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Study of Recall Time of Associative Memory in a Memristive Hopfield Neural Network

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ABSTRACT By associative memory, people can remember a pattern in microseconds to seconds. In order to emulate human memory, an artificial neural network should also spend a reasonable time in recalling matters of different task difficulties or task familiarities. In this paper, we study the recall time in a memristive Hopfield network (MHN) implemented with memristor-based synapses. With the operating frequencies of 1–100 kHz, patterns can be stored into the network by altering the resistance of the memristors, and the pre-stored patterns can be successfully recalled, being similar to the associative memory behavior. For the same target pattern (the same familiarity), recall time of the MHN varies with the inputs, which is similar to the effect in the human brain that recall time depends on task difficulty. On the other hand, for the same input (i.e., the same initial state), the recall time may be different for different target patterns, which is similar to the effect in the brain that recall time depends on the familiarity. In addition, the effect of stimulation (updating frequency) on recall time may be complicated: a higher stimulation frequency may not always lead to a faster recall (it may even slow the recalling process in some circumstances). Our memristive Hopfield network shows good potential in mimicking the characteristics of human associative memory.

INDEX TERMS Memristors, associative memory, Hopfield neural networks, neuromorphics.

I. INTRODUCTION

Memory, which permits an organism to bridge the past with the present, is a critical and integral part of our cognitive functions [1]. As one type of memory, declarative memory comprises memory for personal experiences and for facts and concepts. It is essentially associative, linking components (e.g., aroma and flower) either directly or via spatial, temporal or other kinds of relationships [2]. Associative memory, as a particular form of declarative memory, is defined as memory for the relationship between initially unrelated items [3]. It is well established that the hippocampus and surrounding medial temporal lobe cortices play an essential role in associative memory [2]–[4]. And it is widely believed that modification of the strength/weight of connections between neurons (i.e., synapses) is the mechanism underlying learning and memory [5]–[8]. One of the most viable theories of cortical associative memory is Hebb's theory of cell assemblies [9], which have inspired many attractor-memory models of cortex. One of the most studied attractor-memory models is the Hopfield network [10]–[13], which is a recurrent network and has been proved useful in content-addressable memories [14] and combinatorial optimization problems [12]. Recall time (or recall speed) varies from person to person, and depends on many factors, such as the difficulty of task [15] and spatial contextual familiarity [16]. Typically, the recall time ranges from microseconds to seconds [15]–[19]. Hardware implementation of artificial neural networks (ANNs) is necessary for realizing associative memories as well as studying the recall time. Recently, memristor has been considered as a promising candidate for implementing the basic element of ANNs, the electronic synapses, due to its excellent scalability, continuously adjustable resistance, nonvolatility, low-operating voltage, low-power consumption, and good compatibility with standard complementary metal oxide semiconductor (CMOS)

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technology [20]–[23]. Memoristor integrates the function of storage and computing. Synaptic behaviors have been demonstrated in memristors at single-device or circuit level [24]–[29], and also some ANNs based on memristors have been demonstrated [30]–[35]. In our previous work, associative memory has been realized in a memristive Hopfield network, which has inspired some other researchers [36]. However, none of them have studied the recall time of the memristive associative memory.

In this work, the recall time of the memristive Hopfield network is studied. Different patterns are stored into and recalled from the Hopfield network at the frequencies of 1-100 kHz. The effects of task familiarity, difficulty and stimulation frequency on the recall time are studied. The result shows that the MHN is promising in mimicking the characteristics of human associative memory.

II. METHODS

Different from back propagation neural networks, the weight matrix of the Hopfield network is calculated according to certain rules. The state of the network changes over time, but the weight matrix remains the same. The output state of each neuron at time $t+1$ is related to the state of the network at time t, according to the following rule [36]

$$X(t+1) = sign(X(t) \cdot W - T) \tag{1}$$

where t denotes the number of updating cycles; $X = (x_1, x_2, x_3)$; and $X(0)$ denotes the initial state vector. Detailed updating mechanism can be found in our previous work [36]. The weight of the network does not change throughout the network iteration. In other words, there is no "training" process to optimize the weight matrix of the network. However, the Hopfield network does need a "energy function" to ensure its stability. Since the weight of the network remains constant throughout the iteration, the energy function of the network must converge to a limited number of stable states over time. In this study, the output state of the network converges to a preset state.

The memristor used to implement the Hopfield network has a metal-insulator-metal (MIM) structure based on HfO_2 thin films. The detail for the memristor fabrication was reported in our previous work [36]. The Hopfield network was constructed with six memristors and commercial IC chips including four transmission gates, seven operational amplifiers and one comparator. Resistance of the memristors was modified off-line with a Keithley-4200 semiconductor characterization system. A field programming gate array (Model No. ALTERA EP2C8Q208C8) was used to generate clock signals, and a RIGOL oscilloscope (Model No. DS4024) was used to record the waveforms of the clock signals and outputs.

III. RESULTS AND DISCUSSIONS

As shown in Fig. 1(a), the Hopfield network consists of three neurons and nine synapses. The circuit implementation of the synapses and neurons is illustrated in Fig. 1(b). The detailed working mechanism of the network can be found in our previous work [36].

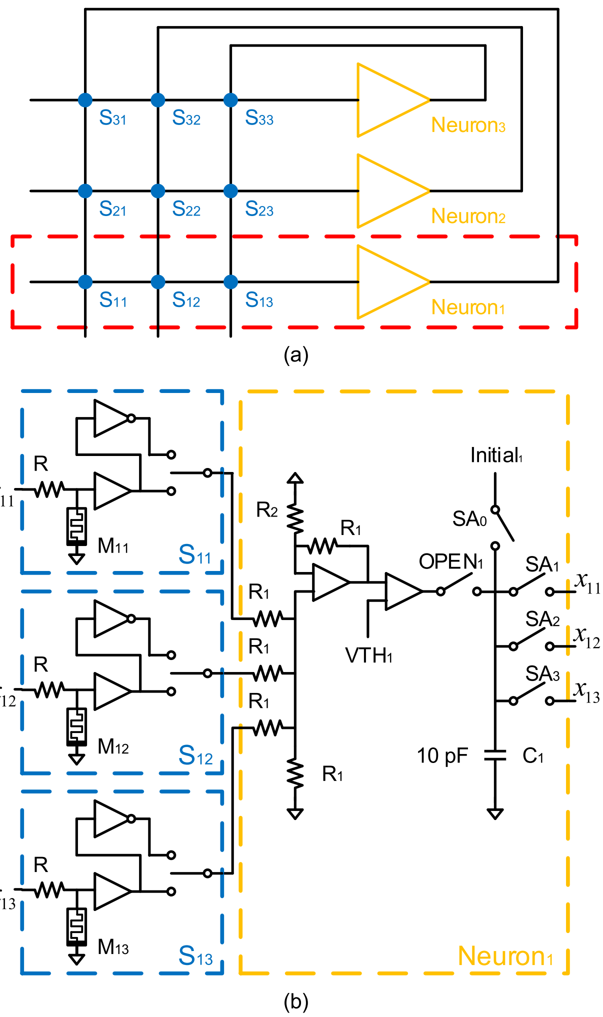

FIGURE 1. The memristive Hopfield network. (a) Architecture of the Hopfield network consisting of nine synapses (filled circles) and three neurons (triangles); (b) circuit implementation of the block (including three synapses and one neuron) enclosed by the dotted lines in (a). Switch SA_0 is used for initial states input into the network.

A. WEIGHT MATRIX IMPLEMENT

To store a single pattern into the Hopfield network, the weight matrix of the Hopfield network can be determined based on the modified Hebbian learning rule or the scheme used in our previous work [37].

When given a target state, the synaptic weight matrix must be symmetric, and the neurons must have no self-feedback, then

$$\begin{cases} \omega_{11} = \omega_{22} = \omega_{33} = 0 \\ \omega_{12} = \omega_{21} \\ \omega_{23} = \omega_{32} \\ \omega_{31} = \omega_{13} \end{cases} \tag{2}$$

To store pattern "101" into the Hopfield network, Equation (1) gives an output state of "101", when the initial state

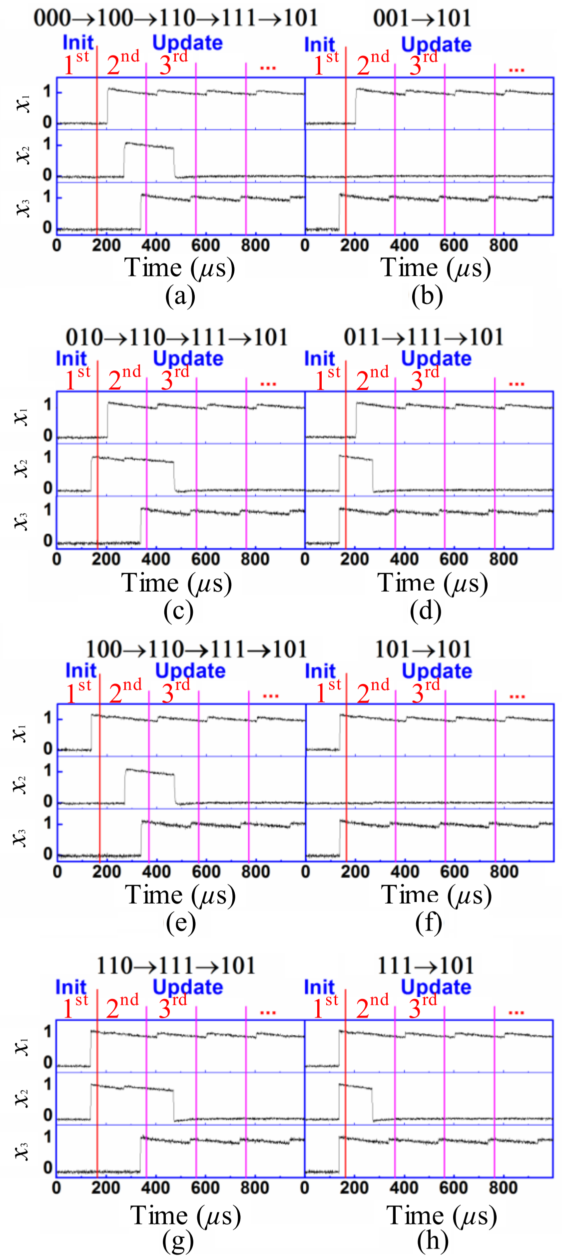

FIGURE 2. Waveforms of x_1, x_2, and x_3 in the process of recalling pre-stored "101" starting from different initial states. (a) "000"; (b) "001"; (c) "010"; (d) "011"; (e) "100"; (f) "101"; (g) "110"; (h) "111". The control clock is 5 kHz.

is "101" already. Then the weight and threshold matrix meets the following relationship

$$\begin{cases} 1 * \omega_{11} + 0 * \omega_{21} + 1 * \omega_{31} - T_1 \geq 0 \\ 1 * \omega_{12} + 0 * \omega_{22} + 1 * \omega_{32} - T_2 < 0 \\ 1 * \omega_{13} + 0 * \omega_{23} + 1 * \omega_{33} - T_3 \geq 0 \end{cases} \tag{3}$$

The state converge order of the network in this study was set as Fig. 2. Then more relationships between weight and threshold matrix similar to Equation (3) can be obtained.

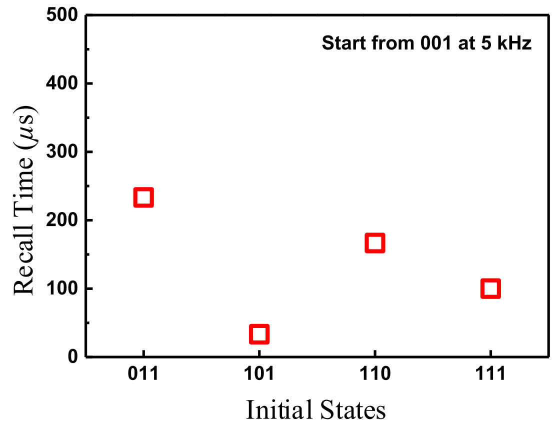

FIGURE 3. Recall time for different initial states for the same target pattern "101". The control clock is 5 kHz.

Since the actual resistance matrix has a limited range of values, the weight matrix was then set as

$$W = \begin{bmatrix} 0 & 0.01755 & 0.07715 \\ 0.01755 & 0 & -0.077377 \\ 0.07715 & -0.077377 & 0 \end{bmatrix} \tag{4}$$

The threshold voltage was set to

$$T = (-0.033 \quad -0.033 \quad -0.033) \tag{5}$$

And the resistance matrix was set to

$$M = \begin{bmatrix} 0.1 & 53.6 & 250.8 \\ 53.6 & 0.1 & -251.6 \\ 250.8 & -251.6 & 0.1 \end{bmatrix} k\Omega. \tag{6}$$

B. STUDY OF TASK DIFFICULTY

Figure 2 shows the waveforms of neuron states (x_1, x_2 and x_3) in the process to recall the pre-stored "101" for different initial states. In Fig. 2, the output low voltage (around 0 V) and high voltage (around 2 V) are normalized to "0" and "1", respectively. Three clocks with the frequency of 5 kHz and the duty ratios of 1/3 were used to control the switches SA_1, SA_2 and SA_3 (Fig. 1(b)), respectively. As can be observed in Fig. 2, starting from any initial state, the Hopfield network eventually stabilizes at "101", i.e., it successfully recalls "101", which can be used to emulate associative memory. Taking Fig. 2(a) as an example, starting from "000", in the updating cycles, neuron states were updated asynchronously from x_1, x_2 and x_3, respectively, according to the following rule [36] as Equation (1). Detailed updating mechanism can be found in our previous work [36].

Similarly, starting from the other seven initial states, the Hopfield network can successfully recall the pre-stored "101" by experiencing some intermediate states as shown in Fig. 2. The recall time is defined as the duration from the updating state to the final state at which the network stabilizes. The time required for recalling "101" at 5 kHz ranges from 33.3 μs to 300 μs depending on the initial state (Fig. 3). The target pattern "101" for all of the different initial states means that the MHN has the same familiarity for the

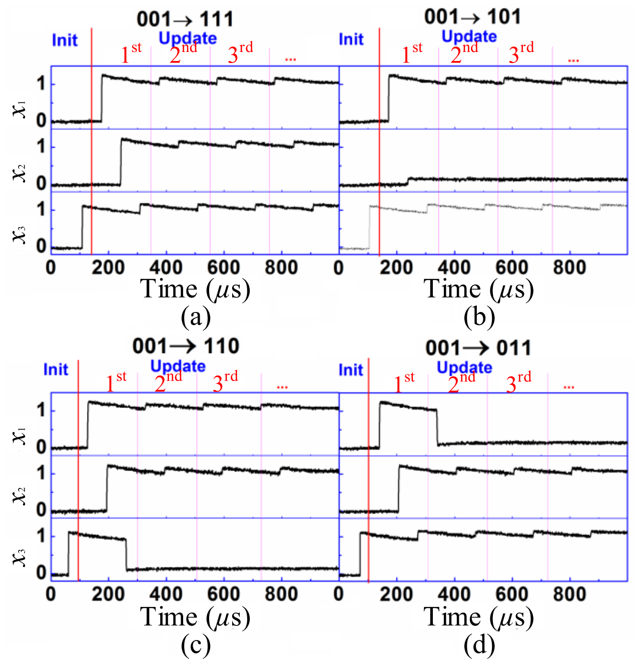

FIGURE 4. Waveforms of x_1, x_2, and x_3 in the process of recalling different target patterns of (a) "111"; (b) "101"; (c) "110" and (d) "011". The initial state is "001" for all the target patterns. The control clock is 5 kHz.

target, while the different initial states lead to different task difficulties in memorization. In the associative memories, there are some simple tasks such as convergences from "001" to "101" (Fig. 2(b)), and from "111" to "101" (Fig. 2(h)), which cost a shorter time to recall. There are also difficult tasks, e.g. the convergence from "000" to "101", which take much longer time to recall. The difficulty level depends on the initial state, the Hopfield matrix, the threshold and the updating sequence [36].

C. STUDY OF FAMILIARITY

Figure 4 shows the waveforms of recalling (a) "111", (b) "101", (c) "110" and (d) "011" for the same initial state of "001" at a control frequency of 5 kHz. Different final states (i.e. the patterns) as shown in Fig. 4 can be considered as tasks with different familiarities. In human memory, tasks of different familiarities may lead to different recall time also. Indeed, as can be observed in Fig. 5, recalling "101" is a familiar task (the recall time is 33.3 μs), while retrieving "011" is an unfamiliar task (the recall time is 233.3 μs).

D. STUDY OF STIMULATION EFFECT

Varying the updating frequency is a simple way to study the stimulation effect. In human memory, stimulation may be a "double-edged sword". Normally, a high frequency of stimulation (updating) may lead to a faster recall. However, in some circumstances, when a stimulation with a very high frequency is applied to our brain, we might, on the contrary, recall a thing slowly. The MHN also exhibited such behavior. Figure 6 shows the evolution of neuron states during recall

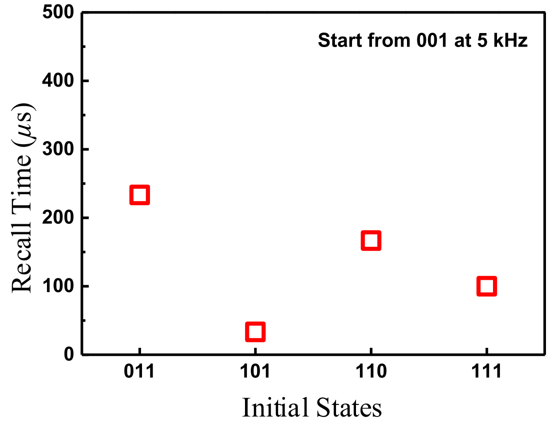

FIGURE 5. Recall time for different target patterns but the same initial state of "001". The control clock is 5 kHz.

process at the operating frequency of 50 kHz. As can be observed in Fig. 6 (a), (c), (e), and (g), the network can recall the pre-stored state "101" starting from "000", "010", "100", and "110" in the same recalling sequence as that at the frequency of 5 kHz (Fig. 2 (a), (c), (e), and (g)). However, the recall time at the frequency of 50 kHz is shorter than that at the frequency of 5 kHz. The recall time for different initial states but the same target pattern "101" at the frequency of 50 kHz extracted from Fig. 6 is summarized in Fig. 7. As can be observed in the figure, the recall time is the same for different initial states.

On the other hand, as shown in Fig. 6(b), (d), (f) and (h), to recall state "101" from initial states "001" and "101" at the frequency of 50 kHz, more updating cycles are experienced than in the operations at the frequency of 5 kHz (Fig. 2(b), (d), (f) and (h)). Taking initial state "001" for example, in Fig 2(b), in the 1st updating cycle, the neuron states evolved from "001" to "101", and then it remained unchanged following Eq. (4); while in Fig. 6(b), in the 1st updating cycle, the Hopfield network evolved from "001" to "101", and then it changed to "111", not following Equation (1); in the 2nd updating cycle, the neuron states evolved from "111" to the final state "101". Similarly, additional "111" appeared in Fig. 6(f) as compared to Fig 2(f). And in Fig. 6(d) and (h), the intermediate state "111" experienced one more updating cycle compared with that in Fig. 2(d) and (h), respectively. Fortunately, although some additional states may be experienced and more updating cycles may be needed at the operating frequency of 50 kHz, the Hopfield network can retrieve the pre-stored "101" from all initial states, i.e., recall correctly. The additional states and more updating cycles are induced by the high operating frequency. When the Hopfield network works at a high frequency, there is no enough time for capacitor C_i of Neuron i (Fig. 1(b)) to completely charge or discharge. That means there may be not enough time to update the state of a neuron. And thus the recall process may not exactly follow Equation (1). However, as the network can converge to some states that do not need switching between charging and discharging states,

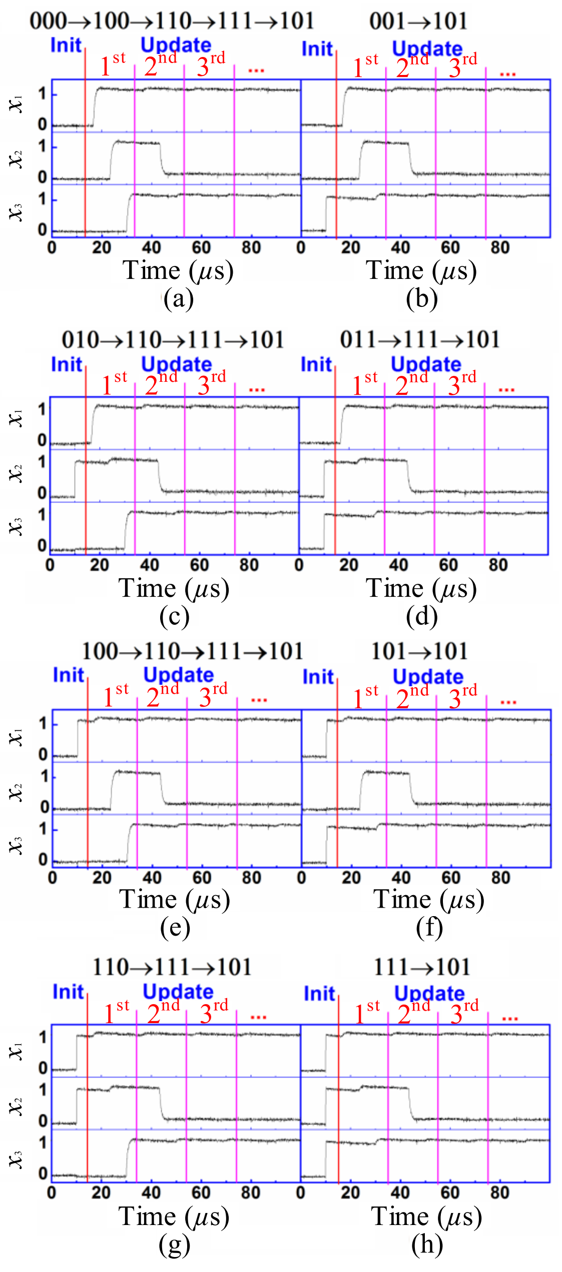

FIGURE 6. Waveforms of x_1, x_2, and x_3 in the process of recalling pre-stored "101" starting from different initial states. The control clock is 50 kHz.

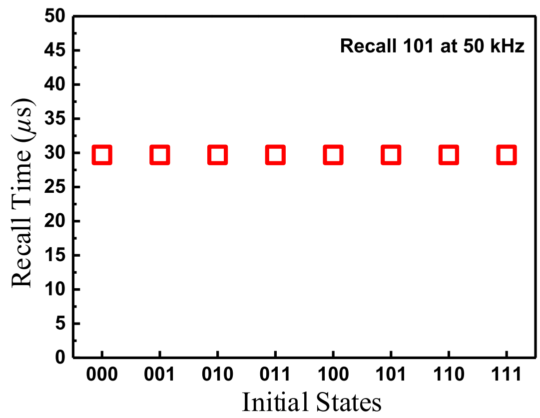

FIGURE 7. Recall time for different initial states but the same target pattern "101". The control clock is 50 kHz.

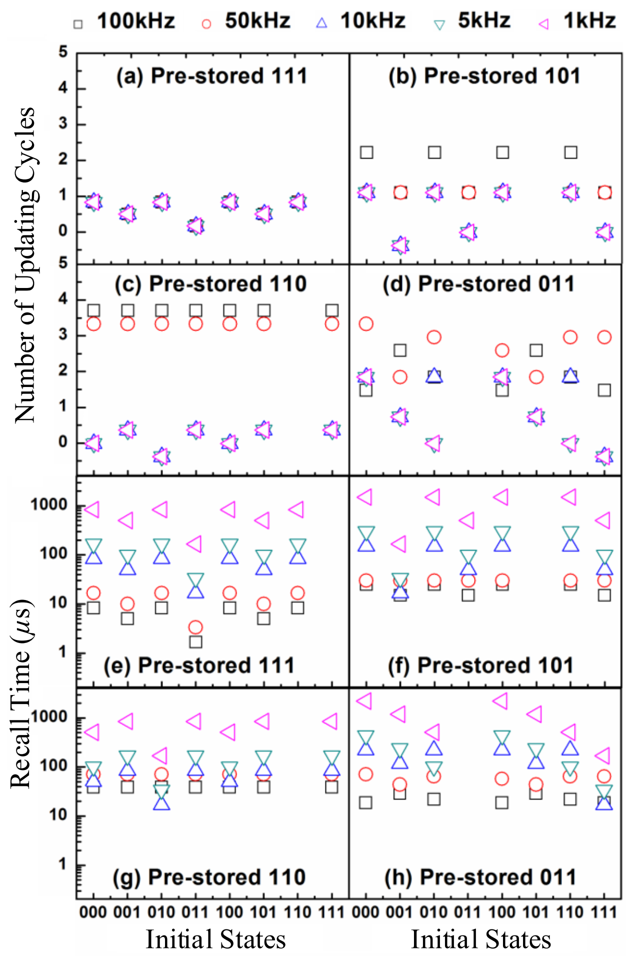

FIGURE 8. Number of updating cycles required to recall the pre-stored states of (a) 000; (b) 111; (c) 110 and (d) 101 from different initial states; Recalling time from different initial states to pre-stored states of (e) 000; (f) 111; (g) 110 and (h) 101.

like "111", it can finally recall the target state. There are two characteristics in the MHN that can be used to emulate the human memory: (1) as discussed early, a higher stimulation frequency may not lead to a faster recall in some circumstances; and (2) in many cases recalling follows a recall rule like Eq. (4) step by step, but in other cases intermediate states or more updating cycles that cannot be predicted are experienced.

As the recall process may be influenced by updating frequency, the number of updating cycles needed to recall the pre-stored patterns "111", "101", "110" and "011" are summarized in Fig. 8 (a)-(d), respectively, for different operating frequencies. And the recall time are shown in Fig. 8(e)-(h), correspondingly. As shown in Fig. 8(a)-(d), at low frequencies (1 kHz and 5 kHz), the recall process from any initial states follows Eq. (4) perfectly; i.e., the sequential states shown in the figures can be calculated according to Eq. (4). The number of updating cycles required to recall "111" "101", "110" and "011" does not change with frequency when the frequency is low (1 kHz and 5 kHz). However, at the higher frequencies (10 kHz, 50 kHz and 100 kHz), the recall process shows some complexities. As shown in Fig. 8(a) and (e) for recalling "111", the number of updating cycles for recalling "111" is the same for different operation frequencies. And thus the recall time only depends on the frequency, i.e., a high updating frequency leads to a short recall time. In recalling "111" from other initial states, only charging of capacitor C_i was required to achieve the state of "1". No discharging of C_i at high frequencies results in the converging process following Eq. (4), i.e., no additional intermediate states were experienced. As one example of such scenario, recalling "111" at the frequency of 100 kHz is shown in Supplementary Fig. 1 in supplementary material. Similar situation is observed for recalling "000" at the frequency of 100 kHz as shown in Supplementary Fig. 2 in supplementary material. On the other hand, for recalling other patterns of "101", "110", and "011", switching between "1" and "0" were experienced, i.e., switching between charging and discharging of C_i is necessary. And thus at high operation frequencies, additional updating cycles are needed.

There are two factors that affect the recall time: one is the number of updating cycles; and the other is the updating frequency (or stimulation frequency). Therefore, as observed in Fig. 8(e)-(h), in many cases the recall time is shorter at a higher frequency. However, in some cases the recall durations may be larger at a higher operation frequency; for example, as shown in Fig. 8 (g), for initial state "010", the recall time at 50 kHz ($\sim$70 μs) is longer than that at 5 kHz (33.3 μs) and 10 kHz (16.7 μs). This situation is interesting, and it could emulate the complex reaction of human brain when a matter has the same familiarity and same initial input. For example, sometimes someone pushes us at a high frequency to remember something; however, we may, on the contrary, take it in mind more slowly.

In [15]–[19], associative memory recall time ranges from microseconds to several seconds. The recall durations in this work seem to be shorter. Delay circuits or a larger C_i can be used to realize millisecond memorizations or slower situation. In order to realize a network that can work even faster than our human brain, a quick associative memorization is necessary. In this case, a smaller C_i or high speed operational amplifiers could be employed.

E. NETWORK STABILITY STUDY

Effect of the variations in the Hopfield threshold and matrix element on the recall time has been studied also. The details can be found in Supplementary Notes 1 and 2, Supplementary Tables 1 and 2, and Supplementary Figures 3-6 in the supplementary materials. The results show that the variations in threshold and matrix element take effect on the recall time of the MHN: In many cases the recall time remains unchanged and in some cases the variations in threshold and matrix elements prolong the recall time.

IV. CONCLUSION

The recall process of a memristive Hopfield network consisting of nine synapses and three neurons has been studied. The recall time shows dependence on both task familiarity and difficulty. In addition, the stimulation effect on recall has also been investigated. The result shows that stimulation may have a complex effect on recall. In many cases, a high stimulation frequency leads to a fast recall; but in some cases it slows down the recall process.

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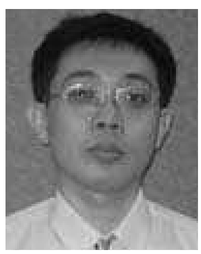

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