A physics-informed neural network-based for elastic wavefield separation

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Introduction

Elastic waves realistically describe seismic waves inside the Earth by propagating P and S modes. These modes are coupled in inhomogeneous media, making it difficult to use them directly for imaging and inversion purposes. The Helmholtz decomposition can separate these modes by imposing a divergence-free (for S wave) and a curl-free (for P wave) condition. In particular, this mode decomposition can be used to mitigate crosstalk effects, improving the reverse time migration (RTM) and full-waveform inversion (FWI). Moreover, vector P and S components possess physical interpretation, correct amplitudes, and phases. This wavefield separation method can be efficiently computed by solving an auxiliary vector Poisson equation, where the source term carries information regarding the elastic displacement. To reduce the computational cost of this approach, a scalar formulation has been proposed as an alternative to the vector formulation. P and S waves are then constructed by employing adequate vector operations on the solution of a scalar Poisson equation. We refer to this approach as the scalar decomposition method.

Physics-informed neural networks (PINNs) have recently emerged as an effective machine learning approach for solving partial differential equations (PDEs), with successful applications in problems related to wave dynamics. Recently, PINN has been proposed as a method to decompose the elastic wavefield by solving the vector Poisson equation. Motivated by that, we propose a PINN-based Poisson solver for elastic wavefield separation. In this regard, the scalar-decomposition method also aims to reduce the computational cost.

Methods

As numerical experiment, we consider a two-dimensional homogeneous and isotropic elastic model with parameters $\rho = 0.44$ g/cm³, V_p = 4.0 km/s, and V_s = 2.35 km/s. The spatial domain was modeled with 101 x 101 grid points and a 10 Hz Ricker wavelet is used as a vertical source at the model's center.

We incorporated Fourier Features to help the network to learn high frequency patterns. The number of neurons in the hidden layers gradually decreases as follows: 256, 256, 128, 128, 64, 64, 32, 32. We employed the sine function as the activation in all hidden layers, following the common practice in models that use Fourier-based encodings. Furthermore, the network was trained for over 12,000 epochs using an AdamW optimizer, starting with a learning rate of 0.001, which was reduced by half every 2,000 epochs. The loss function consists of two terms: one regarding the PDE and another associated with the boundary conditions. In this work, we use a weight of 0.1 to control the PDE term and impose that the wavefield vanishes at the boundaries.

Results and Conclusions

The PINN's solution is compared with a conventional numerical method, which solves the Poisson equation using Discrete Sine Transform (DST). The results show strong agreement between the two methods, indicating that the PINN is capable of accurately making the elastic wavefield separation. Furthermore, these results provide encouraging evidence that PINN's can serve as a viable and flexible alternative to conventional elastic wavefield decomposition solvers, enabling future extensions to more complex and heterogeneous media.