

Enhancing Electron Computational Ghost Imaging Using Artificial Neural Networks

Lorenzo Viani¹, Paolo Rosi², Enzo Rotunno^{2*}, Stefano Frabboni³, Roberto Balboni⁴ and Vincenzo Grillo²

¹. Ph.D. School in Physics and Nanosciences, University of Modena and Reggio Emilia, Modena, Italy

². Consiglio Nazionale delle Ricerche (CNR)-NANO, Modena, Italy

³. Department of Physics, University of Modena and Reggio Emilia, Modena, Italy

⁴. Consiglio Nazionale delle Ricerche (CNR)-IMM, Bologna, Italy

* Corresponding author: enzo.rotunno@nano.cnr.it

The observation of beam sensitive materials is a challenging field that benefits from the use of low electron doses and fast acquisition, to obtain as much information as possible before damaging the sample. Following this guiding principle, it is possible to borrow a technique first developed for light microscopy and adapt it to transmission electron microscopy.

Computational Ghost Imaging (CGI) [1, 2], or single-pixel imaging, consists in recovering the transmission function of the sample by using structured illumination, i.e. not a plane wave or convergent probe but a modulated wave in the form of an illumination pattern. Several different illumination patterns are produced by shaping the electron beam with a specific set of electrodes in the probe-forming aperture and then sending them to the sample in quick succession. The patterns are predicted with precision by simulations calibrated with experiments. The sample-transmitted intensity for each pattern is acquired by a single-pixel detector. Then, the full transmission function is reconstructed as a weighted sum of all the illumination patterns, using the single-pixel measured intensities as weights (the process is schematized in Figure 1). The quality of the reconstruction is affected by two main factors: the level of control over the complexity of the generated patterns and the correspondence between the calculated patterns and the actual ones used while measuring.

The advantage of using electron CGI with respect to ordinary TEM imaging is that this technique combines the use of low electron dose for each pattern with the efficiency of compressed sensing methods, that reduce the number of total patterns required to reconstruct the transmission function. In this initial implementation, CGI is mainly suited to observe amplitude objects, making it complementary to electron Ptychography.

To this aim, we propose a new electro-optical device based on the Micro ElectroMechanical System (MEMS) technology to use as an optical modulator for electrons. It consists of a planar arrangement of six microscopic needles that can be biased independently to produce an electrostatic potential distribution. As the electron beam crosses the potential distribution, it acquires a position-dependent phase shift which translates to an intensity modulation when observing the beam in Fraunhofer condition [3]. Thus, the generator allows for controlled beam shaping with six degrees of freedom and fast pattern generation through dedicated electronics.

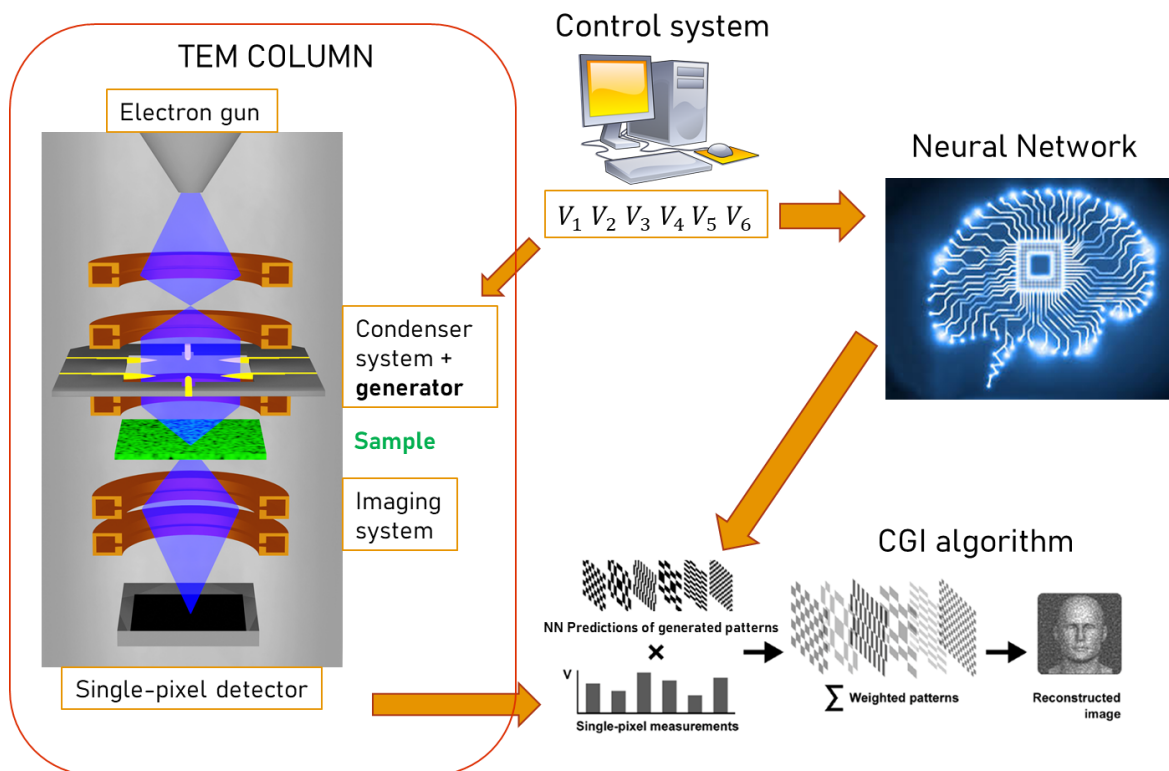


Figure 1. Proposed experimental setup. The pattern generator is introduced at the level of the condenser system. The electron beam passes through the generator and is transformed into a structured probe. Then, the beam propagates to the sample and interacts with it. The transmitted beam is imaged on the single-pixel detector and integrated as an intensity. Combining the calculated patterns and the measured intensities allows recovering the image.

The calculation of the illumination patterns is performed via machine learning methods. The calculated patterns must match those used to illuminate the sample, otherwise the whole procedure would fail. Using a Convolutional Neural Network (CNN) [4, 5], a kind of machine learning algorithm well-suited to work with images, it is possible to train it (via simulated or experimental images) to output the expected illumination pattern by taking the six bias voltages as input. There are multiple advantages in using a CNN instead of a traditional algorithm. For instance, a CNN is typically faster because it directly processes the result without the need for time-consuming Fourier transforms. Also, traditional algorithms are somewhat refractory to the incorporation of machine-dependent effects, that are hard to implement in the code. Instead, a CNN is well suited to incorporate those effects. That improves the prediction of the illumination patterns, providing an overall more accurate set. We trained a CNN based on the well-known VGG16 architecture [6] to acquire the six biases as input and predict the pattern seen in the TEM as output. The fast calculation of the patterns allowed by the CNN is used to predict optimal new patterns during experiments to further reduce the dose.

An example of final image is shown in Figure 2. We used a common six-spoke Siemens star target as sample and simulated the reconstruction process. The resulting image, obtained with 5000 summed patterns, shows a fairly accurate reconstruction around the centre. The very central region displays a loss of detail due to the limited resolution of the technique.

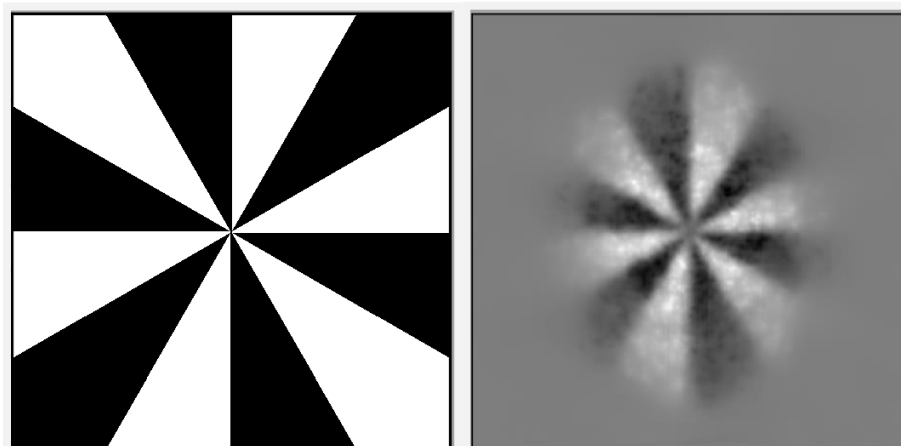


Figure 2. Comparison of the target image (left) and reconstruction (right). The gray background of the reconstruction and the ellipticity of the reconstructed portion of the target are due to the way in which the patterns are generated and sent to the sample. The reconstruction hits a resolution limit close to the center, where the spokes of the Siemens star become too narrow to be resolved.

In this work we demonstrate an electron analogue of Computational Ghost Imaging that, in combination with AI methods, allows for the retrieval of the transmission function of a sample. We developed and tested a device to rapidly generate structured illumination in a controlled way. The results show the great potential of the technique, providing accurate retrieval of the transmission function with good contrast. This type of imaging could, in some sense, become the generalization of a STEM technique and be combined with 4DSTEM.

References:

- [1] M J Padgett, R Aspden, G Gibson, M Edgar, and G Spalding, *Optics & Photonics News* **27** (October 2016), p. 38-45
- [2] J H Shapiro, *PHYSICAL REVIEW A* **78**, p. 061802(R) doi:10.1103/PhysRevA.78.061802
- [3] A H Tavabi, V Migunov, C Dwyer, R E. Dunin-Borkowski and G Pozzi, *Ultramicroscopy* **157** (2015), p. 57-64 doi: 10.1016/j.ultramic.2015.04.003
- [4] Michael A. Nielsen in “Neural Networks and Deep Learning”, ed. Determination Press, 2015 (accessed February 08, 2022)
- [5] E. Rotunno, A.H. Tavabi, P. Rosi, S. Frabboni, P. Tiemeijer, R.E. Dunin-Borkowski and V. Grillo, *Ultramicroscopy* **228** (2021), p. 113338 doi:10.1016/j.ultramic.2021.113338
- [6] K. Simonyan, A. Zisserman, arXiv eprint (2014) arXiv:1409.1556