} = f \cdot C_2 \cdot R_2 \cdot (V_{o2} - V_{D_1} - V_{Q_1}), \tag{4}$$

where f is the firing rate of the neuron circuit, V_{o2} is the output of the pulse generator. C_2 and R_2 are the circuit parameters. V_{D_1} and V_{Q_1} are the breakover voltage of diode D_1 and transistor Q_1, respectively. As shown in Fig. 3, V_{c3} can be held by the sample and hold (S/H) circuit. Voltage resources V_{bas} and $V_{inherent}$ in the circuit represent the minimum neuron threshold voltage and the voltage value responding to the inherent firing frequency $f_{inherent}$, respectively. The neuron threshold voltage V_{thr} comes from the two parts, V_{o4} and V_{bas}. This relationship is given by as follows

$$V_{thr} = (\frac{R_9}{R_7} V_{o4} + \frac{R_9}{R_8} V_{bas}) \frac{R_{11}}{R_{10}}, \tag{5}$$

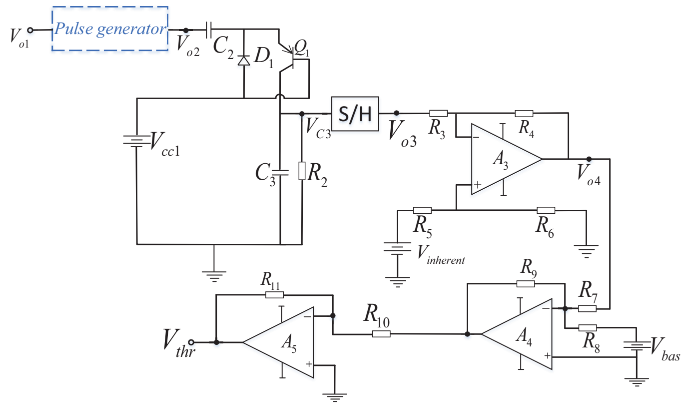


Fig. 3. Circuit implementation of adaptive adjustment on neuron threshold.

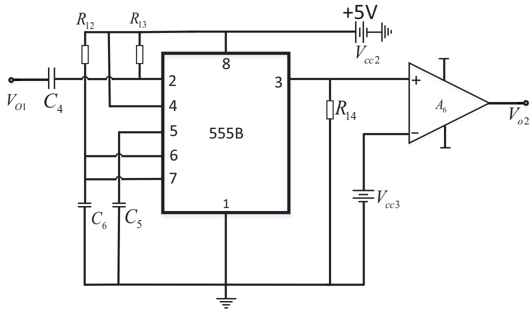


Fig. 4. The pulse generator used in simulation.

where V_{o4} is the difference between V_{c3} and $V_{inherent}$, which is dominated by firing rate and inherent firing rate of neuron circuit. According to the Fig. 3, it can be written as follows

$$V_{o4} = K \cdot (V_{c3} - V_{inherent}), \tag{6}$$

where K is the changing rate, when $\frac{R_4}{R_3} = \frac{R_6}{R_5}$, $K = \frac{R_4}{R_3}$; $V_{inherent}$ is a fixed voltage value, and it can be obtained according to (4), which can be written as follows

$$V_{inherent} = f_{inherent} \cdot C_2 \cdot R_2 \cdot (V_{o2} - V_{D_1} - V_{Q_1}). \tag{7}$$

where $f_{inherent}$ represents the inherent frequency of neuron. Combine the regulation on membrane sensitivity, when V_{o4} is positive, S_3^a and S_3^b turn on while S_2^a and S_2^b turn off. When V_{o4} is negative, S_2^a and S_2^b turn on while S_3^a and S_3^b turn off. In addition, voltage difference V_{o4} is limited in a valid range. The boundary of this range can be written as follows

$$V_{o4 \cdot min} = -K \cdot V_{inherent}, \tag{8}$$

$$V_{o4 \cdot max} = K \cdot (V_{c3 \cdot max} - V_{inherent}), \tag{9}$$

where $V_{c3 \cdot max}$ can be set as different values according to the simulation requirement. Therefore, the threshold voltage V_{thr} of the neuron circuit can be varied in a range, which is

$$V_{thr} \in [V_{o4 \cdot min} + V_{bas}, V_{o4 \cdot max} + V_{bas}]. \tag{10}$$

As a result, the regulation on neuron threshold is realized at circuit level. The neuron threshold voltage can be adjusted adaptively and further to influence the firing rate of neuron circuit.

C. Circuit Simulation

In order to verify the functionality of the proposed neuron circuit, the circuit simulation is carried out on PSPICE. Combined the regulation on membrane sensitivity and neuron threshold voltage, a memristor-based neuron circuit with adaptive firing rate is realized. In addition, the pulse generator in this paper is uncertain, which could be various for different research requirements. In the circuit simulation, one of the common pulse generators, a monostable flip-flop with a comparator, is applied to the circuit simulation (see Fig. 4).

1) Parameters setting: As shown in Fig. 4, the 555 timer is constructed as a monostable flip-flop. In order to ensure that the output pulse can be generated successfully, the width of trigger pulse should be less than the width of output pulse T_w. Therefore, the circuit parameters should satisfy the following limitation

$$R_M \cdot C_1 < R_{12} C_6 \ln\left(\frac{V_{cc2} - 0}{V_{cc2} - 2 \cdot \frac{V_{cc2}}{3}}\right). \tag{11}$$

Furthermore, as for the regulation on neuron threshold, the highest firing rate that neuron circuit could generate should be limited. And also the highest V_{c3} should be limited too. In this paper, the highest firing rate of neuron f_{max} is set as $500hz$ while the maximum of V_{c3} is set to 10V. Therefore, according to the principle of transistor pump frequency discriminator, the parameter R_2 and C_2 should be set as follows

$$R_2 \cdot C_2 = \frac{V_{c3}}{f_{\max} \cdot (V_{o2} - V_{Q1} - V_{D1})}, \tag{12}$$

when C_2 is selected as 1.05μf, R_3 would be calculated as $10K\Omega$. In addition, C_3 is used to smooth out the ripple, which derives from Q_1. The value of C_3 will determine the ripple degree, if the frequency of ripple f_{ripple} is set as a fixed value such as $100Khz$, the value of C_3 can be estimated as

$$C_3 = \frac{\alpha}{2 \cdot \pi \cdot R_2 \cdot f_{ripple}}, \tag{13}$$

where α is a constant (set as 50 here). Based on the above limitations and assumptions, the circuit parameters could be set according to TABLE I.

2) Result analysis: Both of the regulation on membrane sensitivity and neuron threshold could adjust the firing rate adaptively to the inherent level ($20 \pm 3hz$). However, these two regulations have some differences. Fig. 5 shows the simulation results. Where, Fig. 5(a) shows the simulation result that only the regulation on the membrane sensitivity works. The firing rate of neuron circuit decreases slowly, after 3 seconds, the firing rate of neuron is decreased from $105hz$ to $35hz$, which do not remain in the inherent level. Fig. 5(b) shows the simulation result that only regulation on neuron threshold voltage works. The firing rate of neuron could be changed at a quicker pace. The firing rate of neuron could be decreased from $105hz$ to $30hz$, which also do not remain

TABLE I
CIRCUIT PARAMETERS

Symbol	Value
V_{tr}, V_{tl}	$2V$, $-2V$
k_{tr}, k_{tl}	$-4.\ \ e4$, $\ .5e6$
a_{tr}, a_{tl}	-8, $-$
$R_{M \cdot ini}$	00Ω
R_1, C_1	0Ω, $250nf$
C_2, C_3	1.05μf, 39.6μf
R_3, R_4	$0K\Omega$, $20K\Omega$
R_5, R_6	$0K\Omega$, $20K\Omega$
R_7, R_8	$50K\Omega$, $50K\Omega$
R_9, R_{10}	$50K\Omega$, $50K\Omega$
R_{11}, R_{12}	$50K\Omega$, $20K\Omega$
R_{13}, R_{14}	$0K\Omega$, $\ G\Omega$
C_4, C_5	$000pf$, $0.0\ \ \mu$f
C_6, V_{cc}	0.2μf, $5V$
$V_{inherent}$	$2V$
V_{reg}, V_{bas}	$8V$, $\ V$

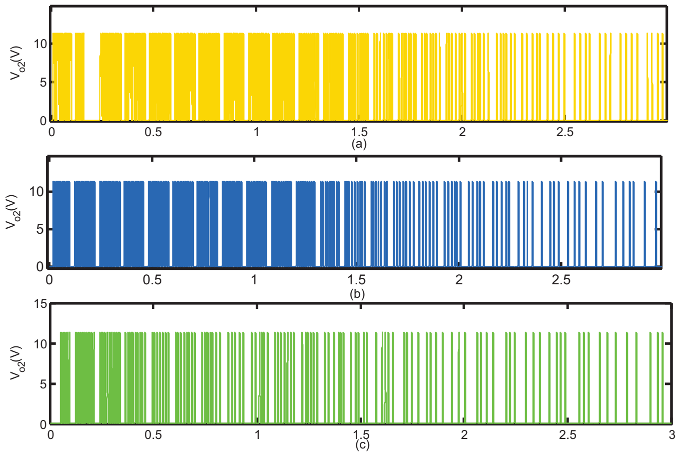


Fig. 5. Simulation results in different regulations. (a) Simulation result of V_{o2} with the only regulation on membrane sensitivity, where the firing rate could be decreased to approach the inherent level slowly. (b) Simulation result of V_{o2} with the only regulation on neuron threshold, where the firing rate is also adjusted to approach the inherent level with a quicker pace. (c) Simulation result of V_{o2} with both of the membrane sensitivity and neuron threshold regulation, where the firing rate of neuron could be adjusted to approach the inherent level quickly.

in the inherent level. Fig. 5(c) shows the simulation result that the full-regulation of firing rate works, where the firing rate of neuron circuit change to $23hz$ quickly in 3 seconds. As a result, the intensity of regulation on neuron threshold is higher than that of on membrane sensitivity. Full-regulation of membrane sensitivity and neuron threshold could make the firing rate return to the inherent level quickly.

III. APPLICATION

Past research proposed that adaptive firing rate play an extremely valuable role in pattern recognition. Therefore, it is reasonable to apply the proposed memristor-based neuron circuit with the adaptive spiking rate to the spiking neural network. The diagram of the spiking neural network is shown in Fig. 7. The pattern recognition of memristor-based spiking neural network has two procedures, which are the training

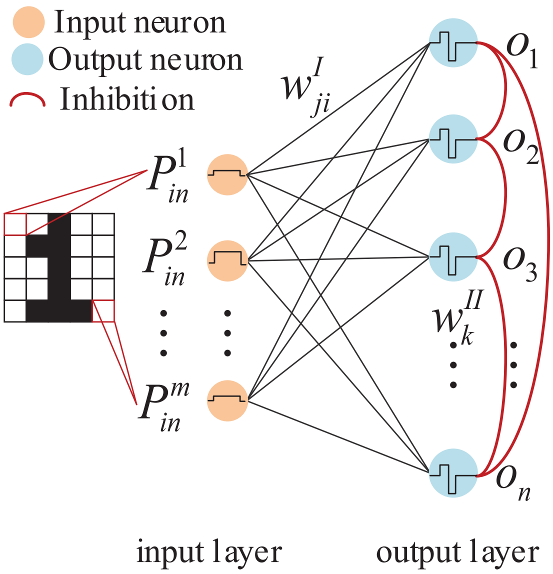


Fig. 6. The diagram of the spiking neural network. The patterns P_{in}^1 to P_{in}^m input the spiking neural network. The orange circle represents the input neurons, which will generate wide pulse with different amplitudes according to the image pixels. The blue circle represents the output neuron, which will generate the bipolar narrow pulse.

and test respectively. In the training, the input patterns will compare with the given patterns that are stored in synapses as initial weights. Only one of the output neurons, which has the highest input stimuli, will fire. In another word, the pattern stored in the weights that are connected to the firing neuron has the highest similarity with input pattern. Then, these weights that are connected to the firing neuron are going to be adjusted. In the test period, every input pattern will cause one of the output neurons firing, which means the input pattern is classified to one pattern.

The spiking neural network has two layers, the input layer and output layer, where the input neurons are used to encode the input pattern while the output neurons can fire spikes to train the weights of the spiking neural network. After the training, the spiking neural network will realize the function of classification. In addition, due to the characteristic of adaptive firing rate in output neuron, some of the recognition errors would be prevented.

A. Input Layer

In this paper, the binary images are used as the input patterns. The input neurons can encode these input patterns to different voltages. When the in put pixel P_{in} is 1, the input voltage is set as $-1.5V$ with 100ms width. When the input pixel P_{in} is 0, the input voltage is set as $-0.05V$ with 100ms width. It can be described as follows

$$V_{in} = \begin{cases} -1.5V, \text{ if } P_{in} = 1 \\ -0.05V, \text{ if } P_{in} = 0 \end{cases} \tag{14}$$

B. Synapses

In order to emulate the parallel computing in biological neural network, a memristor-based crossbar is applied to implement the synapses of spiking neural network, where the weights in different columns could be trained parallelly. In addition, the memristor model used in the weight crossbar is the one mentioned in Section II, whose conductances are regarded as weights.

In the training period, a simplified STDP rule based on the Hebb rule is used in this paper. In biological neural network, the weight of the synapse could be increased, when the two neurons which are connected via the synapse fire synchronously. Otherwise, the weights will be decreased. Correspondingly, there are three scenarios in the circuit. Firstly, when the two neurons, which are connected via the synapse, fire synchronously, the maximum of the voltage applied on the two terminals of the memristor will exceed the threshold voltage of memristor. Secondly, when the postsynaptic neuron fires while the presynaptic neuron does not fire, the weight between these two neurons will be decreased. Thirdly, when the presynaptic neuron fires while the postsynaptic neuron does not fire, the weight between these two neurons will not change.

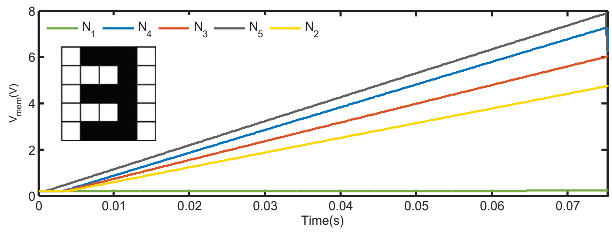
C. Output Layer

The output neurons are based on the memristor-based neuron circuit with adaptive spiking rate proposed above. Every neuron of output layer represents a certain pattern. Furthermore, WTA (winner-takes-all) mechanism is also required in output neuron of spiking neural network, which can make the output neurons exhibit the lateral inhibition. In the test period, the states of the neurons in the output layer can manifest the classification results. When a test pattern inputs the network, if it could be classified to the right pattern, the corresponding output neuron would fire. However, when the test pattern cannot be classified to the right pattern, the corresponding neuron will not fire. The specific situations are shown in TABLE II. N_1 to N_2 represents the output neurons, and the yellow stat represents the firing state of neuron while the grey star represents the quiet state of neuron. When the test patterns input the spiking neural network, if its corresponding neuron fires, the test pattern is classified successfully and marked with a check mark. On the contrary, if the firing states of neuron mismatch the test pattern, the pattern recognition would fail and marked with a cross.

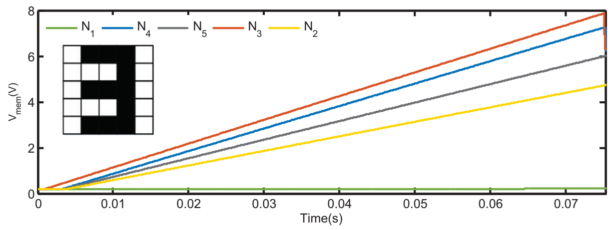
TABLE II
TEST PATTERNS AND THE STATE OF OUTPUT NPEURON

Pattern	N_1		N_2		N_3		N_4		N_5	
	★	★	★	★	★	★	★	★	★	★
1	✓	✗	✗	✓	✗	✓	✗	✓	✗	✓
2	✗	✓	✓	✗	✗	✓	✗	✓	✗	✓
3	✗	✓	✗	✓	✓	✗	✗	✓	✗	✓
4	✗	✓	✗	✓	✗	✓	✓	✗	✗	✓
5	✗	✓	✗	✓	✗	✓	✗	✓	✓	✗

D. Experiment



(a)



(b)

Fig. 7. Experiment result of proposed spiking neural network under the test pattern 3. (a) Simulation result of V_{mem}, where the output neurons are the conventional neurons that do not exhibit the adaptive firing rate. (b) Simulation result of V_{mem}, where the proposed memristor-based neuron circuit with adaptive firing rate is used as the output neuron.

In order to highlight the superiority of the proposed memristor-based neuron with adaptive firing rate in pattern recognition, the comparison simulation is carried out in this section. Fig. 6(a) shows the simulation result that the output neuron does not have the ability to adjust firing rate adaptively. The test pattern is 3, however, the neuron N_5 fires firstly, which demonstrates that the pattern 3 is classified unsuccessfully. There are two reasons to explain it. First, since the initial weights that are connected to the neuron N_3 are too low or the initial threshold voltage of N_3 is too high, then the firing rate of N_3 cannot reach the inherent level, as a result, the weights connected to the neuron N_3 are undertrained during the training period. Secondly, there is another reason for the recognition mistake. The initial weights that are connected to the neuron N_5 are too high or the initial threshold voltage of N_5 is too low. Therefore, the firing rate of neuron N_5 will exceed the inherent level during the training period and the weights connected to the neuron N_5 could be overtrained. As a result, the pattern 3 could be classified into pattern 5 improperly.

Under the same simulation condition, only the output neuron is replaced with the proposed neuron circuit. The circuit simulation is also carried out in PSPICE. Fig. 6(b) shows the simulation result that the proposed memristor-based neuron circuit is applied to the spiking neural network. In this scenario, the neuron N_3 fires firstly, when the pattern 3 input the network. Therefore, the test pattern 3 can be recognized successfully with the adaptive firing rate.

Compared with the first scenario, where the output neurons do not exhibit the ability of adaptive firing rate, the network based on the proposed neuron circuit has fewer recognition errors.

IV. Conclusion

The aforementioned sections demonstrate two ways of implementing the adaptive firing rate of neuron, which are the regulation on membrane sensitivity and neuron threshold, respectively. A memristor model is used in implementing the membrane sensitivity of neuron, where the memristance could be varied gradually according to the difference between the present firing rate and inherent firing rate. Another method to adjust firing rate of neuron adaptively is also proposed. By regulating the neuron threshold, the neuron threshold could be adjusted quickly. Based on these two ways with different paces, the adaptive firing rate of neuron can be realized at circuit level, In addition, pattern recognition of spiking neural network is also proposed based on the proposed memristive neuron. Although the verification platform is based on the binary images, the proposed design could be the groundwork for applying to more complicated scenarios due to the characteristics of memristor.

Acknowledgment

The work was supported by the Natural Science Foundation of China under Grants 61673188 and 61761130081, the National Key Research and Development Program of China under Grant 2016YFB0800402, the Foundation for Innovative Research Groups of Hubei Province of China under Grant 2017CFA005 and the Fundamental Research Funds for the Central Universities under Grant 2017KFXKJC002.

References

[1] M. R. Azghadi, B. Linares-Barranco, D. Abbott, and P. H. W. Leong, "A hybrid cmos-memristor neuromorphic synapse," *IEEE Trans. Biomed. Circuits Syst.*, vol. 11, no. 2, pp. 434–445, 2017.

[2] M. Prezioso, F. M. Bayat, B. Hoskins, K. Likharev, and D. Strukov, "Self-adaptive spike-time-dependent plasticity of metal-oxide memristors," *Sci. Rep.*, vol. 6, p. 21331, 2016.

[3] Y. Zhang, Z. Zeng, and S. Wen, "Implementation of memristive neural networks with spike-rate-dependent plasticity synapses," in *Prco. Int. Joint Conf. Neural Netw. (IJCNN)*, 2014, pp. 2226–2233.

[4] W. Cai, F. Ellinger, and R. Tetzlaff, "Neuronal synapse as a memristor: modeling pair- and triplet-based stdp rule," *IEEE Trans. Biomed. Circuits Syst.*, vol. 9, no. 1, p. 87, 2015.

[5] L. Chua, "Memristor, hodgkin–huxley, and edge of chaos," *Nanotechnology*, vol. 24, no. 38, p. 383001, 2013.

[6] M. D. Pickett, G. Medeiros-Ribeiro, and R. S. Williams, "A scalable neuristor built with mott memristors," *Nat. Mater.*, vol. 12, no. 2, p. 114, 2013.

[7] G. G. Turrigiano and S. B. Nelson, "Hebb and homeostasis in neuronal plasticity," *Curr. Opin. Neurobiol.*, vol. 10, no. 3, pp. 358–364, 2000.

[8] G. G. Turrigiano, "Homeostatic plasticity in neuronal networks: the more things change, the more they stay the same," *Trends Neurosci.*, vol. 22, no. 5, pp. 221–227, 1999.

[9] D. Querlioz, O. Bichler, and C. Gamrat, "Simulation of a memristor-based spiking neural network immune to device variations," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, 2011, pp. 1775–1781.

[10] M. Hansen, F. Zahari, M. Ziegler, and H. Kohlstedt, "Double-barrier memristive devices for unsupervised learning and pattern recognition," *Frontiers Neurosci.*, vol. 11, pp. 2045–2322, 2017.

[11] C. Bartolozzi, O. Nikolayeva, and G. Indiveri, "Implementing homeostatic plasticity in vlsi networks of spiking neurons," in *Proc.IEEE Int. Conf. Electron. Circuits Syst. (ICECS)*, 2008, pp. 682–685.

[12] S. C. Liu and B. A. Minch, "Silicon synaptic adaptation mechanisms for homeostasis and contrast gain control," *IEEE Trans. Neural Netw.*, vol. 13, no. 6, pp. 1497–1503, 2002.

[13] R. Brette, M. Rudolph, T. Carnevale, M. Hines, D. Beeman, J. M. Bower, M. Diesmann, A. Morrison, P. H. Goodman, and F. C. Harris, "Simulation of networks of spiking neurons: A review of tools and strategies," *J. Comput. Neurosci.*, vol. 23, no. 3, pp. 349–398, 2007.

[14] T. Prodromakis, B. P. Peh, C. Papavassiliou, and C. Toumazou, "A versatile memristor model with nonlinear dopant kinetics," *IEEE Trans. Electron Devices*, vol. 58, no. 9, pp. 3099–3105, 2011.

[15] T. K. Hemingway, *Electronic Designer's Handbook: A Practical Guide to Transistor Circuit Design*. Business Publication, 1970.