Unsupervised Deep Learning for Lensless Imaging

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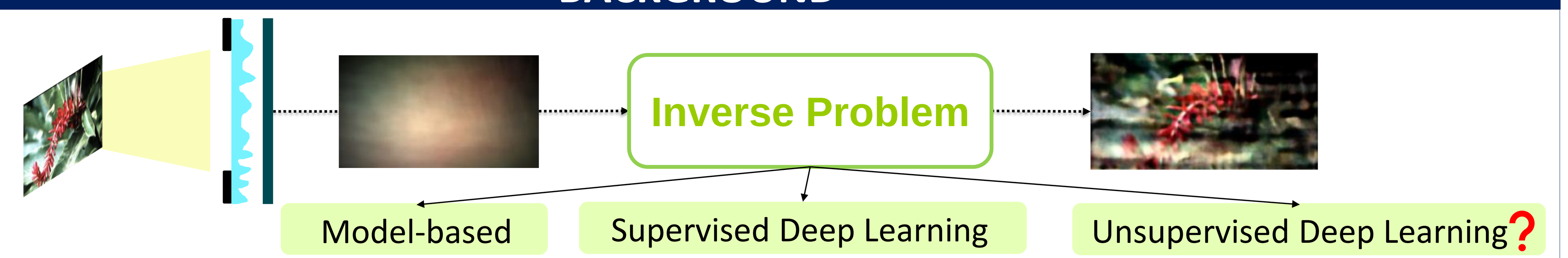
ABSTRACT

Lensless camera systems replace the lens with a light-weight diffuser that maps a point source in the scene to a caustic pattern on the camera sensor. This allows the imaging system to be compact and cheap. Traditionally, the scene is recovered from the multiplexed measurement by solving an inverse problem. However, the reconstructed image often suffers from model mismatch and artifacts. In this research, we explore unsupervised deep learning methods, which train neural networks on the reconstruction task using single image measurement, without the need for a ground truth labels or large dataset. Since ground truth data is hard to acquire for many mask-based imagers, this approach has the potential to produce high-quality reconstructions in the absence of ground truth training images.

BACKGROUND

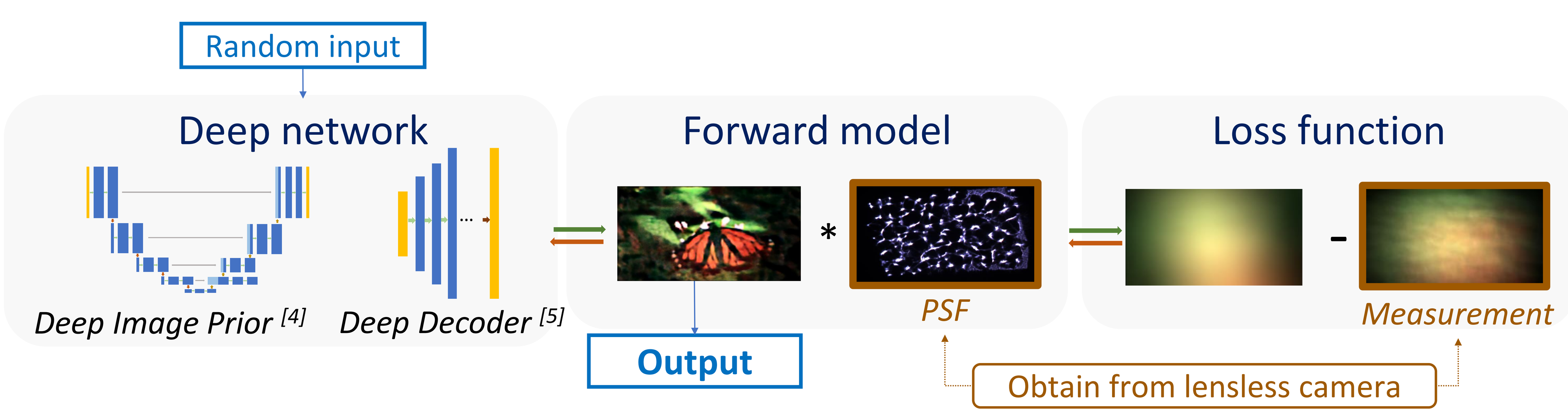


Model-based methods with FISTA[1] or ADMM[2] ⇒ Has reconstruction artifacts

Supervised Deep Learning[3] method uses ground truth/measurements pairs to train the neural network ⇒ Requires training data

INTRODUCTION

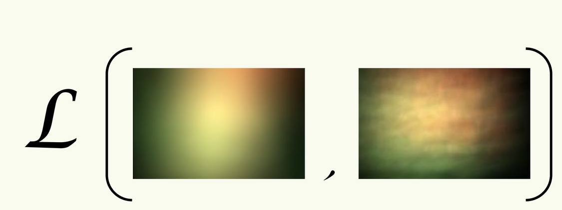
Unsupervised deep learning reconstructs image using only the point-spread function (PSF) and sensor measurement. No ground truth images, or large datasets required.



Loss Function are implemented with Mean Square Error (MSE) Loss or Frequency Loss:

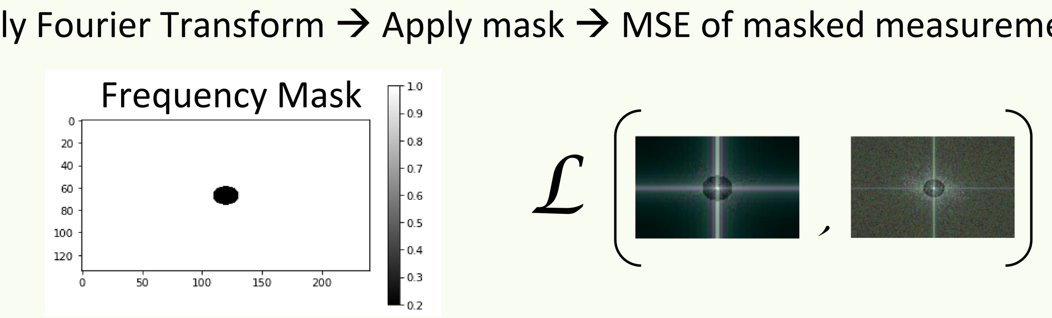
MSE Loss

MSE of direct measurements



Frequency Loss

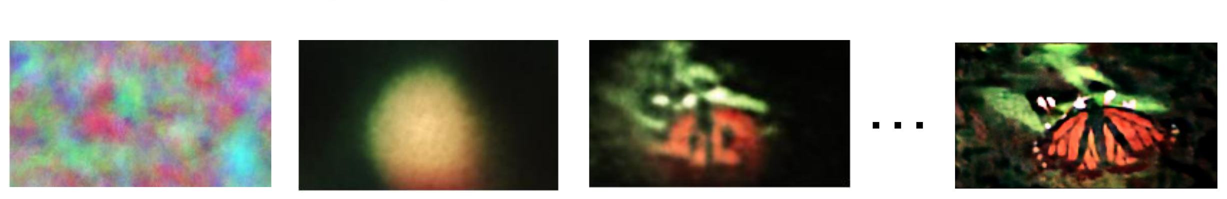
Apply Fourier Transform → Apply mask → MSE of masked measurements



METHODOLOGY

1. **Taking images:**
   Sample data: Images from previous experiment in [2].
   Experiment data: Images are taken with a DiffuserCam prototype built upon UI-3890LE-C-HQ camera.

2. **Reconstructing images:**



Experiment image: Lensless camera with its PSF and a sensor measurement of a Rubik cube

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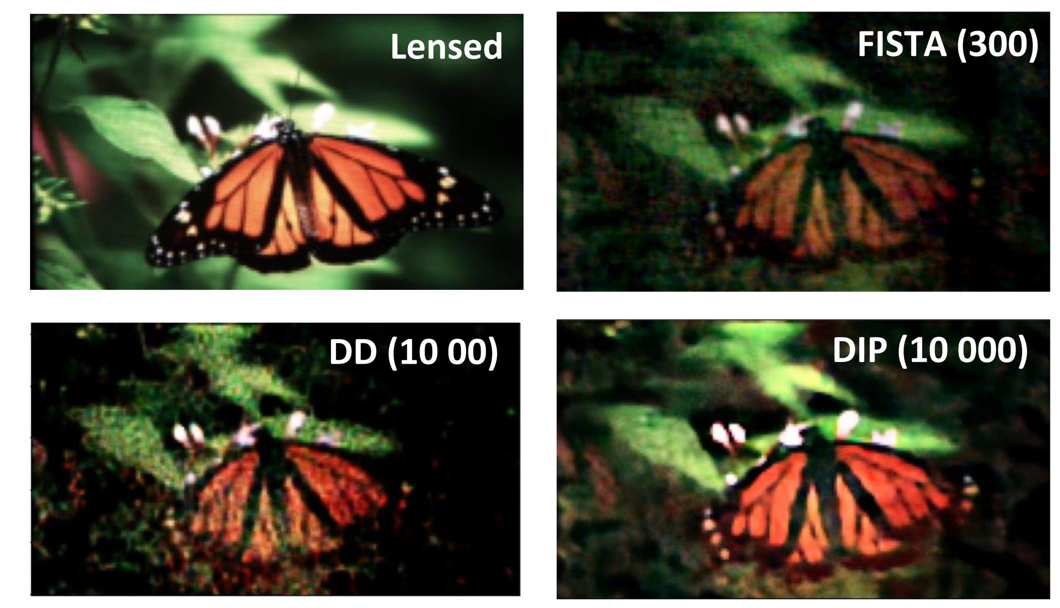
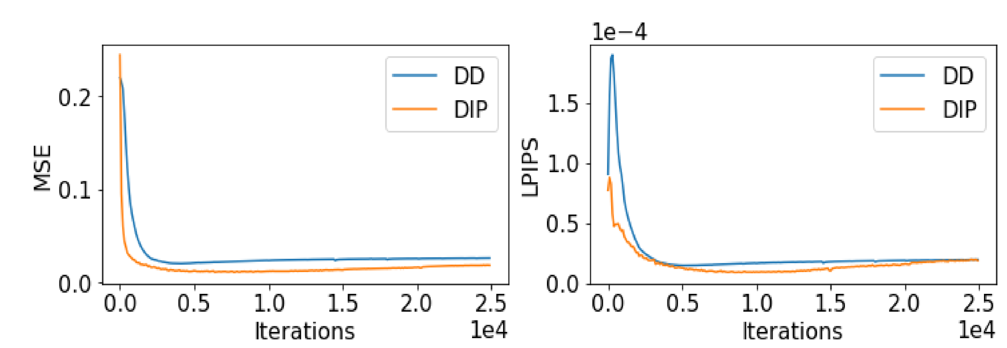
RESULTS

Sample data of natural images



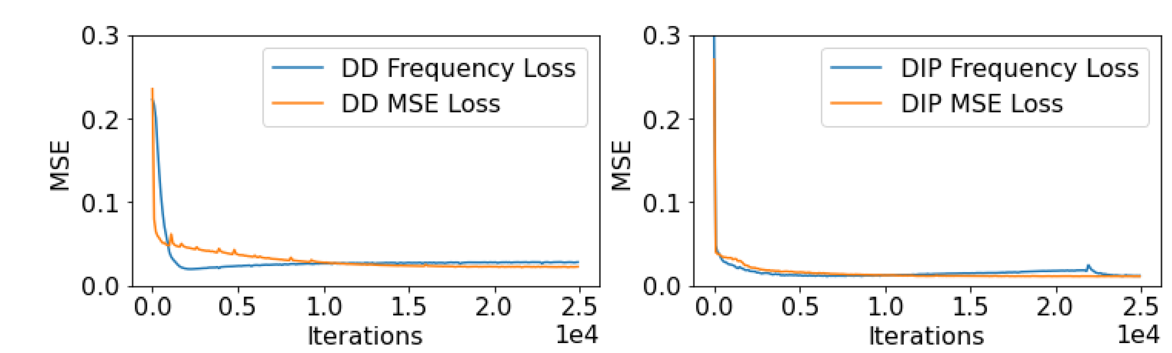
Performance Comparision	Time(minutes)	MSE	LPIPS
FISTA (300)	**0.62**	0.029	3.12e-5
DD *(4800)*	4.32	0.024	1.66e-5
DIP (10000)	14.06	**0.012**	**0.94e-5**

Loss vs. Iterations



Deep Image Prior achieves lower MSE and LPIPS scores compares to Deep Decoder

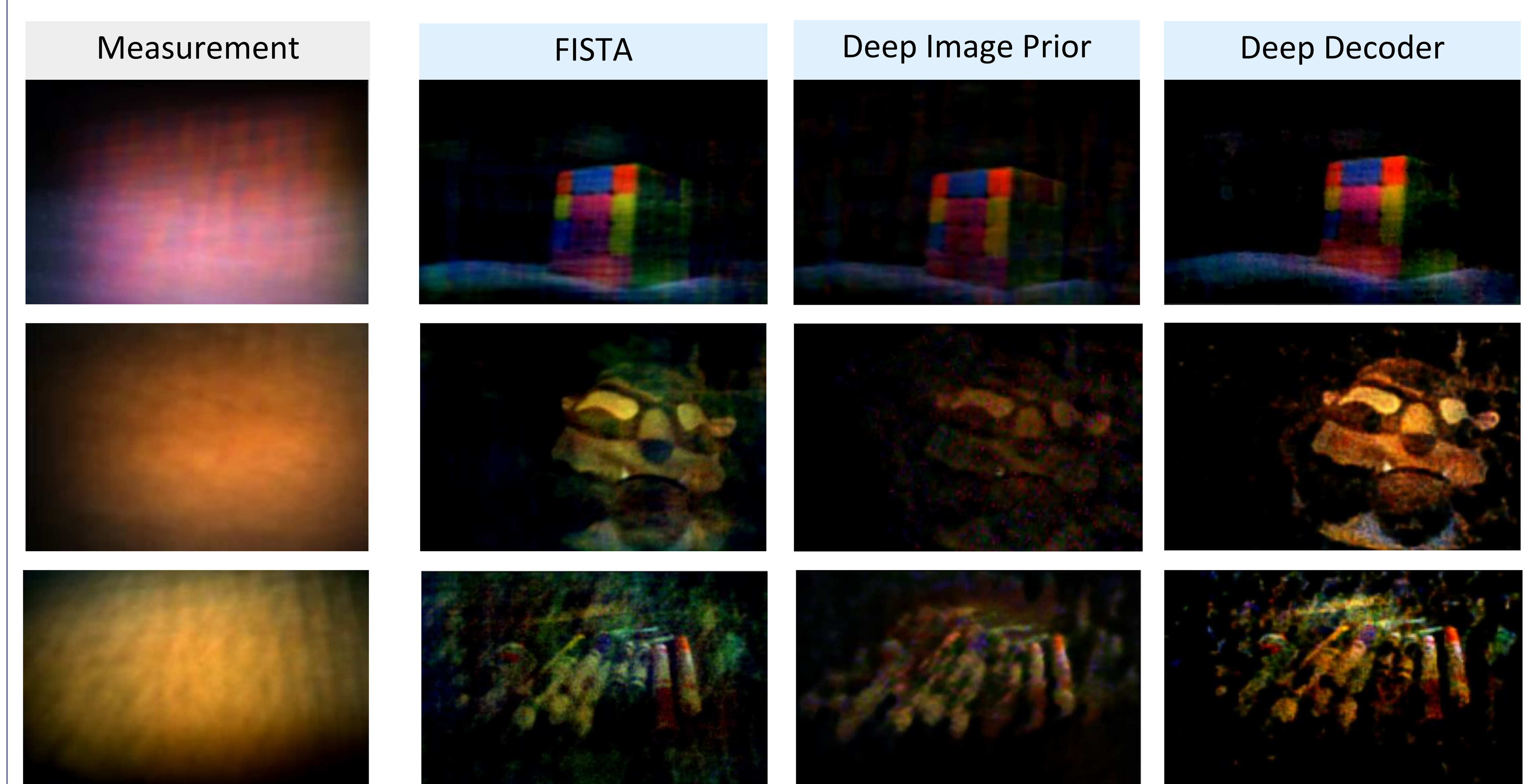
Frequency Loss vs. MSE Loss



The network converges faster with Frequency Loss than with MSE Loss

Experiment data of real objects

With image quality: Deep Image Prior < Deep Decoder ≈ FISTA



FUTURE WORK

- Improve the implementation to automate hand-tuned network hyperparameters.
- Explore the applications of unsupervised deep learning in compressive sensing

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