Memristive model of amoeba's learning

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Recently, behavioural intelligence of the plasmodia of the true slime mold has been demonstrated[1]. It was shown that a large amoeba-like cell *Physarum polycephalum* subject to a pattern of periodic environmental changes learns and changes its behaviour in anticipation of the next stimulus to come. Currently, it is not known what specific mechanisms are responsible for such behaviour. Here, we show that such behaviour can be mapped into the response of a simple electronic circuit consisting of an *LC* contour and a memory-resistor (a memristor) to a train of voltage pulses that mimic environment changes. We identify a possible microscopic origin of the memristive behaviour in the *Physarum polycephalum,* which together with the naturally occurring biological oscillators, forms the basis of the amoeba's learning. These microscopic memristive features are likely to occur in other unicellular as well as multicellular organisms, albeit in different forms. Therefore, the above memristive circuit model, which has learning properties, is useful to better understand the origins of primitive intelligence.

Although it is a unicellular organism, *Physarum polycephalum* displays remarkably intelligent abilities: it is able to solve mazes[2] and geometrical puzzles[3], control robots[4], and may even be able to learn and recall past events[1]. According to Ref. [1], when subjected to three spikes of cold temperature and low humidity, set at specific lengths of time and given at regular intervals, the *Physarum* decreased its

movement speed at the same time as the shocks. However, after the spikes had stopped, the *Physarum* still decreased its speed at the times when the spikes would have occurred, effectively predicting the time of the spikes from the pattern it had been given. These "memory patters" dissipate over time, but a single spike in temperature can trigger the oscillations again, provided it is within a certain time frame. This shows the amoeba "learned" that a single temperature spike can be followed by others at the given period.

A partial model to describe this behaviour has also been advanced in Ref. [1] in terms of the ubiquitous biological oscillators. According to this model, these internal oscillators have a natural frequency, and may possibly deviate from that frequency so that multiple oscillators can respond to the same frequency. The frequency of natural shocks excites one or more of these oscillators, which could be the source of *Physarum's* ability to recognize patterns and predict events. The model however does not fully explain the memory response of the amoeba and does not take into account the fact that, at a microscopic level, changes in the physiology of the organism occur independently of the biological oscillators. These changes also occur over a finite period of time and must be dependent on the state of the system at previous times.

This last point is particularly important: it is in fact this state-dependent feature which is likely to produce memory effects rather than the excitation of biological oscillators. Instead, the latter ones seem to control the rhythmical flow of the ectoplasm through protoplasmic veins[5]. Fig. 1(a) shows a simplified image of the veins. In addition to these oscillators, however, there are internal processes which depend on the state of the system and on its dynamical history thus giving rise to its memory. These mechanisms are as follows. The *Physarum* contains in its interior a gel-sol solution. The gel, present in the ectoplasm, is more gelatinous than the less viscous sol, present in the endoplasm, and the sol flows through the gel almost in the same way as water through a sponge. Now, the gel-sol solution is thixotropic, meaning that the viscosity

can change as a function of pressure. When the amoeba is moving, the actin-myosin fibers present in the ectoplasm contract radially and longitudinally, creating a pressure gradient pushing the endoplasm in the direction of motion. This gradient can increase to the point in which it causes the gel to break down into sol so that new low-viscosity channels form, which may even become permanent pathways (see Fig. 1(b))[6,7]. Therefore, if the external temperature and humidity of the environment are changed, the sol flow changes in a non-linear way. A restoration of initial conditions upon change of the environment thus requires time, and depends on the number and shape of the formed low-viscosity channels. This mechanism is similar to the one underlying the memory-resistance (memristor) behaviour of certain electronic devices[8-13]. In these, the variation of an external parameter (e.g., the voltage) creates new or modifies existing conducting channels, thus altering the resistance in a non-linear way. It is thus natural to argue that in the very same way that a memristor has its inherent memory, the *Physarum* acquires a memory through the interactions of the gel-sol solution, specifically through the formation of new, low-viscosity channels, and perhaps by other related complex interactions.

In order to show this connection more clearly we seek to present a juxtaposition of the mechanisms behind the movement process of *Physarum* with the operation of an equivalent electrical circuit made of just the four basic passive electrical elements: the resistor (R), capacitor (C), inductor (L), and memristor[14] (M) (see Table 1). Indeed, we show that, like the amoeba, this circuit can learn and predict subsequent signals. Due to the complexity of biological systems, the present analogy will be a simplification of what specifically happens during the learning process.

In this respect the biological oscillators can be simulated with the oscillations of an *LC* component. The resistance R describes the fact that there must be some signal impedance and dissipation inside the amoeba, or else signals would travel instantaneously and indefinitely. Finally the memristor M summarizes the memory

mechanisms we have described above. The temperature and humidity that control the motion of the amoeba correspond to the external voltage that controls the circuit. The response, namely the amoeba's velocity, is nothing else than the voltage at the memristor.

The electronic scheme that accomplishes the learning process in response to a train of voltage pulses is shown in Fig. 2(a). The capacitor and memristor are connected in parallel. The main idea behind functioning of this scheme is to use the internal state of memristor in order to store information about the past and control oscillations in the LC contour. In particular, we use the model of a voltage-controlled memristor, inspired by recent experiments[11], in which the resistance of memristor M can be changed between two limiting values M_1 and M_2, $M_1 < M_2$. In our scheme, M increases as a result of increased number of periodic stimuli and thus as a result of learning.

The change of M is described by the following equation

$$\frac{dM}{dt} = f(V_C)[\theta(V_C)\theta(M - M_1) + \theta(-V_C)\theta(M_2 - M)], \qquad (1)$$

where $f(V_C)$ is a function describing the change of the memristor state, V_C is the voltage applied to the memristor (equal to the voltage drop on the capacitor) and $\theta(...)$ is a step function. The expression in square brackets guarantees that M changes between M_1 and M_2. Here, we assume that $f(V_C)$ consist of several linear segments as shown in Fig. 2(b). This is the simplest memristor model which takes into account the activation change of the memristor state[15]. In other words, the memristor learns faster when $|V_C| > V_T$ and slower when $|V_C| < V_T$, where V_T is a threshold voltage.

The response of the circuit shown in Fig. 2(a) is described by the following equations:

$$V_C + L\dot{I} + IR = V(t), \qquad (2)$$

$$CV̇_C + \frac{V_C}{M} = I\,, \tag{3}$$

where V_C is the voltage on the capacitor, I is the total current and $V(t)$ is the applied voltage. Eq. (2) simply states that the applied voltage is equal to the sum of voltage drops on each element of the circuit, and Eq. (3) is the Kirchhoff's current law at the point of connection of capacitor, inductor and memristor. We solve Eqs. (2) and (3) numerically using close to a steady state initial conditions and different $V(t)$.

In our circuit scheme, a favourable (standard) environmental condition corresponds to a positive applied voltage and unfavourable condition to a negative applied voltage. If the favourable condition is applied for a long period of time, then, during this period of time, a positive voltage is applied to the memristor. According to Eq. (1) and $f(V_C)$ as in Fig. 2(b), the latter switches into the low resistance state M_1. In this case, the LC contour is damped and excited oscillations decay fast. Fig. 3(a) demonstrates that when a non-periodic sequence of pulses is applied to the scheme, the circuit learning ability (or change of M) is small and oscillations in the contour are strongly damped. In the opposite case, when we apply periodic pulses with a frequency close to the LC contour's resonant frequency, the change of M is much more pronounced, memristor switches into its higher resistance state and, since the LC contour becomes less damped, oscillations in the contour survive for a longer time. Such behaviour is related to the fact that during the application of resonant pulses the amplitude of voltage oscillations on the capacitor increases with each pulse and at some point exceeds V_T in amplitude. As a consequence, the memristor learns fast and its state changes significantly.

Fig. 3 shows simulations of spontaneous in-phase slowdown (SPS) and SPS after one disappearance (SPSD) experiments[1]. In these simulations we use the scheme described above with the only restriction that the response signal can not exceed a certain value, which in our particular calculations is selected to be equal to the voltage

corresponding to standard conditions V_F. This signal is selected to be equal to V_C if $V_C < V_F$ and to V_F if $V_C > V_F$. Electronically, such a response signal can be obtained using a resistor connected from one side to the junction of the inductor, capacitor and memristor in Fig. 3(a) and a diode connected between another side of the resistor and a power source at V_F voltage.

In SPS experiments, the amoeba was subjected to three intervals of unfavourable conditions (namely, low temperature and humidity). Each time, the locomotion speed decreased during these. After that, standard (favourable) conditions were applied. However, the movement of the amoeba has been found to slow spontaneously when the next intervals of unfavourable conditions would have occurred. Exactly the same behaviour is found in our circuit model. This is shown in Fig. 4, where a pulse sequence $V_2(t)$ is applied. It is clearly seen that in response to the application of three regular pulses, the response signal decreases each time these pulses are applied as well as at subsequent times when following pulses should occur. The opposite behaviour is demonstrated when the three training pulses are not periodic as shown in Fig. 4 with an irregular pulse sequence $V_1(t)$. In this case, the anticipated response is significantly smaller.

Application of the fourth pulses in Fig. 4 corresponds to conditions of SPSD experiments[1] in which the anticipated slowdown after a single unfavourable condition was observed only among previously trained organisms. Again, we can see a striking similarity with the experimental results on amoeba's learning: in the case of a pulse sequence with the first three non-periodic pulses ($V_1(t)$), the subsequent application of a single pulse does not result in a significant anticipated slow-down after the pulse. On the other hand, a "trained" circuit (by applying the $V_2(t)$ pulse sequence) manifests several well-defined slowdown events after the fourth pulse.

Finally, we plot in Fig. 5 the final state of the memristor just after the application of three learning pulses as a function of time interval between the pulses. It can be

noticed that a good learning occurs in the interval $8s < \tau < 10s$, which is close to the *LC* contour sequence. To some extent, this plot resembles Fig. 3 in Ref. [1] for amoeba's learning

In conclusion, we have presented an electronic circuit model to describe the amoeba's ability to recognize patterns and predict events. This model contains a memory-resistor which simulates the mechanisms that occur in the protoplasm of the *Physarum,* which produce a sol flow that depends on the history and state of the system. The model completely simulates the learning ability of the amoeba, and provides a microscopic picture of the memory in this unicellular organism. It is worth noting that such electronic circuit is made only of passive elements and can be realized in the laboratory. It may thus find applications in electronic applications that require "circuit learning". Finally, this model may be extended to multiple learning elements and may thus find application in neural networks and guide us in understanding the origins of primitive intelligence.

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14. In this Letter we use the word memristor in a broad sense to include both perfect memristors[8] and memristive systems[9].

15. This model follows from the recent experimental paper[11], where it is shown that the memristor state changes fast at high applied voltages and almost does not change at low voltages.

Author Information The authors declare no competing financial interests. Correspondence and requests for materials should be addressed to Y.V.P. (pershin@physics.sc.edu) or M.D. (diventra@physics.ucsd.edu).

Figure Captions

Figure 1 | View of *Physarum* during movement. a, *Physarum* moves via shuttle streaming, a process of periodic flow of the ectoplasm and endoplasm, with a greater net flow towards the direction of movement, or the anterior end. The ectoplasm contains radial and longitudinal actin-myosin fibers whose oscillating contractions help produce the pressure gradient which drives shuttle streaming[5]. Ref. [5] contains a more detailed depiction of *Physarum*. **b,** During movement, the anterior of *Physarum* may develop a sheet of gel that inhibits streaming. But when the pressure gradient builds to a certain threshold, the gel can break down allowing for the formation of new channels of flow. These channels may become permanent veins for streaming.

Figure 2 | Electronic circuit that models amoeba's learning. a, Schematic representation of the learning circuit made of four fundamental two-terminal circuit elements: resistor R, inductor L, capacitor C and memristor M. **b,** Sketch of the selected memristor function f which depends on the voltage applied to the memristor (more details are given in the text). Formally, it is defined as $f(V) = -\alpha V$ for $|V| < V_T$ and $f(V) = -\beta V + (\beta - \alpha)V_T$ for $|V| > V_T$, where α and β are positive constants.

Figure 3 | Simulations of the circuit response to applied pulse sequences. a, Arbitrary pulse sequence. **b,** Learning pulse sequence. The calculations were made using the following system parameters: $R = 0.1\,\Omega$, $L = 2\,$H, $C = 1\,$F, $M_1 = 3\,\Omega$, $M_2 = 20\,\Omega$, $\alpha = 0.1\,\Omega/$V, $\beta = 3\,\Omega/$V, and $V_T = 2.5\,$V. The applied pulse sequence was selected in the form $V(t) = V_F - V_p \sum_i \left(\cos(2\pi(t - t_i)/W_p) - 1 \right)\theta(t - t_i)\theta(t_i + W_p - t)/2$, where V_F is the voltage corresponding to the standard (favourable) conditions, V_p is the pulse amplitude, t_i is the time of start and W_p is the pulse width. In the calculations,

we used $V_F = 0.1\,\text{V}$, $V_p = 2\,\text{V}$, and $W_p = 5\,\text{s}$. The t_i's can be identified from the figure.

Figure 4 | Modeling of the spontaneous in-phase slowdown responses. This plot demonstrates that good responses for both spontaneous in-phase slowdown and spontaneous in-phase slowdown after one disappearance of the stimulus are observed only when the circuit was previously "trained" by a periodic sequence of three pulses as present in $V_2(t)$. The voltage $V_1(t)$ is irregular and thus does not "train" the circuit to learn. The simulation parameters are as in Fig. 3. The lines were displaced vertically for clarity.

Figure 5 | Resistance of memristor as a function of time interval τ **between the pulses.** Here, we plot the value of the memristance M right after the last (third) pulse in the learning sequence. The memristor state significantly changes when pulse period is close to the *LC* contour frequency. The simulation parameters are as in Fig. 3.

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Figure 1

a.

Physarum Polycephalum

Posterior

Anterior

Protoplasmic Vein

Ectoplasm

Endoplasm

Plasmalemma

Cytoplasmic Streaming

b.

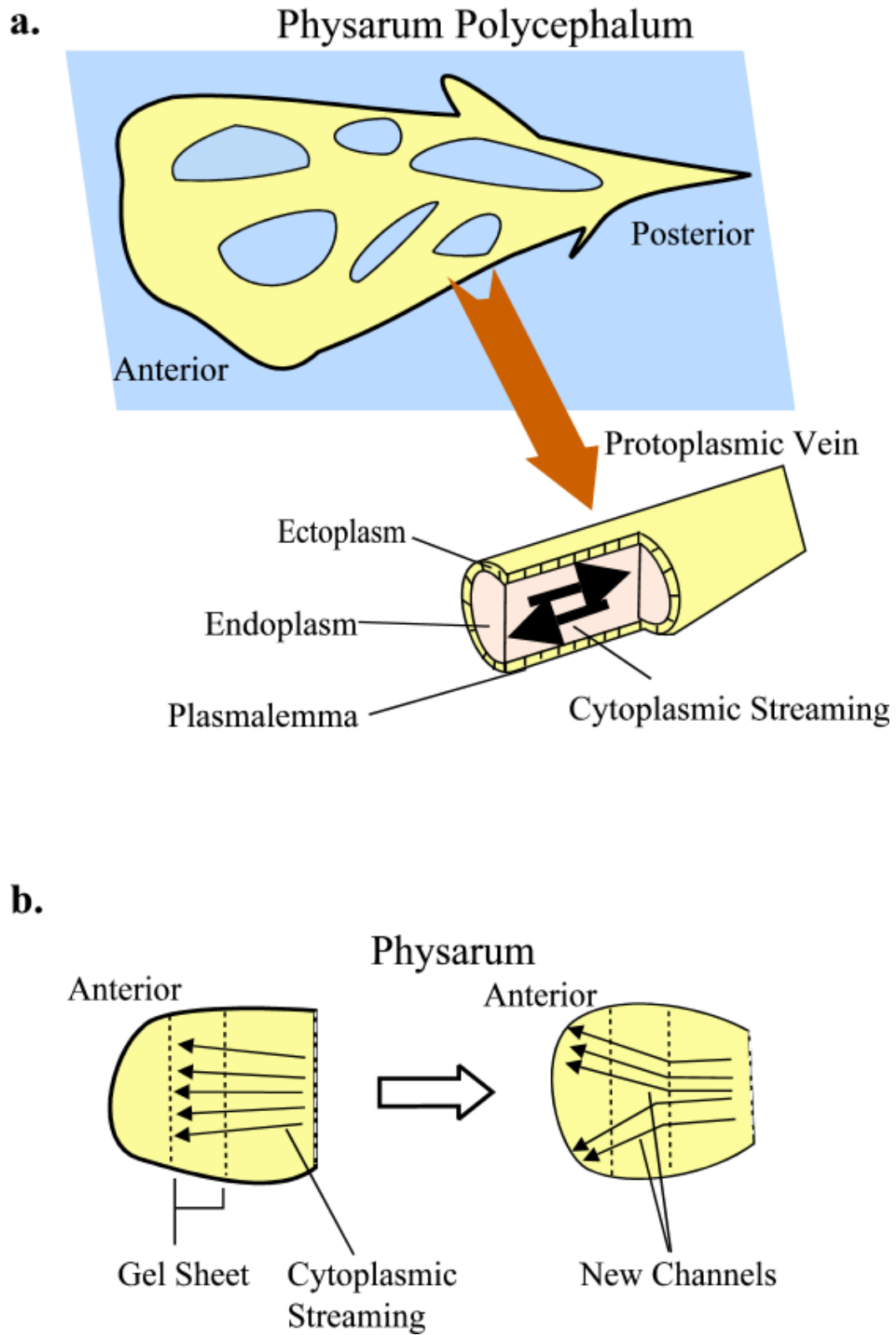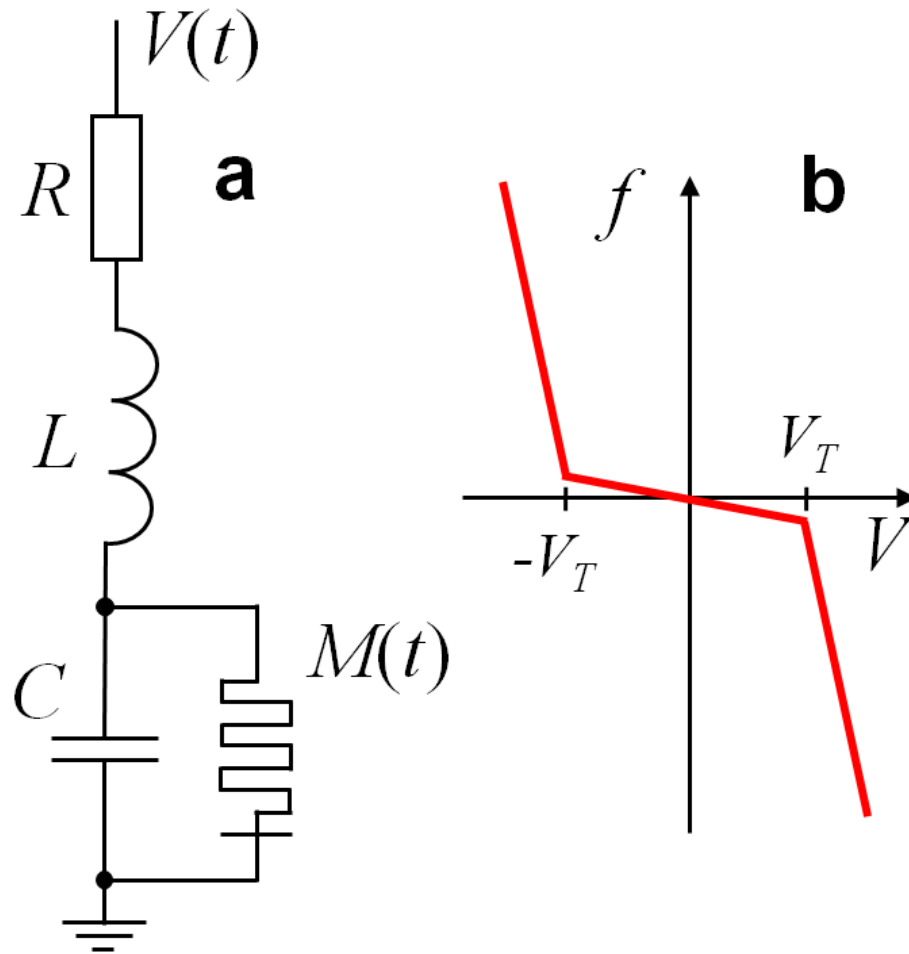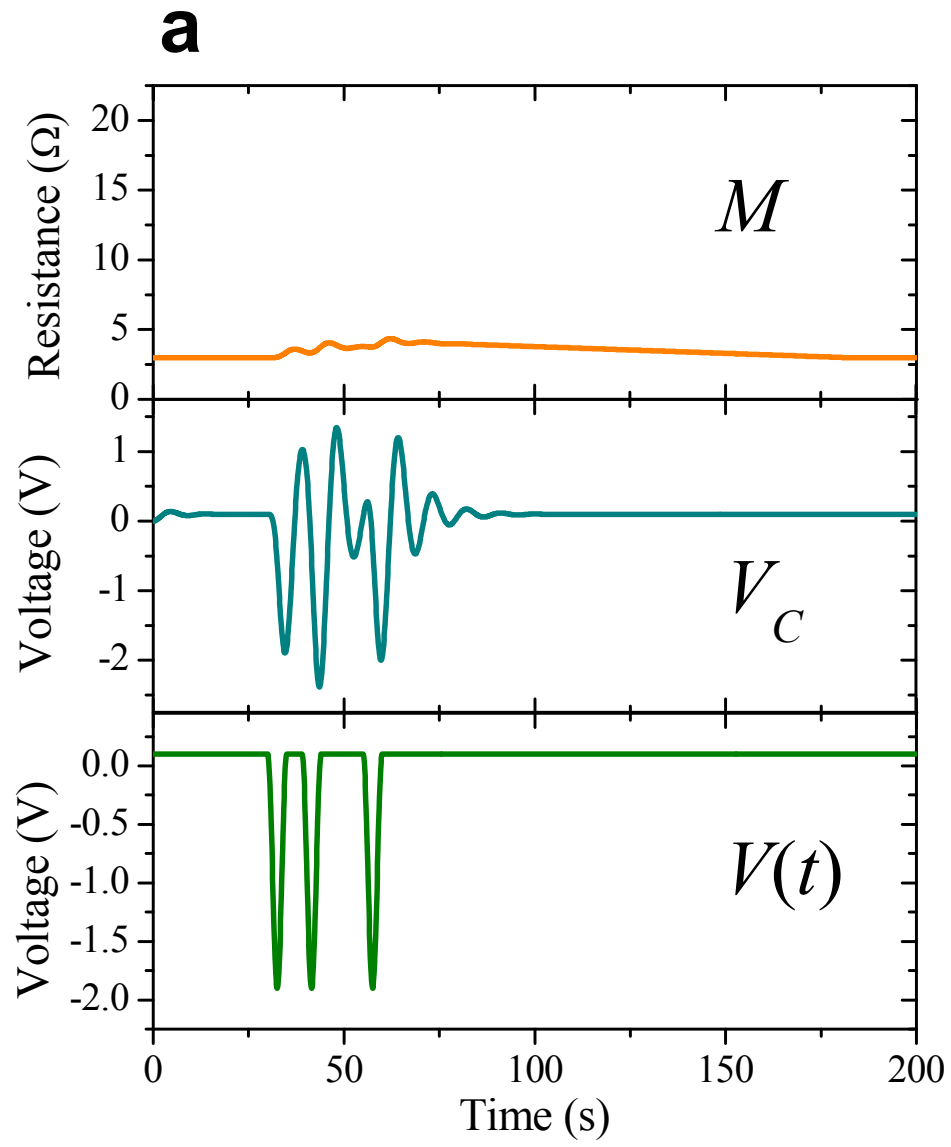Physarum

Anterior

Anterior

Gel Sheet

Cytoplasmic Streaming
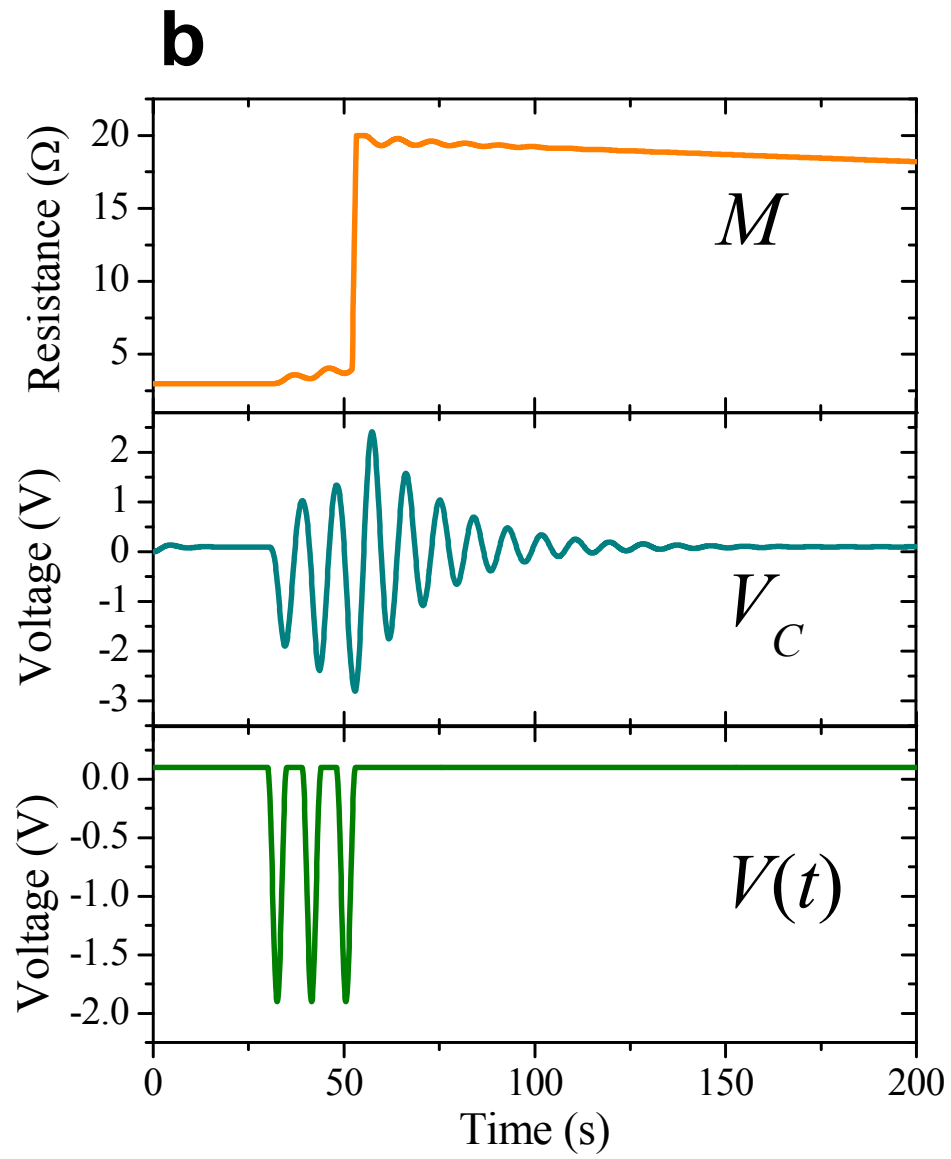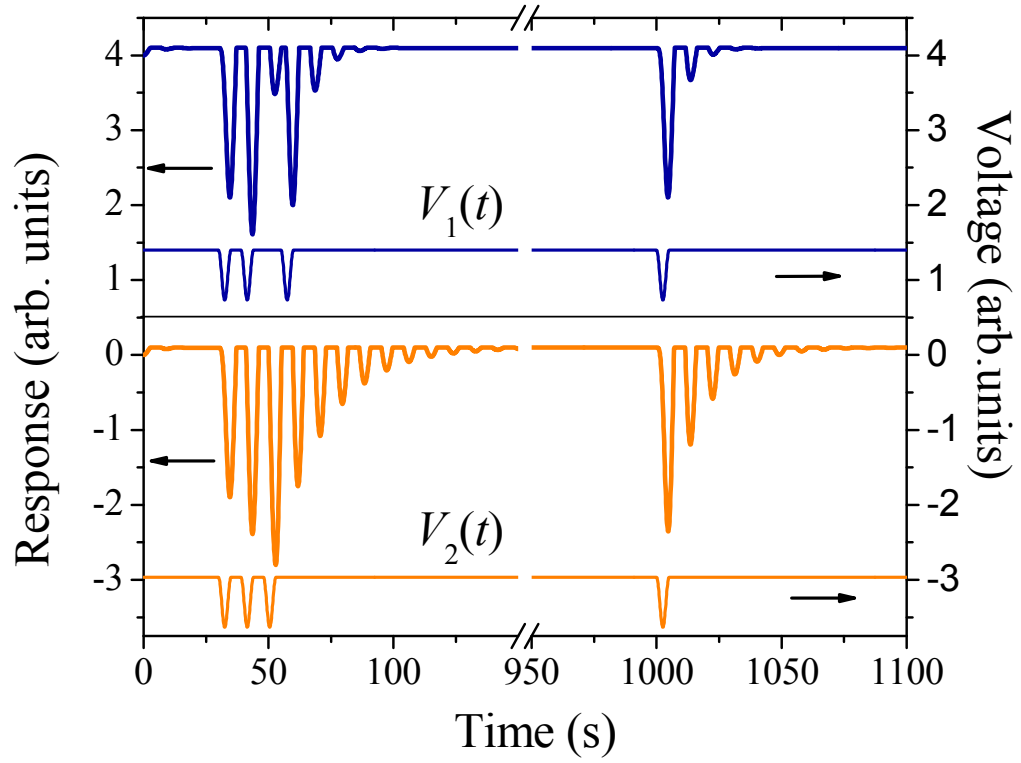
New Channels

Figure 2
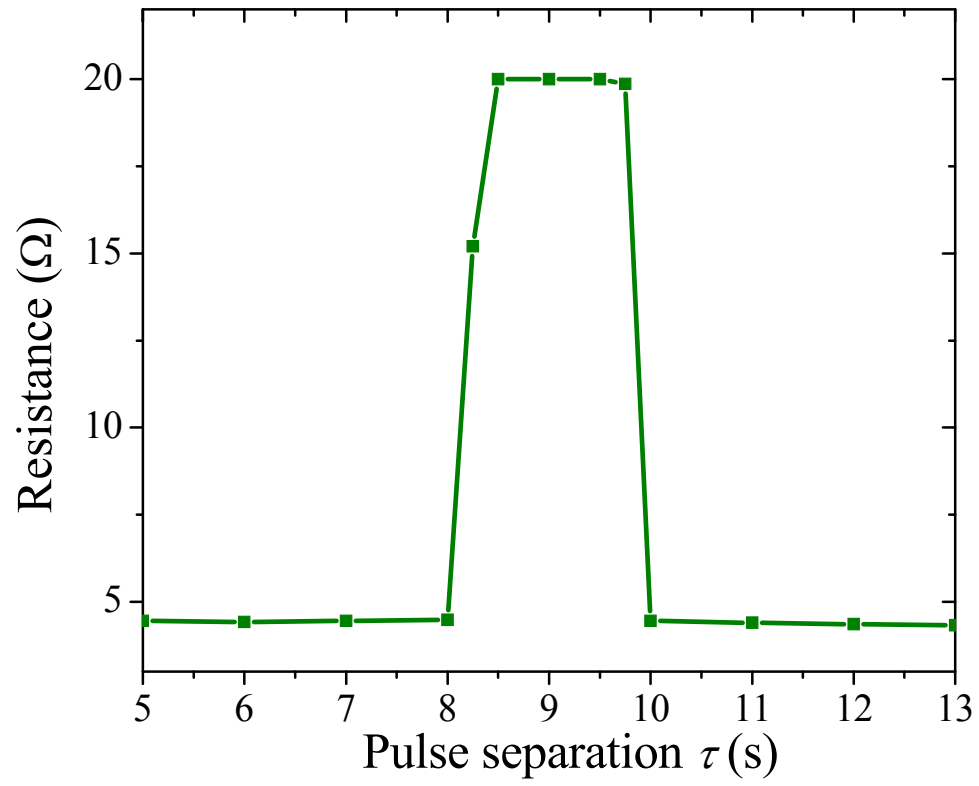
Figure 3

Figure 3

Figure 4

Figure 5

Tables

Table 1 | **Correspondence between learning of an amoeba and an electronic circuit.**

Component	Amoeba	Electronic circuit
Control parameter	Temperature and humidity	Applied voltage
Output signal	Velocity	Voltage
Oscillator	Biochemical oscillators	*LC* contour
Memory element	Gel/sol interactions	Memristor
Parameter containing information	Veins and low-viscosity channels	Resistance of memristor