

A Data-Driven Framework for 3D Shape Reconstruction from Phaseless Scattering Far-Field Data

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The ability to identify shapes from observational data is a vital problem in applied electromagnetics. It has widespread applications from target identification both above- and below-ground to nondestructive evaluation. Given the scope and impact of applications, extensive work has been done in this area (Dikbayır et al., arXiv:2407.09525). Our approach to this problem is different. We seek to build a deep learning network that maps scattered farfield data to the object that generated that field, and builds upon the framework introduced by some of the aforementioned authors.

To effect this reconstruction, we use two networks in concert with each other. (a) A PointNet-based three-dimensional (3D) autoencoder (R. Q. Charles et al., 2017 IEEE CVPR, 77-85) (M. Zamorski et al., Comput. Vis. Image Underst., 193, 102921) and (b) an inverse network. Of course, scattered field data for each of the objects is obtained using a well validated combined field integral equation code. The autoencoder is trained with point clouds sampled on 3D meshes from the *aircraft* class of the ShapeNet (Chang et al., arXiv:1512.03012) data set, using the farthest point sampling method. The encoder learns geometric features and maps each shape to a probabilistic latent vector representation. An inverse relationship mapping back to the geometry is also learned and trains the decoder. After training the 3D autoencoder, the inverse network processes precomputed far-field scattering data through a series of convolution layers, to map to meaningful geometry features. These features are mapped to a latent vector. By passing the resultant vector, which is now a compressed version of the input scatterer, into the pre-trained decoder, the framework then reconstructs a 3D point cloud of the scatterer by optimizing the Chamfer distance between the reconstruction and the ground-truth geometry data. The design of the inverse network ensures robust feature extraction and effective mapping from the scattering data to the 3D geometric representation. In the conference, in addition to the network architecture, we will present a number of examples that shed light on performance of the network when tested on a class of airplanes. In addition to reconstructing point clouds, we will present a methodology for reconstruction of surfaces from these point clouds.