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Synaptic long-term potentiation realized in Pavlov's dog model based on a NiO_x-based memristor

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Synaptic Long-Term Potentiation (LTP), which is a long-lasting enhancement in signal transmission between neurons, is widely considered as the major cellular mechanism during learning and memorization. In this work, a NiO_x-based memristor is found to be able to emulate the synaptic LTP. Electrical conductance of the memristor is increased by electrical pulse stimulation and then spontaneously decays towards its initial state, which resembles the synaptic LTP. The lasting time of the LTP in the memristor can be estimated with the relaxation equation, which well describes the conductance decay behavior. The LTP effect of the memristor has a dependence on the stimulation parameters, including pulse height, width, interval, and number of pulses. An artificial network consisting of three neurons and two synapses is constructed to demonstrate the associative learning and LTP behavior in extinction of association in Pavlov's dog experiment. © *2014 AIP Publishing LLC*. [http://dx.doi.org/10.1063/1.4902515]

I. INTRODUCTION

In cognitive neuroscience, memories are thought to be encoded by modification of synaptic strength (i.e., transmission efficacy of synapse). However, the human brain consists of extremely large number of neurons ($\sim 10^{11}$) and synapses ($\sim 10^{15}$), and each neuron may have more than 1000 synapse connections with other neurons.[1] Various electronic synapses, which can emulate the functions of biological synapse, have been proposed and studied. In the past, many efforts have been made to build an electronic synapse with CMOS technology.[2,3] However, with this method, each electronic synapse needs at least 10 transistors, and thus leading to large silicon area and power consumption. Recently, a new type of device, memristor, shows great potential in realizing synaptic behaviors for its continuously adjustable conductance. Based on memristors, brain-like behaviors, such as learning and forgetting effects,[4] and several synapse-like effects, such as short-term plasticity,[5,6] long-term plasticity,[6] and spike-time dependent plasticity,[7–12] have been realized.

Since the pioneer studies performed 40 years ago by Bliss *et al.*,[13,14] synaptic Long-Term Potentiation (LTP), which is a long-lasting enhancement in signal transmission between two neurons (i.e., the weight of synapse), has been widely studied as a cellular and synaptic model for learning and memory.[16–19] In the early works,[5,6,9,11,12] LTP in memristors was generally treated as a permanent state or nonvolatile state. However, its lasting time is actually not infinite, and the LTP fades away over time following an exponential decay. Recently, the decay behavior of LTP in single InGaZnO-based memristor[20] and WO_x-based memristor[21] was reported. Associative learning in Pavlov's dog experiment has been realized with a neural network based on memristors,[22] which is a straightforward possible application of memristors in neural network. However, the post-learning behaviors including the LTP decay/forgetting behavior should be examined in the experiment.

In the present work, we demonstrate that the behaviors of electrical conductance of a NiO_x-based memristor stimulated by electrical pulses resemble some key characteristics of synaptic LTP. Moreover, the magnitude of the memristor LTP decreases over time, which bears a striking similarity to the synaptic LTP in biological systems. Furthermore, a neural network based on the NiO_x-based memristors is constructed to implement the Pavlov's dog experiment. In addition to the widely demonstrated associative memory, the extinction of associative memory is observed with the neural network.

II. EXPERIMENTAL DETAILS

Fabrication of the memristor was started with a thermal growth of a 400 nm SiO_2 thin film on a p-type silicon wafer. After that, a 120 nm Ni layer was deposited on the SiO_2 film with electron-beam evaporation. A NiO_x thin film of $\sim$150 nm was then deposited onto the Ni/SiO_2/Si substrate by rf (13.6 MHz) magnetron sputtering of a NiO_x target (>99.99% in purity). Finally, a 150 nm Au/15 nm Ni layer was deposited onto the NiO_x thin film by electron-beam evaporation to form the top circular electrodes with 200 μm in diameter. The chemical states of the synthesized nickel oxide thin film were analyzed by a Kratos AXIS Ultra XSAM800 X-ray photoelectron spectroscopy (XPS) equipped with monochromatic Al $K\alpha$ (1486.71 eV) X-ray radiation (12 kV and 15 mA). As shown in Fig. 1(a), the Ni

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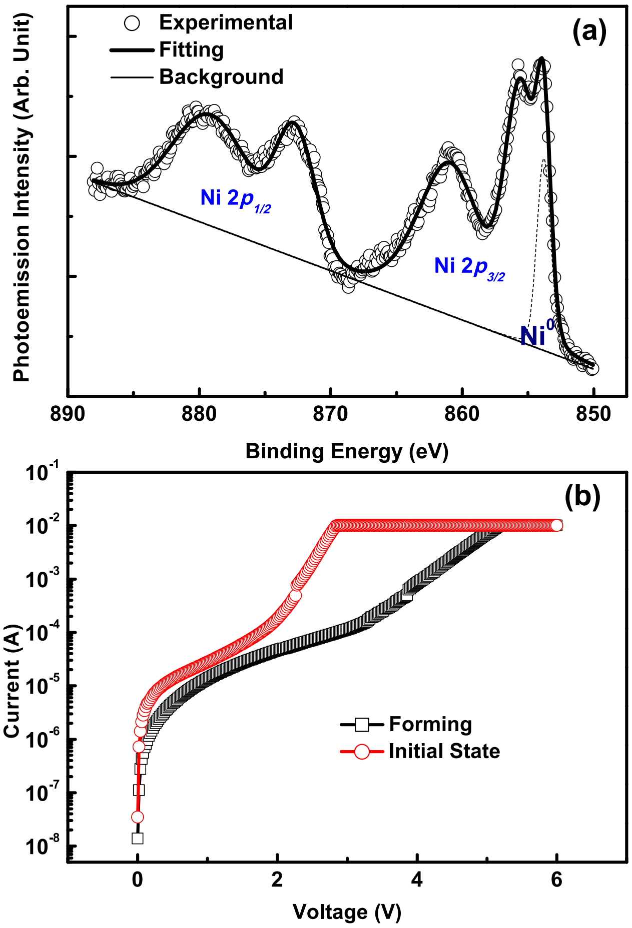


FIG. 1. (a) XPS spectrum of Ni 2p core levels of as-fabricated NiO_x film; and (b) I-V characteristic of a fresh device and the forming process occurring during the voltage sweeping.

2p core level spectrum shows a Ni^0 peak, indicating that the as-deposited nickel oxide thin film is Ni-rich. Electrical characterizations were carried out with a Keithley-4200 semiconductor characterization system at room temperature. Fig. 1(b) shows the I-V characteristic of a fresh device and the forming process occurring during the voltage sweeping. A compliance current of 0.01 A was set to avoid hard breakdown of the oxide thin films. The rise and fall time of a voltage pulse are both 0.1 ms. The minimum pulse width used in this study is 5 ms, which is 50 times of the rise/fall time.

III. RESULTS AND DISCUSSION

Synaptic LTP, which can last from hours to weeks or even to months, is a long-lasting enhancement in signal transmission between two neurons that results from repeated stimulations to pre-synape.[16–19] In a LTP experiment as shown in Fig. 2, in the initial state a stimulation to the pre-neuron can cause excitatory postsynaptic potential or current (EPSP or EPSC) on the post-neuron. After a train of stimuli is applied to the pre-neuron, a single-pulse stimulation to pre-neuron leads to larger EPSP or EPSC in the post-neuron. The magnitude of LTP at time t after a train of stimuli is usually expressed with the equation[23]

$$P(t) = \frac{EPSP(t)}{EPSP_0} \times 100\%, \tag{1}$$

where $EPSP_0$ and $EPSP(t)$ are the magnitudes of the EPSPs before and time t after stimulation, respectively. Another key feature of LTP is that it can last a long time (normally for more than 30 minutes), and the magnitude of LTP shows an exponential decay following the following expression:[24,25]

$$P(t) = P_0 \cdot \exp(-t/\tau), \tag{2}$$

where t is the time from the end of stimulation ($0 \le t \le$ LTP *lasting time*[14,15]) and τ is the time constant of decay; and P_0 is the first magnitude of LTP immediately after stimulation. P_0 is given by

$$P_0 = \frac{EPSP(0)}{EPSP_0} \times 100\%, \tag{3}$$

where $EPSP(0)$ is the first EPSP recorded immediately after stimulation. The synaptic LTP depends on stimulation-caused post-synaptic N-methyl-D-aspartate (NMDA) receptor activation and a resultant influx of Ca^{2+} ions, and one consequence of this rise in postsynaptic Ca^{2+} concentration is to trigger an increase of the transmission.[16–19]

In this work, the electrical conductance of the memristor is analogous to the synaptic transmission efficacy represented by the EPSP or EPSC, while an electrical pulse applied to the memristor is similar to a synaptic stimulus. To demonstrate the LTP-like behaviors in the memristor, electrical conductance of the memristor was first measured at 30 mV for a period of 15 min before stimulation. Then, the stimuli of 100 electrical pulses were applied to the memristor. The pulse height, width, and interval were set to 1.8 V, 10 ms, and 100 ms, respectively. After the stimulation, the conductance of the memristor was measured at 30 mV for a period of 60 min. Figs. 3(a) and 3(b) show the evolution of the conductance with time in various stages including before, during, and after stimulation. The conductance measurement was conducted by programming with a settling time <1 s, as shown in Fig. 3(b). The conductance shown in Figs. 3(a) and 3(b) is normalized to the first value of conductance recorded before stimulation. The conductance before stimulation remained unchanged over time, and it is referred to as the initial state of conductance, G_{init}. The stimulation was carried out with 100 pulses with a pulse height of 1.8 V, pulse width of 10 ms, and pulse interval of 100 ms. The conductance increased immediately after the stimulation, and it then spontaneously decayed, which is similar to the synaptic LTP behavior.[23]

According to Eq. (1), the magnitude of LTP in the memristor is defined as

$$LTP(t) = \frac{G(t)}{G_{init}} \times 100\%, \tag{4}$$

where $G(t)$ is the conductance at the time of t after the stimulation. Fig. 3 shows that the magnitude of LTP increased to 448% immediately after the stimulation and then spontaneously decayed to 156% after 60 min. It is interesting to note

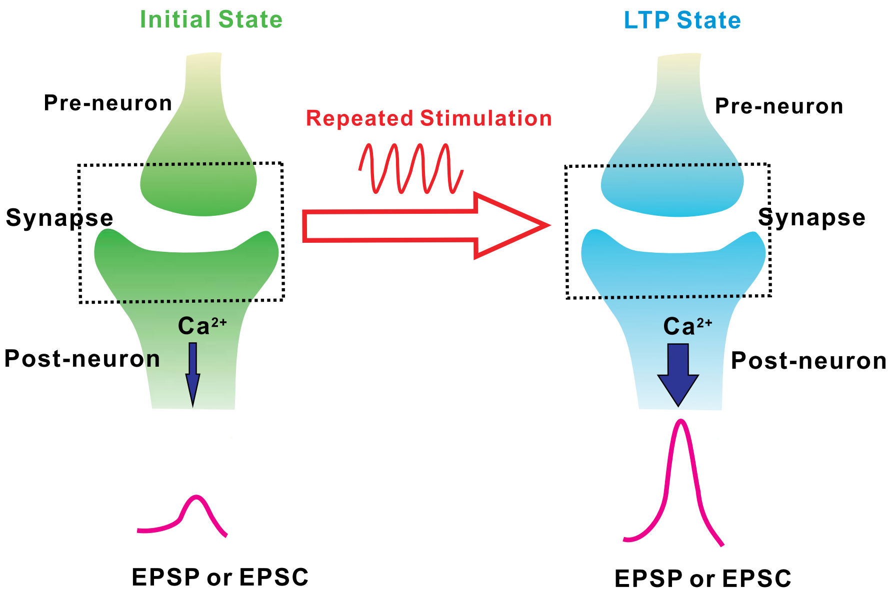


FIG. 2. Schematic illustration of synaptic LTP behavior.[17]

that the conductance behaviors shown in Fig. 3 exhibit a strong resemblance to the synaptic LTP behaviors depicted in Ref. 23. The decay behavior of LTP in the memristor can be described with the stretched exponential function[6,26]

$$LTP(t) = LTP_0 \cdot \exp[-(t/\tau)^{\beta}], \tag{5}$$

where t is the time from the end of stimulation ($0 \leq t \leq$ LTP *lasting time*); τ is the time constant of decay; β is an index

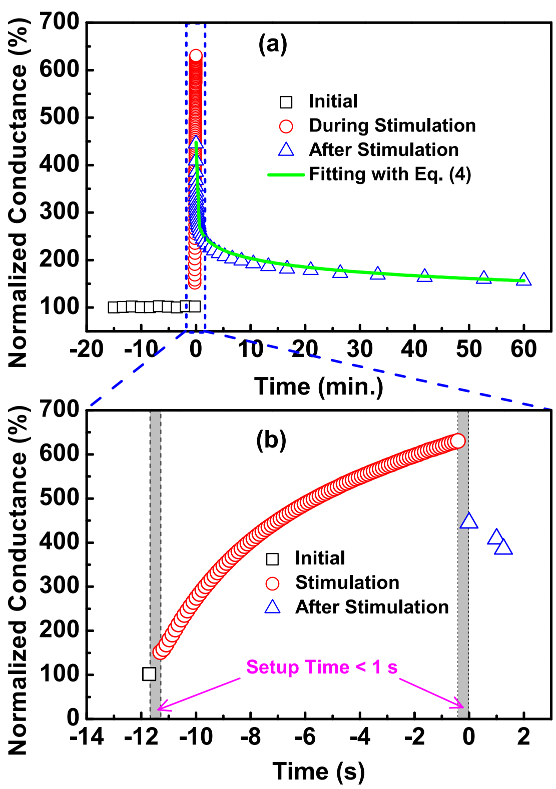


FIG. 3. (a) Evolution of the normalized conductance with time in various stages including before, during, and after stimulation and (b) zoomed part of conductance states in stimulation. The stimulation was carried out with 100 consecutive pulses with the pulse height, width, and interval of 1.8 V, 10 ms, and 100 ms, respectively.

ranging from 0 to 1; and LTP_0 is the initial magnitude of LTP immediately after stimulation, which is given by

$$LTP_0 = \frac{G_0}{G_{init}} \times 100\%, \tag{6}$$

where G_0 is the first conductance recorded immediately after stimulation. The fitting to the experimental data shown in Fig. 3(a) was carried out with Eqs. (4)–(6) and is shown in Fig. 3(a) also. The decay of LTP is well described by the stretched exponential function of Eq. (5) with $LTP_0 = 448\%$ (note that the setup time for the LTP_0 measurement was less than 1 s), $\tau = 43.7$ min, and $\beta = 0.16$. The time taken to reach $LTP(t) = 100\%$ is 550 min, which is the LTP *lasting time*.

The LTP-like behaviors of the memristor can be explained by the microscopic changes in the Ni-interstitial based conductance in the NiO_x thin films occurring during the application of the electrical pulses as well as in the subsequent relaxation process. The conductive filament (CF) concept can be used to explain the conductance change caused by electrical pulses.[27–33] Resistance/conductance switching of NiO_x layers has been attributed to rupture/formation of conducting filaments of Ni interstitials.[34,35] Joule heating effects (e.g., thermally activated material migration) and field effects (e.g., migration of the ions under the applied electric fields) produced by the electrical pulses may play an important role in linking up the Ni interstitials with each other to form conductive filaments.[35,36] When the external electric field is removed, the concentration gradient leads to the back diffusion of Ni interstitials. As a result, the conductive filaments are partially/fully deformed, thus reducing the device conductance.

The LTP behavior of the conductance depends on the stimulation parameters including number of pulses, pulse height, width, and interval. As suggested by the above equations, LTP_0, τ, and *lasting time* of LTP are useful indicators when evaluating the LTP behavior. Fig. 4(a) shows the dependence of LTP_0, τ, and *lasting time* on the number of pulses with the pulse height, width, and interval fixed at

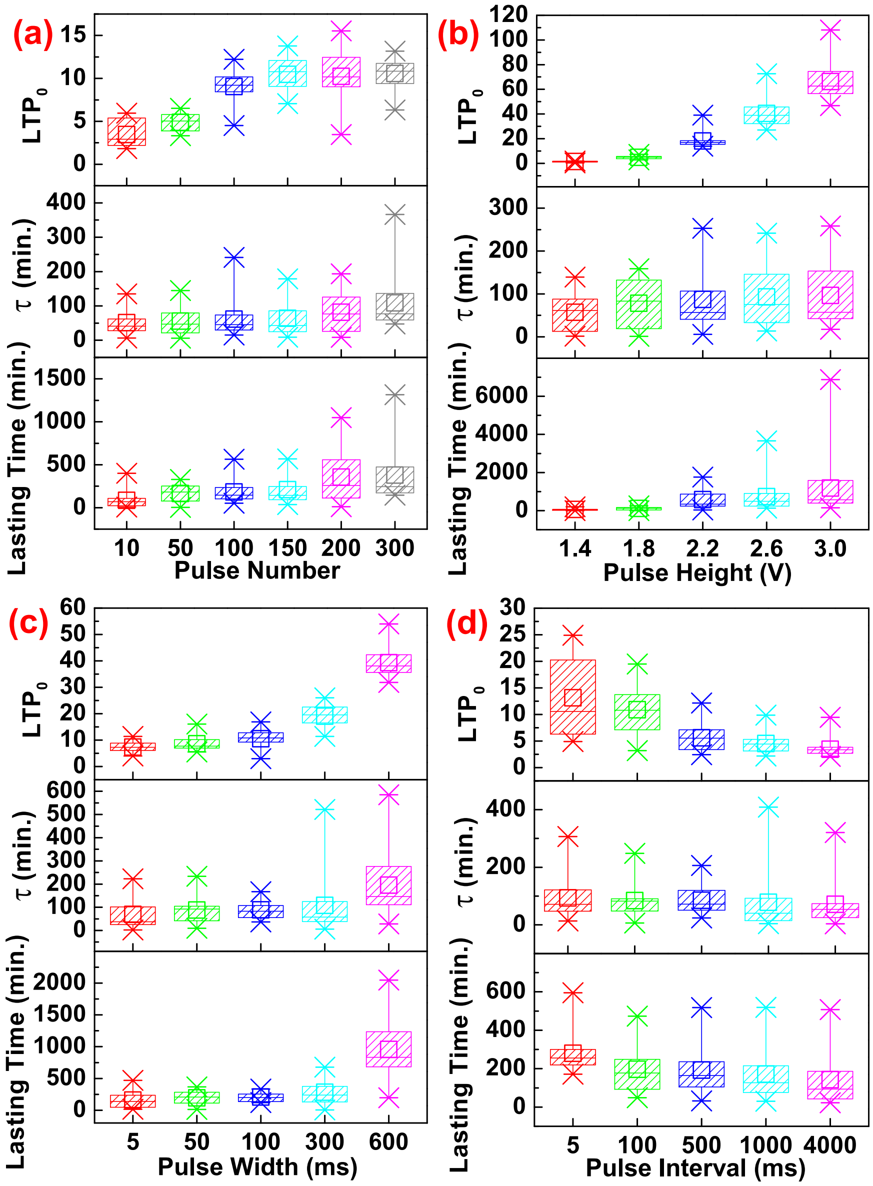


FIG. 4. Statistics of LTP_0, τ, and LTP *lasting time* as functions of (a) pulse number; (b) pulse height; (c) pulse width; and (d) pulse interval. For each condition, at least 10 devices at different locations on the wafer were examined.

1.8 V, 10 ms, and 100 ms, respectively. The average values of LTP_0, τ, and *lasting time* all increase with the pulse number. The average value of LTP_0 increases gradually with the pulse number; both τ and the LTP *lasting time* show a small or insignificant increase for the pulse numbers smaller than ~200, but they increase significantly for pulse numbers larger than ~200. These results reflect the fact that more or larger and stronger conductive filaments are formed in the NiO_x thin films with more pulses.

LTP also shows dependence on stimulation strength, including pulse height and width. In Fig. 4(b), pulse height was varied, while the pulse number, pulse width, and interval are set to 30, 100 ms, and 100 ms, respectively. As can be seen in the figure, when the pulse height is increased from 1 V to 3 V, the LTP_0, τ, and LTP *lasting time* all show a trend of increase with pulse height. In Fig. 4(c), pulse width is increased from 5 ms to 600 ms, while the pulse number, pulse height, and interval are fixed at 20, 2 V, and 100 ms, respectively. The LTP_0, τ, and *lasting time* show an increase when the pulse width is longer than 300 ms. Obviously, a higher electrical field or a longer duration of the electric field results in more or larger and stronger conductive filaments formed in the NiO_x thin films,[30] leading to an increase in LTP_0, τ, and *lasting time*. This is analogous to the situation that synaptic EPSP or EPSC is enhanced with a stronger or longer external stimulation.

Fig. 4(d) shows the dependences of LTP_0, τ, and *lasting time* on pulse interval. The pulse number, pulse height, and width were set to 20, 2 V, and 100 ms, respectively. The LTP_0, τ, and *lasting time* all show a trend of decrease with pulse interval. This is due to the above-mentioned relaxation process occurring during the pulse interval. The effect of pulse interval is analogous to the synaptic behavior that the EPSP or EPSC is suppressed if there is a longer waiting time between stimulation events.

The results shown in Figs. 4(a)–4(c) actually show the impact of the electrical energy injected into the device. With more pulses, a larger pulse height or a wider pulse width, more electrical energy is injected into the device; a wider conductive filament or more conductive filaments and thus a larger LTP_0 can be expected. In addition, more relaxation time is needed for spontaneous back-diffusion of the nickel interstitials. Therefore, a larger τ and a longer *lasting time* can be observed.

The NiO_x-based memristor with LTP behaviors could be used for constructing neural networks. Based on the design in Ref. 37, we constructed an artificial neural network consisting of three neurons and two synapses to demonstrate the associative learning in Pavlov's dog experiment.[38,39] The electronic system was realized with metal-oxide-semiconductor (MOS) devices and a memristor, as schematically illustrated in Fig. 5(a). Either bipolar or unipolar memristors can be used to construct the neural network. Due to the modifiable conductance of the memristor, it is convenient to modify the synaptic weight of the electronic synapse. Fig. 5(b) shows the hardware implementation of the neural network.

As shown in Fig. 6, the associative learning in Pavlov's dog experiment could be realized with the neural network, with V_{in1}, V_{in2}, and V_{out} representing the "food" (unconditioned stimulus), the "bell" (conditioned stimulus), and the "salivation" (response), respectively. V_m is used to detect the weight of synapse 2 and V_{ref} is set to 0.83 as a reference voltage. Initially, the weights of synapse 1 and synapse 2 were

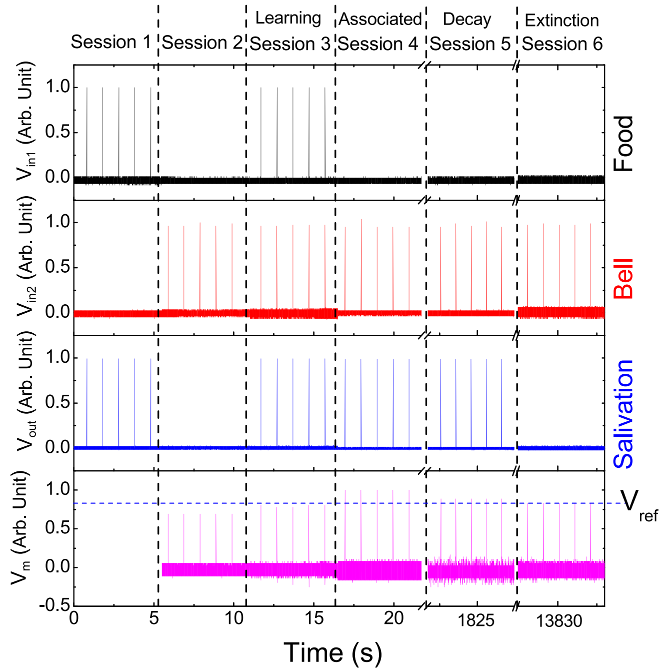
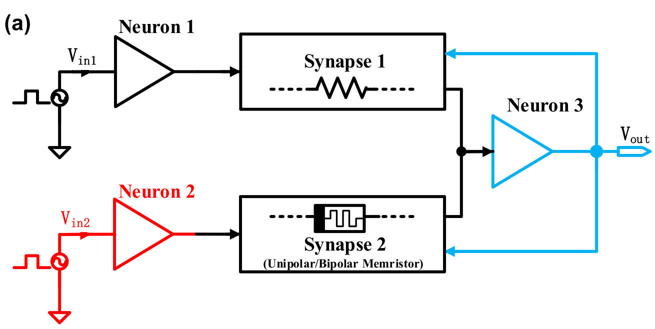


FIG. 6. Associative learning and extinction of association in Pavlov's dog experiment realized with the three-neuron neural network.



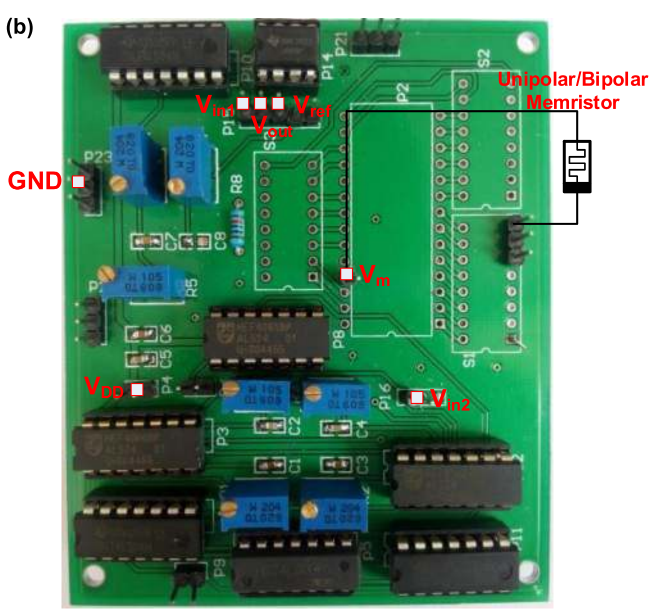


FIG. 5. (a) An artificial neural network constructed with three neurons and two synapses to implement the associative learning; (b) hardware implementation of the neural network.

set to high and low levels, respectively. As shown in session 1 of Fig. 6, the input of "food" triggers the "salivation;" while in session 2, the "bell" alone cannot elicit "salivation" for the weight of synapse 2 is low. In session 3, "salivation" is triggered by the "food." At the same time, the "food" is companied with the "bell." The "dog" (i.e., the neural network) is conditioned to associate the "bell" with "food" by increasing the weight of synapse 2, which is called associative learning. As shown in session 4, once the "dog" has been conditioned to associate the "bell" with "food," the "bell" alone can trigger the "salivation" due to the increase of the weight of synapse 2. About 30 min later, the "bell" alone could still trigger the "salivation," while V_m of session 5 is lower than that in session 4 but still larger than V_{ref}, which is attributed to the decrease of the weight of synapse 2 resulting from the spontaneous decay of LTP amplitude of the NiO_x-based memristor. About 230 min after session 4, the weight of synapse 2 decreases to a certain degree, i.e., $V_m < V_{ref}$; as a consequence, the "bell" cannot elicit "salivation," as shown in session 6. This situation is similar to that the "dog" may "forget" the association between the food and bell in Pavlov's dog model, which is called the extinction.

IV. CONCLUSION

In summary, the synaptic LTP can be well emulated with a NiO_x-based memristor. The conductance of the memristor can be increased by the application of electrical pulses, which is analogous to the synaptic LTP behavior. The increased conductance decays spontaneously towards the initial state, which bears a similarity to the decay of the synaptic LTP. Like the synaptic LTP behavior, the memristor LTP depends on the number of stimulation events (i.e., the pulse number), stimulation strengths (i.e., the pulse height and pulse width), and stimulation interval (i.e., the pulse interval). Finally, an artificial neural network was constructed to realize the associative learning as well as the extinction of association.

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