**Overview**

Classic optimal experiment design methods consider linear systems and thus cannot 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.

**Physics-based Network**

Conventional Image Reconstruction:

\[
x^* = \arg \min_x \sum_{k=1}^{K} ||y_k - A_k(x)||^2_2 + \mathcal{P}(x)
\]

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

Given, \((y_k)_{k=1}^{K}, x^{(0)}, \mu \in [0, 1]

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

\[
x^{(n)} = x^{(n-1)} - \alpha \nabla_x \mathcal{D}(x^{(n-1)}); (y_k)^{K}_{k=1}
\]

\[
w^{(n)} = \text{prox}_\mu(w^{(n)})
\]

\[
x^{(n)} = \mu w^{(n)} + (1 - \mu) w^{(n-1)}
\]

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.

\[
C^* = \arg \min_c \frac{1}{L} \sum_{l=1}^{L} ||x^{(N)}(C) - x||^2_2
\]

s.t. \(c_{ij} \geq 0, ||c_i||_1 = 1, m^T_i c_i = 0 \forall i
\]

**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**


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