Neuromorphic silicon photonics on foundry and cryogenic platforms

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***Abstract*—Silicon photonics presents an opportunity for complex, multi-purpose information processing with optoelectronics. Using foundry devices, some photonic neural networks support sub-nanosecond signals. Using cryogenic devices, others support single-photon signals. We compare these platforms and summarize recent experimental results on programmability in photonic neurons and networks.**

Silicon photonics is capable of supporting integrated systems of large scale, not just large volume. The prospect of information processing based on integrated photonics depends on advances in programmable hardware. Programmable systems for filtering [1] and matrix multiplication [2], [3] have demonstrated new, extensible architectures for analog processing. To surpass a certain scale, a processing model must contain nonlinear elements to prevent the accumulation of noise. Neural network models are well-matched to the qualities of optics, particularly in their heavy-reliance on communication that is linear, parallel, and asynchronous. Photonic devices mathematically isomorphic to a neuron–the nonlinear element–have received significant research attention over the past seven years [4]. Until recently, however, research on the dynamics of isolated photonic neurons has outpaced experimental progress on neurons that can drive other alike neurons and that co-integrate with scalable routing architectures.

Here, we consider two neuromorphic architectures based on silicon optoelectronics: silicon photonic neural networks (SiPhNNs) [5] and superconducting optoelectronic networks (SOENs) [6]. All SiPhNN components have been demonstrated on currently available silicon photonic foundry platforms. They can leverage mainstream datacom. and telecom. technology, including ultrafast modulators and photodiodes [7], in-ring photoconductive heaters [8], [9], and packaging techniques. SOEN components have been demonstrated on an emerging cryogenic silicon photonic platform. Using superconducting nanowire single-photon detectors (SNSPDs), SOENs communicate at the lowest light levels possible. SOEN can then employ other low temperature devices (e.g. all-silicon emitters, superconducting switches, Josephson junctions) to accomplish neural functions. Cryogenic photonic platforms could conceivably be offered by foundries with relatively minor process modification: a superconducting metal layer and a Si^{+} ion bombardment step.

The primary form of configurability in neural networks is in the weighted network connections. SOEN and SiPhNN take complementary approaches to configurable weights. SiPhNNs configure the weight matrix with tunable transmission elements called microring resonator (MRR) weight banks. It was recently shown that MRR weight banks can achieve better accuracy and environmental robustness by lightly doping the MRR, shown in Fig. 1(b), so that a fraction of circulating light is absorbed, sensed, and used as a feedback signal [9]. Optical domain weights simplify the electronic pathway, but they are only capable of simple multiplication. In contrast, synapses in the electronic domain can perform more sophisticated functions. Low temperature Josephson junction (JJ) circuits exhibit a variety of features believed to be critical in biology, namely heterogeneous time constants, synaptic plasticity, and synaptic desensitization [10]. SOEN has proposed to use a combination of JJ circuits for configuration/adaptation and fixed optical routing manifolds for signal transport. These manifolds can be fabricated to have a desired connectivity pattern, as demonstrated with a 10×10 interconnect (see Fig. 1(f)) whose weight matrix is shown in Fig. 1(e) [11].

A key commonality between SiPhNN and SOEN architectures is their use of optical-electrical-optical (O/E/O) neuron signal pathways. The electronic and optoelectronic domains present several mechanisms for neuron programming and learning. A MRR modulator neuron can be tuned to exhibit enhancing or saturating nonlinearities, adjustible by the offset between MRR resonance and pump wavelengths [7] (see Fig. 1(d)). The superconducting-to-normal transition exhibits a sharp threshold in resistance at the critical current. This threshold is adjustable by the difference between bias and critical currents. A superconducting switch, called an hTron, can drive an LED while exhibiting this threshold response [12]. Threshold configuration has also been demonstrated in III-V O/E/O neurons [13], which are potentially compatible with silicon networks using heterogeneous Si/III-V integration.

The O/E/O neuron approach shared by SiPhNN and SOEN also provides nonlinearity at light levels much weaker than needed for all-optical nonlinearities. Using an O/E/O signal pathway, light can be used for communication while optoelectronic devices provide strong nonlinearity, wavelength conversion, optical phase regeneration, fan-in, and net optical-to-optical gain. Bandwidth is minimally affected because elec-

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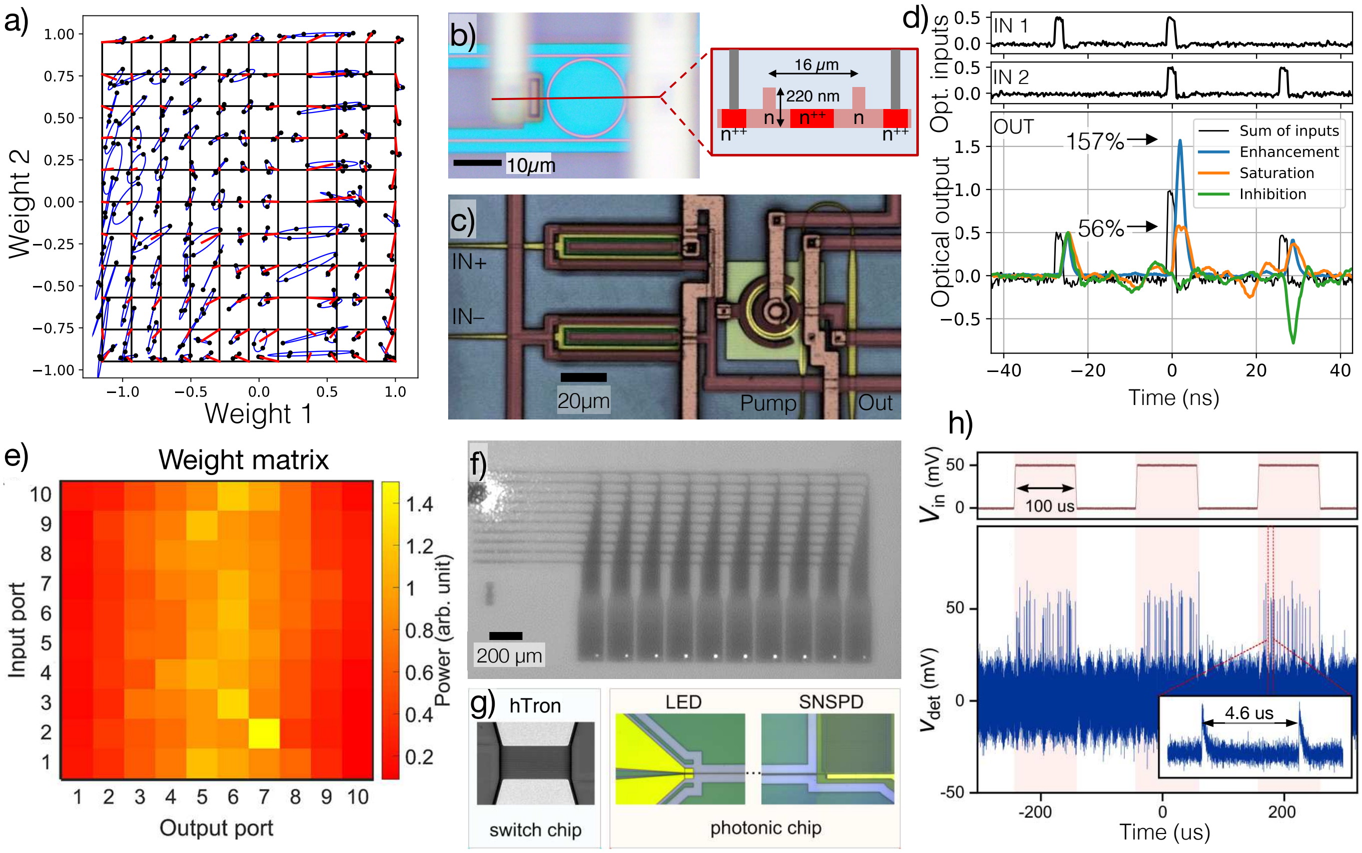

Fig. 1. a) Two-channel weight control with 5.1 bit accuracy in a microring (MRR) weight bank, from [9]. b) One MRR weight in which weak absorption in the ring provides a feedback control signal [8]. c) A silicon photonic modulator neuron with programmable responses to coincident pulses in (d), from [7]. e) A 10x10 transmission weight matrix of a multi-planar routing manifold, shown in (f), from [11]. g) The signal pathway of a superconducting optoelectronic neuron using a single-photon detector, hTron, and an all-silicon LED, shown producing pulses with near-unity gain in (h), from [12].

trical wires within the signal pathway are much shorter than the electrical transmission line wavelength. These properties were instrumental in recent demonstrations of cascadability.

Cascadability is the ability of a neuron or gate to drive alike devices, including itself, with sufficient strength. The physical principle of SOEN cascadability was shown in an LED-to-SNSPD link [14]. A net gain near unity was shown after incorporating an hTron into the pathway [12], shown in Fig. 1(g, h). The cascadability of the SiPhNN modulator neuron was shown using an autapse technique [7]: one neuron driving itself into a bistable state corresponding to unity gain. Parts of these demonstrations were not monolithically integrated, yet they lay a clear path towards monolithic demonstrations of cascadable photonic neurons on silicon.

SOEN and SiPhNN, while based on starkly distinct sets of optoelectronic physics and devices, share conceptual overlaps in information processing models, silicon platforms, O/E/O neurons, and demonstrated programmability. A diversity of approaches to neuromorphic photonics could address complementary regimes of machine information processing where speed, complexity, and reconfigurability are crucial.

References

[1] D. Pérez *et al.*, "Programmable multifunctional integrated nanophotonics," Nanophotonics **7**, 1351 (2018).

[2] J. Carolan *et al.*, "Universal linear optics," Science **349**, 711 (2015).

[3] Y. Shen *et al.*, "Deep learning with coherent nanophotonic circuits," Nat. Photon. **11**, 441–446 (2017).

[4] P. R. Prucnal *et al.*, "Recent progress in semiconductor excitable lasers for photonic spike processing," Adv. Opt. Photon. **8**, 228–299 (2016).

[5] A. N. Tait *et al.*, "Neuromorphic photonic networks using silicon photonic weight banks," Scientific Reports **7**, 7430 (2017).

[6] J. M. Shainline *et al.*, "Superconducting optoelectronic circuits for neuromorphic computing," Phys. Rev. Applied **7**, 034013 (2017).

[7] A. N. Tait *et al.*, "A silicon photonic modulator neuron," arXiv preprint arXiv:1812.11898 (2018). Accepted Phys. Rev. Applied.

[8] H. Jayatilleka *et al.*, "Wavelength tuning and stabilization of microring-based filters using silicon in-resonator photoconductive heaters," Opt. Express **23**, 25084–25097 (2015).

[9] A. N. Tait *et al.*, "Feedback control for microring weight banks," Opt. Express **26**, 26422–26443 (2018).

[10] J. M. Shainline *et al.*, "Circuit designs for superconducting optoelectronic loop neurons," Journal of Applied Physics **124**, 152130 (2018).

[11] J. Chiles *et al.*, "Design, fabrication, and metrology of 10x100 multi-planar integrated photonic routing manifolds for neural networks," APL Photonics **3**, 106101 (2018).

[12] A. N. McCaughan *et al.*, "A compact, ultrahigh impedance superconducting thermal switch for interfacing superconductors with semiconductors and optoelectronics," Nature Electronics (submitted) (2019).

[13] H. T. Peng *et al.*, "Neuromorphic photonic integrated circuits," IEEE Journal of Selected Topics in Quantum Electronics **24** (2018).

[14] S. Buckley *et al.*, "All-silicon light-emitting diodes waveguide-integrated with superconducting single-photon detectors," Applied Physics Letters **111**, 141101 (2017).