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Memory Impulse Neural Networks for Text Recognition

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Abstract: Current text recognition tasks rely on evolutionary algorithms based on Convolutional Neural Networks (CNN), which achieve good accuracy in the task, but it relies on large datasets and has high latency. In this paper, a complete amnesia based impulse neural network (SNN) model is constructed and the STDP unsupervised learning algorithm is taken for training thereby performing the text recognition work. Using this scheme, this paper incorporates the nonlinear properties of the memristor and constructs a LIF model that is more consistent with the pulse output of a real biological neuron. Based on this, an STDP learning network based on the synaptic properties of amnesia-like synapses is constructed and trained, and the introduction of amnesia can save storage space and power consumption as well as improve real-time performance. This scheme can accurately and quickly identify the sample text through simulation, and the research scheme in this paper has inspirational effects for number recognition, pattern recognition, etc.

Keywords: Spiking Neural Network(SNN), Memristor (memory transistor), Spike Timing Dependent Plasticity(STDP), Optical Character Recognition(OCR)

1. Introduction

In recent years, neuromorphic computing has gained wide attention and great development in the field of artificial intelligence, and one of its important goals is to simulate the computational process of biological neural networks through hardware to achieve brain-like computing.[1] Since the first generation of neural networks was proposed, the development of technology has also led to more problems, the first generation of neural networks, also known as the perceptron, which only has an input layer and an output layer, and can not solve the problem of linear indivisibility, the emergence of the second generation of neural networks solved the defects of the first generation of neural networks can not simulate the heterogeneous or logic, but also introduces the problem of locally optimal solutions.[2,3] As a result, the third generation of neural networks, Spiking Neural Networks (SNN), has emerged. The working mechanism of Spiking Neural Networks is developed based on the way neurons in the brain interact, and therefore has better interpretability in the biosciences and is able to deal with more complex and difficult tasks, and therefore it is closer to real biological neural networks' neuron models. neuronal models, aiming to bridge the gap between bioscience and machine learning.[4] The biggest advantage of SNN is that the signals are in the form of pulses, which interact with each other in binary, i.e. there are only ‘yes’ and ‘no’ cases. SNN is an event-driven neural network, i.e., the neural units in an impulse neural network are activated and active only in the presence of an impulse drive, whereas the network is in a resting state in the absence of an impulse

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input, because of which this property determines that such a network can efficiently utilise the neuron's active time, thus saving energy consumption.[4]

Text recognition, as a human perceptual function, is of great significance to the development of artificial intelligence, and OCR technology has been widely used in various fields, such as licence plate recognition, document processing, face recognition and so on.[5] In order to improve the accuracy of text recognition, some studies have combined CNN and RNN to obtain recurrent neural network (CRNN), which relies on large-scale labelled datasets for supervised learning, and the algorithm mainly consists of image input, preprocessing, text detection, text recognition, and result output, which exchanges the algorithm's complexity for the accuracy of recognition.[6] However, it still suffers from, for example, complex pre-processing of large amounts of labelled data in the process of data processing and training models, as well as a large number of model parameters and high latency, making it difficult to run in real time on low-power devices. In addition, some supervised learning algorithms applied to artificial neural networks are less compatible and difficult to apply in pulsed neural networks, since the information in the latter is transmitted in the form of a sequence of pulses, which are non-continuous.[7]

Improvements in the form of information transfer as well as learning algorithms are needed to better apply third generation neural networks in the field of text recognition. In recent years, amnesia-based memory-computer integration technology has received widespread attention due to its low resource overhead and high computational efficiency. A memristor acts as a piece of hardware whose resistance can be varied with the voltage applied to its terminals, which is equivalent to being able to mimic a synapse undergoing a process of adaptive regulation.[8] And it can be used to store synaptic connection weights itself, thus eliminating the need for additional memory, saving storage space and energy consumption, and improving system integration.[9] Therefore, amnesia has become one of the best choices for artificial synapses.

The research in this paper consists of constructing a model of impulse neural network based on amnesia, and the said impulse neural network enables the recognition of some words. In this paper, we use the nonlinear characteristics of the memristor to improve the pulse generation and output circuit on the basis of the LIF neuron model, to get the output closer to the biological neuron pulse, so as to build the pulse neuron circuit model based on the memristor, and use the simulation experiments to verify that the designed neuron model is able to simulate the shape of the pulse which is more in line with the biological action potentials. Then this paper uses the variable resistance value of the memristor to simulate biological synapses, in which the conductance value of the memristor indicates the synaptic weight value, builds the STDP learning circuit with the help of the memristor and adopts the STDP unsupervised learning law to train the network, and finally verifies that the memristor pulse neural network can complete the classification and recognition task of the simple text under a relatively fast speed through simulation.

2. Theoretical studies

2.1. Mechanisms of neuronal modelling

The most basic component unit in an impulse neural network is the impulse neuron. Important components of neurons include dendrites, cell bodies and axons, from which input signals from other neurons are collected and transmitted to the cell body, where the main determinants of impulsive neuronal action are membrane potentials and threshold voltages. When the cell body collects current or voltage accumulation from the input signal resulting in a membrane potential at or above the threshold voltage, it releases an impulse signal, which propagates along the axon without attenuation and passes to the next neuron through the synapse at the end of the axon, and a large number of interconnected neurons form a neural network.

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Researchers and scholars have proposed several typical mathematical models to simulate the action potentials of real biological neurons. In 1952, Hodgkin and Huxley proposed the Hodgkin Huxley (HH) model based on the nonlinear differential equations for the physiological phenomena of neuronal cell membrane potentials. The HH model can accurately simulate the process of membrane voltage changes and pulse issuance in biological neurons, but due to its large number of micro and integral operations, the hardware implementation is difficult.[10] Compared to the HH model, the LIF neuron model greatly reduces the computational complexity while retaining certain bionic features, and can be easily deployed to hardware platforms with greater hardware friendliness.

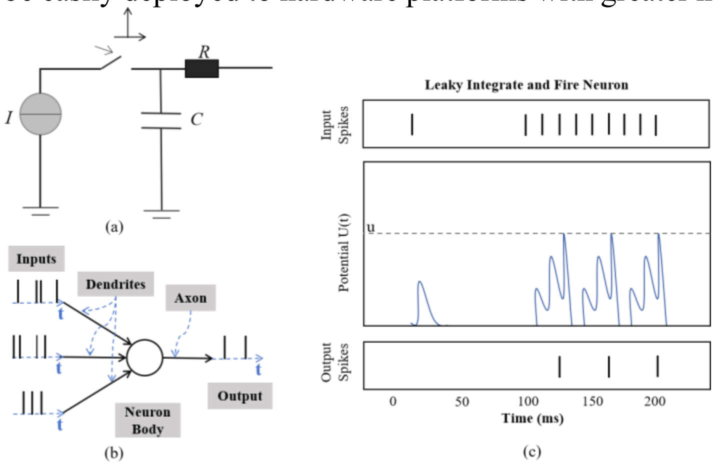

Figure 1: LIF modelling diagram.(a)Simplified RC circuit diagram of the LIF model.(b)Input impulses generated by the neuron are transmitted through the dendrites to the neuronal body, where sufficient excitation triggers impulse firing at the output.(c)The simulation depicts an image of the membrane potential U(t) reaching a threshold value, with an arbitrarily set threshold voltage of u, producing an output pulse.

The LIF model diagram is shown in (a) of Fig. 1. Under the action of the current flowing through the ion channel, the cell membrane of the pulsatile neuron will generate an action potential u(t). When the action potential reaches the threshold, the neuron will emit a pulse, and this process can be described as:

$$u(t^{(f)}) = u_{th} \tag{1}$$

$$\frac{du(t)}{dt}\Big|_{t=t^{(f)}} > 0 \tag{2}$$

where $t^{(f)}$ is the time for the neuron to emit a pulse and u_{th} is the threshold voltage.

The LIF model achieves effective modelling of the biological properties of neurons by simulating the process of neurons accumulating charge and releasing impulses, and its simple structure makes it widely applicable to the modelling of most impulsive neural networks. The input current is integrated through the capacitor, and the voltage across the capacitor in turn represents the membrane potential of the neuron, which is activated when the membrane potential exceeds the neuron's threshold voltage, thus releasing the impulse, while the charge on the capacitor leaks through the branch, resulting in the reset of the neuron's membrane potential to a resting state. These steps correspond to the entire process of integration, pulse issuance and leakage in the model, and thus it has the core mechanism by which biological neurons are activated to release pulses.

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2.2. An impulse neural network synaptic weight learning method(STDP)

STDP can be traced back to Hebb's rule that ‘neurons that fire together make their connections stronger’, a concept first proposed by Canadian psychologist Donald Hebb in 1949 that describes how neurons adjust their synaptic strengths in response to each other's frequency and synchronisation of activity.[11]

STDP not only considers the frequency of activity between neurons, but also introduces a temporal factor to further refine the rules of adjustment between synapses, which has a good biological basis. According to neuroscience it is known that if a presynaptic impulse arrives within a few milliseconds before a postsynaptic impulse, it causes LTP; conversely, it causes LTD. Changes in synaptic weights are represented by a function of the relative timing of presynaptic pulse arrivals and postsynaptic excitations, called the STDP function, which is biologically interpretable.

The total weight change can be expressed as:

$$\Delta w_j = \sum_{f=1}^{N} \sum_{n=1}^{N} W(t_i^n - t_j^f) \tag{3}$$

where t_i^n is the time at which the postsynaptic pulse is emitted and t_j^f is the time at which the presynaptic pulse is emitted.

The STDP function is as follows:

$$\begin{cases} W(x) = A_+ \exp(-x/\tau_+) & \text{for } x > 0 \\ W(x) = -A_- \exp(x/\tau_-) & \text{for } x < 0 \end{cases} \tag{4}$$

Where A_+ and A_- are the magnitude sizes that regulate weight increases and decreases, and τ_+ and τ_- are the time constants of weight increases and decreases that determine the rate of weight change.

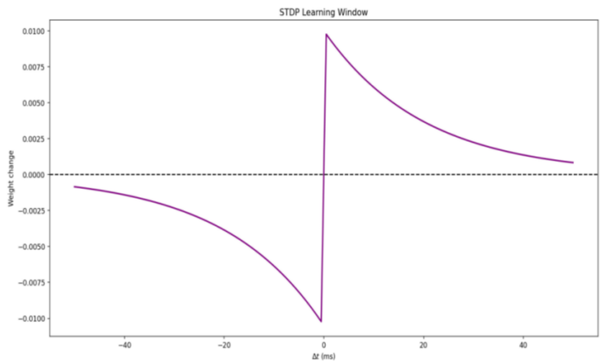

Figure 2:STDP Learning Curve

In impulse timing-dependent plasticity, an input signal to a neuron becomes stronger if it occurs at an instant before the output signal of the entire neuron; conversely, it becomes weaker. This plasticity is believed to be the core basis for functions such as learning, memory, and real-time computation. For example, when learning the same point, it is easier to learn it a second time than the first time because the strength of the connections at the synapses corresponding to this point has been enhanced by the previous learning process. The STDP law is a ‘natural’ biological learning law in biological systems. Unlike traditional artificial neural networks that use various algorithms such as gradient descent algorithms for network optimisation, the application of the STDP law allows the impulse neural network to spontaneously optimise its learning.

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2.3. Article research content and validation

2.4. Constructing a Memristor-Based LIF Neuron Model

Based on the above analysis of the typical neuron model LIF, its advantage is that it is simple to compute and easy to implement on hardware circuits, but since the LIF model emphasises on the performance of releasing pulses, according to the circuit diagram of the LIF model proposed in the article, the shape of the pulses obtained from its simulation is spike-like, which is very different from the shape of the pulse signals generated by real biological neural networks.

In this paper, the non-linear nature of the memristor is exploited and added to the neural network to make the simulated pulses more consistent with the real pulse variations. Since the state of the memristor can be modulated by pulses so that its conductance value reflects the synaptic weights, signalling between neurons can be achieved in pulsed neural networks. Meanwhile, the voltage threshold setting of the memristor modulation can be used as a condition to trigger the adjustment of the synaptic weights and realise the dynamic update of the synaptic weights, which makes the memristor synaptic circuits have a wide range of applications in constructing the impulse neural network.

In this paper, in order to obtain a voltage scenario more in line with real biological neural network pulses, the original LIF circuit has been improved by combining the neuron circuits in the literature, and the improved circuit contains: one memristor, eleven MOS tubes and two capacitors.

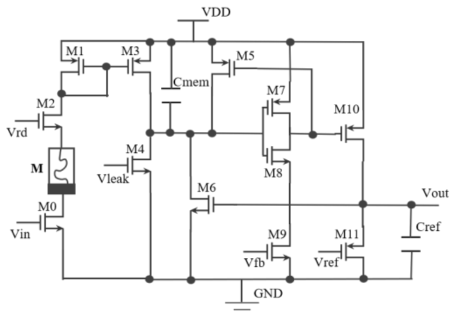

Figure 3:Circuitry of the improved impulse neuron model

There are five main voltages that are important in the diagram:

1.V_{rd}:The read voltage of the memristor M, a small voltage that does not allow the memristor state to be modulated (clamped by M2)

2.V_{in}:Input Voltage

3.V_{mem}:Neuronal membrane potential (both ends)

4.V_{th}:Threshold voltage to make the inverters (M7,M8) flip-flop

5.V_{fb}:The voltage that controls the size of V_{th}

The complete circuit can be roughly divided into three main sections:

1.Integral function:Composed of M1,M2,M3,M4 and M1,M3 will mirror the current of the memristor, capacitance C_{mem} integral and thus accumulate the voltage V_{mem} at both ends.

2.Pulse generation function:Composed of M5, M7, M8, M9 and M7, M8 form the inverter, when V_{mem} greater than the threshold voltage decided by the M9 gate voltage inverter flip-flop, M5 and the inverter constitutes a positive feedback circuit will be pulled V_{mem} to a high level thus the circuit will generate a pulse

3.Depolarisation function:Composed of M6,M10,M11 and M6 will pull V_{mem} back to GND, and the charge accumulated on C_{ref} will be released through M11.

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By hardware simulation, when the input pulse is a periodic pulse sequence, the circuit integrates the input pulse sequence until the membrane potential exceeds the threshold voltage and then releases the pulse, after which it enters a period of inappropriateness, which involves the process of depolarisation, repolarisation and hyperpolarisation of the membrane potential of the neuronal cell. Comparison with the pulses generated by real biological neurons shows that the improved amnesia-based pulsed neuron model yields shapes that are more in line with the pulses of real biological neurons, and the pulse images can be simplified to the curves shown in Figure 4.

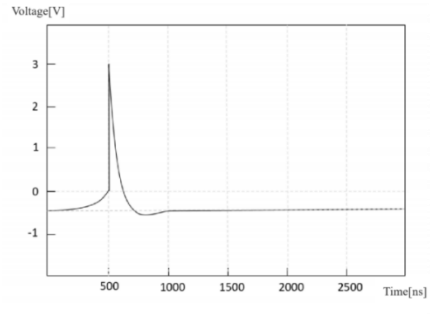

Figure 4:Simulated simplified image of the output pulse

2.5. Construction of learning circuits based on amnestic synapses with STDP-binding lateral inhibitory mechanisms

In this paper, we use STDP unsupervised algorithm for learning in impulse neural network, we need to get the time before and after the synapse the neuron releases the impulse to reach the synapse as well as the amount of change in the synaptic weights. Since the conductance value of the memristor is used to reflect the synaptic weights in this paper, the update of the synaptic weights i.e., the modulation of the state of the memristor is carried out.

The memory pulse neuron circuit built in this paper is denoted by M. In order to stabilise the output voltage, two voltage followers are added to its voltage output, one connected to the presynaptic neuron, which is noted as the output V_{pre}; and one connected to the postsynaptic neuron, which is noted as the output V_{post}, so as to construct the synaptic connectivity network, and thus to carry out the information interaction in the neural network. It is then encapsulated as a new memory impulse neuron module, denoted as MN, as shown in Fig. 5.

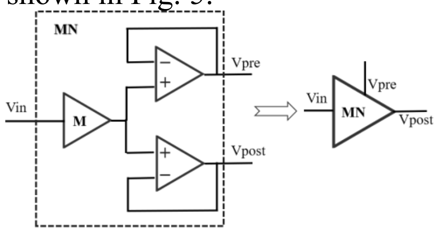

Figure 5:Improved Memory Pulse Neuron Module

Next, the STDP learning circuit is built according to the memory pulse neuron module, taking a 2 × 2 crossed array (input neurons SN1, SN2; output neurons SN3, SN4) as an example, synapses are formed by connecting neurons in the input layer with those in the output layer and synapses are represented by the memristors M13, M14, M23, and M24, and a switch S is used to change the synaptic back end connected to the pathway, the STDP learning circuit diagram is shown in Fig. 6.

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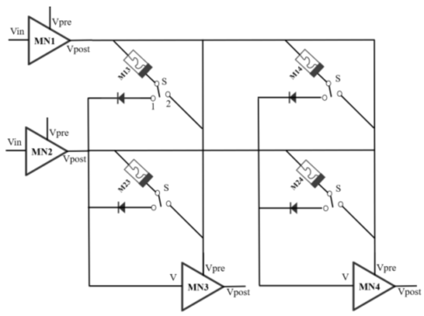

Figure 6:STDP Learning Circuit

The 2 × 2 cross array contains four amnestors representing synaptic nodes. In the initial state S is connected to end 1 and the diode is forward coupled to transmit the pulse sequence generated by SN1 to the neuron SN3 through the post end via M13, when this output voltage is greater than the threshold voltage for SN3 to issue a pulse, SN3 outputs a pulse and connects the switch to end 2, and the pulse output from SN3 is transmitted through the end V_{pre} to the other end of M13. At this time, the voltages at the two ends of M13 are the pulses issued by the presynaptic neuron SN1 and the postsynaptic neuron SN3, respectively. If the pulses released by the presynaptic and postsynaptic neurons arrive at the two ends of the synapse at different times, a voltage difference will be generated at the two ends of the amnesia, and the value of its resistance will be changed spontaneously as a result. Since the synaptic weights in the circuit are represented by the conductance values of the memristors, this enables a process of training and learning of the synaptic weights spontaneously with the input pulses to obtain the final synaptic weights. The role of the diode is to prevent the creation of a pathway between the two input neurons, which affects the input voltage to the postsynaptic neuron, and similarly this 2×2 cross array can be expanded to obtain a larger neuronal network.

The impulse neural network in this paper also introduces lateral inhibition, a mechanism of interaction between neurons, which manifests itself in the fact that the activation of a neuron inhibits the activity of the rest of the neurons that are connected to it via synapses. It enhances the edge detection capability of the network, suppresses noise and improves robustness and stability. In impulse neural networks based on the STDP learning law, the lateral inhibition mechanism often requires a large number of connections to be implemented. The first layer of the network is the input layer of the image and the second layer is the processing layer, where lateral inhibition is achieved by adding the same number of inhibitory neurons as the number of excitatory neurons, where each excitatory neuron is connected to the corresponding inhibitory neuron and each inhibitory neuron is connected to all the excitatory neurons, which inhibit the other excitatory neurons to discharge when one excitatory neuron takes the lead in delivering the pulse. A schematic diagram of this connection is shown in Figure 7.

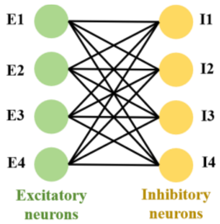

Figure 7:Schematic diagram of lateral inhibition mechanism

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2.6. Simulation experiment: recognizing letter images from A-J

The research goal of this paper is to make the network able to recognize the letter images from A to J. Under the lateral inhibition mechanism, when a neuron in the processing layer is the first to release an impulse, it means that the input pattern at this point is more closely related to the features learned by that neuron, and the training behaviour of the irrelevant neurons is inhibited, which leads to a more accurate recognition of the letters in the network, and at the same time, reduces the unnecessary power consumption. In the letter recognition task this paper uses feed-forward impulse neural network for the construction and training of amnesic impulse neural network, using hardware description language to write the neuron module and STDP learning module in the network, the overall structure of the network is shown in Figure 8.

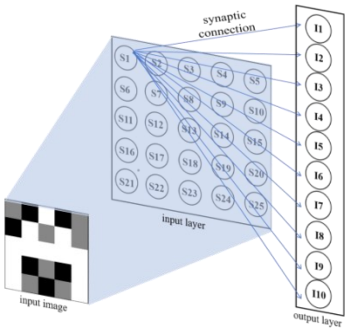

Figure 8:Feed-forward pulse network structure

The amnestic impulse neural network consists of an input layer and an output layer, where neurons in the input layer and neurons in the output layer are connected by synapses and neurons within the same layer are independent of each other. Since the input layer consists of 5×5 neurons, in order to reduce the input features, the images in the dataset need to be degraded and resized, i.e., the digital images are resized to 5×5 pixels, with one neuron corresponding to one pixel on the input image. During resizing and downgrading, much of the information in the image is affected, which reduces the image quality, so inter-area interpolation is performed. The output layer consists of 10 neurons corresponding to the output of the ten letters A-J. The network is trained by updating the synaptic weights of the input layer neurons connected to the output layer neurons by the STDP algorithm.

The dataset in this paper consists of greyscale images of letters from A to J and contains 6,000 training examples and 1,000 test examples. Pulse frequency coding is the most commonly used coding method, i.e., the frequency at which a neuron emits pulses is proportional to the intensity of the information it represents. In this paper, we incorporate pulse frequency coding to transform each pixel in the input image into a set of pulse sequences whose average discharge frequency is proportional to the grey value of that pixel, and the process can be expressed as:

$$p_i = \frac{g_i}{255} \tag{5}$$

$$S_i(t) = \begin{cases} 1, \text{if random}(0,1) < p_i \\ 0, \text{otherwise} \end{cases} \tag{6}$$

In equation(5) the grey value g_i is first normalised by dividing the same by the maximum pixel intensity 255, followed by generating a sequence $S_i(t)$ representing each pixel, whereby, according to the principle of random number generation, when the grey value of a pixel is greater, the number of pulses in the pulse sequence corresponding thereto is greater, thus generating a pulse sequence with an average discharge frequency proportional to the grey value of that pixel. A schematic diagram using this coding approach is shown in Figure 9.

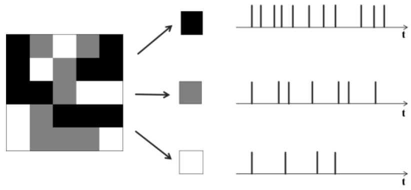

Figure 9:coding schematic

The code for the complete impulse neural network is obtained by writing the code for each module, and according to the STDP learning law, the time difference between the release of impulses by the neurons before and after the synapse acts on the synapses, causing a change in the synaptic weights in the network. The initial weights of the network are set arbitrarily, taking the letter recognition of letter 'A' as an example, the image information is encoded in the form of pulse sequence to interact in the impulse neural network, and the network is trained by STDP unsupervised learning algorithm, the change waveform of the synaptic weights during the training of letter 'A' is shown in Fig. 10(a). After training by the STDP unsupervised learning algorithm, the change of synaptic weights of the network during the training is shown in Figure 10(a). w1_1~w1_25 represent the 25 synaptic weights connected to the first processing layer neuron respectively. It was observed that the synaptic weights were able to reach the final weight values after performing about 3 updates. The synaptic weights are entered into MATLAB in the form of a matrix, and Fig. 10(b) shows the image of the letter 'A' obtained after training, where synaptic weights 0, 1, and 2 correspond to different shades of grey: a synaptic weight of 0 corresponds to black, 1 to grey, and 2 to white. The letters A-J were sequentially trained for recognition by this amnesic pulse neural network, and the network was eventually able to correctly recognise the 5×5 letter images, proving that the neural network functioned correctly and that the written STDP unsupervised learning algorithm was effective.

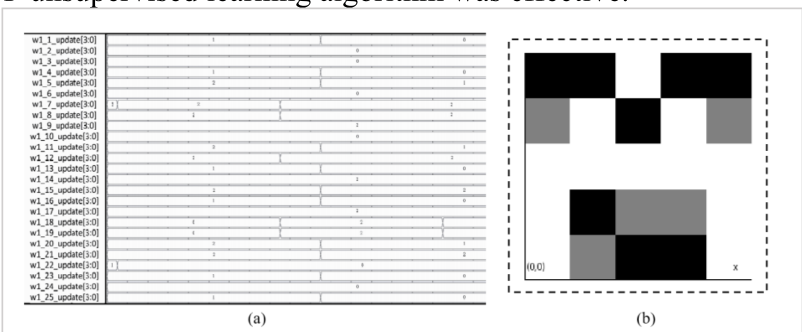

Figure 10:Training process and results of letter A

3. Conclusion

In this paper, we investigate a memristor-based impulse neural network to achieve letter recognition based on 5×5 network on a purely digital hardware platform. One of the main research work is as follows:

(1)Based on the principle of amnesia, a model of impulse neuron based on amnesia is built:The concept of neuronal LIF model is introduced, and the working principles of LIF model and memristor are analysed. The non-linear characteristics of memristor are innovatively combined to the LIF model and improved, so as to get the simulated pulse pattern which is more in line with the real biological action voltage, and the simulation results are analysed and obtained to be in line with the expectation.

(2)The STDP unsupervised learning algorithm was implemented in a memory pulse neural network:Based on the neural network studied in this paper, the STDP unsupervised learning algorithm was finally selected and applied to the STDP learning circuit based on the variable resistance value of the memristor. The ability to use the conductance value of the memristor to reflect the synaptic weights makes the synaptic weights in this memristor pulse neural network can be learned spontaneously, and the network does not need additional memory to store the synaptic weights.

Based on the STDP memristive learning circuit, a memristive impulse neural network is written in Verilog language. Then an A-J black-and-white digital image with preprocessed pixels of 5×5 is used to train the network for image classification, and the input image is preprocessed for frequency coding, i.e., the image information is converted into pulse information to be input into the network, to complete the functional verification of the code. Finally, the trained synaptic weights are input into MATLAB software in matrix form, and the learned digital images are restored using MATLAB's image function, and the analysis results show that the amnesic impulse neural network proposed in this paper has faster recognition speed and higher recognition accuracy.

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