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Pavlov associative memory in a memristive neural network and its circuit implementation

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ABSTRACT

Associative memory is the process by which an association between two stimuli or a behavior and a stimulus is learned. This paper contributes to propose a memristive neural network and realize the Pavlov associative memory through (a) putting forward a novel average-input-feedback (AIF) learning law; (b) proposing a detailed two-terminal charge-controlled SPICE memristor models; (c) building a memristive neural network (MNN) circuit, for the first time, to realize the Pavlov associative memory. The results prove the effectiveness of AIF on facilitating the memristor for associative learning in memristive neural networks.

1. Introduction

Memristors, theoretically postulated by Chua in 1971 [1] and physically developed by William and his team at HP labs in 2008 [2], has received increasing attention from both academic as well as industrial communities. Till now, people in growing numbers have applied it to many research fields based on a variety of characteristics of the memristor [25,23,24,22,7]. The memristor and synapses share extremely similar characteristics in the aspect that the memristor can also continue to increase or decrease the resistance. Therefore, it makes undoubtedly the research on using memristors to construct artificial neural networks a hot spot [4–6,9–13,16,20,14].

Since associative memory can be induced in animals and we, humans, use it extensively in our daily lives, the network of neurons in brains can execute it very easily. Arguably, the most famous example of this is the experiment conducted on dogs by Pavlov [3], which makes people believe such behavior can also be reproduced in artificial neural networks [17–20]. Pavlov put forward the concept of unconditioned response through a series of experimental studies of dogs [3]. For example, the ptyaloreaction result of our putting food into the dog's mouth, is a brain response; and there is a direct connection between sense of sensory or hypencephalon and motor nerves. In contrast, for conditional reflex, when the dogs hear the bell or others which in the past are neutral stimulus sound, they will emerge saliva phenomenon. That is the result of formation of new reflection channel in cerebral cortex when the condition is established.

Meanwhile, Hebbian learning law is ordinarily regarded as an effective algorithm to achieve the associative learning for a neural network [8,18]. And we will describe it here again. That is to say, if two neurons often generate action potentials or trigger (fire) simultaneously, the connection between two neurons will become stronger, otherwise weaker. However, it is unfortunate that Hebbian learning law cannot be applied to associative correcting. In fact, during the correcting process, the connection between the pre-synaptic neuron (ring) and the post-synaptic neuron (salivation) should become weaker and weaker, but based on Hebbian learning law, it will become increased. To solve this problem, some papers presented a new learning law, that is, the max-input-feedback learning law (MIF law) [20]. In the interesting work [20], the Pavlov experiment was done to demonstrate the associative memory process in a memristive artificial neural network (ANN). Although MIF law can bridge the gap that Hebbian learning law cannot be used for associative correction, it also has own problem. It will highlight the maximum stimulating voltage as input signals. Since only one maximum input can be used by all of the following process, the network cannot judge whether there is only one maximum input or several other inputs to form conditional reflex in the neural network. Furthermore, the neural associative mechanism will not be able to set up new channels of reflection.

Therefore, in order to solve the above problem, in this paper the average input feedback law (AIF) is addressed. In addition, we

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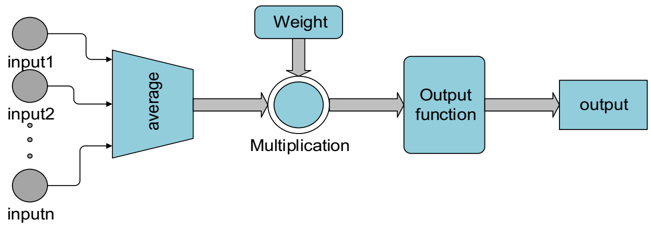

Fig. 1. The neuron structure.

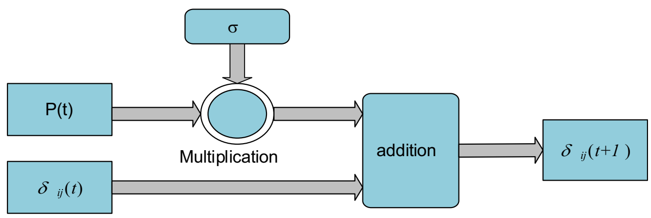

Fig. 2. The learning law of the synapse.

will apply this rule to mathematical modeling and circuit simulation of associative memory based on a memristor neural network.

2. The nerve cell model with AIF learning rule

Neuronal model structure is shown in Fig. 1. Firstly, input the respective average value, which is also the final input value. Then the corresponding weights are multiplied with input value, and the product is obtained after processing the final output of the function output. According to the cell structure, we can build a mathematical model cell. The main basis of establishing the model is a multi-input single-output, and it needs some processing between the output and the input. Proposed AIF rules will be applied in the model (Fig. 2):

Neuronal space function is

$$\begin{cases} IN_{ij}(t) = O_i(t) \quad \delta_{ij}(t) \\ U(t) = \dfrac{\sum_{k=1}^{n} in_k(t)}{n} \end{cases} \tag{1}$$

where $IN_{ij}(t)$ is the input value from pre-synaptic neuron i to the post-synaptic neuron j; $O_i(t)$ is the output of the pre-synaptic neuron i; $\delta_{ij}(t)$ is the weight of synapse connecting neuron i and neuron j; $U(t)$ is the last input value to the neuron; $in_k(t)$ is the k input.

The neuron's working function is

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

where $F(t)$ is the feedback value of the neuron; $Y_O(U(t))$ is the output function; $G_F(t)$ is the feedback function.

The learning law of the synapse is proposed as

$$\begin{cases} \Delta\delta_{ij}(t) = \sigma \quad (O_i(t) \quad F_i(t)) \\ \delta_{ij}(t+1) = \delta_{ij}(t) + \Delta\delta_{ij}(t) \end{cases} \tag{3}$$

where σ is the learning factor; $F_i(t)$ is the feedback value of the neuron i; $\Delta\delta_{ij}(t)$ is the modification of synapse weight.We can set $P_{ij}(t)$ as a work voltage for synapse weight $\delta_{ij}(t)$:

$$p_{ij}(t) = O_i(t) - F_i(t) \tag{4}$$

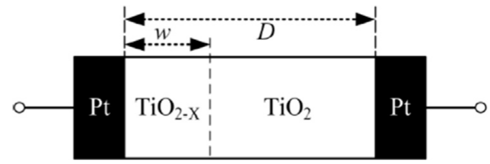

Fig. 3. The HP memristor model.

3. A memristor-based MNN model

A memristor is a passive two-terminal electronic device described by a nonlinear constitutive relation,$v = M(q)*i$, between the device terminal voltage v and the terminal current i. The nonlinear function $M(q)$ termed the memristance is defined by

$$M(q) = \frac{d\,(q)}{dq} \tag{5}$$

Eq. (5) represents the slope of a scalar function $\varphi = \varphi(q)$ termed the memristor constitutive relation. The HP memristor model is shown in Fig. 3.

The HP memristor consists of a thin film (5 nm thick) with one layer of insulating TiO_2 and oxygen-poor TiO_{2-x} each, sandwiched between platinum contacts. The memristance M of such a device can be described as

$$M(w) = R_{ON}\left(\frac{W}{D}\right) + R_{OFF}\left(1 \frac{W}{D}\right) \tag{6}$$

And then the following equation is established:

$$w(t) = \mu_v \frac{R_{ON}}{D} q(t) + w_0 \tag{7}$$

where μ_v is the average ion mobility and w_0 is the initial state for state variable w. From Eq. (7), the state of the memristor begins to move from w_0 with the charge supplied to the memristor. However, the memristor state has a physical constraint, namely $0 \le w(t)/D \le 1$. Note that the memristance is governed by the charge (or flux) through the device, which works normally for $M \in [R_{ON}, R_{OFF}]$; and beyond this range its nonlinearity will degenerate to be linear. The internal memristor state corresponds to the following effective charge range: $q(t) \in [Q_{min}, Q_{max}]$. Specifically

$$Q_{min} = \frac{w_0 D}{\mu_v R_{ON}} \quad \text{AND}$$

$$Q_{max} = \frac{(Dw_0)d}{\mu_v R_{ON}} \tag{8}$$

Therefore, the following equation is obtained:

$$x(t) = \frac{w(t)}{D} = l \quad q(t) + x_0 \tag{9}$$

where $x_0 = w_0/D, l = \mu_v (R_{ON}/D^2)$.

From (6) and (8), one can obtain the linear model of the memristor:

$$M(t) = \begin{cases} R_{OFF}, & q(t) \le Q_{min} \\ M(0) + \eta \quad q(t), & Q_{\min} < q(t) < Q_{max} \\ R_{ON}, & q(t) \ge Q_{\max} \end{cases} \tag{10}$$

where $\eta = (R_{ON} - R_{OFF})*l$.

Because the memristor has the characteristics of memory, it will keep the properties under the discrete-time voltage.

The discrete form of Eq. (6):

$$M(t+\Delta t) = \begin{cases} M(t) = R_{OFF}, & q(t) \le Q_{min} \\ M(t) + \eta * \Delta q(\Delta t), & Q_{min} < q(t) < Q_{max} \\ M(t) = R_{ON}, & q(t) \ge Q_{max} \end{cases} \tag{11}$$