Data-Driven Design for Computational Imaging

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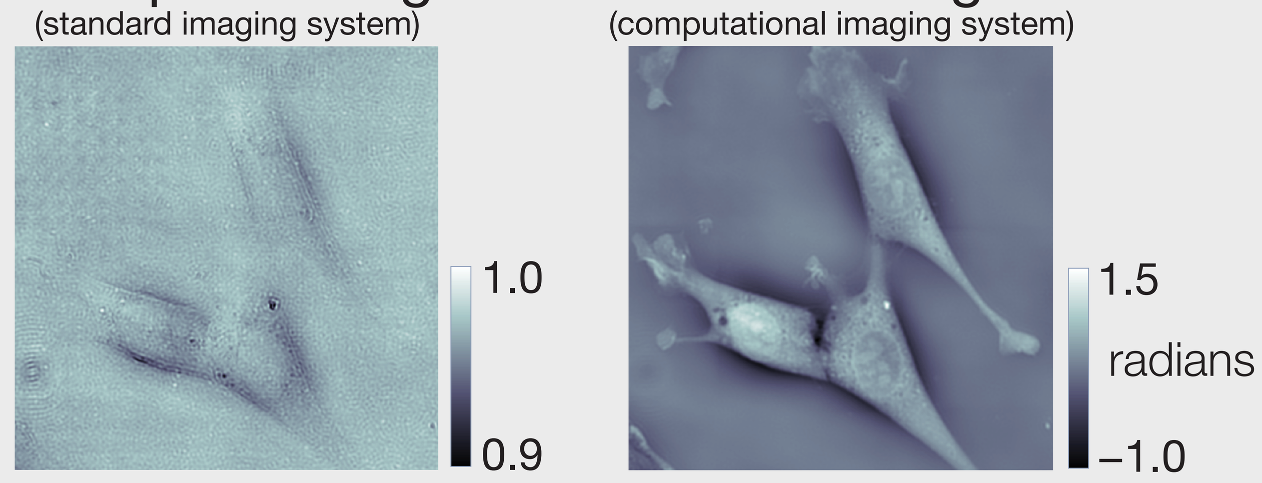
Overview

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

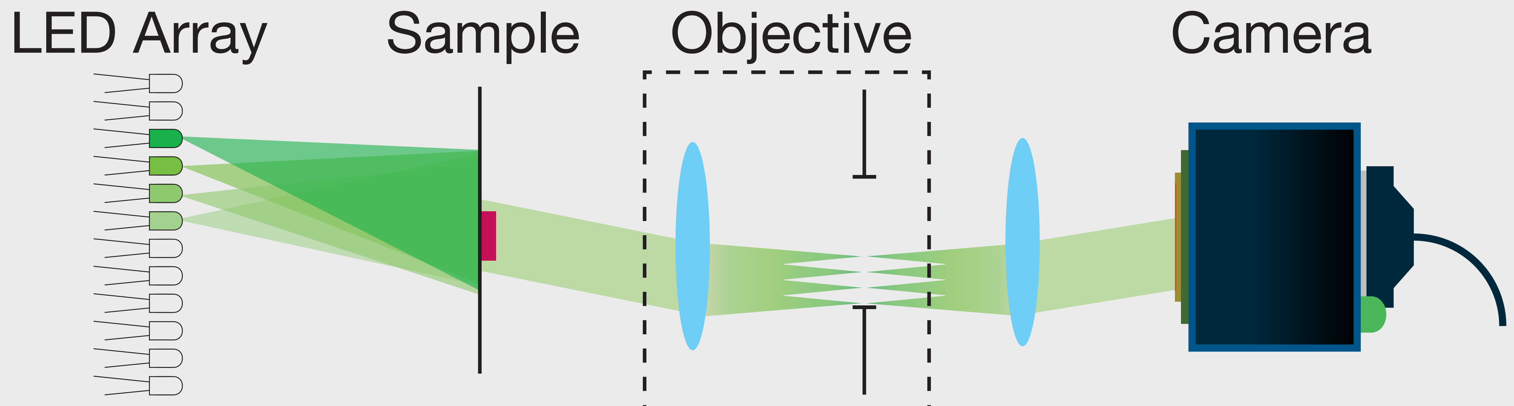
+ We propose a new method, **Physics-based Learned Design** [1], that incorporates system model non-linearities and prior information in the design process.

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 Learned Design

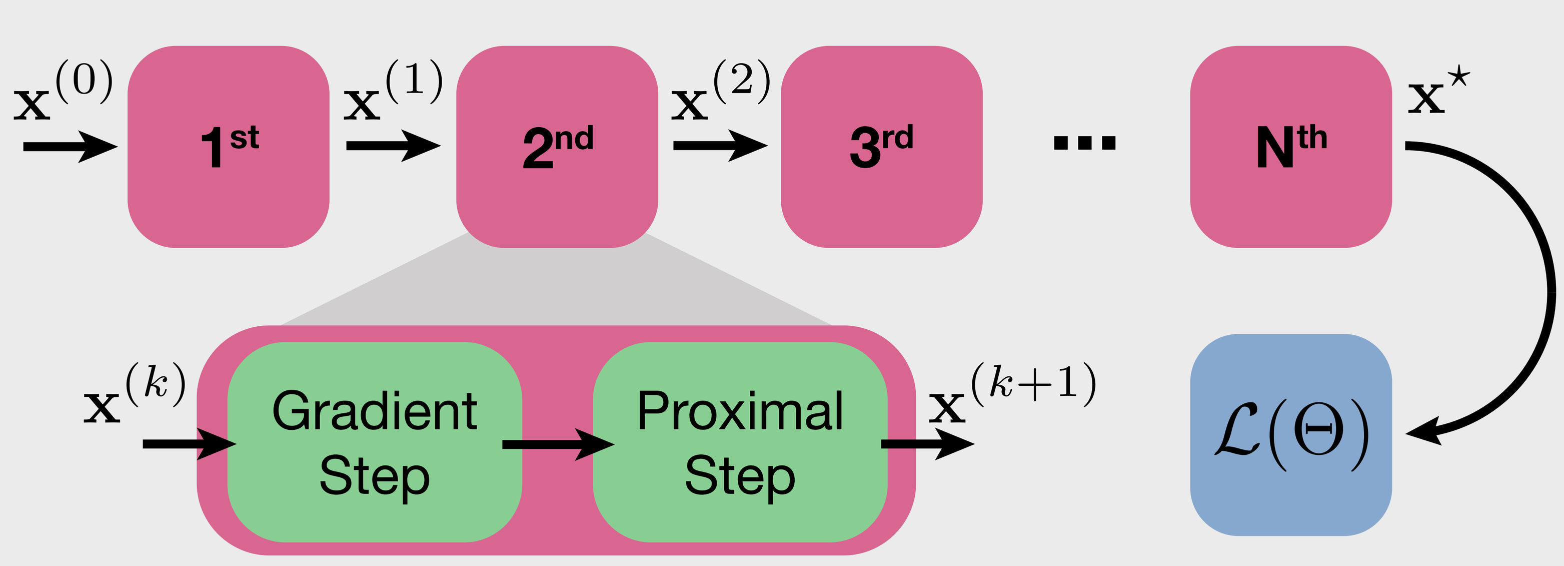
Conventional Image Reconstruction:

Data Consistency Term — Prior Term

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

Measurements — System Model

Treat the iterations of the optimizer to this reconstruction loss as the layers of a network. Proximal Gradient Descent (PGD) constructs this network [3]:



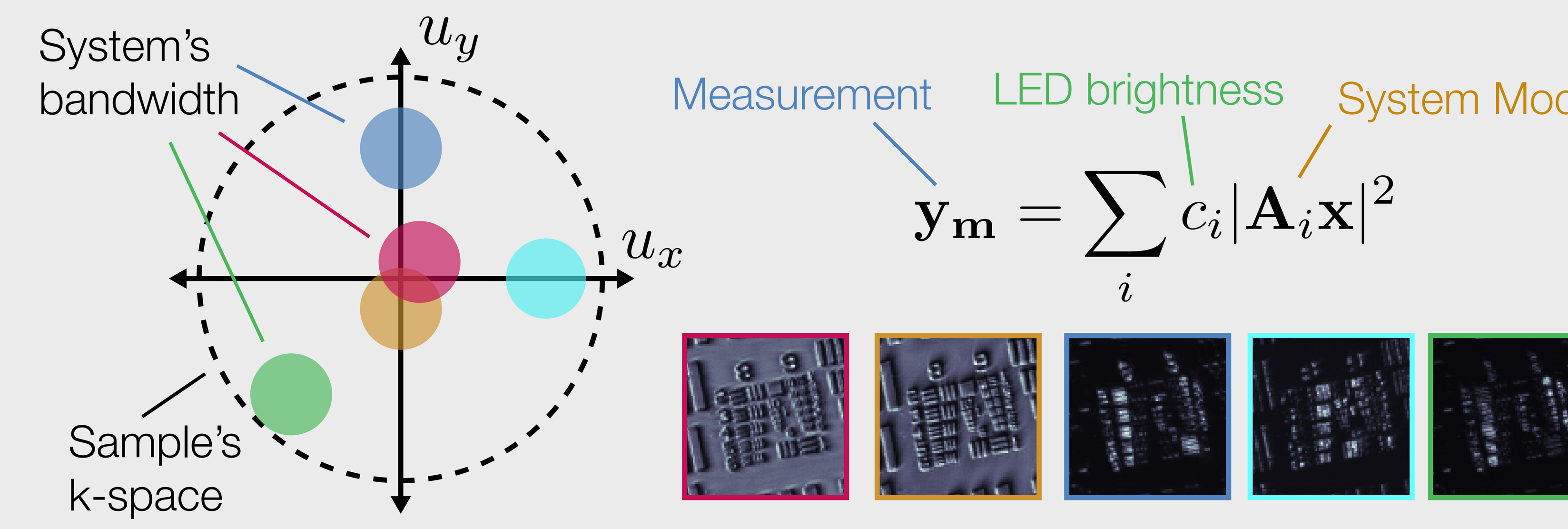
Using L pairs of measurements and ground truth, we can learn how to best encode and decode information.

$$\mathcal{L}(\Theta) = \sum_{l=1}^{L} \|\mathbf{x}_l^\star(\Theta) - \mathbf{x}_l'\|_2^2$$

Learnable parameters — Network output — Ground Truth

Super-resolution Microscopy

Each LED measures a unique section of the sample's k-space.

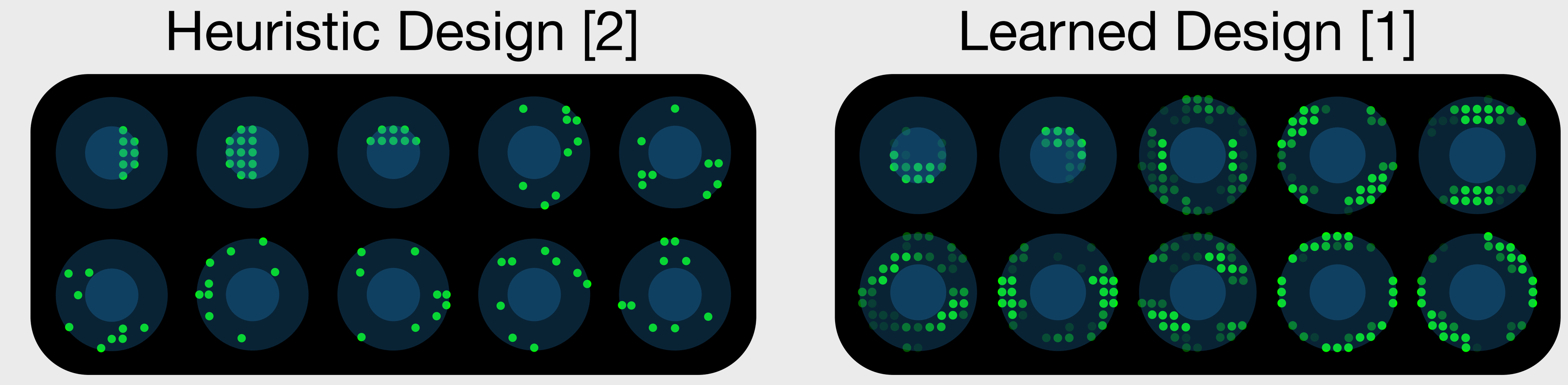


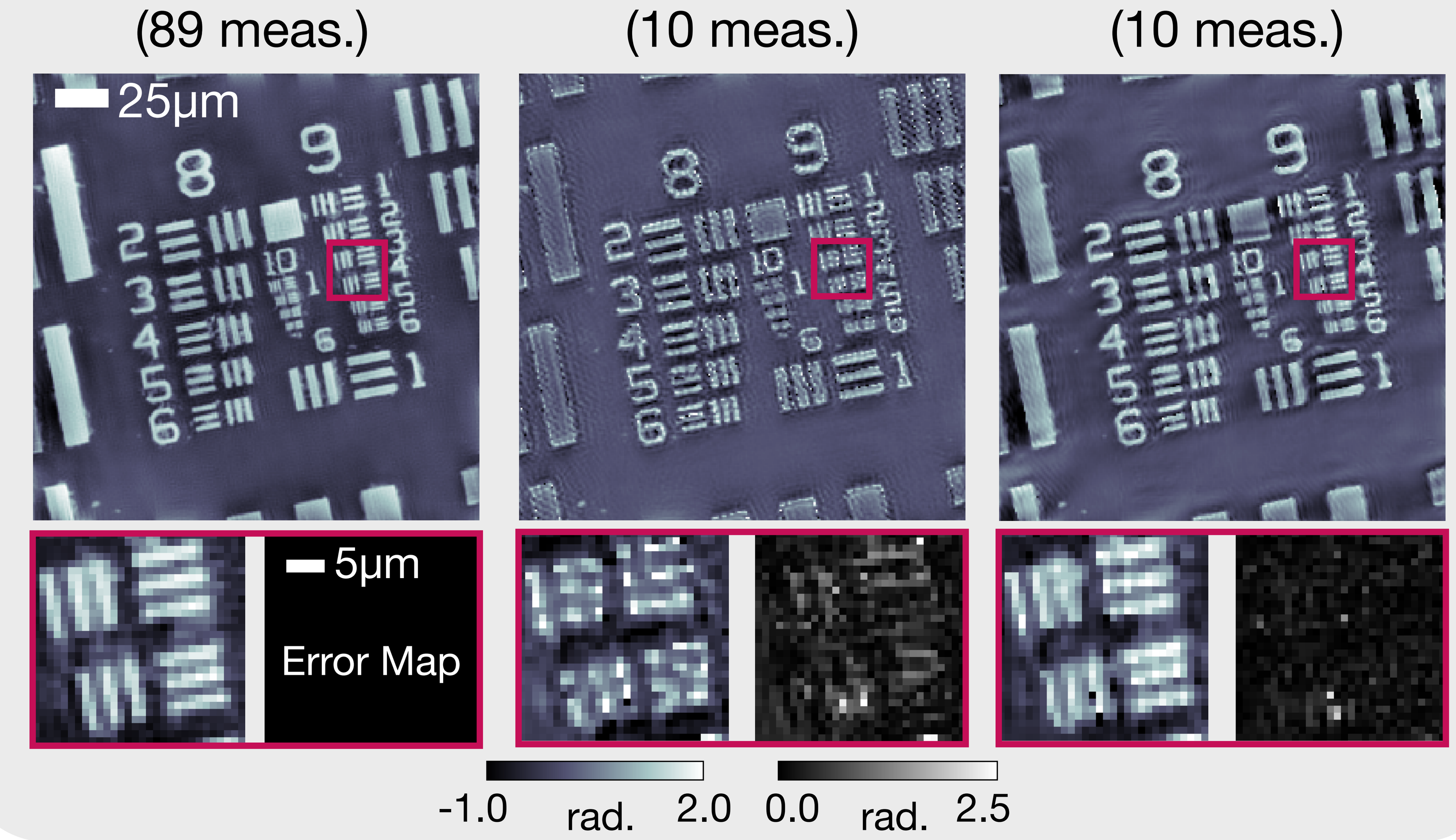
Measurement — LED brightness — System Model

$$\mathbf{y_m} = \sum_i c_i |\mathbf{A}_i \mathbf{x}|^2$$

+ **Design** the LED brightnesses to **compress the information** into fewer measurements (improving temporal resolution).

Learned Illumination Encoding





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," IEEE Transactions on Computational Imaging, 2019.

[2] L. Tian, X. Li, K. Ramchandran and L. Waller, "Multiplexed coded illumination for Fourier Ptychography with an LED array microscope," Biomed. Opt. Express. 2014.

[3] K. Gregor and Y. LeCun. "Learning fast approximations of sparse coding." International Conference on Machine Learning. 2010.

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