Ronchigram-based Optical Neural Inference for Aberration Detection (RONIN)

Sriram Sankar (ASU),
Manikandan Sundararaman (ASU),
Aditya Raghavan (UTK)

Abstract

Aberration correction is critical for achieving high spatial resolution in scanning transmission electron microscopy (STEM). Conventional correction relies on expert interpretation of ronchigrams, making the process slow and difficult to automate. In this project, we present RONIN, a physics-informed deep learning framework that predicts dominant electron-optical aberrations directly from ronchigram images. Using synthetically generated ronchigrams and a ResNet-based regression model, RONIN demonstrates accurate inference of several low-order aberrations, highlighting its potential for closed-loop and autonomous microscope alignment.

1. Introduction

In S/TEM, imperfections in magnetic lenses introduce phase distortions in the electron wavefront, commonly described by an aberration function expanded in Krivanek notation.[1] Ronchigrams—shadow images formed on amorphous specimens—encode these aberrations through characteristic symmetry distortions.[2,3] While experienced microscopists can manually infer aberrations such as defocus or astigmatism from ronchigrams, the process is subjective and time-consuming.

Automating aberration identification is essential for high-throughput and autonomous microscopy. RONIN addresses this need by treating aberration correction as an image-to-parameter regression problem, where a neural network infers aberration magnitudes directly from ronchigram images.

2. Methodology

A physics-based ronchigram generator was developed to create labeled training data. The simulation models electron wavelength, aperture geometry, and selected aberration terms (C10, C12, C21, C23, and C30), producing realistic ronchigrams under varied optical conditions. Thousands of images were generated using integer-valued aberration magnitudes within physically meaningful ranges.

A ResNet-18 architecture pretrained on ImageNet was used as the backbone, with a regression head predicting multiple aberration coefficients simultaneously. Training employed on-the-fly data generation, L1 loss for robustness, and learning-rate scheduling to improve convergence. This approach avoids overfitting to specific specimen textures and enables scalable dataset expansion.

3. Results

The trained model was evaluated on a held-out synthetic test set. Strong performance was observed for aberrations with clear ronchigram signatures:

- **C12 (two-fold astigmatism):** ~93% accuracy, R2≈0.91R^2 \approx 0.91R2≈0.91
- **C10 (defocus):** ~72% accuracy

Moderate to lower accuracy was obtained for coma (C21) and three-fold astigmatism (C23), while spherical aberration (C30) showed limited predictability. These trends reflect the varying visual prominence of different aberrations in ronchigram patterns

4. Conclusion

RONIN demonstrates that deep learning models, trained on physics-based synthetic data, can successfully infer electron-optical aberrations from ronchigrams. The framework provides a foundation for integrating neural agents into automated aberration correction workflows and represents a step toward self-optimizing electron microscopes.

[1] Krivanek, O. L., N. Dellby, and A. R. Lupini. "Towards sub-Å electron beams." Ultramicroscopy 78.1-4 (1999): 1-11.

[2] Hawkes, Peter W., and Erich Kasper. Principles of electron optics: Wave Optics. Vol. 2. Academic press, 1996.

[3]Sawada, H., et al. "Measurement method of aberration from Ronchigram by autocorrelation function." Ultramicroscopy 108.11 (2008): 1467-1475.