Data-Driven Design for Computational Imaging

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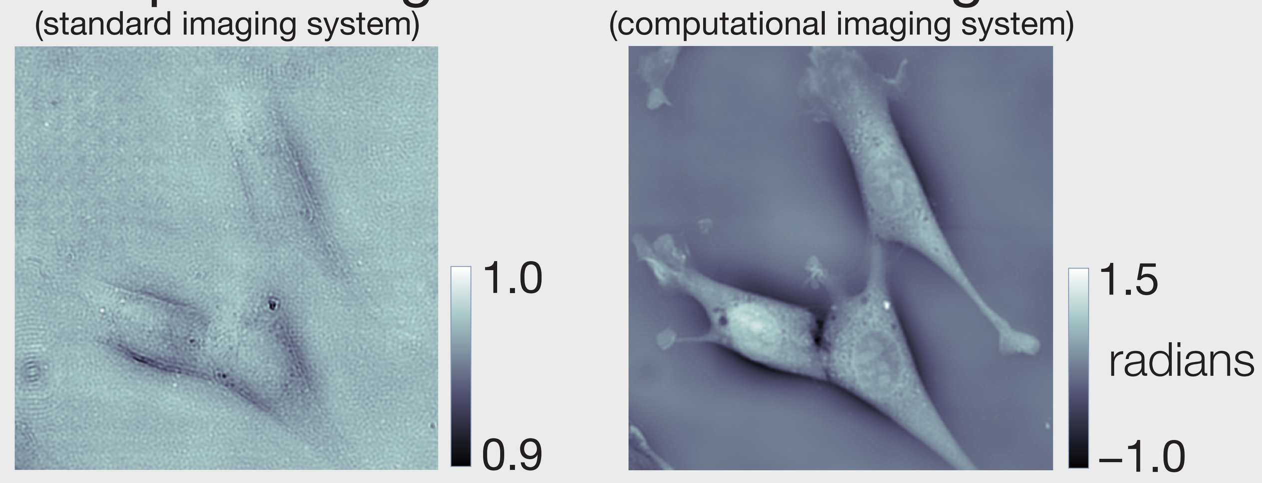
Overview

! **Classic optimal experiment design methods** consider linear systems and thus cannot account for a computation imaging system's non-linearities.

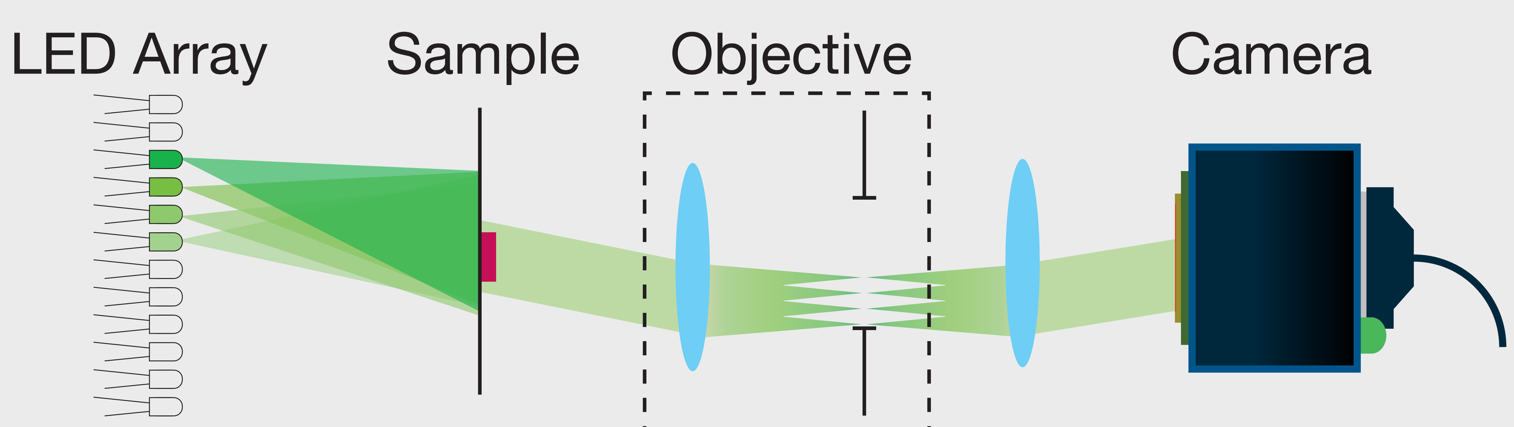
+ We propose a new method, **Physics-based Learned Design** [1], that incorporates system model non-linearities and prior information in the design process.

Introduction

Conventional microscopes image only a sample's absorption. However, when staining is not possible, phase can provide a mechanism for contrast and quantitative information.



The LED array microscope [2] is a computational imaging system that marries hardware and software design to enable quantitative phase, super-resolution, and volumetric imaging.



! All modalities **require several to hundreds of measurements** and thus are limited in temporal resolution.

Physics-based Network

Conventional Image Reconstruction:

$$\mathbf{x}^\star = \arg\min_{\mathbf{x}} \sum_{k=1}^{K} \|\mathbf{y}_k - \mathcal{A}_k(\mathbf{x})\|_2^2 + \mathcal{P}(\mathbf{x})$$

Data Consistency Term; Prior Term; Measurements; System Model

Usually solved with proximal gradient descent (PGD) [3].

Given, $\{\mathbf{y}_k\}_{k=1}^{K}, \mathbf{x}^{(0)}, \mu \in [0,1]$

For n in range$(1, N)$:

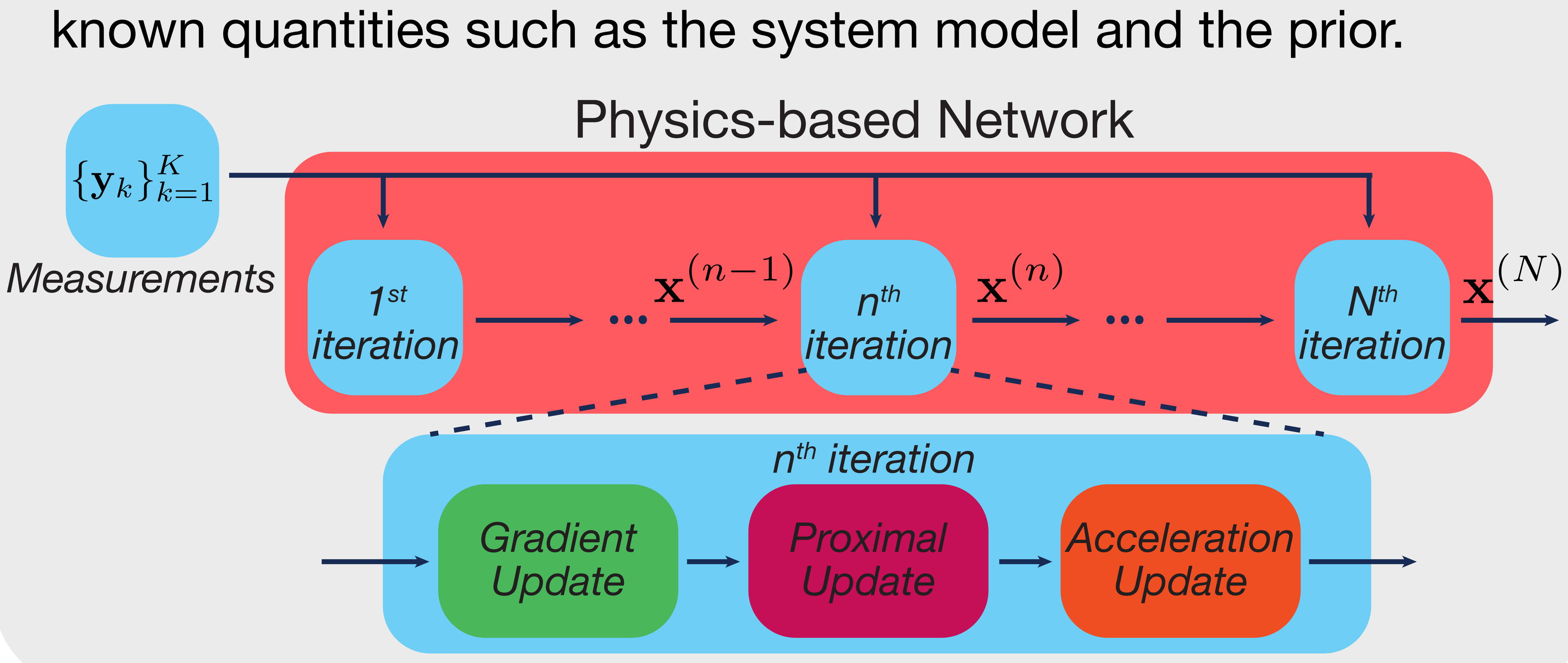
$\quad \mathbf{z}^{(n)} = \mathbf{x}^{(n-1)} - \alpha \nabla_{\mathbf{x}} \mathcal{D}(\mathbf{x}^{(n-1)}; \{\mathbf{y}_k\}_{k=1}^{K})$

$\quad \mathbf{w}^{(n)} = \mathrm{prox}_{\mathcal{P}}(\mathbf{z}^{(n)})$

$\quad \mathbf{x}^{(n)} = \mu \mathbf{w}^{(n)} + (1-\mu)\mathbf{w}^{(n-1)}$

return $\mathbf{x}^{(N)}$

PGD is *unrolled* to form a neural network that incorporates known quantities such as the system model and the prior.



Learned Design

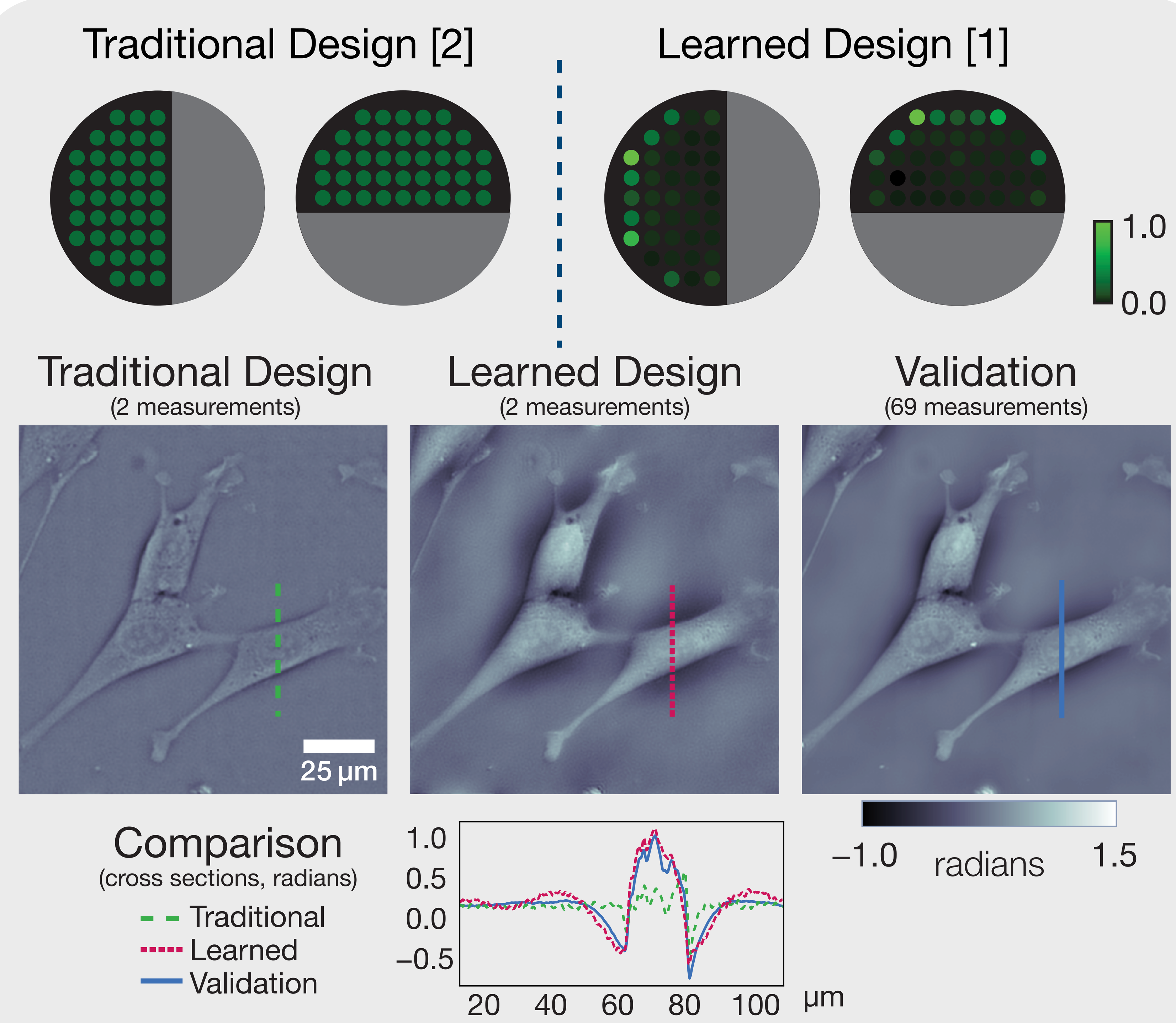
We use supervised learning to design the LED brightnesses for each measurement to maximize the overall performance of the system.

$$\mathbf{C}^\star = \arg\min_{\mathbf{C}} \frac{1}{L} \sum_{l=1}^{L} \|\mathbf{x}^{(N)}(\mathbf{C}) - \mathbf{x}'\|_2^2$$

$$\text{s.t. } c_{ij} \geq 0, \|\mathbf{c}_i\|_1 = 1, \mathbf{m}_i^T \mathbf{c}_i = 0 \ \forall i$$

Design matrix (*i.e.* LED brightnesses); Physics-based Network; Ground Truth; Practical Constraints: Positivity, Scaling, Structural

Experimental Results



Remarks

We propose a new method that learns the experiment design for a computational imaging system:

+ **Physics-based Network:** Incorporates known quantities such as the system model and prior information.

+ **Efficiency:** Network is completely parameterized by only a few design variables and thus we do not require a large number of training examples.

+ **Generality:** We are able to learn context-specific designs using simulated data that test well in experiment.

References

[1] M. R. Kellman, E. Bostan, N. Repina and L. Waller, "Physics-based Learned Design: Optimized Coded-Illumination for Quantitative Phase Imaging," arXiv preprint arXiv:1808.03571, 2018.

[2] L. Tian and L. Waller, "Quantitative differential phase contrast imaging in an LED array microscope," Opt. Express 23, 11394-11403, 2015.

[3] N. Parikh and S. Boyd, "Proximal algorithms," Foundations and Trends in Optimization, 127-239, 2014.

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