

Using the Supervised Descent Method to improve the Initial Guess of Optimization-based Microwave Imaging Methods

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Machine learning techniques for microwave imaging have seen significant recent progress (N. Khalid et al., npj Imaging, 2, 1, 2024). However, optimization-based algorithms (e.g. Contrast Source Inversion (P. M. van den Berg and A. Abubakar, Prog. Electromagn. Res., 34, 189–218, 2001)) still have the benefit of generalizability without a large training dataset, as well as using the underlying physics of the problem. One of the costs of using ML imaging methods is that they are only as good as the training data set and how well it covers the target space. In order to have a generalizable ML algorithm, thousands of training examples are usually required (even in 2D imaging). One of the issues with optimization imaging methods is the dependence on the quality of the initial guess (in our experience, this is especially true with 3D imaging with limited data).

The goal of this work is to investigate using a single-iteration of the Supervised Descent Machine-Learning algorithm (R. Guo et al., IEEE Trans. Antennas. Propag., 67, 5, 3550–3554, 2019) as an initial guess for optimization algorithms (in this case, the Contrast-Source Inversion Algorithm). The traditional CSI algorithm uses back-propagation as the initial guess. Although algorithms initialized with the back-propagated solution often converge in 2D, sporadic performance in 3D suggest that there is a higher sensitivity to the quality of the initial guess. A combined approach can use Machine Learning’s ability to directly map fields to permittivity to achieve a close estimate, followed by optimization to refine the result using the proper physics.

This proposed combined SDM-CSI method does have the downside of requiring training data. One of our goals is to keep the number of training data sets for the SDM method low (e.g. 200 targets for 3D data sets). Nonetheless, the SDM image does not need to be extremely representative as we only need a rough estimate of the target to provide an improvement over back-propagation. Fig. 1 displays promising initial results of single-step SDM trained on an experimental 2D data set (S. Cathers et al., Proc. Eur. Conf. Antennas Propag., 2024) compared to the back-propagated solution. Another goal of this work is to accelerate the convergence of the optimization-based algorithms as the cost of a forward solve scales quickly in 3D, thus any reduction in the number of iterations can be significant.

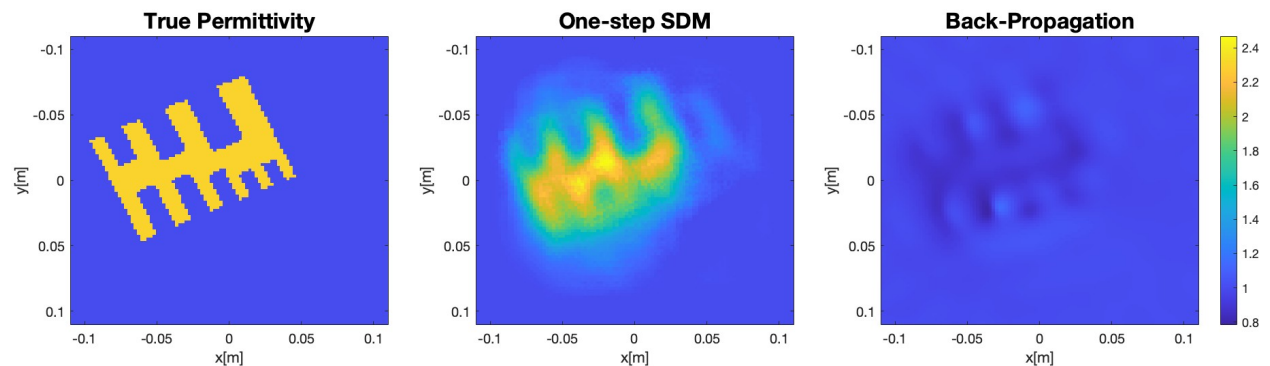


Figure 1: Initial guesses for the imaging algorithm. The true permittivity (left). The initial guess produced by the first step of SDM (center). The initial guess produced from the back-propagation method (right).