ClassificationCam: How can optics be used in convolutional neural networks? (not final)

Anonymous ECCV submission

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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. Paper page limit is 14 pages, excluding references.

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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 [2,3]. 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 [4]. Optical nonlinearities include saturable absorption and bistability. Convolutions are commonly performed with PSF engineering. We use these to propose 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.

reduce the workload of the electronic processor

We choose a simple classification task, e.g. MNIST, GoogleQuickdraw, or CIFAR-10, and build a prototype that performs classification on projected images. We precompute the weights by supervised learning on a computer, then fabricate the optical elements accordingly. We compare performance with the same inference performed on the computer, with and without the simulated physical constraints of an optical setup. 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.
- Simulation framework
- We build a hybrid optoelectronic two-layer network with an optical convolutional layer and electronic fully connected layer for CIFAR-10 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

Efficient convolutional neural networks. Since our work is motivated by the potential of optics to increase the effiiciency of CNN applications, we first review algorithms and electronic hardware also designed to address this challenge.

Pruning, trained quantization, huffman encoding, and altered architectural design have been successfully used to compress CNN models, preserving AlexNet-level accuracy on ImageNet even with 510× less memory usage and 50× fewer parameters [2,3]. 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). All of these are complementary to our approach, which still requires offline training to optimize the optical components. Other inference-focused efforts aimed at embedded vision applications have tried to incorporate a portion of the image processing on the sensor chip, eliminating or reducing the need to shuttle full image data to a processor. Analog circuitry has been used to detect edges and orientations, to perform wavelet or discrete cosine transforms, and even to execute layers of a CNN [7,8]. These approaches still rely on electronic computation on the image sensor chip, whereas our goal is to push more of the computation into optical hardware that requires no power input.

Computational cameras. Optical computation is attractive because it offers inherent parallelism and high interconnectivity, both of which are encountered when passing signals through neural networks. In the computational imaging community, many system designs already exploit the physical propagation of light through custom optics to encode information about a scene that would be lost in a standard 2D image capture. Co-design of optics and algorithms has enabled computational cameras to record depth, light fields, light transport, and more with a toolbox including coded apertures, lenses and lenslets, active illumination, and wavefront shapers [9,10,**?**,11,12]. In this work, we propose a computational imaging system modeled after a CNN that assists in performing classification of input images. We begin by learning an optical correlator consisting of a single convolutional layer that essentially performs template matching on images, as has been explored for optical target detection and tracking [13,14], and then expand beyond a single matched filter in hybrid optoelectronic and fully optical designs.

Optical neural networks. The concept of an optical neural network (ONN) captured the attention of many in the late 1980s to mid-1990s, primarily due to the capability of optics to perform the expensive matrix multiply of a fully connected layer. In 1985, an optoelectronic implementation of the Hopfield model, a basic model of a recurrent neural network, was created with 1D LED array input signals and a binary transmission mask [15]. This model divided the weight matrix into two parts, positive and negative, and required electronics for subtraction of the two parts and signal thresholding. Psaltis et al. further explored the potential of dynamic photorefractive crystals to store neural network weights, which could allow for optical backpropagation-based learning in ONNs [16]. Meanwhile, the optoelectronic network of a Hopfield model was extended to 2D signals by partitioning the pixels of a liquid crystal television to store an array of smaller 2D patterns [17]. Furthermore, an optical thresholding perceptron was implemented with liquid crystal light valves (LCLV), which disposed of the need to convert between optical and electronic signals between layers [18]. We draw on some of these insights for the design of our optical CNN. A more extensive overview of the varied implementations of ONNs can be found in [19].

Despite the progress in this area, as neural networks fell out of the spotlight, the demand for ONNs also waned. However, with the resurgence of CNNs that are far more powerful and computationally expensive than before, there is renewed interest in optical computing [1]. Recent works that connect efforts of the last century to modern hardware include a two-layer fully connected neural network based on programmable photonic circuits [4] and a recurrent neural network with DMD-based weights [20]. However, none of the ONNs mentioned previously involve convolutional layers, which have become essential in computer vision applications. The ASP Vision system approaches the task of designing a hybrid optoelectronic CNN, using angle sensitive pixels to approximate the first convolutional layer of a typical CNN, but it is limited to a fixed set of convolution kernels [21]. Our goal is to design a system with optimizable optical elements to demonstrate low-power inference by a custom optical or optoelectronic CNN.

3 ONN Toolbox, pp. 5-7

In this section we present building blocks for an optically implemented CNN. In this rest of this paper we focus on the convolutional layer, but we will briefly discuss other layers here too.

- Convolutional layer: Small kernel, tiled kernels, single large kernel (Fig. 1)
- Other layers that we didnt test in detail:
  Optical nonlinearities
  Max/avg pooling with spectral pooling
  Fully connected layers

4 Training, pp. 7

Here we talk about how we train the ONN offline in Tensorflow. PSF optimization followed by phase mask optimization OR end-to-end phase mask optimization.

5 Simulations, pp. 8-10

We use simulations to better understand the performance of optical CNNs. Fig. 2: diagram of possible ONN models. Table 1: Results.

- Introduce toy classification problem(s?), discuss constraints.

[1] Fathom Computing (`fathomcomputing.com`), Lightelligence (`lightelligence.ai`), Optalysis (`optalysys.com`)

- Learned optical correlator (single optical conv. layer)
  Here we are able to use end-to-end learning.
  Possible figure with learned phase mask and PSF.
- Hybrid optoelectronic (one optical conv. layer)
  Talk about the dual channel positive and negative weights
  Grayscale
  With color filters Vincent?
  Fig. 3: Hybrid ONN phase masks and PSFs.
- All-optical convolutional neural network
  Doesnt fully work, but can discuss some results

6 Optical Prototype, pp. 10-11

Implement the hybrid optoelectronic two-layer neural network. Goal is to show that the hybrid ONN can perform on par with the electronic ONN, with the same number of layers, and better than the electronic ONN with one fewer layer.
Fig. 4: optical setup
Fig. 5: actual PSF and sample images
Table. 2: results

7 Discussion, pp. 12-13

- Not straightforward to generalize first optical conv. layer to multiple optical layers
- Discuss importance of negative weights Vincent?
- Instead of trying to replicate a CNN exactly, could take advantage of optical transformations that aren't as practical in computations. For example, we use a 4f system for convolution, but this requires two extra lenses. Perhaps a single custom learned optical element can be used instead.
- In the future, exploit other properties of light (polarization, phase)
- Specifically, coherent light and holography, photonics

8 Conclusion, p. 14

Important step towards optical CNNs. We hope this will inspire more research in the area.

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