Memristive Circuit Implementation of Context-Dependent Emotional Learning Network and Its Application in Multi-Task

Cong Xu, Chunhua Wang, Jinguang Jiang, Jingru Sun, and Hairong Lin

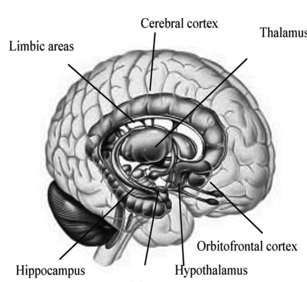
***Abstract*—Emotional intelligence plays an important role in artificial intelligence. The brain circuitry of emotion mainly includes the prefrontal cortex, the amygdala, hippocampus and *et al.* Many brain emotional learning models were proposed in recent years, the existing brain emotional learning models failed to consider the contextual information in practical applications, and do not discuss the corresponding circuit implementation. In this paper, a context-dependent emotional learning network and its memristive circuit implementation are introduced. The added context-dependent module is used to process the contextual information, which makes the network context-dependent when receiving the same input signals. For circuit implementation, the memristive circuit design mainly contains the amygdala module and orbitofrontal cortex module, which imitates the emotion learning process in the brain. Besides, a multi-input multi-output memristive circuit of the context-dependent emotional network is applied to multi-task classification. PSPICE simulation results verified the adaptability and flexibility of the context-dependent emotional learning network.**

***Index Terms*—Memristor; emotional learning; multi-task; classification; circuit implementation;**

I. Introduction

WITH the development of artificial intelligence (AI), the neural network appears more frequently in pattern recognition, natural language processing, intelligent robot, autonomous driving, and other fields. The neural network greatly enhances the development of artificial intelligence with deeper researches. However, the traditional neural networks have some defects in practical applications, such as slow convergence rate, high computational complexity, and slow training speed [1].

Recently, with extensive neuroscience researches on emotion [2, 3], emotional intelligence is starting to play an important role in AI. Since emotional intelligence was first proposed by Salovey and Mayer in 1990 [4], it has been also studied by many computer scientists. The researches of emotional neuroscience showed that the limbic system theory of emotion is an anatomical model of emotional brain [5, 6]. As shown in Fig. 1 [7], the limbic system mainly includes the thalamus, the amygdala, the orbitofrontal cortex (OFC), the hippocampus, the hypothalamus, and *et al.* The amygdala can generate emotion and consolidate memory by sensory stimulus, which is located in the center of the emotional circuit. By imitating the emotional learning mechanism between the OFC and the amygdala, the brain emotional learning (BEL) model was proposed in 2002 [8], which has the advantages of simple structure, low calculation complexity, and fast calculation speed. Besides, the network based on BEL overcomes the defect of long training time of the traditional neural network, so it has been widely used in classification [9], prediction [10, 11], and pattern recognition [12-14]. To increase the practicability and commonality of the BEL model, many modified versions of the BEL model were proposed. Lotfi *et al.* [7, 10, 15] proposed improved BEL-based emotional neural networks. In those networks, the reward signal determined the rule of weight adjustment, which is similar to the emotional learning process in the brain. The improved emotional neural networks have been applied in pattern recognition and prediction successfully. Also, Lotfi [16] used the target output value to replace the reward signal and updated the weight of the BEL network by feedforward computing, but the adaptability of this method is not strong. On this basis, the attenuation factor was introduced into the reward signal [17], and the improved network was used in the time series prediction problem, but this method is not suitable for classification problems. To improve the classification and recognition ability of the BEL model, many intelligent algorithms, such as genetic algorithm (GA) [9] [18] and particle swarm optimization (PSO) [19], were introduced for parameter optimization, which improved the classification accuracy.



- **Amygdala**: It collects sensory inputs from the thalamus and coordinates responses to the environment, playing an important role in the processing of fear and anger.
- **Orbitofrontal cortex (OFC)**: One part of the prefrontal cortex. It is a prefrontal cortex region in the frontal lobes of the brain which is involved in the cognitive process of decision-making.
- **Thalamus**: It collects sensory inputs (visual, auditory and somatosensory) and has neurons which project impulses to relay these inputs to the amygdala and higher cortical regions for processing.
- **Cerebral cortex**: It contains sensory areas and motor areas. Sensory areas receive input from the thalamus and process information related to the senses.
- **Hypothalamus**: It regulates the autonomic nervous system by regulating the endocrine system which is involved in the release of different hormones into the bloodstream.
- **Hippocampus**: It retains memories and converts short-term memory to long-term memory.

Fig. 1. The limbic system in the brain.

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In the above proposed BEL neural networks, they failed to consider the contextual information in practical applications, which cannot meet the complexity and inconstant application requirements. Besides, they do not discuss the corresponding circuit implementation. As we all know, human beings can make different responses to the same stimuli according to environments, different targets, internal states, and *et al.*, which is one of the hallmarks of advanced intelligence. That is to say, the responses of humans are context-dependent, which is named cognitive control in neuroscience [20]. The prefrontal cortex (PFC) is the key biological basis for context-dependent. According to the different environments, PFC will do different actions for the same sensory input and respond to uncertain and complex environmental changes flexibly [21].

Inspired by the mechanism of context-dependent processing of PFC, we propose a context-dependent emotional learning network and its circuit implementation, which can flexibly work in the multi-task application. The proposed network processes the contextual information by adding a context-dependent module, which makes the network context-dependent when it receives the same input signals. This method accords with the properties of PFC, which receives the sensory input and contextual information simultaneously. So, the proposed network not only considers the features of the input signal, but also considers contextual information in practical application. As a nonvolatile programmable resistor, memristor [22] has the advantages of high density, low power, good scalability, and has the same regulation mechanism as the weight regulation of synapse. So, the circuit of the context-dependent emotional learning network is designed based on memristor. The memristive circuit design mainly contains the amygdala module and OFC module, which imitates the emotional learning in the brain. Emotional learning is context-dependent, the context can influence some classical emotional learning processes [23, 24], such as habituation, acquisition and extinction, which is demonstrated by the simulations of the proposed memristive circuit. Besides, considering that the most memristive neural networks are usually used to deal with a single problem or task [25-29], we propose a multi-input multi-output circuit of the context-dependent emotional learning network and apply it to multi-task classification. In the implementation of the circuit, the multiple tasks are trained in parallel based on contextual information, which breaks the traditional ideal of divide-conquer. The PSPICE simulation of results indicated that the context-dependent emotional learning network is adaptable and flexible. The main contributions of this work are listed as follows.

1) A context-dependent emotional learning network is proposed. The network receives the sensory input and contextual information simultaneously by adding the context-dependent module, which makes the network context-dependent in practical application.
2) A memristive circuit of the context-dependent emotional learning network is designed. The circuit is mainly composed of the amygdala module, OFC module, and context-dependent module, which imitates the brain emotional learning process. The influence of context on the classical emotional learning process is verified by PSPICE simulation.
3) The multi-input multi-output memristive circuit is applied to multi-task classification, which verified the adaptability and flexibility of the context-dependent emotional learning network. Based on the contextual information, the multiple tasks are training in parallel, which breaks the traditional method of divide and rule.

The remainder of this paper is organized as follows. In Section II, the basic backgrounds of brain emotional learning, context-dependent, and memristor are given. Section III introduces the context-dependent emotional network. Section IV proposes the detailed circuit design of the emotional learning network and shows the simulation results and analysis. Section V proposes a multi-input multi-output memristive circuit of the proposed network, applies the circuit in multi-task classification, and analyzes the simulation results. Section VI makes a discussion on the performance of proposed network. Section VII presents the conclusion drawn from this work.

II. BACKGROUNDS

A. Brain emotional learning model

Emotion is a special ability of the human brain, which make humans adapt to the changes in the environment and have a different emotional response. If encountering external stimulus which is beneficial to oneself, people will produce positive or pleasant emotion and pay more attention to similar stimuli. On the contrary, people will produce negative or disgusting emotions, and lose attention or avoid these stimuli. Moreover, the memory of the corresponding stimulus is generated in the brain, it is strengthened when receives the same stimulus constantly, and then corresponding emotions are produced to the same or similar stimuli. Based on the limbic system theory [6], these emotional reactions are mainly implemented by the amygdala, OFC, thalamus, and other organs in the brain. Anatomically, the amygdala is located in the center of the emotional circuit, and it is the most critical part of emotion processing. The OFC enhances or inhibits the learning of the amygdala, which assists the emotional processing of the amygdala.

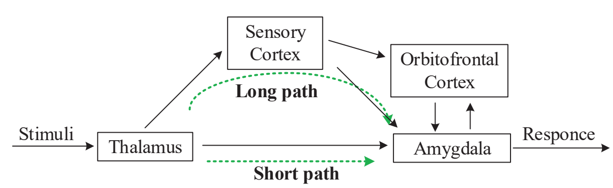

Fig. 2. The emotion circuit.

The thalamus receives an external stimulus and transfers it to the amygdala through two paths [30] as shown in Fig. 2. The first is a long path, in which stimulus transfers to the sensory cortex, then to the amygdala, the second is a short path, in which stimulus transfers to the amygdala directly from the thalamus. In the long path, the OFC plays an auxiliary

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role in the learning of the amygdala [31]. The information transmission path between amygdala and thalamus is short and the processing speed is fast, which makes the calculation complexity of the model is low, and the operating speed is high. Inspired by the limbic system, the BEL model was first proposed by Moren in 2002 [8], which imitates the information transmission between the amygdala and OFC. As shown in Fig. 3, the BEL model is composed of the thalamus, sensory cortex, OFC, and amygdala.

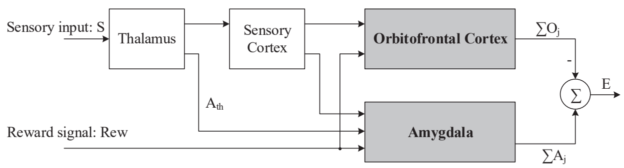

Fig. 3. The framework of the BEL model.

The essence of the brain emotion learning process is to adjust the weights of the amygdala and OFC constantly. The sensory input is S, the output of OFC is O_j, A_j is the output of the amygdala. Based on the description in [8], the rules of learning are described as follows.

$$\Delta v_i = \alpha(S \cdot \max(0, \mathrm{Rew} - \sum_j A_j)) \tag{1}$$

$$\Delta w_i = \beta(S \cdot \sum_j (O_j - \mathrm{Rew})) \tag{2}$$

where v_i and w_i are the weights of amygdala and OFC, respectively, α and β are the learning rates, which range from 0 to 1.

B. Context-dependent

As one of the hallmarks of advanced intelligence, human beings can make different responses to the same stimuli according to environments, different targets, internal states, and *et al.*, [32], that is to say, responses of humans are context-dependent. The PFC is the key biological basis for context-dependent [20]. In different environments, PFC can respond to the same sensory input with different actions, then respond to the uncertain environmental changes flexibly [21] [33]. In the experiment of human cognition, patients with PFC impairment lose the ability to respond to the weak but highly task-related stimulus correctly [34]. The cognitive experiment proved that PFC is the key to context-dependent learning, and many electrophysiological studies in non-human primates have also proved that PFC neurons can represent some kinds of context-dependent information [21] [33]. As we all know, PFC is the core cortex responsible for cognitive control in the brain, it receives sensory inputs and contextual information simultaneously, and guides the response relevant to the tasks. Overall, the method of context-dependent processing is more flexible in practical application, which is different from the traditional neural network.

C. Memristor

Nowadays, the hardware design of the neural network is gaining more and more attention. The analog circuits of the neural network have properties of high speed and parallel computing, which meet the needs of practical application. As the fourth basic circuit element, the memristor was proposed in 1971 by Leon Chua [22] and physically realized in 2008 by HP labs [35]. For the memristor model with a threshold voltage, when the input voltage exceeds the threshold voltage of the memristor, the memristance will change. Otherwise, the memristance remains unchanged. As a nonvolatile programmable resistor, memristor has the advantages of high density, low power, good scalability, and its application is wide, such as memristive chaotic circuit [36-41], memristive neural network [42-47]. Besides, memristor has the same regulation mechanism as the weight regulation of synapse. So, the memristor has become the most promising device for implementing electronic synapses and designing circuits of neural networks [48-51], which have been applied in pattern recognition, classification, image processing, and other fields of AI.

III. Proposed context-dependent emotional learning network

A. Architecture

The BEL model with simple structure has good performance in learning, it has been widely used in classification [9], prediction [10, 11], and recognition [12-14]. In the existing BEL model, the OFC module only contains the sensory information, without considering the impact of contextual information. However, OFC not only receives sensory information but also receives contextual information [20, 21, 33]. To mimic this biological characteristic of OFC, the contextual information is used as the input to the OFC module like sensory information. Sensory information and contextual information are connected in the OFC module. The architecture of the proposed context-dependent emotional learning network (CD-ELN) is shown in Fig. 4.

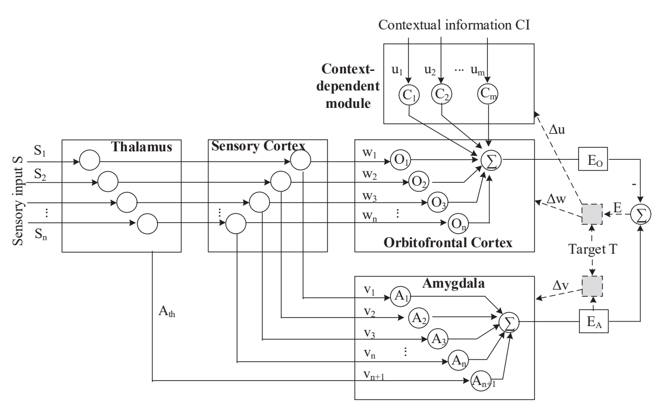

Fig. 4. The architecture of context-dependent emotional learning network.

The proposed CD-ELN has five main modules. The information transmission among the thalamus module, sensory cortex module, OFC module, and amygdala module is based on the amygdala-OFC interconnection in the emotion circuit of the brain. The added context-dependent module is inspired by the biological feature of OFC, which is used to process contextual information. Each module contains some nodes, which are corresponding to the dimension of input. The plastic weights are used to connect input and output in amygdala module, OFC module, and context-dependent module.

As shown in Fig. 4, the sensory input $S = [S_1, S_2, , S_n]$, the A_{th} is the max stimulus from thalamus:

$$A_{th} = \max[S_1, S_2, ..., S_{\mathrm{n}}] \tag{3}$$

The weight of the amygdala is v, the output of the amygdala is E_A, and it is obtained by the following equations:

$$A_i = S_i \cdot v_i, i = 1, 2, ..., n \tag{4}$$

$$E_A = \sum_{i=1}^{n} S_i \cdot v_i + A_{th} \cdot v_{n+1} \tag{5}$$

For the context-dependent module, CI is contextual information, and weight is denoted as u. For OFC, the weight is w, and its output E_o can be calculated by

$$E_O = \sum_{i=1}^{n} S_i \cdot w_i + \sum_{j=1}^{m} CI_j \cdot u_j \tag{6}$$

By adding the contextual information, the output of the proposed CD-ELN is expressed as follows:

$$\begin{aligned} E{=}&E_A - E_O \\ =(&\sum_{i=1}^{n} S_i v_i + A_{th} \cdot v_{n+1}){-}(\sum_{i=1}^{n} S_i \cdot w_i + \sum_{j=1}^{m} CI_j \cdot u_j) \end{aligned} \tag{7}$$

E_A is the output of the amygdala. E_O is the output of the OFC, which contains sensory information S and contextual information CI. A_{th} is the max value of S. v, w, u are denoted weights. When giving the same sensory input S and fixed weights, the output E is affected by the contextual information CI. The added context-dependent module can change the output while keeping sensory inputs unchanged. That is to say, it enables the CD-ELN context-dependent when receiving identical sensory inputs. In conclusion, the proposed CD-ELN can treat the same sensory inputs differently based on contextual information.

In the learning process of the CD-ELN, the weights are adjusted by award signal Rew, when solving the practical problem, the reward signal is set as the target valve T. Refer to the learning rules in [8], the learning rules of CD-ELN are expressed as follows.

$$\Delta v_i = \alpha(S_i \cdot \max(0{,}T{-}E_A)){,}i = 1, 2, ...n + 1 \tag{8}$$

$$\Delta w_i = \beta(S_i \cdot (E - T)), i = 1, 2, ...n \tag{9}$$

$$\Delta u_i = \delta(CI_i \cdot (E - T)), i = 1, 2, ...m \tag{10}$$

where α, β, and δ are the learning rates, which range from 0 to 1.

B. Analysis of the learning process

The learning process of CD-ELN mainly includes the learning of the amygdala and OFC. The learning process of the amygdala is the dynamic adjustment of weight v, and the OFC assists the learning of the amygdala by adjusting the weight w, it makes the actual output close to the target value. The detailed analysis of weight adjustment are as follows.

a. The adjustment of weight v

Case 1: The input signal is positive ($S_i > 0$). If the output of the amygdala is less than the target value T ($E_A < T$), based on (8), the weight v_i will increases constantly until the output reached the target value. If the output is greater than or equal to T, the weight v_i will cease to adjust.

Case 2: The input signal is negative ($S_i < 0$). If the output of the amygdala is less than the target value T ($E_A < T$), then based on (8), the weight v_i will decreases constantly until the output reached the target value. If the output is greater than or equal to T, the weight v_i will cease to adjust.

Base on the above analysis, the adjustment of weight v is monotonically increasing or decreasing depending on the positive or negative of input signals, these rules accord with the learning characteristics of the amygdala in the brain, which is permanent once an emotional response is learned by the amygdala.

b. The adjustment of weight w

Case 1: The input signal is positive ($S_i > 0$), if the output of the network is less than the target value $(E < T)$, the weight w_i will decreases as expressed in (9), then the output O of OFC have a negative increase. So the output E will increases. This process indicates that the OFC plays a positive feedback role in the learning of the amygdala.

Case 2: The input signal is positive ($S_i > 0$), if the output of the network is greater than the target value $(E > T)$, the weight w_i will increase as expressed in (9), then the output O of OFC has a positive increase. So the output E will decrease. This process indicates that the OFC has an inhibition effect on the learning of the amygdala.

Similarly, if the input signal is negative $(S_i < 0)$, the weight adjustment of w_i also can make the output E approaching the target value T. Based on the above analysis, the rule adjustment of weight w reflects that the OFC assists the learning of the amygdala by enhancement or inhibition, which avoid “insufficient learning” or “over learning” of the network.

IV. Circuit design of CD-ELN and simulation results

A. Memristor model

In this paper, the voltage-controlled memristor model with threshold voltage [52] is used in all simulations. If the input voltage exceeds the threshold, the memristance will change, else it remains unchanged. The expression of the memristor model is described as follows.

$$R(t) = R_{on}\frac{\omega(t)}{D} + R_{off}(1 - \frac{\omega(t)}{D}) \tag{11}$$

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$$\frac{d\omega(t)}{dt}=\begin{cases}\mu_v\frac{R_{on}}{D}\frac{i_{off}}{i_{on}}f(\omega(t)), & v(t)<V_{T-}<0\\ 0, & V_{T-}\leq v(t)\leq V_{T+}\\ \mu_v\frac{R_{on}}{D}\frac{i_{off}}{i(t)-i_0}f(\omega(t)), v(t)>V_{T+}>0 & \end{cases} \tag{12}$$

where μ_v denotes the average ion mobility, i_0, i_{off}, and i_{on} are constants, V_{T-} and V_{T+} is the negative and positive threshold voltage, respectively, and the window function is

$$f(\omega(t))=1-(\frac{2\omega(t)}{D}-1)^{2p} \tag{13}$$

where the positive integer p is a parameter of the window function.

As shown in Fig. 5, the change of memristance is opposite under a positive and a negative voltage, which is larger than the threshold of the memristor. The memristance remains unchanged under the input voltage below the threshold. Besides, the memristor parameters of the simulation are shown in Table I.

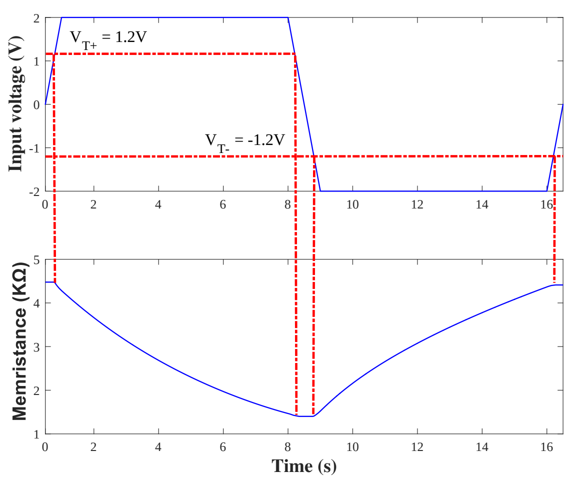

Fig. 5. PSPICE simulation of memristance change.

TABLE I
SIMULATION PARAMETERS OF MEMRISTOR

Parameter	Value
R_{on}	800Ω
R_{off}	$10k\Omega$
D	10nm
u_v	$1{\times}10^{-12}m^2s^{-1}\Omega^{-1}$
i_{on}	1A
i_{off}	5.1×10^{-7}A
i_0	1×10^{-5}A
V_{T+}	1.2V
V_{T-}	-1.2V
p	10

B. Circuit design of CD-ELN

Based on the amygdala and OFC learning method in the brain, a memristor-based circuit of CD-ELN is shown in Fig. 6. The learning operation of memristive emotional learning mainly consists of two stages: (1) Learning in the amygdala module. (2) Learning in OFC module for assisting the learning of the amygdala module.

a. Amygdala module

Based on the adjustment rule of weight in the amygdala, the main blocks of the amygdala module consist of input signal control with switch, memristive weight, max function, difference calculation, and threshold selector. In this module, the switching of input voltage is performed by transmission gate switches SW, the memristive weight is adjusted by the input signal S and the feedback signal V_{fa} alternately.

As shown in Fig. 6, V_a is the output of the amygdala, it can be expressed as:

$$V_a=\sum_{i=1}^{n}\frac{R_2}{M_i}\cdot V_i=R_2\sum_{i=1}^{n}v_i\cdot V_i \tag{14}$$

where

$$v_i=\frac{1}{M_i} \tag{15}$$

$$V_i=\begin{cases}S_i, if V_c>0\\ V_{fai}, if V_c<0\end{cases} \tag{16}$$

the memristance of M_i is updated by the corresponding feedback voltages V_{fai}. The memristance will decrease if the feedback voltage is positive, otherwise, it will increase. The calculation of feedback voltages as following:

$$\Delta V_a=\max(0,T-V_a)=\begin{cases}0, if V_a\geq T\\ T-V_a, if V_a<T\end{cases} \tag{17}$$

$$V_{fai}=\begin{cases}S_i\cdot(\Delta V_a+V_{T+}), if\Delta V_a>0\\ S_i\cdot(\Delta V_a+V_{T-}), if\Delta V_a<0\end{cases} \tag{18}$$

where T is the target value, V_{T+}, and V_{T-} are the positive and negative threshold of the memristor.

The max function circuit is designed by difference calculation and an analog voltage-controlled switch, which implemented the calculation of equation (17). Besides, only the applied input voltage exceeds the threshold, the memristance will change, else it remains unchanged. So, the threshold selector ensures that the feedback voltages are larger than the threshold of the memristor. When the difference between actual and target ouput is zero, the adjustment of memristor will cease.

b. The OFC module

The module of OFC is used for assisting the learning of the amygdala module, which can ensure the output V_{out} of the network approaching the target value T correctly. This module mainly consists of input signal control with switch SW, memristive weight, difference calculation, and threshold selector.

In one branch of the OFC module, the polarity of memristor M_{i1} is opposite to that of M_{i2}, so the memristance change of M_{i1} and M_{i2} is opposite under a positive or a negative voltage, which can implement positive and negative weights. In the OFC module, the memristance is adjusted by the input signal

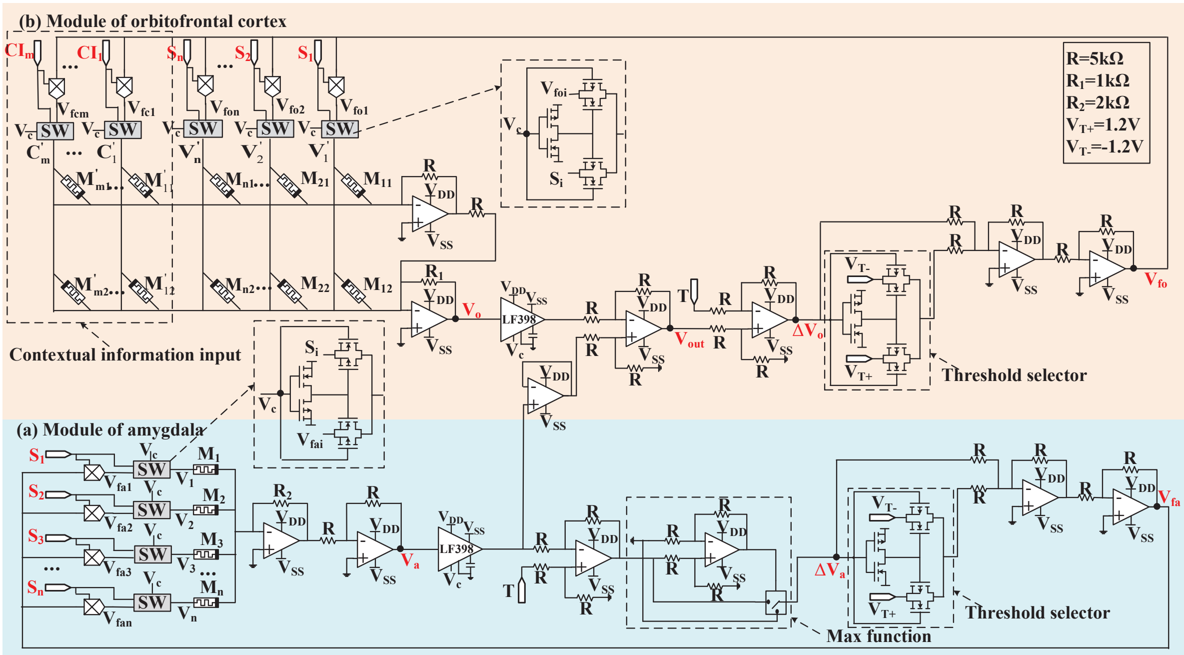

Fig. 6. The memristor-based circuit design of CD-ELN.

and feedback voltage V_{fo} alternately, which is controlled by the transmission gate switch. The output V_o is expressed as

$$V_o = R_1\left(\sum_{i=1}^{n}\left(\frac{1}{M_{i1}}-\frac{1}{M_{i2}}\right)\cdot V_i' + \sum_{j=1}^{m}\left(\frac{1}{M_{j1}'}-\frac{1}{M_{j2}'}\right)\cdot C_j'\right) = R_1\left(\sum_{i=1}^{n} w_i\cdot V_i' + \sum_{j=1}^{m} u_j\cdot C_j'\right) \tag{19}$$

where

$$w_i = \frac{1}{M_{i1}} - \frac{1}{M_{i2}} \tag{20}$$

$$u_j = \frac{1}{M_{j1}'} - \frac{1}{M_{j2}'} \tag{21}$$

$$V_i' = \begin{cases} S_i, if V_c > 0 \\ V_{foi}, if V_c < 0 \end{cases} \tag{22}$$

$$C_j' = \begin{cases} CI_j, if V_c > 0 \\ V_{fcj}, if V_c < 0 \end{cases} \tag{23}$$

Based on (9) and the circuit design, the feedback voltages V_{foi} and V_{fcj} are calculated as follows:

$$\Delta V_o = (V_a - V_o) - T \tag{24}$$

$$V_{foi} = \begin{cases} S_i\cdot(\Delta V_o + V_{T+}), if \Delta V_o > 0 \\ S_i\cdot(\Delta V_o + V_{T-}), if \Delta V_o < 0 \end{cases} \tag{25}$$

$$V_{fcj} = \begin{cases} CI_j\cdot(\Delta V_o + V_{T+}), if \Delta V_o > 0 \\ CI_j\cdot(\Delta V_o + V_{T-}), if \Delta V_o < 0 \end{cases} \tag{26}$$

Fig. 7 showed the learning process in the OFC module. The forward propagation and feedback adjustment are executed alternately, which is controlled by signal V_c. For instance, in one cycle (0-1s), the input signal is set 1V in the forward propagation stage (0-0.5s), which is below the threshold of the memristor, so the memristances remain unchanged. The positive feedback voltage V_{fo} is larger than the threshold in the feedback adjustment stage (0.5-1s), the memristance of M_{11} is decreased and M_{12} is increased. The feedback adjustment voltage V_{fo} decreased constantly in the whole learning process, until equal to the threshold of the memristor. The memristance and output voltage are remain unchanged after 5s, it indicated that the learning process completed.

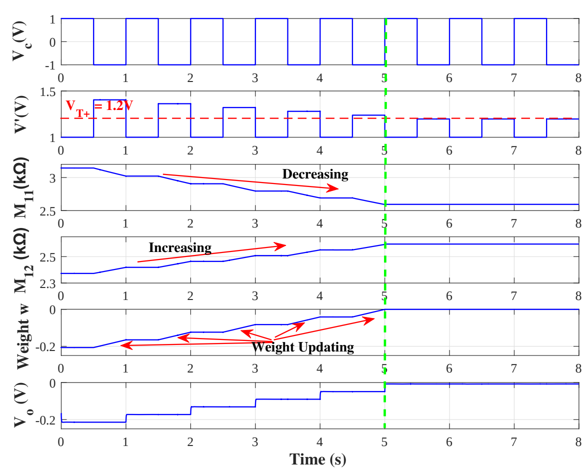

Fig. 7. Learning process in OFC module. V_c is the control signal of the switch. V' is the alternation of S and V_{fo}. M_{11} and M_{12} are the memristances. w is the weight of the OFC module. V_o is the output voltage of the OFC module.

c. Learning process analysis of the memristive CD-ELN

In the emotional learning process, the weight of amygdala increase or decrease monotonously, which may cause the phenomenon of "insufficient learning" or "over learning". The OFC can avoid this phenomenon by enhancing or inhibiting the learning of the amygdala. To verify the effectiveness of the proposed circuit, the PSPICE simulation results of the learning process are shown in Fig. 8, which is consistent with the above theoretical analysis in Section III.

The output of the memristive circuit is V_{out}, the output voltage of the amygdala module and OFC module is V_a and V_o, respectively. Fig. 8 showed the changes of all output variables with time in the learning process. This process is mainly divided into two stages as follows.

c.a. "Insufficient learning"

In this stage (0-34s), the output V_{out} did not reach the target value. For the module of amygdala module, and the output V_a increases monotonously throughout the whole stage. For the OFC module, the output V_o decrease in the positive direction firstly, then increase in the negative direction, it enhanced the learning of the amygdala, which make the output V_{out} approaching the target value.

c.b. "Over learning"

In this stage (34-46s), the output V_{out} exceeded the target value. The output V_{out} of the model reached the target value at 34s, but it did not stop increasing by the learning of the amygdala module, which caused the over learning of the network.

As we can see, during 34-41s, the output V_o decrease in the negative direction, and the increased speed of output V_{out} became lower, it indicated that the OFC module inhibited the learning of the amygdala in this stage. During 41-46s, the amygdala module stops learning, then the output V_{out} decreased gradually by the inhibition of the OFC module.

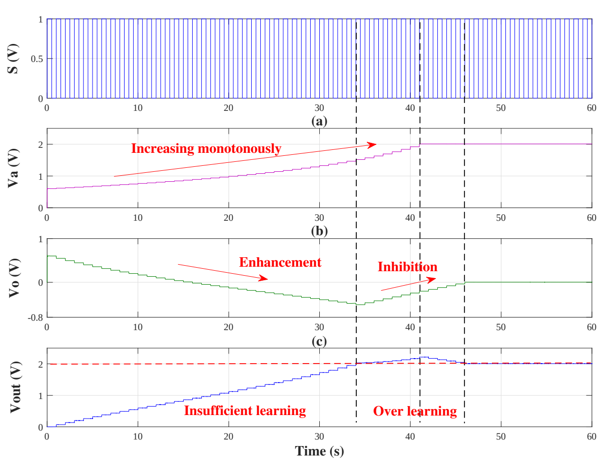

Fig. 8. The learning process of the memristive circuit. (a) The sensory input: positive voltage pulse (Duty cycle is 50%). (b) The output V_a of the amygdala module. (c) The output V_o of the OFC module. (d) The output V_{out} of the memristive network.

C. Simulation results of classical emotional learning

Emotional learning is context-dependent, the context influences some classical emotional learning [23, 24], such as habituation, emotional acquisition and extinction. In this section, two simple simulations are used to show the role of context in emotional learning. In this work, the voltage-threshold memristor model [52] is used to imitate weight regulation of neural network, and its memristance is controlled by the voltage pulse applied to both ends. When input pulse is applied to the memristor, the memristance is decreased or increased depending on voltage pulse amplitude and width. Besides, in the circuit implementation of bionic systems based on memristor, consecutive positive voltage pulses are used to imitate the repetitive stimuli from the external environment [53-56], then these voltage pulse signals modulate the change of synaptic weight, then results in responses of habituation, sensitization, and so on, which are similar to the biological ones. Classical emotional learning (such as habituation, acquisition, and extinction) is a process in which the response to identically repeated stimuli [23, 24]. Therefore, the positive voltage pulse is selected to represent the repeated stimuli of sensory information and contextual information in this work, then classical emotional learning process of CD-ELN is simulated under these voltage pulse stimuli.

a. Habituation

The habituation phenomenon is that a spontaneous response is weak or gradually disappeared when the repeated stimulus does not predict any important or interesting things. The input sensory signal is a positive voltage pulse, the habituation phenomenon can be divided into two phases as shown in Fig. 9. In the first phase (0-50s), a weak response is generated firstly and then disappeared without a reward signal. In the second phase (50-100s), a weak emotional response is regenerated when the contextual information changed, and then habituation again without a reward signal. The results indicate that contextual information can influence habituation, the change of context will cause the reappear of response.

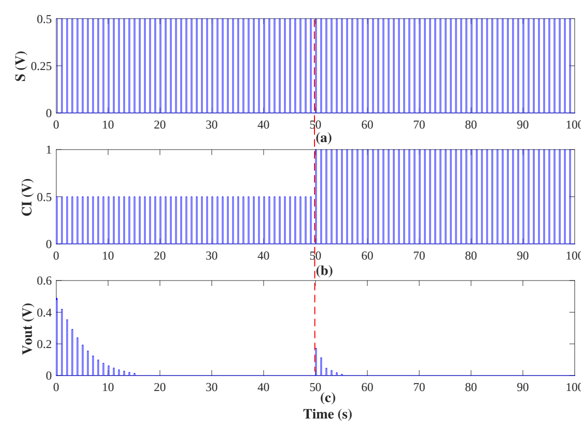

Fig. 9. PSPICE simulation results of habituation by context change. (a) The input signal: positive voltage pulse (Duty cycle is 30%), which imitated a repeated stimulus. (b) The input contextual information. (c) The output voltage of the memristive circuit, which imitated the emotional response.

b. Emotional acquisition and extinction

An emotional response generates when receiving a stimulus with a reward or reinforces signal, then it will extinguish gradually once the reward or reinforce signal disappears. As shown in Fig. 10. From top to down, S is the input signal,

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CI is contextual information, Rew is the reward signal, V_{out} is the output of the memristive circuit, which represents the emotional reaction. In the first phase of acquisition (0-60s), the intensity of the reaction increased when the input signal is paired with a reward signal. In the second extinction phase (60-200s), the emotional reaction is gradually disappeared when the reward signal disappears. In the third phase (200-250s), when the context change, an emotional reaction is generated and extinguished again owing to the absence of a reward signal. So, the change of context will cause a new reaction in the extinction phase.

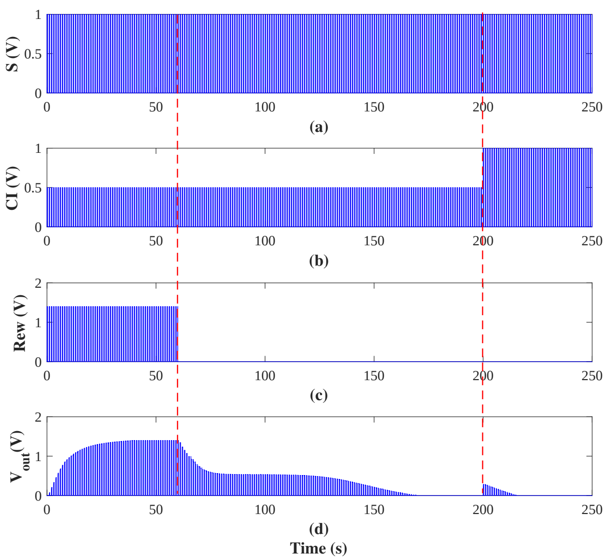

Fig. 10. PSPICE simulation results of acquisition and extinction by context change. (a) The input signal: positive voltage pulse (Duty cycle is 30%). (b) The contextual information. (c) The reward signal. (d) The output voltage of the memristive circuit.

V. Circuit Design of Multi-Input Multi-Output CD-ELN and Applications

Based on the architecture of the CD-ELN, which is shown in Fig. 4, the memristive circuit of the multi-input single-output CD-ELN is designed as shown in Fig. 11. It can be expanded to a multi-input multi-output network as shown in Fig. 12, and the number of output based on the categories in practical classification. Besides, the memristive circuit is applied to a multi-task classification, which benefits from the method of context-dependent. The classification results not only depend on the features of the input but also related to contextual information.

A. Circuit design

As shown in Fig. 11, S is the sensory input signal, CI is the contextual information, and T is the target label. The memristive circuit of the CD-ELN consists of input of contextual information and the selector of the label, which ensure the implementation of the context-dependent method. When receiving the sensory signal, the proposed circuit can handle multiple classification tasks based on contextual information. The detailed blocks of the memristive circuit are described as follows.

(A) The input signal control of OFC: The OFC module receives sensory input S and contextual information CI simultaneously. The memristive weight is adjusted by the input signal and the feedback signal V_{fo}, which is controlled by switch SW. Besides, the switch is composed of two transmission gates.

(B) The calculator of the network output: Difference calculating between OFC output V_o and amygdala output V_a.

(C) Error calculator of the OFC: Error calculating between the network output V_{out} and target value Rew.

(D) The input signal control of the amygdala: The memristive weight is adjusted by the input signal S and the feedback signal V_{fa}, which is controlled by switch SW.

(E) Error calculator of the amygdala: Error calculating between amygdala output V_a and target value Rew.

(F) The selector of multi-label: For supervised learning, there are multiple labels in multi-task applications. In the proposed circuit, the corresponding label is selected by the transmission gate for multiple tasks, which is controlled by contextual information CI. When CI is at a high logic level, the switch is turned on, otherwise, the switch is turned off. So the result of classification is not only related to the sensory input, but also related to the contextual information.

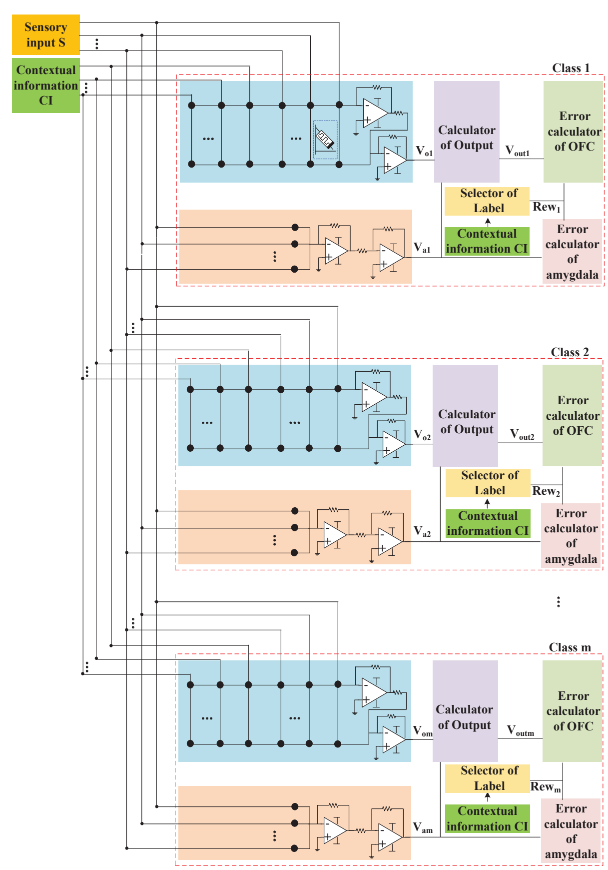

Fig. 12. The simplified circuit framework of multi-input multi-output CD-ELN.

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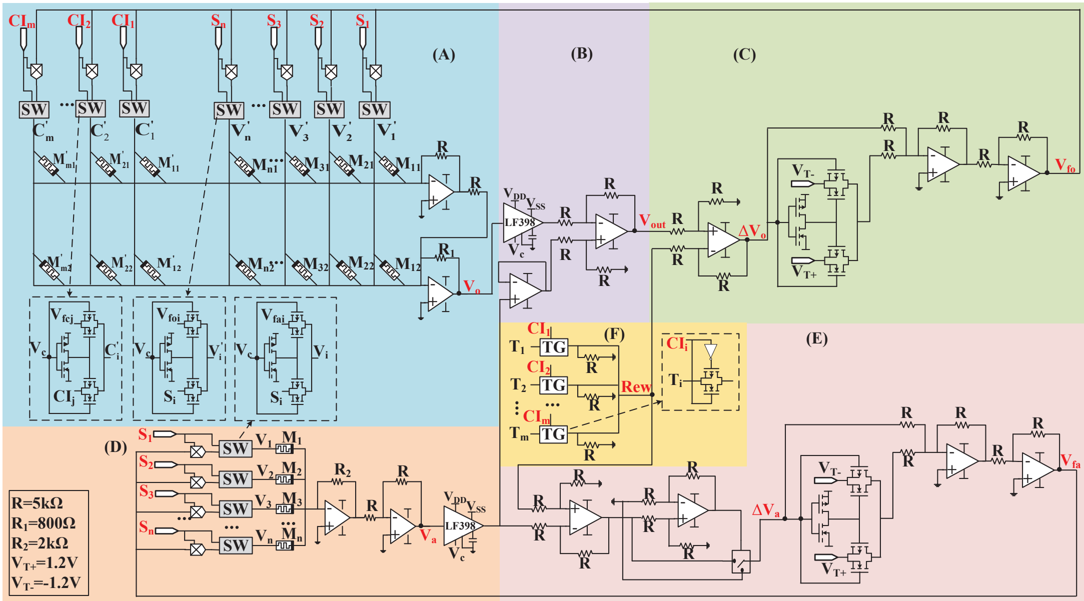

Fig. 11. The circuit architecture of the CD-ELN. (a) The input signal control of OFC. (b) The calculator of the network output. (c) Error calculator of the OFC. (d) The input signal control of the amygdala. (e) Error calculator of the amygdala. (f) The selector of the multi-label.

TABLE II
THE SETTING RULE OF LABEL FOR THREE TASKS

Tasks	Digit					Color			Parity	
Input	'0'	'1'	'2'	···	'6'	Red	Green	Blue	odd	even
Label	0 0 0	0 0 1	0 1 0	···	1 1 0	0 1	1 0	1 1	0 1	1 0

TABLE III
THE MAPPING RULE OF CONTEXT AND LABEL IN MULTI-TASK CLASSIFICATION

Sensory input S	Context CI			Label T						
	CI_1	CI_2	CI_3	T[1]	T[2]	T[3]	T[4]	T[5]	T[6]	T[7]
Green image '1'	1	0	0	0	0	1	0	0	0	0
	0	1	0	0	0	0	1	0	0	0
	0	0	1	0	0	0	0	0	0	1
Red image '4'	1	0	0	1	0	0	0	0	0	0
	0	1	0	0	0	0	0	1	0	0
	0	0	1	0	0	0	0	0	1	0

B. Application

Nowadays, most memristive neural networks are used to deal with a single problem or task. There are internal connections between many problems or tasks. Multi-task learning was first proposed by Caruana [57], it breaks the traditional idea of divide and rule, the relationship between related tasks can be considered when training multiple related tasks in parallel. Combined with the context-dependent method, the proposed memristive CD-ELN is applied to a multi-task classification. In the simulations, the voltage-controlled memristor model [52] is used, which is described in detail in section IV-A. The parameters of memristor used for simulation were set as: $R_{on} = 500\Omega, R_{off} = 16k\Omega, \mu_v = 1 \times 10^{-12} m^2 s^{-1} \Omega^{-1}, i_{on} = 1A, i_{off} = 5.1{\times}10^{-7}A, i_0 = 1{\times}10^{-5}A, V_{T+} = 1.2V, V_{T-} = -1.2V, p = 10$. Besides, The frequency of the circuit was 1Hz, and the supply voltage was $\pm 5V$.

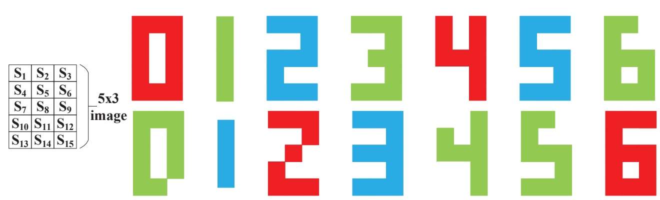

Fig. 13. The color digit images.

To prove the adaptability and flexibility of the proposed network, the memristive network was trained to classify the digital images according to multiple task requirements. There are five groups data set of image for classification training, and seven images in every group. Fig. 13 shows two sets of images. The color digit images have a size of 5×3. Three classification tasks are set in simulation: classified according to digit, color, and parity, respectively. The contextual information is used

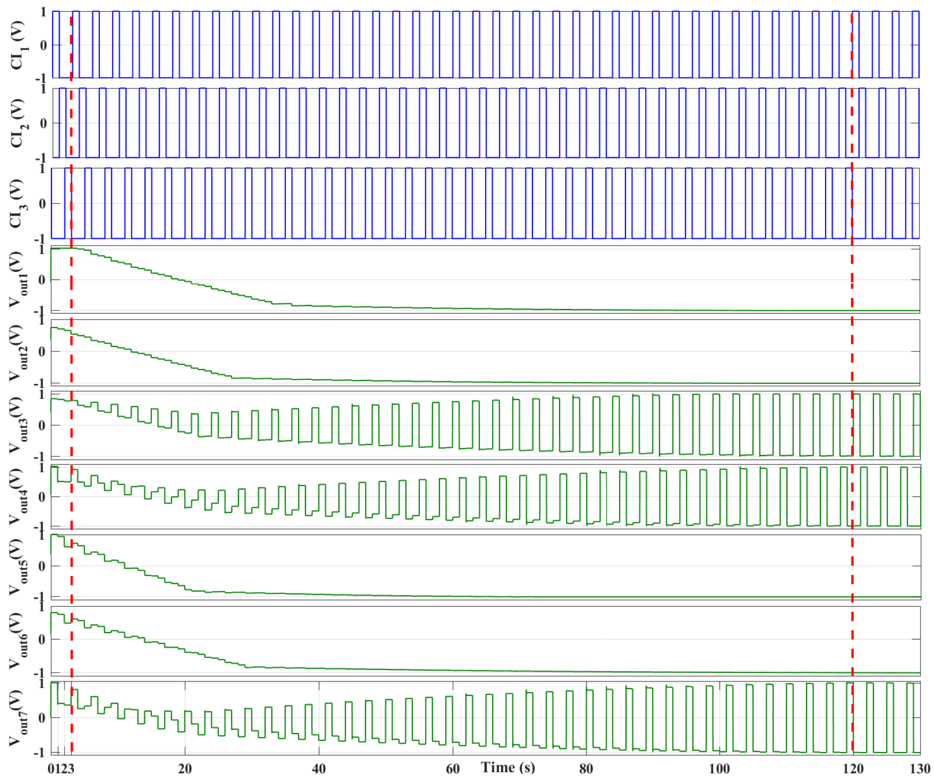

Fig. 14. PSPICE simulation of multi-task classification for green image '1'. CI_1-CI_3 are the contextual information. V_{out1}-V_{out7} are the output of network. [CI_1, CI_2, CI_3]= [1V, -1V, -1V] represents the classification task by digit. [CI_1, CI_2, CI_3]= [-1V, 1V, -1V] represents the classification task by color. [CI_1, CI_2, CI_3]= [-1V, -1V, 1V] represents the classification task by parity.

to represent the task name. According to the three tasks, the rule of label setting is shown in Table II. For multi-task classification, the mapping rule of context and label in multi-task classification is shown in Table III, which takes the digit '1' and the digit '4' as examples. The contexts represent task name, for example, [1,0,0] represent the first classification task by digital, [0,1,0] represent the second classification task by color, [0,0,1] represent the third classification task by parity of number. For the label vector, the first three number is related to digital classification task, the fourth to fifth number is related to color classification task, and the last two number is related to the parity classification task.

In the simulation, the proposed memristive circuit of CD-ELN for multi-task contains 15 inputs and 7 outputs. The sensory inputs were denoted as $S = [S_1, S_2, ..., S_{15}]$, which are the pixel average value of R, G, B three channels. The inputs were normalized to (-1, 1) firstly, and then translated to (-0.5V, 0.5V). The contextual information (0, 1) were translated to (-1V, 1V). The output target value (0, 1) were translated to (-1V, 1V). The pixel of image '1' and the corresponding contextual information of three tasks are set as the input of the circuit. The PSPICE simulation results of image '1' are shown in Fig. 14. For the multi-task learning phase (0-120s), the memristive circuit of CD-ELN was trained iteratively based on three tasks. For example, 0-3s was an iteration cycle, it contains the three contextual information, which corresponding to three tasks. The results of the training process shown that the outputs changed gradually and then kept in a stable state. For the testing phase (120s-130s), the image '1' and the corresponding contextual information as inputs. As we can see, when the contexts is [1, -1, -1]V, the outputs are [-1, -1, 1, -1, -1, -1, -1] V, the contexts is [-1, 1, -1] V, the outputs are [-1, -1, -1, 1, -1, -1, -1] V. the contexts is [-1, -1, 1] V, the outputs are [-1, -1, -1, -1, -1, -1, 1] V. The test results indicated that the output of the proposed network is context-dependent when receiving the same sensory input.

After trained by using all image training data set, the memristive circuit of CD-ELN is tested by validation sets. The classification accuracy for the color digit images is 97.2%. The testing result of three cases is shown in Fig. 15. During the testing process, the sensory input is green digit '1'(0-3s), red digit '4'(3-6s) and blue digit '6'(6-9s), respectively. In the first phase (0-3s), three classification tasks are tested in order when receiving the same sensory input. The classification results are not only related to the sensory input but also related to the contextual information. Based on the target label in Table III, the digit image is correctly classified by the proposed memristive circuit. So, the proposed memristive circuit of CD-ELN is effective in multi-task classification.

C. Comparison with other memristor-based neural networks

A comparison between the memristor-based CD-ELN and other memristor-based neural networks is shown in Table IV. In [25], the proposed memristor-based network realized synchronous weight adjustment, but the training mode of network is off-chip, which means that the adjustment of weights are

TABLE IV
COMPARISON OF MEMRISTOR-BASED CD-ELN WITH OTHER MEMRISTOR-BASED NEURAL NETWORKS

	The proposed CD-ELN	The work in Yang *et al.* [25]	The work in Mohammad *et al.* [26]
Training mode	On-chip	Off-chip	On-chip
Training algorithm	Brain emotional learning	Widrow-Hoff	OCTAN algorithm
Context-dependent	Yes	No	No
Pattern classification	multi-task classification	single task classification	single task classification

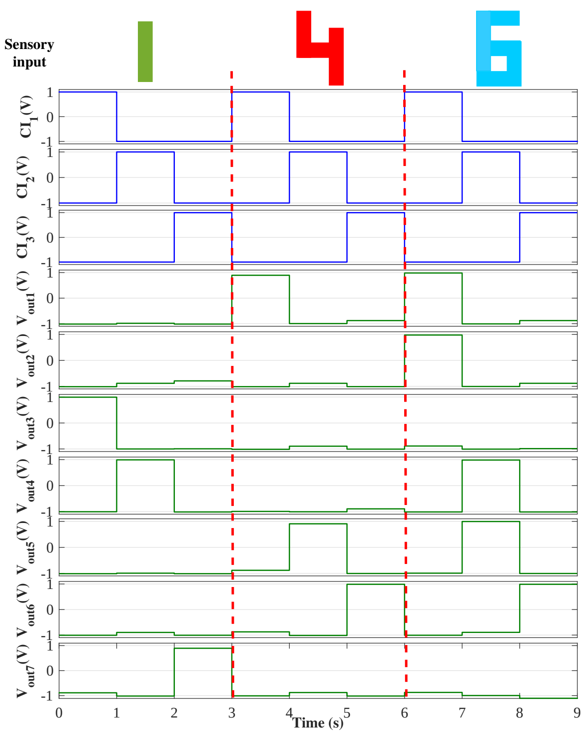

Fig. 15. The validation results of the proposed memristive network by PSPICE simulation. CI_1-CI_3 are the contextual information. V_{out1}-V_{out7} are the output of network. [CI_1, CI_2, CI_3]= [1V, -1V, -1V] represents the classification task by digit. [CI_1, CI_2, CI_3]= [-1V, 1V, -1V] represents the classification task by color. [CI_1, CI_2, CI_3]= [-1V, -1V, 1V] represents the classification task by parity.

calculated by the software and then downloaded to the circuit. Off-chip training failed to consider the variations between devices. In [26], an on-chip training algorithm for memristive circuits was introduced, while the memristor-based network with OCTAN (On-Chip Training Algorithm for the memristive Neuromorphic circuits) was only applied to solving single task pattern classification. The rule of brain emotional learning of the proposed CD-ELN imitates the learning mechanism in the human brain, which has advantages of simple structure and low calculation. Besides, the proposed memristor-based CD-ELN with on-chip training is context-dependent when receiving the same sensory input. In practical application, there are internal connections between multiple tasks, so the ability of processing multi-task is important. Based on mechanism of the contextual-dependent processing, the memristive circuit of CD-ELN can handle multi-task classification effectively, which breaks the traditional method of divide and rule.

VI. DISCUSSION

The performance of the proposed CD-ELN network is assessed in this section. Firstly, comparison to the-state-of-art training algorithms are described. Then, the impacts of temperature and process variation are presented by considering the imperfections of the fabrication process.

A. Comparison to the-state-of-art training algorithms

1) Training time and accuracy: To test the effectiveness of the proposed CD-ELN on a larger dataset, a multi-task classification was implemented on the MNIST dataset. For the contextual information, [1, 0] represents the classification by digit, [0, 1] represents the classification by parity. The pixels of images were normalized to (-1, 1) firstly, and then translated to (-0.5V, 0.5V). The contextual information (0, 1) were translated to (-0.5V, 0.5V). The parameters of memristor were set as: $R_{on} = 500\Omega, R_{off} = 16k\Omega, \mu_v = 1 \times 10^{-10} m^2 s^{-1} \Omega^{-1}, i_{on} = 1A, i_{off} = 5.1 \times 10^{-7} A, i_0 = 1 \times 10^{-5} A, V_{T+} = 1V, V_{T-} = -1V, p = 10$.

Based on the training results of OCTAN (On-Chip Training Algorithm for the memristive Neuromorphic circuits), and RWC (Random Weight Change) algorithm on the MNIST dataset, which were reported in [26]. Comparisons of training time and training error among CD-ELN, OCTAN, and RWC are shown in Fig. 16. Compared with the RWC algorithm, the proposed CD-ELN has better training time and training accuracy. Besides, the training time of CD-ELN is longer than that of OCATN while its training accuracy is better than that of OCTAN. Also, the classification accuracy of CD-ELN was 95%, which is higher than that of OCTAN (91% in [26]).

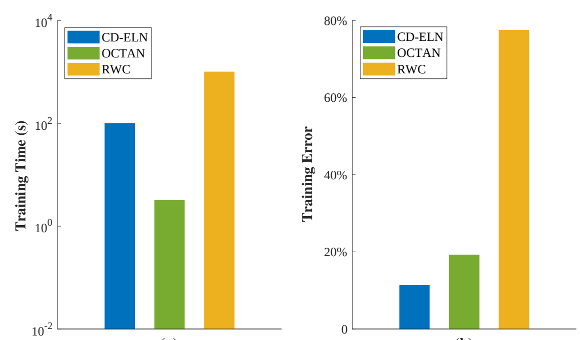

Fig. 16. The training time and training error of CD-ELN, OCTAN, and RWC.

2) Power consumption: Power consumption is a key performance index in circuit implementation. In the proposed circuit of CD-ELN, the switches in the circuit are composed of MOSFETs, so the powers of switches are too small and can be neglected. In the circuit simulation, the circuit power consumption was shown in Table V, which was obtained by the PSPICE simulation report. It is indicated that the main power is composed of the components such as memristor, operation amplifier, and resistor. The number of these components can be calculated from Fig. 6. In the case of one set sensory input and one set of contexts input, the number of memristor, amplifier, and resistor is 5, 15, and 32, respectively. By simple mathematical calculation, the total power consumption of a circuit with only one set of inputs is 9.010mW. Besides, in the case of multiple sets of inputs, the number of memristor is changed based on the number of inputs, and the total power consumption can be approximate calculated based on the number and average power consumption of circuit components.

TABLE V
POWER CONSUMPTION FOR THE MAIN COMPONENTS OF THE CIRCUIT

Circuit Components	Average Power Consumption
Memristor	0.05mW
Amplifier	0.20mW
Resistor	0.18mW

The proposed CD-ELN was simulated for the 2-input parity problem, then a comparison of power consumption is shown in Table VI. The results reveal that the power consumption of the CD-ELN is lower than that of RWC and OCTAN, which were reported in [26]. In addition, the power consumption of resistance is affected by the voltage provided, so the power consumption of the circuit can be lowered by reducing the voltage threshold of the memristor appropriately. Besides, reducing the number of amplifiers is beneficial for achieving lower power consumption.

TABLE VI
COMPARISON OF POWER CONSUMPTION

On-chip method	Power Consumption
CD-ELN	9.160mW
OCTAN	9.979mW
RWC	9.982mW

B. Impacts of process variation and temperature

The uncertainly of the memristor parameters is one of the main challenges in the hardware design. The variations of parameters during the fabrication process of memristor may affect the performance of the circuit system. To study the effect of variations in memristor parameters, the classification accuracy was measured in different cases with variation of 5%, 10%, and 20% in parameters.

For the process variation of memristor, three major parameters $(R_{on}, R_{off}, V_{th})$ were considered in the simulation. Random noises with a normal distribution are added to the main parameters, then the accuracy of the network is measured in the presence of these variations. The impacts of R_{on}, R_{off}, V_{th} with a variation of 5%, 10%, and 20% are tested successively, and the corresponding results were shown in Fig. 17. The results indicated that the impact of parameter R_{on} is minimal. Furthermore, the classification accuracy of the network with a memristor variation of 20% remains above 90%.

In addition to the memristor process variation, the temperature in the environment may impact the performance of the circuit. A simulation of temperature sweep was performed in PSPICE to test the effect of temperature on the whole circuit. In the simulation of temperature sweep, the circuit was tested under different temperature conditions. The error output (ΔV_o) between the actual output and target output was shown in Fig. 18. It is indicated that the impact of temperature is small.

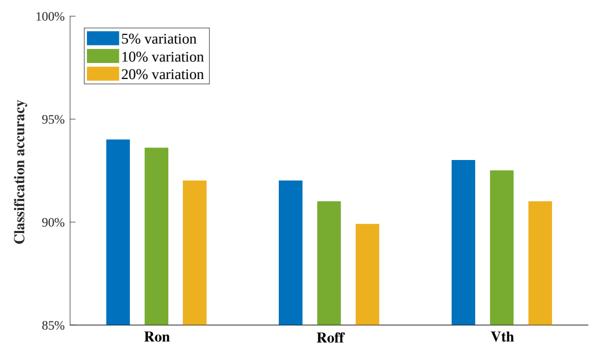

Fig. 17. Classification accuracy of the proposed network in the presence of parameters variation of 5%, 10%, and 20%.

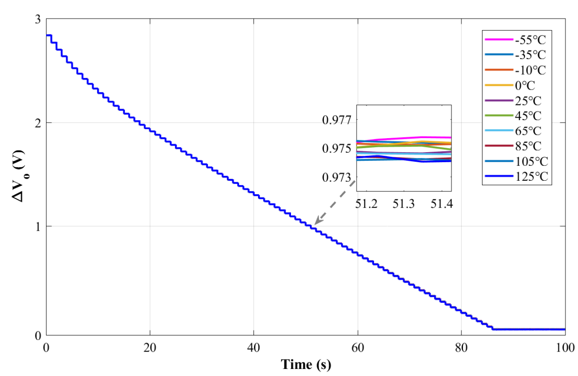

Fig. 18. Temperature analysis.

VII. CONCLUSION

In this paper, a context-dependent emotional learning network and its circuit implementation were proposed. The proposed CD-ELN mainly contains the amygdala module, OFC module, and context-dependent module, which receives the sensory input and contextual information simultaneously. The working of the learning rule of the CD-ELN was analyzed and verified. Besides, the circuit of CD-ELN was designed based on memristor. Some classical emotional learning processes, such as habituation, acquisition and extinction, were simulated by PSPICE. Finally, the memristive circuit of multi-input multi-output was applied to multi-task classification.

The multiple tasks were trained in parallel, which breaks the traditional method of divided and conquer. The training results on MNIST database revealed that the accuracy of the proposed CD-ELN is better than that of OCTAN and RWC algorithms. Besides, the impacts of temperature and memristor process variation on the circuit accuracy were also investigated.

In the simulation, the application ability of the memristor-based CD-ELN was tested. The simulation results verified the adaptability and flexibility of the CD-ELN in practical application. However, the proposed memristive circuit adopts discrete components to realize the training process and weight adjustment, which is still power-wasting and is not suitable for large-scale integration. In the future, our work will focus on designing a more concise and low power consumption memristive neural network and its hardware implementation. Besides, we will imitate the more complex learning process in the human brain to promote the development of artificial intelligence.

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