ODEMI: One Dimensional Electromagnetic Inversion Dataset to Study Machine Learning and Lessons Learned

Ergun Simsek
Department of Computer Science and Electrical Engineering
University of Maryland Baltimore County
1000 Hilltop Circle, Baltimore, MD 21250, United States

Abstract— In the past a few years, electromagnetic inversion with machine learning has been one of the most popular subjects in the computational electromagnetics (CEM) society. Unlike many other more mature fields, e.g., computer vision, there is a lack of large datasets allowing both junior and senior members of the CEM society to experiment their machine learning algorithms with. In this talk, first, I would like to introduce a moderately large dataset: One Dimensional Electromagnetic Inversion (ODEMI), which includes hundreds of thousands of cases assuming different measurement configurations and multilayered medium scenarios [1]. In the second part, I will focus on some fundamental yet important lessons learned from our study conducted on this dataset using four machine learning methods: linear regression, k-nearest neighbors, random forests, and neural-networks [2]. In terms of accuracy, deep-learning outperforms the other aforementioned machine learning techniques at the expense of computational cost. Our numerical studies show that bringing antennas closer to the domain of interest and increasing the number of antennas help with reducing the error but this reduction is not linear. Similar to suggested mesh sampling density in classical CEM applications, use of 20-30 antennas per wavelength is the ideal case for the highest accuracy and further increase of the number of receiver antennas is not helpful. We also confirm an outcome of very recent studies carried by other research groups [3]: training and testing a learning system with broadband excitations outperforms the learning systems deploying single-frequency datasets. Last but not least, we show that training datasets created with random grids rather than uniform grids can significantly increase the inversion accuracy, especially for the single-frequency applications.

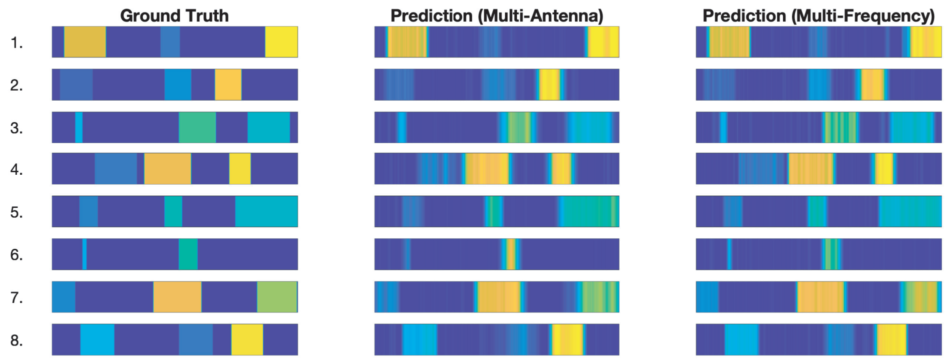

Figure 1: The region between $z = 0$ and $z = -\lambda$ is divided into 240 layers. Three objects with a random thickness and relative permittivity are formed in this region. Left column: Permittivity profiles of randomly chosen 8 examples out of the 1000 cases studied. Middle and right columns show the permittivity profiles predicted by the neural-network system with multi-antennas/single frequency and single antenna/multi-frequency, respectively.

REFERENCES

1. Simsek, E., "ODEMI," https://github.com/simsekergun/1D_EMI.
2. Simsek, E., "Machine learning exercises on one dimensional electromagnetic inversion," to appear in *IEEE Transactions on Antennas and Propagation*, 2021, doi: 10.1109/TAP.2021.3069519.
3. Guo, R., M. Li, F. Yang, S. Xu, and A. Abubakar, "Application of supervised descent method for 2D magnetotelluric data inversion," *Geophysics*, Vol. 85, No. 4, WA53–WA65, 2020.