Deep Generative Physical Modeling for Blind Imaging Inverse Problems

Jon Tamir, Assistant Professor,
Chandra Family Department of Electrical and Computer Engineering

Abstract: Recently, deep learning has been used to build powerful data-driven reconstruction methods for imaging systems, and in particular has led to reduced scan times in magnetic resonance imaging (MRI). Typically, these methods are implemented using end-to-end black-box supervised learning based on idealized imaging conditions. While these approaches have resulted in highly promising "benchtop laboratory demonstrations," reconstruction quality is known to degrade when applied to real-world settings consisting of natural measurement and environmental perturbations, and the measurement model must be exactly specified. ***The overall goal of this proposal is to develop a learning framework for robust image reconstruction with principled methods and recovery guarantees.*** We leverage deep generative models, a class of neural networks that can be used to model rich data distributions, and explicitly decouple the measurement model from the statistical image prior. In this work, we consider **blind inverse problems**, in which the forward model is not fully specified or known. While our framework will broadly apply to imaging inverse problems, we focus on two applications: nonrigid motion correction in MRI, and mask-based lensless imaging, where new innovations could increase access to imaging technologies that have traditionally been costly and time-intensive. We refer to our approach as **Deep Generative Physical Modeling.**