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<tr><td>authors</td><td>

- Georgios Detorakis
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- Charles Augustine
- Somnath Paul
- Bruno U. Pedroni
- Nikil Dutt
- Jeffrey Krichmar
- Gert Cauwenberghs
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<tr><td>title</td><td>Neural and Synaptic Array Transceiver: A Brain-Inspired Computing Framework for Embedded Learning</td></tr>
<tr><td>publication_date</td><td>2018-08-29 00:00:00</td></tr>
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<tr><td>id</td><td>id-5046240059542323170</td></tr>
<tr><td>abstract</td><td>Embedded, continual learning for autonomous and adaptive behavior is a key application of neuromorphic hardware designed to mimic the dynamics and architecture of biological neural networks. However, neuromorphic implementations of embedded learning at large scales that are both flexible and efficient have been hindered by a lack of a suitable algorithmic framework. As a result, most neuromorphic hardware are trained off-line on large clusters of dedicated processors or GPUs and transferred post hoc to the device. We address this by introducing the neural and synaptic array transceiver (NSAT), a neuromorphic computational framework facilitating flexible and efficient embedded learning. NSAT supports event-driven supervised, unsupervised and reinforcement learning algorithms including deep learning. We demonstrate the NSAT in a wide range of tasks, including the simulation of Mihalas-Niebur neuron, dynamic neural fields, event-driven random back-propagation for event-based deep learning, event-based contrastive divergence for unsupervised learning, and voltage-based learning rules for sequence learning. We anticipate that this contribution will establish the foundation for a new generation of devices enabling adaptive mobile systems, wearable devices, and robots with data-driven autonomy. these constraints, learning must be performed in an on-going fashion, using data streaming to the device. Recent work on neuromorphic systems can potentially achieve this feat with a thousandfold less power than GPUs [69, 70] , while matching or surpassing the accuracy of dedicated machine learning accelerators [16, 40] , and operating on-line. This article presents one such system, called Neural and Synaptic Array Transceiver (NSAT), and demonstrates proof-of-concept learning applications. The NSAT is a general-purpose spiking neural network simulator designed on the assumptions that extreme efficiency in scalable neuromorphic learning frameworks for data-driven autonomy and algorithmic efficiency hinges on the establishment of neural algorithms in which the computational power of the Synaptic Operation (SynOp) are on the same order as that of a Multiply Accumulate (MAC) unit; and a neuromorphic design that emphasizes locally dense and globally sparse communication using hierarchical event-based communication [47, 71] . To achieve extreme efficiency, the NSAT framework takes advantage of tractable linear neural model dynamics, multiplier-less design, fixed-width representation and event-driven communication, while being able to simulate a wide range of neural and plasticity dynamics. An NSAT core is composed of a large number of state components that can be flexibly coupled to form multi-compartment generalized integrateand-fire neurons, allowing the implementation of several existing neural models [60, 38] (Fig. 1) . While biological interpretation is not necessary, the state components forming the neuron can be interpreted as somatic potential, dendritic potential, synaptic currents, neuromodulator concentration or calcium currents, depending on its interactions with other state components or pre-synaptic neurons. The communication between cores and event-driven sensors is routed via inter-core spike events. While there already exist neuromorphic VLSI circuits for synaptic learning [77, 83, 5] , our framework is novel in that it is equipped with a flexible and scalable event-based plasticity rule that is tightly guided by algorithmic considerations and matched to the neuron model. Scalability is achieved using only forward lookup access of the synaptic connectivity table [72] , permitting scalable, memory-efficient implementation compared to other implementations requiring reverse table lookups or memory-intensive architectures such as crossbar arrays. Flexibility in the learning dynamics is achieved using a reconfigurable event-based threefactor rule [95, 19] consistent with other established plasticity dynamics such as STDP [12, 54] , membranevoltage based rules [19] and calcium based dynamics [87, 41] . Its three factor dynamics enable unsupervised, supervised and reinforcement learning [27] using local information. We demonstrate that NSAT supports a form of gradient back-propagation in deep networks [80, 28, 102] , unsupervised learning in spike-based Restricted Boltzmann Machines (RBMs) [68] , and unsupervised learning of sequences using a competitive learning [42] . Furthermore, we show that learning in digital NSAT requires fewer SynOps compared to MACs in equivalent digital hardware, suggesting that a custom hardware implementation of NSAT can be more efficient than mainstream computing technologies by a factor equal to the J/MAC to J/Synop ratio. This article is organized as follows: In the Material & Methods section we describe the neuron model and its mathematical equations. We present the NSAT architecture and software simulator (publicly available under GPLv3 license). In the Results section we show that the neuron model can simulate the Mihalas-Niebur neuron [60] and thus demonstrate a rich repertoire of spike behaviors. In addition, we simulate three different neural fields models [3] , and event-driven variants of commonly used machine learning algorithms. Materials and Methods In this section we introduce the mathematical description of the NSAT framework and the details regarding its architecture and its software implementation.</td></tr>
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