Title
A Fully Programmable On-Chip Planar Waveguide for Machine Learning

Authors
Stein, Martin M

Onodera, Tatsuhiro

Ash, Benjamin A

et al.

Publication Date
2024

DOI
10.1364/cleo_si.2024.sf2m.1

A Fully Programmable On-Chip Planar Waveguide for Machine Learning

Martin M. Stein[1,*], Tatsuhiro Onodera[1,2,*], Benjamin A. Ash[1], Mandar M. Sohoni[1], Melissa Bosch[1], Ryotatsu Yanagimoto[1,2], Marc Jankowski[2,3], Timothy P. McKenna[2,3], Tianyu Wang[1] , Gennady Shvets[1], Maxim R. Shcherbakov[1,†], Logan G. Wright[1,2,‡], Peter L. McMahon[1,4]

[1]School of Applied and Engineering Physics, Cornell University, 142 Sciences Dr, Ithaca, NY 14853, USA
[2]NTT Physics and Informatics Laboratories, NTT Research, Inc., 940 Stewart Drive, Sunnyvale, CA 94085, USA
[3]E. L. Ginzton Laboratory, Stanford University, 348 Via Pueblo, Stanford, CA 94305, USA
[4]Kavli Institute at Cornell for Nanoscale Science, Cornell University, 245 Feeney Way, Ithaca, NY 14853, USA
[†]Present address: Department of Electrical Engineering and Computer Science, UC Irvine, 5200 Engineering Hall, Irvine, CA 92697, USA
[‡]Present address: Department of Applied Physics, Yale University, 15 Prospect Street, New Haven, CT 06511, USA
**These authors contributed equally.*
Author e-mail addresses: ms3452@cornell.edu, to232@cornell.edu, pmcmahon@cornell.edu

Abstract: We introduce a device containing a planar waveguide whose spatial refractive index profile $n(x, z)$ can be programmed in real time. We demonstrate use this device as an optical neural network.

Optical neural networks (ONNs) aim to harness the unique physical properties of light to energy-efficiently perform neural-network computations [1,2]. Integrated photonics is a particularly attractive platform for ONNs due to its excellent stability, the availability of high-bandwidth modulators and detectors, as well as ease of integration with electronics [1-3]. However, it has been challenging to scale on-chip ONNs to large input vector sizes for several reasons. This includes the large spatial footprint of photonic devices, fabrication imperfections, and often lengthy and costly design cycles. In response, there is growing interest in developing photonic hardware with greater programmability, to provide for more flexibility to adjust and tune a device's functionality post-fabrication [4-7].

In this work, we realize a fully programmable planar waveguide, capable of in situ, real-time modification of its spatial refractive index distribution $n(x, z)$ [8]. In contrast to the traditional approach of interfering light in discrete waveguide modes, we instead leverage complex multimode wave propagation for machine learning [7,9,10]. Specifically, we demonstrate that the device has approximately 10,000 programmable parameters that can be rewritten every 300 ms, free from any measurable memory effects or cyclic degradation. We train these parameters, i.e., the spatial distribution of the refractive index, with a hybrid *in situ–in silico* backpropagation algorithm to perform vowel classification [11].

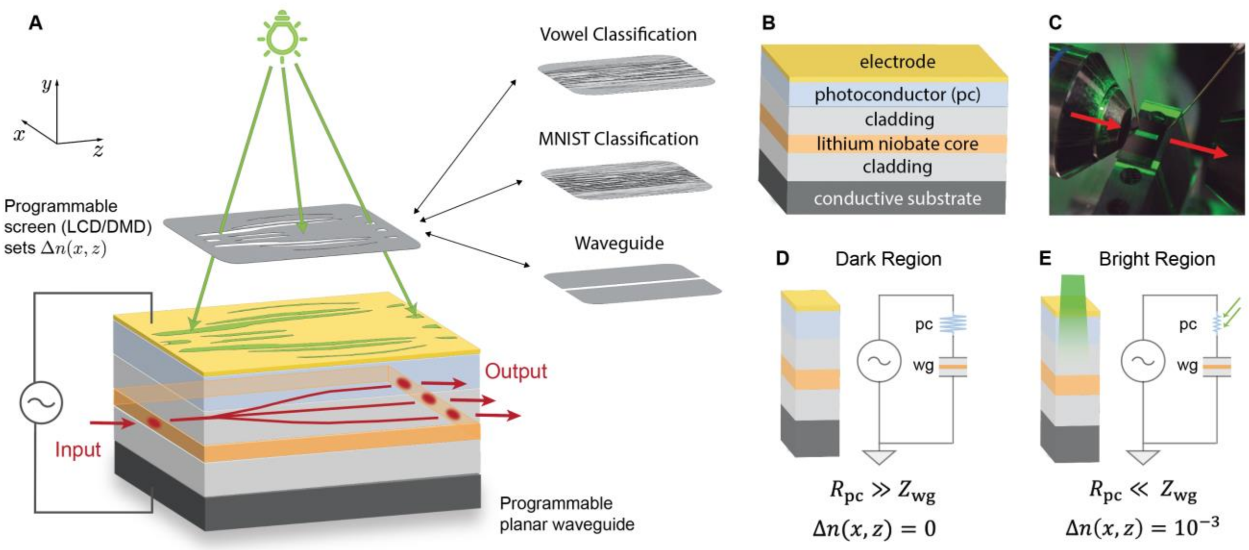

Figure 1: Concept of the programmable planar waveguide. **A**: Device schematic showing how illuminated pattern on the top of the chip in situ sets the spatial refractive index distribution $\Delta n(x, z)$. **B, D, E**: Illustration of the device's working principle: voltage division between the photoconductive film and a waveguide composed of an electro-optic material. R_{pc} and Z_{wg} stands for the resistance of the photoconductor and impedance of the waveguide respectively. **C**: Photograph of device. Figure adapted from Ref. [8].

As shown in Fig. 1A, the spatial refractive index distribution of the programmable planar waveguide is set by the illumination pattern incident on the top of the chip. Therefore, by projecting different light patterns onto the device, we can program various functionalities post-fabrication. This includes the realization of photonic components such as waveguides and splitters as well as the ability to perform machine learning. The device consists of a photoconductive film on the top of a lithium niobate planar waveguide (see Fig. 1B). Applying a voltage across the device induces a refractive index change in the lithium niobate waveguide via the electro-optic effect. As depicted in Figs. 1D and 1E, altering the illumination of the photoconductive film changes the voltage division between the waveguide and photoconductor, enabling control over the refractive index of the planar waveguide. In our current device, the refractive index contrast is 10^{-3}, but we anticipate that it could be as high as 0.5×10^{-2} with a more optimized design.

Our results on performing machine learning with this programmable planar waveguide are shown in Figure 2. We focused on vowel classification, where the inputs are twelve-dimensional vectors representing vowel formant frequencies, and the output corresponds to one of seven possible vowel classes. Each element of the input vector corresponds to the amplitude of distinct input channel modes, which are spatially separated. In our experiment, we utilized a spatial light modulator-based beam shaper for inputting these beams via butt coupling. A digital micromirror device (DMD) patterns the green light incident on the top of the device. The intensity distribution at the output facet is then measured with a camera. This output is divided into seven distinct spatial bins, with the bin having the highest energy corresponding to the vowel predicted by the ONN. We trained the illumination pattern (i.e., the refractive index distribution) using physics-aware training, a hybrid physical-digital backpropagation algorithm [11]. In the forward pass, inputs are sent through the experiment. To obtain the gradients of the illumination pattern, we backpropagate the measured intensity distribution through a differentiable simulation of the experiment. This in situ training procedure takes one hour on our setup for this vowel classification task, after which we achieve a 98% validation accuracy (1 incorrect out of 63 validation examples; see Fig. 2B).

We note that minimal digital pre- and post-processing was applied to perform this task and that almost all the computation is performed by the controllable wave dynamics in a complex inhomogeneous media. The only exception is the energy summation in spatial bins, which can be performed by a lens in the future. We envision that both the beam shaper and camera will be replaced by much faster on-chip modulators and photodetectors in the future.

In summary, this work realizes a fully programmable planar waveguide and uses it as an optical neural network. More broadly, we believe that this novel platform can serve as a dual-purpose testbed both for exploring machine learning algorithms to improve photonic design and for experimentally studying novel architectures for on-chip ONNs.

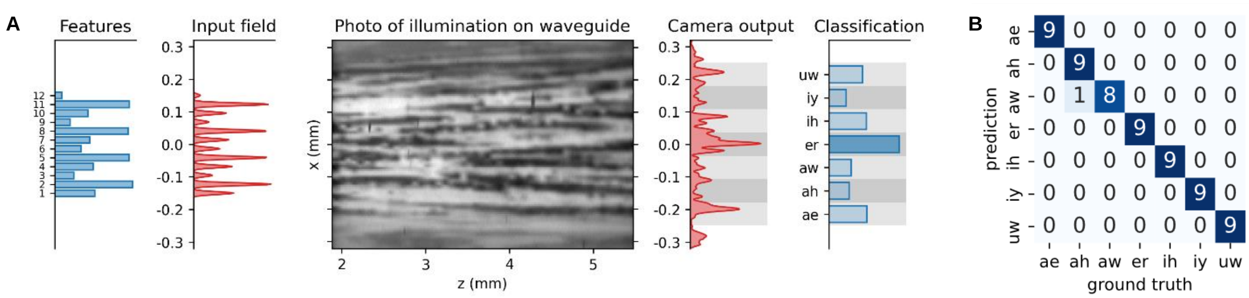

Figure 2: Experimental results on machine learning. **A**: Input vectors from the vowel dataset are converted into an input optical field $E(x, z=0)$, which propagates through the programmable planar waveguide as the trained illumination profile is projected. The intensity on the output facet, $I(x, z=L)$, is measured. This output is divided into seven distinct spatial bins, and the bin with the highest energy corresponds to the vowel predicted by the ONN. **B**: Confusion matrix for the validation dataset. Figure adapted from Ref. [8].

References

[1] G. Wetzstein *et al.*, Inference in artificial intelligence with deep optics and photonics, *Nature* **588**, 39 (2020).
[2] B.J. Shastri, A.N. Tait *et al.*, Photonics for artificial intelligence and neuromorphic computing, *Nature Photonics* **15**, 102 (2021).
[3] F. Ashtiani *et al*., An on-chip photonic deep neural network for image classification, *Nature* **606**, 501 (2022).
[4] T. Wu *et al.*, Lithography-free reconfigurable integrated photonic processor, *Nature Photonics* **17**, 710 (2023).
[5] W. Bogaerts *et al.*, Programmable photonic circuits, *Nature* **586**, 207 (2020).
[6] C. Ríos *et al.*, In-memory computing on a photonic platform, *Science Advances* **5**, eaau5759 (2019).
[7] H. Larocque, D. Englund, Universal linear optics by programmable multimode interference, *Optics Express* **29**, 38257 (2021).
[8] T. Onodera, M. M. Stein *et al.*, manuscript in preparation.
[9] T. Hughes, I. A. Williamson *et al.*, Wave physics as an analog recurrent neural network, *Science Advances* **5**, eaay6946 (2019).
[10] E. Khoram *et al.*, Nanophotonic media for artificial neural inference, *Photonics Research*, **7**, 8 (2019).
[11] L. G. Wright, T. Onodera *et al.*, Deep physical neural networks trained with backpropagation, *Nature* **601**, 549 (2022).