Introducing Astrocytes on a Neuromorphic Processor:
Synchronization, Local Plasticity and Edge of Chaos

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ABSTRACT
While there is still a lot to learn about astrocytes and their neuromodulatory role associated with their spatial and temporal integration of synaptic activity, the introduction of an additional to neurons processing unit into neuromorphic hardware is timely, facilitating their computational exploration in basic science questions and their exploitation in real-world applications. Here, we present an astrocytic module that enables the development of a spiking Neuronal-Astrocytic Network (SNAN) into Intel's Loihi neuromorphic chip. The basis of our module is an end-to-end biophysically plausible compartmental model of an astrocyte that simulates how intracellular activity may encode synaptic activity in space and time. To demonstrate the functional role of astrocytes in SNANs, we describe how an astrocyte may sense and induce activity-dependent neuronal synchronization, can endow single-shot learning capabilities in spike-time-dependent plasticity (STDP), and sense the transition between ordered and chaotic activity in the neuronal component of an SNAN. Our astrocytic module may serve as a natural extension for neuromorphic hardware by mimicking the distinct computational roles of its biological counterpart.

CCS CONCEPTS
• Computer systems organization → Neural networks; • Software and its engineering → Software libraries and repositories;

KEYWORDS
Neuromorphic Computing, Astrocyte, Spiking Neuronal-Astrocytic Network

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1 INTRODUCTION
Shadowed by a century of neural recordings, astrocytes, the most abundant yet electrically silent non-neuronal cells in the brain, have long remained absent from most studies on the biological principles of intelligence and from translative efforts towards artificial intelligence. Recent advancements in Ca^{2+} imaging [68] and selective stimulation [49] have signified the active signaling that occurs among astrocytes as well as between astrocytes and neurons [69]. Astrocytes and other glial cells are now known to do far more than just providing nutritional and structural support to neurons [69]. Among the many roles attributed to astrocytes in brain function and dysfunction [4], a striking one is their neuromodulatory ability that originates at the cellular level, where synaptic plasticity [27, 51] and neuronal synchronization [19, 52] take place, and extends to the network level, where brain rhythms are observed [10, 22, 30], a major component of behavioral functions including memory [1, 31] and cognition [22, 26, 48].

Astrocytic neuromodulation is so widely dispersed across distinct brain regions [3, 12, 34, 49] that has now elevated the synapse to a tripartite information processing unit (Fig. 1A), where neurons and astrocytes work independently and collaboratively [47]. The current hypothesis is that, by forming a large number of tripartite synapses, a single astrocytic cell acts as a spatiotemporal integrator of the synaptic activity [16, 24]. Replicating experimental results, our recent computational studies suggested intracellular mechanisms that the astrocytes may be using to modulate both excitatory [51, 52] and inhibitory [53] synaptic activity. In our model, astrocytes modulate the neuronal activity by sensing neurotransmitters’ spillover from the presynaptic neurons and releasing gliotransmitters to the postsynaptic neurons. Specifically, when the presynaptic neurotransmitters are bounded to astrocytic receptors, they cause
the production of a second intracellular messenger molecule, Inositol 1,4,5-Triphosphate (IP$_3$). When IP$_3$ concentration reaches a threshold from below, an intracellular Ca$^{2+}$ wave is generated with a similar temporal and spatial profile to the one observed in 	extit{in-vitro} studies [61]. The Ca$^{2+}$ wave triggers the release of gliotransmitters which in turn induce a Slow Inward Current ($I_{SIC}$) affecting the activity of the postsynaptic neuron [44].

Following the prevailing dogma that brain computation equals neuronal processing, neuromorphic processors are built on the premise that neurons are the only computing unit. In an effort to overcome the intrinsic limitations of the connectionist models of neuronal computation, multiple neuromorphic chips are now available [15, 23, 38, 58]. These chips employ a time-dependent computational formalism, spiking neural networks (SNN), where asynchronous computing units are simulated as spiking neurons and memory is distributed at the neuronal synapses. Notably, Intel’s Loihi processor [15] represents the most recent advances in large-scale neuromorphic hardware and offers asynchronous parallelism and therefore power efficiency for applications ranging from batch-mode image processing [15, 35] and speech recognition [9] to real-time control of robotics [65].

Alongside recent efforts to implement back-propagation algorithms in SNNs [6, 62], most neuromorphic solutions are either restricted enough to be dictated by the known connectome of the underlying neural areas associated with the targeted function [65], or simple enough to be trained via some variation of spike-time-dependent plasticity (STDP), a biologically relevant yet computationally weak rule [8, 18]. By correlating presynaptic and postsynaptic activity, STDP rules contribute to the asynchronous parallelism of neuromorphic chips but they rather oversimplify other types of global or “regional” learning rules occurring in the brain [36, 59]. And as energy efficient as it may be, asynchronous neuromorphic hardware is still lacking an activity-dependent mechanism that would entrain its sub-networks into rhythmic activities, much like the brain does to efficiently process time-sensitive information [21, 22]. Additionally, SNNs have inherited from the ANNs the assumption that learning takes place in the overall connection strengths between neurons; Although structural plasticity rules that expand beyond the single synapse have been known for many years to increase the computational capacity of neurons [37, 50], local plasticity has yet to be incorporated into SNN learning. In fact, learning and memory are optimally balanced in networks that macroscopically operate at the edge of chaos [7], which is a narrow dynamical regime largely ignored in learning algorithms, yet also exhibited by the brain [5]. Overall, SNNs and their hardware realizations seem to be missing a mesoscopic learning mechanism that may combine the computational efficiency of having a global network goal with the versatility of a local, activity-dependent, plastic mechanism.

In this paper, we introduce the notion of spiking Neuronal-Astrocytic Networks (SNANs) and demonstrate some of the distinct computational and learning abilities that astrocytes may introduce into a neuromorphic hardware. We first describe our Loihi moduleootnote{The module is available at https://github.com/combra-lab/combra_loihi}, where astrocytes may be used as an additional - to neurons - information processing unit, communicating with neurons in the tripartite synapses and with each other via intra- and inter-cellular Ca$^{2+}$ waves [57]. We then exhibit three example uses of our Loihi module, where astrocytes can extend learning at the meso-scale: Specifically, a) we show how astrocytes may modulate the neuronal component of the SNANs, by using their Ca$^{2+}$ dependent SIC to impose an on-demand synchronization across neuronal areas; b) We present how they can be used for single-shot pattern memorization via astrocyte-reinforced STDP; c) We finally show a single astrocytic cell may be used to be continuously sensing for the transition between order and chaos in the neuronal component. With NaNs already showing their potential in a growing number of applications as reinforcement to neuronal networks [31, 54, 67], the proposed Loihi module can become a computational framework for exploring and exploiting the unique computational principles that astrocytes are now known to exhibit.

2 THE LOIHI ASTROCYTIC MODULE (LAM)

2.1 Module Overview

Our Loihi Astrocytic Module (LAM) emulates the basic communication pathways between neurons and astrocytes in the tripartite synapse as well as the sub-cellular processes that astrocytes use to generate calcium waves in response to synaptic activity. The module’s building block is the astrocytic cell that is created as an assembly of 4 Loihi compartments that approximate in hardware...
the leaky-integrate-and-fire neuronal model. We connected these compartments and tweaked their internal dynamics to represent the slower astrocytic processes (Fig. 1B). This ensures that the astrocytic component can be seamlessly integrated into any spiking neural network (SNN), by only declaring the connections between any of its spiking neurons and astrocytes.

2.2 Module Implementation
The LAM has 2 main components: (i) The input integration component that senses the neuronal activity by emulating the astrocytic receptors and IP3 production, and (ii) the output generation component that modulates the neuronal component of the SNAN. The input integration component comprises of 2 spiking Loihi compartments, the input Spike Receiver (SR) and the IP3 integrator (IP3). The SR compartment integrates synaptic activity into IP3, resembling the behavior of astrocytic receptors. The IP3 dynamics are much slower than the neuronal dynamics, with their time-scale ranging from hundreds of milliseconds to tens of seconds. This allows for a temporal integration of the synaptic activity. When IP3 spikes, the output generation generates bursting spikes to either the postsynaptic neurons or the Loihi’s reinforcement channel of neuronal connections. The output generation component has a dendritic tree where the non-spiking SIC generator compartment (SIC) feeds its voltage into the burst Spike Generator compartment (SG). The SIC produces a continuous voltage signal similar in shape to the observed biological $I_{SIC}$. The SG descretizes that signal into bursting spikes sent to the user-defined destinations.

2.3 Developing a Feedforward SNAN using the LAM
To demonstrate the internal dynamics of the astrocyte compartments as the mechanisms that an astrocyte uses to impose synchronous activity in postsynaptic neurons [19], we present a simple 2-layer feedforward SNAN (Fig. 2A). In this network, presynaptic neurons with Poisson spike trains were randomly connected to the same number of postsynaptic neurons. The astrocyte integrated the presynaptic activity and generated an IP3 spike at 6 seconds, which, in turn, triggered the SG bursting spikes and generated synchronous activity in the postsynaptic neurons for 400 milliseconds (Fig. 2B). The astrocytic dynamics are configurable in our astrocyte SDK that is described below.

3 ASTROCYTE SDK
3.1 SDK Architecture
The Astrocyte SDK builds on the existing NxSDK Python-based programming model for Loihi [35] and it is designed to facilitate the integration of astrocytes with SNNs. The SDK’s API provides access to 3 main classes, depicted in Figure 3:

Figure 2: A feedforward SNAN where an astrocyte senses and imposes synchronous neuronal activity. A. SNAN Architecture. B. Astrocytic and neuronal activity on Loihi.

Figure 3: Overall Astrocyte SDK Structure.
(1) **AstrocytePrototype**: The prototype class for defining astrocytes allows users to configure the properties of each of the four compartments within the astrocyte, including the spiking thresholds for the IP3 compartment, the current decay of the SIC compartment and the weights between the compartments.

(2) **Astrocyte**: An astrocyte instance describes the internal compartments of the astrocyte model. This class provides the functions for specifying the presynaptic (input) neurons and the postsynaptic (output) neurons, to create tripartite synapses. Each instance of the Astrocyte class requires an AstrocytePrototype; If none is provided, a default prototype is created.

(3) **AstrocyteGroup**: A wrapper class that instantiates multiple astrocytes. The constructor accepts lists of prototypes, the size of the group of astrocytes and other configurations for mapping astrocyte instances to prototypes and Loihi’s logical cores.

### 3.2 Automatic Parameter Setup

Our Astrocyte SDK allows the user to define astrocyte behavior by controlling the following three parameters in the AstrocytePrototype class:

1. **ip3_sensitivity**: the weight between the SR and the IP3.
2. **sic_amplitude**: the maximum firing rate of the SG.
3. **sic_window**: time duration in milliseconds between the first and last of the spikes generated by the SG.

These SDK level parameters are automatically mapped to Loihi parameters using a precalculated configuration table, generated using the `sic_data_table.py` file located within the utils folder of the module. This script performs a brute force search of Loihi parameter configurations, saving all configurations that yield a minimal discretized SIC output, or a single burst spike. Finally, the closest matching configuration is selected based on the Euclidean distance metric defined as

\[
\text{cost} = (\text{sic_amplitude}_{\text{target}} - \text{sic_amplitude}_{\text{config}})^2
- (\text{sic_window}_{\text{target}} - \text{sic_window}_{\text{config}})^2.
\]

Users can define their own range of values for the weights or current decays by regenerating the configurations table using the `sic_data_table.py` file.

### 4 ASTROCYTES INDUCE NEURONAL SYNCHRONIZATION

We now demonstrate how a group of astrocytes can be instantiated automatically, as described in Section 3.2, to synchronize sub-networks of neurons in an SNAN. We provide the code to create a single-layer feedforward SNN with 20 input neurons and 20 output neurons (Fig. 4). In this example, the synapses between the input and output neurons were randomly created with a probability of 8% and a weight of 3. Briefly, to form the SNAN, we created the astrocyte group by defining an AstrocytePrototype (Fig. 4a). We then created a group of astrocytes (Fig. 4b) by specifying the N x N instance it belonged to, the prototype(s) to use for instantiation and the number of astrocytes to create within the AstrocyteGroup. We

```python
# (a) net, pre_neurons, post_neurons = setupFNetwork(
    pre_num, post_num, conn_prob, weight)
# generate_input_spikes(pre_num, pre_neurons, sim_time)
# (b)
astrocyte_prototype = AstrocytePrototype(ip3_sensitivity=4500,
    sic_window=385, sic_amplitude=176, sip3_sensitivity=15)
astrocyte_group = AstrocyteGroup(net,
    prototype=astrocyte_prototype, size=2)
# (c)
input_conn_mask = np.int_(np.ones((2, 20)))
output_conn_mask = np.int_(np.zeros((20, 2)))
output_conn_mask[10:20, 0] = 1
input_conn_w = input_conn_mask
input_conn_w[0, :] = 0
input_conn_w[1, :] = 10
output_conn_w = 5 * output_conn_mask
# (d)
astrocyte_group.connectInputNeurons(pre_neurons, pre_num,
    input_conn_mask, input_conn_w)
astrocyte_group.connectOutputNeurons(post_neurons, post_num,
    output_conn_mask, output_conn_w)
# Create probes for plots
probes = create_probes(astrocyte_group, post_neurons)
# run network
net.run(sim_time)
net.disconnect()
```

**Figure 4**: An example Astrocyte SDK program for integrating 2 astrocytes into an SNAN using the AstrocyteGroup.

**Figure 5**: An astrocyte group inducing synchronized activities in postsynaptic neurons.

We also demonstrate how to form tripartite synapses based on the connection masks, indicating which of the possible neurons to connect to, and the weights for those connections (Figs. 4c, d). Replicating experimental studies as well as our computational results [19, 52], the two Loihi astrocytes imposed distinct synchronization patterns in the neuronal component, forming two synchronized groups (Fig. 5).

### 5 ASTROCYTES EXPAND HEBBIAN LEARNING IN SPACE AND TIME

#### 5.1 Experimental and Computational Evidence

Astrocytes are now known to take active part in a wide number of behaviors, from improving cognitive function and memory [26] to suppressing futile unsuccessful behavior [40]; Interestingly enough,
they have also been found to not only be necessary but also sufficient for new memory formation [1]. As the third part of the tripartite synapse, astrocytes modify behavior by modulating plasticity and, ultimately, learning. What distinguishes astrocytes from neurons is that they are integrating synaptic activity over a much wider spatial scale and much longer temporal scale [3] and that they can increase or decrease synaptic weights, individually from neurons.

Therefore, the newly identified mechanisms in astrocytes can be used to expand two main characteristics of Hebbian-type learning. First, astrocytes can be used to introduce regional learning: Hebbian learning is localized and lacks any knowledge of the neuronal activity in the vicinity of the synapse. Any change in synaptic weights is driven by the spiking activity of the presynaptic and postsynaptic terminals that form a single synapse. However, the spatial scale of astrocyte-induced plasticity spans from neighboring spines [72] to synapses found hundreds of micrometers away from the active synapse [45], extending the spatial reach of plasticity. Second, astrocytes can integrate synaptic activity over time, ranging from hundreds of milliseconds to seconds, extending plasticity beyond the short-term correlations between pre- and post-synaptic activities. Therefore, a change of synaptic weights that currently depends on very short temporal dependencies, can now be influenced by the activity in a much larger time window, allowing, e.g., for temporally delayed plasticity effects [11, 34, 60]. Overall, these are two main reasons why astrocytes are not only an important computational unit for the biological network but can become a new processing component for the artificial networks.

5.2 Astrocytic-induced Heterosynaptic Depression (HSD)

Heterosynaptic plasticity offers a straightforward astrocyte-implanted extension of Hebbian learning, in both time and space. For example, astrocytes are found to detect the high (tetanic) activity of a pathway and respond to it by inducing presynaptic depression on the neighboring inactive pathways [60]. This astrocyte-driven Heterosynaptic Depression (HSD) [36] complements the associative nature of STDP and this combination of the two distinct rules is believed to counterbalance the homosynaptic alterations, making the heterosynaptic modifications more prominent [2]. In the next session, we show how HSD can use its spatial information to augment STDP, introducing single-shot memories.

5.3 Example Implementation of HSD in LAM to Introduce Single-Shot Memory

LAM supports astrocyte-driven plasticity mechanisms, to induce spatially and temporally expanded modifications of synaptic weights. To showcase this functionality, we present a 2-layer feedforward SNAN (Fig. 6A), with the astrocyte monitoring the activity of the sensory neurons. LAM uses the reward channels of Loihi’s learning engine to implement the astrocyte-induced HSD on top of the regular neuronal STDP component.

The astrocyte-reinforced learning rule is defined as a sum of trace products [35],

\[ dw = \sum_j S_j \prod_j T_{ij}, \]

where \( T_{ij} \) is the trace and \( S_j \) is the learning rate.

The regular STDP component implemented on Loihi is defined as

\[ dw_{stdp} = a * x_1 * y_0 - b * x_0 * y_1, \]

where \( x_0 \) and \( y_0 \) represent the presence of pre- and post-synaptic spikes, respectively, and \( x_1 \) and \( y_1 \) are the pre- and post-synaptic spike traces, decaying exponentially.

The astrocyte-induced HSD component is defined as

\[ dw_{hsd} = -(c * y_0 - d * x_0 + r_1) \]

\[ = -c * y_0 * r_1 + d * x_0 * r_1, \]

where the reward spike trace \( r_1 \) represents the activity of the astrocyte. The HSD component decreases the weights of all neuronal synapses when the astrocyte is active. For more prominent heterosynaptic changes, the component induces slower weight decrease for sensory synapses with stronger activity and faster decrease for those with weaker activity.

We finally define the HSD-reinforced STDP on Loihi as follows,

\[ dw = dw_{stdp} + dw_{hsd} \]

5.3.1 Experiment. To demonstrate the use of an HSD-reinforced STDP, we used the LAM to develop a feedforward SNAN (Fig. 6A). We used 5 different patterns in a 3x3 grid as the input to the network. Each pattern had 3 active blocks and all patterns shared 1 overlapping active block. The patterns were encoded into Poisson spike trains, with each sensory neuron encoding one block in the grid. Sensory neurons had a baseline firing rate of 5 Hz (for white blocks) and an active firing rate of 100 Hz (for black blocks). For this implementation, \( a = 2^{-5}, b = 2^{-6}, c = 2^{-2}, d = 2^{-1}, \) the impulses for \( x_1 \) and \( y_1 \) were 16 whereas for \( r_1 \) was 8, and the decay time constants for all traces were 2. We presented each pattern for 2 seconds during memory learning, and for 0.2 seconds during memory retrieval. It was the persistent neuronal activity that triggered the astrocytic SIC. In other words, the astrocyte switched between on- and off-learning models, allowing learning only when the stimulus was presented long enough.

5.3.2 Results. The postynaptic (memory) neuron fired maximally when the learned pattern was presented, during retrieval (Fig. 6B). When the astrocyte got activated, all synapses encoding inactive blocks decreased their weights to negative values (through HSD), inhibiting the activity of the memory neuron (Fig. 6C). This creates a clear distinction between regular STDP and the HSD-reinforced STDP: With regular STDP, any active block that overlaps among patterns (e.g. the central block in the first two and the fourth patterns - Fig. 6A) would increase the weight of its synapse every time any pattern was shown. With the astrocytic contribution, when active blocks overlapped across patterns, the memory neuron was inhibited by the other sensory neurons that encoded active blocks forming the different pattern than the one learned. In other words, by integrating inputs from the regional synapses, the astrocyte became active only when the overall input was strong enough. Without astrocytic activity, the learning rule downgrades to a regular STDP (Fig. 6C). The negative weights of the irrelevant to the learned pattern neurons inhibited postsynaptic firing. With decreased postsynaptic activity, regular STDP could not affect synaptic weights. This way, the astrocyte controlled when the
network memorizes a new pattern. Overall, our LAM provides an astrocytic gating mechanism towards neuronal learning that adds to the regular STDP a spatial and temporal extension.

6 ASTROCYTES LEARN TO SENSE TRANSITION INTO CHAOS

6.1 LAM Support of Astrocytic Learning

LAM allows construction of astrocytes with custom input plasticity mechanisms, limited only by the set of operations defined within Loihi. It is known that astrocytes perform large-scale spatial and temporal integration of synaptic activity [sources 4, 44, 49] and exhibit bidirectional homeostatic plasticity (BHP), where astrocytic connections continuously increase (decrease) sensitivity to synapses with low (high) activity over the course of several hours [70]. This suggests that learning dependent on neuronal firing rate is both functionally and experimentally appropriate for astrocytic learning. LAM supports rate-dependent learning as a general learning rule incorporating spatial and temporal information:

\[
\begin{align*}
    \frac{dt}{dt} &= f_r(x_0) \\
    dw &= f_w(w, t),
\end{align*}
\]

where \(f_r\) dynamically integrates synaptic input spikes sensed by the astrocyte, resulting in a spike rate approximation variable \(t\) for each tripartite synapse, and \(f_w(w, t)\) implements astrocytic weight learning defined on the astrocyte input compartment. A recently proposed astrocyte model with rate-based learning has demonstrated the ability to detect and encode the presence of network chaos.

6.2 An Astrocytic Model For Network Chaos Detection

SNNs fall under the general category of complex nonlinear dynamical systems, which maximize their computational capacity when they operate at the edge of chaos, as shown by studies ranging from cellular automata to boolean networks [7, 14, 39, 43, 63]. It is at the critical point between ordered and chaotic dynamics where balance of robustness and versatility emerges not only in brain-imitating networks [32, 33] but also in the brain itself [20, 41, 64]. Interestingly, the design of learning algorithms largely does not take into account this general computing principle that would enable SNNs to operate at the edge of chaos. In our ongoing effort to develop self-tuning near-critical SNNs, we proposed and developed a homeostatically plastic, astrocyte model capable of detecting and signaling the approach of network chaos, detailed in our modeling paper [29], and abstracted here as:

\[
f_{\text{astro}}(r_i, \hat{r}_i) = g \left( \frac{1}{N} \sum_{i=1}^{N} \frac{r_i}{r_{\text{max}}} \log \left( \frac{1}{r_{\text{max}}} \right) \right),
\]

where \(r_i\) is the short-term synaptic firing rate, \(\hat{r}_i\) is the long-term synaptic firing rate, \(r_{\text{max}}\) is the maximum synaptic firing rate, \(g\) is a nonlinear activation function, and \(N\) is the number of synaptic inputs into the model. Intuitively, this model compares the run-time, short-term synaptic firing rates, \(r_i\), to the memorized, long-term synaptic firing rates, \(\hat{r}_i\), and aggregates the extent of the individual synaptic differences in the overall astrocytic output frequency, \(f_{\text{astro}}\).
6.3 Example Implementation of Astrocytic Learning in LAM to Detect Chaos

To demonstrate LAM defined astrocyte plasticity, we implemented a SNAN with a single layer of neurons connected to an astrocyte endowed with the BHP learning mechanism (Fig. 7A). To approximate the BHP rule on Loihi, Equation (5) was decomposed into a weighted sum as follows,

\[ f_{astro}(r_i, \hat{r}_i) = \eta \sum_{i=1}^{N} W_i \ast N_i \]

\[ W_i = \log \left( \frac{1}{r_i / r_{max}} \right), \quad N_i = \frac{r_i}{r_{max}} \]  

Input \( N_i \) was represented as the integrated current of real-time presynaptic spikes \( I_i \) and parameter \( W_i \) acted as the weight of the neural-astrocytic connection \( w_i \), described by

\[ \text{Activity}_{astro} = \text{Astrocyte} \left( \sum_{i=1}^{N} w_i \ast I_i \right). \]  

Following the general form in (5), the weight \( w_i \) was learned with the BHP learning rule, defined as,

\[ dt = a \ast x_0 \]

\[ dw = b \ast u_k \ast (w_{max} - w) - c \ast u_k \ast t, \]  

where \( t \) represents the estimated long-term, presynaptic neuron firing rate, and \( w \) approximates the inverse relationship between the neural-astrocytic weight and the presynaptic firing rate described by \( W_i \). Intuitively, the learning rule kept decreasing (increasing) \( w \) for high (low) \( t \) values in a predefined learning time window, where \( t \) did not saturate (Fig 7B.).

Figure 7: Homeostatic astrocyte on Loihi sensing transition from ordered to chaotic network state. A. SNAN architecture showing training and testing phases. B. Learned weights for all the neuronal-astrocytic connections. C. (upper row) Ordered and chaotic neuronal network state (middle row) number of active neurons in both states showing similar neuronal activity (bottom row) astrocytic activity during the transition from order to chaos.
6.3.1 Experiment. The astrocyte was trained using the BHP rule (Eq. (8)) on a single layer of spiking neurons driven by activity generated off-chip. To represent the neuronal activity, we used a non-isotropic Ising model, which is fully described in [29]. Briefly, we modeled synaptic activity as $256 \times 256$ magnetic spins positioned on a 2-dimensional lattice with non-uniform, clustered couplings between spins resulting in stationary spin state patterns. We used the Markov Chain Monte Carlo (MCMC) algorithm to simulate the evolution of spin states by minimizing the system’s overall energy. We determined ordered and chaotic Ising states (Fig. 7C) using the magnetic susceptibility measure [71]. To drive the neurons on Loihi, we downsampled 42x42 spins from the original Ising system, evenly distributed throughout the Ising lattice, and converted each binary Ising spin state to a corresponding neuronal spike state. All Ising spins were updated and transformed into neuronal spikes every 5 milliseconds, keeping the maximum neuron firing rate to 200 Hz (Fig. 7C). The astrocyte’s receptor weights were trained for 25 seconds on neuronal dynamics driven by ordered Ising spin evolution. Then, the model’s activity was tested with respect to both states for 25 seconds each. The parameters for the BHP rule were $a = 2^{-6}$, $b = 2^{-2}$, $c = 2^{-3}$, $w_{\text{max}} = 16$, and $k = 4$ in $a_k$ which controlled the $w$ to only update every $2^k$ learning epochs.

6.3.2 Results. The astrocyte activity increased when the neuronal component transitioned from an ordered state to a chaotic state of firing (Fig. 7C). This nearly 100% increase in astrocyte activity resulted from the weights learned through the BHP rule, since network activity levels remained unchanged throughout the transition (middle row, Fig. 7C). The learned weights generated by the BHP rule were inversely correlated with the long-term mean firing rates of the Ising neurons in training (Fig. 7B), thereby imitating the functional form of $W_i$ in Equation (6). Specifically, as minimally active neurons increased their firing rates with the transition to the chaotic state (first row, Fig. 7C), their higher weights induced increased input current to the astrocyte, resulting in increased astrocyte activity and in sensing the chaotic network state.

7 DISCUSSION AND CONCLUSION

In this paper, we described LAM, an astrocytic module that enables Loihi to incorporate astrocytes as an additional computational unit for SNNs with slower temporal dynamics and more extended spatial modulatory ability, compared to neurons. This new brain-morphic computing paradigm is based on the recent exploration of astrocytes, overturning our assumptions of how the brain functions and dysfunctions and igniting a revolution in our fundamental understanding of neuroplasticity [1]. Using LAM, we demonstrated several implementations of astrocytic plasticity mechanisms that exhibited the versatility of the astrocyte module and the potential for the astrocytic units to form SNANs and extend the computing capacity of SNNs.

Our Loihi astrocyte module supports a wide range of astrocyte-neuron interactions. Recent experimental and computational studies suggest great diversity of astrocytic effects on the neuronal network function. On the biological side, astrocytes have been shown to induce a wide variety of synaptic plasticity mechanisms including homosynaptic [48, 55] and heterosynaptic [42, 60] effects, both at presynaptic [46] and postsynaptic [25, 28] sites. Our astrocyte module can functionally replicate (i) Heterosynaptic Depression (HSD), that was shown to be computationally implicated in single shot persistent pattern memorization, and (ii) Bidirectional Homeostatic Plasticity (BHP), that was demonstrated as they key mechanism that single cell may have to sense the transition of the neuronal network into chaos. Additionally, the astrocytes in our module was shown to induce neuronal synchronization, replicating both experimental and computational studies [52, 66]. On the computational side, studies have implicated astrocytes in network frequency modulation [30, 66], improved network polychronicity [67], and memory transition in attractor networks [31]. In taking our next steps to expand LAM, our focus is to first identify functional roles for the recently astrocytic activities and then translate them into neuromorphic hardware. It has not escaped our attention that LAM may be used as a computational framework enabling astrocytic functions to be both explored in brain hypotheses and exploited for computing purposes.

LAM develops astrocytes as point-process, dimensionless units, with no inter-unit communication. A natural extension for our module is to extend astrocytic computation to (i) the subcellular level and (ii) network level. For example, both imaging [17] and stimulation techniques [56] provide conclusive evidence that the majority of astrocytic activity is spatially confined to functionally independent subcellular compartments, rarely spanning the whole cellular domain. Adding dimensions in our astrocytic cells and networks would enable them to operate, process and learn, on a semi-local, “regional” scale. Additionally, astrocytes, coupled through inter-astrocytic gap junctions, form a network syncytium, thereby enabling long distance communication on top of neuronal networks [13]. Expansion of the astrocyte module to handle both multi-compartment astrocytic units and inter-astrocytic communication would further bridge the computation capabilities of our module with that of biological astrocytes. Overall, although they probably require a lot more small insights before they can be fully integrated into highly developed technologies, the fact that our Loihi-run SNANs are already forming fundamental principles of robustness and versatility, indicates that a seamless integration of our LAM into a neuromorphic hardware is a direction worth exploring.

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