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A Memristive Neural Network Model With Associative Memory for Modeling Affections

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ABSTRACT Memristor is a nonlinear resistor with memory, which has the characteristics of neuron synapses and can be used to design a new generation of memristive neural networks. Based on the Pavlov associative memory, a novel memristive associative memory neural network model is designed by using the charge-controlled nanoscale HP memristor model as the electronic synapse. This model includes neurons, memristor synapses, and weighted input feedback learning rule. Based on the proposed memristive associative memory model, a memristor-based neural network structure for simulating human emotions is further designed. The emotion simulation takes into account the excitation and inhibition between different neurons, making it more bionic. In order to simulate the memristive neural network structure, a relatively simplified emotional simulation circuit is constructed, which effectively reduces the network complexity and circuit power consumption. Finally, PSPICE is used to simulate the circuit. The simulation results not only verify the correctness of the model but also achieve a simple simulation of human emotions, which is helpful for the further development of the artificial neural network in the field of artificial intelligence.

INDEX TERMS Associative memory, memristive neural network, modeling affections, weighted-input-feedback.

I. INTRODUCTION

In 1971, Chua [1] deduced the existence of memristor theoretically. In 2008, HP lab [2] successfully realized the nanoscale devices with memristive performance by using TiO_2. Memristor is a nonlinear resistor with memory, which can store information without internal power, and has great potential applications in digital storage, artificial neural networks, digital logic circuits and nonlinear circuits.

The unique characteristics of memristors make them suitable candidates for synspses [3]. The basic computational processing units of human brain are synapses and axons. It has been known that local passive nonvolatile memristors can simulate synaptic characteristics well, and are the basic modules of imitation, memory and learning [4]. It has been reported that human brain is made up of memristors [5], which are particularly suitable for realizing neuromorphic systems since these devices are nanoscale two-terminal devices and can be efficiently integrated within crossbar array circuits [6]. A major gain in using memristors, which results from their small scale and low power consumption, is their ability to build practical neural networks with great amount of neurons and synaptic connections [7].

In recent years, using memristor to simulate synapses in Artificial Neural Network (ANN) and realize associative memory [8], [9] in memristive neural networks has become a frontier and key research area. Recently, [10] reported that a crossbar array consisting of memristors has been implemented, which can simulate the operation of the whole neural network. It has made an important step for the realization of large scale memristive complex neural networks. References [11] and [12] proposed a new four-variable HR neuron model, which uses the flux of the memristor as a variable to regulate the membrane potential.

The human brain is a complex parallel processing system of information, and human thinking is accomplished by the brain. As it is known, a brain consists of about $10^{11} \sim 10^{12}$ neurons, each of which is connected with $10^4 \sim 10^5$ neurons to receive and process information. In other words, a human has a density of about 10^{10} synapses/cm^2 [13]. Coincidentally, a HP memristor with size smaller than $50 \times 50 \times 50$ nm^3 is an appropriate candidate of electronic synapses, since the memristor-based neuromorphic chip may achieve a roughly equal synapse density to the human brain [14].

In particular, a memristor has the advantages of non-volatility, low power, high density and good extensibility [15], making it an appropriate component for the effective implementation of the neuron synaptic circuit [16].

Up to now, researchers have done a lot of research on memristive neural networks [17], [18]. Very recently, [19] reported an experimental study of memristor-based neural networks, which tested its suitability for memristive synapse functioning and implementing of associative memory using a digital memristor simulator. Reference [20] presented new conditions for global asymptotic stability of memristor-based neural networks. A compact memristor-based dynamic synapse for spiking neural networks was also studied in [21]. Learning in memristor crossbar-based spiking neural networks and efficient and self-adaptive in-situ learning in multilayer memristor neural networks are also reported [22], [23].

A lot of research on associative memory based on the memristor neural network have been done. The most famous example of associative memory is the Pavlov Experiment [24], which leads people to believe that the same behavior can be implemented in artificial neural networks.

When the dog sees the food, it triggers a brain reaction, and there is a direct connection between the brain and saliva neurons, which results in saliva secretion. When the dog is trained for a certain period of time (when the dog sees the food and hears the bell or other neutral stimuli), there will be only the bell or other neutral stimuli, and the dog will also secrete saliva. People call this phenomenon Pavlov associative memory. When the dog is trained for a certain period of time (when the dog sees the food and hears the ring or other neutral stimuli at the meantime), and there is only the bell or other neutral stimuli, the dog will also secrete saliva. This phenomenon is called Pavlov associative memory.

By analogy, we can use the associative memory of memristive neural network to simulate some emotional changes in our daily life. Hebbian learning method [25], [26] is usually considered as an effective algorithm for associative learning of neural networks. However, the Hebbian learning method cannot make the relationship between presynaptic and postsynaptic neurons weaker and weaker during the correction process. In order to solve this problem, some new learning methods have been proposed, such as MIF [27] (max-input-feedback) learning law, AIF [28] (average-input-feedback) learning law, etc., which can realize associative learning well, but there are still some shortcomings.

Although the MIF method has the function of correlation correction, it takes the maximum stimulus voltage as the input signal, and its neural network cannot judge whether there is only one maximum input in the network, and it also ignores the effect of other inputs on the formed associative memory. Although the MIF method can implement correlation correction, it uses the maximum stimulus voltage as input signal, which leads to the effect that its neural network cannot judge whether there is only one largest input in the network, as well as it ignores the role of associative memory formed by other inputs. Although all inputs are synthesized to some extent, the AIF method that performs a simple averaging process, cannot show the difference of connection strength between different neurons, and its memristive neural network circuit structure is redundant which contains so many operational amplifiers, and results in increased network complexity and power consumption.

Different from [27] and [28], this paper proposes a novel learning method, called weighted-input-feedback (WIF). Based on WIF, a relatively simplified memristive neural network circuit is proposed to realize the function of associative memory. Its electronic synapses are implemented by an improved mathematical model of the HP memristor [29]. In PSPICE simulation, the memristor can match the biological synapse perfectly. In addition, by studying the excitation and inhibition effects of different neurons, the proposed memristor neural network associative memory model is more bionic, which is applied to simulate some simple emotional changes in life.

II. IMPORTANT COMPONENTS OF THE MEMRISTIVE NEURAL NETWORK

A. NEURON MODEL AND WIF LEARNING RULE

An artificial neural network is composed of several neurons in accordance with certain rules, in which under the action of input signal, each neuron can change from the current state to another state, producing corresponding output signal. Neuron determines the characteristics and functions of the whole neural network, which has multiple inputs and single output. Here we present a novel WIF learning method, based on which a neuron receives the summation input of different weighted values of each neuron before the synapse and generates the corresponding output signal. We use this neuron model shown in Fig. 1 to simulate the change of human emotion.

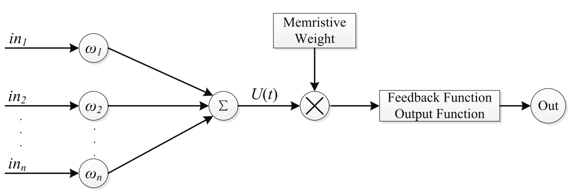

FIGURE 1. **Basic structure of neuron.**

Combined with the neuron model shown in Fig. 1, the description of the WIF learning law is as follows.

Firstly, considering the difference in the strength of connections between different presynaptic neurons and postsynaptic neurons, and according to the connection between presynaptic neurons and postsynaptic neurons, i.e., they are connected inherently or trained to form connections, we set different connection weights (ω_k).

Secondly, the weighted sum of the input signals of all presynaptic neurons was used as the input value $U(t)$ of postsynaptic neurons.

Finally, when the input value $U(t)$ is multiplied by the corresponding weight value of the amnestic synapse, and then passes through the feedback and output functions, the output value of the postsynaptic neuron can be obtained, and the memristive synaptic weight can be updated., which based on the WIF learning rules. The synaptic learning rule is shown in Fig. 2.

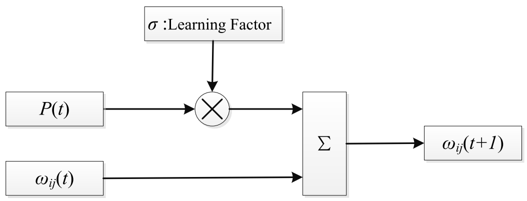

FIGURE 2. Learning rule of synapses.

Generally, neuron consists of input, feedback and output functions. The input function is a weighted sum function and can be represented as:

$$\begin{cases} IN_{ij}(t) = O_i(t)\omega_{ij}(t), \\ U(t) = \sum_{k=1}^{n} \omega_k in_k, \end{cases} \tag{1}$$

where $IN_{ij}(t)$ represents the input value from presynaptic neuron i to postsynaptic neuron j; $O_i(t)$ is the output of presynaptic neuron i; $\omega_{ij}(t)$ is the weight of synaptic connections between the presynaptic neuron i and postsynaptic neuron j; $U(t)$ represents the input value of postsynaptic neurons that come from all presynaptic neurons; in_k is the input signal of the neuron k; and ω_k is the weight of the input neuron k and $\Sigma\omega_k = 1$.

The working function of a neuron can be written as:

$$\begin{cases} O(t) = F_O(U(t)) \\ F(t) = F_f(U(t)) \end{cases} \tag{2}$$

where $F_O(U(t))$ denotes the output function; $F(t)$ denotes the feedback value of the neuron and $F_f(U(t))$ represents the feedback function.

The synaptic learning rule based on the WIF learning rule is shown in Fig. 2, and the memristive synaptic weight update function is:

$$\begin{cases} \omega_{ij}(t+\Delta t) = \omega_{ij}(t) + \Delta\omega_{ij}(t) \\ \Delta\omega_{ij}(t) = \sigma P_{ij}(t) \\ P_{ij}(t) = O_i(t) - F_j(t) \end{cases} \tag{3}$$

where $\omega_{ij}(t)$ is the current weight strength; σ is a learning factor; $F_j(t)$ is the feedback value of the postsynaptic neuron j; $\Delta\omega_{ij}(t)$ represents the variation of synaptic weight; and $P_{ij}(t)$ is the working voltage of the synaptic weight $\omega_{ij}(t)$.

Based on Eqs. (1)-(3), when the presynaptic and postsynaptic neurons are triggered, the synaptic weight is changed to simulate the learning and forgetting process of neurons by defining the appropriate output and feedback functions.

The output function is defined as a piecewise function, and the hyperbolic tangent function is used as a feedback function. Their waveforms are shown in Fig. 3 and corresponding

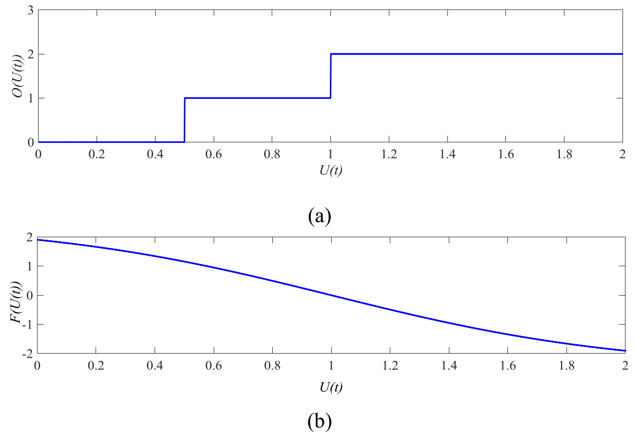

FIGURE 3. Output and feedback functions. (a) Output function. (b) Feedback function.

mathematical expressions are given as:

$$O(U(t)) = \begin{cases} 0, & U(t) \le 0.5 \\ 1, & 0.5 \le U(t) \le 1 \\ 2, & U(t) \ge 1 \end{cases} \tag{4}$$

$$F(U(t)) = -2.5\tanh(U(t) - 1) \tag{5}$$

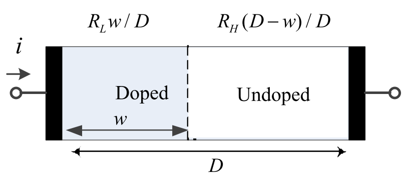

FIGURE 4. HP memristor model.

B. MEMRISTOR SYNAPSE MODEL

Based on the model of memristor in [29] and [30], an improved mathematical model of HP TiO_2 memristor is proposed, which can be used to realize different configurations of electronic synapses and enhance synaptic action. The physical structure a of HP memristor is shown in Fig. 4. Under the applied excitation, the changes of the doping region width w leads to the changes of the memristance, which in turn updates the weight of memristor synaptic [8]. The mathematical model of the HP memristor is described by:

$$R_M(t) = R_H + (R_L - R_H)x(t) \tag{6}$$

$$x(t) = \frac{w(t)}{D} \in (0, 1) \tag{7}$$

$$\frac{dx(t)}{dt} = ki(t), \quad k = \frac{\mu_v R_L}{D^2} \tag{8}$$

where $w(t)$ represents the thickness of the doped region, and $0 \le w(t) \le D$; D is the thickness of the memristor; R_L and R_H are the lowest and highest memristances for $w(t) = D$ and $w(t) = 0$, respectively; $x(t)$ represents the boundary drift function between the doped and undoped regions; μ_v is the mobility of ions; and $i(t)$ represents the current through the memristor.

By integrating (8), we can obtain:

$$x(t) = kq(t) + x(0) \tag{9}$$

The memristance is controlled by the amount of charge passing through it. When $R_M \epsilon (R_L, R_H)$, the memristor works as a nonlinear resistor, and the range of the effective charge is $q(t) \epsilon (Q_{min}, Q_{max})$. Based on Eqs. (7) and (9), we can obtain:

$$Q_{\min} = \frac{w_0 D}{\mu_v R_L}, \quad Q_{\max} = \frac{(D - w_0)D}{\mu_v R_L} \tag{10}$$

According to Eqs. (6)-(10), the memristor model can be obtained as:

$$R_M(t) = \begin{cases} R_H, & q(t) \le Q_{\min} \\ R_M(0) + lq(t), & Q_{\min} < q(t) < Q_{\max} \\ R_{L,}, & q(t) \ge Q_{\max} \end{cases} \tag{11}$$

where $l = (R_L - R_H)k$.

Since Memristor has the property of keeping the original state after losing power [8], we obtain the following equation by discretizing (11):

$$R_M(t + \Delta t) = R_M(t) + l\Delta q(\Delta t) \tag{12}$$

Within the time $\Delta t, \Delta q$ can be calculated based on the voltage v and then the updated memristance can be obtained as:

$$\begin{cases} \Delta q(\Delta t) = \dfrac{v(t)}{R_M(t)} \Delta t \\ \Delta R_M(t) = \dfrac{lv(t)}{R_M(t)} \Delta t \end{cases} \Rightarrow R_M(t+\Delta t) = R_M(t) + \Delta R_M(t) \tag{13}$$

The memristor model still keeps the character of the HP Labs' model, as shown in Fig. 5.

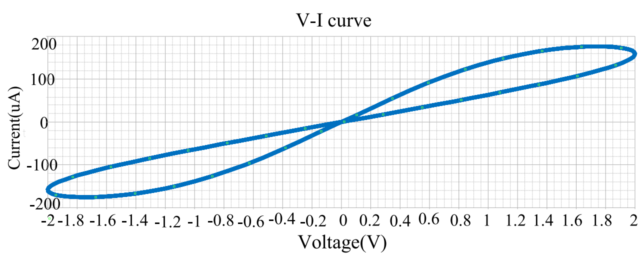

FIGURE 5. The memristor with parameters $R_L = 100\Omega$, $R_H = 18K\Omega$, $R_M(0) = 16K\Omega$, driven by a sinusoidal voltage with an amplitude of 2V and frequency of 1Hz.

The boundary drift function $x(t)$ related to the change of the memristance is used as the synapse weight $\omega(t)$. Based on (6), it can be derived as:

$$x(t) = \frac{R_H - R_M(t)}{R_H - R_L}, \quad x(t) \in [0, 1] \tag{14}$$

Then the space function of the neuron can be rewritten as:

$$\begin{cases} IN_{ij}(t) = O_i(t)x_{ij}(t), \\ U(t) = \sum_{k=1}^{n} \omega_k in_k \end{cases} \tag{15}$$

The value of ω_k is set according to whether the connections between presynaptic neurons and postsynaptic neurons are inherent or acquired learning association, where $\omega_k = 1$.

Let $p_{ij}(t)$ be the working voltage of the synaptic weight $\omega_{ij}(t)$, the synaptic memrestance function can be obtained according to (13):

$$R_{ij}(t + \Delta t) = R_{ij}(t) + lP_{ij}(t)/R_{ij}(t)\Delta t \tag{16}$$

In addition, memristor synapses can display biological synaptic plasticity, indicating the synaptic learning ability. According to (14), we can derive the memristive synapse weight function:

$$x_{ij}(t + \Delta t) = x_{ij}(t) + \Delta x_{ij}(t) \tag{17}$$

where $\Delta x_{ij}(t) = -\frac{\Delta R_M(t)}{R_H - R_L}$.

A detailed expression for updating the synaptic weight can be derived further:

$$x_{ij}(t+\Delta t) = x_{ij}(t) + \frac{lP_{ij}(t)/R_{ij}(t)\Delta t}{(R_H - x_{ij}(t)(R_H - R_L))(R_L - R_H)} \tag{18}$$

where $P_{ij}(t)$ is the synaptic voltage of the memristor connected to the ith neuron and the jth neuron.

A compact memristor is used as an electronic synapse that can provide maximum synaptic density, and is in line with our design and application requirements. Hence the memristor weight in Fig. 1 can be produced by the memristor synapse.

III. MEMRISTIVE ASSOCIATIVE MEMORY NEURAL NETWORK MODEL AND ITS APPLICATION

A. SC ENARIO HYPOTHESIS

In real life, there is no specific emotional change for "message notification". But when the message content has a good or bad attribute, people will have different feelings. Suppose for a period of time that all the news received by a person are always good news. In the long run, when he heard the news, he thinks it is good news without looking at the content and is very happy. However, there is another possibility that these messages are all bad news, and so he gets upset as soon as he hears it. If there is no notification for a long time, the previous association with happiness or sadness will disappear, and when another message is further announced, he will take it easy and have no obvious emotional fluctuations [31].

It is well known that the human brain and its emotions are complex and sometimes even elusive. However, some emotional changes induced by simple behavior can be explained by simplified models. From a neuroscience perspective, the link between message notification and emotional changes in this scenario can be interpreted as associative memory in the brain [13].

B. EMOTIONAL SIMULATION BASED ON MEMRISTIVE ASSOCIATIVE MEMORY NEURAL NETWORK MODEL

In a biological nervous system, each neuron has two states of excitement or inhibition. When the afferent impulses of neurons increase the membrane potential over the threshold of the action potential, they are in excitement state, which produces the nerve impulses spreading through the axons to the end of the nerve. When the afferent impulses of neurons reduce the membrane potential under the threshold of the action potential, they are in inhibition state and no nerve impulse is produced.

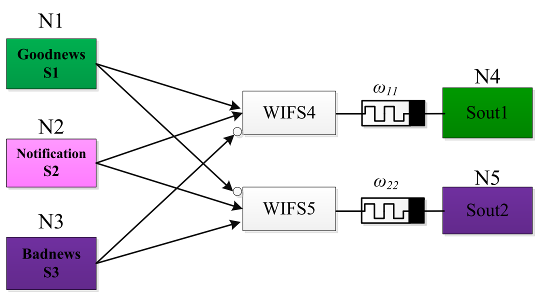

FIGURE 6. Model of the memristive neural network with associative memory.

Based on the neuron model, developed WIF learning rule and memristor synapse model, which are described in section II, a memristive associative memory neural network model is designed, as shown in Fig. 6. It can be used to simulate the human emotion change process in the above assumed scenario. The state of the output neurons in the neural network is determined by the input signals weighted via the memristive weight ω. It is assumed that the response signals of the neurons N4 and N5 are set as "happy" and "sad" respectively, and they are defined as happy neuron and sad neuron. The input signals of "good news" and "bad news" lead to "happy" and "sad", respectively, and these stimuli are considered intrinsic, as the "food" and "saliva" in Pavlov's experiment. Message notification is neutral stimuli and does not initially work on "happy" or "sad" neuron at the beginning, which is similar to the relationship between "ring" and "saliva" in Pavlov's experiment [32]. Therefore, in this network, we set the input weights ω_1 and ω_3 of the intrinsic correlation of neurons to high weights, and their weighting coefficients are all 0.4. The input weight ω_2 of message notification is set to low weight and the weighting coefficient is 0.2. In addition, the "good news" between the intrinsic associations stimulate the excitatory effect on the happy neuron N4, and the "bad news" inhibit the excitatory effect on the happy neuron N4, whereas they are opposite for the sad neuron N5. In short, there is a competitive relationship between the two presynaptic neurons N1 and N2. Furthermore, the "message notification" does not have a significant effect on the emotions of the human being at the beginning, and works on the corresponding neurons after a period of learning. According to the rules of human memory, the association established through learning without training for a long time will be lost.

From Fig. 6, the memristor based neural network contains two memristor synapses (ω_{11}, ω_{22}) and five neurons, including three presynaptic neurons (N1, N2, N3) and two postsynaptic neurons (N4, N5). It is important to note that there are two small circles in Fig. 6, which represent the inhibitory effects of the corresponding presynaptic neurons. In the biological nervous system, one neuron may receive excitation or inhibitory stimulation from other neurons, and these neurons can be regarded as excitatory or inhibitory neurons [13]. We interpret the excitation and inhibition of different neurons as the competition and cooperation between different presynaptic neurons in the process of synaptic learning. For the same postsynaptic neuron, the excitatory effect is a cooperative relationship, and the inhibitory effect is a competitive relationship. In the circuit implementation, the inhibitory effect can be achieved by an inverter.

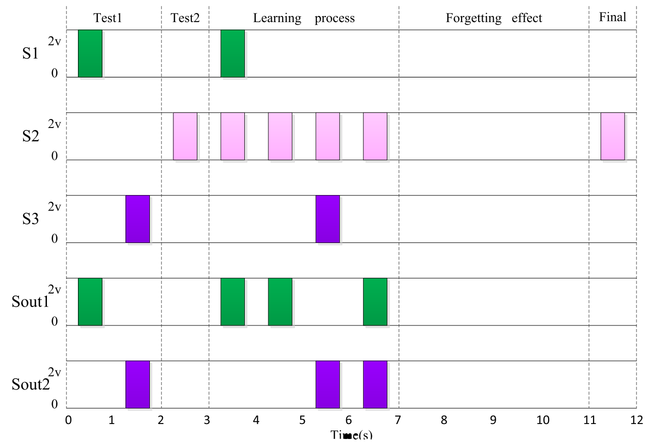

FIGURE 7. The whole process of memristive neural network emotion simulation.

The whole process of memristive neural network emotion simulation is described by using five states (S1, S2, S3, Sout1, and Sout2), and five processes (Test1, Test2, Learning Process, Forgetting effect and Final), as shown in Fig. 7, where S1 is the input of good news; S2 is the input of message notification; S3 is the input of bad news; Sout1 is the output of the happy neuron N4; and Sout2 is the output of the sad neuron N5. Finally, the changes in human emotions are simulated through the output states of the neuron N4 and N5.

First, the initial state of the nervous network is tested, respectively in Test1 and Test2. In Test1 ($0 \sim 2$s), when only the state S1 has input, Sout1 has output; and only when the state S3 has input, the Sout2 has output. That is to say, when we receive good news, we will feel happy; while when we receive bad news, we will feel sad. In Test2 ($2 \sim 3$s), only when the state S2 has input, both Sout1 and Sout2 have no output, which means that we only receive message notifications at the beginning, and there is no emotional change. Then, in Learning process ($3 \sim 7$s), when S1 and S2 have input at the same time, Sout1 will definitely have output;

and when S3 and S2 have input at the same time, Sout2 will have output. That is to say, when we receive the message notifications and see the good news, we will be very happy; while when we see the bad news, we will become very sad. Moreover, after the corresponding learning, only when the state S2 has input, Sout1 and Sout2 will also have output, which means that people will feel happy or sad when they receive the notification after learning. The different results of Test2 and Learning process show that the memristive neural network will form associative memory after the Learning process. In addition, we set up a Forgetting process (7 ∼ 11s) that has the same result as the Test2 when the "message notification" is input at the Final stage (11 ∼ 12s). It is further explained that if the two states of S1 and S3 have no input for a long time, the associative memory of memristive neural network will disappear.

If the stimuli of "message notification" and "good news" appear simultaneously, the happy neuron N4 becomes active. The total voltage around the memristor synapse $R_{M1}(t)$ may exceed the neuron threshold, resulting in the synaptic weight ω_{11}increases, which makes the happy neuron N4 in a state of excitement. This is the "training" process of the synapse. After proper training, the synaptic weight value will increase to a sufficiently high state, and the happy neuron N4 will only be related to the input of "message notification". The associative memory between "message notification" and "happiness" is formed, and the formation of associative memory between "message notification" and "sadness" is available in the same way. In a particular case, when the stimuli of "message notification", "good news" and "bad news" occur at the same time, we can simplify the emotional changes of a person, depending on the value of the input voltage of S1 and S3, it was determined whether to stimulate the happy neuron N4 or the sad neuron N5. If the input voltages of S1 and S3 are the same or the difference is small, neither neuron is excited, indicating that happiness and sadness cancel out each other, and there is no emotional change. In addition, the forgetting effect of the neural network is represented by the reduction of the corresponding synaptic weight.

IV. CIRCUIT DESIGN AND PSPICE SIMULATION RESULTS

The HP memristor model is used to simulate the electronic synapses in the simulation circuit, and implement the memristive neural network circuit. In the circuit, synaptic weights ω_{11} and ω_{22} are updated by the memristors $R_{M1}(t)$ and $R_{M2}(t)$. The initial conditions of the two memristors are all $R_M(0) = 16$ kΩ, the highest value of $R_H = 20$kΩ and the lowest value of $R_L = 100\Omega$, respectively. Other parameters and detailed descriptions can be found in [30] and [33], its physical model and the interface in PSPICE are shown in Fig. 8.

The complete circuit simulated by the memristive neural network is shown in Fig. 9. The operational amplifiers in the circuits are TL082 powered with VCC = 15V and VEE = −15V. In order to facilitate drawing, we construct the circuits for the two output neurons respectively, as shown

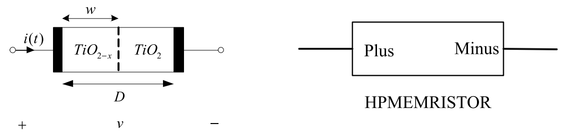

FIGURE 8. Physical model of HP memristor and the memristor model after the PSPICE packaging.

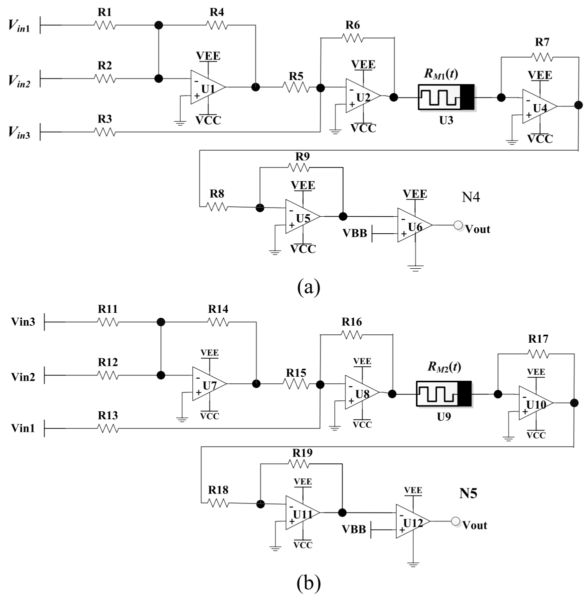

FIGURE 9. The complete circuit diagram of the memristive neural network. (a) Input and output circuit for the neuron N4. (b) Input and output circuit for the neuron N5.

in Fig. 9, where the function of amplifier U1, U2, U7 and U8 is to realize the weighted summation of the input of the presynaptic neurons V_{in1}, V_{in2} and V_{in3}. The function of U4, U5, U10 and U11 is to realize synaptic learning based on the WIF rules, the operational relationships are shown in (21) and (22). U6 and U12 are voltage comparators and their outputs are the final outputs of the neurons.

The weighted summation formula of presynaptic neuron inputs V_{in1}, V_{in2} and V_{in3} are described as:

$$V_{U2} = \frac{R_4R_6}{R_1R_5}V_{in1} + \frac{R_4R_6}{R_2R_5}V_{in2} - \frac{R_6}{R_3}V_{in3} \tag{19}$$

$$V_{U8} = -\frac{R_{16}}{R_{13}}V_{in1} + \frac{R_{14}R_{16}}{R_{12}R_{15}}V_{in2} + \frac{R_{14}R_{16}}{R_{11}R_{15}}V_{in3} \tag{20}$$

The final input signals of the postsynaptic neuron N4 and N5 after the synaptic learning are expressed as:

$$\begin{aligned} V_{U5} &= \frac{R_7R_9}{R_{M1}(t)R_8}V_{U2} \\ &= \frac{R_7R_9}{R_{M1}(t)R_8}\left(\frac{R_4R_6}{R_1R_5}V_{in1}+\frac{R_4R_6}{R_2R_5}V_{in2}-\frac{R_6}{R_3}V_{in3}\right) \end{aligned} \tag{21}$$

$$\begin{aligned} V_{U11} &= \frac{R_{17}R_{19}}{R_{M2}(t)R_{18}}V_{U8} \\ &= \frac{R_{17}R_{19}}{R_{M2}(t)R_8}\left(-\frac{R_{16}}{R_{13}}V_{in1}+\frac{R_{14}R_{16}}{R_{12}R_{15}}V_{in2}+\frac{R_{14}R_{16}}{R_{11}R_{15}}V_{in3}\right) \end{aligned} \tag{22}$$

In particular, the memristor plays a crucial role in the circuit of the neural network. It is equivalent to synapses of biological neural network. For different potentials of presynaptic neurons at different time of stimulation, the memristance will change and the synaptic weight is updated. The parameters in the circuit are set to R1 = R3 = R11 = R13 = 25kΩ, R2 = R12 = 50kΩ, and all other resistors have the same value of 10kΩ.

The comparators U6 and U12 are described as the output function of activating output neurons. When the total input exceeds the threshold voltage VBB (0.4V), the comparator outputs the voltage of VTT (5V). Otherwise, the output is zero. The positive output pulse represents the neuron is in the excited state, and the zero output indicates that the neuron is in the state of inhibition. The signal generation circuits of the input V_{in1}, V_{in2} and V_{in3} are shown in Fig. 10. They are composed of the voltage sources V0-V5 and the multipliers MUT1-MUT3, in which V0, V1 and V4 are piecewise linear functions, and V2, V3 and V5 are pulse signals.

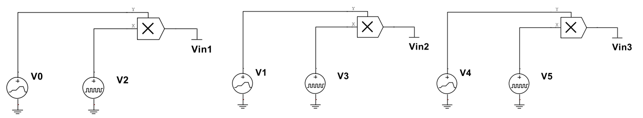

FIGURE 10. Signal generation circuit of the input Vin1, Vin2 and Vin3.

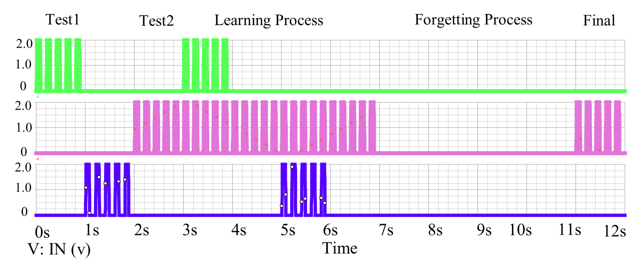

FIGURE 11. Input waves of Vin1, Vin2 and Vin3.

Through the PSPICE simulation circuit, the scenario described at the Section III. ***A***. is demonstrated. Synaptic learning and associative memory are explained using the following processes, in which the waveforms of the input signals V_{in1}, V_{in2} and V_{in3} are shown in Fig. 11. The final input and output waveforms for neuron N4, and N5 are shown in Fig. 12 and Fig. 13 respectively.

In the process of Test1 (0 ∼ 2s), the circuit only inputs the voltage when the good news (or bad news) is obtained, and the neuron N4 (or N5) can output the standard square wave. In the process of Test2 (2 ∼ 3s), when the circuit only inputs the voltage of "message notification", the neurons N4 and N5 have no output. The results show that the message notification could not stimulate output neurons to get excited state in the initial state. That is to say, when a person hears message notification, he will not produce a happy or sad emotion change without training or learning. In the process of learning process (3-7s), we train and learn for good messages

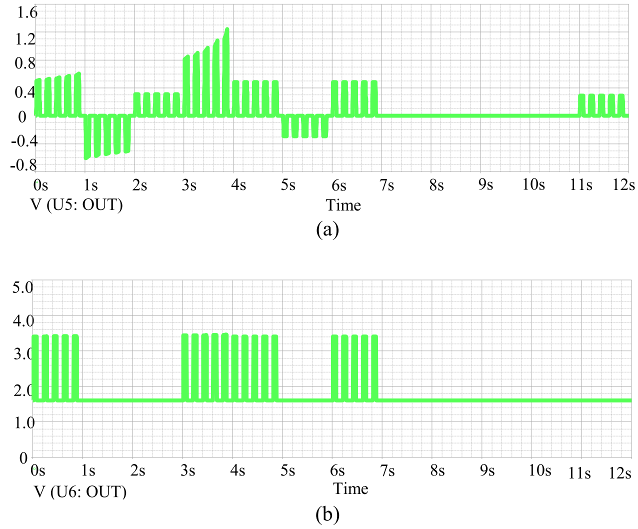

FIGURE 12. Experimental results. (a) The input waveforms of the happy neuron N4. (b) The output waveforms of the happy neuron N4.

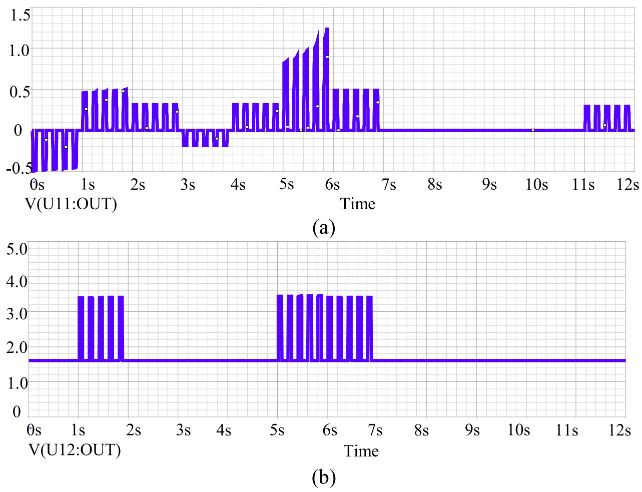

FIGURE 13. Experimental results. (a) The input waveforms of the sad neuron N5. (b) The output waveforms of the sad neuron N5.

and message notification firstly. After training, the neuron N4 can output the square wave when only the message is notified. Similarly, the memristive neural network circuit can also realize associative memory after the training of bad news and message notification, indicating that human brain can produce associative memory after a period of training or learning. In addition, after the forgetting process, the same results as in the Test2 process are generated when the Final process only has a message notification input.

Time evolution of memristances of the memristor synapses is shown in Fig. 14. We know that the synaptic weight of the memristor is inversely proportional to its memristance. The variation of the memristance depending on the voltage drops can reflect the change of the corresponding memristor synaptic weight. In the process of Test1 (0-2s), the circuit only inputs the voltage when the good news is obtained, and

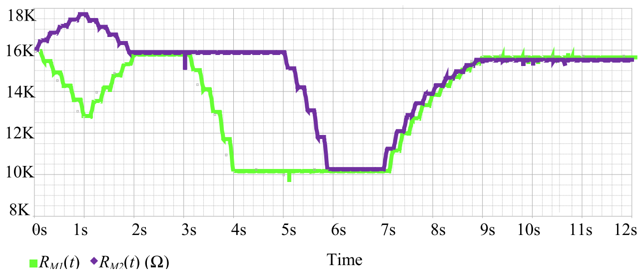

FIGURE 14. **Time evolution of memristances of the memristor synapses. $R_{M1}(t)$ represents the memristance of the memristor synapse connected to the happy neuron N4. $R_{M2}(t)$ represents the memristance of the memristor synapse connected to the sad neuron N5.**

the connection weight between the presynaptic neuron and the happy neuron N4 becomes larger. The connection weight with the sad neuron N5 is reduced. So the corresponding memristor value $R_{M1}(t)$ increases, and $R_{M2}(t)$ decreases. In the same way, we can understand the variation of the memristances of the whole emotional simulation processes.

In conclusion, the circuit simulation results verify the correctness of the theoretical analysis.

Compared with the traditional CMOS circuits, the memristor-based circuits have advantages over the CMOS circuits in terms of area, energy consumption and compatibility of the preparation process in the actual preparation process.

There is a bottleneck for CMOS circuits to scale up the hardware in an appropriate biology size to build large scale ANN circuits and realize complex bionic functions [6]. For example, cortex of human has a density of about 10^{10} synapses/cm^2 and now microprocessors can pack roughly 10^9 synapses /cm^2 in CMOS [34]. However, the key for hardware realization of the neural networks is to design weight units that can locally compute, store and update their own weights simultaneously and independently of the other synapses [35]. Previously proposed dedicated hardware solutions have required numerous transistors per synaptic weight [36] which resulted in big area and power consumption. In addition, creating a non-volatile weight unit is difficult with standard CMOS technology. Compared with the CMOS-based design, the proposed circuit in this paper uses a single memristor as a synapse, which has significantly lower area than CMOS-based synapses and meets the requirements of biological size, and which greatly reduces the power consumption. In the meantime, HP memristor [2] is smaller than 50^3 nm^3 [31] in size, and the compatibility of memristor with advanced CMOS technology was claimed by the HP laboratory and other institutions [37]. We believe that further investigation will improve the accuracy and performance of ANN circuits.

V. CONCLUSION

In this paper, a simple simulation of human emotion is realized based on the associative memory model of the memristive neural network. Through the proposed WIF learning rule and the improved electronic synapse implemented by HP memristor, the proposed the memristive network associative memory model can exhibit similar learning and forgetting properties with biological synapses. At the same time, the excitatory and inhibitory effects of different presynaptic neurons on the postsynaptic neurons were considered, and the biological characteristics were better simulated. In addition, the neural network analog circuit is built and simulated by PSPICE, and it is easy to expand in function and structure. For example, based on the existing network structure, we can increase the number of input signals and neurons, and change the way of connection between neurons to achieve more complex emotional simulation. We can also use this neural network as an emotional simulation module, whose output is directly used as input to the underlying neural network to simulate more complex human behavior. Further research can be used to realize more complex intelligent behavior.

This neural network not only performs associative memory well, but also uses a single memristor as an electronic synapse, which provides the maximum density for the hardware to realize the synapse circuit, and facilitate the realization of the synapse simulation at the nanoscale level. The memristor synapse exhibits plasticity similar to that of the biological synapse, which can realize synaptic learning, information storage and so on.

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