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

Anonymous ECCV submission

Paper ID ***

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.

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

1 Introduction, pp. 1-2

CNNs are very important, but they require a lot of computation. Optics can offer passive, fast, highly parallel computation. This project explores incorporating optical computing in convolutional neural networks. We present several models and assess their limitations and potential.

2 Related Work, pp. 2-4

Convolutional neural networks. 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.

As embedded vision and even continuous mobile vision become hardware 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 [**?**] [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.

CNN architecture variations Our goal is to match performance with a constrained optical setup, so also relevant to highlight are CNNs 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 [1,2]. Analysis of CNN operations in the Fourier domain, introducing spectral pooling and regularization [3]. Relevant because we can also access optical Fourier plane. We also note the work in the complex-valued deep neural networks [4], as coherent optical signals may be an effective means of propagating complex-valued data.

Optical computing and computational light transport. In the computational imaging community, many new optical system designs exploit the physical propagation of light to The co-design of optics and algorithms

Optical computing offers high bandwidth, but high cost. Optoelectronics and fully optical. Optical solutions to NP-complete problems that are faster than electronic computation [5].

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 one-dimensional (1D) LED array input signals and a binary transmission mask [6]. 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 [7]. 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 [8]. 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 [9]. A more extensive overview of the varied implementations of ONNs can be found in [10].

Despite the accumulation of insights 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 [11] and a recurrent neural network with DMD-based weights [12]. 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 [13]. Our goal is to design a system with optimizable optical elements to demonstrate low-power inference by a custom optical or optoelectronic CNN.

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

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.
- 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.

References

1. Lin, M., Chen, Q., Yan, S.: Network in network. arXiv preprint arXiv:1312.4400 (2013)
2. Iandola, F.N., Han, S., Moskewicz, M.W., Ashraf, K., Dally, W.J., Keutzer, K.: Squeezenet: Alexnet-level accuracy with 50x fewer parameters and¡ 0.5 mb model size. arXiv preprint arXiv:1602.07360 (2016)
3. Rippel, O., Snoek, J., Adams, R.P.: Spectral representations for convolutional neural networks. In: Advances in Neural Information Processing Systems. (2015) 2449–2457
4. Trabelsi, C., Bilaniuk, O., Serdyuk, D., Subramanian, S., Santos, J.F., Mehri, S., Rostamzadeh, N., Bengio, Y., Pal, C.J.: Deep complex networks. arXiv preprint arXiv:1705.09792 (2017)
5. Wu, K., De Abajo, J.G., Soci, C., Shum, P.P., Zheludev, N.I.: An optical fiber network oracle for np-complete problems. Light: Science & Applications **3**(2) (2014) e147
6. Farhat, N.H., Psaltis, D., Prata, A., Paek, E.: Optical implementation of the hopfield model. Applied optics **24**(10) (1985) 1469–1475
7. Psaltis, D., Brady, D., Wagner, K.: Adaptive optical networks using photorefractive crystals. Applied Optics **27**(9) (1988) 1752–1759
8. Lu, T., Wu, S., Xu, X., Francis, T.: Two-dimensional programmable optical neural network. Applied optics **28**(22) (1989) 4908–4913
9. Saxena, I., Fiesler, E.: Adaptive multilayer optical neural network with optical thresholding. Optical Engineering **34**(8) (1995) 2435–2440
10. Denz, C.: Optical neural networks. Springer Science & Business Media (2013)
11. Shen, Y., Harris, N.C., Skirlo, S., Englund, D., Soljačić, M.: Deep learning with coherent nanophotonic circuits. In: Photonics Society Summer Topical Meeting Series (SUM), 2017 IEEE, IEEE (2017) 189–190
12. Bueno, J., Maktoobi, S., Froehly, L., Fischer, I., Jacquot, M., Larger, L., Brunner, D.: Reinforcement learning in a large scale photonic recurrent neural network. arXiv preprint arXiv:1711.05133 (2017)
13. Chen, H.G., Jayasuriya, S., Yang, J., Stephen, J., Sivaramakrishnan, S., Veeraraghavan, A., Molnar, A.: Asp vision: Optically computing the first layer of convolutional neural networks using angle sensitive pixels. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2016) 903–912