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Denoising of 4D-STEM Dataset using Pix2Pix GAN Algorithm and Artifact Reduction Strategy

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Background and Aims

4D Scanning Transmission Electron Microscopy (4D-STEM) has revolutionized the study of nanoscale materials by offering localized structural imaging capabilities through electron diffraction patterns [1]. However, the inherent noise within these patterns often impedes critical structural details, posing challenges to accurate analysis, particularly in orientation-based clustering [2]. In response, this paper presents a comprehensive approach to denoising 4D-STEM datasets, focusing on leveraging Pix2Pix Generative Adversarial Networks (GANs) to reduce noise and the influence of the artefacts [3].

Methods

The methodology is to focus on training a Pix2Pix GAN architecture using paired noisy-clean 4D-STEM image data. Adjusting the conditional GAN framework, the generator network learns to map noise from input images to their corresponding clean counterparts, guided by the discriminator network, which distinguishes between real-clean images and generated ones [3]. This approach effectively captures the intricate relationships between noisy and clean data, facilitating precise denoising. To address artifacts commonly encountered in GAN-generated images [4], we integrate additional regularization techniques and architectural modifications into the generator. Furthermore, architectural adjustments such as skip connections and multi-scale discriminators are implemented to enhance image fidelity and minimize artifact occurrence.

Results

Extensive experimentation was conducted on both synthetic and real-world 4D-STEM datasets to evaluate the effectiveness of our approach. Quantitative metrics, including peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), were employed to assess denoising performance, complemented by visual comparisons to highlight the clarity and fidelity of denoised images. Results demonstrate significant noise reduction and artifact suppression, enabling clearer visualization of nanoscale structures and more precise analysis. Importantly, our approach offers a substantial time-saving

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advantage compared to traditional methods, reducing processing time from 15 hours (using e-Pattern processing [5]) to just 0.2 hours.

Conclusion

In conclusion, our methodology provides a robust solution for denoising 4D-STEM datasets, leveraging Pix2Pix GANs while effectively addressing the challenge of artifact reduction. Significantly, this work contributes to advancing the field of materials science by enhancing the utility of 4D-STEM imaging techniques and emphasising the potential of GAN-based approaches in complex image-processing tasks.

Graphic:

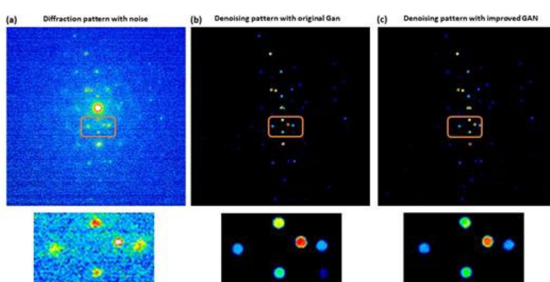

Figure 1. (a) The original dataset. **(b)** Artifacts in the context of GANs refer to unwanted or undesired patterns, distortions, or imperfections that can appear in the generated data. **(c)** The ideal result with the elimination of the artifact.

Keywords:

Deep Learning, Pix2PixGan, Denoising, 4D-STEM

Reference:

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