Photonic Neural Network Nonlinear Activation Functions by Electrooptic Absorption Modulators

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Abstract: We report on using the transfer function of electrooptic absorption modulators as nonlinear activation functions of photonic neurons and show 95% accuracy of MNIST classification inference on an AlexNet in optical artificial neural networks.
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Neural networks require both a weighting of inputs and a nonlinear activation function operating on their sum. Neural network weighting has been demonstrated in integrated photonics with both interferometric and ring-based wavelength division multiplexing [1]. While direct nonlinearity in optics is difficult to achieve without high optical powers, an electro-optic nonlinearity can be created by directly coupling a photodiode to electro-optic modulator. The low capacitance of directly coupling the components results in operating speeds >10GHz with relatively low power consumption. Here we present a closed form equation for the activation functions created by graphene and quantum well electro-optic absorption modulators capacitive coupled to photodiodes. Our modulator-geometry based and thermal-noise analysis shows that such electro-optic neurons produce SNRs around 60. Performing an MNIST classification inference test on an AlexNet-based neural network with these electro-optic nodes, with accuracies of about 95% starting a laser power level around 3mW and 10mW for the QW and Graphene- based modulator, respectively. Our findings show regions of realistic operating performance of future optical and photonic neural networks using electro-optic analogue (non-spiking) neurons.

An activation function is a nonlinear function that is applied to the weighted sum of the inputs of a neuron (Fig. 1**a**). The nonlinearity of the activation function allows the network to converge into definitive states by eliminate infinitely cascading noise, similar to the nonlinearity of the transistor latching a digital computer into binary states. Apart from the requirement of nonlinearity, and differentiability for training (e.g. gradient decent), there are no limits to the shape of the activation function itself and many activation functions have been proposed each with strengths in different applications. In the electro-optic neuron, consisting of a photodiode connected either directly or through a small electrical circuit to an optical modulator, the nonlinear response of the modulator itself can be used to generate the necessary nonlinearity in the signal transfer function. In this case, the choice of modulator type will immediately impact the shape of the activation function and thus the operation of the network. The traditional design goals for optical modulators, while still relevant, must be evaluated with respect to cascadability and overall network performance rather than individually. Electro-absorption modulators (EAMs) absorb more light at zero bias and less light as the bias increases in magnitude. This effect is used in optical communications to encode electrical signals on optical carriers. The shape of the voltage to absorption curve varies by EAM type [2] (Fig. 1**b**). All EAM absorption curves are nonlinear due to the eventual saturation in the limited number of carriers, or inability to further impact the optical waveguide mode. Here we model two specific types of absorption modulators, namely those based on the active materials, graphene and quantum well (QW). First, graphene a 2D material with high electron mobility has been demonstrated as both a phase and absorption modulator in several high-speed integrated photonic devices [3–5]. Second, the QW absorption modulator as a quantum-confined Stark effect (QCSE) absorption modulator is promising for low energy operation. Here QCSE absorption modulation is likely the strongest optical absorption modulation process [6]. Second, the QW absorption modulator as a quantum-confined Stark effect (QCSE) absorption modulator is promising for low energy operation [7]. The photodiode is modeled electrically as a current source, while the electro-optic modulator as a voltage- dependent capacitive load. The current produced by the photo- diode must be converted into a voltage of sufficient magnitude to drive the modulator. The magnitude of the voltage depends on the modulator size, its materials impacting absorption and the optical mode, and electric field confinement [7,8]. There are three options for coupling the photodiode to the modulator, while here we selected capacitive coupling because the load resistance required to convert the current source to a voltage can be eliminated (Fig. 1b, inset). This reduces the energy cost and increases the operating speed by allowing a reduction in the R portion of the RC low-pass filter at the cost of creating a saw-tooth charging waveform in the output voltage. The sawtooth-waveform in the analog signal received can be overcome by adding a clocked gate to the coupling circuit. The clocked gate holds the capacitor at the final voltage while the next layer is charged. This divides the operating frequency into a two-cycle process where first a layer is charged and then is isolated from the photodiode and held at a constant voltage while the layer above it is charged, thus this process eliminates the high resistance required by resistive loading and the energy, complexity, and area costs of TIA coupling. The circuit and modulator models were combined to sweep the parameter space of optical input power and modulator length with signal to noise ratio (SNR) (Fig. 1**c&d**).

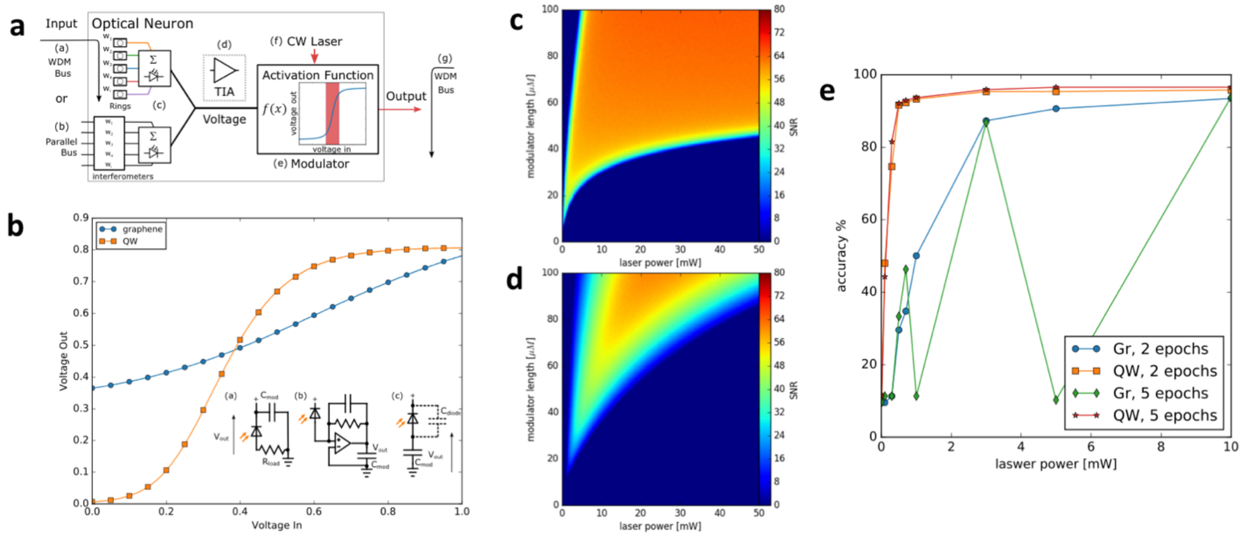

Fig. 1. **a**, An electrooptic neuron taking an input from a WDM bus and weighting by wavelength with rings (a) or from a parallel bus weighting with an interferometer network (b), sums the optical signal with a photodiode converting the signal to a voltage (c), optionally amplified by a transimpedance amplifier (TIA) (d), drives an electro-optic modulator (e) modulating a CW laser (f), produces a nonlinear transfer function at the output (g). **b**, The modeled nonlinear activation function of an electrooptic neuron where a photodiode is capacitivly coupled to an absorption modulator with 5 mW of optical power and 10 nm of effective dielectric thickness. The quantum well (QW) modulator (squares) as a QCSE absorption modulator shows significantly more nonlinearity than the graphene modulator (diamonds) over the same voltage range. **c&d**, Sweeping the parameter space of the absorption modulator length and laser power for the QW (a) and graphene (b) modulators with SNR plotted with a 0 limit shows the QW modulator operating with reasonable SNR over a greater range of the parameter space than the graphene modulator. Significant advantage is seen in the QW modulator over the graphene modulator in the low power, small size region towards the bottom left. **e**, Modulator based electro-optic neurons in a simulated 210 neuron neural network trained with 2 and 5 epochs using adaptive subgradient training [14] and categorical cross-entropy evaluation plotted against laser power shows QW out performing graphene as laser power is decreased.

We used these optical absorption modulator and circuit models to develop a neural network simulation using Keras [9] and TensorFlow [10]. We then evaluate the performance of the modeled photonic neural network via the MNIST [11] classification (Fig. 1**e**). The neural network is composed of 3 layers; the first layer is fully connected and has 784 inputs from the MNIST data and 100 outputs. The second layer is a hidden layer and has 100 inputs and 100 outputs. The final layer has 10 outputs for the ten possible digit classes, making for a total of 210 nodes for the neural network considered here. The graphene and quantum well neural networks were both trained and evaluated over optical powers from 10 µW to 10 mW with two different epochs of 2 and 5. We find that both modulator neurons are able to produce neural network accuracies up to about 95%. However, the QW-based one scales relatively flat with laser power, as its modulator transfer function is easily differentiable even after propagating through several layers. In contrast the graphene- based neural network accuracy dramatically drops in the low- power limit. The graphene neuron is also much more sensitive to under-fitting as compared to the QW counterpart.

4. References

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