Unsupervised Learning of Digit Recognition Through Spike-Timing-Dependent Plasticity Based on Memristors

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Abstract. Neuromorphic computing based on spiking neural networks (SNNs) is a promising alternative in the field of intelligent computing, especially when traditional Von Neumann architectures is facing several choke point. Memristors, as the fourth-generation fundamental circuit element, play a crucial role in neuromorphic computing systems and are commonly employed as neural and synaptic devices. Due to their spike-based operation, memristive spiking neural networks (MSNNs) are considered to be superior and biologically plausible compared to alternative systems in terms of effectiveness. Here, the spike-timing-dependent plasticity (STDP) learning characteristic is reaped from our manufactured equipment. Utilizing memristor-based leaky integrate-and-fire (LIF) neurons and synapses, unsupervised learning of spiking neural networks with 784 × 324 × 324 architectures are constructed.

Keywords: Spiking neural network (SNN) · Spike-timing-dependent plasticity (STDP) · Artificial synaptic and neuron · Memristor

1 Introduction

With the explosive growth of today's data, traditional Von Neumann architecture is facing increasing difficulties in performance and power efficiency because of the separation of memory and computing units [1, 2]. In order to avoid or alleviate these problems, researchers have done much work to find new architectures. The investigations on brain-inspired SNN have been increasing sharply with high parallelism and higher efficiency [3, 4], which is inspired by the efficient human brain. The operational mechanism of the human brain has served as a significant inspiration for numerous researchers, prompting their focus on spike-timing-dependent plasticity (STDP) learning rules that exhibit greater biological plausibility [5]. The investigation of artificial synapses and neurons is

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crucial for the advancement of hardware implementation in neuromorphic systems relying on spiking neural networks (SNNs) [6, 7]. Memristor, as an emerging two-terminal device, is regarded as promising building blocks to realize artificial synapses and neurons, so it can be used to build hardware neural networks [8–10]. These systems utilize memristors as synaptic elements for the storage of synaptic weights and to achieve multiplication and addition operations through physical mechanisms, renowned for their energy-efficient characteristics.

We have successfully realized both artificial synapses and leaky integrate-and-fire (LIF) neurons stem from Ag/TiO_2/Pt memristor without the need for auxiliary circuits, utilizing the same memristor through specific electrical operations. Additionally, the spike-timing-dependent plasticity (STDP) learning rule has been implemented. We have also designed an LIF model that is applicable for Spiking Neural Networks (SNNs) with a network scale of 784 × 324 × 324 in a three-layer configuration. In the MNIST database test, the recognition rate can reach at 90.2%.

2 The LIF Neuron Model

Figure 1 presents our memristor-based LIF neuron, which accumulates inputs from various pre-neurons through memristor synapses to enable the functionality of a spiking neural network. The mathematical representation of the LIF neuron is described by the following differential equation:

$$\tau \frac{dv}{dt} = RI(t) - E \tag{1}$$

wherein, $\tau = 9.41$ ms, $E = 0.43$ mv (experimental data).

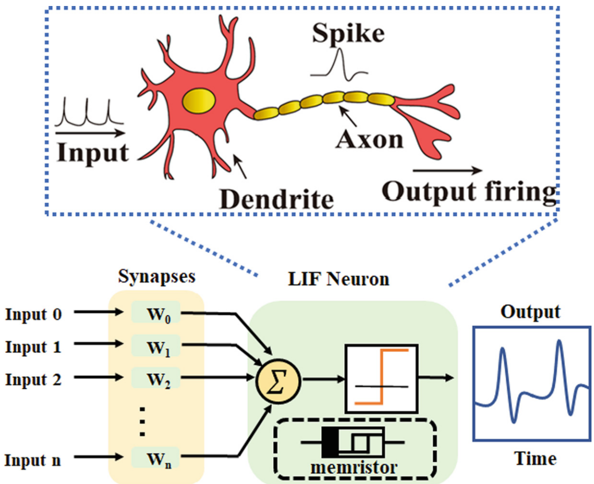

Fig. 1. Schematic illustration of neuromorphic system.

3 The STDP Characteristics

Regarding the synaptic weight adjustment rule in SNNs, STDP operates that change of synaptic weight is decided by the arrival time of presynaptic and postsynaptic spikes in working procedure. The memristor used in this study consisted of a top electrode (Ag) and a bottom electrode (Pt), which served to simulate the presynaptic and postsynaptic connections of the neurons, respectively. The memristor's conductivity was modulated by varying the pulse intervals applied between the top and bottom electrodes. Figure 2(a) illustrates the schematic diagram of a biological synapse and the structure of the synaptic device. To investigate its functionality, the pulse sequence depicted in Fig. 2(b) was simultaneously applied to both the top and bottom electrodes of the device. The implementation of STDP learning rule used in the proposed MSNN is shown in Fig. 2(c). Taking the interval between the presynaptic pulse and the postsynaptic pulse as Δt. The change in synaptic weight (Δw) is determined by the variation in conductance, which can be described using the exponential Eq. (2) as proposed:

$$\Delta w = \begin{cases} W_{+}e^{\left(-\frac{|\Delta t|}{\tau_1}\right)}, \ if\ \Delta t > 0 \\ W_{-}e^{\left(-\frac{|\Delta t|}{\tau_2}\right)}, \ if\ \Delta t < 0 \end{cases} \tag{2}$$

wherein, $W_{+} = 138.62$ and $W_{-} = 103.46$ represent the initial weight, $\tau_1 = 64.1$ ms and $\tau_2 = 29.2$ ms are the membrane time constant (experimental data).

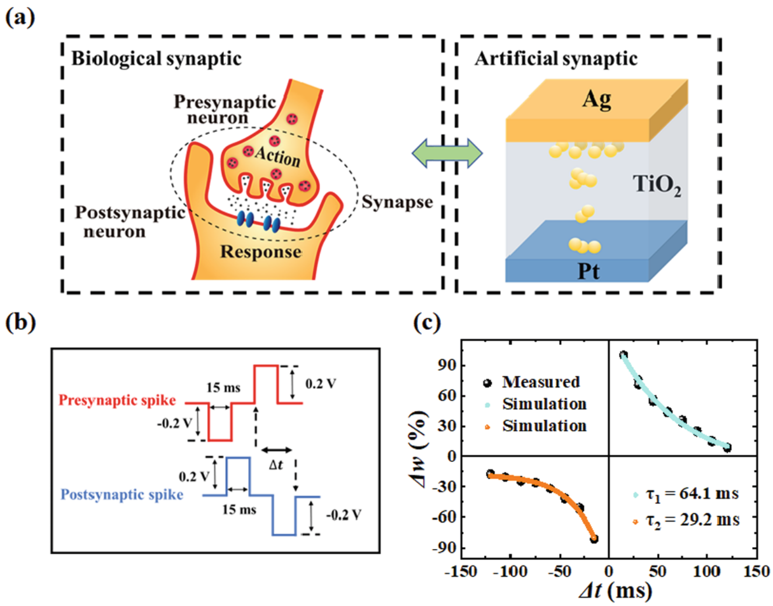

Fig. 2. (a) Schematic diagram of biological and memristive synapse. (b) Pulse shapes of the experimental for STDP implementation. (c) The implementation of STDP learning rule

4 Pattern Recognition in Spiking Neural Networks

Figure 3 illustrates the architecture of a fully-connected spiking neural network, which comprises an input layer, an excitatory layer, and a lateral inhibition layer. The 784 input layer units, consisting of 28 × 28 LIF neurons, representing the pixels of each character image in MNIST. Additionally, they are connected to the 324 excitatory layer neurons through 28 × 28 × 324 memristive synapses. The lateral inhibition layer is adopted to availably impede all neurons in the excitatory layer from learning similar patterns.

During the unsupervised learning phase, the MNIST training database is fed into the network, where the input layer's LIF neurons follow the leaky-integrate-and-fire mechanism and generate spikes accordingly. The initial weights in the network are randomly distributed. Subsequently, the weight update is triggered by the initial spike from the presynaptic spike trains and the postsynaptic spike, and adjusted based on the observed spike-timing-dependent plasticity (STDP) learning rule illustrated in Fig. 2(c). The excitatory neurons are categorized based on their highest average response to digit classes in the training set after the learning process. The pattern recognition accuracy, as depicted in Fig. 4, reached around 90.2% with a network size of 784 × 324 × 324.

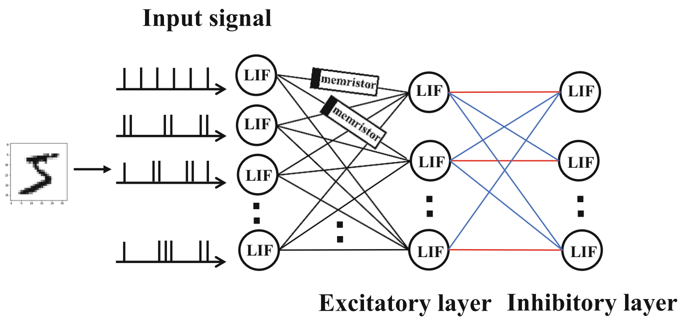

Fig. 3. Schematic layout of the fully-connected Spiking neural networks

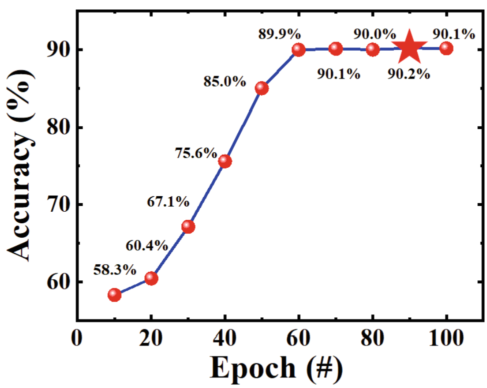

Fig. 4. The recognition accuracy of 90.2%

5 Conclusion

In conclusion, an Ag/TiO_2/Pt memristor was fabricated as an artificial synaptic and LIF neuron component for neuromorphic computing. By calibrating the STDP of artificial synapses and implementing LIF models for artificial neurons, we have successfully simulated the leakage, spatiotemporal integration, and discharge functions observed in biological neurons. The successful demonstration of MNIST digit recognition in a three-layer network has an encouraging recognition accuracy. The memristors, serving as the fundamental unit for neuromorphic computing, exhibit promising capabilities that are the focus of our work.

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