A Laser Spiking Neuron in a Photonic Integrated Circuit

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There has been a recent surge of interest in the implementation of linear operations such as matrix multiplications using photonic integrated circuit technology. However, these approaches require an efficient and flexible way to perform nonlinear operations in the photonic domain. We have fabricated an optoelectronic nonlinear device—*a laser neuron*—that uses excitable laser dynamics to achieve biologically-inspired spiking behavior. We demonstrate functionality with simultaneous excitation, inhibition, and summation across multiple wavelengths. We also demonstrate cascadability and compatibility with a wavelength multiplexing protocol, both essential for larger scale system integration. Laser neurons represent an important class of optoelectronic nonlinear processors that can complement both the enormous bandwidth density and energy efficiency of photonic computing operations.

High performance computing has experienced accelerating growth in the last decade, driven largely by the rapid expansion of machine learning applications. For example, deep learning training is doubling at a rate at 3.5 months, far outpacing Moore’s law of performance doubling every 18 months. This gap in supply and demand is exacerbated by the increasing difficulty of continuing Moore’s law in hardware: since electronic devices are reaching feature size limits and are no longer subject to Dennard’s law, they require more exotic geometries and material platforms to sustain their past exponential growth in performance.

These limitations, together with the vast computing requirements of artificial intelligence, have motivated the development of application specific integrated circuits (ASICs) for deep learning, a notable example of which is Google’s tensor processing unit (TPU). More exotic approaches involving non-volatile, co-located memory [5] including phase-change analog [5] or memristor [9] promise orders of magnitude increases in efficiency and processing density. However, electronic approaches must grapple with two significant sources of energy consumption: data movement—especially between the memory and processor—and capacity for compute (i.e., operations per second), largely dominated by linear operations such as matrix multiplications.

Photonics has been well studied for its potential to address both bottlenecks (see Ref. [12][13]). Electronic data movement involves capacitive charging and discharging metal interconnects, with energy consumption that is roughly proportional to the length of each wire. In contrast, although photonic channels require energy for E/O or O/E conversion, it is no longer the critical path in transceivers, and the energy consumption of each link scales nearly independently of its length. Current photonic systems are competitive with on-chip electronic interconnects (<1 pJ/bit), and will increase in efficiency as optoelectronic devices see continued improvements.

Deep learning compute primarily involves matrix-vector multiplications, which are composed of multiply-accumulate (MAC) operations: a single operation consists of $a ← a + w \times x$ with accumulation variable $a$, signal $x$, and weight $w$. For these operations, photonic components exhibit major advantages over digital electronics in energy, speed, and computational power. First, as noted by Ref. [10], passive analog energy consumption is not necessarily proportional to the number of operations being performed. As an example, for a matrix operation with $M$-sized vector inputs and outputs, the number of computations is proportional to $M^2$, but the signal generation cost is proportional to the number of channels $M$. This property also extends to photonic systems [14]. Secondly, photonic components can operate at much higher speeds (>5 GHz); they are not limited by thermal dissipation, clock distribution, and interconnect jitter. Third, digital MAC operations—typically implemented via adders and multipliers—requires thousands of transistors, whereas photonic MAC operations only require one (or several) passive photonic devices to accomplish the same functionality. This simplicity, together with a higher clock rate, allow on-chip photonics to exhibit higher processing densities than state-of-the-art digital electronic matrix multipliers, despite the large sizes of photonic devices.

However, implementing nonlinear operations or interfacing with stored digital data requires high speed analog-to-digital conversion, which can consume a significant amount of energy. Instead, photonic nonlinearities can reduce the number of conversion steps by implementing many processing layers in the photonic domain. However, current approaches, which include resonator-enhanced optical nonlinearities or optoelectronic nonlinearities, require either exotic materials or large threshold powers. They also have difficulty exhibiting complex nonlinear behaviors such as spiking. To this end, a number of approaches have explored ap-
FIG. 1: Schematic of a spiking neural network implemented in a photonic integrated circuit (PIC). Networks can be instantiated using III-V laser arrays bonded to silicon photonic chips (bottom left), which include passive couplers and microresonators. Both recurrent and feedforward network topologies are possible using the B&W framework, which assigns a unique wavelength $\lambda_i$ to each laser neuron (bottom right). The processing node itself consists of a pair of balanced photodetectors connected to a laser followed by a semiconductor optical amplifier, emulating a biological spiking neuron (top left). The photodetectors perform a summation operation, while the gain $G$, loss $Q$, and cavity intensity $I$ interact to generation excitable dynamics (top right).

approaches to emulate spiking functionality, but many of them require specialized devices which are incompatible with emerging standards in the photonic integrated circuit (PIC) industry.

In this paper, we demonstrate that a laser neuron—consisting of a balanced photodetector pair that directly modulates a laser—can emulate a Leaky Integrate-and-Fire (LIF) neuron—the most widely used model in computational neuroscience—across many simultaneous wavelength channels in a standard PIC platform. In contrast to their microelectronic counterparts, laser neurons can process data at high speeds (> GHz) while dissipating relatively little energy during data movement. We experimentally demonstrate a variety of critical functions, characterize speed and energy consumption, and discuss strategies for implementing units into larger-scale networks.

I. LASER NEURON ARCHITECTURE

A. Model

Each laser neuron models the behavior of a simple spiking neuron using optical pulses to code information (for a further discussion on spiking, see the Supplementary materials). As shown in Figure 1, a single processing unit consists of a pair of photodetectors directly wired to the input terminal of a laser, followed by an amplifier. Inputs of multiple wavelengths $\lambda_0, \lambda_1, \ldots, \lambda_M$—in which the intensities $x_i$ are weighted by $w_i$ using a passive silicon network external to each processing unit—are incident on a pair of balanced photodetectors. Excited carriers relax and sum together the $M$ input signals, resulting in a current signal proportional to $\sum w_i x_i$. The resulting push-pull current travels into a laser biased just below threshold. The input acts as a perturbation to the laser’s internal dynamical system $\dot{s} = f(s)$, and with enough positive inputs, the laser can excite and fire an optical pulse as the output $y(t)$.

The laser’s dynamical system is represented via the interactions between a gain medium, an absorbing medium, and the light within the cavity. This system performs several nonlinear processing functions on the input data, including integration, thresholding, and time discretization (i.e., refractoriness) via a mechanism called excitability. A simplified, undimensionalized version of the
The equations governing this system can be represented by:

\[
\dot{G}(t) = \gamma_G [A - G(t) - G(t)I(t)] \quad (1)
\]

\[
\dot{Q}(t) = \gamma_Q [B - Q(t) - aQ(t)I(t)] \quad (2)
\]

\[
\dot{I}(t) = \gamma_I [G(t) - Q(t) - 1]I(t) + \epsilon f(G) \quad (3)
\]

for gain variable \(G(t)\), absorber variable \(Q(t)\), cavity intensity \(I(t)\), and parameters \((A,B,a,\gamma_G,\gamma_Q,\gamma_I,\epsilon)\). As discovered in Ref. 33, under certain conditions, these equations simplify to a model of a Leaky Integrate-and-Fire (LIF) neuron, a popular spiking model in computational neuroscience:

\[
\dot{G}(t) = -\gamma_G(G(t) - A) + \theta(t); \\
\text{if } G(t) > G_{\text{thresh}} \text{ then } (4) \\
\text{release a pulse, and set } G(t) \rightarrow G_{\text{reset}}. \\
\]

Together, a balanced photodetector, laser and amplifier can emulate the basic functions of a spiking neuron. In principle, networks of spiking neurons can perform any algorithm or simulate any nonlinear dynamical system.

### B. Networking

Laser neurons are designed to be compatible with Broadcast-and-Weight (B\&W), a reconfigurable optical neural networking method proposed in Ref. 36. The B\&W protocol assigns each laser neuron a unique wavelength \(\lambda_i\). Wavelength division multiplexing (WDM) allows for the aggregation of these signals along common bus waveguides, which distribute the signals with unique transmission profiles to each processing node. Tunable filter banks adjust the strength of each connection, or weight \(w_{ij} \in [-1, 1]\). The resulting weighted signals sum together via the balanced photodetectors (BPDs) driving each laser. This system can implement both negative and positive weights \((w_{ij} \in [-1, 1])\), allowing for fully reconfigurable neural network models. Coupling to a waveguides in a loop topology allows for recurrent connections, while coupling from one waveguide to another allows for feedforward connections, as illustrated in Fig. 1.

In contrast to several other networking frameworks (i.e., coherent matrix multiplication or optical reser-
C. Fabrication

Each laser neuron consists of III-V photonic devices that can be found in most standard process design kits (PDKs) common to large-scale foundry models: a distributed feedback laser (DFB), a balanced photodetector (BPD) pair, and a semiconductor optical amplifier (SOA). Lithographically-defined metal wires connect the components together in a way that allows for direct interactions between the detectors and the laser. The DFB lasers are composed of electrically pumped multi-quantum wells (MQW) with emission near ~1550 nm embedded in a ridge-waveguide structure. The laser includes both a primary gain section as well as a smaller absorber section, with lengths \( L_G = 125.0 \mu m \) and \( L_Q = 75.0 \mu m \), respectively. An etched, intracavity electrical isolation section of length \( L_{iso} = 75.0 \mu m \) divides the two sections, and a small absorber placed on the non-emitting port of each laser reduces back reflections. The SOA also includes an active MQW structure, with a length set to \( L_{SOA} = 400.0 \mu m \). Device layouts were generated in collaboration with the Fraunhofer Institute for Telecommunications, at the Heinrich Hertz Institute (HHI) as part of the Joint European Platform for Photonic Integration of Components and Circuits (JePPiX) consortium.

II. RESULTS

A. Multi-Wavelength Functionality

To utilize the dense interconnectivity possible in the B&W protocol, a laser spiking neuron \( j \) must be able to receive \( M \) intensity signals with unique wavelengths \( \lambda_1, \lambda_2, \ldots, \lambda_M \), and emit a single wavelength \( \lambda_j \). We experimentally demonstrate this functionality together with spiking dynamics, measuring the nonlinear response to both excitatory (positive) and inhibitory (negative) pulses (Fig. 4), and measure the output spectrum for above-threshold signals (Fig. 5). For this experiment, we used a laser neuron unit without amplifier (unit B, as illustrated in Fig. 3).

For simplicity, the experimental demonstration used a total of eight wavelength channels with independent spiking signals: four inputs incident on each photodetector. A topographical micrograph of the device is shown in Fig. 5. The laser current is biased just below the lasing threshold (11 mA) to initiate the system in a state of excitability. The excitatory photodetector is reversed biased at 3.6 V, whereas the inhibitory photodetector is reversed biased at 1.43 V. As shown in Fig. 4(a), the laser neuron only responds with an output pulse if a cluster of excitatory pulses arrives closely spaced in time. This demonstrates several key attributes: summation across multiple wavelengths inputs \( x_i, \lambda_i \), the ability to integrate...
pulse activity across some integration time interval $T_{\text{int}}$, and the ability to make a binarized $(0,1)$ threshold decision based on input spike activity.

A BPD pair allows for the implementation of both positive and negative weights. Fig. 4(b) shows that inhibitory pulses can oppose the activity excitatory pulses: generating a cluster of inhibitory pulses that coincide with the first excitatory cluster results in a cancellation of the output pulse (i.e., via a negative weighting of the inhibitory signals that opposes the positive weighting of the excitatory signals). Another important condition is a well-defined output wavelength, critical for wavelength identification and filtering in the B&W protocol. Fig 5 shows the output spectrum of the laser modulated with excitatory pulses above threshold: it outputs with a stable and narrow linewidth $\Delta \lambda < 0.001 \text{nm}$.

Although just eight channels were demonstrated here, the B&W protocol allows for flexible channel scaling through the addition of more wavelengths and laser processing nodes. In B&W networks, two primary limiting factors include the finesse $F$ of the passive filters in the network, and the gain bandwidth of the lasers. If high finesse, miniaturized resonator lasers are combined with a standard III-V laser gain spectrum covering the optical C-band, $M$ can reach on the order of several hundred channels.

This allows us to characterize the potential processing speed of each laser as a function of the number of wavelength channels $M$. With refractory period $\Delta T$, a single laser neuron can make a spike or no-spike decision across $M$ inputs every $\Delta T$. The number of MACs per second—the speed of each processor—is therefore $S = M/\Delta T$. With a refractory period $\Delta T \approx 200 \text{ps}$ and $M \approx 200$ (assuming $< 3$ dB power penalty, see Refs. [13, 15, 16]), we arrive at $1 \times 10^{12}$ MACs/s, or 1 TMAC/s. This speed is quite enormous for a single device, exceeding the total processing capacity of many microelectronic processors. Note that since the speed per node is $\propto M$, it is dependent on channel scalability: higher processing capacity requires a fully-scaled processing system as depicted in Fig. 4 with several hundred wavelength channels per broadcast waveguide.

![FIG. 5: Measured output spectrum of a type B laser neuron during operation (peak normalized to 0 dB). Light is generated by a distributed feedback laser and outputs with a narrow linewidth $\Delta \lambda < 0.001 \text{nm}$ (right).](image)

**B. Cascadability**

An important condition for larger networks is that the nonlinear processors are cascadable. As discussed in Ref. [20], signals must be able to propagate through a network without degradation. This divides into both gain cascadability—the ability to drive the next stage of neurons with enough energy—and signal cascadability, the fidelity of the information encoding from one stage to another. In this section, we experimentally demonstrate that a laser spiking neuron can meet a number of cascadability conditions in both domains, and characterize its performance and energy consumption during operation.

We first show that a laser neuron with an amplifier (type A in Fig. 2) can meet the closed-loop gain condition with fixed point precision (see Sec. IV.A for a discussion on precision). To simulate peak processing conditions, we generate a dense, random stream of excitatory inputs spikes and measure the laser output response. We assume a Poisson point process (a common assumption in spiking signal [47]). The probability distribution of $N(t)$, where $N(t)$ is the number of spikes that occur on the interval $[0, t]$ is given by:

$$P\{N(t) = n\} = \frac{(\mu_p t)^n}{n!} e^{-\mu_p t}$$

We set $\mu_p = 1 \text{GHz}$ and defined the input pulse width as $\tau_p = 0.2 \text{ns}$ over a repeated time interval 50 ns (see Sec. IV.A for more discussion on experimental conditions). Meeting the closed loop gain condition requires that the optical output power exceeds the input ($P_{\text{out}} > P_{\text{in}}$). We adjusted the SOA input current until the output power exceeds the input by about $\sim 3$ dB to account for the projected coupling and microresonator insertion losses in the system. This occurred for an SOA current of $I_{\text{SOA}} > 105 \text{mA}$ at 2.5 V. We show time traces of both the input and output in Fig. 6 for this condition.

Secondly, we confirmed that each neuron has nonlinear pulse regeneration capabilities. As discussed in Ref. [20], to assure that spikes remain binarized over many stages, nonlinear processors must regenerate pulses as the are incident on each device. We demonstrated pulse width compression and stability (Fig. 6 right): pulses stay approximately constant a full-width half maximum (FWHM) width $\tau_p$ of 0.2 ns to 0.3 ns. This assures that spikes do not lose their timing characteristics as they propagate forward, maintaining a temporal precision of $\sim \tau_p$. The results indicate more than just a simple nonlinearity—input activity (even a square pulse, as shown in Fig. 6) manifests in the output as characteristic pulse with a fairly stable FWHM.

Based on these measurements, we can calculate the energy consumption of each laser processor. The vast majority of dissipation occurs in the amplifier, consuming approximately $P_n = 0.26 \text{W}$ per node. With a processing speed of $S_n = 1 \text{TMACs/s}$, this amounts to $P_n/S_n = \sim 260 \text{fJ}$ per MAC. This is the range of current deep learning hardware (i.e., see comparison in Ref. [20]).
and depends on a large channel number $M \sim 200$ to realize its advantages. Nonetheless, it is far from the most efficient processing model possible. For example, efficient directly-driven lasers (i.e., lower threshold models\textsuperscript{48,49}) negate the need for an amplifier. Alternatively, to stay compatible with emerging PIC standards, transimpedance amplifiers in platforms with co-integration between electronics and photonics can provide efficient electrical gain between detectors and lasers (many examples of which are provided in Ref.\textsuperscript{50}).

III. CONCLUSION

We have demonstrated that a laser neuron, fabricated in a photonic integrated circuit platform, can function as a processing node in a larger scale spiking neural network. Laser neurons communicate photonically, sidestepping many of the costs associated with both data movement and the implementation of linear operations in electronics. This leads to the potential for much higher speeds and energy efficiencies compared to neuromorphic electronic processors. We experimentally validated LIF neuron model functionality across multiple wavelength channels, including the ability to integrate multiple signals together across time, accept both positive (excitatory) and negative (inhibitory) inputs, and make a binary (0.1) spike classification based on pulsed activity. We verified its compatibility with the B&W protocol, assuring that it can utilize the full bandwidth density available to optical waveguides for connectivity. We also demonstrated cascadability, both in the laser neuron’s ability to sustain and amplify signals and its ability to maintain the integrity of pulsed signals from one layer to another.

Our calculated speed and energy efficiencies—1 TMAC/s per neuron and 260 fJ/MAC, respectively—exceed current microelectronic performance figures, particularly in speed. Further developments in optoelectronic devices\textsuperscript{13}, co-integration between photonic and electronic platforms\textsuperscript{26,179}, or the utilization of novel materials such as graphene\textsuperscript{52} provide ample avenues for further exploration. These techniques would realize the potential 3-5 orders-of-magnitude improvement\textsuperscript{39} that neuromorphic photonic computing has to offer.

IV. SUPPLEMENTARY MATERIALS

A. Precision

The precision of each computation, bounded by noise and device variations, limits information capacity. We can define precision with respect to multiply-and-accumulate (MAC) operations: each laser neuron computes a dot product $\vec{w} \cdot \vec{x}$ of vector length $M$ with $k$ bits of precision, giving a total of $k \times M$ bits being computed over $M$ MAC operations. To avoid processing degradation, cascadability requires that signals with $k$ bits of precision stay above some set threshold $k > k_{F}$. The case of spiking, the amplitude is binary (1 bit of precision), while the spike times should remain analog ($\log_{2}(t_{q}/\tau_{p})$) bits of precision for time between spikes $t_{q}$ for spike $q$ and pulse width $\tau_{p}$). Therefore, laser processors must assure that outputs remain spatially coherent, while preventing a reduction in analog temporal precision by keeping $\tau_{p}$ below a threshold value $\tau_{p} < \tau_{p}(T)$. The lack of this condition can eventually cause pulses to widen, and degrade as they propagate through a network.

MAC operations can either be floating point—in which the quantization threshold is proportional to the output amplitude, as seen in most digital processors—or they can be fixed point, in which the quantization threshold is set independently of the output amplitude. AI researchers have shown that fixed point matrix multiplication can work just as well for deep learning models, even for training.\textsuperscript{33} Inference, in particular, does not require high resolution: typically several bits of precision can achieve near state-of-the-art performance.\textsuperscript{35,40} B&W weight networks best approximate fixed point linear operations, since precision is typically bounded by some
physical noise threshold by the signal or receiver. In fixed point arithmetic, a minimum power resolution threshold $P_T$ is set at the detector, and the number of bits of precision for signal $P$ is equal to $N_b = \log_2 (P/P_T)$. To prevent degradation, the total signal amplitude $\sum_i y_i$ from one stage to another must be conserved. Divided individually, a laser neuron must, on average, provide enough gain to compensate for node-to-node losses. In a fixed point framework, the total power required to meet this condition is proportional to the number of processors, $N$, not the number of connections $NM$, an advantage that arises from the non-dissipative nature of passive analog operations. If the B&W network remains passive, the closed loop gain condition becomes the most critical source of energy consumption.

B. Optoelectronic Nonlinearities

Researchers have used a variety of implementations to realize nonlinear functions in the optical domain. All-optical approaches have utilized nonlinear effects in both fiber and on-chip resonators. Other approaches include carrier nonlinearities in SOAs, plasmonics, intracavity semiconductor saturable absorbers, and graphene. However, these approaches consistently exhibit several common limitations: they either require exotic fabrication processes to create, or large optical threshold powers to activate. This can greatly increase the energy consumption to a level that negates the advantages of using optics at all.

Laser neurons use a detector-transducer configuration, a common optoelectronic nonlinear device template explored in the literature. O/E/O models (i.e., involving optical to electrical conversion and vise versa) can exploit nonlinearities in detectors and modulators or lasers, but are constrained by electrical parasitics and the costs of O/E and E/O conversion. However, electro-optic conversion costs are shrinking: high performance detectors, modulators, and lasers are continuing to emerge in developing PIC platforms. In addition, placing detectors and transducers in close proximity can greatly minimize undesirable parasitics, including dispersion, microwave reflections, and timing delays.

Another exciting prospect is the close integration between developing microelectronic and photonic platforms, which could combine a high O/E/O conversion efficiency with powerful nonlinear electronic operations. For example, operational amplifiers can be placed after detectors, compensating for loss and leading to greater system-level energy efficiency. Such hybrid units could potentially perform generic nonlinear tasks such as wavelength conversion very efficiently and may provide ample machinery for nonlinear neural network processing in future systems.

C. Spiking

Spiking is a communication encoding strategy that is equivalent to analog pulse position modulation in photonic systems. Information is primarily encoded in the timing between a series of pulses, or spikes. Spike amplitudes are binarized (i.e., either 0 or 1), but the timing of each pulse can take on any analog value. For example, an analog vector $[v_0, v_1, \ldots]$ can be encoded by associating each value $v_i$ with the time $T_0, T_1, \ldots$ between each pulse, wherein the amount of information encoded is limited by the temporal resolution or timing jitter of the communication system.

Spike encoding has many advantages over continuous wave signals. For one, it is less susceptible to amplitude noise, which can be useful in physical systems with high stochasticity (i.e., biology). Secondly, it benefits from sparse coding, which can lead to significant power advantages for photonic signals. As an illustrative example, for temporal resolution $\Delta t$, and delay $T_i$ between pulse $i$ and $i - 1$, if $T_i > \Delta t$, a single pulse can carry more than 1 bit of information: as much as $N_b = \log_2 (T_i/\Delta t)$. This reduces the J/bit cost by a factor $N_b$ in a communication channel (see for example Ref [23], which can also improve the implementation of operations, such as MACs, in neuromorphic photonic systems.

Unfortunately, although spiking neural networks in hardware have continued to show significant power efficiency gains over other neural network processors, they are currently challenging to program and train. Spike-based learning algorithms—such as synaptic time dependent plasticity (STDP)—have difficulty propagating gradients back many layers, a prerequisite condition for deep learning. Nonetheless, improvements in this arena remains an active research topic with many results on spiking training appearing recently. As more sophisticated techniques are developed for the control of spiking neural networks, machine learning approaches may one day reap the robustness and energy efficiency that such encoding can deliver.

V. METHODS

A. Experimental Signal Generation

Excitatory and inhibitory pulses were programmed using a custom input generation system, allowing N intensity-modulated bit patterns along different wavelengths $\lambda_1, \lambda_2, \ldots, \lambda_N$ in some desired test window $t \in [0, \Delta T]$. As illustrated in Fig. 7, it consisted of a WDM source (an external array of DFB lasers), a single high speed Mach Zehnder (MZ) modulator connected to a pulse pattern generator (PPG) driven by a clock source, and a series of long delay lines nested between arrayed waveguide gratings (AWGs). The outputs were measured by a sampling scope connected to the same clock source. The system has many similarities to the generation mec-
anisms explored in Ref. [8]. We describe its mechanism of operation below.

Suppose we have a series of desired bit patterns denoted by \( P_1[t], P_2[t], P_3[t], \ldots, P_N[t] \) along wavelength channels \( k = 1 \ldots N \) that include bit values \((0, 1)\) programmed in the time interval \( t \in [0, \Delta T] \). First, we set the PPG bit pattern as each desired pattern consecutively in time, i.e.,

\[
PPG[t] = P_k[t - (k - 1)\Delta T] \text{ for } t \in [(k - 1)\Delta T, k\Delta T]\n\]

for \( k = 1 \ldots N \). The total length of the PPG bit pattern is therefore \([0, N\Delta T]\). This pattern is modulated onto all wavelengths \( \lambda_k \) using a wideband modulator simultaneously. Next, we send the signal through a Demux AWG and apply consecutive physical time delays \( k\Delta T \) to each wavelength channel \( k \) to cancel out the programmed time delays in the PPG. As a result, we generate our desired pattern in the time interval \([0, T]\):

\[
P_{in}[t] = \sum_{k=1}^{N} P_k[t] \text{ at } \lambda_k \quad (7)
\]

In this experiment, we represented \( N = 8 \) wavelength channels using long fiber delays at intervals of \( D_1 \sim 90\text{ ns}, D_2 \sim 180\text{ ns} \), etc. Small variations in the physical delay for each fiber (around \( \sigma \sim 3\text{ ns} \)) that resulted from splicing errors were compensated for digitally in the PPG delay time, i.e.,

\[
PPG[t] = P_k[t - D_k] \text{ for } t \in [D_k, D_k + \Delta T]
\]

for physically measured delays \( D_1 \ldots D_N \), where we set the time window to \( \Delta T = \min(D_k - D_{k-1}) \) for all channels \( k \) to avoid overlapping \( (\Delta T \sim 88\text{ ns}) \). The delayed output signals were multiplexed onto two output fibers using another set of AWGs, shown as the excitatory and inhibitory inputs in Fig. 7. Three erbium doped fiber amplifiers (EDFAs) were placed in various parts of the signal pathway to compensate for losses: one after the MZ modulator and before the Demux AWG, and one for each excitatory and inhibitory input channel after each Mux AWG. The resulting fiber channels were input into a V-groove fiber array, which interfaced with both the inputs and output of each laser neuron via spot size converters (SSCs) on the edge of the chip. The output also received amplification via an Edfa to compensate for chip coupling losses.

Before inputs were coupled into the chip, 90:10 couplers were placed after each Edfa, wherein the smaller signals act both as power monitors and as outputs for measurements. Excitatory inputs shown in Fig. 7 were set at \( \lambda_1 = 1540.56, \lambda_2 = 1543.72, \lambda_3 = 1546.92, \lambda_4 = 1550.12 \), while inhibitory inputs are set at \( \lambda_5 = 1542.14, \lambda_6 = 1545.32, \lambda_7 = 1548.52, \lambda_8 = 1551.72 \). The output of each spiking laser neuron was measured using both sampling scope (for time-dependent traces in Figs 4 and 6) and a spectrum analyzer (for spectral measurements in Fig 5).

To generate Poisson inputs for the experiments conducted in Sec. 4.1 we used only one wavelength input \( (\lambda_4 = 1550.12) \) fed into the excitatory port of a type A neuron. The Poisson model was set with \( \mu_p = 1\text{ GHz} \) and a clock rate of \( 5\text{ GHz} \) (each bit has \( \tau_p = 0.2\text{ ns} \)) over a 50 ns time window, which was generated a priori before being programmed into the PPG. The result was modulated onto a signal carrier wave at \( \lambda_4 = 1550.12 \). For both experiments, input and output powers traveling in and out of both the laser and BPD pair were calculated using a power calibration procedure based on the measured losses between the SSCs and fiber V-groove arrays.

### B. Data Analysis

The powers of time-dependent traces were calibrated using a set of reference traces normalized via continu-
uous wave power measurements. Up to three reference traces existed for each experiment: total excitatory input power, total inhibitory input power, and total laser output power, measured across the entire time window (i.e., $[0,N\Delta T]$). Once reference traces become normalized to average power measurements, all remaining data sets in the window of interest $[0,\Delta T]$ were calibrated to this reference set. Time-dependent traces for each wavelength $\lambda_i$ and the laser output were measured independently before calibration. This resulted in the final data plot seen in Fig. 5 and Fig. 6 in the main article (for which the latter plot used only one input wavelength channel).

VI. DATA AVAILABILITY

The datasets generated during and/or analysed for this experiment are available from the corresponding author on reasonable request.

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