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Simultaneous Seismic Inversion and Wavelet Estimation Through a Physics-Informed Neural Network Architecture.

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Abstract Summary

Seismic inversion is a challenging, ill-posed, and highly nonlinear problem. Neural networks have shown great potential in addressing these challenges due to their ability to model the nonlinearity of observed data. In this work, we propose a Physics-Informed Neural Network (PINN) architecture for seismic inversion and wavelet estimation. The novelty of our approach relies in an architecture designed to designed to estimate the wavelet during the inversion process. The model was tested on the benchmark Marmousi2 synthetic dataset. The results indicate that our model outperforms traditional neural network models on the synthetic dataset and accurately estimates the wavelet.

Introduction

Seismic inversion, an essential technique in geophysics, aims to determine the elastic and petrophysical parameters of subsurface rocks based on seismic data. This process involves establishing a mapping—typically nonlinear—between the observed data and the parameters to be inverted. Traditional model-based methods, while effective, are computationally intensive and rely on rigorous physical theories (Dvorkin et al. (2014)). Neural networks offer an efficient alternative for mapping these nonlinear relationships (Li et al. (2024),Rasht-Behesht et al. (2022)).

Physics-Informed Neural Networks (PINNs) present a neural network approach that integrates physical knowledge directly into the training process. Unlike traditional neural networks, which typically learn from raw data, PINNs incorporate physical laws—such as partial or ordinary differential equations—to guide and constrain learning, ensuring that the model produces predictions consistent with established physical principles.

By embedding physical constraints, PINNs enhance both the efficiency and accuracy of seismic inversion, overcoming the limitations of traditional methods and purely data-driven neural networks. This enables a more robust and reliable characterization of the subsurface.

Method and/or Theory

The seismic inversion problem can be stated as the task of predicting elastic properties $\mathbf{m}$ given a set of seismic measurements $\mathbf{d}$, with a relationship defined by a physics-based forward model $\mathcal{F}$ in the form $\mathbf{d} = \mathcal{F}(\mathbf{m}) + \mathbf{e}$, where $\mathbf{e}$ represents noise in the seismic measurements.

A standard deep learning approach can be used to estimate the inverse operator $\mathcal{G} \approx \mathcal{F}^{-1}$ by minimizing the total error between the known properties and the estimated properties. This error is called the property loss (LP) and is defined as

$$L_p = \sum_{i}^{n} C(\mathcal{G}(d_i, \theta), m_i), \quad (1)$$

where C is a cost function, n is the number of training samples and θ represents the learnable parameters of the deep learning model.

Physics-Informed Neural Network

To build a Physics-Informed Neural Network (PINN), an additional loss term (seismic loss) is introduced, incorporating the physics embedded in the convolutional forward model:

$$L_s = \sum_{i}^{k} C(\mathcal{F}(\mathcal{G}(d_i)), d_i). \quad (2)$$

This loss term is independent of the elastic properties from well log data, adding an unsupervised training step and allowing for the use of all available seismic data during training.

Wavelet Estimation

The main contribution of this work is the development of a wavelet estimation network. The network learns the wavelet in parallel with the training of the inverse network, similar to the reparameterization network from Li et al. (2024). In fact, the training of both networks is correlated, as the same error is used to update their weights.

The wavelet estimation workflow consists of an fully connected network. The network is trained to generate the coefficients $a_0, a_1, ..., b_N$ of a Fourier series, which are then fed into the fourier equation

$$s_N(x) = a_0 + \sum_{n=1}^{N} \left(a_n \cos\left(2\pi \frac{n}{P} x\right) + b_n \sin\left(2\pi \frac{n}{P} x\right)\right), \quad (3)$$

and subsequently used in the forward model to generate synthetic seismic data. Finally, the total loss function, considering the wavelet model, is given by a weighted sum of the property loss (LP), seismic loss (LS) and wavelet loss (LW), resulting in $L_t = \alpha L_p + \beta L_s + \gamma L_w$, where α, β and γ weights the contribution of each term to the total loss.

Training Workflow

The training of the inverse network is divided into supervised and unsupervised steps (Fig. 1). In the supervised step, training occurs using pairs of seismic data and elastic properties from well logs. This training set is limited in size due to the scarcity of well log data. In the unsupervised step, the network is trained exclusively with seismic data, allowing it to leverage all available seismic information.

In our work, we propose a simple fully connected network with no explicit inputs. Instead, its first layer consists only of bias terms. This design choice is justified by the fact that the network is learning a single wavelet, making it a constant function that does not require variable inputs.

Results

The synthetic data used in this work is the Marmousi2 dataset (Martin et al. (2006)), and the data preparation follows the same steps as in (Alfarraj and AlRegib (2019)). First, the elastic impedances are calculated for four angles of incidence: $\theta \in \{0, 10, 20, 30\}$. Then the reflection coefficients

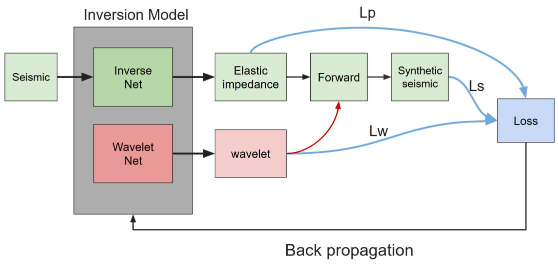

Figure 1: Model training workflow: Arrows indicate the flow of information during the training. L_p, L_s and L_w are respectively the property loss, seismic loss and wavelet loss. In each epoch the networks weights are updated via backpropagation algorithm using a linear combination of the presented losses.

are computed from these elastic impedances. To generate the synthetic seismic data, an Ormsby wavelet (5-10-60-89Hz) is convolved with the reflection coefficient data. The final step is adding normal white noise with 15dB to the seismic data to simulate measurement noise.

In the proposed training procedure, 10 evenly spaced traces of seismic and elastic impedance were selected for supervised training, while all seismic traces were used for unsupervised training.

The qualitative results demonstrate a strong similarity between the predicted elastic impedance (EI) and the expected EI, with a low absolute difference across all incident angles (Fig. 2).

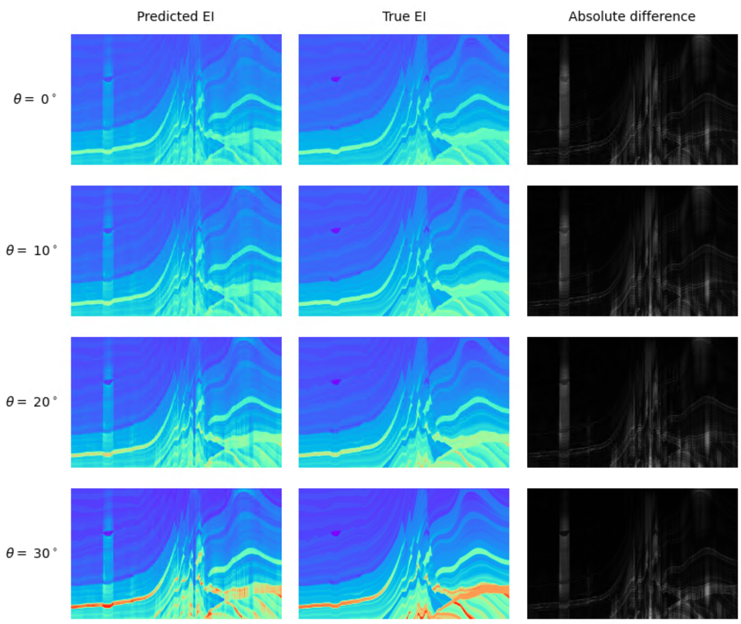

Figure 2: First column shows the predicted elastic impedance by our model. Second column shows the reference elastic impedance for comparison. Third column shows the absolute difference between first two columns.

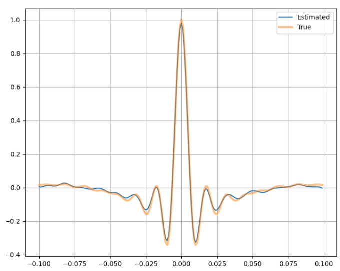

Figure 3: In orange the Ormsby wavelet used to generate the synthetic data. In blue the wavelet estimated by our model.

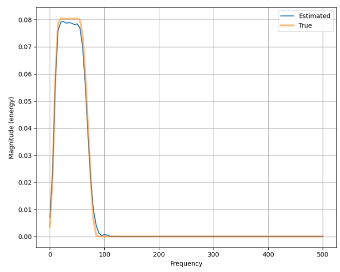

Figure 4: In orange the spectrum of the Ormsby wavelet used to generate the synthetic data. In blue the spectrum of the wavelet estimated by our model.

Table 1 compares the performance of the PINN model against the standard NN model (setting

$\beta = 0$ in L_t removes the contribution of the unsupervised training, transforming the PINN into a NN model) on the test data. It shows that the PINN model results have a higher correlation with the reference data, as well as better prediction performance, as suggested by the R^2 coefficient.

Table 1: Comparison of NN and PINN performance at different angles

Metric	Angle	NN	PINN
Correlation	0°	0.9310	**0.9745**
	10°	0.9302	**0.9741**
	20°	0.9268	**0.9724**
	30°	0.9192	**0.9678**
R^2 Coefficient	0°	0.7699	**0.9033**
	10°	0.7683	**0.9030**
	20°	0.7609	**0.8991**
	30°	0.7419	**0.8894**

The overall results suggests that the PINN model not only predicts elastic impedance more accurately then the NN model, but also effectively learns the wavelet used to generate the seismic data with high fidelity (Fig. 3). Beyond that, it preserves the wavelet's frequency spectrum (Fig. 4), ensuring that the reconstructed seismic signal maintains its physical characteristics.

Conclusions

In this work, we proposed a new Physics-Informed Neural Network model for seismic inversion that automatically estimates the seismic wavelet during the training. Our results shown that the PINN model outperforms the traditional NN model in the Marmousi2 dataset, suggesting that PINNs are more appropriate for the seismic inversion context. Future work will focus on extending the experiments in real datasets, comparing the results with alternative wavelet generation methods.

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