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Fast and Accurate Wavefield Modeling via Fourier Neural Operators

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Introduction

Accurately and efficiently simulating wave propagation is challenging, especially for large-scale, high-resolution models. While finite-difference methods offer high fidelity, they are computationally expensive. Recently, machine learning approaches that embed physical knowledge, along with new architectural frameworks, have emerged as promising alternatives. In this work, we enhance Fourier Neural Operators (FNOs) Kovachki et al. (2021) with physics-based constraints. The resulting model achieves faster inference than conventional solvers and reduces prediction errors by enforcing physical consistency.

Method and/or Theory

The Fourier Neural Operator (FNO) learns mappings between input functions and PDE solutions in function space, rather than pointwise. This enables FNOs to generalize across spatial resolutions, allowing training on coarse grids and inference on finer ones. In our setup, training was conducted using Marmousi2 and corresponding wavefield snapshots generated with Devito's finite-difference solver. The model receives the velocity model and initial time steps of the wavefield as input, and predicts subsequent time steps. The FNO was trained by minimizing a loss function combining the mean squared error between predicted and true wavefields over time. Additionally, a physics-based term was incorporated to penalize deviations from the wave equation, encouraging physically consistent predictions and improving generalization.

Results and Conclusions

By incorporating the wave equation into the loss function the model significantly improved temporal stability and reduced cumulative prediction error over time steps, particularly in regions with strong velocity contrasts. Compared to traditional finite-difference modeling, PI-FNO achieved inference speeds over an order of magnitude faster, with relative errors below 10^{-2}. These results highlight the potential of combining operator learning with physical constraints for efficient and accurate forward modeling. Future work will extend this approach to 3D scenarios, as well as explore its integration into inverse problems such as full waveform inversion.

References

Kovachki, N. B., Z. Li, B. Liu, K. Azizzadenesheli, K. Bhattacharya, A. M. Stuart, and A. Anandkumar, 2021, Neural operator: Learning maps between function spaces: CoRR, **abs/2108.08481**.