An all-optical convolutional neural network

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Abstract. The abstract should summarize the contents of the paper. LNCS guidelines indicate it should be at least 70 and at most 150 words. It should be set in 9-point font size and should be inset 1.0 cm from the right and left margins. . . .

Keywords: We would like to encourage you to list your keywords within the abstract section

1 Introduction

Deep neural networks have found success in a wide variety of applications, ranging from computer vision to natural language processing to game playing [1]. Since the explosion of interest following the achievements of convolutional neural networks on ImageNet classification, deep learning has transformed algorithms in both academic and commercial environments. While accuracy has improved to a remarkable level, the number of parameters and connections has grown dramatically, and the power requirements to build and use these networks have increased correspondingly.

While the training phase of learning parameter weights is often considered the slow stage, large models also demand significant energy during inference due to millions of repeated memory references. For example, AlphaGo has a power consumption of approximately 300 W. To this end, there is a large effort to develop new software methods and specialty hardware for improved efficiency. Algorithms for improved efficiency include pruning, quantization, low rank, parallelization, mixed precision, and model distillation. Compressed models have demonstrated preserved accuracy with much fewer parameters [2, 8]. On the hardware front, there are now specialized processing units for deep learning, such as TrueNorth, Movidius's USB-based neural compute stick (NCS), and Google's tensor processing unit (TPU). Despite all these efforts, it remains difficult for embedded systems such as mobile vision, autonomous vehicles/robots, and wireless smart sensors to deploy CNNs due to stringent constraints on power and bandwidth.

Optical computing has been tantalizing for its high bandwidth and inherently parallel processing. If we can come up with scalable optical configurations that together act as a framework for an optical CNN, this would be of interest to computer vision, robotics, machine learning, and optics communities. Optical neural networks (ONNs) could also potentially exploit wave optics for complex-valued neural networks and new types of non-linearities that are currently unavailable to digital computation. Linear transformations can be performed with lens systems or interferometer meshes [3]. Optical nonlinearities include saturable absorption and bistability. Liquid crystal light valves have been used as optical thresholding devices [4]. Convolutions are commonly performed with PSF engineering. We use these to design a model for cascaded parallel convolutions with sandwiched nonlinearity layers.

In this paper, we follow the vein of computational photography to create we zero-power, all-optical convolutional neural network for image classification. We choose a simple classification task, e.g. classify handwritten digits, and build a prototype that performs inference on projected images. We precompute the weights by training with the MNIST dataset on a computer, then fabricate the optical elements accordingly. We compare performance with the same inference performed on the computer. Here we demonstrate proof-of-concept with bulk optics and free-space propagation, but we recommend photonic integrated circuits for scalability. Photonic circuits with up to 4,096 optical devices have been demonstrated [5], and there have also been new three-dimensional photonic integrations that could enable larger networks [6]. Combination of these next-generation large-scale photonic circuits with compressed deep learning models could provide a potential route for high performance ONNs.

To summarize, we make the following contributions:

- We propose an optical toolbox of building blocks for convolutional neural networks.
- We build a zero-power, all-optical two-layer network with precomputed weights for image classification.
- We evaluate against the computer implementation of the same network and show that we achieve similar accuracy.

Overview of limitations. We are limited to non-negative values since we are working with light intensities. This may be avoided with coherent processing. We also hope to proceed without normalization. We focus here on inference and do training on the computer. In our current implementation without active elements, we lose flexibility to update the network. However, in fixed applications, this is not a problem. Photonic circuits remain expensive to fabricate as they are not used in common consumer applications.

2 Related Work

CNNs and architecture variations. Artificial neural networks were proposed in X. Early networks were composed of fully connected layers with nonlinear activation functions in between, inspired by the canonical biological neuron and its thresholded activation. Convolutional layers were popularized by LeCun and ... in image classification CITE. Convolutional layers allow for weight sharing... Since then, deeper, more complex, etc. Since an optical implementation of a CNN comes with certain constraints and challenges, we wanted to see what types of CNNs have been explored with non-standard architectures that may align with physical designs. Omission of fully connected layers, i.e. fully convolutional with global average pooling at the top layer has proven to be successful in [7, 8]. Analysis of CNN operations in the Fourier domain, introducing spectral pooling and regularization [9]. Relevant because we can also access optical Fourier plane. We also note the work in the complex-valued deep neural networks [10], as coherent optical signals may be an effective means of propagating complex-valued data.

Optical computing High bandwidth, but high cost. Optoelectronics and fully optical. Optical solutions to NP-complete problems that are faster than electronic computation [11]. In the early days of CNNs, there was also momentum for optical implementation, optical neural networks (ONNs). Adaptive optical network using volume holographic interconnects in photorefractive crystals [12]. Hybrid optoelectronic network with feedback loop, computer for subtraction and thresholding operations [13]. Optical thresholding perceptron implemented with liquid crystal light valves (LCLV) [4]. There has also been much development in photonic computing. Recently, two-layer fully connected NN demonstrated with intermediate simulated nonlinearity units on 1D data [3]. However, this required photodetection and reinjection, and it did not involve convolutional layers. Optalysys? We do not work with photonic circuits here, but we think they may be worth exploring for larger networks.

Computational cameras. Computational photography has some intersection with optical computing in that they may perform some operations on the input signal optically, but they are also distinct in that they work with spatially organized inputs that come from physical world (incoherent light). Coded apertures and PSF engineering can perform filtering [CITE]. Optical correlators that essentially perform template matching on images have been explored for optical target detection and tracking [14, **?**]. Somewhat similar to our goal is focal plane processing, which refers to the incorporation of image processing on the sensor chip, eliminating or reducing the need to shuttle full image data to a processor. These chips have been designed to detect edges and orientations and to perform wavelet or discrete cosine transforms [15] [RedEye]. Most of these approaches still rely on electronic computation on the image sensor chip, whereas our goal is all-optical implementation with no additional power input. Chen et al. use optically designed angle sensitive pixels, photodiodes with integrated diffraction gratings producing Gabor wavelet impulse responses, to approximate the kernels of the first layer of a typical convolutional neural network [16]. However, this design is limited to a fixed set of convolution kernels, and the output still has to be shuttled to a computer for further processing. Our goal is to build an end-to-end classification system with flexible and rearrangeable optical units that allows for custom optical CNNs.

3 ONN Toolbox

4 Understanding ONNs

5 Optical Prototype

6 Discussion

7 Conclusion

We hope this will inspire more research in the area.

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