ECE228 Project Proposal: Extending Fourier-DeepONet for Full Waveform Inversion

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1 Problem Background & Motivation

Full waveform inversion (FWI) is a computational technique used in geophysics to infer subsurface properties by minimizing the difference between observed and simulated seismic waveforms. Traditional FWI methods involve solving complex partial differential equations (PDEs) iteratively, which can be computationally intensive and sensitive to initial conditions. Recent advancements in machine learning have introduced data-driven approaches to FWI, aiming to reduce computational costs and improve robustness. However, challenges remain in generalizing these models to varying seismic source parameters and handling noisy or incomplete data. Addressing these challenges is crucial for reliable subsurface imaging in applications such as energy exploration and earthquake hazard assessment.

2 Related Works

The Fourier-DeepONet model [Zhu et al., 2023] introduces a neural operator framework that enhances the DeepONet architecture with Fourier features, enabling it to generalize across varying seismic source frequencies and locations. This model demonstrates improved accuracy and robustness compared to previous data-driven FWI methods. The Kaggle competition hosted by Yale and UNC-Chapel Hill [University and of North Carolina at Chapel Hill, 2025] provides a dataset and platform for evaluating FWI models on realistic seismic data, encouraging the development of physics-guided machine learning approaches. Additionally, the OpenFWI dataset [Deng et al., 2022] offers large-scale, multi-structural synthetic datasets for benchmarking FWI methods. These resources collectively provide a foundation for reproducing and extending the Fourier-DeepONet model in practical settings.

3 High-Level Methodology

Our project aims to reproduce the Fourier-DeepONet model and evaluate its performance on the Kaggle Geophysical Waveform Inversion competition dataset. We will reimplement the architecture and training procedure described in Zhu et al. [2023], adapting it to the competition format, which requires predicting subsurface velocity maps from seismic waveform inputs. Although the Kaggle dataset differs from the synthetic datasets used in the original paper in terms of geological complexity, noise, and data structure, it was created by the same research group and tests similar inversion capabilities. Our goal is to achieve strong performance under the competition's evaluation metric, which is mean absolute error (MAE) across predicted subsurface velocity values at odd-indexed spatial positions.

We will train Fourier-DeepONet on subsets of the data corresponding to different geological styles and source configurations and test generalization to unseen styles. To extend the baseline, we will also experiment with standard DeepONets, Fourier Neural Operators (FNOs), and uncertainty quantification techniques such as Monte Carlo dropout. For evaluation, we will report both MAE and secondary metrics such as mean squared error (MSE) and structural similarity index measure (SSIM) to assess image quality. The best models will be submitted to the Kaggle competition to benchmark their real-world effectiveness on this challenging physics-guided inversion task.

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References

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