

## Compressed sensing for reconstruction in ptychography

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Ptychography is a method that solves the phase problem from a series of diffraction patterns, each of which is obtained by illuminating the sample with a spatially limited probe. For each measurement, the probe is shifted such that a sufficient overlap of the illuminated areas guarantees information redundancy. This means, however, that reconstruction of the object requires processing large data sets from hundreds or even millions of probe positions. The experimental acquisition of the data and the computational reconstruction cost may therefore be very large. A solution for speed-up is to use compressed sensing (CS). Here, we make use of the multislice algorithm [1] and apply CS by minimizing the  $l_1$ -norm of the projected potential  $V$ , while keeping the measurements as constraints following the approach in [2]. This corresponds to the minimization problem:

$$V^* = \min L(I(V), J) + \mu R(V) \quad (1)$$

Where  $L$  is a non-negatively valued loss function that compares the model  $I(V)$  to the experimental data  $J$  and  $R$  is the regularizer that is the sum of  $|V|$  and whose relative importance is controlled by  $\mu$ .

The proposed method is applied to a dataset of a Pt-wedge that has been obtained in a JEOL ARM 200F microscope fitted with the JEOL 4D Canvas system. The recorded 4D STEM dataset consists of  $512 \times 512$  probe positions with a scan step of  $0.137 \text{ \AA}$  and a  $66 \times 66$  pixel diffraction pattern (see Fig. 1) is recorded for each position. Reconstructions are performed with a reduced number of probe positions ( $1/4, 1/9, 1/16, 1/25, 1/36, 1/49, 1/64$ ) that are distributed over the sample in a random or a grid-shaped fashion. A comparison to the ground truth reconstruction, where the full data is used, is done by calculating the root mean square error between the ground truth and the renormalized testing reconstruction.

Reducing the number of probe positions and thus decreasing the overlap in general hampers iterative phase retrieval algorithms. Compressed sensing can counteract against this trend. More precisely, applying the regularization term in eq. 1 results in a better reconstruction of the sample compared to the un-regularized case for a probe reduction of below  $1/9$  and when grid scanned.

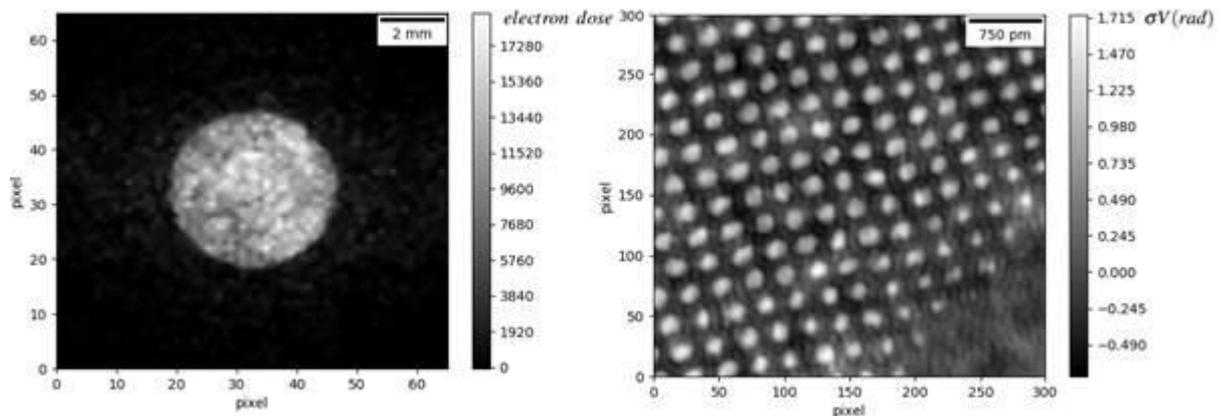


Figure 1: (Left side) A typical diffraction pattern that is taken from the 4D dataset. (Right side) The ground truth reconstruction of the projected potential that takes into account all probe positions and where regularization is not applied.

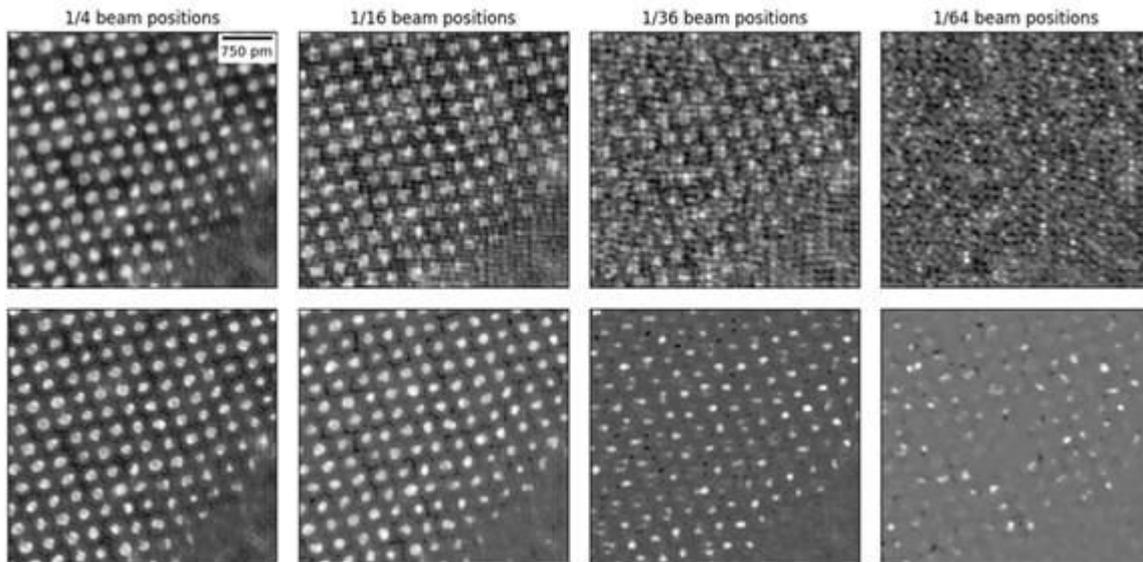


Figure 2: Examples for grid scan based reconstructions with reduced number of probe positions. The upper row shows the reconstruction without applying the regularization and the lower row illustrates the effect of the regularization term on the same probe positions. The square-shaped artifacts are greatly reduced.

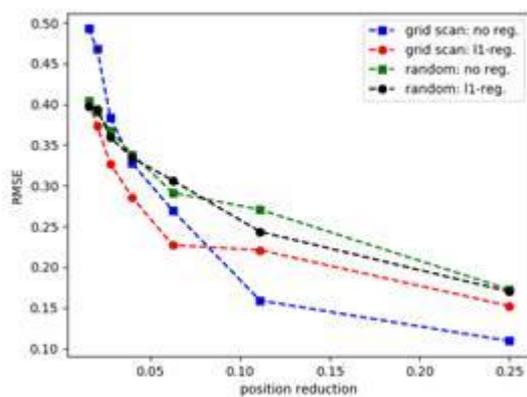


Figure 3: Comparison of the reconstruction quality for different test cases by using the RMSE. Note how regularization reduces the error in the case of grid scanning for reductions of 1/9 and lower.

#### References:

- [1] E. J. Kirkland, *Advanced computing in electron microscopy*. Springer Science & Business Media, 2010.
- [2] W. Van den Broek et al., *Physical review letters* 109.24 (2012): 245502.

M.S. and W.V.d.B. acknowledge financial support from the DFG Grant No. BR 5095/2-1 and G.T.M. and P.D.N. acknowledge support from the EPSRC Grant No. EP/M010708/1.