Lu.i – A low-cost electronic neuron for education and outreach

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ABSTRACT With an increasing presence of science throughout all parts of society, there is a rising expectation for researchers to effectively communicate their work and, equally, for teachers to discuss contemporary findings in their classrooms. While the community can resort to an established set of teaching aids for the fundamental concepts of most natural sciences, there is a need for similarly illustrative experiments and demonstrators in neuroscience. We therefore introduce Lu.i: a parametrizable electronic implementation of the leaky-integrate-and-fire neuron model in an engaging form factor. These palm-sized neurons can be used to visualize and experience the dynamics of individual cells and small spiking neural networks. When stimulated with real or simulated sensory input, Lu.i demonstrates brain-inspired information processing in the hands of a student. As such, it is actively used at workshops, in classrooms, and for science communication. As a versatile tool for teaching and outreach, Lu.i nurtures the comprehension of neuroscience research and neuromorphic engineering among future generations of scientists and in the general public.

INDEX TERMS education, leaky-integrate-and-fire, low-cost, neuron, outreach, PCB

I. Introduction

Expanding our understanding of the mammalian brain is among the central frontiers of modern science and yet implies some of the longest standing questions humanity has posed to itself. Their fundamental nature induces an intrinsic curiosity about the progress of neuroscience, artificial intelligence, and brain-inspired technology. In contrast to this demand, the repertoire of demonstrators to communicate principles and recent achievements in brain research is limited (Gage, 2019). In comparison, other fields can build on many centuries of experience for conveying their essential concepts.

In our current understanding, the fundamental principles of information processing in nervous systems lie in neuronal dynamics and synaptic interactions. A strong intuition for these mechanisms is, therefore, the foundation for understanding and investigating more complex processes and emerging phenomena. In the following, we thus present Lu.i – an analog electronic implementation of the leaky-integrate-and-fire (LIF) neuron model targeted for educational use as well as scientific outreach. Lu.i features current-based synaptic inputs that enable the formation of simple spiking neural networks (SNNs) and offers control over many parameters, including the time constants and the synaptic weights. The printed circuit board (PCB) visualizes the time-continuous dynamics of the emulated membrane potential and allows interfacing with digital and analog periphery for advanced experiments. It has been optimized for low-cost production, long battery life, and intuitive operation.

Figure 1. A single Lu.i neuron PCB, with a 2-Euro coin for scale. To relay information from one neuron to the other, excitatory and inhibitory synapses can be formed by wiring the axonal output (right) to one of the three dendritic terminals (left).
II. Neuron and synapse dynamics

Lu.i implements the LIF neuron model, arguably the simplest abstraction that still captures the most fundamental properties of neuronal information processing: time-continuous computation, spatio-temporal integration, and event-based communication. This model was originally put forward by Louis Lapicque in 1907, after whom the PCB was fittingly named. The LIF model describes the dynamics of a neuron’s membrane potential \( V_{\text{mem}}(t) \), which are governed by the following differential equation

\[
C_{\text{mem}} \frac{dV_{\text{mem}}(t)}{dt} = -g_{\text{leak}} [V_{\text{mem}}(t) - V_{\text{leak}}] + I_{\text{syn}}(t), \tag{1}
\]

where \( C_{\text{mem}} \) denotes the membrane capacitance, \( g_{\text{leak}} \) the leak conductance, and \( V_{\text{leak}} \) its resting potential. \( I_{\text{syn}}(t) \) subsumes the time-dependent synaptic currents stimulating the neuron. This differential equation describes a membrane potential which continuously decays to the resting state. It is, however, augmented by a reset condition to mimic the hyperpolarization following the action potentials observed in biological neurons: Whenever the membrane potential crosses the threshold \( \vartheta \), the neuron emits a spike. This effenter signal is accompanied by a reset of the membrane potential, where the latter is simply clamped to \( V_{\text{reset}} \) for the refractory period.

Lu.i further implements current-based synapses with post-synaptic currents following exponential kernels with time constant \( \tau_{\text{syn}} \). This additional temporal filter mimics the kinetics of synaptic ion channels: Each presynaptic spike \( j \) arriving at time \( t_{\text{pre}}^j \) at synapse \( i \), triggers an exponentially decaying current

\[
I_{\text{syn}}^j(t) = w_i \cdot \exp \left( -\frac{t - t_{\text{pre}}^j}{\tau_{\text{syn}}} \right), \tag{2}
\]

where \( w_i \) denotes the weight of the respective synapse \( i \). The total synaptic current then results as a sum over all of these individual contributions.

III. Electronic implementation

Lu.i realizes the LIF dynamics through a set of analog electronic circuits (Fig. 2) and thus forms a physical model thereof. Equation (1) is rendered by the combination of capacitor \( C_{\text{mem}} \) and potentiometer \( g_{\text{leak}} \), which form an RC integrator with adjustable time constant \( \tau_{\text{mem}} \). Without external stimuli, \( V_{\text{mem}} \) decays towards the resting potential \( V_{\text{leak}} \), which we generate by the combination of an adjustable voltage divider with a subsequent unity gain buffer. The spike mechanism is implemented by continuously comparing the membrane potential to the threshold (Fig. 2D). Once the membrane reaches \( \vartheta = V_{\text{ref}}/2 \), the threshold comparator trips, indicating a spike and causing a membrane reset. To avoid instabilities, it is fitted with a hysteresis circuit that temporarily reduces the comparator’s reference potential to \( V_{\text{ref}}/4 \) during the onset of a spike. At that point, the capacitor \( C_{\text{ref}} \) is discharged and the connected comparator trips, thus shorting the membrane to \( V_{\text{reset}} = 0 \) via the transistor \( Q_{\text{reset}} \) to implement the refractory period. \( R_{\text{ref}} \) and \( C_{\text{ref}} \) determine the fixed refractory time of approximately 12 ms, which starts once \( V_{\text{mem}} \) is discharged below \( V_{\text{ref}}/4 \), where the threshold comparator releases. The control signal for \( Q_{\text{reset}} \) is re-used as the neuron’s axonal output, with a pulse width equivalent to the refractory time.

Lu.i features three synapses implementing the current-based model with an exponential kernel as introduced by Eq. (2). Each of them possesses a tunable weight and can be switched between excitation and inhibition. The synapses share a common synaptic time constant \( \tau_{\text{syn}} \), which is
IV. Exploring Neural Computation with Lu.i

Lu.i was designed to illustrate two of the fundamental aspects of biological neurons: spatio-temporal accumulation of input and event-based communication, both of which are captured adjustable over a broad range. For an area- and cost-effective implementation, we minimize the amount of integrated components per synaptic connection: Events from presynaptic neurons control the gate of the n-channel MOSFET $Q_{\text{low}}$ (Fig. 2B). Depending on the selected polarity $S_{\text{sign}}$, this transistor either directly discharges the shared synaptic integrator or indirectly charges it via the p-channel MOSFET $Q_{\text{high}}$. For each event, this synaptic trace is in- or decremented by a fixed amount of charge proportional to the respective weight $g^i_{\text{weight}}$ which can be configured through a potentiometer. The time constant $\tau_{\text{syn}} = C_{\text{syn}}/g_{\text{weight}}$ of the integrator can be similarly tuned. Especially in light of the additional filter introduced by the membrane, this closely approximates the instantaneous response of the original model. The synaptic current $I_{\text{syn}}$ is derived from the integrator state through a V-I conversion stage. As such, it consists of two voltage-controlled current sources – each built from a resistor, a MOSFET, and an operational amplifier. $Q_{\text{push}}$ and $Q_{\text{pull}}$ operate in a push-pull configuration and generate two antagonistic currents. Their difference is proportional to the deflection of the integrator and corresponds to the total postsynaptic current $I_{\text{syn}}$ that stimulates the membrane.

Lu.i displays its state through a set of LEDs. Six of them form a bar that visualizes the membrane potential, and a seventh LED indicates efferent spikes with a flash. This interface is sketched in Fig. 3A for various states of the neuron. The voltmeter is implemented through a set of comparators and a resistor ladder to generate the respective reference potentials. While these circuits take up significant area on the PCB, they have been omitted from the schematic for clarity. This intuitive on-board interface enables standalone operation and the visualization of network activity and signal propagation therein. Experimentation with external equipment is, however, encouraged and allows more detailed insights into the neuron dynamics. For that purpose, the emulated membrane is accessible through a pad at the board edge for interfacing with, e.g., current sources and oscilloscopes.

The PCB is powered from a single CR2032 coin cell, which we chose for its small form factor, wide availability, and comparably high capacity at low cost. All voltage references of the circuit are derived relative to this supply. The temporal dynamics are thus, on first order, invariant to the battery voltage. This ensures mostly stable operation across the entire lifetime of the cell, which results in approximately 24 h of continuous use. Lu.i can be powered down completely through a switch on its back side.

While aiming for an intuitive and appealing form factor, the PCB has been strongly optimized for low-cost fabrication. This is reflected in the selection of components as well as the layout, which only relies on a simple two-layer PCB. As a result, we achieved a unit price of around US$3 already for batches below 1 000 Lu.i neurons. As the backside only contains the battery holder and an optional power switch, fabrication costs can be further reduced by restricting automated assembly to the top layer.
by the LIF model. These aspects can be demonstrated in a set of experiments of increasing complexity, some of them shown in Fig. 3.

The first property – leaky integration of input – can be seen in Fig. 3A: The membrane potential rises after weak excitatory stimuli and decays back to the resting potential, similarly with inhibitory input. The resulting trajectories are shaped by the adjustable time constants $\tau_{\text{syn}}$ and $\tau_{\text{mem}}$. These determine the time scales on which consecutive inputs are integrated and stacked. Only when the threshold is reached, an efferent spike is triggered and visible externally. On Lu.i, these dynamics can be observed using an on-board LED strip visualizing the membrane state and spike output, as shown in Fig. 3A. Neurons compute through this combination of analog integration and thresholding, for example by performing spatio-temporal coincidence detection. Exploring the impact of the model parameters on this computation – in case of coincidence detection on the sensitivity and detection window – is a worthwhile educational exercise.

In contrast to the local computation on their membranes, neurons communicate through temporally sparse spike events. This signal propagation can be demonstrated in a simple two-neuron network (Fig. 3C), where a synaptic connection is formed by a cable between the presynaptic axon and a postsynaptic dendrite. By choosing a resting potential above the threshold, the first neuron can act as a regularly firing spike source to the second. As before, the stacking of excitatory stimuli and the reset upon threshold crossing can be observed on the membrane of the postsynaptic cell. The behavior of both neurons is clearly visible using the built-in LEDs without an external oscilloscope. Already in this simple setup, the influence of the synaptic parameters can be explored: For example, the combination of a short synaptic time constant and a strong excitatory weight can be used to trigger one spike for each incoming event. Increasing the synaptic time constant, while lowering the weight, can lead to a delayed propagation of single spikes. This can be used to build delay chains, which vividly illustrate the finite propagation speed of neural signals. Once these chains are closed (Fig. 3D), their activity becomes self-sustained. Figure 3E shows a more complex example, where rate-based AND, OR and – in combination – XOR gates are implemented using three Lu.i neurons. In this case, the OR (AND) gate is implemented by a single neuron that has been tuned to fire for at least one (two) active presynaptic neurons. The output of the OR neuron excites the XOR cell, with the AND neuron acting inhibitory.

While the inputs A and B can be presented using Lu.i neurons (e.g., in leak-over-threshold configuration), we have used an external microcontroller to stimulate the network in Fig. 3E. With a signal level of approximately 2.5 V, Lu.i’s event output signal can be detected by most 3.3 V and 5 V microcontrollers. The event inputs on Lu.i are compatible with signal levels from 1.8 V to 20 V, allowing to interface with a great variety of sensors and devices.

Due to its simplicity, the XOR network is attractive in educational and outreach environments. Inspired by existing literature, more complex networks have emerged from collaborations of researchers across all areas of neuroscience, including realtime sound localization (Jeffress, 1948), a balanced random network (Brunel, 2000), a ring attractor model (Pisokas, Heinze, and Webb, 2020), an echo localiza-

Figure 4. Lu.i has played an integral role at various events all over the world for teaching and outreach applications: Nacht der Forschung (Switzerland, 2022), CapoCaccia Workshop toward Neuromorphic Intelligence (Italy, 2023), TReND in Africa (Ghana, 2023), and Deutsche Schülerakademie (Germany, 2023).
tion latch (Wen and Horiuchi, 2022), and – with preprocessing of the analog signals – a brightness change detection circuit. Lu.i has been used repeatedly to teach a younger audience about fundamentals of neuroscience and physical computing, especially in combination with a subsequent transition to neuromorphic research systems made accessible through EBRAINS. Across all described applications, it was used to compellingly illustrate fundamental topics across a wide range of research areas from robotics to systems neuroscience.

V. Discussion
This manuscript presents Lu.i, a palm-sized electronic neuron with versatile applications for teaching and scientific outreach. It can be used to illustrate the dynamics of individual neurons under different parametrizations and their interaction in small spiking neural networks (Fig. 3). Featuring various connectivity options as well as on-board visualization aids, Lu.i can be used stand-alone or in combination with external equipment, like oscilloscopes, current sources, or microcontrollers.

Lu.i complements a range of pedagogical tools spanning from experimental to computational neuroscience (Marzullo and Gage, 2012; Latimer et al., 2018). Among those are guided experiments on tissue and living animals, which are arguably the most natural way to convey biological concepts but always imply ethical and logistical challenges. Simulation-based curricula, on the contrary, trade immediacy with ease-of-use and simplicity, especially when considering graphical user interfaces (Bekolay et al., 2014; Spreitzer et al., 2021). To combine the advantages of both approaches, the concept of tangible hardware has been put forward before (Eng et al., 2008; Kvello et al., 2017; Baden et al., 2018; Burdo, 2018; Renault, 2020). As another effort in this direction, Lu.i combines an inviting interface with an analog yet accurate implementation of the LIF model. The latter is sufficiently complex and flexible to allow illustration of fundamental biological phenomena as well as the concept of physical computation. The PCB is optimized for cost-effective manufacturing to ease acquisition especially for educational institutions. With its engaging form factor, Lu.i has been welcomed at various conferences and workshops, leading to adoption by teachers and tutors in classrooms (Fig. 4). As such, the project received enthusiastic responses initiating collaborations across both different areas of expertise and from pupils to faculty.

The Lu.i project is available as open hardware¹ and undergoes active development. The circuits are continuously improved and future versions might be accompanied by additional extensions, such as sensory spike sources or actuators. In conjunction with the above-mentioned collaborations on courses and workshops using Lu.i, a curriculum of teaching material is being collected to nurture adoption among teaching personnel.

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