

Deep convolutional neural networks for atomic imaging in STEM

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Scanning Transmission Electron Microscopy (STEM) is a well-established method for looking into the physical properties of complex nanostructures. However, a major drawback is that acquiring very high-resolution images may lead to negative effects such as radiolysis and knock-on damage [1]. It has been shown that by lowering the electron beam dose, sample damage is reduced, however this leads to a lower signal-to-noise ratio (SNR) reducing the final quality of the image [2].

Convolutional Neural Networks (CNN) are a type of feed-forward neural network that is used as a powerful tool for improving image SNR through methods such as denoising. Recently, aberration-corrected STEM using CNNs has shown promising results, achieving resolutions below 0.1 nm. Specifically, improved SNR without using high-dose electron beams has been achieved by using CNNs trained on large datasets of microscopy data [3]. These methods have demonstrated the capability of CNNs to reduce damage to samples by improving image quality of low-dose STEM below 0.1 nm.

Inspired by the successful use of deep learning-based convolution for noise reduction [4] outside of STEM, we propose the use of self-supervised deep CNNs trained on both real and synthetic high-dose data to improve the SNR of low-dose data. We aim to create a robust network that is portable to methods outside of denoising by using the high-dose data to retrain the network for a variety of conditions [5] (such as hysteresis, defocus, and image blur).

This talk will present the results of utilizing self-supervised deep learning CNNs to improve the quality of low-dose data below 0.1 nm. We will also compare our proposed method to the STEM neural network autoencoder [3] and SDnDTI for Magnetic Resonance Imaging (MRI) [4] and discuss the potential of our method to improve upon on current methods within STEM as

well as other domains by analyzing the SNR with the final image structural similarity (SSIM).

Graphic:

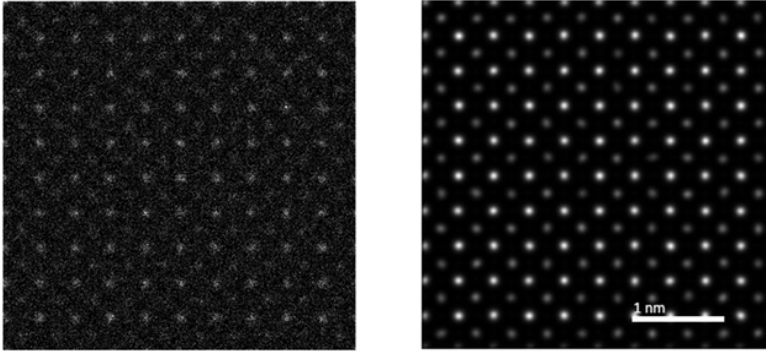


Fig 1. Example of simulated STEM noise with a beam current of 50pA, dwell time of 1.4 μ s, and a general noise bias of 0.2 which strengthens the generated noise in dark regions (left), showing a PSNR of 18.244 and SSIM of 0.157. Denoised by an 8-layer reverse-hourglass CNN, which works by increasing feature filters the closer you get to the middle of the network (right). Resulting in a PSNR of 28.123 and an SSIM of 0.85.

Keywords:

STEM, Deep Learning, Aberration Correction

Reference:

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