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Dendritic Computation for Neuromorphic Applications

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ABSTRACT

In this paper, we highlight how computational properties of biological dendrites can be leveraged for neuromorphic applications. Specifically, we demonstrate analog silicon dendrites that support multiplication mediated by conductance-based input in an interception model inspired by the biological dragonfly. We also demonstrate spatiotemporal pattern recognition and direction selectivity using dendrites on the Loihi neuromorphic platform. These dendritic circuits can be assembled hierarchically as building blocks for classifying complex spatiotemporal patterns.

CCS CONCEPTS

• Hardware → Emerging technologies; **• Theory of computation → Theory and algorithms for application domains**; **• Computing methodologies** → *Artificial intelligence.*

KEYWORDS

Dendritic Computation, Silicon dendrites, Artificial Dendrites, Neuromorphic Computing, Neural Networks using Dendrites

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1 INTRODUCTION

Dendrites are the computational interconnects of the brain. However, they are often overlooked while modeling neuromorphic architectures and algorithms in favor of point neurons. Biological dendrites have demonstrated a range of nonlinear properties that support a range of computations including direction selectivity, coincidence detection, spatiotemporal filtering, and segregation and amplification of inputs, suggesting a 'dendritic toolkit' [15] that offers computational richness that is yet to be effectively exploited in neuromorphic architectures.

Nonlinear interactions between different conductances on dendritic branches, typically driven by synaptic input, can be used to implement multiple logic operations [15]. This paper discusses our ongoing work to demonstrate the efficacy of dendritic computation for various applications for neuromorphic systems. We present two examples of leveraging properties of biological dendrites to implement neural-inspired algorithms on neuromorphic architectures. First, we have recently proposed shunting inhibition as a mechanism to do multiplication 'cheaply' in silicon dendrites [4]. Here we demonstrate leveraging dendritic multiplication to implement interception in a model of dragonfly prey-interception neural circuitry based on [3]. Second, we show direction-selective dendritic circuits on Intel's Loihi chip which can be directly coupled with an event sensor for pattern detection. These examples were chosen to illustrate how implementing biologically-inspired mechanisms in a neuromorphic model can enable a computational operation that is applicable for a wide range of applications.

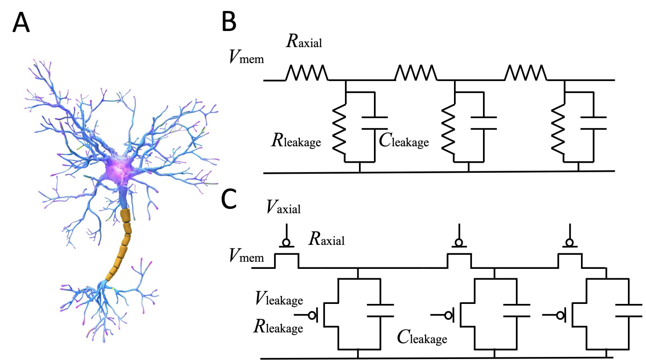

Figure 1: Modeling passive dendrites in silicon. (A) Illustration of a neuron with dendritic branches. Image from Alfred Pasieka/Science Photo Library via Getty Images. (B) Passive resistor-capacitor circuit to model a linear cable where V_{mem} is the membrane potential, R_{axial} is the axial resistance and $R_{leakage}, C_{leakage}$ are the leakage resistance and capacitance respectively. (C) Transistors used to model a passive cable in silicon where V_{axial} is the gate voltage for the axial transistor and V_{leak} is the gate voltage for the leakage transistor.

2 ARTIFICIAL DENDRITES

There is growing interest to leverage silicon dendrites as computational interconnects to model multi-compartment neurons [1, 12]. It is hypothesized that dendrites will add to the computational complexity of deep learning algorithms by enabling increased computation and pre-processing in single neurons and additional learning rules [1, 5]. Recent work utilizes active dendrites for continual learning and avoiding catastrophic forgetting for multi-task learning in a dynamic environment [11].

A resistor-capacitor (RC) circuit such as that shown in Figure 1B captures the 'passive' properties of a biological dendrite. This RC circuit, in turn, can be modeled using CMOS transistors operating in a linear region [8, 18] as shown in Figure 1C. Active

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components [19, 23] may be included to emulate the complexity of active, time-varying conductances that are present in biological dendrites, for example a silicon model of the NMDA (N-Methyl D-Aspartate) conductance [12, 19, 23]. There are also several efforts to leverage emerging devices, for example memristors [14] or multi-gate ferroelectric FETs [2, 21], to build artificial dendrites. These devices promise low-power solutions, can be integrated with CMOS (Complementary Metal-Oxide Semiconductor), and have the potential to leverage three-dimensional stacking techniques to increase connectivity that will amplify the advantages offered by neuromorphic dendrites.

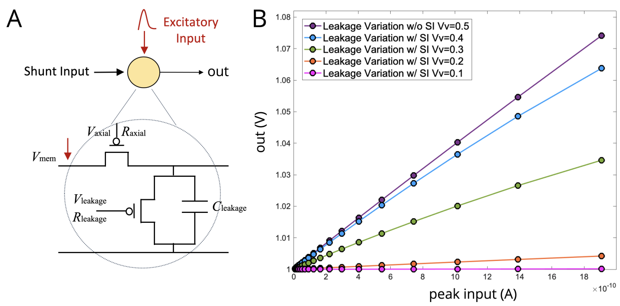

Figure 2: A. Single compartment dendrite with an excitatory input (red) and a shunt input (controlling R_{leakage}). B. Varying the shunt input can multiplicatively scale the response to excitatory input. V_{leakage} or V_{v} is the gate voltage of the leakage transistor.

Here we focus on exploiting non-linear properties of dendrites for computation. To this end, we leverage a simulation code that models a CMOS passive dendrite cable using transistors operating in the subthreshold regime as demonstrated in [18] and [8]. We have recently shown shunting inhibition as a potential mechanism for multiplication in passive dendrites [4]. As illustrated in Figure 2, shunt input multiplicatively scales the response to excitatory input, enabling multiplication of two *independently time-varying* inputs, a distinct operation from programmable fixed weights typically associated with a neural network. We demonstrate this operation in a neural network model of a biological prey-interception circuit in the next section.

3 DRAGONFLY-INSPIRED INTERCEPTION USING MULTIPLICATIVE DENDRITES

Recent studies [10, 16, 17] have demonstrated that the Drosophila nervous system builds representations (e.g. for navigation) by multiplying different streams of sensory input. Multiplication is an expensive but critical operation for many applications. Here we investigate using our dendrite (see Figure 2) to implement multiplication in a dragonfly-inspired neural network model.

Figure 3 describes the basic architecture of the neural network. The input layer is composed of two populations of neurons. One population (denoted by the red circles) receives visual input, for example from a camera. The response of visual neuron i is

$$f_i(x) = \exp\left(-\frac{(x - a_i)^2}{2\sigma_r^2}\right),$$

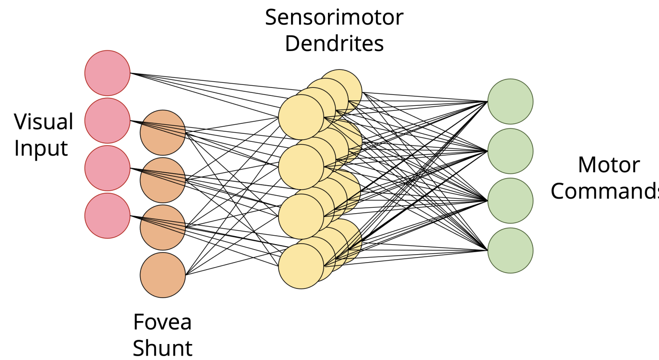

Figure 3: Schematic of the dendrite-enabled dragonfly neural network. Red and orange neurons in the input layer encode visual and fovea-position information, respectively. Yellow circles denote sensorimotor dendrite-enabled neurons. Green neurons are the motor-output neurons.

where x is the location of the target's image on the camera's plane, a_i is the preferred target-image location of neuron i, and σ_r determines the width of the tuning curve. Neurons in the second population of input neurons (orange circles, referred to here as 'fovea neurons') encode the desired location of the target's image on the sensor (unlike a biological fovea, the model fovea is a variable location). Like visual neurons, the responses of fovea neurons are characterized by Gaussian tuning curves:

$$g_j(y) = \exp\left(-\frac{(y - b_j)^2}{2\sigma_g^2}\right),$$

where y is the fovea location, b_j is the preferred fovea location of neuron j, and σ_g determines the width of the tuning curve.

For the model presented in [3], the response S_{ij} of a single sensorimotor neuron (yellow circles in Figure 3) was the product of input from visual-input neuron i and fovea neuron j:

$$S_{ij} = f_i(x) g_j(y).$$

The sensorimotor population therefore included neurons tuned for all possible combinations of target-image and fovea positions.

To demonstrate the viability of using shunting inhibition for multiplication in a neuromorphic application, we have replaced sensorimotor neurons with multi-compartment neurons consisting of a single dendritic compartment model (see Figure 2 and details below). The dendritic compartment enables multiplicatively scaling of the excitatory input by the shunt input. The excitatory input (red arrow in Figure 2 is sent to the dendrite by the visual neurons in Figure 3), and the shunt input is controlled by fovea neuron activity.

Our dendrite compartment is modeled as a passive cable using transistors operating in the subthreshold regime. The subthreshold regime of transistors is dominated by diffusion much like biological processes with an exponential current-voltage relationship. We use Matlab code to solve the coupled ODEs (Ordinary Differential Equations) that capture the behavioral properties of this CMOS-based dendrite. This is needed to capture the subthreshold dynamics of a transistor.

For an n compartment dendrite, we solve for the voltage at each 'tap' of the dendrite as shown in Figure 2. We define all the constants in the equations based on the transistors used on the FPAA (Field Programmable Analog Array) (Constants κ, I_0, thermal voltage U_T, capacitance C) [9] along with the input parameters as defined for the block (leakage conductance modulated by $V_{leakage}$, axial conductance modulated by V_{axial}, potential E_k). For more details on the model, please refer to [8, 18].

$$\begin{aligned}\frac{d\vec{V}}{dt} = \frac{1}{C}(a_1.I_{inj} &+ k_1(e^{a_2.\vec{V}/U_T} - e^{a_3.\vec{V}/U_T}) \\ &+ k_1(e^{a_4.\vec{V}/U_T} - e^{a_5.\vec{V}/U_T}) \\ &+ k_2(e^{a_6.\vec{V}/U_T} - e^{E_k/U_T}) + I_{bias})\end{aligned} \tag{1}$$

where

$$\vec{V} = \begin{bmatrix} V_1 & V_2 & V_3 & \ldots & V_n \end{bmatrix}$$

a_1,a_2,a_3, a_4, a_5 and a_6 are constant matrices whose size is dependent on the number of stages/taps of the dendrite.

The motor-output neurons (green circles in Figure 3) encode the direction to which the dragonfly should turn. The response R_k of motor-output neuron k is a weighted sum over all inputs from the sensorimotor population:

$$R_k = \sum_{i,j} W_{ijk} S_{ij}.$$

The synaptic weight between sensorimotor neuron S_{ij} and motor output neuron k is described by

$$W_{ij} \propto \iint \exp\left(-\frac{(y+z-a_i)^2)}{2\sigma_r^2} - \frac{(y-b_j)^2)}{2\sigma_g^2} - \frac{(z-c_k)^2)}{2\sigma_m^2}\right) dydz,$$

where c_k is the preferred turn direction for neuron k and σ_m is a parameter that controls the tuning of the motor neurons for turn direction (see [3, 22] for more details). The dragonfly executes a change in yaw,

$$d = \frac{\sum_k c_k R_k}{\sum_k R_k},$$

decoded by performing a weighted average of motor output neuron activities. For simplicity, we constrain the dragonfly and its target to move in one plane of motion, which significantly reduces the size of the neural network.

Figure 4 presents two examples of successful interception trajectories as calculated by the dendrite-enabled dragonfly model. At the beginning of each simulation time step, the target moves to a new location (in plane of motion). The location of the target's image on the camera representing the dragonfly's eye determines the activities of the visual input neurons. The neural network model calculates the dragonfly's turn as described above and the dragonfly advances in the new direction. The new fovea location is calculated as $e = e_0 - d$, where e_0 is the previous location of the fovea, and the activities of the fovea neurons are updated accordingly. This update is equivalent to shifting the fovea position in an equal but opposite direction to the shift in the target image's location on the camera that results from the dragonfly's turning.

In a full experimental implementation, the input and output neurons would be position-encoded without a Gaussian to represent their firing rates. For the purpose of this experiment we only

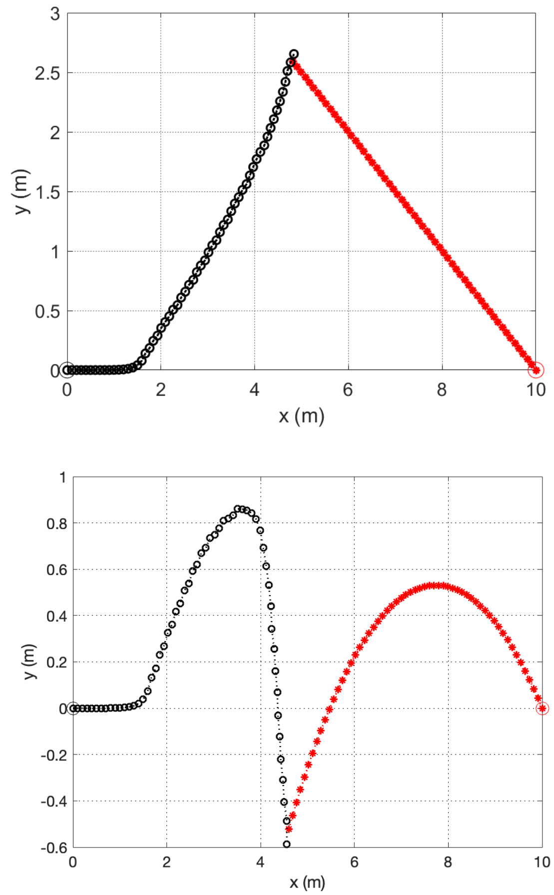

Figure 4: Dendrite-enabled dragonfly network with multiplicative dendrites successfully calculates interception. Dragonfly (open black circles) and prey (filled red circles) positions are plotted at each simulation time step for example straight (top) and curved (bottom) prey trajectories.

modeled the dendrites in hardware. The software-simulated retina and fovea inputs of the network were mapped to the appropriate current and voltage ranges for the hardware dendrite. The dendrite output was then mapped to the software-simulated motor neurons. In future implementations, pre-processing for this network would depend on the application constraints and the system design.

4 DIRECTION SELECTIVITY USING DENDRITES

Direction selectivity and coincidence detection are other interesting properties of dendrites. These can be exploited to classify spatio-temporal patterns. Here, we demonstrate a direction-selective circuit built using dendrites on Intel's Loihi 1 chip [6]. The example demonstrated is relevant for event sensor inputs. Event sensors are bio-inspired sensors that asynchronously measure per-pixel brightness changes and encode an output stream of events that encode time, location and sign of the brightness change [7]. They

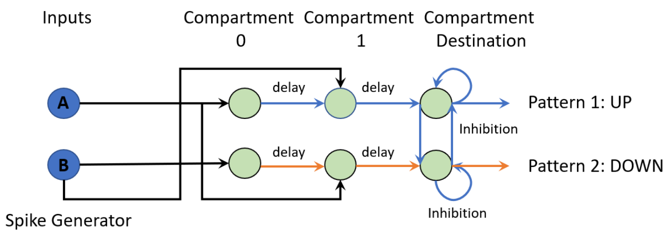

Figure 5: Figure illustrating the direction-selective dendrite circuit implemented on Loihi 1.

have high temporal resolution, high dynamic range, low power consumption, and reduced motion blur. Event cameras are especially useful since they encode only motion in a given scene. The inputs for the experiment model pixel activation in the UP and DOWN direction.

The direction-selective circuit as shown in Figure 5 takes inputs from multiple pixels along the Loihi dendrite. Each dendritic compartment adds input from one spike generator as well as the the 'upstream' compartment. There is a fixed transmission delay of one timestep between each dendritic compartment. We demonstrate our experiment for two patterns for upward and downward motion as seen by an event camera. For simplicity, we model two adjacent-in-space pixel inputs. Each pixel sends input to compartment 0 of one dendrite and compartment 1 of the other dendrite. We use the Loihi spike generator to simulate the pixel input spikes for the circuit. As shown in Figure 6, each dendrite is tuned to detect a certain direction. It is important to note here that both compartments receive inputs driven by both UP and DOWN patterns (see Figure 6D and E). However, as soon as a dendrite detects a pattern (e.g. the DOWN dendrite detects the DOWN pattern), it laterally inhibits the other dendrite, causing it to reset. This ensures only the correct destination compartment spikes. The destination compartment also inhibits itself once it spikes. The destination compartment and voltage trends are not exactly mirror images as seen in Figure 6 D and E because the destination compartment voltage is not completely reset to initial conditions after the first pattern is detected.

The direction-selective local dendritic circuit is an example of spatiotemporal processing that could be incorporated into a hierarchical model to detect more complex patterns [25]. It is also important to note that while there is practically no difference in the energy cost of a neuron versus a dendritic compartment on the Loihi platform, if the dendrites were implemented in analog, the circuit footprint would be much lower compared to the same circuit constructed from multiple neurons.

5 SUMMARY AND CONCLUSIONS

We have presented initial findings from leveraging dendritic properties for two different applications, the dragonfly-interception-inspired neural network model and direction selectivity for event-sensor input. The dragonfly interception model successfully leverages subthreshold analog dendrites for biologically-inspired multiplicative integration of two distinct time-varying inputs. We have also demonstrated a pattern-recognition circuit using digital dendrites implemented on the Loihi neuromorphic chip.

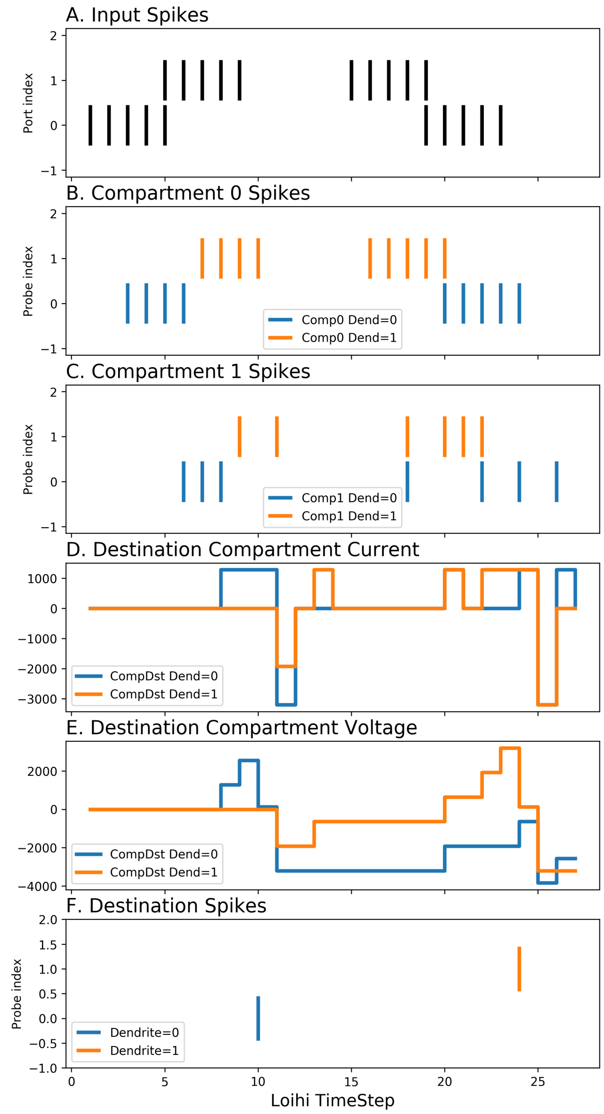

Figure 6: direction-selective dendrite circuit output for UP and DOWN pattern on Loihi 1. The inputs are modeled as spikes generated by an event sensor responding to a LED point source moving in the UP or DOWN direction. (A) Spike Generator patterns for UP (time steps 1 to 9) and DOWN (time steps 15 to 23). (B) Input spikes to Compartment 0 of both dendrites (spikes to UP and DOWN dendrites in 5 are in blue and orange, respectively). (C) Input spikes to Compartment 1 of both dendrites. (D) Destination compartment current for both dendrites. (E) Destination compartment voltage for both dendrites. (F) Destination compartment spikes of UP and DOWN dendrites report UP and DOWN patterns, respectively.

The artificial intelligence/deep learning field has benefited from brain inspiration whether it is for the perceptron model by Rosenblatt [20], convolutional kernels [13] or even regularization/dropout [24] techniques. We assert that taking inspiration from the brain for the underlying hardware will prove to be extremely important when modeling and mapping brain-inspired algorithms. After all, the brain is a product of 'biological codesign', where the underlying noisy substrate has been utilized to achieve various complex cognitive functions. Thus, it is imperative that algorithm designers, computer architects and hardware engineers alike exploit the inherent physics of the underlying hardware for computation. While neuromorphic hardware has achieved scaling to a billion neurons, current systems sacrifice complexity in favor of scaling. In order to achieve brain-like abilities, we need scaling, complexity, computational efficiency *and* computational density. We believe that modeling dendrites will be a key property to exploit for next-generation neuromorphic architectures and applications. This requires computational elements in hardware that not only support dense three-dimensional connectivity but also enable other key computational properties like non-linear filtering, direction selectivity, and coincidence detection.

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