

ClassificationCam: An exploration of hybrid and fully optical convolutional neural networks

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

- CNNs for computer vision
- Computational imaging and embedded vision
- Optical computing, optical neural networks

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
Doesn't 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?**
- In the future, exploit other properties of light (polarization, phase)
- Specifically, coherent light and holography

8 Conclusion, p. 14

Important step towards optical CNNs.

References

1. LeCun, Y., Bengio, Y., Hinton, G.: Deep learning. *Nature* **521**(7553) (2015) 436–444
2. Han, S., Mao, H., Dally, W.J.: Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding. *arXiv preprint arXiv:1510.00149* (2015)
3. 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)
4. 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
5. Saxena, I., Fiesler, E.: Adaptive multilayer optical neural network with optical thresholding. *Optical Engineering* **34**(8) (1995) 2435–2440
6. Sun, J., Timurdogan, E., Yaacobi, A., Hosseini, E.S., Watts, M.R.: Large-scale nanophotonic phased array. *Nature* **493**(7431) (2013) 195–199
7. Rechtsman, M.C., Zeuner, J.M., Plotnik, Y., Lumer, Y., Segev, M., Szameit, A.: Photonic floquet topological insulators. In: *Lasers and Electro-Optics (CLEO), 2013 Conference on, IEEE* (2013) 1–2
8. Lin, M., Chen, Q., Yan, S.: Network in network. *arXiv preprint arXiv:1312.4400* (2013)
9. Rippel, O., Snoek, J., Adams, R.P.: Spectral representations for convolutional neural networks. In: *Advances in Neural Information Processing Systems*. (2015) 2449–2457
10. 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)
11. 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
12. Psaltis, D., Brady, D., Wagner, K.: Adaptive optical networks using photorefractive crystals. *Applied Optics* **27**(9) (1988) 1752–1759
13. Lu, T., Wu, S., Xu, X., Francis, T.: Two-dimensional programmable optical neural network. *Applied optics* **28**(22) (1989) 4908–4913
14. Manzur, T., Zeller, J., Serati, S.: Optical correlator based target detection, recognition, classification, and tracking. *Applied optics* **51**(21) (2012) 4976–4983
15. Gruev, V., Etienne-Cummings, R.: Implementation of steerable spatiotemporal image filters on the focal plane. *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing* **49**(4) (2002) 233–244
16. 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