Full CMOS Analog Circuit Implementation of Multi-Functional Pavlov Associative Memory using STDP Learning

Sahibia Kaur Vohra, Mahendra Sakare and Devarshi Mrinal Das
Department of Electrical Engineering
Indian Institute of Technology, Ropar
Ropar, India
sahibia.19eez0002@iitrpr.ac.in

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***Abstract*—This paper demonstrates the complete Pavlov associative memory at the CMOS transistor level. Unlike many works focusing on digital implementation with area-intensive and power-hungry circuits, the proposed design for Pavlov associative memory is realised in the analog domain. Apart from learning and forgetting shown in various literature, the proposed circuit for Pavlov associative memory also incorporates the other biologically inspired functions of associative memory, such as learning with stimuli interval, variable learning rates, and generalisation and differentiation. Besides, most papers employ Pavlov training by forming a strong synaptic connection between the sensory auditory and output salivary neurons. In contrast, the actual Pavlov conditioning strengthens the synaptic connection between the auditory and gustatory neurons, as implemented in this paper. Unlike many works that use software-based SPICE models of a memristor as a synapse, the complete system uses on-chip trainable CMOS STDP memristive synapses and LIF neurons. The post-layout simulations of the proposed circuit implemented in TSMC 180 nm CMOS technology verify the functionality of the complete system.**

***Index Terms*—Pavlov associative memory, spike-timing-dependent plasticity (STDP), Leaky-integrate-and-fire (LIF) neuron, genralisation, differentiation.**

I. Introduction

The biological brain's efficiencies inspire neuromorphic computing architectures in performing cognitive tasks [1]. Associative memory is a brain's unique behaviour of storing one piece of information in association with another. Neuromorphic systems use this property of the brain's associative learning for various applications such as building cognitive characteristics in robotics like emotion building and pattern recognition [2]–[4]. Pavlov associative memory is the most famous example of associative learning based on the dog experiment first conducted by Ivan Pavlov [5]. The simplified biological structure of Pavlov conditioning is shown in Fig. 1. When the dog smells the food (unconditional stimulus), the neuron in the gustatory cortex encodes this information in spikes and activates the salivary neuron. Before associative learning, the ringing of a bell sensed and encoded by an auditory neuron does not trigger the dog to salivate. After associative learning, the new synaptic connection between gustatory and auditory neurons strengthens as a result of the activation of gustatory and auditory neurons simultaneously. Consequently, even without food, the salivary neuron gets activated in response to the ring signal. The strengthened synapse can also be weakened when only one input sensory neuron is activated for a long time. This strengthening and weakening of synapses define the learning and forgetting function of Pavlov associative memory.

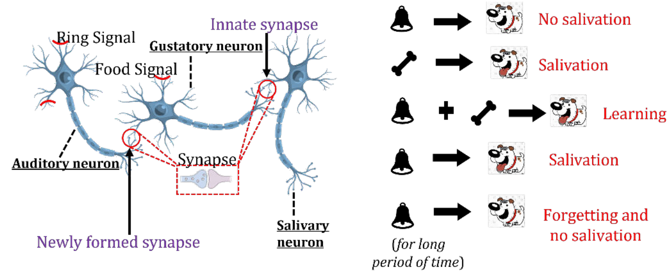


Fig. 1. Simplified biological model of Pavlov associative memory.

Various circuit designs of Pavlov associative memory are implemented in some works [2], [4], [6], [7]. However, these designs proposed digital architecture, which consumes more area and power than analog architecture. In addition, complex digital training circuitry, including registers, and logic gates, is used for associative learning. Also, unlike [2]–[4], [6], [7] that uses software-based SPICE models of a memristor as a synapse, the CMOS-based STDP synapse is used for more realistic circuit-level implementation. The applicability of the CMOS circuit as a synapse in the crossbar emulating the behaviour of the memristor is also shown in our previous works [8]–[11] for pattern recognition application. Although works [12], [13] implement the analog CMOS circuit emulating the Pavlov auditory using in-situ training. However, instead of strengthening the synapse between the auditory and gustatory neurons, the synapse strength between the auditory and output salivary neurons is strengthened based on the spike timing difference between the output salivary neuron and the input auditory neuron. In actual Pavlov conditioning, the new synapse between the auditory and gustatory neurons

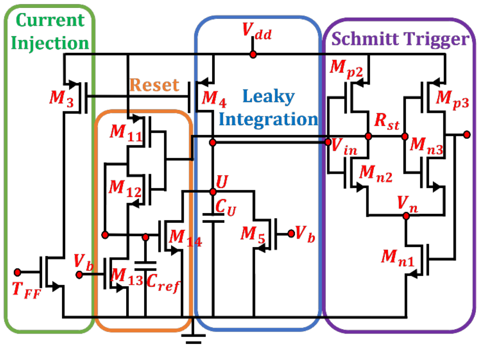


Fig. 2. CMOS LIF neuron circuit comprising various sections of current injection, leaky integration, schmitt trigger for firing and a reset section [14].

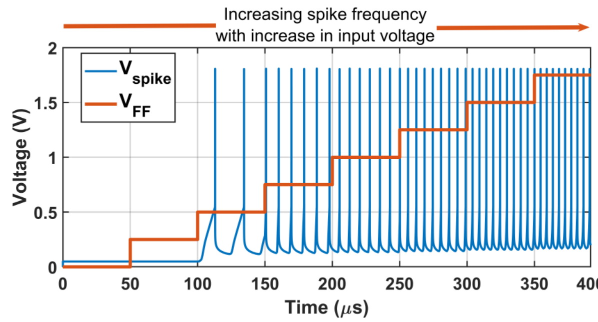


Fig. 4. Response of spiking LIF neuron to different input step voltages given at T_{FF}.

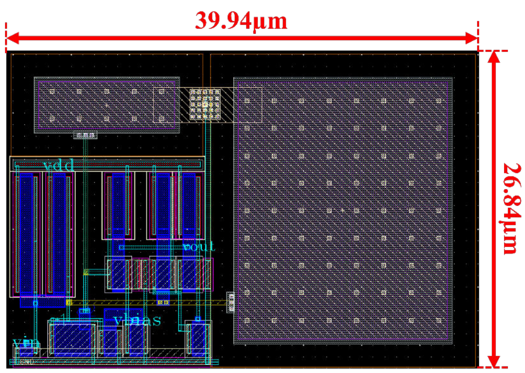
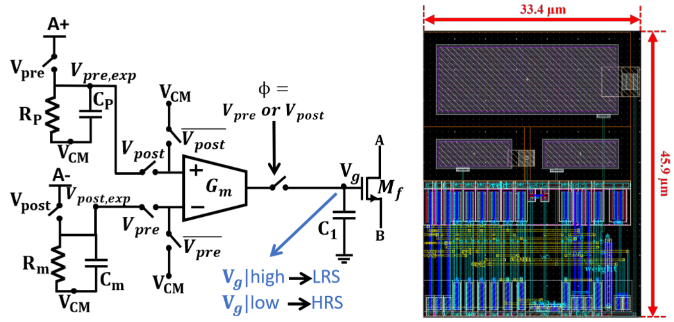


Fig. 3. Layout of LIF neuron circuit.



(a) (b)

Fig. 5. (a) CMOS circuit of memristive STDP learning synapse [15]. (b) Layout of STDP synapse circuit.

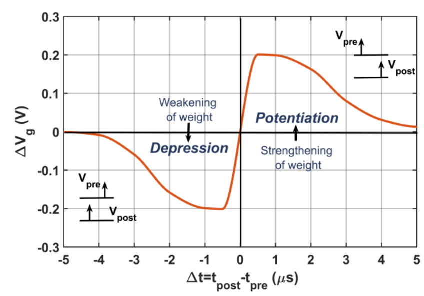


Fig. 6. STDP characteristic curve obtained from the synapse circuit. Depression and potentiation leads to weakening and strengthening of weight respectively.

strengthens due to the spiking of both neurons [4]. Besides learning, other neural-inspired functions (listed in [4]), such as forgetting, associative learning when signals arrive with certain time intervals, generalisation and differentiation caused by similar stimuli, are not demonstrated in [12], [13]. In contrast to the above, this work has the following contribution:

1) The entire circuit of the Pavlov associative memory is implemented in the analog domain at the CMOS transistor level.
2) In contrast to the previous works [2]–[4], [6], [7], our architecture uses a CMOS-based memristor synapse circuit for actual circuit implementation rather than using any software-based SPICE models of the memristor. The proposed Pavlov associative circuit is built using on-chip trainable CMOS memristive STDP synapses and LIF neurons.
3) Apart from learning and forgetting, the other biological inspired functions (details of these functions are provided in section III) are also implemented in a much simpler way with less circuit complexity compared to previous works [2], [4]–[6].

II. Background

This section briefs about the basic building blocks used in the proposed circuit design of Pavlov associative memory.

A. CMOS Leaky Integrate-and-Fire (LIF) Neuron

The simplified and low complexity LIF neuron circuit (shown in Fig. 2) proposed in [14] is used in our proposed design of Pavlov associative memory. We have adapted the circuit by changing its parameters to integrate it with CMOS memristive synapse circuit as done in our recent work [10]. The circuit occupies the area of 39.94μm $\times$ 26.84μm as shown in Fig. 3. The post-layout simulation result shown in Fig. 4 depicts the firing response of the LIF neuron to the different step input voltage. This shows the LIF neuron circuit encodes the information in the rate-encoded spike train. This property can be used to achieve learning at different rates

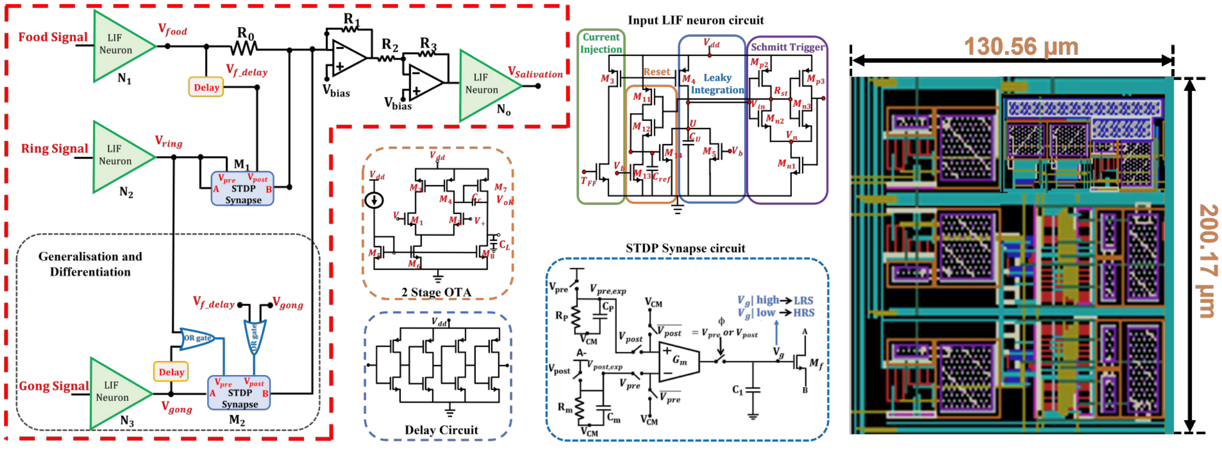


Fig. 7. (a) The proposed full analog CMOS circuit of the Pavlov associative memory. (b) Layout of the Pavlov associative memory's circuit.

B. CMOS STDP Memristive Synapse

STDP is a bioplausible learning mechanism observed in biological neurons to update synaptic strength. The compact memristive synapse circuit adapted from [15], capable of showing the STDP mechanism, is used to demonstrate the on-chip training in our proposed analog design of Pavlov associative memory. The schematic and the layout of the circuit are shown in Fig. 5. The STDP learning curve obtained from the circuit, as depicted in Fig. 6 shows that the synaptic weight gets strengthened (weakened) when the postsynaptic spike arrives after (before) the presynaptic spike. Thus, it shows the synaptic plasticity essential for building the association between conditional and unconditional stimuli in associative learning.

III. Proposed Circuit for Pavlov Associative Memory

This section describes the proposed analog CMOS circuit design of Pavlov associative memory (shown in Fig. 7) for various bio-inspired functions. The complete system consists of four LIF neurons, one innate synapse R_o having a fixed low resistance value of 100 Ω, and two STDP synapses M_1 and M_2 showing plasticity. The gustatory neuron N_1 sensing the food signal will always activate the salivary neuron to produce spikes. Therefore, both neurons are connected through a low resistance or a high-weighted synapse R_o. The working of the entire system implementing various functions can be understood in the following cases.

A. Learning

The STDP memristive synapse circuit shown in Fig. 5 shows a low resistance state (LRS) and high resistance state (HRS) for maximum (Vg|high) and minimum voltage (Vg|low) over the capacitor C_1 respectively. Initially, the M_1 will be at HRS. Therefore when there is only a ring signal eliciting the spikes of the auditory neuron N_2, the salivary neuron N_0 will not be activated due to insufficient current at the input of the salivary neuron. When auditory and gustatory neurons (N_1 and N_2) are activated at the same time. M_1 will receive the presynaptic signal V_{ring} from the auditory neuron N_1 and delayed postsynaptic signal V_{fdelay} from the gustatory neuron N_2. Thus, every postsynaptic spike will occur after the presynaptic spike, changing the state of M_1 from HRS to LRS. This corresponds to the situation shown in Fig. 8, leading to the strengthening or potentiation of the synapse. As a result of this learning, the salivary neuron N_0 will get sufficient input current to produce spikes even when only a ring signal arrives.

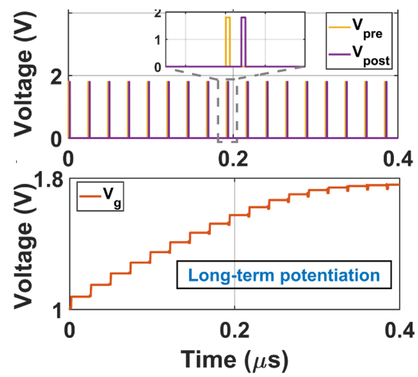


Fig. 8. Simulation of a STDP circuit showing long-term potentiation (LTP) and strengthening of the synapse.

B. Forgetting

Forgetting refers to a process of losing the acquired state of the synapse during learning. When only one signal is given for a long time, the acquired synaptic weight of the STDP synapse starts reducing. State changing from LRS to HRS can be observed as Vg changes from high value to low value due to the capacitor C_1 charge leakage as shown in Fig. 9.

C. Consolidating learning

It should be noted that the STDP memristive synapse circuit shows intermediate states between HRS and LRS. While the

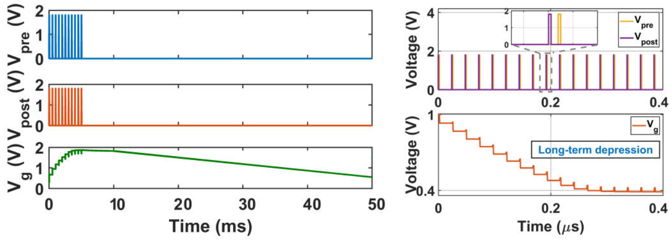


Fig. 9. Change in the gate voltage V_g of the synapse circuit (a) due to charge leakage and (b) due to long-term depression caused by postsynaptic spike occuring before presynaptic spikes.

gate voltage Vg of intermediate dynamic states leaks away faster, the binary states HRS and LRS corresponding to Vg|low and Vg|high will take longer to fade away. Thus, consolidating learning or repeated learning helps retain the memory for a longer time by changing the states into binary values.

D. Learning with stimuli interval

In Pavlov associative memory, the conditioned reflex (producing saliva in response to the ring signal) can also be formed even when there is a time interval between unconditional stimuli (food signal) and conditional stimuli (ring signal). The longer the time interval, the slower the rate of learning [16]. This can be observed in our more straightforward circuit implementation using an on-chip trainable STDP synapse. From the learning curve shown in Fig. 6, it is evident that the rate of increase in the synaptic weight will be higher for closer occurring stimuli in the time since the M_1 synapse receives a presynaptic spike from the auditory neuron and a delayed postsynaptic spike from the gustatory neuron. When the synapse receives both signals, it leads to potentiation or an increase in the synaptic weight (also shown in Fig. 8). However, the increase in the weight will be more for shorter time intervals between the ring and the food signal. In this way, the condition of stimuli interval is implemented in our design of Pavlov associative memory without requiring any other complex circuit module to add this property.

E. Generalisation and differentiation

Generalisation and differentiation refer to the response of the conditioned reflex to similar stimuli. When the association learning is established, the dog will salivate in response to similar stimuli (a gong signal). This corresponds to the case of generalisation. However, in the case of differentiation, similar stimuli do not cause the conditioned reflex [4]. To implement this function, a LIF neuron (N_3) sensing the similar stimuli of a gong signal is used, which is connected to the salivary neuron N_0 through a STDP synapse M_2. During the learning process, when both the food and the ring signal arrive, M_2 synaptic weight will increase as it receives the presynaptic spike (V_{ring}) from a ring signal followed by a delayed postsynaptic spike (V_{fdelay}) from the food signal. Thus, initially, when the gong signal appears, the output salivary neuron N_0 will receive sufficient current to produce spikes due to LRS of M_2. This results in the generalisation

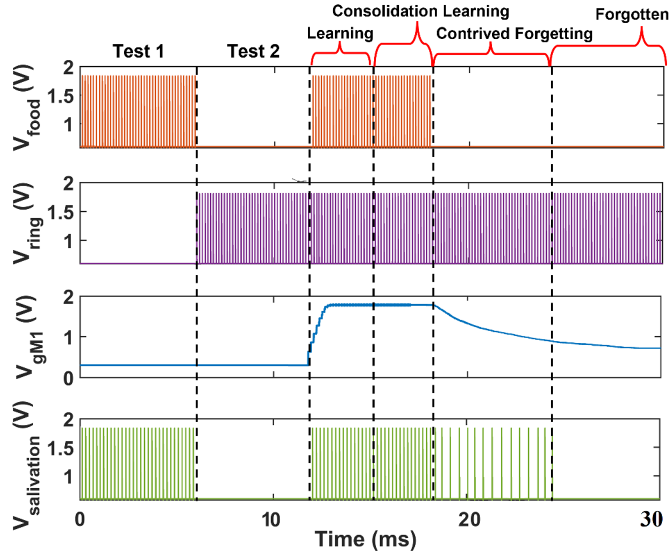


Fig. 10. Simulation of a Pavlov associative memory circuit showing learning, consolidating learning and forgetting.

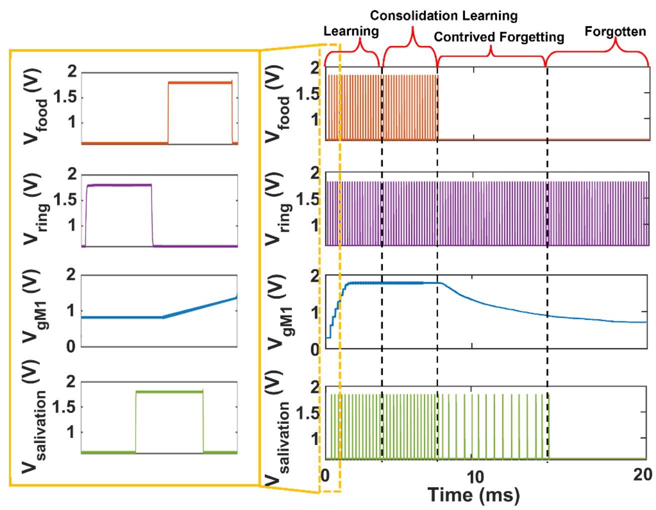


Fig. 11. Simulation of a Pavlov associative memory circuit showing learning, consolidating learning and forgetting in response to interval stimuli.

of similar stimuli. However, when no food signal and only a gong signal is received for a long time, the M_2 weight will start decreasing as now it gets the postsynaptic spikes (V_{gong}) followed by delayed presynaptic spikes (V_{gdelay}) shown in Fig. 9(b). This leads to the differentiation of similar stimuli since now the output salivary neuron will not produce spikes due to the insufficient input summing current.

IV. Simulation Results

This section will discuss the post-layout simulation results of the complete Pavlov associative memory in three different cases.

A. Case1: Learning, consolidating learning and Forgetting

Fig. 10 demonstrates the learning process, consolidating learning and forgetting captured in the designed Pavlov associative memory. In test 1, only a food signal (unconditional stimuli (US)) is given, which activates the salivary neuron and produces $V_{salivation}$. In test 2, only the ring signal (condition stimuli (CS)) is received, and the gate voltage V_{gM1} modelling the weight of the synapse M_1 remains unchanged. Thus, M_1 remain in HRS resulting in the inactivation of a salivary neuron. Now both the US and CS are provided, increasing the synaptic weight of M_1 and establishing associative learning. This learning process is repeated until V_{gM1} reaches its maximum value. This process of consolidating learning helps to change short-term memory to long-term memory. After achieving the learning, when only a ring signal is provided, the weight will start decreasing again. The resistance of M_1 will begin to increase, resulting in less input current at the output salivary neuron. Thus, decrease in the spiking frequency of the output salivary neuron. After this continuous process of contrived forgetting, the weight of the M_1 falls so much that now the input current of the output salivary neuron is insufficient to elicit spikes and the learned state of M_1 is forgotten.

B. Case2: Learning with stimuli interval

The same functions listed in case 1 above can also be observed when there is a time interval between the occurrence of CS and US. Fig. 11 verifies that the proposed Pavlov associative memory can establish learning even when the food signal lags the ring signal. It should be noted that now the number of spike pairs for strengthening or increasing the synapse's weight will be more compared to case 1. Also, the delay should not exceed the STDP time window (refer to Fig. 6) of the synaptic circuit used in our proposed design.

C. Case3: Generalisation and differentiation

The case of generalisation and differentiation is illustrated in Fig. 12. Learning and generalisation happen when both the food and ring signal appears. This leads to an increase in the weight (or decrease in the resistance) of both M_1 and M_2. As a result, the salivary neuron will spike when either the ring signal or a gong signal is sensed. When only the gong signal is provided for a long time, the differentiation process starts, where the weight of M_2 will decrease, and resistance will increase from LRS to HRS. Thus, the salivary neuron will stop spiking in response to the Gong signal. However, when the ring signal is given, the salivary neuron still spikes. This is made possible in circuit implementation because the weight decrease rate of M_2 is much more than the M_1. It can be evident from Fig. 9, the change in the V_{gM1} due to charge leakage of capacitor C_1 is much less than the V_{gM2} change caused by the depression when postsynaptic spikes come before the presynaptic spikes.

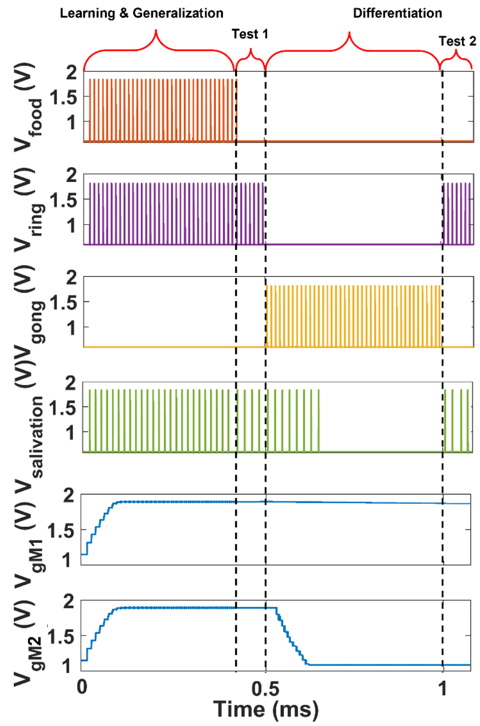


Fig. 12. Simulation of a Pavlov associative memory circuit showing generalisation and differentiation of similar stimuli of gong signal and ring signal.

V. Comparison and Discussion

In comparison to the works [4], [6] listed in Table I, the proposed circuit of Pavlov associative memory is implemented in the analog domain with reduced circuit complexity. In addition, the proposed work demonstrates complete functionality at the CMOS transistor level for actual circuit implementation. In [4], the modules like variable rate control, time interval module, containing op-amps, digital circuits, high-value resistors, and feedback learning circuits are used to implement various neural-inspired functions. In contrast, we have implemented and incorporated the neural-inspired function with the least circuit complexity and using an on-chip trainable STDP mechanism. Analog Pavlov associative memory implemented in [12], [13] demonstrates only learning. Also, the associative learning in [12], [13] (shown with read checkmarks in Table I) does not resembles the neural perspective, as their circuits forms the association between the sensory cortex (gustatory neuron) and the salivary gland. However, the basis of the human brain associative mechanism forms the association between the neurons of the sensory cortex (between gustatory and auditory neurons) [4]. Thus, a more neural-inspired circuit of Pavlov associative memory with multi-function is proposed in this work.

Given the prospect, the proposed system can be adapted for the association between multi-sensory neurons. This would help to correlate one type of sensory information to the other. The wide applications of associative memories are explored in works [2], [3] for developing emotions and cognitive abilities

TABLE I
COMPARISON OF CIRCUIT IMPLEMENTATION OF DIFFERENT PAVLOV ASSOCIATIVE MEMORY CIRCUITS

	[4]	[6]	[12]	[13]	This work
Implementation type	Digital	Digital	Analog	Analog	Analog
Learning	✓	✓	✓*	✓*	✓
Forgetting	✓	✓	×	×	✓
Generalisation	✓	✓	×	×	✓
Differentiation	✓	✓	×	×	✓
Stimuli interval	✓	×	×	×	✓
Circuit complexity	High	High	Low	Low	Low
Full CMOS circuit at transistor level	×	×	✓	✓	✓

*The demonstrated learning does not resemble the true neural-inspired Pavlov learning.

in robots.

VI. CONCLUSION

The complete circuit of Pavlov associative learning is demonstrated at the CMOS transistor level. Apart from learning and forgetting, other neural-inspired functions (such as learning with stimuli interval, generalisation and differential of similar stimuli) are also incorporated in the proposed circuit with less circuit complexity in comparison to previous works. Instead of forming the association between the sensory neuron and the salivary gland implemented in most of the earlier works, the correct neural-based associative learning is established in our work between the sensory neurons in the gustatory and auditory cortex. In addition, the CMOS memristive STDP synapse circuit is used for actual circuit implementation rather than any software-based SPICE model of memristors or synapses. The learning is achieved using on-chip trainable STDP synapses without extra digital control circuitry. The post-layout simulation results verify the functionality of the proposed full CMOS circuit of Pavlov associative memory.

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