

Ultra-Fast Photonic Neural Networks



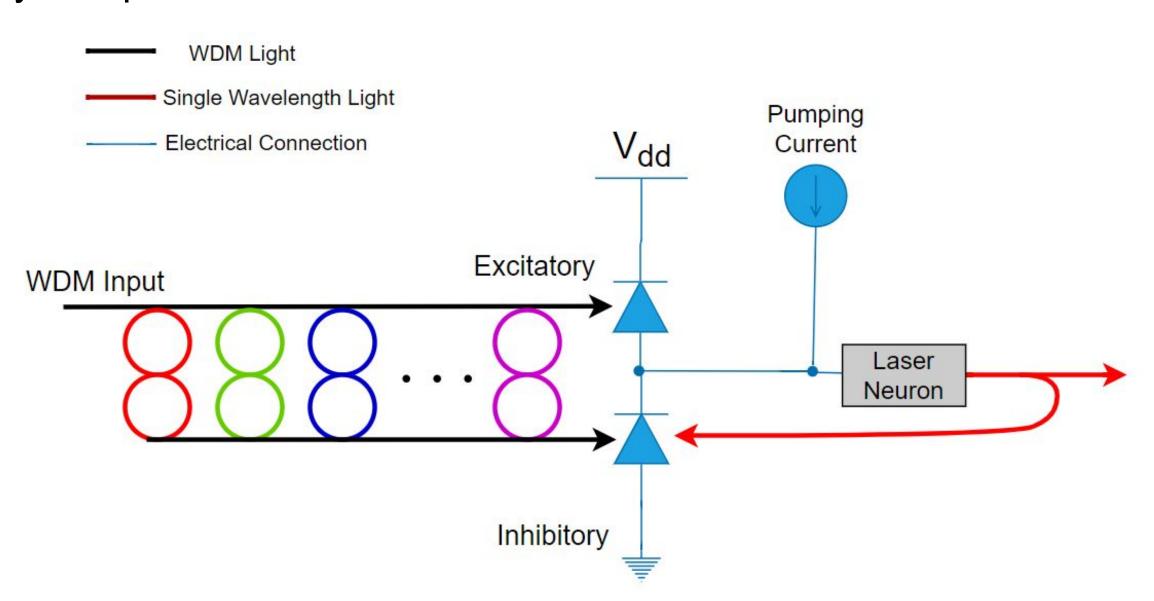
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Problem Statement:

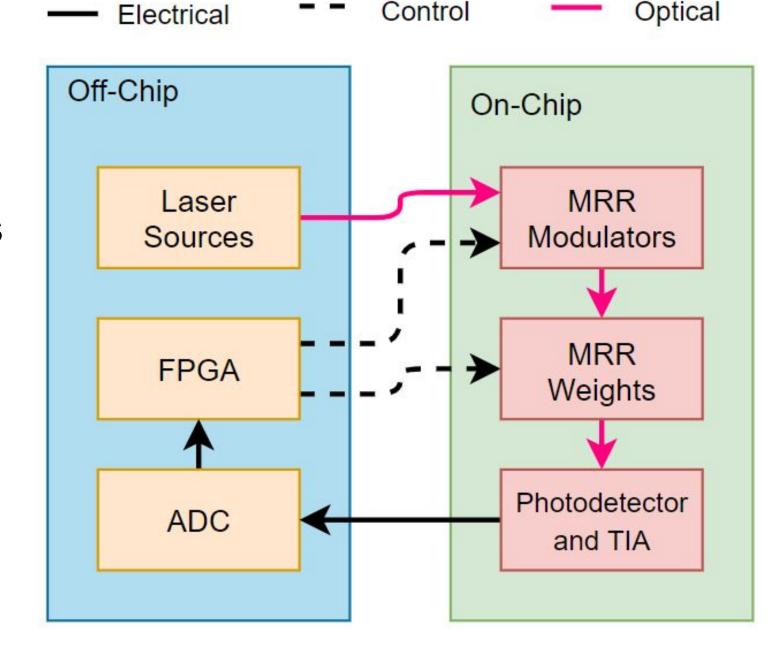
- High data rates of Analog and Optical channels create challenges for digital signal processing applications
- Artificial neural networks are of particular concern, as their effectiveness in signal processing applications is counteracted by their computational intensity for high speed applications
- Deep neural networks suffer more from this issue, requiring GPU's or specialized accelerators to achieve throughput rates in the KHz range
- Specialized hardware that performs calculations in the optical domain could be made to circumvent these challenges

Current State of the Art:

- Optical dot product engines allow for implementations of both constant value and spiking networks on photonic integrated circuits
- Minimum waveguide dimensions severely limit the neuron density of chips in static layer implementations

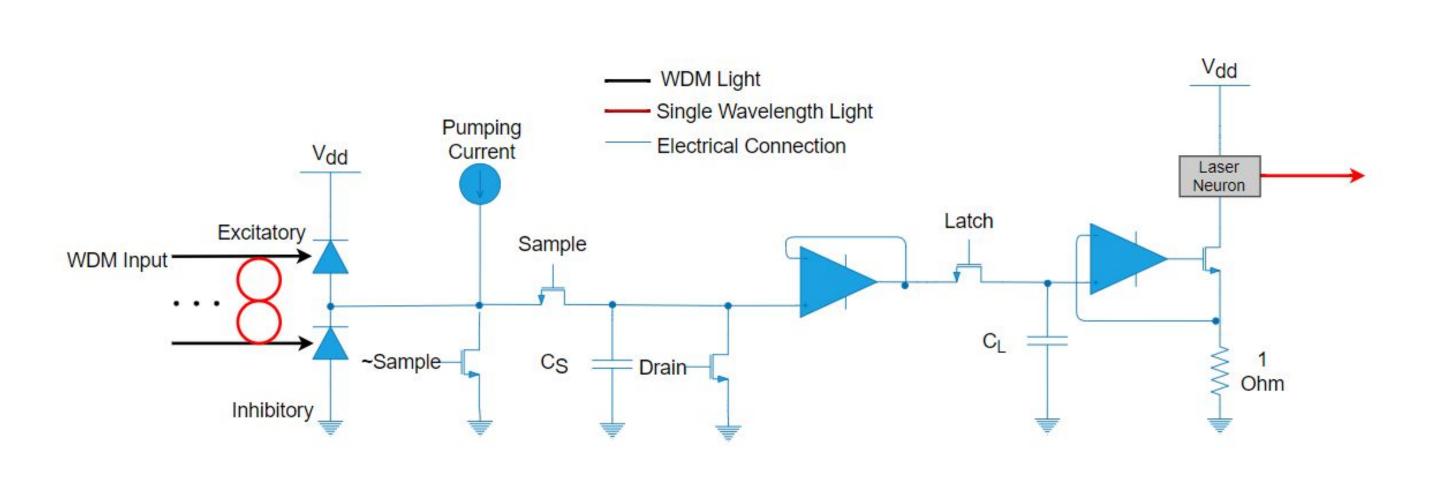


- Infinite scalability is achievable by way of time-division multiplexing of weight bank resources
- Adding layers in this configuration adds delay at a rate of O(n)
- Adding neurons to each layer adds delay at a rate of O(ceil(n/w)) where w is the number of available hardware neurons in a chip
- The most impactful bottleneck cited in this system is described to be the digitization of data between layers [1]



Design and Methodology:

- The goal for the circuit can be simplified to saving a current and reproducing it indefinitely
- Sampling the current
 - Simple task with constant current values
 - Time dependent signals cannot be stored and reproduced
 - Time-averaging makes the most sense when planning for LIF neurons
- Saving the current
 - Capacitors can be used to store values as voltages
 - Circuit is designed for high frequency, so restorative circuitry shouldn't be necessary
 - Lower capacitances have higher bandwidths, higher capacitances are more robust to leakage current
- Reproducing current
- Voltage to current conversion can be done with a MOSFET and a resistor to ground for a feedback voltage
- Can represent a wide range of currents so long as the required drain voltage is significantly far from Vdd



Circuit Operation:

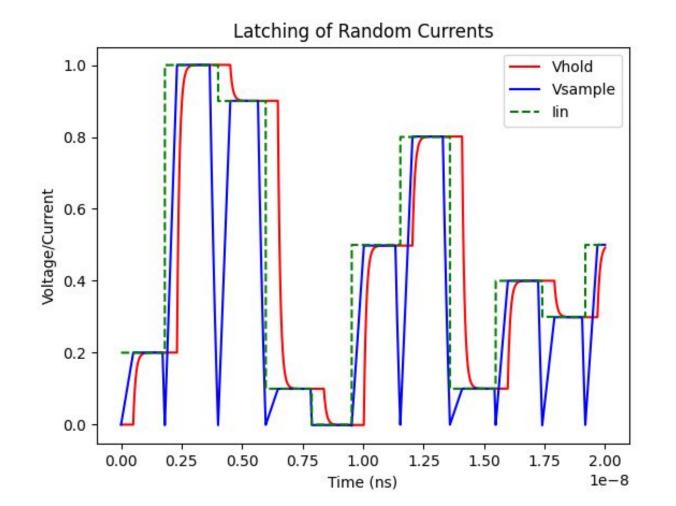
• After a short sample pulse τ , the voltage across C_s is defined by the equation

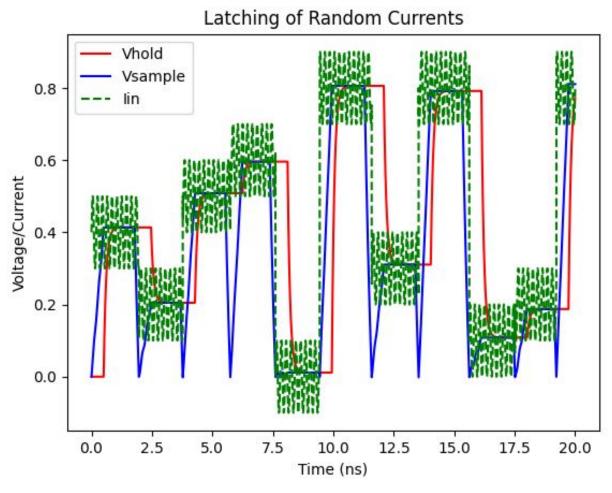
$$V_{CS} = \frac{1}{C_S} \int_{t_0}^{t_0 + \tau} i_{in}(t) dt$$

- This equation exactly mirrors the time average integral if $\tau = C_{c}$
- Higher or lower capacitances can scale this value for larger or smaller expected input current ranges
- After the sample is taken, the latch signal is triggered and the value is stored
- Once V_{CS}≈V_{CI}, the correct optical power is being output, the latch FET is turned off, and C₁ is drained for reuse while the MRR weight bank is changed
- When V_{CI} = 0 and the MRR weights have been successfully changed, the sampling process can begin again

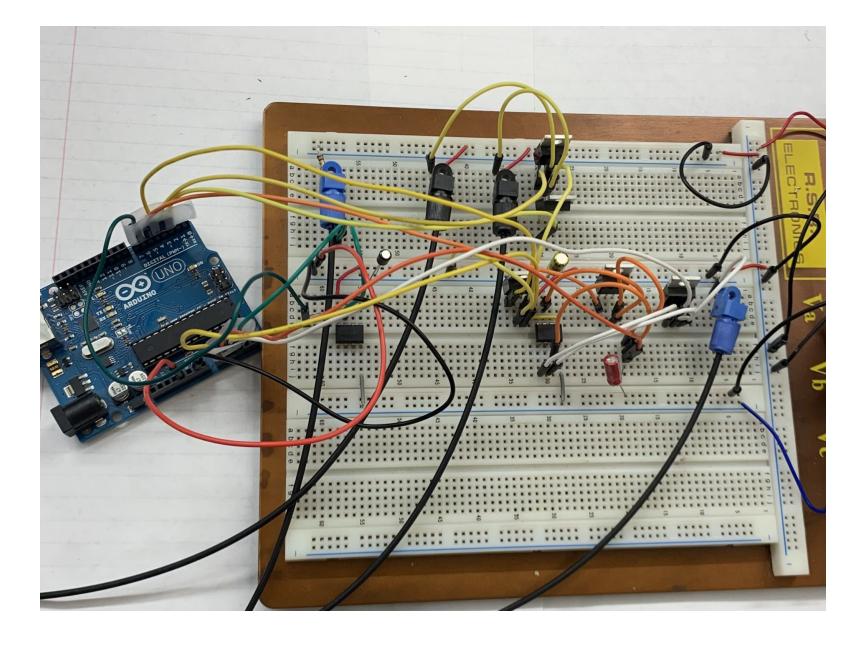
Verification and Physical Circuit:

- Individual portions of the circuit were verified using Keysight's Advanced Design System circuit simulator
- These tests were used to construct the final circuit architecture
- Python mathematical model was created to more easily test the circuit's response to different signals
- Capacitor differential equations were discretized to solve for values at successive time steps
- Discrete input current signals were artificially generated prior to solving for circuit voltages
- Thresholds were detected using "if" statements in the software
- Both constant and time dependent inputs were simulated





- Maximum data rate was significantly improved when the sample capacitor was made to drain to a negative voltage rather than to 0 volts
- Current bottleneck is the latching time, which can be decreased by moving negative feedback node past the latching MOSFET to create op-amp overshoot
- Simulated results were promising enough to warrant construction of a proof-of concept circuit, intended to operate with a much slower data rate
- The model circuit was build on a breadboard using a set of photodetectors and LED's, discrete transistors and capacitors, and an Arduino Uno microprocessor for circuit monitoring and control
- The circuit is not yet in working order, as the MOSFETs being used for signal switching do not gate current bidirectionally
- Efforts have begun to change these MOSFETs to solid state switch ICs



Research Goals:

- Design a circuit to replace the digital path of the infinitely scalable photonic neuromorphic model shown in [1]
- Verify functionality of the ideal model of the circuit through simulations
- Test compatibility with optical components using a low frequency discrete component model
- Examine potential limitations with respect to bandwidth and compare them to that of the existing design

Design Impact Factors:

Constraints

- Should be able to handle both constant value and spiking input signals
- Must be fully parallelized for maximum data rate
- Should ideally have as small of a footprint as possible to allow for a full system-on-chip approach

Engineering Standards

- Design should support common feed-forward network architectures like convolutional layers, pooling layers, etc.
- Optical outputs to communication fibers should have predictable wavelengths and bandwidths that adhere to FCC standards

Considerations

- Ease of use will affect consumer
- willingness to adopt product Smaller circuits with fewer transistors will reduce system
- Optical arithmetic units are shown to have better energy efficiency than CMOS technology
- Implementations must be dependable to be trusted for use on sensitive data

Future Work:

- Replace signal gating MOSFETs with solid state switch ICs
- Operate and collect data from working circuit
- Analyze data to determine signal quality entering and exiting the circuit
- Use results to make predictions regarding the bandwidth of the proposed circuit in integration
- Write a conference paper on findings for submission to the Frontiers in Optics and Laser Science conference

Acknowledgements:

- This work is inspired by the work of the Princeton University Lightwave Communications Research Lab
- [1] M. J. Filipovich, Z. Guo, B. A. Marquez, H. D. Morrison, and B. J. Shastri.

• Primary reference:

"Training Deep Neural Networks in situ with neuromorphic photonics," IEEE Xplore, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/925 2268/. [Accessed: 27-Apr-2022].