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Predicting House Price With a Memristor-Based Artificial Neural Network

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ABSTRACT Synaptic memristor has attracted much attention for its potential applications in artificial neural networks (ANNs). However useful applications in real life with such memristor-based networks have seldom been reported. In this paper, an ANN based on memristors is designed to learn a multi-variable regression model with a back-propagation algorithm. A weight unit circuit based on memristor, which can be programmed as an excitatory synapse or inhibitory synapse, is introduced. The weight of the electronic synapse is determined by the conductance of the memristor, and the current of the synapse follows the charge-dependent relationship. The ANN has the ability to learn from labeled samples and make predictions after online training. As an example, the ANN was used to learn a regression model of the house prices of several Boston towns in the USA and the predicted results are found to be close to the target data.

INDEX TERMS House price predicting, neural network, memristor, memristive synapse.

I. INTRODUCTION

The idea of building an artificial brain has existed for a long time. Artificial neural network (ANN) is a possible method to realize artificial intelligence. Until now, researchers have made many amazing achievements in the applications like pattern recognition [1]–[3], face detection [4], [5], learning cat concept from cat videos in the internet [6], classifying [7], and playing Go game [8]. However, most of these works were implemented with CPUs and GPUs. Both have separated memories and processors and consume a large amount of energy [8]. Another way to realize artificial intelligence is to design a customized integrated circuit (IC), which consumes much less power and works in a high speed [7], [9]. However, the customized IC has difficulties in online training, and usually, the neural network in the customized IC [10] has to be trained with the help of von-Neumann computers.

In 1983, Michalski proposed a machine that can learn from labeled samples [11]. In 1986, Rumelhart introduced a back-propagation (BP) algorithm to train ANN online automatically [12], [13]. In 1971, Chua [14] predicted the fourth basic circuit element, namely, the memristor, which was later demonstrated in laboratory by Strukov et al. [15] in 2008. Subsequently, some studies showed that memristors could be used as electronic synapses in ANN [16], [18]. For example, ANN consisting of neurons and memristor-based synapses was used to mimic the associate function of human brain [16], [19].

In this work, a multi-layer feed-forward neural network has been designed using memristors as electronic synapses to realize automatic online training. Memristor weights of the ANN can be adjusted by the BP algorithm to build up a regression model spontaneously, which is different from the classification model realized with memristor-based network in [1]. The trained ANN has been used to predict the house price of several Boston towns in the USA, and the predicted result is close to the target data.

II. SIMULATION AND METHODS

A. THE ARCHITECTURE OF ANN

The house price predicting system is illustrated in Figure 1. The ANN used in the house price predicting system is constructed with memristor synapses. The relevant labeled information (i.e. a labeled data includes thirteen parameters and its corresponding target house price) is used to train
As shown in Figure 2(b), \( V_{bpi} \) is the back propagation voltage applied to the \( i \)th line in \( V \), while \( V_{sj} \) is the input voltage applied to the \( j \)th column in \( V \). As shown in Figure 2(c), \( V_{bp} \) is the back propagation voltage, and \( V_{hi} \) is the voltage transferred from the hidden layer to the \( i \)th column in \( W \). \( V_{fix} \) is a constant voltage applied to \( b_1 \) and \( b_2 \). The circuit of the weight unit with one memristor is illustrated in Figure 2(d). All of the circuits shown in Figure 2 are designed and simulated with Cadence and MATLAB, respectively.

As shown in Figure 3, the weight matrix element \( v_{ij} \) (\( i = 1, 2, \ldots, m \); and \( j = 1, 2, 3, \ldots, n \)) is connected to the input vector \( x_j (j = 1, 2, \ldots, n) \) in \( X \). The \( j \)th Neuron of the hidden layer \( (N_j^{(Hidden)}) \) collects the currents \( i_{ij} \) (\( j = 1, 2, 3, \ldots, n \)) from the weight units \( v_{ij} (j = 1, 2, 3, \ldots, n) \), and the currents are integrated in the membrane potential capacitor \( C_{MEM_i}^{(Hidden)} \) (\( i = 1, 2, \ldots, m \)) connected to the transfer function module \( f_1 \). The output \( h \) of the neuron is determined by \( f_1 \) according to
Equations (5) and (6).

\[ h = f_1 (V \cdot X + b_1) \]  \hspace{1cm} (5)

where \( f_1 (x) = \frac{1}{1 - e^{-x}} \).

\[ \beta_i = f_1 (\beta_i + \gamma_i) \]  \hspace{1cm} (6)

\( \beta_i \) is the sum of the synaptic currents flowing through all membranes of \( N_i^{1 \text{ hidden}} \) and \( \gamma_i \) is the possible leak current of the \( i \)th membrane of \( N_i^{1 \text{ hidden}} \).

\[ \hat{y} = f_2 (W \cdot h + b_2) \]  \hspace{1cm} (7)

where \( f_2 (x) = cx \) and \( c \) is a constant. \( \hat{y} \) can also be rewritten as

\[ \hat{y} = f_2 (\alpha + \theta) \]  \hspace{1cm} (8)

where \( \alpha = \sum_{j=1}^{m} (w_{ij} \cdot h_j) \) is the sum of synaptic currents which flow through the membranes of \( N^{\text{output}} \) and \( \theta \) is the possible leak current of the membrane of \( N^{\text{output}} \).

\section*{B. WEIGHT UNIT DESIGN BASED ON MEMRISTOR}

The memristor was predicted by Chua according to the symmetry of circuit theory [14]. In this work, we adopt the memristor model reported in [18]. Supplementary Notes 1 and Supplementary Figure 1 present the details of electrical characteristics of the memristor model used in this work. Voltage pulses above \( v_{th} \) can also be used to adjust the conductance of memristor as well as the weight. In this work, \( v_{th} \) is set to 0.5 V.

Weight matrix contains weight units and biasing units as shown in Figure 2(b) and Figure 2(c), respectively. The biasing unit is similar to the weight unit except that its magnitude is fixed at 0.5 V. As shown in Figure 2(d), the memristor-based weight unit consists of two switches, a memristor, a micro current detector and a multi-output current mirror. The memristance (i.e., the resistance of the memristor) can be adjusted to an appropriate magnitude by the voltage across the memristor. The multiplication can be realized by obtaining the current flowing through the memristor which is driven by the voltage pulse. In order to avoid convergence of the ANN to a local minimum point, the memristances of the memristors are set to random values in a uniform distribution during system initialization. When the current sink is connected to the output, a positive weight is obtained; when the current source is connected to the output, a negative weight is obtained.

In the training mode, the back propagation pulse amplitude is fixed at 0.5 V. The switches at the anode and cathode of one memristor can change the polarity of the voltage pulse. When the weight is positive, positive pulses can increase the conductance of the memristor as well as the weight, while negative pulses can reduce the conductance and also the weight. The detailed circuit design for the whole ANN is discussed in Supplementary Note 2 and Supplementary Figure 2.

\section*{C. TRAINING AND PREDICTING METHOD}

In the training mode, the ANN is able to adjust the weight online automatically based on the BP algorithm. The square of the error between the target result \( \hat{y} \) and the predicted output \( y^k \) (\( y^k \) represents the predicted result for the \( k \)th input sample data), \( E_k \), represents the precision of prediction. The steepest descent is adopted to adjust the weight matrixes. \( E_k \), \( \Delta v_{ij} \), \( \Delta w_{ij} \), \( \Delta \gamma_j \) and \( \Delta \theta \) are expressed by Equation series (9).

\[ E_k = \frac{1}{2} (y_k - \hat{y}_k)^2 \]

\[ \Delta v_{ij} = -\eta_1 \frac{\partial E_k}{\partial v_{ij}} \]

\[ \Delta \gamma_j = -\eta_1 \frac{\partial E_k}{\partial \gamma_j} \]

\[ \Delta w_{ij} = -\eta_2 \frac{\partial E_k}{\partial w_{ij}} \]

\[ \Delta \theta = -\eta_2 \frac{\partial E_k}{\partial \theta} \]  \hspace{1cm} (9)

The partial derivatives to \( E_k \) are used to calculate the change of weight (i.e., \( \Delta v_{ij} \), \( \Delta w_{ij} \), \( \Delta \gamma_j \) and \( \Delta \theta \)). The derivative of \( f_1 \) is expressed by Equation (10), and the derivative of \( f_2 \) is equal to the constant \( c \). According to the chain derivative method, the partial derivative can be calculated according to Equation (11).

\[ \frac{d}{dx} f_1 (x) = f_1 (x) \cdot (1 - f_1 (x)) \]  \hspace{1cm} (10)

\[ \frac{\partial E_k}{\partial w_{ij}} = \frac{\partial E_k}{\partial \gamma^k} \cdot \frac{\partial \gamma^k}{\partial \alpha} \cdot \frac{\partial \alpha}{\partial w_{ij}} \]  \hspace{1cm} (11)

where \( \frac{\partial \alpha}{\partial w_{ij}} = h_j \).

By defining \( g = \frac{\partial E_k}{\partial x^2} \cdot \frac{\partial x}{\partial \alpha} = c \cdot (y^k - \hat{y}^k) \), the following expression can be obtained:

\[ \frac{\partial E_k}{\partial v_{ij}} = \frac{\partial E_k}{\partial h_i} \cdot \frac{\partial h_i}{\partial v_{ij}} \]

\[ = \left( \frac{\partial E_k}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial \alpha} \cdot \frac{\partial \alpha}{\partial h_i} \right) \cdot \left( \frac{\partial h_i}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial v_{ij}} \right) \]

\[ = (g \cdot w_{ij}) \cdot h_i (1 - h_i) \cdot x_j \]  \hspace{1cm} (12)
By setting $e_h = \frac{\partial E_k}{\partial y_k} = \frac{\partial E_k}{\partial h} \cdot \frac{\partial h}{\partial y_k} = (g_{ij} \cdot w_{1i}) \cdot h_j (1 - h_i)$, Equation series (13) can be obtained:

$$
\begin{align*}
\Delta v_{ij} &= \eta_1 e_h \cdot x_j \\
\Delta y_i &= -\eta_1 e_h \\
\Delta w_{ij} &= -\eta_2 g \cdot h_j \\
\Delta \theta_j &= -\eta \partial E_k / \partial \theta_j = -\eta_2 g
\end{align*}
$$

In the training mode, the initial output $y^k$ is calculated by the ANN, and the teacher’s signals are applied to the output layer. With the BP algorithm, the weight of the output layer is updated, and the weight of the hidden layer is updated according to Equation series (13).

In the circuit design, the difference between the output $y^k$ and the teacher’s signal $h_j$ can be represented by the BP signal $(y^k - y^k)$. Then the BP signal modulates the delay time.

By applying the teacher’s signal, the feed-forward signal $h_j$ of the hidden layer is generated again. The implementation of the BP algorithm is based on the linear increase segment of the STDP rule (Supplementary Figure 3(f)) [18], [19]. The voltage of the pre-synapse is modulated by the amplitude, while the voltage of the post-synapse with amplitude $V_{th}$ is modulated by the delay time. When the delay time is zero, the voltages on both the anode and cathode are the same such that the voltage across the memristor is zero. If the delay time is longer than 1 ms, it is considered as positive; otherwise it is negative. When the delay time is positive, the voltage during the delay time at the transient edge is beyond the threshold voltage, and the memristance changes following Equation (14). The change of memristance is proportional to both the delay time and amplitude of the post-synapse voltage. Neglecting the high order series of Equation (15), $\Delta M$ is proportional to the product of delay time $t_d$ and $V_{pre-syn}$.

$$
\begin{align*}
\Delta M_{ij} (t_d, V_{pre-syn}) &= \int_0^{t_d} f (V_{pre-syn}, V_{th}) dt \\
&= \int_0^{t_d} I_0 \left( e^{V_{pre-syn} + V_{th}} - e^{V_{th}} \right) dt
\end{align*}
$$

where $t_d = A_m \cdot (y^k - y^k)$ and $V_{pre-syn} = h_j \cdot V_{th}$.

Then

$$
\begin{align*}
\Delta M_{ij} (t_d, V_{pre-syn}) &= \int_0^{t_d} I_0 e^{V_{th}} \left( e^{V_{pre-syn}} - 1 \right) dt \\
&\approx \int_0^{t_d} I_0 e^{V_{th}} \left( 1 + \frac{V_{pre-syn}}{V_0} - 1 \right) dt \\
&= I_0 e^{V_{th}} \cdot \frac{V_{pre-syn}}{V_0} \cdot t_d \\
&= I_0 e^{V_{th}} \cdot (h_j \cdot V_{th}) \cdot A_m (y^k - y^k) \\
&= A_p \cdot h_j \cdot (y^k - y^k)
\end{align*}
$$

where $A_p = \frac{h_j}{V_0} V_{th} \cdot A_m \cdot e^{V_{th}}$

The input layer generates the amplitude-modulated signal, while the hidden layer generates the waveform which is modulated by the delay time $t_d$ based on Equation series (13). $t_d$ can be generated by an analog multiplier which produces the output $t_{ij} = A_m \cdot (g \cdot w_{1i}) \cdot h_j (1 - h_i)$. In this case, the change of $M_{ij}$ follows

$$
\Delta M_{ij} (t_d, V_{pre-syn}) = A_p \cdot g \cdot w_{1i} \cdot h_j (1 - h_i)
$$

In the predicting mode, the input module converts the input data vector $(x^k = (x_1^k, x_2^k, \ldots, x_j^k, \ldots, x_N^k), k \in (1, 2, 3, \ldots N)$ to individual voltage pulses whose levels are proportional to the input data $x_j$. The voltage pulses are applied to the anodes of the first weight matrix unit (the $V_{th}$ is set to 0 V), and the voltage pulses are multiplied with the corresponding weights to output current signals. The currents are collected by $C_{MEMI}^{Hidden}$ ($i = 1, 2, \ldots, m$) of the neuron in the hidden layer. In the output layer, $C_{MEM}^{Output}$ is used in a way similar to that of $C_{MEMI}^{Hidden}$ to collect the currents, and the output is finally obtained by the conversion from the current to voltage signal by the linear function module $f_2$.

### III. RESULTS

The house price can be predicted by inputting relevant parameters, such as crime rate, property-tax rate, pupil-teacher ratio, etc. As an example, the data in suburbs of Boston obtained from [20] is used. The relevant data is normalized to its maximum value of each parameter. The data is divided into two sets: one is for training and the other is for prediction. Before training, the weights are randomly set in the uniform distribution, and the error histogram is showed in Figure 5(a). As observed in the figure, the errors are large and randomly distributed.

Then, the ANN is switched to the training mode, and the relevant parameters are input to the ANN; at the same time, the target house price is fed to the output layer as the supervision signal. The weights are adjusted according to the

![FIGURE 5. Occurrence rate of errors before training (a), after training with the parameters from the training set (b) and test set (c), and loss function (MSE) vs epoch (d).](image-url)
BP algorithm to make the outputs close to the target prices during the training process.

The mean square error (MSE) loss function ($\text{Loss function} = \sum_{k=1}^{N} (y_k - \hat{y}_k)^2$) is used to estimate the performance of the network. The loss function decreases gradually with the increase of training epoch, and reaches a saturation value of \(\sim 0.24\) after \(\sim 50\) epochs, indicating successfully learning of house price prediction, as shown in figure 5(d). The error histogram is roughly concentrated to zero after 200 training epochs, as shown in Figure 5(b). Finally, the parameters of the test set, which are not used to train the model, are fed to the trained ANN, and the error histogram is showed in Figure 5(c). The errors between the predicted prices and the target prices are small and distribute in a very narrow region (about \([-0.25, 0.25]\)), which again proves that the trained ANN is able to precisely predict the house prices.

IV. CONCLUSIONS

In this paper, a 2-layer feed-forward neural network is designed using memristors as synapses. The weights of synapses can be adjusted online by the pulse voltage with BP algorithm. The ANN has the ability to learn to predict the house price under training mode, and then can successfully predict the house price in the predicting mode. The ANN was trained with the house price samples of several Boston towns in the US to make predictions, and the predicted results are found to be close to the target data.

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