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Deep learning for phase retrieval from Fresnel diffraction patterns

M. Langer, K. Mom, and B. Sixou

We present our recent developments in phase retrieval from propagation-based X-ray phase contrast images using deep learning-based approaches. Previously, deep convolutional neural networks had been used as post-processing step to a linear phase retrieval algorithm [1]. In a first approach, we investigated the use of deep convolutional neural networks to directly retrieve phase and amplitude from a propagation distance series of phase contrast images [2]. Due to a structure that seems well adapted to the properties of the phase contrast images, taking into account features at several scales and connecting the corresponding feature maps, we chose the mixed-scale dense network (MS-DN) [3] architecture as network structure. We developed a transfer learning approach where the network is trained on simulated phase contrast images generated from projections of random objects with simple geometric shape.

We showed that the use of a simple pre-processing to transform the input to the image domain improved results, providing some support to the hypothesis that including knowledge of the image formation process in the network improves reconstruction quality. Some work has been done in this direction using generative adversarial networks by introducing a model of the image formation in a CycleGAN network [4].

Going one step further, information on how to solve the phase retrieval problem can be introduced into the neural network, algorithm unrolling being one such approach [5]. In algorithm unrolling, parts of an iterative algorithm, usually the regularization part, are replaced by neural networks. The networks learn the steps of the chosen iterative algorithm. These networks can then be applied in a sequential fashion, making the run-time application very efficient, moving the calculation load from the iterative reconstruction to the off-line training of the networks.

Based on this idea, we proposed the Deep Gauss-Newton network (DGN) [6]. Gauss-Newton type algorithms have been successfully used for phase retrieval from Fresnel diffraction patterns [7]. Inspired by this, we developed an unrolling-type algorithm based on a Gauss-Newton iteration. Both the regularization and the inverse Hessian are replaced by neural networks. The same network is used for each iteration, making the method very economical in terms of network weights. An initial reconstruction is not required; the algorithm can be initialized at zero. It can retrieve simultaneously the phase and attenuation sorption from one single diffraction pattern. We applied the DGN to both simulated and experimental data, for which it substantially improved the reconstruction error and the resolution compared both to the standard iterative algorithm and the MSDN-based method.

Future work includes extension of the algorithms to tomographic and time-resolved imaging, as well as to other imaging problems. Code for both algorithms will be made available through the PyPhase package [8] in a future release.

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