Lecture 21: Physics-based CNN examples and ethical questions

Machine Learning and Imaging

BME 548L
Roarke Horstmeyer
What physical parameters effect image formation?

- **Illumination**
  - Spatial pattern
  - Angle of incidence
  - Color, polarization

- **Lens and optics**
  - Position/orientation
  - Shape
  - Focus
  - Transparency

- **Detector**
  - Pixel size
  - Pixel shape & fill factor
  - Color filters
  - Other filters

- **Digitization**
  - E to P curves
  - Digitization schemes/thresholds
  - Data transmission, multiplexing
  - Physical object
Examples: Lenses and optics
Hybrid optical-electronic convolutional neural networks with optimized diffractive optics for image classification

Julie Chang, Vincent Sitzmann, Xiong Dun, Wolfgang Heidrich & Gordon Wetzstein

Figure 1. Optical convolutional layer design. (a) Diagram of a 4f system that could be adapted to implement optical convolutional (opt-conv) layers by placing a phase mask in the Fourier plane. (b) The standard components of a digital convolutional layer, including an input image, a stack of convolutional kernels, and a corresponding output volume. (c) The equivalent components in an opt-conv layer, where the kernels and outputs are tiled in a 2D array instead of stacked in the depth dimension.
Figure 2. Learned optical correlator. (a) Schematic of an optical correlator, where the conv block consists of the 4f system shown in Fig. 1. (b) Characteristic optimized kernels of a multichannel unconstrained digital convolutional layer, a multichannel nonnegative digital convolutional layer, a single channel opt-conv layer with tiled kernels, and the PSF produced by phase mask optimization with the previous optimized tiled kernels as the target.
Figure 3. Hybrid optoelectronic CNN. (a) Schematic of a model with a single opt-conv layer, after which the sensor image is processed and fed into subsequent digital CNN layers. (b) The optimized phase mask template and microscope images of the fabricated phase mask, at different zoom levels. (c) Comparison of simulated and captured versions of the PSF produced by the phase mask, a sample input image, the respective sensor image, and pseudonegative sub-images after subtraction of corresponding positive (top two rows) and negative (bottom two rows) sub-images.
End-to-end Optimization of Optics and Image Processing for Achromatic Extended Depth of Field and Super-resolution Imaging

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Machine Learning and Imaging – Roarke Horstmeyer (2020)
Learned phase coded aperture for the benefit of depth of field extension

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A scene with objects in different depths

Phase coded aperture imaging

Coded Image

All-in-Focus CNN

Reconstructed All-in-Focus Image

Clean Image (no blur, no noise)

Optical Imaging Layer (Defocus blurring + AWGN)

CONV (d=1) BN ReLU
CONV (d=2) BN ReLU
CONV (d=3) BN ReLU
CONV (d=4) BN ReLU
CONV (d=3) BN ReLU
CONV (d=2) BN ReLU
CONV (d=1)

All-in-Focus Image

L1 Loss

(a)

(b)

(c)
Multicolor localization microscopy and point-spread-function engineering by deep learning

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DeepSTORM3D: dense three dimensional localization microscopy and point spread function design by deep learning

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Input: physical object

Output: Detected image

$n \times m$ pixel array

Digitization

Photons to electrons

Detector

Digitization schemes/thresholds

Data transmission, multiplexing

Lens and optics

Illumination

Physical object
Examples: Detection and sampling
ReconNet: Non-Iterative Reconstruction of Images from Compressively Sensed Random Measurements

Kuldeep Kulkarni\textsuperscript{1,2}, Suhas Lohit\textsuperscript{1}, Pavan Turaga\textsuperscript{1,2}, Ronan Kerviche\textsuperscript{3}, and Amit Ashok\textsuperscript{3}

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**DEEP LEARNING SPARSE TERNARY PROJECTIONS FOR COMPRESSED SENSING OF IMAGES**

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DeepBinaryMask: Learning a Binary Mask for Video Compressive Sensing

Michael Iliadis, Member, IEEE, Leonidas Spinoulas, Member, IEEE, and Aggelos K. Katsaggelos, Fellow, IEEE

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**Figure 6:** Compressive imager testbed layout with the object imaging arm in the center, the two DMD imaging arms are on the sides.
Standard compressive sensing problem:

$$\min_x \| \Psi x \|_1 \quad s.t. \quad \| y - \Phi x \|_2 \leq \epsilon.$$  

Use iterative solvers to determine $x$.

Proposed reconstruction method via CNN:

Figure 8: The figure shows reconstruction results on 3 images collected using our block SPC operating at measurement rate of 0.04. The reconstructions of our algorithm are qualitatively better than those of TVAL3 and D-AMP.
Adaptive Image Sampling using Deep Learning and its Application on X-Ray Fluorescence Image Reconstruction

Qiun Dai, Henry Chopp, Emeline Poubey, Oliver Cossairt, Marc Walton, and Aggelos K. Katsaggelos, Fellow, IEEE

Fig. 1. (a) XRF map showing the distribution of Pb L\textsubscript{\alpha} XRF emission line (sum of channel #582 - 602) of the “Bloemen en insecten” (ca 1645), by Jan Davidsz. de Heem, in the collection of Koninklijk Museum voor Schone Kunsten (KMKSA) Antwerp and (b) the HR RGB image.

Fig. 2. (a) Random binary sampling mask that skips 80% of pixels and (b) Adaptive binary sampling mask that skips 80% of pixels based on the input RGB images in Fig 1 (b).
Learning a Variational Network for Reconstruction of Accelerated MRI Data

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(a) Data processing pipeline

(b) Structure of the variational network (VN)
Facebook Fast MRI Challenge:
https://ai.facebook.com/blog/using-reinforcement-learning-to-personalize-ai-accelerated-mri-scans/
Reducing Uncertainty in Undersampled MRI Reconstruction with Active Acquisition

Zizhao Zhang\textsuperscript{1,2,*}, Adriana Romero\textsuperscript{2}, Matthew J. Muckley\textsuperscript{3}, Pascal Vincent\textsuperscript{2}, Lin Yang\textsuperscript{1}, Michal Drozdzal\textsuperscript{2}
\textsuperscript{1} University of Florida \textsuperscript{2} Facebook AI Research \textsuperscript{3} NYU School of Medicine

Figure 3: The training pipeline of the proposed method.
Learning a Probabilistic Strategy for Computational Imaging Sensor Selection

He Sun, Member, IEEE, and Adrian V. Dalca, Member, IEEE, and Katherine L. Bouman, Member, IEEE

Fig. 3. Site map of potential future EHT telescope locations. Twelve sites ("EHT") marked with blue stars are existing telescopes currently participating in or planning to join the EHT. The other nine sites ("FUTURE"), marked with orange dots, are potential locations where new telescopes could be added. "FUTURE" sites are selected as locations that can observe at the necessary 230 GHz (1.3 mm wavelength) observed by the EHT.
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Examples: Illumination
Accurate and efficient classification with LED illumination

Physics-based Learned Design: Optimized Coded-Illumination for Quantitative Phase Imaging

Michael R. Kellman*†  Emrah Bostan*  Nicole Repina,‡  Michael Lustig,*  Laura Waller*

August 13, 2018

Figure 1: Learning Coded-Illumination Design for Quantitative Phase Imaging: (a) Schematic of the LED-illumination microscope where multiple intensity measurements are captured under unique coded-illumination patterns, (b) Computational phase reconstruction of the sample’s optical phase with coded-illumination measurements. (c) Optimization for learning of coded-illumination design based on the non-linear iterative reconstruction.
Deep learning with coherent nanophotonic circuits

Yichen Shen, Nicholas C. Harris, Scott Skirlo, Mihika Prabhu, Tom Baehr-Jones, Hochberg, Xin Sun, Shijie Zhao, Hugo Larochelle, Dirk Englund & Marin Soljačić

_Nature Photonics_ **11**, 441–446 (2017) | Download Citation

**Figure 1: General architecture of the ONN.**

**a,** General artificial neural network architecture composed of an input layer, a number of hidden layers and an output layer. **b,** Decomposition of the general neural network into individual layers. **c,** Optical interference and nonlinearity units that compose each layer of the artificial neural network. **d,** Proposal for an all-optical, fully integrated neural network.
Figure 2: Illustration of OIU.

Figure 3: Vowel recognition.
Machine learning based compact photonic structure design for strong light confinement

MIRBEK TURDUEV\textsuperscript{1,5,*}, CAGRI LATIFOGLU\textsuperscript{2,5}, IBRAHIM HALIL GIDEN\textsuperscript{3,6}, and Y. SINAN HANAY\textsuperscript{4,5}