2024-2025 Moncrief Grand Challenge Award Final Report

Awardee: **Jon Tamir, Assistant Professor, ECE**

Research Award Title: **Deep Generative Physical Modeling for Blind Imaging Inverse Problems**

Research Summary

Remarkable advances to solving ill-posed imaging inverse problems have been achieved through deep learning-based reconstructions, and in particular by using diffusion-based generative models. These methods use a model of the imaging system together with a pre-trained generative model to reconstruct samples from the posterior distribution of plausible images given observed measurements. However, in many settings, the measurement model either contains uncertainties, or is approximated by a simple model. In these cases, performance of the standard posterior sampling algorithm will degrade. In this project, we proposed algorithmic extensions to posterior sampling for blind imaging inverse problems in which the measurement model is not fully specified. This arises in real-world imaging settings; for example, due to motion in the scene, due to lens aberrations, due to field inhomogeneities in magnetic resonance imaging (MRI), and more.

Results of Aim 1: Nonrigid motion correction in MRI

In our initial work, we developed a *joint posterior sampling* algorithm based on diffusion models to estimate rigid motion that occurs during an MRI scan. The approach leveraged the fact that image translation corresponds to linear phase modulation in the Fourier space, and image rotation corresponds to Fourier rotation. For nonrigid motion, however, these relationships no longer hold. In addition, nonrigid motion has substantially higher number of degrees of freedom, and therefore many plausible parameters may fit the measurements. To overcome these issues, we developed a *coarse-to-fine* denoising diffusion strategy to capture large overall motion and reconstruct the lower frequencies of the image first, providing a better inductive bias for motion estimation than that of standard diffusion models. The motion is first parameterized by a small number of b-spline coefficients, and is then represented as a progressively denser vector field. Through an alternating minimization procedure, the underlying image and the motion field are jointly estimated over the reverse diffusion process. We demonstrated on both simulated rigid motion as well as to prospectively acquired cardiac MRI data. Our approach, which we call C2F-MC, achieved state of the art reconstruction performance over alternative options, as shown in Figure 1.

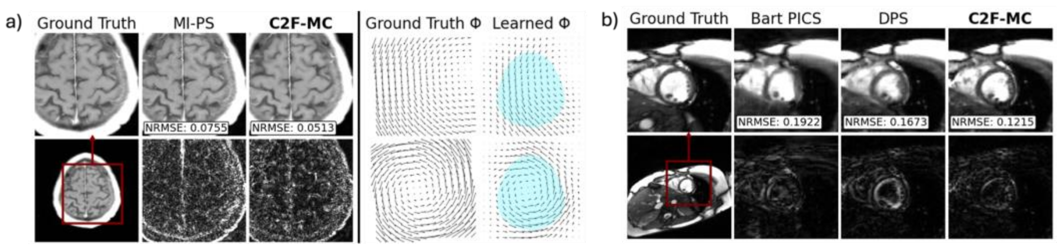

Fig 1. Blind motion correction in MRI. (a) Our approach outperforms state of the art methods in rigid motion estimation, even though we do not explicitly model rigid motion. (b) Our approach applied to reconstruction of cardiac MRI data outperforms other methods by jointly solving for nonrigid motion parameters.

Results of Aim 2: Double-blind imaging

In the second aim we developed a flexible method that learns the uncertainties in the measurement system from a training set of example measurements, as described in Figure 2. Our initial results focused on linear shift invariant systems, though the approach is more general. We assume access to a training set of acquired measurements (for example, a collection of blurry images), without knowledge of the true image or how it was corrupted. Using these measurements, we fit a generative model that captures the statistics of the shift-invariant point spread function of the imaging system. This is accomplished by passing clean images through the statistical model to create synthetic measurements, and matching the statistics of these synthetic measurements to those of the true measurements. As our results show in Figure 3, we are able to learn the statistics of the measurement point spread function for a variety of cases, including image blur and motion blur. Then, using these models, we can solve the downstream blind inverse problem task.

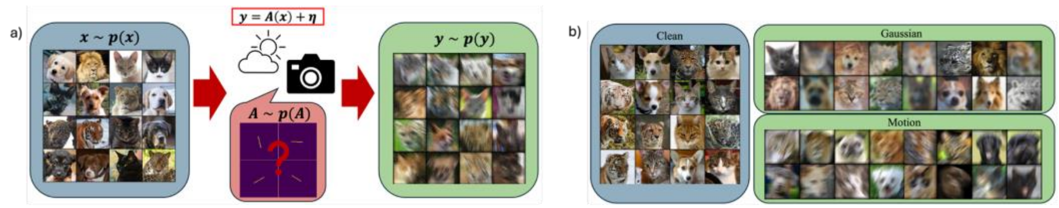

Fig 2. Double-blind imaging setup. (a) We assume access to corrupted measurements for a particular imaging task. (b) Example random Gaussian blurs and random motion blurs.

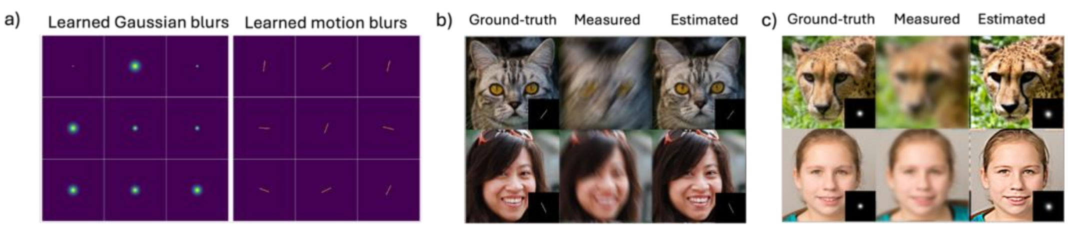

Fig 3. Double-blind imaging results. (a) We learn a generative model that captures the statistics of the measurement system. (b) Example blind reconstruction of motion blur. (c) Example blind reconstruction of Gaussian blur.

Presentations

- Non-rigid Motion Correction for MRI Reconstruction via Coarse-To-Fine Diffusion Models, *IEEE International Conference on Image Processing (ICIP)*, Anchorage, AK, September 2025. Speaker: Jon Tamir
- Deploying learning-based MRI reconstruction to the clinic: challenges and strategies **(invited)**, *Asilomar Conference on Signals, Systems, and Computers*, Asilomar, CA, October, 2025. Speaker: Jon Tamir
- Deep Generative Physical Modeling for MRI Reconstruction **(invited),** *University of Virginia Charles L. and Ann Brown Distinguished Colloquium Series*, Charlottesville, VA, September, 2025. Speaker: Jon Tamir
- Can We Build a Foundation Model for MRI? (**invited),** *Memorial Sloan Kettering Cancer Center Medical Physics Grand Rounds*, New York, NY, July 2025. Speaker: Jon Tamir
- Building a Foundation Model for MRI Reconstruction **(invited)**, *Oden Institute Babuska Forum Series,* University of Texas at Austin, Feb 27, 2025.

- Building a Foundation Model for MRI Reconstruction **(invited)**, *Cognition Brain and Behavior Seminar*, University of Texas at Austin, January 31, 2025.
- Deep Generative Physical Modeling for MRI Reconstruction **(invited)**, *University of Wisconsin Machine Learning for Medical Imaging Seminar Series,* Online, January 27, 2025.
- Can we build a foundation model for MRI? **(invited)**, *Peds Cardio AI Conference*, Austin, TX, September 6, 2024.

Publications

- Frederic Wang, Jonathan I Tamir, "Non-rigid Motion Correction for MRI Reconstruction via Coarse-To-Fine Diffusion Models," Accepted to *IEEE International Conference on Image Processing (ICIP) 2025*, pp.1-6. arXiv preprint arXiv:2505.15057. Accepted May 20, 2025. https://arxiv.org/abs/2505.15057.
- Yamin Arefeen, Brett Levac, Jonathan I Tamir, "A Generative Diffusion Model to Solve Inverse Problems for Accelerated and Motion Robust In-NICU Neonatal MRI," Accepted to *IEEE International Conference on Image Processing (ICIP) 2025*, pp. 1-6. arXiv preprint arXiv:2410.21602. Accepted May 20, 2025. https://arxiv.org/abs/2410.21602.
- Yamin Arefeen, Brett Levac, Bhairav Patel, Chang Ho, Jonathan I Tamir, "Diffusion Probabilistic Generative Models for Accelerated, in-NICU Permanent Magnet Neonatal MRI," *Magnetic Resonance in Medicine* [Early View]. pp. 1-17, June 2025. doi: https://doi.org/10.1002/mrm.30585.

Recognitions received

- Invited Medical Physics Grand Rounds talk at Memorial Sloan Kettering Cancer Center
- Invited Charles L. and Ann Brown Distinguished Colloquium talk at University of Virginia ECE Department