

2013 Special Issue

Adaptive Neuromorphic Architecture (ANA)

Frank Zhigang Wang^{a,*}, Leon O. Chua^{a,b}, Xiao Yang^a, Na Helian^c, Ronald Tetzlaff^d, Torsten Schmidt^d, Caroline Li^a, Jose Manuel Garcia Carrasco^e, Wanlong Chen^a, Dominique Chu^a

^a School of Computing, University of Kent, UK^b Department of Electrical Engineering and Computer Science, University of California, Berkeley, USA^c School of Computer Science, University of Hertfordshire, UK^d Electrical Engineering, Technische Universität Dresden, Dresden, Germany^e Facultad de Informatica, Universidad de Murcia, Spain

ARTICLE INFO

Keywords:

Memristors
Neuromorphic engineering
Neural circuits
Brain-like engineered systems

ABSTRACT

We designed Adaptive Neuromorphic Architecture (ANA) that self-adjusts its inherent parameters (for instance, the resonant frequency) naturally following the stimuli frequency. Such an architecture is required for brain-like engineered systems because some parameters of the stimuli (for instance, the stimuli frequency) are not known in advance. Such adaptivity comes from a circuit element with memory, namely mem-inductor or mem-capacitor (memristor's sisters), which is history-dependent in its behavior. As a hardware model of biological systems, ANA can be used to adaptively reproduce the observed biological phenomena in amoebae.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

Nature shows many unconventional ways of information processing and memristor is such an example. A memristor mimics the synapses between neurons in the brain in terms of being plastic according to the dynamical history of the system (Chua, 1971; Pershin & Ventra, 2009). We reported recently that a memristor neural network performs the Pavlovian experiment on Conditioned Reflex (Wang et al., 2011). Based on our discovered “delayed switching” effect (Wang et al., 2010), it was found that the (stimuli) sequence length, (stimuli) sequence frequency and spike width need to be carefully controlled in such a way that the memristor synapse time delay point should not be overtaken while only one neuron fires. Such neuromorphic architectures could be used in situations, in which it is impossible or infeasible to solve the problems with conventional methods and models of computation (i.e. von Neumann, Turing).

In a typical human brain, there are 10^{11} neurons and 10^{14} synapses (on average, each neuron is connected to other neurons through about 20,000 synapses). It is a great challenge to understand the brain with such extreme complexity and nonlinear dynamics. However, organisms like amoebae display amazing intelligence (Pershin, La Fontaine, & Ventra, 2009; Saigusa, Tero, Nakagaki, & Kuramoto, 2008) and the (memorizing, timing and anticipating, etc.) mechanism in a unicellular amoeba may represent the

origins of primitive learning. Amoebae are one of the simplest creatures that have existed since life began on planet earth. Evolution of life is the process of ever increasing intelligence based, in part, on predicting and controlling the behavior. As shown in Fig. 1(a), an amoeba has a nucleus enclosed in its cell membrane, which is a brain-like organ that controls its actions.

Amoebae have no definite shape and can form an arm, extending from any part of its body (McGrath & Blachford, 2001), as shown in Fig. 1(a). When an amoeba senses food in its surroundings it extends its pseudopodia in that direction and moves towards the food. As shown in Fig. 1(b), the amoeba slows down when the ambient temperature drops at time points S_1 , S_2 and S_3 . When the temperature does not drop any longer, the amoeba can still predict the time of the next temperature drop by slowing down again at the times when the drop would have occurred at time points C_1 , C_2 and C_3 . Furthermore, the amoeba can trigger the oscillations (the learnt temperature varying pattern) when the temperature drops again at S_4 (Saigusa et al., 2008).

The above behavior of amoebae is astonishing in terms of: 1. memorizing the past; 2. predicting the future; 3. the timing of periodic events. To explain this physiological observation, there existed a hypothesis assuming that multiple chemical oscillators of a series of periods underlie the multirhythmicity of locomotion (Coggin & Pazun, 1996). Any environmental change with a certain frequency excites one or more of these oscillators, which could be the source of amoeba's ability to recognize patterns and predict events. The downside of this model is that, there should be a huge number of continuous frequencies of oscillation to cover a series of periods (from 1 s to 24 h). A more realistic assumption is

* Corresponding author.

E-mail address: frankwang@ieee.org (F.Z. Wang).

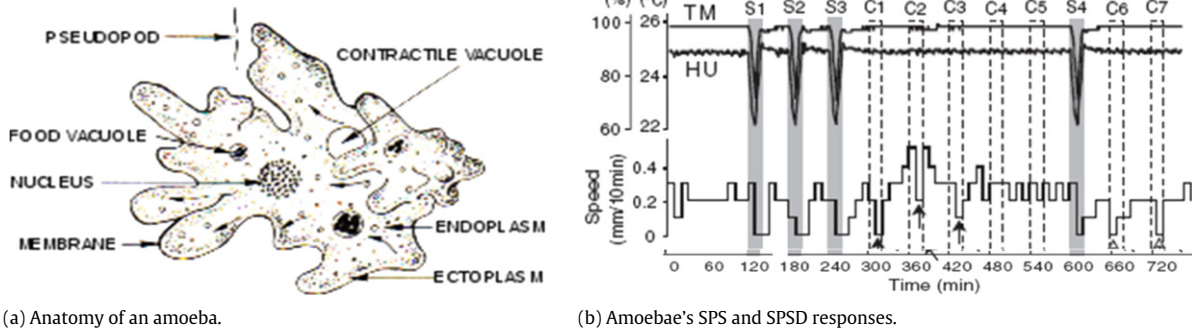


Fig. 1. Anatomy of an amoeba and its behaviors (re-depicted according to McGrath & Blachford, 2001, Saigusa et al., 2008). The amoeba slows down when the temperature drops; when the temperature does not drop any longer, the amoeba can still predict the time of the next temperature drop by slowing down again at the times when the drop would have occurred. SPS: spontaneous in-phase slowdown after three periodic stimuli ($S_1, S_2,$ and S_3); SPSD: SPS after one disappearance after a single stimulus (S_4).

that the actual frequency distribution consists of several discrete major frequencies with deviations that overlap neighboring major frequencies (Saigusa et al., 2008).

It was reported that amoebae's adaptive behavior can be emulated by "Di Ventra's circuit" (a memristor-based RLC circuit) (Per-shin et al., 2009). Inspired by this work, we will design Adaptive Neuromorphic Architecture (ANA) that self-adjusts its inherent parameters (for instance, the resonant frequency) naturally following the stimuli frequency. The architecture uses a circuit element with memory (Chua, 1980, 2009, 2012), namely mem-inductor or mem-capacitor (memristor's sisters), to increment its time constant and subsequently decrement its resonant frequency to match the stimuli frequency. Hopefully, our architecture will help better understand the cellular origins of primitive intelligence.

2. Delayed switch in memristor, mem-capacitor and inductor

We reported that memristor has a peculiar effect in which the switching takes place with a time delay because a memristor possesses certain inertia. This effect was named "The Delayed Switching Effect" (Wang et al., 2010, 2011). In this section, we will prove that this effect should also exist in memristor's sister, memory-inductor (mem-inductor), to be used as a key element in our Adaptive Neuromorphic Architecture (ANA).

As shown in Fig. 2(b), the switching from the high inductance (L_1) to the low inductance (L_2) takes place with a time delay T_d after the application of an input flux. In a neuromorphic circuit, a square-wave signal is equivalent, in terms of switching a mem-inductor, to a sequence of spikes with the same net area of the observation region bounded by the graph of the signal and the time axis (Fig. 2(c)). This is because charge is the time integral of current and the inductance of a mem-inductor is normally a function of charge.

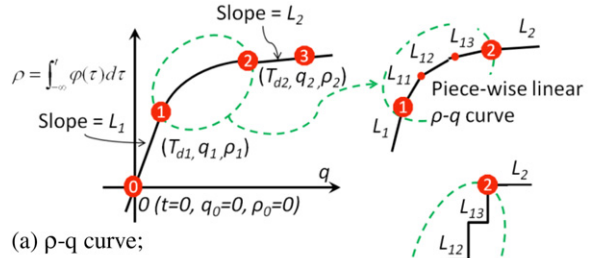
The inductance L of a mem-inductor depends on the complete past history of the current, i.e. the time integral of the current from $\tau = -\infty$ to $\tau = t$. As mentioned above, the current is a sequence of spikes with a stimuli frequency, f_{sti} , and an (equal) spike width, T_w . Therefore

$$i(t) = \frac{\varphi(t)}{L} \tag{1}$$

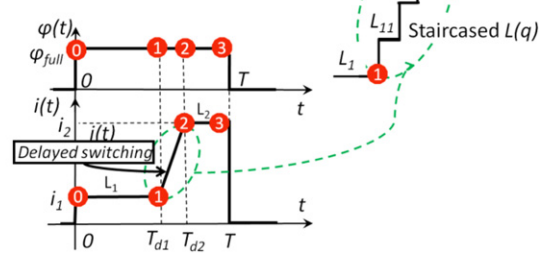
Note that, the output current in Eq. (1) is not an electric current of moving charges (there is no way to flow an electric current in an open-circuited inductor), but a quantity reflecting the strength of the flux via $i = \varphi/L$, which is similar to "displacement current" in Maxwell's electromagnetic equations.

$$q(t) = \int_{-\infty}^{+t} i(\tau) d\tau = \frac{1}{L} \int_{-\infty}^{+t} \varphi(\tau) d\tau$$

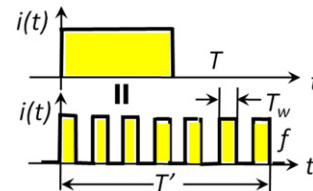
$$= \frac{\varphi_{full} \cdot T_w \cdot f_{sti}}{L} t. \tag{2}$$



(a) ρ - q curve;



(b) Delayed switching;



(c) A square-wave signal is equivalent to a sequence of spikes with the same total area over in terms of delayed switching.

Fig. 2. Mem-inductor's delayed switching effect: the switching from one state (L_1) to another (L_2) due to an input flux pulse takes place with a time delay. The effect also applies to a train of spikes, which are also known as "action potentials" in neurons (short-lasting events in which the electrical membrane potential of a cell rapidly rises and falls). As illustrated in the inset, if the transition period (Time point 1-2) of the ρ - q curve consists of a number of linear segments, the same number of stairs in the current $i(t)$ can be generated.

At the transition points where $t = T_{d1,2}$, we have $q(T_{d1,2}) = q_{1,2}$ and $\rho(T_{d1,2}) = \rho_{1,2}$. Therefore

$$q_{1,2} = \frac{\varphi_{full} \cdot T_w \cdot f_{sti}}{\rho_{1,2}} \cdot T_{d1,2} \tag{3}$$

$$T_{d1,2} = \frac{\rho_{1,2}}{\varphi_{full} \cdot T_w \cdot f_{sti}} \tag{4}$$

That is

$$T_{d1} = \frac{\rho_1}{\varphi_{full} \cdot T_w \cdot f_{sti}} \tag{5}$$

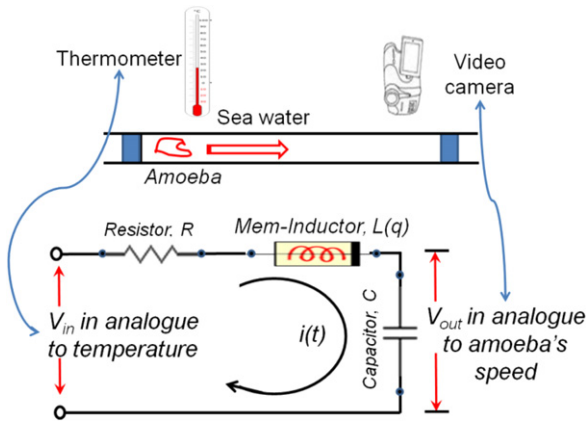


Fig. 3. An RLC neuromorphic circuit using a mem-inductor, $L(q)$, to cover a major frequency with a deviation. In the schematics at the top, an amoeba is put in a long tube full of sea water at a controllable temperature measured by a thermometer. The amoeba migrates along the tube and its position is measured by a video camera.

$$T_{d2} = \frac{\rho_2}{\varphi_{full} \cdot T_w \cdot f_{sti}} \quad (6)$$

Eqs. (4)–(6) clearly demonstrate that T_d decreases with an increased spike amplitude, φ_{full} , an increased spike width, T_w , or an increased spike frequency, f_{sti} . If the input is removed before the switching takes place, i.e. the width T of the input pulse is smaller than $T_d \approx T_{d1} \approx T_{d2}$, the mem-inductor remains unaltered. Therefore, in order to switch a mem-inductor, T should be chosen in such a way that $T > T_d$.

The main part of Fig. 2 represents the simplest scenario, in which only one stair of $L(q)$ from L_1 to L_2 is generated, corresponding to a “quadratic” segment in the transition period between time point 1 and 2 (a piece-wise linear model) of the ρ - q curve. One can imagine that, if the transition period of the ρ - q curve consists of a number of linear segments, the same number of stairs in $i(t)$ can be generated, as illustrated in the inset of the figure.

3. A neuromorphic circuit using mem-inductor

The purpose of this research is to reveal the cellular origins of primitive intelligence by utilizing a neuromorphic circuit to reproduce amoebae’s adaptive behaviors. As the most primitive eukaryotic form of life known in the contemporary world, amoebae have developed a crude nervous system (Chaisson, 2012). As shown in Fig. 3, a simple RLC neuromorphic circuit using a mem-inductor, $L(q)$, is designed. The temperature and humidity that control the motion of the amoeba correspond to an input voltage, V_{in} , whereas an output voltage across the capacitor, V_{out} , is an analogue to amoeba’s locomotive speed. Hopefully, this architecture used to model the neural reactivity in amoebae may find applications in neural networks and brain-like engineered systems helping us understand the origins of primitive adaptive behavior.

In an RLC circuit, only the capacitor C or the inductor L stores energy in a form of electric field or magnetic field, respectively, whereas the resistor R only consumes energy. Energy can be transferred from one form to the other within the circuit and this can be oscillatory, resulting in resonance. A mechanical analogy is a weight suspended on a spring which will oscillate up and down when released, reflecting the oscillation between kinetic energy and potential energy. A mechanical analogy to the resistor R in the circuit is friction in the spring/weight system, which will slow down the oscillation. In a similar way, the resistance R in an RLC circuit will “damp” the oscillation, diminishing it with time.

An amoeba’s behaviors will be simulated with the oscillations of the above RLC circuit. In this work, RLC circuits are used for picking

out a signal at a particular (resonant) frequency, $f_{res} = \frac{1}{2\pi\sqrt{LC}}$, from a more complex signal. \sqrt{LC} is sometimes called the time constant of an RLC circuit.

As mentioned above, damping is caused by the resistance of a resistor, R , in the circuit, which determines whether or not the circuit will resonate naturally (that is, without a driving source). Circuits which will resonate in this way are described as under-damped and those that will not are over-damped. There must be some signal impedance and dissipation inside the amoeba, otherwise signals would travel instantaneously and indefinitely (Pershin et al., 2009).

A (current-controlled) memory-inductor (mem-inductor, memristor’s sister) (Chua, 1980, 2009, 2012), $L(q)$, is used to automatically scan a range of frequencies. The inductance of a mem-inductor is a function of charge or the accumulation (time integral) of the current flowing through the inductor, as illustrated as below:

$$L = L(q) = L \left(\int i(t) dt \right). \quad (7)$$

With the progress of time, the circuit’s resonant frequency scans a range of frequencies as below:

$$f_{res} = \frac{1}{2\pi\sqrt{LC}} = \frac{1}{2\pi\sqrt{L \left(\int i(t) dt \right) C}} \quad (8)$$

When the varying circuit resonant frequency, f_{res} , equals the (temperature) stimulus frequency, f_{sti} , at a time point, t_{res} , a (speed) resonance will be triggered. We should have:

$$f_{res} = \frac{1}{2\pi\sqrt{L \left(\int i(t) dt \right) C}} \Bigg|_{t=t_{res}} = f_{sti} \quad (9)$$

As an assumption, the circuit will be locked at that frequency and the learning of a regular event is accomplished. At this stage, we are not clear whether it is physiologically plausible that an analogous biological “frequency-comparing” and triggering mechanism might exist in the amoeba.

The response of the circuit shown in Fig. 3 is described by the following equations:

$$V_{out}(t) + \frac{d[L(q) \cdot i(t)]}{dt} + i(t) \cdot R = V_{in}(t) \quad (10)$$

$$C \cdot \frac{dV_{out}(t)}{dt} = i(t) \quad (11)$$

where $i(t)$ is the total current, V_{in} is the input voltage and V_{out} is the output voltage. Eq. (10) simply states that the applied voltage is equal to the sum of voltage drops on each element of the circuit and Eq. (11) is the voltage drop across the capacitor. The above equations were solved numerically using initial conditions.

Fig. 4 shows the response of the above neuromorphic circuit using a mem-inductor to a train of voltage pulses. The mem-inductor is assumed to have a piece-wise linear curve ρ - q with multiple linear segments in the transition (Time point 1–2 as shown in Fig. 2). The circuit’s resonant frequency due to $L(q)$ increases like a staircase following increased number of periodic stimuli (the Delayed Switching Effect).

Fig. 4 demonstrates that a strong and longer-lasting response for SPS (spontaneous in-phase slow down Saigusa et al., 2008, Fig. 1) is observed because the increased circuit’s resonant frequency after the three stimulus pulses matches with the stimulus frequency and a resonance is triggered. As shown in an SPS experiment (Fig. 1), the amoeba was exposed to three temperature/humidity drops at S_1 , S_2 and S_3 and the locomotion

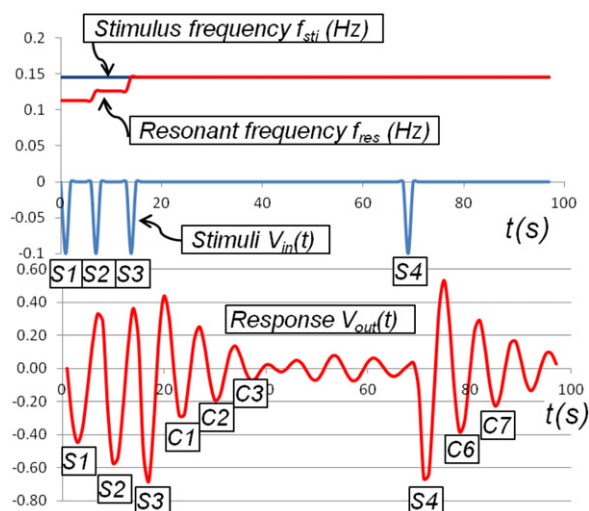


Fig. 4. Simulations of the circuit response to applied pulse sequences. $R = 1$, $C = 1$ F. The mem-inductor is assumed to have a piece-wise linear curve ρ - q with multiple linear segments in the transition (1–2 in Fig. 2). L starts with 2 H and then drops by 20% after each stimulus pulse. The circuit's resonant frequency due to $L(q)$ increases like a staircase as a result of increased number of periodic stimulus (the Delayed Switching Effect).

speed of the amoeba decreased accordingly. After the temperature/humidity drops, favorable condition intervals were applied. Amazingly, the amoeba has been found to slow down spontaneously when the next temperature/humidity drop would have occurred at C_1 , C_2 and C_3 . The neuromorphic circuit using a mem-inductor reproduces a similar response to the observed behavior in amoebae: in response to the three regular pulses at S_1 , S_2 and S_3 , the output voltage decreases at each time point when the pulse is applied and even at the subsequent time points at C_1 , C_2 and C_3 when following pulses would have occurred.

Fig. 4 also demonstrates that a resonance is triggered for SPSD (spontaneous in-phase slow down after one disappearance of the stimulus Saigusa et al., 2008, Fig. 1). The application of the fourth pulse at S_4 in $V_{in}(t)$ corresponds to a SPSD stimulus. Several output voltage drops at C_6 and C_7 in $V_{out}(t)$ (in analogue to amoebae's speed slow-downs) following the fourth pulse S_4 (in analogue to a temperature drop) are observed after the circuit was previously trained by a periodic sequence of three equally spaced pulses S_1 , S_2 and S_3 and the circuit with a changing resonant frequency f_{res} is locked at the stimuli frequency f_{sti} .

Our work was inspired by Di Ventra's circuit (Pershin et al., 2009). In Di Ventra's circuit with a memristor (Pershin et al., 2009), the memristor in parallel with a capacitor was used to change the damping factor of the RLC circuit with a fixed time constant, \sqrt{LC} . In our work (ANA), a mem-inductor is used and thereby a changing time constant, $\sqrt{L(q)C}$, is introduced to increment/decrement the resonant frequency naturally to trace the applied stimuli based on the Delayed Switching Effect (Wang et al., 2010, 2011). To cover a frequency range of from 1 s to 24 h displayed in the observed behavior in biological systems (Coggin & Pazun, 1996; Saigusa et al., 2008), complex models will be needed. In addition to the circuit with a memristor, Di Ventra et al. also proposed "a single circuit with the replacement of the capacitor and/or inductor with the newly introduced memory capacitor (memcapacitor) and memory inductor (meminductor)" (Pershin et al., 2009). We now realize that the proposed R - $L(q)$ - C circuit in this paper is similar to the latter in Pershin et al. (2009) and therefore our work should be viewed as a knowledge advancement in actually implementing the meminductor-based circuit and working out its unique theory based on our discovered Delayed Switching Effect (Wang et al., 2010). Note that, the meminductor-based circuit is not a simple

extension of the memristor-based one as it adapts its time constant rather than damping factor. The method adopted in our work is non-trivial with a sound mathematical foundation.

A reasonable similarity between the observed phenomenon (Fig. 1) and the ANA-based emulation (Fig. 4) demonstrates that simple nonlinear dynamics might suffice to explain the primitive learning.

4. Real-world circuit experiments

The objective is to develop a real-world circuit based in order to not only validate the above simulation results but also provide/prove a design for silicon implementation. Adaptive Neuromorphic Architecture (ANA) is composed of conventional circuit elements with newly-invented elements with memory that implement hardware models of biological systems.

The invention of memristor as well as its sisters, mem-inductor and mem-capacitor, opens a new way to unveil the origin of the operations of the human brain and possibly of many other adaptive and spontaneous behaviors/mechanisms in living organisms. A memristor/mem-inductor/mem-capacitor is a simple 2-terminal element, which means a vast number of memristors could be integrated together with other CMOS elements, in a single chip. A LaAlO₃/SrTiO₃ junction presents a uni-polar pinched hysteresis loop and also shows the potential that a memristor could be scaled down to half a nanometer (Fix, MacManus-Driscoll, & Blamire, 2009). When implemented in VLSI (including FPGA) technology, neuromorphic systems often have similar strategies for maximizing compactness and minimizing power consumption. Memristor/mem-inductor/mem-capacitor are non-volatile, allowing for low-power computation and storage. To date, a number of exemplar memristors (titanium dioxide memristor, spin memristor, polymeric memristor, manganese memristor, etc.) broaden the possible range of memristors (Wang et al., 2011). Since there exists controversy as to the memristance behavior of these specific devices, the emulation of circuit elements with memory provides a generalized way to investigate their behavior.

We constructed mem-inductor emulator as shown in Fig. 5. The differential ADC converts the voltage into a digital value. The microcontroller reads the digital code from ADC and controls a switch K to connect an inductor out of a series to increment/decrement the inductance continuously. These operations are performed continuously. The aforementioned "frequency-locking" mechanism is being tested in two ways: 1. Using the microcontroller to lock the time constant compulsorily according to a predefined function; 2. Using a memristor (emulated by a potentiometer Pershin & Ventra, 2010) to "isolate" the RLC circuit from the stimuli. In our circuit, we used a microcontroller dsPIC30F2011 with internal 12 bits ADC and a 256 positions 10 k non-volatile digital potentiometer MCP4261 from Microchip.

As a matter of fact, the above mentioned "The Delayed Switching Effect (Wang et al., 2010, 2011)" was discovered based on Chua's Circuit Model (Chua, 1971). The advantages of physically constructing and characterizing a circuit model of memristor/mem-inductor/mem-capacitor include a broad generalization to an interesting class, rather than a specific element and the ease of changing the parameters.

The inductance of an inductor was obtained by using a Gauss meter to measure the strength of magnetic field. As shown in Fig. 6, measured inductance of an experimental mem-inductor setup decreases like a staircase as a result of an increased number of periodic stimuli (the Delayed Switching Effect). An agreement with the theoretical analysis can be seen.

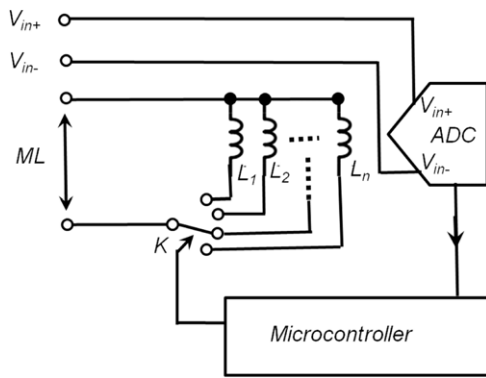


Fig. 5. Schematic of the main units of the mem-inductor emulator. The differential ADC converts the voltage into a digital value. The microcontroller reads the digital code from ADC and controls Switch K to connect an inductor out of a series to increment/decrement the inductance (ML) continuously.

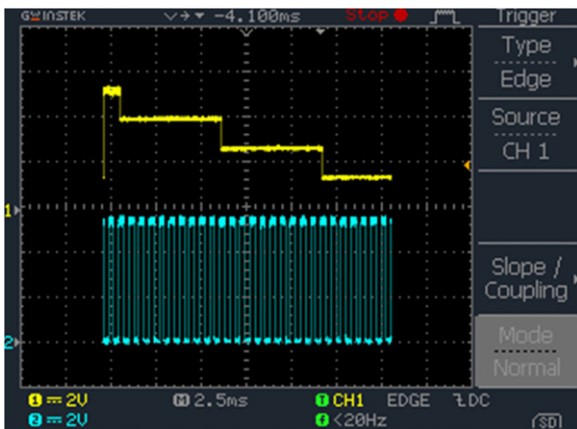


Fig. 6. Measured inductance on an experimental mem-inductor setup. It decreases like a staircase as a result of increased number of periodic stimuli (the Delayed Switching Effect). A striking similarity with the simulation results can be seen.

5. Conclusions and discussions

Three questions may naturally be raised about amoebae's mysterious adaptive behaviors: 1. How an amoeba remembers the past; 2. How an amoeba predicts the future; 3. How an amoeba encodes time.

Regarding Question 1, this work shows that an amoeba may have a nonlinear element like memristor/mem-inductor/mem-capacitor and use the internal state of this element to store information about the past.

Regarding Question 2, this work shows that an amoeba may have a biological oscillator with a variable resonant frequency and lock this oscillator, assuming that such a mechanism might exist in the amoeba, at the stimulus frequency to respond strongly to similar events in the future.

Regarding Question 3, this work shows that an amoeba may adapt the time constant of its biological oscillator to environmental change in order to encode time.

Summarizing Questions 1–3, we conclude that a nonlinear element with memory like memristor/mem-inductor/mem-capacitor plays a key role in the above mechanisms (memorizing/predicting/timing). Memristor/mem-inductor/mem-capacitor mimics many living things in terms of being plastic according to the dynamical history. Irrespective of whether there is a biological analogue, our Adaptive Neuromorphic Architecture (ANA) as a hardware model of biological systems is in excellent agreement

with the observed biological responses in amoebae, which implies that simple nonlinear dynamics might suffice to explain the amoebae learning. Especially, using a (passive) nonlinear element with memory to encode time is potentially important to brain-like engineered systems.

However, we do not really know much about how an amoeba might do the above. Inspired by Di Ventra's circuit (Pershin et al., 2009), we have a proposal for how a hardware model called ANA might simulate behavior exhibited by amoebae. However that says little about how an amoeba might do it without connecting our model to amoebae physiology. For example, can an amoeba implement memristors, mem-inductors or mem-capacitors?

It is worth mentioning that Alan Lloyd Hodgkin and Andrew Huxley described a model (including an equivalent circuit) in 1952 to explain the ionic mechanisms underlying the initiation and propagation of action potentials in the squid giant axon (Hodgkin & Huxley, 1952). They received the 1963 Nobel Prize in Physiology or Medicine for this work. In the Hodgkin–Huxley model, each cell is an electrical circuit consisting of a capacitor, a linear resistor, three batteries, and two unconventional elements identified by Hodgkin and Huxley as time-varying resistors, which we now know was a serious blunder that had led to numerous anomalies and paradoxes, and had hindered progress on neural physiology and brain science for over 70 years. Such anomalies had recently been definitively resolved by substituting the potassium and sodium time-varying resistors, by a potassium ion-channel memristor, and a sodium ion-channel memristor, respectively (Chua, Sbitnev, & Kim, 2012a, 2012b). These may be lessons of history for us to learn in exploring the origins of primitive learning from an evolutionary point of view.

Acknowledgment

The authors would like to thank an anonymous reviewer for pointing out that there are actually two circuits suggested in Pershin et al. (2009): one is based on memristor and another one based on memcapacitor/meminductor (although no technical detail was provided). The ANA architecture considered in this paper was actually inspired by the 1st one in Pershin et al. (2009) as we overlooked the sentence about the 2nd one in Pershin et al. (2009) while preparing the first draft. We now realized the ANA circuit is technically similar to the 2nd one in Pershin et al. (2009). Anyway we agree that the authors of Pershin et al. (2009) deserve more credit by proposing the idea of replacing an inductor with a meminductor and our paper should still be viewed as an important knowledge advancement in actually implementing the meminductor-based circuit (note that this circuit is not a simple extension of the memristor-based one as it adapts its time constant rather than damping factor) and working out its unique theory based on our discovered Delayed Switching Effect (Wang et al., 2010). The method adopted in our work is non-trivial with a sound mathematical foundation.

References

- Chaisson, Eric J. (2012). Cosmic Evolution–Biological. Harvard University Course Syllabus, Version 7.
- Chua, Leon (1971). Memristor—the missing circuit element. *IEEE Transactions on Circuit Theory*, CT-18(5).
- Chua, L. O. (1980). Device modeling via basic nonlinear circuit elements. *IEEE Transactions on Circuits and Systems*, CAS-27(11), 1014–1044.
- Chua, L. O. (2009). Introduction to memristors. *IEEE Expert Now*.
- Chua, L. O. (2012). The fourth element. *Proceedings of the IEEE*, 100(6), 1920–1927.
- Chua, L. O., Sbitnev, V., & Kim, H. (2012a). Hodgkin–Huxley axon is made of memristors. *International Journal of Bifurcation and Chaos*, 22, 1230011 (48 pages).
- Chua, L. O., Sbitnev, V., & Kim, H. (2012b). Neurons are poised near the edge of chaos. *International Journal of Bifurcation and Chaos*, 22(4), 1250098.
- Coggin, S. J., & Pazun, J. L. (1996). *Protoplasma*, 194, 243.

- Fix, T., MacManus-Driscoll, J. L., & Blamire, M. G. (2009). Delta-doped LaAlO₃/SrTiO₃ interfaces. *Applied Physics Letters*, 94.
- Hodgkin, A., & Huxley, A. (1952). A quantitative description of membrane current and its application to conduction and excitation in nerve. *Journal of Physiology*, 117, 500–544. PMID 12991237.
- McGrath, Kimberley, & Blachford, Stacey (Eds.) (2001). *Gale encyclopedia of science vol. 1: Aardvark-catalyst* (2nd ed.). Gale Group, ISBN: 0-7876-4370-X, OCLC 46337140.
- Pershin, Yuriy V., & Ventra, Massimiliano Di (2010). Experimental demonstration of associative memory with memristive neural networks. *Neural Networks*, 23, 881–886.
- Pershin, Yuriy V., La Fontaine, Steven, & Ventra, Massimiliano Di (2009). Memristive model of amoeba learning. *Physical Review E*, 80, 021926.
- Pershin, Y., & Ventra, M. D. (2009). Experimental demonstration of associative memory with memristive neural networks. *Nature Precedings*, 18.
- Saigusa, T., Tero, A., Nakagaki, T., & Kuramoto, Y. (2008). *Physical Review Letters*, 100, 018101.
- Wang, F. Z., et al. (2010). Delayed switching in memristors and memristive systems. *IEEE Electron Device Letters*, 31(7).
- Wang, F. Z., et al. (2011). Delayed switching applied to memristor neural networks. *Journal of Applied Physics*. <http://dx.doi.org/10.1063/1.3672409>.