Automated velocity model building using Fourier neural operators

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SUMMARY

We propose a deep-learning strategy based on Fourier neural operators (FNOs) for estimating velocity models from field shot gathers with minimal pre-preprocessing. In contrast with conventional CNN-based architectures based on local operators, FNOs are global convolutional operators efficiently computed in the Fourier domain. We show the advantages of using global FNOs over conventional convolutional neural networks (CNN), to achieve a better non-linear mapping between the recorded data and the subsurface velocity. We show that FNOs can be used to automate velocity model building from field data with minimal preprocessing, as demonstrated by successful inferences on data acquired with multi-sensor technology in offshore Canada.

IINTRODUCTION

Full automation of the velocity model building (VMB) process has been one of the main goals in exploration geophysics. The challenge is to construct high-resolution velocity fields with the minimal pre-processing of the data. Full waveform inversion (FWI) technology has evolved toward this goal by, for example, introducing objective functions capable of minimizing cycle skipping produced by inaccurate initial models. Although with some limitations, these approaches can relax the constraint of kinematically accurate initial models and consequently reduce the turnaround time of the VMB workflow. Likewise, there is in increasing interest in developing deep learning-based algorithms to estimate high resolution velocity fields directly from the shot gathers (Araya-Polo et al, 2018; Wang et al, 2018; Shibayama et al., 2021), and to provide accurate initial background velocity models to input to FWI (e.g., Farris et al., 2018). In general, one of the common features of such approaches is the use of convolutional neural networks (CNN) architectures, which use local convolutional operators.

On the other hand, Fourier neural operators (FNO) were introduced as surrogates of numerical methods to solve partial differential equations (PDE's) (Li et al., 2021). In seismic wave propagation, for example, Yang et al. (2021), Konuk and Shragge (2021) and Li et al. (2022) used them to solve the acoustic wave equation. One of main advantages of such operators is that they efficiently compute global convolutional operators. In addition, they are mesh independent, i.e., the training can be performed in coarser grids than those used in the inferences (Li et al., 2021). In this work, we use an adapted FNO architecture to perform the highly non-linear mapping from recorded shot gathers to subsurface earth acoustic velocity. We use synthetic datasets computed on thousands of velocity and density models. These synthetics are the input to the adapted FNO architecture for determining the optimal neural operator parameters that will be used in the inference phase.

First, we describe the adaptations to the macro and micro design of the FNO architecture. Then we describe the characteristics of the earth models and their respective synthetic data used in the training. Finally, we show a successful application of the trained FNO operator to perform inferences on field data with minimal preprocessing.

METHOD

The original architecture introduced by Li et al. (2021) is modified in its macro design as shown in Figure 1a. First, it was adapted for mapping consistently the different domains in which the input and output data are defined: shot gathers defined in the space-time domain, and the velocity fields defined in the space domain. In addition, convolutional layers between the integral operator blocks were introduced. One change in the micro design (Figure 1b) from the original architecture was in the type of activation functions used. In this adapted architecture, we utilized gaussian error linear unit (GELUS) functions. Lara-Benitez et al. (2023) present the mathematical proof of a similar architecture used to solve the Helmholtz equation.

The first step of our FNO-based VMB workflow consists of generating about 40,000 random velocity models. We build the corresponding density models using Hamilton and Gardner relations. The earth models are stratigraphic layers with different shapes, thicknesses and different velocity and density contrasts. To consider shallow- and deep-water scenarios, a variety of water-bottom depths and bathymetries are considered. We simulate 10 shots for each model using the pseudo analytical method to solve the acoustic wave equation (Ramos-Martinez et al, 2011). In Figure 2, we show sample velocity models and their corresponding simulated shot gathers. A standard streamer survey geometry with a maximum offset of 8 km was considered. A zero-phase source wavelet with frequencies between 3 and 13 Hz was used in the simulations, which include free surface effects. The direct arrival is removed from the gathers. From the full dataset, we use 38,000 earth models and their corresponding shot gathers for training and the other 2000 datasets for the validation stage, which is the second step in the workflow.

In Figure 3, we show the performance of the trained operator during the validation stage for the synthetic datasets not used in the training. As observed, a smoothed version of the true model is well recovered. To validate our results, we compute the structural similarity index, which is displayed in the inferred models. Moreover, we compute RTM angle gathers from the inferred models. As observed, the flatness of the image gathers is almost perfect through all depths.

FIELD DATA INFERENCE

The third step in our workflow is the inference on field data. In the example shown here, we use data acquired with multi-sensor technology in offshore Canada with a maximum inline offset of 8.1 km. Minimal pre-processing to the field data is applied. This consists of direct arrival removal, conversion to zero phase, denoising and filtering in the same frequency bandwidth of the synthetic data used in the training. No multiple attenuation is performed in the data. We show sample shot gathers in Figure 4. Individual inferences for 10 adjacent shots are performed. Then, these individual inferences were merged to construct the velocity model shown in Figure 4.

We validate the results by performing RTM imaging. Figure 5 shows the migrated image that clearly reveals structural features such as the systems of faults above and below the unconformity. Likewise, image gathers are flat throughout the image. This velocity model also can be used as an input for FWI.

CONCLUSIONS

We described a deep-learning VMB workflow that uses an adapted architecture based on FNO operators. We trained our deep learning model using synthetic data representing various geologic scenarios, and inferences were subsequently derived from field shot gathers with minimal preprocessing in nearly real time. We demonstrated the power of using these global operators for successfully mapping recorded shot gathers to a subsurface velocity model on field data acquired in offshore Canada. The inferred macro velocity model is accurate enough to be used for imaging or for FWI. Velocity model inferred from field data was independently validated through RTM imaging. This workflow can lead to a significant reduction in the turnaround time of imaging projects.

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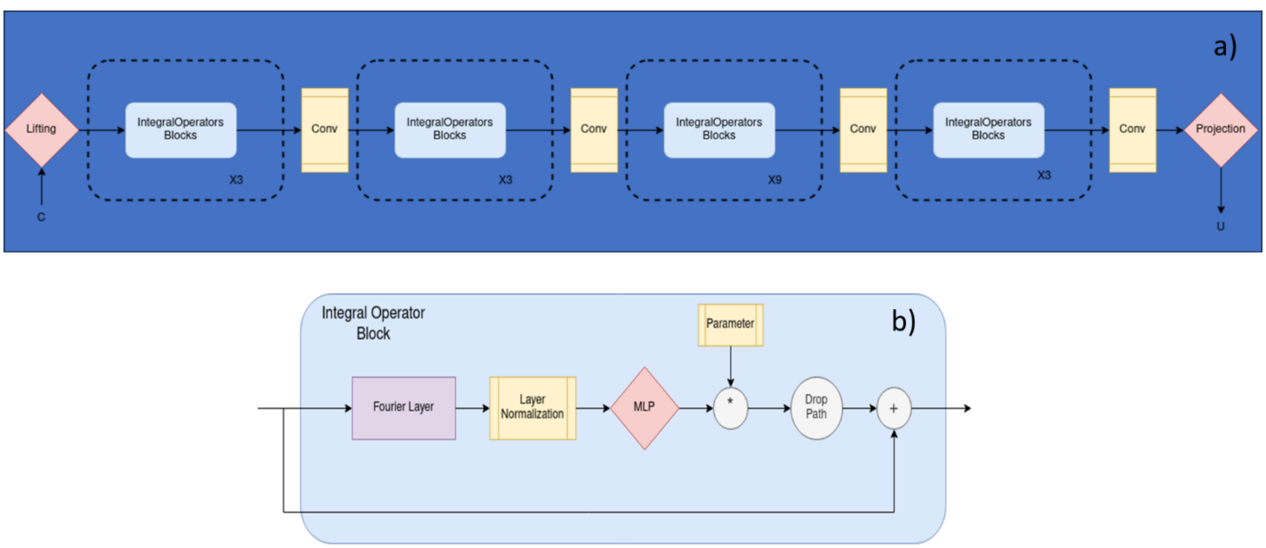

Figure1. a) Macro and b) micro design of the Fourier neural operator architecture used in this work.

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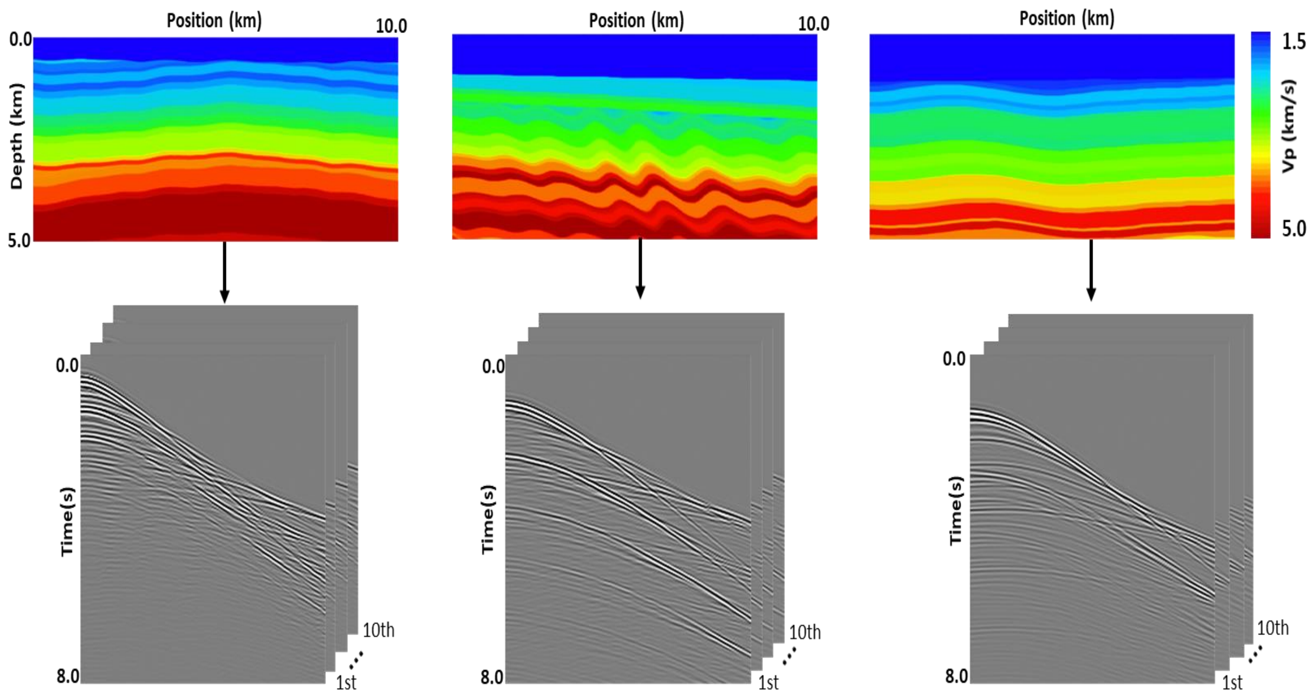

Figure 2. Sample velocity models and their corresponding shot gathers generated for the training stage.

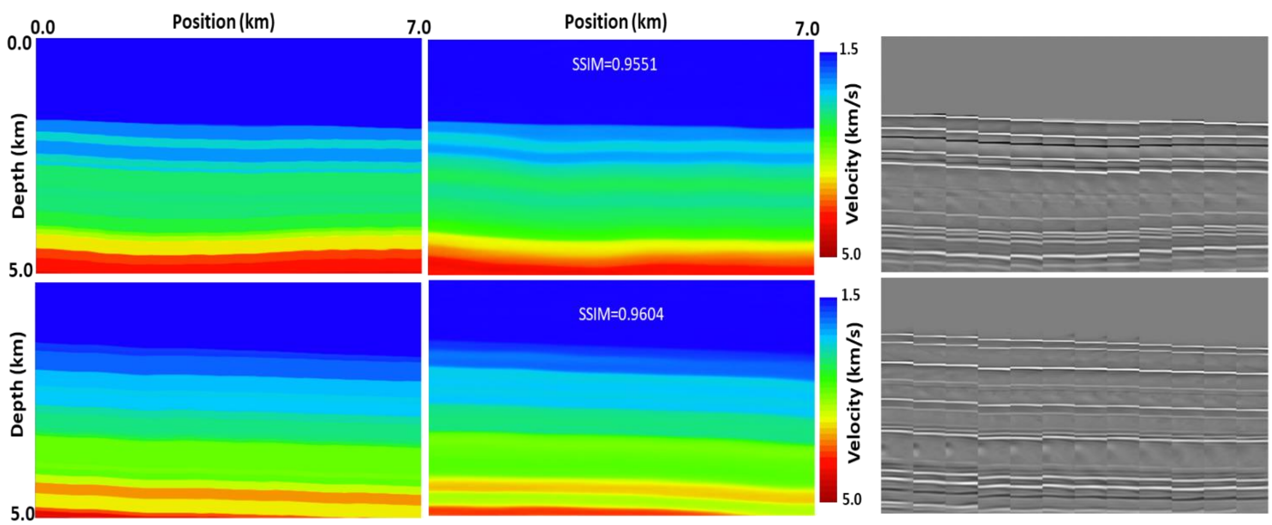

Figure 3. Synthetic data inference: true (left column) and inferred (central column) velocity models from the trained Fourier neural operator. Structural similarity index measure (SSIM) and RTM angle gathers (right column) were used for QC the inferred models.

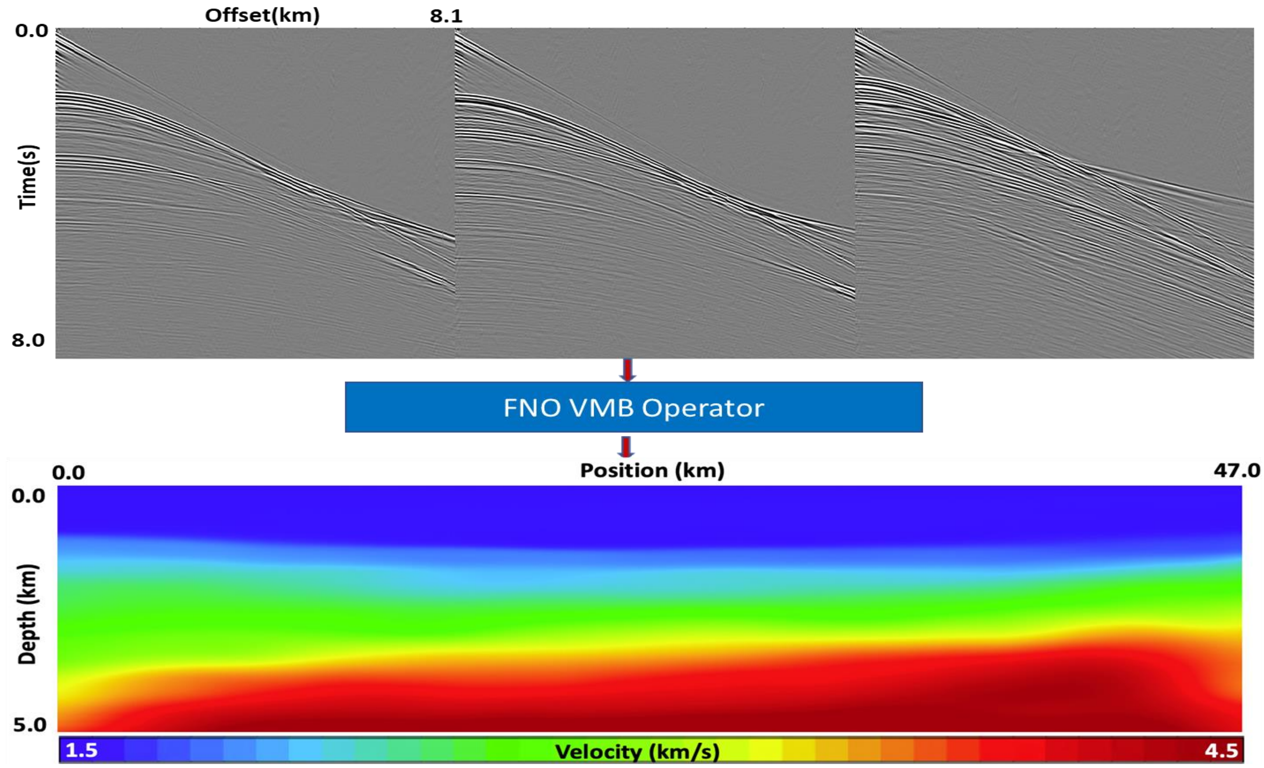

Figure 4. Offshore Canada field data inference: Sample shot records with minimal pre-processing (top panel) are the input to the adapted FNO trained operator. The output is the inferred velocity field (bottom panel).

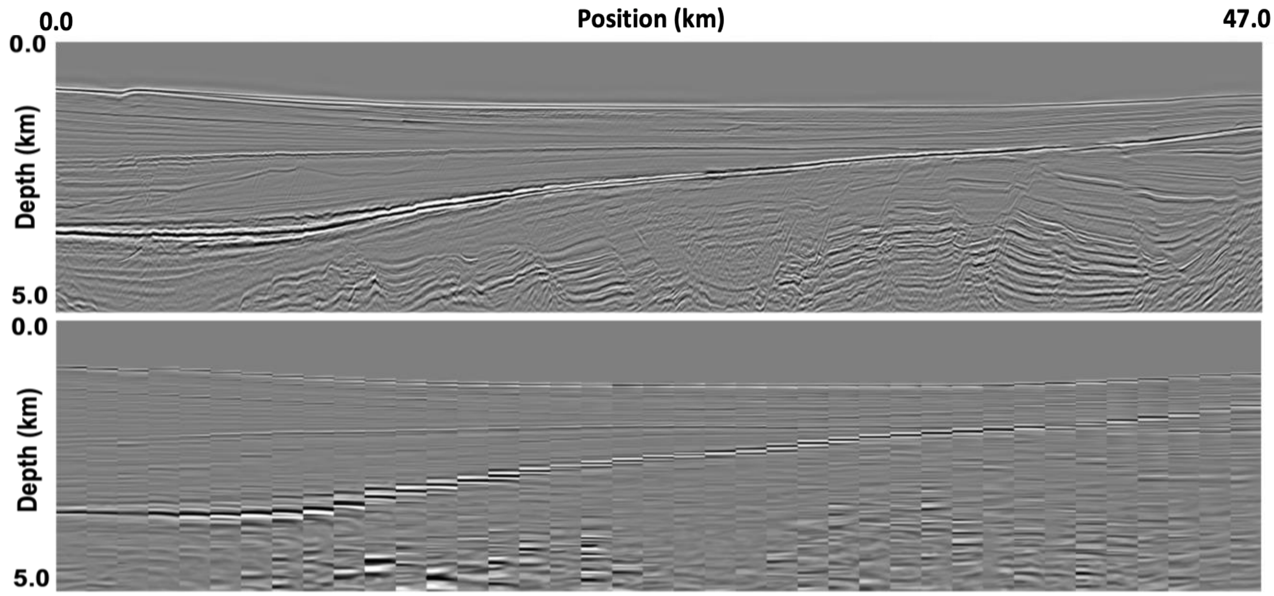

Figure 5. Offshore Canada field data example: RTM image stack (top panel) and angle gathers (bottom panel) computed from the inferred velocity displayed in Figure 4.