Spatiotemporal Pattern Recognition with Cascadable Graphene Excitable Lasers

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Abstract: We demonstrate a simple photonic spatiotemporal pattern recognition (polychronization) circuit enabled by cascading two graphene excitable lasers. This technology is a potential candidate for information processing and computing.

An unconventional computing paradigm inspired by neuroscience [1] is being intensely explored for its potential to outperform von Neumann architectures in certain problem domains. Pairing neuromorphic technology with photonics could potentially grant the capacity for complex, ultrafast categorization and decision-making [2]. The ideas of biophysical computation algorithms in the context of harnessing the high speed, high bandwidth, and low crosstalk available to photonic interconnects [3][4] could provide a wide range of computing and signal processing applications (e.g. adaptive control, real-time embedded system analysis, and cognitive RF processing). Neuromorphic signal processing incorporates a sparse coding scheme called spiking. This hybrid analog and digital processing technique takes advantage of both the bandwidth efficiency of analog computation and the noise robustness of digital computation [5], making the spike-based approach attractive for information processing. We recently discovered [6][7] a close analogy between the dynamics of lasers and those of spiking biological neurons, both of which can exhibit excitability [8]. However, to enable this emerging computation paradigm the following key criteria must be met: logic-level restoration, input-output isolation, and cascadability [9].

Here, we demonstrate a photonic spatiotemporal pattern recognition circuit. This simple experiment provides a proof-of-concept for cascadability and input-output isolation in excitable lasers for spiking neural networks (SNNs) while simultaneously demonstrating polychrony [10]—an important concept in computational neuroscience, defined as an event relationship that is precisely time-locked to firing patterns but not necessarily synchronized to a global clock reference. Polychronization presents a minimal spiking network that consists of cortical spiking neurons with axonal delays and spike-timing-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.

The computational primitive in our experiment is a graphene excitable laser. Graphene, a 2D atomic-scale hexagonal crystal lattice of carbon atoms [11], could be an excellent candidate in excitable laser processing devices [12][13] as a consequence of its nonlinear saturable absorption due to Pauli blocking, which includes ultrafast carrier relaxation, low saturable absorption threshold, large modulation depth, and wavelength-independent absorption (due to linear dispersion near the Fermi energy). We experimentally demonstrated [12][14] an excitable fiber laser incorporating a graphene saturable absorber (SA) for a variety of complex operations including pulse regeneration and reshaping, asynchronous phase locking, interspike time encoding, and coincidence detection.

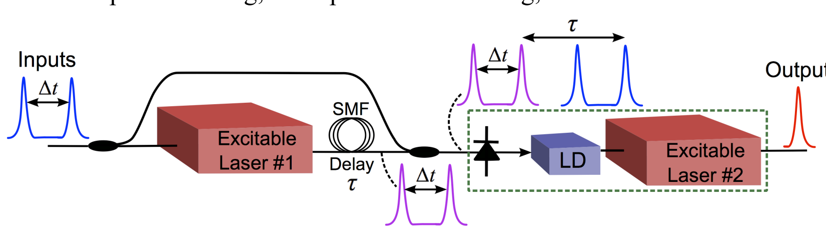

Fig. 1. Spatiotemporal pattern recognition circuit with two cascaded graphene excitable lasers.

One of the key properties of polychronization is the ability to perform *delay logic* to perform spatiotemporal pattern recognition. As shown in Fig. 1, we construct a simple two-unit pattern recognition circuit by cascading two graphene excitable lasers with a delay τ between them. The excitable laser cavity [12] consists of a chemically synthesized graphene-SA sandwiched between two fiber connectors with a fiber adapter and a 75-cm long highly doped erbium-doped fiber (EDF) as the gain medium. A 980 nm signal pumps the EDF providing a constant bias and bringing it above transparency, but saturable cavity losses from graphene prevent lasing. The input channel, 1480 nm excitatory pulses, induce perturbations to the gain section increasing its carrier concentration by an amount proportional to its energy. Enough excitation results in an excursion from equilibrium, causing the laser to emit a pulse at 1560 nm as a result of the saturation of the absorber at transparency.

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In our case the objective is to distinguish (i.e. recognize) a specific input pattern: a pair of pulses separated by time interval $\Delta t \approx \tau$ (equal to the delay between the excitable lasers). These analog inputs are directly modulated with an arbitrary waveform generator and are incident on both the lasers. The outputs from the first laser are fed to the second laser via a single-mode fiber (SMF), which acts as a delay element, and a photodetector (PD) to modulate the laser diode (LD) (allowing wavelength conversion from 1560 to 1480 nm). It has recently been shown [15] that such an excitable laser and PD system can emulate both a leaky integrate-and-fire neuron and a synaptic variable, completing a computational paradigm for scalable optical computing. The dynamics introduced by the PD are analogous to synaptic dynamics governing the concentration of neurotransmitters in between signaling biological neurons. The second laser is biased such that it requires stronger perturbations to fire; it will not fire unless two excitatory pulses (original input and output from the first laser) are temporally close together; that is, when $\Delta t \approx \tau$. Synchronous arrival of these two spikes causes enough excitation above the threshold causing the laser to fire a pulse. The system therefore only reacts to a specific spatio-temporal bit pattern. The resulting experimental data—output pulse profile as a function of the normalized time interval between the two input pulses—is shown in Fig. 2.

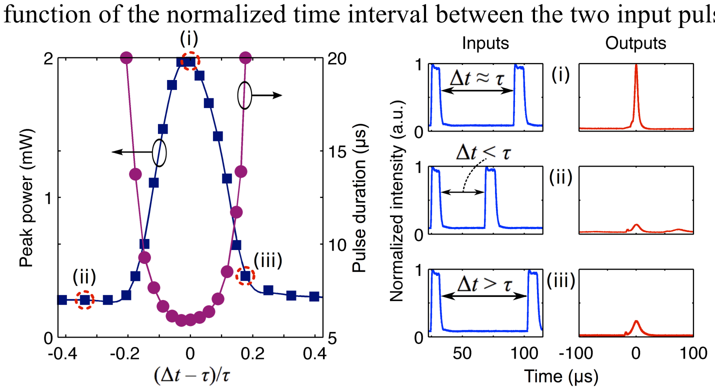

Fig. 1. Measured output pulse peak power, pulse duration, and input and output waveforms as a function of the time interval between the two input pulses. Output pulse energy is the largest when $\Delta t \approx \tau$ showing the system only reacts to a specific spatiotemporal input pattern.

In conclusion, we have demonstrated a spatiotemporal pattern recognition circuit enabled by cascading two graphene excitable lasers. This simple demonstration of temporal logic implies that SNNs of such excitable lasers are capable of categorization and decision making. Combined with learning algorithms such as STDP, networks could potentially perform more complex tasks such as spike-pattern cluster analysis. Because of the length of the cavity, our system's dynamics are observed on μs timescales; however, ongoing research on graphene microfabrication [11] may make it a standard technology accessible in integrated laser platforms and could be an enabler for applications of optical computing [3][4] operating on picosecond timescales which is eight order of magnitude faster than its biological counterpart.

References

[1] M. Mahowald and R. Douglas, "A silicon neuron," Nature **354**(19), 515–518 (1991).
[2] A. N. Tait, M. A. Nahmias, Y. Tian, B. J. Shastri, and P. R. Prucnal, "Photonic neuromorphic signal processing and computing," in *Nanophotonic Information Physics*, ser. Nano-Optics and Nanophotonics, M. Naruse, Ed. Springer Berlin Heidelberg, 2014, pp. 183–222. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-40224-1_8.
[3] D. Woods and T. J. Naughton, "Optical computing: photonic neural networks," Nature Phys. **8**(4), 257–259 (2012).
[4] H. J. Caulfield and S. Dolev, "Why future supercomputing requires optics," Nature Photon. **4**(5), 261–261 (2010).
[5] R. Sarpeshkar, "Analog versus digital: extrapolating from electronics to neurobiology," Neural Comput. **10**(7), 1601–1638 (1998).
[6] M. A. Nahmias, B. J. Shastri, A. N. Tait, and P. R. Prucnal, "A leaky integrate-and-fire laser neuron for ultrafast cognitive computing," IEEE J. Sel. Topics Quantum Electron. **19**(5), 1800212 (2013).
[7] B. J. Shastri, M. A. Nahmias, A. N. Tait, Y. Tian, M. P. Fok, M. P. Chang, B. Wu, and P. R. Prucnal, "Exploring excitability in graphene for spike processing networks," in *Proc. of Numerical Simulation of Optoelectronic Devices (NUSOD)*, Aug. 2013, paper TuC5, pp. 83–84.
[8] B. Krauskopf, K. Schneider, J. Sieber, S. Wieczorek, and M. Wolfrum,"Excitability and self-pulsations near homoclinic bifurcations in semiconductor laser systems," Optics Commun. **215**(46), 367–379 (2003).
[9] D. A. B. Miller, "Are optical transistors the logical next step?" Nature Photon. **4**, 3–5 (2010).
[10] E. M. Izhikevich, "Polychronization: Computation with spikes," Neural Comput.**18**(2), 245–282 (2006).
[11] K. S. Novoselov et al. "A roadmap for graphene," Nature **490**, 192–200 (2012).
[12] B. J. Shastri, M. A. Nahmias, A. N. Tait, Y. Tian, B. Wu, and P. R. Prucnal, "Graphene excitable laser for photonic spike processing," *IEEE Photonics Conf. (IPC)*, Sep. 2013, pp. 1–2. [Online]. Available: http://dx.doi.org/10.1109/IPCon.2013.6656424.
[13] B. J. Shastri, M. A. Nahmias, A. N. Tait, and P. R. Prucnal, "Simulations of a graphene excitable laser for spike processing," Optical and Quantum Electronics, (2014). [Online]. Available: http://dx.doi.org/10.1007/s11082-014-9884-4.
[14] B. J. Shastri, A. N. Tait, M. A. Nahmias, B. Wu, and P. R. Prucnal, "Coincidence detection with graphene excitable laser," in *Proc. Conference on Lasers and Electro-Optics (CLEO)*, Jun. 2014, paper STu3I.5.
[15] M. A. Nahmias, A. N. Tait, B. J. Shastri, and P. R. Prucnal, "An evanescent hybrid silicon laser neuron," in *Proc. IEEE Photonics Conf. (IPC)*, Sep. 2013, paper ME3.4, pp. 93–94.