A Leaky Integrate-and-Fire Laser Neuron for Ultrafast Cognitive Computing

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***Abstract*—We propose an original design for a neuron-inspired photonic computational primitive for a large-scale, ultrafast cognitive computing platform. The laser exhibits excitability and be-**

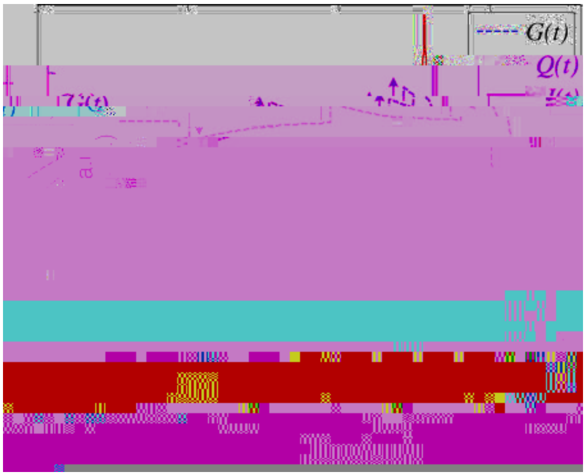

Fig. 5. Simulation results of an SA laser behaving as an LIF neuron. Ar-

A network of excitable lasers connected via weights and delays—consistent with the model described in Section II-A—can be described as a delayed differential equation (DDE) of the form:

$$\frac{d}{dt}\vec{x}(t) = f(\vec{x}(t), \vec{x}(t-\tau_1), \vec{x}(t-\tau_2)\ldots\vec{x}(t-\tau_n)) \quad (10)$$

where the vector $\vec{x}(t)$ contains all the state variable associated with the system. The output to our system is simply the output power $P_{out}(t)$

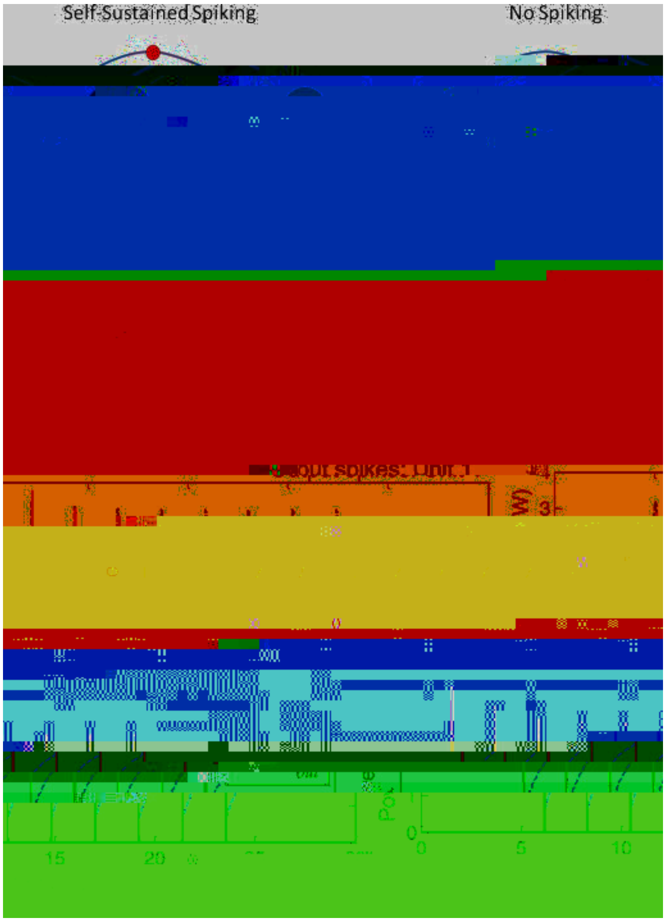

Fig. 10. (a) Bistability schematic—In this configuration, two lasers are connected symmetrically to each other. (b) A simulation of a two laser system exhibiting bistability with connection delays of 1 ns. The input perturbations to unit 1 are plotted, followed by the output powers of units 1 and 2, which include scaled version of the carrier concentrations of their gain sections as the dotted blue lines. Excitatory pulses are represented by positive perturbations while inhibitory pulses are represented by negative perturbations. An excitatory input excites the first unit, causing a pulse to be passed back and forth between the nodes. A precisely timed inhibitory pulse terminates the sequence.

unit expansion of each node in the multistability circuit from Fig. 10(a). Like the multistability circuit, recursion allows the synfire chain to possess hysteric properties; however, the use of two lasers for each logical node provides processing redundancy and increases reliability. Once the spike pattern is input into the system as excitatory inputs injected simultaneously into the first two lasers, it is continuously passed back and forth between each set of two nodes. The spatiotemporal bit pattern persists after several iterations and is thereby stored in the network as depicted in Fig. 11(b).

C. Spatiotemporal Pattern Recognition Circuit

The concept of polychrony, proposed by Izhikevich [42] is defined as an event relationship that is precisely time-locked to firing patterns but not necessarily synchronous. Polychronization presents a minimal spiking network that consists of cortical spiking neurons with axonal delays and synaptic time dependent plasticity (STDP), an important learning rule for spike-encoded neurons. As a result of the interplay between the delays and STDP, spiking neurons spontaneously self-organize into groups and generate patterns of stereotypical polychronous activity.

One of the key properties of polychronization is the ability to perform *delay logic* to perform spatiotemporal pattern recognition. As shown in Fig. 12(a), we construct a simple three unit pattern recognition circuit of excitable lasers with carefully tuned delay lines, where each subsequent neuron in the chain requires stronger perturbations to fire. The resulting simulation is shown in Fig. 12(b). Three excitatory inputs separated sequentially by $\Delta t_1 = 5$ ns and $\Delta t_2 = 10$ ns are incident on all three units. The third is configured only to fire if it receives an input pulse and pulses from the other two simultaneously. The system, therefore, only reacts to a specific spatiotemporal bit pattern.

Although this circuit is simple, the ability to perform temporal logic implies that excitable, neuromorphic systems are capable of categorization and decision making. Two existing applications utilize temporal logic, including light detection and ranging sensitivity that is analogous to an owl's echolocation system and the escape response of a crayfish [54], [55]. Combined with learning algorithms such as STDP which has recently been demonstrated in optics [56], networks could potentially perform more complex tasks such as spike-pattern cluster analysis.

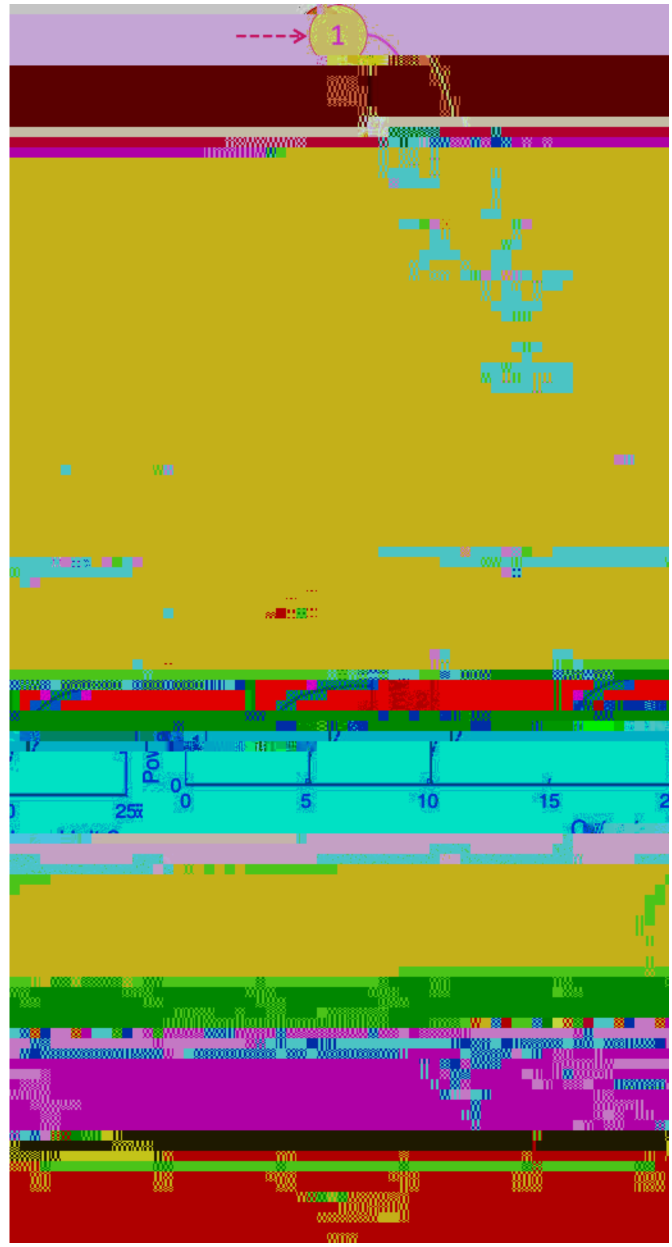

Fig. 12. (a) Schematic of a three-laser circuit that can recognize specific spatiotemporal bit patterns. (b) A simulation of a spatiotemporal recognition circuit with $\Delta t_1 = 5$ ns and $\Delta t_2 = 10$ ns. The input perturbation to unit 1

V. Discussion

A. Comparing Technological Platforms

Cortically-inspired microelectronic architectures have traditionally targeted biological time scales. Several proposals [3], [57] suggest using a crossbar array to network neurons together, essentially a dense mesh of wires overlaying the CMOS (processor) substrate. This is to achieve a massive fan-in and fan-out per connection, which is typical in neural networks but less critical in conventional processors. Several popular approaches aim to achieve clock rates comparable to biological time scales, but transmitting high-bandwidth spikes at the speeds of current processors (gigahertz)—which tend to have high bandwidth

The ability to make a technology that complements the physical constraints that guide it, rather than abstracting them away entirely, represents an important step in streamlining efficiency and performance. Optics is a perfect fit for high bandwidth spike information and could represent a highly efficient processing scheme that ties closely to its underlying physics.

B. Improvements Over Previous Models

Past photonic neurons have demonstrated important features of biological neurons but did not integrate enough properties together to make effective processors. One of the first implementations of a photonic spiking neuron [15] achieved noise suppression and thresholding through a nonlinear optical loop

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