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

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ABSTRACT

4D Scanning Transmission Electron Microscopy (4D-STEM) has emerged as a powerful tool for studying nanoscale materials, offering local structural imaging capabilities using electron diffraction patterns [1]. However, the inherent noise generated in electron diffraction patterns often obscures crucial structural details, interfering with accurate analysis, especially, causing a challenge in the clustering process according to its orientation [2]. In this paper, we propose a comprehensive approach to denoising 4D-STEM datasets, focusing on the utilization of Pix2Pix Generative Adversarial Networks (GANs) for noise reduction and addressing the challenge of artefact mitigation [3].

The methodology focuses on training a Pix2Pix GAN architecture using paired noisy-clean 4D-STEM image data. Leveraging the conditional GAN framework, the generator network learns to map noisy 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 complex relationships between noisy and clean data, enabling accurate denoising. The problem of artefacts in the generation is commonly encountered in the GAN series [4]. The solution is to incorporate additional regularization techniques and architectural modifications into the generator to tackle the issue of artefacts. Furthermore, architectural adjustments such as skip connections and multi-scale discriminators are implemented to enhance image fidelity and reduce artefact occurrence. Extensive experimentation is 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) are employed to assess denoising performance, while visual comparisons highlight the clarity and fidelity of denoised images [5][6]. Results demonstrate significant noise reduction and artefact suppression, enabling clearer visualization of nanoscale structures and more accurate analysis, meanwhile, the time saving compared to traditional method (ePattern processing [7]) is reduced from 15 h (ePattern) to 0.2 h (paper approach).

Overall, the methodology renders a robust solution for denoising 4D-STEM datasets, leveraging Pix2Pix GANs while addressing the challenge of artefact reduction. This work contributes to advancing the field of materials science by enhancing the utility of 4D-STEM imaging techniques and underscores the potential of GAN-based approaches in complex image-processing tasks.

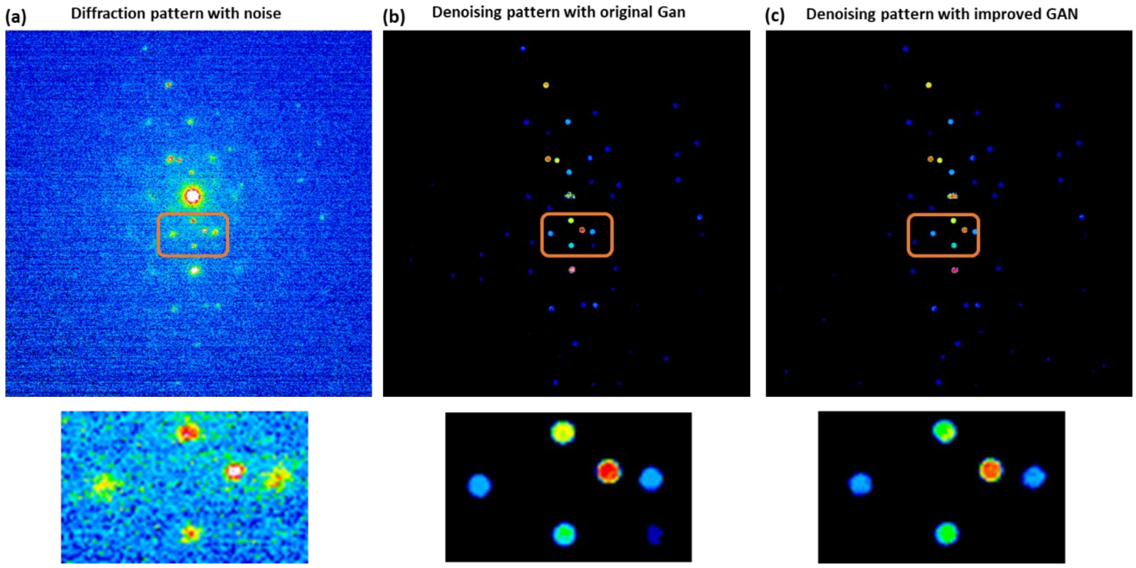

Figure 1. (a) The original dataset. **(b)** Artifacts in the context of GANs refer to unwanted or undesired patterns, distortions, or imperfections that can appear in the generated data. **(c)** The ideal result with the elimination of the artefact.

Reference

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