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A multi-task deep-learning network for low-frequency extrapolation – Case study from the Aquistore site

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Summary

Full-waveform inversion (FWI) of seismic data is a powerful method for estimating high-resolution models of the subsurface. This method requires an accurate initial model and low-frequency data to avoid cycle skipping. In the absence of this information, FWI is doomed to fail as it is likely to converge in local misfit minima. With the recent advancements in artificial intelligence (AI), studies have shown that absent low-frequency data can be extrapolated using deep learning (DL) and improve the accuracy of FWI estimates. These studies have been mostly focused on surface seismic data whose frequency content is different from cross-well data. In this study, we assess the use of DL for low-frequency extrapolation for a cross-well survey that was done at the Aquistore CO_2 site in Saskatchewan. Our results show that the proposed strategy leads to an improvement of 22 % and 4% in the model and data domains, respectively.

Introduction

Full-waveform inversion (FWI) of seismic data is a high-resolution inversion technique (Tarantola, 1984) that is used for estimating the properties of the subsurface. FWI is strongly nonlinear and prone to fail due to cycle skipping. To avoid cycle skipping, the inversion should start from an accurate initial model where the estimated data is less than half a period away from the observed data (Beydoun and Tarantola, 1988). A low-resolution initial model can be obtained based on the available information and using various methods such as well velocity logs, travel-time tomography, wave equation tomography, and so forth.

To minimize the cycle skipping issue, Bunks et al. (1995) proposed using a multi-scale inversion process where low-frequency data are inverted in the initial steps to estimate a low-resolution velocity model. This model is then used as an initial model for inverting higher frequency data. Although this approach can address the cycle-skipping issue to some extent, it cannot add low-frequency content to the data. To overcome this problem, different studies have been proposed to extrapolate low-frequency data using physics-based or data-driven approaches (Li and Demanet, 2016; Ovcharenko et al., 2019; Sun and Demanet, 2020).

This study focuses on P-wave estimation from a cross-well survey at the Aquistore CO_2 storage site, Saskatchewan. FWI is more prone to cycle-skipping in inversion of cross-well data due to the higher frequency content of the signals in this configuration compared to surface seismic. We explore the possibility of a deep learning (DL) approach to extrapolate low resolution data and its effects for conducting a FWI study.

The objective of this study is to analyze the possibility of extrapolating low-frequency data using deep learning for a cross-well survey. We present the theory of DL and FWI, followed by the FWI results obtained for the Aquistore cross-well data.

Theory

Deep Learning Framework

A neural network (NN) is defined as $\hat{y} = f(x, w)$ where a network receives training data, x, and learns the values of w (bias and weights) to get a good fit between predicted data ($\hat{y}$) and an expected value (observed value, y). A neural network, f, can have different architecture based on the problem under consideration. The network is updated iteratively to improve the fit between y and $\hat{y}$.

In this study, we attack two problems with one NN:

1. Convert high-frequency data to low frequency data,
2. Reduce the noise in data.

To achieve this goal, we create a synthetic dataset that contains noisy high-frequency data (as x in Eq. 1) and clean low-frequency data (y). During the training, the network learns to return clean low-frequency data ($\hat{y}$ in Eq. 1) given noisy high-frequency data as input. This happens by reducing the loss (J) between the estimated data ($\hat{y}$) and observed data (y),

$$J(\hat{y}, y) = J(f(x, w), y) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|\left|\hat{y} - y\right|\right|^{2}}, \qquad \text{Eq. 1}$$

where N is the number of samples in y. We implemented a six-layer NN that is a modified version of the network used by Sun and Demanet (2020). This NN receives a batch of noisy high-frequency traces and produces clean low-frequency traces. The network comprises six 1D convolution layers with kernel size of 3, stride of 1, and no padding. Every convolution layer is followed by a parametric rectified linear unit (PReLU), a batch normalization, and a dropout layer.

Full-waveform Inversion

FWI is a local optimization technique that minimizes the root-mean-square error between the recorded data (d) and modeled data plus some optional regularization terms as,

$$\min_{\mathrm{m} \in \mathrm{M}} \chi(\mathrm{m}, \mathrm{d}) = J(\mathrm{F}(\mathrm{m}), \mathrm{d}) + \mathrm{R}(\mathrm{m}), \qquad \text{Eq. 2}$$

where m is a vector of physical properties of the subsurface (e.g. P-wave velocity), R is a regularization term, and F is the forward modeling operator.
FWI is a highly nonlinear and ill-posed problem. To make this problem better posed and reduce the generated artifacts, different regularization methods can be used. A Tikhonov regularization controls the variability of the estimate in different directions (Asnaashari et al., 2013; Mardan et al., 2023). This regularization term is imposed as

$$\mathrm{R} = \lambda_{\mathrm{x}}||\mathrm{D}_{\mathrm{x}}\mathrm{m}||_{2}^{2} + \lambda_{\mathrm{z}}||\mathrm{D}_{\mathrm{z}}\mathrm{m}||_{2}^{2}, \qquad \text{Eq. 3}$$

where λ and D are the regularization parameter and spatial derivative operator in X- or Z-directions. Stronger λ in one direction limits the velocity variation in that direction. Considering the geology of the study area, we use $\lambda_z = 0.01$ and $\lambda_x = 0$ to encourage horizontal continuity of the estimate without limiting the vertical variation.

Field Data Inversion

In the Aquistore project, a cross-well seismic survey was conducted in 2013, prior to the injection of CO_2. The source was deployed in the observation well with source points covering the depth interval of 2889-3374 m at 1.5 m spacing. A vibratory source was utilized with sweep frequencies of 100-800 Hz. A 20-level hydrophone array with receivers spaced at 1.5 m was deployed through the tubing in the injection well. The receivers covered the depth interval from 2953 to 3372 m and recorded the data with 0.25 ms sampling rate.

Figure 1a shows a 2D velocity model of the zone of interest that is obtained using well velocity logs. This model is smoothed to be utilized as the initial model of FWI (Figure 1b). To conduct a multiscale FWI study, we focus on three frequencies (150, 300, and 420 Hz). Using an estimated wavelet from the data, we perform a conventional multiscale inversion where data are passed through a low-pass frequency filter before performing the inversion of that specific frequency (Bunks et al., 1995). The result of this approach is shown in Figure 1c.

For the proposed method in this study, the same frequencies are used to create datasets to train the beforementioned network. These data are created using an acoustic forward modeling operator and Ricker wavelet with the same acquisition geometry as the observed data. Then, two networks are trained to transform a noisy 420 Hz dataset to clean 150 and 300 Hz datasets. The networks are then applied to field dataset to estimate two sets of data. These estimated datasets are considered clean with Ricker wavelet with a peak frequency of 150 and 300 Hz. Hence, we perform FWI using three frequencies of 150, 300, and 420 Hz where a Ricker wavelet is used for the two first frequencies and the estimated wavelet (same as for the conventional multiscale FWI) is employed for the last frequency (420 Hz). The result of every step is used as an initial model for the next step (like the conventional multiscale FWI). The result of this inversion strategy is provided in Figure 1d.

Comparing the well data (Figure 1a) with the estimates (Figure 1c and Figure 1d), the superiority of the proposed method for estimating the low-velocity zone at the depth of ~3135 m and the high-velocity zone at the depth of ~3205 m is clear. This superiority is also shown in Figure 2 where the convergence curve of two methods for the last frequency (420 Hz) is shown. This comparison shows that the trained network is completely able to reduce the cycle skipping issue in this problem reducing the FWI loss from 412 to 322 and 318195 to 305297 in model (comparing with well-log-based velocity, Figure 1a) and data domains, respectively.

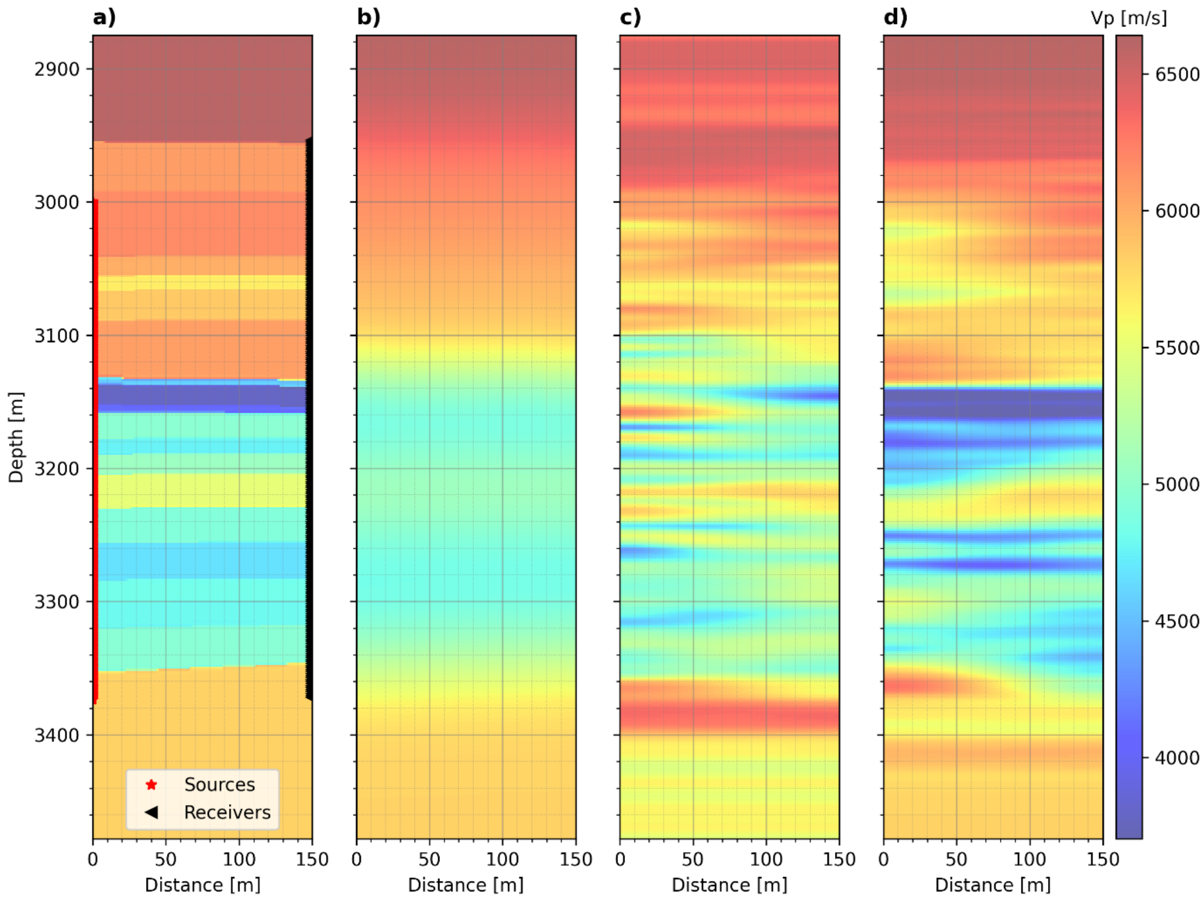

Figure 1 a) Velocity model obtained from well velocity logs. (b) Initial velocity model for performing FWI. (c) Estimated velocity model using conventional FWI. (d) Estimated velocity model using extrapolated low-frequency data.

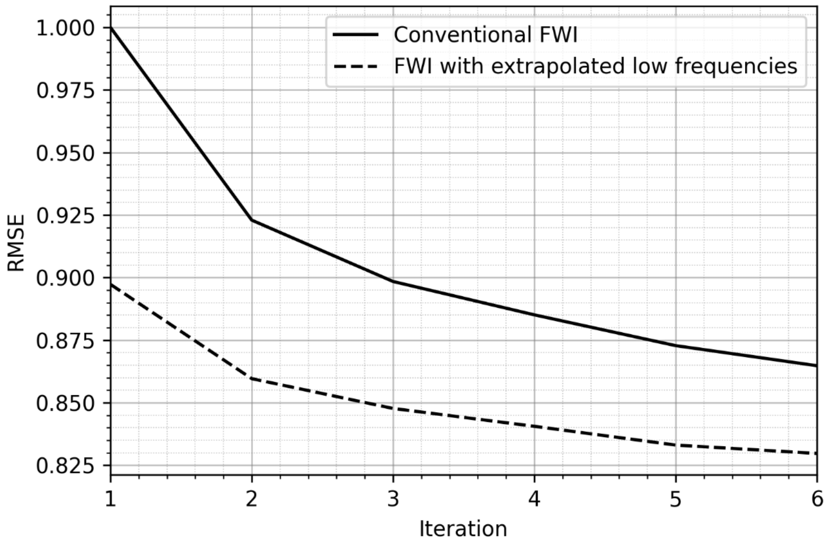

Figure 2 Convergence curve for conventional FWI (solid line) and FWI with extrapolated low-frequency data (dashed line).

Conclusions

In this study, we have assessed the ability of deep learning (DL) to extrapolate low-frequency content for cross-well seismic data that are acquired at the Aquistore site in Saskatchewan. The result is used for performing full-waveform inversion (FWI) and compared with the conventional multiscale FWI. We show that the proposed framework can significantly improve the accuracy and reconstruct the main zones in the study area. Our results show that this approach reduces the loss in the model and data domains by 21.76 % and 4.05%, respectively.

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