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Calculating velocity models and solving seismic inversion problems using physics-informed neural networks

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Extended Abstract

Summary

In recent years, deep learning has achieved remarkable advances across various scientific fields, and earth sciences and seismology have not been left behind. Utilizing deep learning and artificial neural networks for problem-solving, we rely solely on the available data during the network training process to achieve desirable outcomes, often disregarding the existing scientific knowledge about the problem. Recently, a new domain called physics-informed neural networks (PINNs) has emerged, which integrates scientific knowledge with machine learning to improve accuracy and generalization. This approach has the advantage of not requiring large volumes of data and, by incorporating scientific knowledge, significantly alleviates the "black box" challenge associated with traditional machine learning. In this study, PINNs are employed to solve two-dimensional (2D) acoustic wave equation and perform full waveform inversion. The obtained velocity model is compared and examined against the output of physics-uninformed neural networks, demonstrating that the PINNs can achieve superior performance compared to conventional neural networks. Unlike conventional methods, PINNs eliminate the need for meshing and are less sensitive to initial velocity model selection, avoiding local minima. This study demonstrates that PINNs outperform conventional and physics-unaware neural networks in predicting velocity models and solving forward problems, even with limited data. Two-layer and five-layer horizontal velocity models were analyzed, with PINNs achieving precise identification of layer boundaries. By reducing reliance on large datasets and enhancing interpretability, this method bridges the gap between scientific principles and machine learning, offering a promising approach for complex seismic applications. Future work includes extending this framework to three-dimensional (3D) environments and exploring advanced architectures like auto encoders.

Introduction

Recent advancements in artificial intelligence have revolutionized various scientific fields, with earth sciences and seismology leveraging these developments for seismic inversion problems. This research integrates PINNs with 2D acoustic wave equation, providing a mesh-free, generalizable, and efficient solution. PINNs excel by embedding physical laws into the cost function, reducing dependence on large datasets and overcoming challenges like the "black box" nature of traditional neural networks. This study compares the performance of PINNs with physics-uninformed models, highlighting their superiority in accuracy, convergence, and generalization. Addressing key challenges such as limited data and traditional model limitations, this approach paves the way for robust and interpretable seismic imaging and wave simulations, with potential future expansions into 3D environments and advanced architectures.

Methodology and Approaches

This research utilizes PINNs to solve seismic inversion problems by incorporating physical equations into the cost function. Two-layer and five-layer velocity models were used, with simulations performed using highly accurate finite difference modeling codes as observational data. PINNs were trained with 60-time steps using spatial and temporal coordinates as inputs and automatic differentiation for gradient computations. The Adam optimizer was employed for iterative optimization, aiming to minimize the cost function while ensuring adherence to physical constraints. A fully connected feedforward neural network with three hidden layers was implemented, and training was conducted on advanced computational hardware, including a 2080 GPU and a 128 GB of RAM. This approach offers mesh-free modeling, faster convergence, and superior prediction accuracy compared to traditional methods.

Results and Conclusions

Observations and achievements: PINNs demonstrated superior accuracy in velocity models prediction compared to physics-unaware neural networks, especially for identifying layer boundaries. The mesh-free nature and integration of physical constraints provided significant computational advantages, reducing processing times and enhancing generalization capabilities.

Challenges addressed: PINNs effectively mitigated issues like reliance on large datasets and sensitivity to initial velocity models, enabling robust convergence and avoiding local minima.

Practical insights: Incorporating governing equations into the cost function proved essential for improving prediction reliability. The simultaneous solutions for forward and inverse problems improved interpretability, addressing the "black-box" challenge.

Recommendations for future research: Expanding this framework to 3D velocity models and exploring advanced architectures like auto encoders could further enhance prediction accuracy and application scope.

Suggested applications: PINNs can be adapted for real-world seismic exploration, earthquake modeling, and subsurface structure analysis, offering reliable imaging with limited observational data.