3D object reconstruction beyond the depth-of-focus limit using automatic differentiation

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1. Introduction

As the spatial resolution of x-ray imaging is pushed towards the diffraction limit, depth-of-focus (DOF) emerges as a non-negligible problem for 3D imaging. When the specimen becomes larger than the depth of focus, the pure-projection approximation fails. This has been addressed in part by the use of multislice methods to reconstruct several depth planes which are then combined to yield an approximation of a pure projection [1]. We describe here an approach to recover extended 3D with isotropic pixel size. Since the proposed algorithm works with full-field transmission microscopy data, it is compatible with alternative high-resolution imaging techniques such as point-projection x-ray microscopy (PPXM) where one may work with partially coherent sources where the propagation fringes from any single object feature do not extend beyond the coherence width.

2. Methodology

The tomographic measurement of an object yields a projection image \( y_\theta \), each obtained at a tilt angle \( \theta \). For an unknown object matrix \( x \) and a known incident wavefront \( \psi_0 \), the wavefront exiting the object can be calculated using the multislice method [2]. By defining a loss function \( L \) such that \( L = \sum_\theta || M_\theta x \psi_0 - y_\theta ||^2 + R(x) \), where \( M_\theta \) is the multislice propagation operator for orientation \( \theta \) and the current object function \( x \), and \( R(x) \) is a sparsity regularization term, we may reach a solution for \( x \) by minimizing \( L \). A finite support constraint is also applied to \( x \). An important task in the minimization of \( L \) is to derive its partial derivative with regards to every voxel in \( x \). This can be done conveniently utilizing automatic differentiation (AD), such as TensorFlow, a deep learning package first initiated by Google, and now an open-source toolkit.

3. Results

We used TensorFlow as the automatic differentiator in solving \( x \). The numerical study was conducted with a phantom object that is 64x64x64 in size (Fig. 1a). The proposed algorithm successfully reconstructed the object within 234 s (Fig. 1b), though quantitation can be further improved. Conventional tomography reconstruction methods, such as the filtered backprojection method (FBP), failed to reveal all features (Fig. 1c).

4. Conclusion

We developed a 3D reconstruction method for objects thicker than the DOF limit using AD. The algorithm is easily parallelized using the open-source AD implementation, and yields higher quality results than conventional reconstruction methods. When combined with full-field high resolution imaging techniques like PPXM, this offers a path to high throughput imaging beyond DOF limits.

References