Deep Learning Velocity Model Building using Fourier Neural Operators

G. Huang[1], S. Crawley[1], R. Djebbi[1], J. Ramos-Martinez[1], N. Chemingui[1]

[1] PGS

Summary

We introduce a deep learning workflow that uses Fourier Neural Operators (FNOs) to estimate velocity models from field data with minimal pre-conditioning. Compared to convolutional Neural Networks (CNNs), FNO architectures use global long operators that makes them more powerful in the non-linear mapping from seismic records to earth models. We describe the VMB workflow that includes training on synthetic shot gathers computed from thousands of randomly generated earth models. We demonstrate its performance on a field survey acquired offshore Newfoundland, Canada. Results show that an accurate background velocity model can be inferred directly from the field data after minimal pre-processing and without prior information. The deep learning FNO-based workflow has the potential to significantly reduce the turnaround time of model building projects.

Deep Learning Velocity Model Building using Fourier Neural Operators

Introduction

Velocity Model Building (VMB) is the most important problem in exploration geophysics. For that, full waveform inversion (FWI) has emerged as the tool of choice for building Earth models while reflection tomography would provide FWI with a suitable starting model. The goal of VMB is to generate a high-resolution velocity field that improves imaging and enables accurate interpretation, particularly for reservoir characterization. Automation has then become increasingly required to reduce the turnaround time of VMB projects.

In this context, deep learning represents an opportunity to automate the VMB process (e.g., Araya-Polo et al., 2018). The technology by itself, or combined with FWI algorithms (e.g., Farris et al., 2018), has the potential to accurately estimate high-resolution velocity models directly from shot gathers. Most of the deep learning efforts so far have used machine learning (ML) architectures based on Convolutional Neural Networks (CNN). For instance, Araya-Polo et al. (2018) and Wang et al. (2018) used non-recurrent CNN, while Shibayama et al. (2021) applied a ResNet architecture to controlled experiments.

Recently, Fourier Neural Operators (FNOs) were introduced to solve parametric partial differential equations (PDEs) (Li et al., 2021) in the function spaces, independently of the mesh grid. The main advantage of FNOs is the use of global convolutions that can be computed efficiently via Fast Fourier Transform instead of relying on local operators that are used by CNN architectures.

In this work, we use an adapted FNO architecture to estimate velocity models from shot gathers. First, we describe the overall features of FNOs. Then, we discuss how the training was performed using 40,000 synthetic shot gathers generated through variable-density modelling using realistic field acquisition parameters. Finally, we show successful inferences of velocity models from a field survey offshore Canada.

Fourier Neural Operators

Fourier Neural Operators were first introduced as deep-learning model surrogates for solving Partial Differential Equations (PDEs) (Li et al., 2021). FNOs use global convolutional operators efficiently computed with the Fast Fourier transform. The global architecture, combined with non-linear activation function, allows FNOs to represent non-linear and non-local operators more accurately than CNN architectures. Another important characteristic of FNOs is that they are discretization invariant, therefore, training can be performed at a coarser discretization than the one used for validation, which has proven to be a very efficient approach for solving PDEs (Li et al., 2021; Konuk and Shragge, 2021; Choubineh et al., 2022).

FNO and the main components of its Fourier layers are described by Li et al. (2021). We use a modified architecture presented by (Lara-Benitez, 2022). As described in Figure 1, convolutional layers are inserted between the Fourier integral operator layers.

FNO VMB Workflow

The first step of the workflow (Figure 1b) consists of training the network using a significant portion of the randomly generated velocity models (~38,000 models). We also created corresponding density models based on Hamilton's relation for soft sediments and Gardner's relation for more consolidated sediments. For each earth model, we generated ten shots simulating standard streamer acquisition with offset range between 100m and 8100m. Free-surface and internal multiples were also included in the synthetic seismic response. A zero-phase wavelet extracted from field data with a frequency range between 3 and 14 Hz was used as the source wavelet. Figure 1 shows sample velocity models and their corresponding shot gathers.

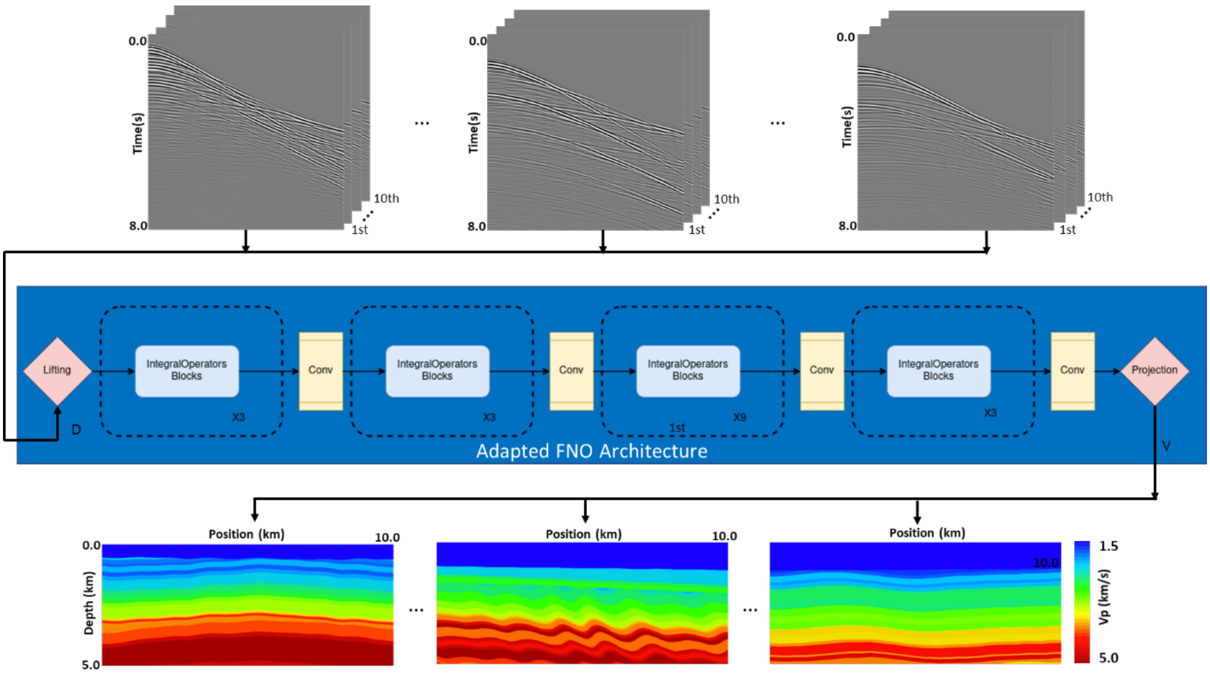

Figure 1 *Workflow to estimate the velocity field using FNO architecture with a modified macro design. Sample velocity models and their corresponding synthetic shots gathers used for training are shown. Ten shots are computed for each earth model.*

The second step of the workflow is to QC the training by inferring velocity models using a validation set from the synthetic data. Figure 2 shows examples of true velocity models, the corresponding inferences, and the RTM angle gathers computed using the inferred models. We also display the structural similarity index measure (SSIM) for the inferred models. The inferences tend to be slightly smoother than the true models considering the limited bandwidth of the training dataset. Accordingly, the background velocity models were accurate to produce flat angle gathers after RTM migration.

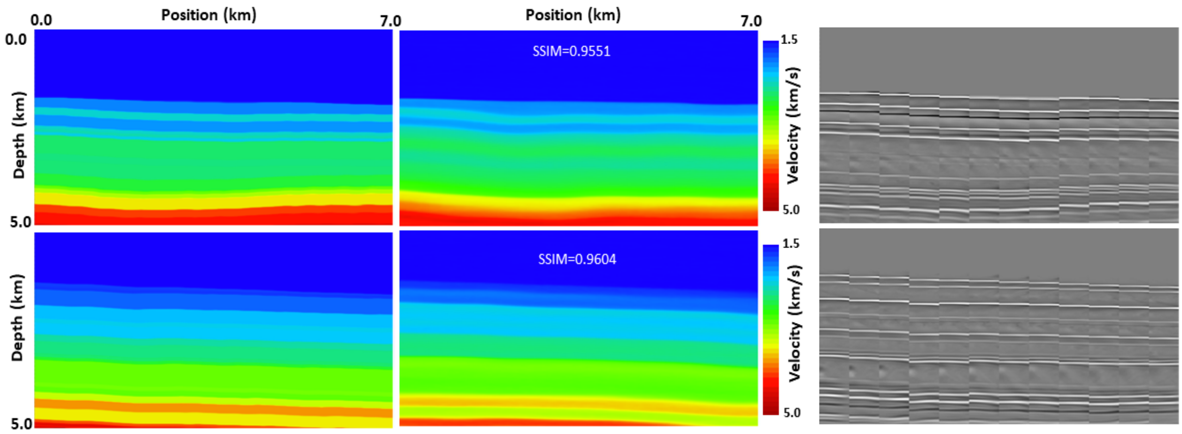

Figure 2 *Synthetic data inference example: True (left panel) and inference (central panel) for two velocity models from the validation set. QC RTM angle gathers (right panel) computed using the inferred models.*

Field data inference example

To illustrate the performance of the deep learning workflow for VMB, we applied the FNO trained model to estimate the velocity from a field survey. The data were acquired offshore Newfoundland, Canada, using multi-sensor streamer technology. The maximum inline offset is about 8100m. Sample shot records are shown in Figure 3. Minimal pre-processing was applied to the data and consisted of direct arrival suppression, noise attenuation, and zero-phase conversion. Additionally, the data were filtered to the same frequency band as the synthetic shot gathers used in the training. No multiple attenuation was applied to the data. One inference was generated for every ten adjacent shots. The estimated velocity models were then merged to construct the full velocity model shown in Figure 4. To validate the inferred model, we show the migrated stack and the corresponding angle gathers computed from RTM. Note the overall flatness of the angle gathers along the model.

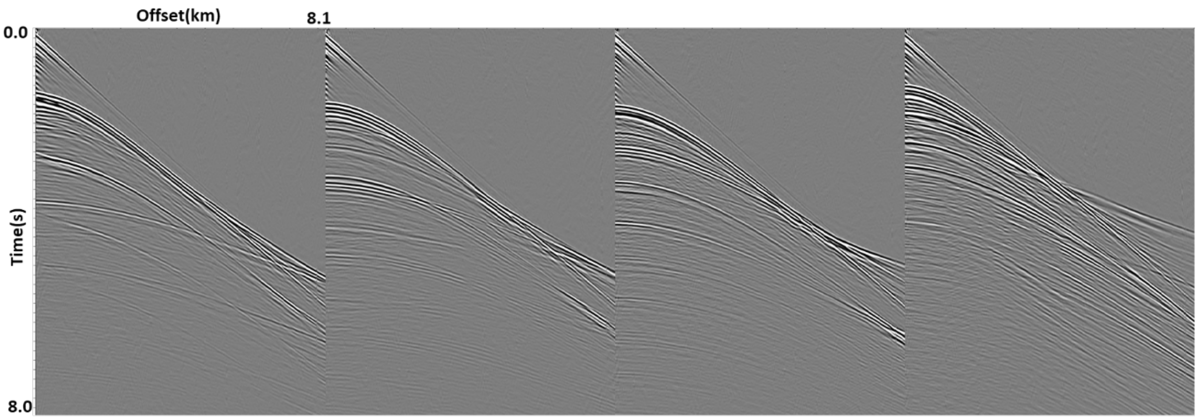

Figure 3 *Field data inference example: Sample shot records acquired offshore Newfoundland.*

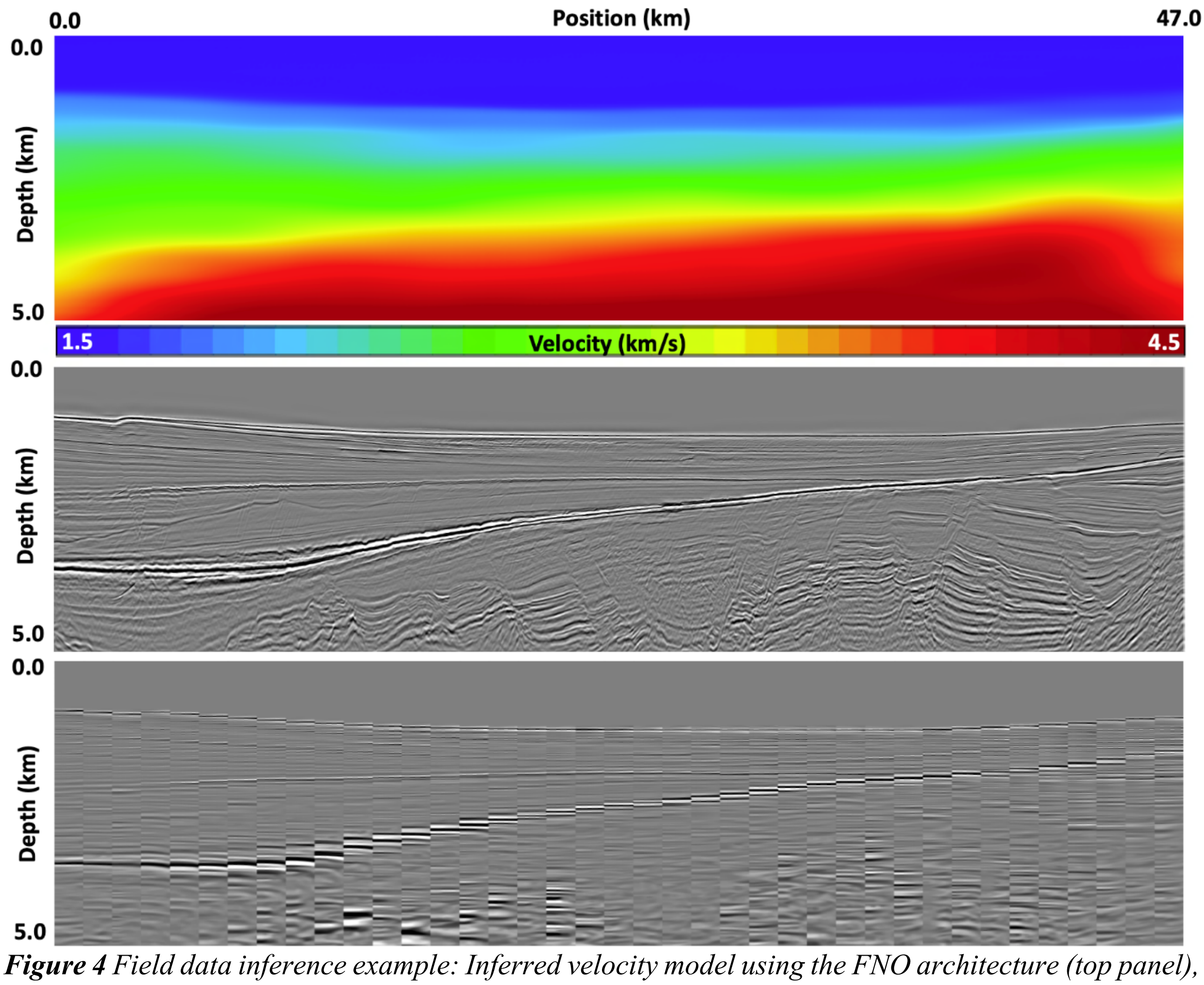

Figure 4 *Field data inference example: Inferred velocity model using the FNO architecture (top panel), QC stacked image (middle panel) and angle gathers (bottom panel) computed from RTM using the inferred model.*

Conclusions

We described a deep-learning workflow using Fourier Neural Operators (FNOs) to estimate velocity models directly from seismic shot records. We successfully applied the workflow to a field survey from offshore Newfoundland, Canada. The modified FNO architecture estimates an accurate background velocity model without any prior information. In addition to its suitability for imaging, the inferred velocity model can be used as starting model for FWI to retrieve a high-resolution velocity field. The deep learning FNO-based workflow has the potential to significantly automate the model building process and reduce the turnaround time of imaging projects.

Acknowledgments

We thank PGS for permission to show this work. We like to acknowledge the contributions of Antonio Lara-Benitez during the early stages of the project. We also thank Yang Yang and Elena Klochikhina for many fruitful discussions.

References

Araya-Polo, M., J. Jennings, A. Adler, and Dahlke, T. [2018] Deep-learning tomography, *The Leading Edge*, **37**, 58-66.

Choubineh, A., Chen, J., Wood, D., Coenen, F., and Ma. F. [2023] Fourier neural operator for fluid flow in small-shape 2D simulated porous media dataset, *Algorithms*, **16,** 24, https://doi.org/10.3390/a16010024.

Farris, S., Araya-Polo, M., Jennings, J., Clapp, B. and Biondi, B. [2018] Tomography: a deep learning vs full-waveform inversion comparison: *EAGE Workshop on High Performance Computing*.

Lara-Benitez, A. [2022] Deep learning FWI using global operators, presented at the *Machine Learning applications for FWI and Seismic Imaging,* Image 22 Post-Convention Workshop W-7.

Li, Z., Kovachki, N., Azizzadenesheli, K., Liu, B., Bhattacharya, K., Stuart, A., and Anandkumar, A. [2021] Fourier Neural Operator for parametric partial differential operators, arXiv:2010.08895.

Konuk, T. and Shragge, J. [2021] Physics -guided deep learning using Fourier neural operators for solving the acoustic VTI wave-equation, *82nd EAGE Annual Conference & Exhibition*, Extended Abstracts, 1–5.

Shibayama, T., Mizuno, N., Kusano, H., Kinoshita, A., Minegishi, M., Sakamoto, R., Hasegawa, K. and Kachi, F. [2021] Practical deep learning inversion using neural architecture search and a flexible training dataset generator. *82nd EAGE Annual Conference & Exhibition*, Extended Abstracts, 1–5.

Wang, W., F. Yang, and Ma, J. [2018] Velocity model building with a modified fully convolutional network*: SEG Technical Program Expanded Abstracts 2018*, Society of Exploration Geophysicists, 2086-290.