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Environmental-gradient emotional memory memristive neural network circuit with TAP cell regulatory mechanism

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The hippocampus and amygdala in the human brain play a crucial role in the processing of emotion and memory. Specifically, the hippocampus encodes environmental information along with its corresponding emotional states, whereas the amygdala integrates emotional stimuli from the environment into the hippocampal memory system. Inspired by this biological mechanism and based on the principle of regulating cellular excitability within the mouse transient amplifying progenitor (TAP) mechanism, this study proposes an environmental-gradient emotional memory memristive neural network circuit. This bio-inspired neuromorphic circuit consists of two main modules: a hippocampal module and an amygdala module. The hippocampal module comprises two sub-modules: the environmental recognition neuron and the emotion generation neuron. The environmental recognition neuron is responsible for memorizing environmental features, while the emotion generation neuron establishes mapping relationships between the environment and emotional states. The amygdala module combines external emotional stimuli with internal current emotional stimuli to generate a comprehensive emotional assessment of the environment, and this emotional state can be stored. This memristive neural network circuit facilitates dynamic coupling between emotion and the environment, with the emotional output being continuous and graded rather than discrete. In PSPICE simulations, the proposed circuit exhibits satisfactory and stable functional performance. The findings of this study can offer valuable insights for the design of neuromorphic hardware circuits and for emotion simulation in bio-inspired robots.

Keywords: memristive neural network circuit, environmental-gradient, emotional memory, TAP cell regulatory mechanism

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1. Introduction

In recent years, artificial intelligence (AI) has experienced exponential growth and has been widely applied in various industries, especially in the field of intelligent robots.[1,2] Equipped with cutting-edge technologies, intelligent robots are poised to make significant contributions to social services. For instance, in elderly care, robots can offer companionship and assist with daily activities. In medical care, they aid in patient monitoring and drug dispensing. Given these roles, it is crucial that robots interact with humans in a natural and effective manner. To achieve this goal, they need to understand, recognize, and simulate human emotions, thereby enabling more empathetic and human-centered interactions.[3–7]

Although software-based affective computing algorithms have endowed robots with the ability to express basic emotions, these implementations often have significant limitations. They tend to exhibit fixed emotional intensities, undergo abrupt changes in emotional states, and lack the fundamental ability to maintain persistent contextual memory.[8–11] These features are in sharp contrast to the dynamic, gradual, and context-dependent emotional behaviors observed in real-life scenarios. Consequently, there is an urgent need for a new paradigm that enables robots not only to express emotions but also to capture the environmental contexts in which these emotions arise, thereby forming associative emotional memories that can guide future interactions.

Similar to the challenges faced in robotics, the exponential growth of big data and artificial intelligence has placed unprecedented demands on computing hardware. Modern computers, based on the classical von Neumann architecture, have a physical separation between memory and processing units, leading to the well-known "memory wall" or "von Neumann bottleneck". To overcome these fundamental limitations, the computing community is increasingly focusing on brain-inspired neuromorphic architectures.[12,13] The operating principle of the biological brain is markedly different, with memory and computation tightly coupled at the synaptic level. Information is stored in synaptic weights and processed in parallel by neurons, which enables massively parallel, event-driven, and highly energy-efficient operation.[14,15] Emulating this neurobiological architecture in hardware has the potential

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to break through the von Neumann bottleneck while achieving the low-power operation that is essential for autonomous systems such as robots.

The memristor, functioning as a non-volatile resistive switching device, has emerged as a cornerstone technology for realizing brain-inspired hardware circuits. Due to its nanoscale dimensions, non-volatility, analog tunability, and threshold characteristics, it is exceptionally well-suited for emulating the plasticity of biological synapses.[16] These features make it an ideal basic component for constructing hardware neural network circuits. Consequently, a significant amount of research has been devoted to the development of memristor-based neural network circuits,[17–20] aiming to implement various cognitive functions, such as associative memory, learning, and emotional processing.[21,22]

Several studies have achieved the integration of emotion and memory within memristive circuits. For example, Ref. [23] proposed a memristor-based associative memory neural network circuit that takes into account mood-congruent memory and mood-dependent memory effects, demonstrating how emotional states influence learning and recall. Reference [24] designed a context-dependent emotional habituation circuit, which shows that repeated emotional stimuli in a specific context result in diminished responses. Reference [25] proposed a memristor-based feature recall neural network circuit capable of emotional temporal differentiation. This circuit integrates feature associative memory with emotion generation and achieves emotion differentiation across past, present, and future temporal states, providing a reference for brain-like intelligence research and applications in efficient parts inspection.

However, several critical gaps persist, impeding the development of emotionally intelligent robots with human-like affective responses. First, many existing circuits treat emotion as discrete, finite-state machines that abruptly switch between preset states such as "happy" and "sad."[26] This approach fails to reflect the continuous and gradual nature of human emotions, as emotional intensity changes smoothly in response to environmental cues. Second, although some circuits incorporate memory, they often lack a dedicated mechanism for forming and retrieving long-term associations between specific environmental features and the corresponding emotional states they trigger. For example, the circuit presented in Ref. [27] focuses on overshadowing dynamics but may not effectively encode the detailed context that gives rise to an emotion. Third, some circuits do not integrate environmental factors with emotional expressions, merely generating emotional outputs while neglecting environmental perception. Reference [28] presented a memristor-based affective associative memory circuit that enables direct and gradual emotional transformations, incorporates temporary forgetting mechanisms, and models biological activation–saturation characteristics. However, it does not consider the correlation between emotions and the environment.

In this paper, to address these challenges, we propose an environmental-gradient emotional memory memristive neural network circuit with the TAP cell regulatory mechanism. The proposed circuit is based on the neurobiological principles of the medial temporal lobe, specifically the interaction between the hippocampus and the amygdala. Meanwhile, TAP cells are found in the mouse brain; they modulate the excitability of neural stem cells and determine whether these stem cells undergo differentiation. The proposed circuit draws inspiration from this working mechanism.

The main contributions of this study are threefold. First, the circuit is divided into a hippocampal module and an amygdala module, mirroring the brain's emotional memory circuitry. The hippocampal module is further subdivided into an environmental recognition neuron and an emotion generation neuron to separate contextual coding from initial emotional responses. Second, the circuit can form long-term associative memories between multi-feature contextual inputs and specific emotional states they trigger. Crucially, the emotional output is not discrete but varies along a continuous gradient, reflecting the strength of both the stored memory and the current stimulus. Finally, inspired by hippocampal interneuron dynamics, the TAP cell regulatory mechanism is introduced to modulate the strength of emotional memory retrieval and expression. This mimics the biological process where emotional memory recall is adaptively controlled to prevent overgeneralization or excessive emotional reactivity. PSPICE simulation results confirm the proposed circuit's ability to: (a) identify and remember current environments; (b) generate initial emotional responses based on the current environment; (c) adjust this response upon receiving new emotional stimuli within that environment; (d) recall the corresponding emotional memory when encountering a previously learned environment again. The emotional transition is smooth and gradual rather than abrupt.

The remaining part of this paper is organized as follows. Section 2 discusses the memory mechanism and the TAP cell regulatory mechanism. Section 3 presents the memristor model and the proposed environmental-gradient emotional memory memristive neural network circuit. Section 4 presents the simulation results and explores the applications of the proposed memristive circuit. Section 5 concludes this paper.

2. The memory mechanism and the TAP cell regulatory mechanism

2.1. The memory mechanism

When a living organism, such as a puppy, enters a new environment, two distinct processes occur in its brain. One

process involves encoding and memorizing the new environment, while the other involves forming an emotional response to it. Subsequently, events that take place in the new environment also shape the organism's overall emotional perception of that environment, and this overall emotion is subject to change. The specific process is illustrated in Fig. 1.

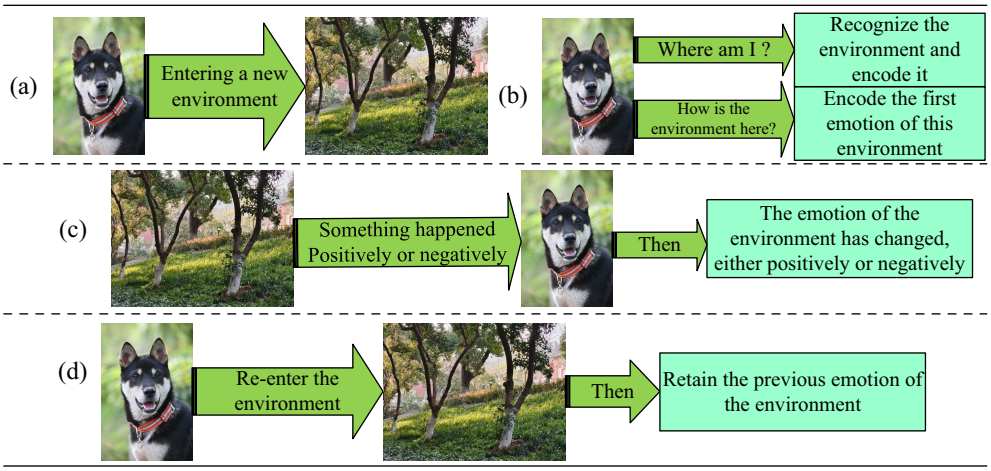


Fig. 1. The psychological process of a puppy entering a new environment.

In process (a), the puppy enters an unfamiliar environment. It needs to determine two things: its own location and whether the new environment poses any danger. This determines its emotional state in the current environment, such as whether it feels happy, sad, or anxious. During this process, the environmental recognition neuron in the hippocampus begins to learn the features of the current environment.

In process (b), two processes occur in the puppy's brain: recognizing and memorizing the current environment, and forming an initial emotion toward the current environment. During this process, the environmental recognition neuron in the hippocampus has already formed a memory of the current environment, and the emotion generation neuron generates and stores the initial emotion based on this environment.

In process (c), the puppy receives emotional stimuli in the new environment, which cause its emotion to shift from positive to negative or vice versa, and the emotional change is gradual. During this process, the amygdala receives external emotional signals from the current environment. These signals combine with the initial emotion to form the current emotion, which is then integrated into the emotion generation neuron of the hippocampus to form an overall emotion that can be stored long-term.

In process (d), when the puppy re-enters the environment, it retains the memory and emotion from its previous visit. During this process, if the current environment has been memorized, the environmental recognition neuron will recognize it, and the emotion generation neuron will maintain the previously learned emotional output.

2.2. The TAP cell regulatory mechanism

For the memristive neural network circuit proposed in this paper, the weight of the memristor synapse is modulated through a regulatory mechanism centered on TAP cells. In the adult mouse brain, a specific subtype of TAP cells is present; these cells envelop neural stem cells (NSCs) and establish direct contact with them.[29,30] TAP cells express membrane-bound *EfnB1* ligands, which directly bind to *EphB2* receptors on NSCs, thereby triggering high-frequency Ca^{2+} oscillations within NSC processes. This oscillatory activity acts as a brake, maintaining NSCs in a quiescent state by preventing their entry into the proliferative cycle.

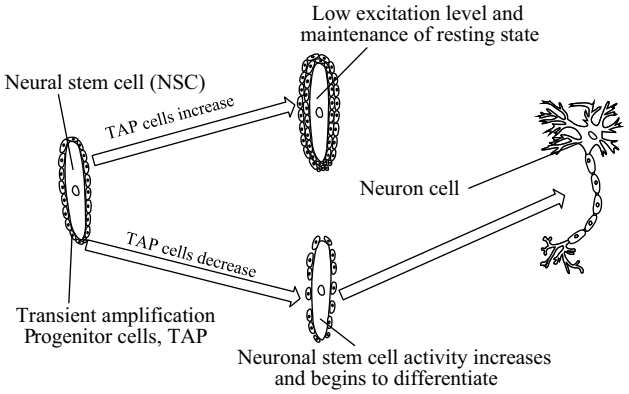


Fig. 2. The TAP cell regulatory mechanism.

When the number of TAP cells decreases, whether due to physiological requirements or pharmacological depletion, the *EfnB1–EphB2* signaling pathway weakens, Ca^{2+} oscillations subside, and the inhibitory effect is removed, prompting NSCs to activate and proliferate extensively to replenish the TAP cell pool. This mechanism enables rapid and reversible control of the quiescence or activation dynamics of NSCs under both homeostatic and regenerative conditions. In summary, there is an inverse relationship between the number of TAP cells and the activity of NSCs. Specifically, a greater reduction in the

number of TAP cells leads to increased NSC activity, while an increase in the number of TAP cells results in more NSCs remaining quiescent with lower activity levels. The detailed process is illustrated in Fig. 2.

3. The proposed environmental-gradient emotional memory memristive neural network circuit

3.1. The memristor model

Memristors are nonlinear components that establish a relationship between magnetic flux and charge. They exhibit characteristics similar to biological synapses, rendering them well-suited for constructing artificial neural networks. Numerous types of memristor models exist, each with distinct structures and materials, such as the HP model, threshold adaptive memristor model (TEAM),[31] voltage threshold adaptive memristor model (VTEAM),[32] and drift speed adaptive memristor model (DSAM).[33] By treating different memristor models as different biological synapses, artificial neural networks can be categorized into various types. These networks demonstrate functions akin to long-term potentiation, long-term depression, and self-learning.[34–38]

In the DSAM model, when the voltage across the memristor exceeds its positive threshold voltage $v_{\rm on}$ or falls below its negative threshold voltage $v_{\rm off}$, the memristance $M(t)$ initially experiences a rapid decrease or increase, followed by a slower transition toward its steady state. The DSAM model adopted in this paper is described as follows:

$$M(t) = R_{\rm on} \cdot \frac{w(t)}{D} + R_{\rm off} \cdot \left(1 - \frac{w(t)}{D}\right), \tag{1}$$

$$\frac{{\rm d}w(t)}{{\rm d}t} = D \cdot g(i,v) \cdot f(x,i), \tag{2}$$

$$g(i,v) = \begin{cases} k_{\rm on} \cdot \Delta R \cdot i(t), & v(t) > v_{\rm on}, \\ 0, & v_{\rm off} \le v(t) \le v_{\rm on}, \\ k_{\rm off} \cdot \Delta R \cdot i(t), & v(t) < v_{\rm off}, \end{cases} \tag{3}$$

$$f(x,i) = \begin{cases} [a \cdot (1-x)]^p, & i > 0, \\ (a \cdot x)^p, & i \le 0, \end{cases} \tag{4}$$

$$\Delta R = R_{\rm off} - R_{\rm on}. \tag{5}$$

Here, $w(t)$ represents the length of the doped region within the memristor, while D denotes the total length of the memristor device. The function $g(i,v)$ describes the voltage-dependent switching behavior. The function $f(x,i)$ is a state-dependent adaptive function, whose dynamics are governed by parameters a and p. Moreover, $k_{\rm on}$ and $k_{\rm off}$ are adjustable coefficients. $R_{\rm off}$ represents the maximum resistance in the undoped state, and $R_{\rm on}$ represents the minimum resistance in the fully doped state. In this paper, all memristor parameters are listed in Table 1.

Table 1. Parameters of memristors.

Parameters	a_1	a_2	k_1	k_2	p_1	p_2	$R_{\rm off}$	$R_{\rm on}$	$V_{\rm off}$	$V_{\rm on}$
Values	0.47	0.27	280	24	2.3	0.52	1000	10	−0.2 V	0.2 V

3.2. The proposed memristive neural network circuit

In this paper, the proposed environmental-gradient emotional memory memristive neural network circuit consists of a hippocampal module and an amygdala module, as shown in Fig. 3. The hippocampal module is composed of an environmental recognition neuron and an emotion generation neuron.

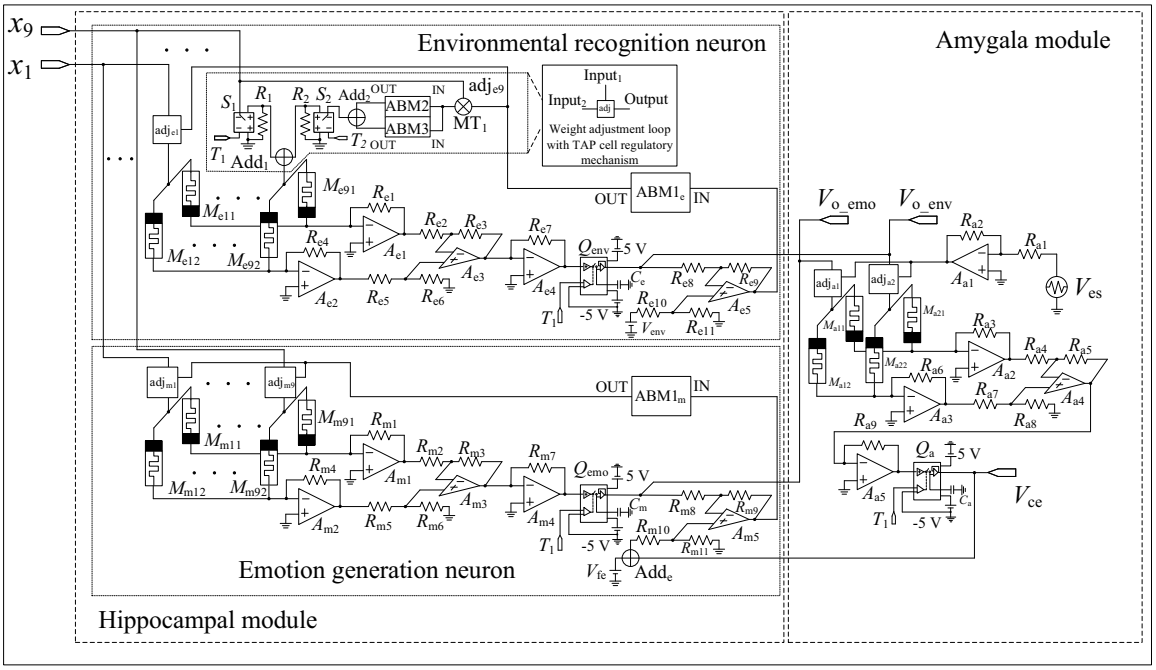


Fig. 3. The proposed environmental-gradient emotional memory memristive neural network circuit.

Specifically, the environmental recognition neuron consists of the function module ABM1$_e$, weight adjustment modules adj$_{e1}$ to adj$_{e9}$, memristors M_{en1} and M_{en2} (where $n = 1,2,\ldots,9$), resistors R_{e1} to R_{e11}, operational amplifiers A_{e1} to A_{e5}, a sample-and-hold device Q_{env} (used for sampling and holding electrical signals), a capacitor C_e, and an environmental feature voltage source V_{env}.

The emotion generation neuron is composed of the function module ABM1$_m$, weight adjustment modules adj$_{m1}$ to adj$_{m9}$, memristors M_{mn1} and M_{mn2}, resistors R_{m1} to R_{m11}, operational amplifiers A_{m1} to A_{m5}, a sample-and-hold device Q_{emo}, a capacitor C_m, an adder Add$_m$, and an initial emotion voltage source V_{fe}.

The amygdala module consists of weight adjustment modules adj$_{a1}$ and adj$_{a2}$, memristors M_{a11}, M_{a12}, M_{a21}, M_{a22}, resistors R_{a1} to R_{a9}, operational amplifiers A_{a1} to A_{a5}, a sample-and-hold device Q_a, and an external emotion stimulation source V_{es}.

3.2.1. The function modules ABM1 to ABM3

First, we focus on the discrete modules of the proposed circuit. Among these modules, we first introduce the function module ABM1. Figure 4 depicts the function module ABM1. This module is present in both the environmental recognition neuron and the emotion generation neuron. In the environmental recognition neuron, it is labeled as ABM1$_e$, while in the emotion generation neuron it is labeled as ABM1$_m$. Since ABM1, ABM1$_e$, and ABM1$_m$ share an identical circuit structure, we take the function module ABM1 as an example for explanation.

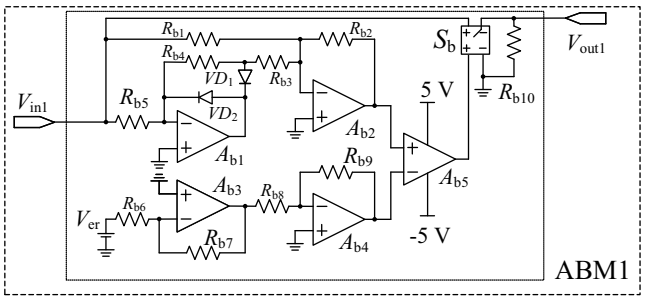


Fig. 4. The schematic diagram of function module ABM1.

The function module ABM1 consists of resistors R_{b1}–R_{b10}, diodes VD_1–VD_2, operational amplifiers A_{b1}–A_{b4}, a voltage comparator A_{b5}, a voltage-controlled switch S_b, and an error voltage source V_{er}. Among these components, resistors R_{b1}–R_{b5}, operational amplifiers A_{b1}–A_{b2}, and diodes VD_1–VD_2 together constitute an absolute-value circuit, which calculates the absolute value of the input voltage V_{in1}. Resistors R_{b6}–R_{b9}, operational amplifiers A_{b3}–A_{b4}, and the error voltage source V_{er} together form a scaling circuit. By adjusting the resistor values, the error voltage source V_{er} can be scaled by a specific ratio. The voltage comparator A_{b5} compares the output voltage of operational amplifier A_{b2} with that of A_{b4}. If the absolute value of V_{in1} is less than the scaled voltage of V_{er}, A_{b5} outputs 0 V; otherwise, it outputs V_{in1}.

The mathematical expression for function module ABM1 is

$$V_{out1} = \begin{cases} 0\ \text{V}, & |V_{in1}| \le \dfrac{R_{b7}R_{b9}}{R_{b6}R_{b8}}V_{er}, \\ V_{in1}, & |V_{in1}| > \dfrac{R_{b7}R_{b9}}{R_{b6}R_{b8}}V_{er}. \end{cases} \tag{6}$$

Next, we introduce the function module ABM2. Figure 5 presents the schematic diagram of the function module ABM2. ABM2 is a component of the weight adjustment module adj, based on the TAP cell regulatory mechanism. The function module ABM2 consists of resistors R_{c1}–R_{c3}, a voltage-controlled switch S_c, a voltage comparator A_{c1}, and an operational amplifier A_{c2}. The input voltage V_{in2} is connected to the non-inverting input of the voltage comparator A_{c1}, while its inverting input is grounded. Resistors R_{c1}–R_{c2} and operational amplifier A_{c2} form an inverter, which inverts the output voltage of A_{c1}. When the input V_{in2} is positive, the switch S_c turns off, and ABM2 outputs 0 V. Conversely, when V_{in2} is negative, the switch S_c turns on, and ABM2 outputs the positive adjustment voltage V_{adj+}.

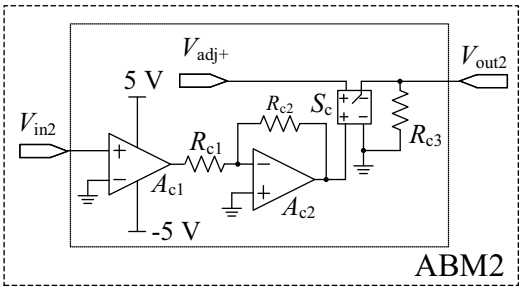


Fig. 5. The schematic diagram of function module ABM2.

The mathematical expression for the function module ABM2 is

$$V_{out2} = \begin{cases} V_{adj+}, & V_{in2} < 0, \\ 0\ \text{V}, & V_{in2} \ge 0. \end{cases} \tag{7}$$

Next, we introduce the function module ABM3. Figure 6 presents the schematic diagram of ABM3. ABM3 consists of a voltage comparator A_d, a voltage-controlled switch S_d, and a resistor R_d. The input voltage V_{in3} is connected to the non-inverting input of the voltage comparator A_d, while its inverting input is grounded. The output of A_d is connected to the control terminal of the voltage-controlled switch S_d. When the input voltage V_{in3} is positive, the switch S_d turns on, and the circuit outputs the negative adjustment voltage V_{adj-}. Conversely, when V_{in3} is negative, the switch S_d turns off, and the circuit outputs 0 V.

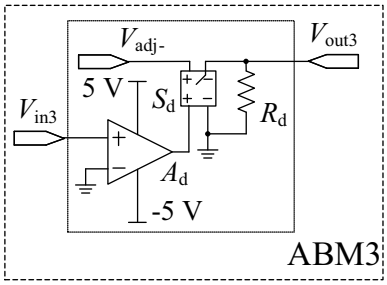


Fig. 6. The schematic diagram of function module ABM3.

The mathematical expression for the function module ABM3 is

$$V_{out3} = \begin{cases} V_{adj-}, & V_{in3} \geq 0, \\ 0\ \text{V}, & V_{in3} < 0. \end{cases} \tag{8}$$

3.2.2. The weight adjustment module

The weight adjustment module adj, which employs the TAP cell regulatory mechanism, is present in the environmental recognition neuron, the emotion generation neuron, and the amygdala module. It is labeled as adj_{e1}–adj_{e9} in the environmental recognition neuron, adj_{m1}–adj_{m9} in the emotion generation neuron, and adj_{a1}–adj_{a2} in the amygdala module. All these instances share an identical circuit structure. Herein, we explain the connections and functions of the weight adjustment module using adj_{e9} as an example, as shown in Fig. 3.

The weight adjustment module adj_{e9} consists of resistors R_1–R_2, voltage-controlled switches S_1–S_2, a multiplier MT_1, adders Add_1–Add_2, and function modules ABM2 and ABM3. The multiplier has two input terminals corresponding to the two input signals of adj_{e9}. One input terminal is connected to the input signal x_9, while the other is connected to the output of the function module ABM1_e. The output of the multiplier MT_1 is connected to the inputs of ABM2 and ABM3, which determine the sign of the multiplier output. Based on the output of MT_1, ABM2 and ABM3 generate output voltages, which are subsequently summed by adder Add_2. T_1 and T_2 form a pair of inverted clock signals: when T_1 is high, T_2 is low. Under this condition, the voltage-controlled switch S_1 is turned on and S_2 is turned off, and adder Add_1 outputs x_9. Conversely, when T_1 is low and T_2 is high, S_1 is turned off, S_2 is turned on, and Add_1 outputs the voltage from Add_2. The function of adj_{e9} is to simulate the regulatory mechanism of TAP cells and adjust the weight of the memristor synapse.

The weight adjustment module adj is designed to emulate the regulatory effect of TAP cell number fluctuations in the mouse brain on the activity of neural stem cells (NSCs). Specifically, an increase in the number of TAP cells suppresses NSC activity, while a reduction enhances NSC excitability and triggers differentiation. Figure 7 illustrates the relationship between the decreased number of TAP cells and the memristor synapse weight. This also represents the process by which adj adjusts the synapse weight based on the TAP cell regulatory mechanism. When the decreased number of TAP cells is greater than zero, the memristor synapse weight gradually increases, and the greater the decrease, the steeper the slope of increase. Conversely, when the TAP cell number increases (i.e., the decrease is less than zero), the synapse weight decreases, and the larger the increase, the steeper the slope of decrease.

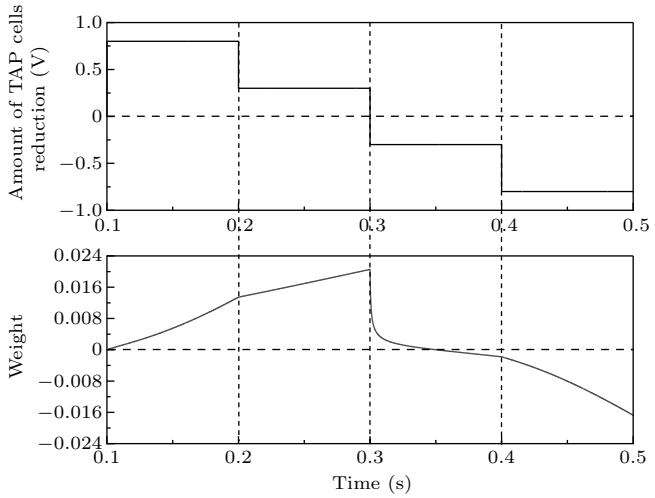


Fig. 7. The relationship between the decreased number of TAP cells and the memristor synapse weight.

3.2.3. The hippocampal module and the amygdala module

In the hippocampal module, the environmental recognition neuron comprises weight adjustment modules adj_{e1}–adj_{e9} based on the TAP cell regulation mechanism, a function module ABM1_e, memristors M_{en1}–M_{en2} (where the subscript n ranges from 1 to 9), resistors R_{e1}–R_{e11}, operational amplifiers A_{e1}–A_{e5}, a sample-and-hold device Q_{env}, a capacitor C_e, and an environmental feature voltage source V_{env}. The negative terminal of memristor M_{en1} and the positive terminal of memristor M_{en2} are connected in series, or vice versa, forming a memristor synapse structure. Resistors R_{e1}–R_{e7}, operational amplifiers A_{e1}–A_{e4}, the sample-and-hold device Q_{env}, and the capacitor C_e collectively constitute a neuron circuit capable of performing weighted summation of input signals. Specifically, when the clock signal T_1 is at a high level, the circuit sums the input environmental feature voltages x_1–x_9. Conversely, when T_1 is at a low level, the circuit updates the weights of the memristor synapses. Resistors R_{e8}–R_{e11}, operational amplifier A_{e5}, and the environmental feature voltage source V_{env} together form a subtractor circuit. This subtractor circuit computes the difference between the environmental feature voltage V_{env} and the neuron output voltage V_{o_env}, and outputs the resulting error signal, which serves as the input to function module ABM1_e.

In the hippocampal module, the emotion recognition neuron comprises weight adjustment modules adj_{m1}–adj_{m9}, a function module ABM1_m, memristors M_{mk1}–M_{mk2} (where the

subscript k ranges from 1 to 9), resistors R_{m1}–R_{m11}, operational amplifiers A_{m1}–A_{m5}, a sample-and-hold device Q_{emo}, a capacitor C_m, an adder Add_m, and an initial emotion voltage source V_{fe}. The circuit structure of the emotion recognition neuron is similar to that of the environmental recognition neuron. The only difference lies in a dedicated subtraction circuit, which is composed of resistors R_{m8}–R_{m11}, operational amplifier A_{m5}, adder Add_m, and the initial emotion voltage source V_{fe}. One input terminal of adder Add_m is connected to the initial emotion voltage source V_{fe}, and the other input terminal is connected to the current emotion voltage V_{ce} of the amygdala module. The emotion recognition neuron is responsible for learning the current environment and generating an initial emotion corresponding to that environment. The adder Add_m plays a crucial role, as it integrates the current emotion voltage V_{ce} from the amygdala module into the emotion generation process, thereby producing an overall emotion associated with the current environment.

The amygdala module consists of weight adjustment modules adj_{a1}–adj_{a2}, memristors M_{a11}–M_{a12}, memristors M_{a21}–M_{a22}, resistors R_{a1}–R_{a9}, operational amplifiers A_{a1}–A_{a5}, a sample-and-hold device Q_a, and a capacitor C_a. The external emotion stimulation source V_{es} and operational amplifier A_{a1} together form an external stimulus circuit, which simulates external emotional inputs applied to the amygdala and generates an emotion signal corresponding to the current environment. The negative terminal of memristor M_{a11} and the positive terminal of M_{a12} are connected in series, or vice versa, forming a memristor synapse. Memristors M_{a21} and M_{a22} share the same structure. Resistors R_{a3}–R_{a9}, operational amplifiers A_{a2}–A_{a5}, the sample-and-hold device Q_a, and the capacitor C_a together form a neuron circuit. Based on the external emotion stimulation source V_{es}, this circuit generates different emotional responses. During emotion adjustment, the intensity of the emotion changes gradually rather than abruptly.

4. Simulation results and applications of the proposed circuit

4.1. Verification of single memristive neural network circuit

Figure 8 shows the processed environmental feature voltage signals, which correspond to variables x_1–x_9. These signals are then fed into the single memristive neural network circuit, participating in the circuit learning process.

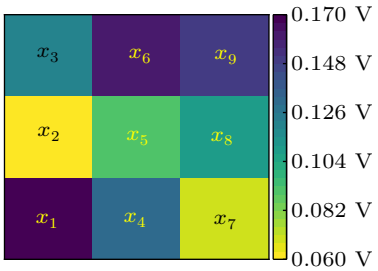


Fig. 8. The processed environmental feature voltage signals.

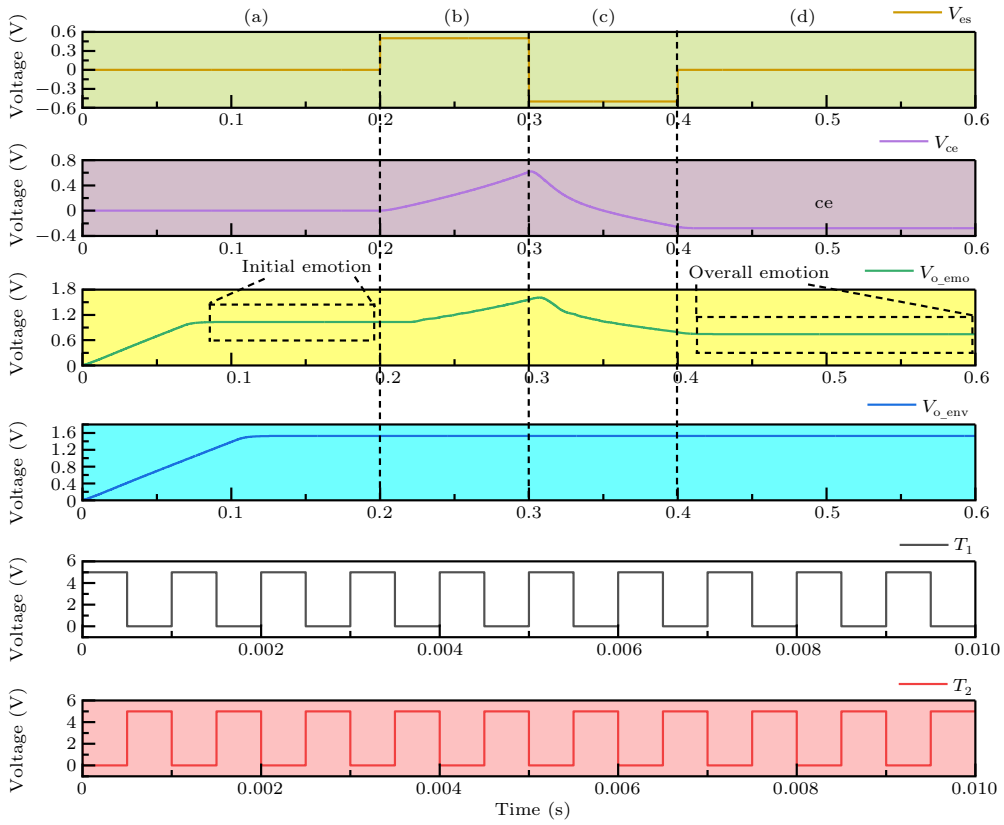


Fig. 9. The output results of single memristive neural network circuit.

Following the learning process, Fig. 9 presents the output results of the single memristive neural network circuit. In Fig. 9, the external emotional stimulation source V_{es} is employed to simulate emotional stimuli from the external environment applied to the amygdala. The current emotional voltage V_{ce} represents the emotional state generated by the amygdala module in response to the present environment, and this state is solely determined by V_{es}. The hippocampal cumulative emotional signal V_{o_emo} reflects how well the hippocampal module has learned the initial emotional state associated with the current environment. When T_1 is at a high level and T_2 is at a low level, the circuit performs a weighted summation of the input signals x_1–x_9. Conversely, when T_1 is at a low level and T_2 is at a high level, based on the TAP cell regulatory mechanism, the sample-and-hold device captures the summed voltage and inputs it into the weight adjustment modules to update the memristive synaptic weights. The complete learning process is divided into four steps.

In step (a), when the circuit encounters a new environment, the hippocampal module learns the input signals x_1–x_9. It adjusts the environmental recognition neuron's output voltage signal V_{o_env} to approach the environmental feature voltage source V_{env}, and it also adjusts the emotion generation neuron's output voltage signal V_{o_emo} to approach the initial emotion voltage source V_{fe}. Here, V_{o_env} indicates how well the hippocampal module has learned the environmental voltage corresponding to the current environment. Since each environment is represented by a characteristic voltage, V_{o_env} remains constant after the learning process is completed.

In step (b), applying a positive emotion stimulus to the amygdala circuit increases the current emotion voltage V_{ce} and the hippocampal cumulative emotion signal V_{o_emo}, reflecting an enhanced positive impression of the environment.

In step (c), applying a negative emotion stimulus to the amygdala circuit decreases the current emotion voltage V_{ce} and the hippocampal cumulative emotion signal V_{o_emo}, indicating a more negative overall emotion toward the environment.

In step (d), in the absence of emotional stimulation, V_{o_emo} and V_{ce} remain stable, demonstrating the circuit's long-term memory capability for environmental emotions.

4.2. Applications of multiple memristive neural network circuits

Building on the previous section demonstrating the functionality of a single memristive neural network circuit, this section focuses on validating the functionality of multiple memristive neural network circuits. By stacking single memristive neural network circuits in a specific layer-by-layer structure n times, multiple memristive neural network circuits capable of memorizing n different environments can be obtained, as depicted in Fig. 10. Here, multiple memristive neural network circuits with three stacked layers are taken as an example to illustrate the entire neural network.

Figure 11 displays the corresponding environmental feature voltage signals x_1–x_9 and external emotional stimulation signals V_{es_1}–V_{es_3}. Assume that the entire neural network circuit is applied to a robot. Taking a neural network composed of three neural circuits as a specific example, the network can memorize three different environments. After training these three neurons, the results of the entire neural network are presented in Fig. 12.

The process of each neural circuit can be divided into three steps. In step (a), the neural circuits recognize environmental features and record initial emotions. Neural circuit 1 has an initial environmental voltage $V_{o_env_1}$ of 1.5 V and an initial emotional voltage $V_{o_emo_1}$ of 1 V. Neural circuit 2 has both voltages $V_{o_env_2}$ and $V_{o_emo_2}$ at 1 V, while neural circuit 3 has both voltages $V_{o_env_3}$ and $V_{o_emo_3}$ at 0.5 V. In step (b), the neural circuits receive emotional stimuli and form an overall emotion that is stored in the hippocampal module. This step includes two substeps involving positive and negative stimuli to evaluate circuit performance. During substeps (b1) and (b2), the effects of the polarity and magnitude of the stimulus voltage on the direction and rate of emotional change can be observed. In neural circuit 3, stronger stimuli lead to faster emotional changes, whereas weaker stimuli result in slower changes. In step (c), after training, reapplying the environmental voltage produces consistent results, confirming the circuit's ability to memorize environments and associated impressions, thereby demonstrating its effectiveness and reliability.

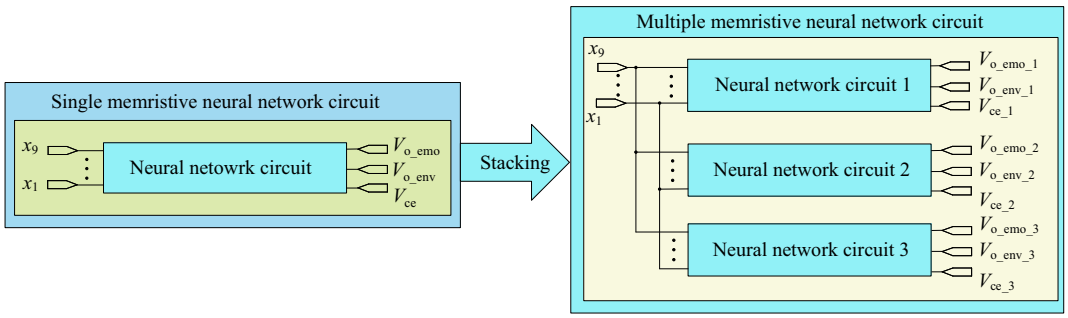


Fig. 10. Stacking n single memristive neural network circuits to form the complete neural network.

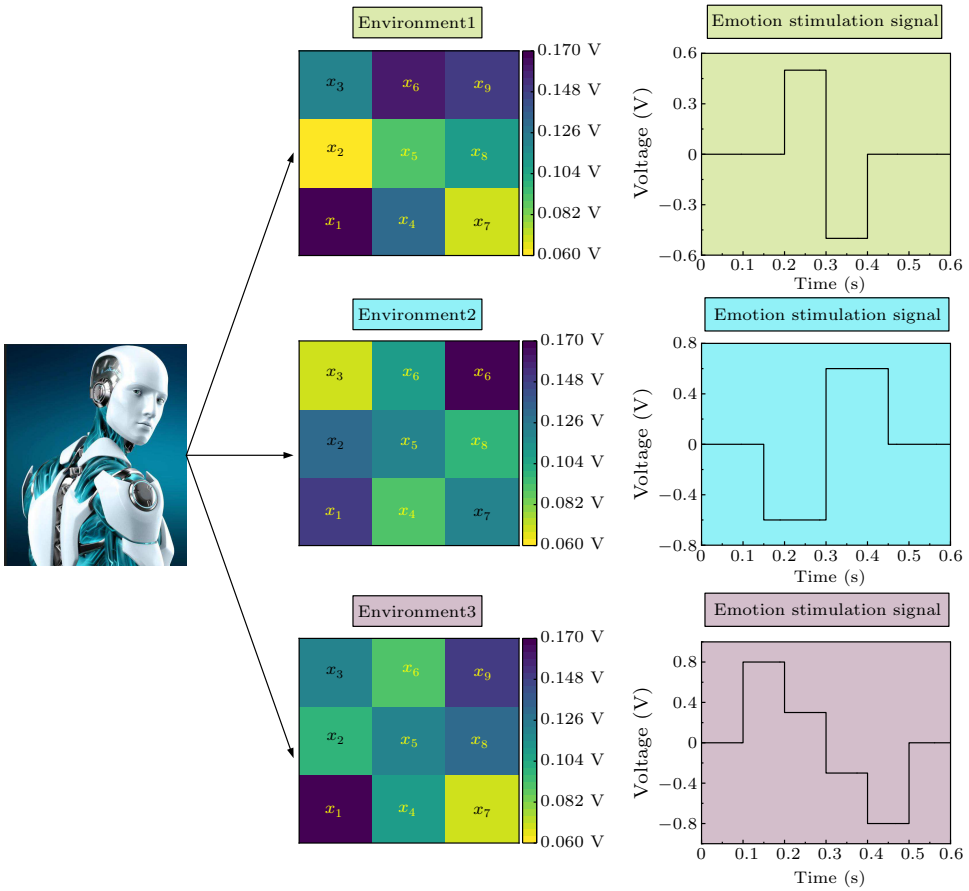


Fig. 11. Three environmental feature voltage signals and corresponding emotion stimulation signals.

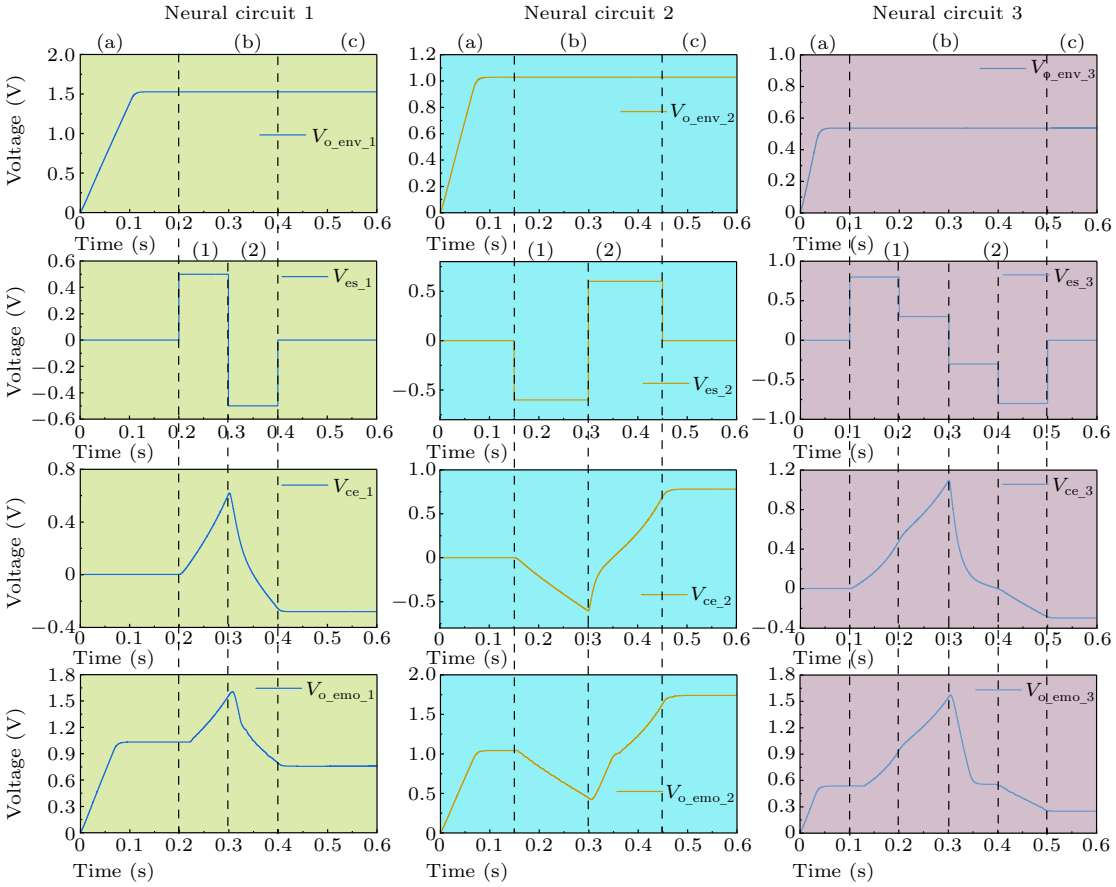


Fig. 12. Training results of the entire neural network under three environmental feature voltage signals.

Table 2. The comparison with the previous works.

References	[2]	[5]	[25]	[26]	[28]	[34]	This work
Emotion-environment association	no	no	no	no	no	no	yes
Emotion gradient	yes	yes	yes	yes	yes	no	yes
Multi-environment and multi-affective memory capabilities	no	no	no	no	no	no	yes
In memory computing	yes	yes	yes	yes	yes	yes	yes
Long-term memory	yes	yes	yes	yes	yes	yes	yes

Besides, Table 2 presents a functional comparison between the proposed work and previous studies. Compared with prior studies, the proposed circuit with the TAP cell regulatory mechanism adopts an in-memory computing architecture, and the output emotion signals support multiple functions, including emotion–environment association, emotional gradient representation, multi-environment and multi-affective memory capabilities, and long-term memory.

5. Conclusion

This paper presents an environmental-gradient emotional memory memristive neural network circuit with the TAP cell regulatory mechanism, aiming to mimic biological emotion–environment association functions. The proposed circuit is constructed based on neural circuits incorporating the TAP cell regulatory mechanism and is composed of a hippocampal module and an amygdala module. The hippocampal module is capable of recognizing and memorizing the current environment, as well as storing the initial emotion associated with it. In contrast, the amygdala module receives emotional stimuli from the current environment, generates the current emotion, and integrates this emotion into the hippocampal module to establish long-term emotional memory.

Moreover, the emotion voltage can be either positive or negative. After the integration process, the emotion generated in the amygdala is combined with the initial emotion stored in the hippocampal module, which is more consistent with biological principles. This circuit can be applied in robots to simulate a series of emotional changes when the robot enters a new environment.

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