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Noise-robust latent vector reconstruction in ptychography using deep generative models

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Abstract: We introduce a novel approach for ptychographic reconstruction, integrating a pre-trained autoencoder within a reconstruction framework based on automatic differentiation. This enables noise-robust imaging and insight into optimization landscapes for applications with prior object knowledge.

1. Introduction

Obtaining clear and accurate images under noisy conditions is paramount in many scientific and industrial applications. Whether in medical diagnostics, materials analysis, or semiconductor inspection, noise-robust imaging techniques can mean the difference between precise understanding and potential misinterpretation. We introduce a method that combines a fully physics-based ptychography reconstruction framework with a pre-trained deep generative model. When prior knowledge indicates that a sample is sparse in an unknown basis, the representation in latent space enables accurate image reconstruction even under extremely challenging noise conditions.

2. Methods

We employ a ptychography setup in transmission geometry as illustrated in Fig. 1 (A). For the ptychographic reconstruction, we employ an ADP framework integrated with a pre-trained deep generative model trained on MNIST [1], as illustrated in Fig. 1 (B). A comprehensive description of the physics-informed ADP framework and a loss function accounting for mixed Poisson-Gaussian noise statistics can be found in [2, 3].

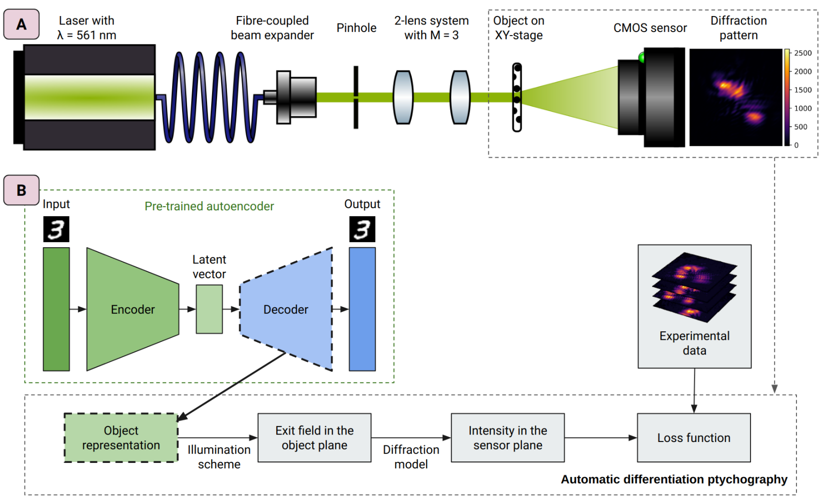

Fig. 1. (A) Schematic of the optical setup used for ptychography. (B) Diagram of the ADP framework. The decoder can be integrated into the ADP framework as a deep generative model, allowing the object to be represented as a latent vector.

3. Results

We present the main experimental result of this paper in Fig. 2. We illuminate an amplitude-only sample shaped like the digit '4' and adjust the camera's exposure time over four orders of magnitude. As a result, we acquire sets of diffraction patterns ranging from high SNR to extremely low SNR. These datasets are then used for ptychographic reconstructions. In conventional reconstruction, the object's amplitude transmission function deteriorates to noise at a 30 µs exposure. In contrast, latent space reconstruction with a pre-trained deep generative model significantly improves low-SNR performance. The reduced rank of the latent space, calculated to be 22, cuts the number of free parameters by $\approx 10,000\times$ compared to the conventional reconstruction method. This allows for successful object determination with remarkably fewer photons.

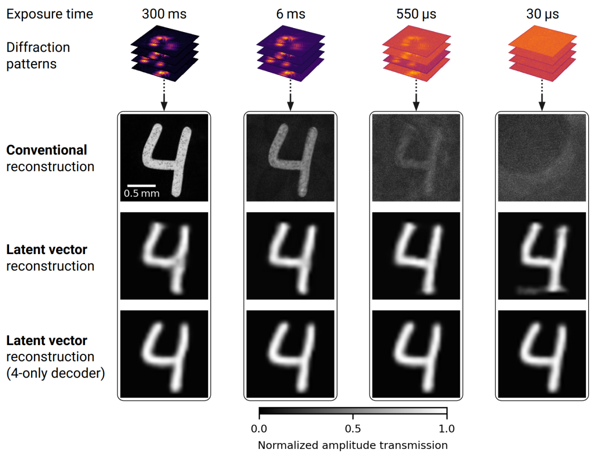

Fig. 2. Ptychographic reconstructions under varying SNRs. The top two rows display the diffraction patterns used for reconstruction and results from conventional reconstruction. Subsequent rows feature latent vector reconstructions using a pre-trained deep generative model, first trained on the full MNIST dataset and secondly on a filtered dataset containing only images resembling the digit '4'.

Given the compact nature of the latent space, we have the unique opportunity to visualize the optimization loss landscape in Fig. 3. Utilizing the two leading orthogonal principal components of the latent space, denoted as $\mathbf{v}_1$ and $\mathbf{v}_2$, we construct a 3D representation of the loss landscape. Given an optimal latent vector $\mathbf{h}_{\text{opt}}$ obtained from experiment, we explore the loss landscape by varying this optimal point along $\mathbf{v}_1$ and $\mathbf{v}_2$:

$$\mathbf{h}(\alpha,\beta) = \mathbf{h}_{\text{opt}} + \alpha\mathbf{v}_1 + \beta\mathbf{v}_2. \tag{1}$$

Here, α and β range from -10 to 10. We then compute the loss value for each $\mathbf{h}(\alpha,\beta)$ to visualize the landscape.

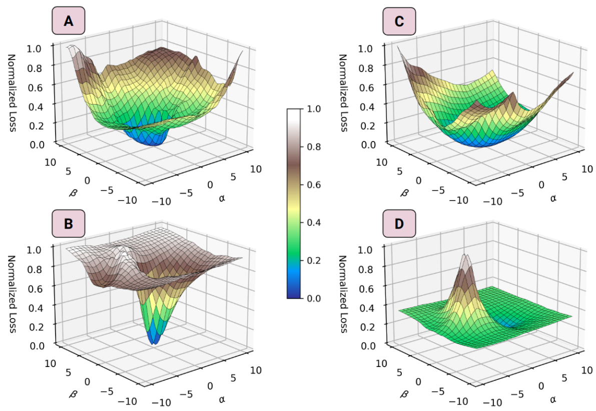

Fig. 3. Visualization of the optimization loss landscapes for different scenarios. (A) The landscape for high signal-to-noise ratio (SNR). (B) The landscape when reconstructing from low-SNR (high-noise) diffraction data. (C) The landscape after training the deep generative model on a filtered MNIST dataset containing only the digit '4'. (D) The landscape when optimizing using a Poisson-only loss function at high SNR, contrasted to the mixed Poisson-Gaussian loss for all other panels.

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