High resolution angle gather tomography with Fourier neural operators

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Summary

Velocity model building (VMB) is among the most important problems is exploration geophysics, and it remains a challenge in many areas. An accurate, high resolution earth model is important for good quality images and accurate interpretation, particularly for reservoir characterization.
We introduce a deep learning workflow that uses Fourier neural operators (FNOs) to estimate corrections to velocity models from migrated images. The workflow is akin to traditional migration velocity analysis (MVA), but it uses a neural network in place of a back projection operator. It can iteratively make high-resolution refinements to an incorrect velocity model.

Introduction

There has been significant interest in recent years in using deep learning-based algorithms to estimate high-resolution velocity models directly from shot gathers (Araya-Polo et al, 2018; Wang et al, 2018; Shibayama et al., 2021). Alternatively, Farris et al (2018) use shot gathers to estimate background velocity models intended as input to FWI. Many of these approaches use convolutional neural network (CNN) architectures, which use local convolutional operators. FNOs were introduced as a machine learning method for solving partial differential equations (Li, et al., 2021). They use global convolutions, efficiently computed with FFTs, rather than local operators typically used by convolution neural networks (CNNs). FNOs are regarded as being more able to represent non-linear, non-local operators than CNNs, and are mesh independent (so there is some flexibility to perform inference on a grid that differs from training). Yang et al. (2021), Konuk and Shragge (2021) and Li et al. (2022) used them to solve the acoustic wave equation, and Huang et al. (2023) used them to estimate velocities from input shot gathers.

One of the important details in generalizing neural networks from synthetic training data to field data is noise. Neural networks tend to perform poorly when their training data don't have the features that inference input data do. Park et al. (2023), Takemoto et al. (2019), and others use neural style transfer to make their training data more realistic in terms of noise content. Besides noise, different field data sets will have different, irregular acquisition geometries, which should also be covered by training data sets (or else, some regularizing process should be employed).

In this paper, we present a method using Fourier neural operators to do migration velocity analysis. Rather than go straight from field shot gathers to velocity, we first migrate the data and produce angle gathers. FNOs are a natural fit for an ML-based MVA because the effects of an error in a migration velocity model are generally seen elsewhere in the migrated image, not at the location of the error itself.

Migration regularizes and filters the data, hopefully closing the gap between training data and field data. Additionally, migrated data already occupies the same domain as the target velocity model (plus some kind of angle/extended image axis). An easier problem which should result in an easier network to train. Gather-based migration velocity analysis may be somewhat limited where velocity models are complex, but can still be valuable by relatively quickly estimating a velocity than will take fewer iterations of FWI to finalize.

First, we briefly describe the adapted FNO architecture used and the general workflow to generate synthetic datasets used for the training step. Then, we demonstrate the performance of our approach on the synthetic datasets allocated for the validation stage. Finally, we show a successful inference from field data acquired with multi-sensor technology in Newfoundland, Canada.

Method

The original architecture introduced by Li et al. (2021) is modified in its macro design as shown in Figure 1b. Convolutional layers were introduced between the integral operator blocks. Another change from the original architecture in the micro design was in the switch to Gaussian error linear unit (GELUS) functions as activation functions. Lara-Benitez et al. (2023) present the mathematical proof of a similar architecture used to solve the Helmholtz equation.

To train the network, we first generated 10k synthetic surveys using randomly generated background velocity models, and density models based on Hamilton's and Gardner's relations. We then added randomly shaped geobodies to the models to simulate salt. We modeled the data with an absorbing surface condition, so they don't contain multiples. We then added errors of various sorts and magnitudes to each background velocity model omitting the salt bodies entirely. Then migrated the synthetic surveys using the resulting incorrect velocity models, producing gathers.

We then trained an FNO-based network to find the correct velocity, given the initial model and migrated gathers as input (Figure 2). Each input sample was a set of migrated

gathers and a velocity model, and each target sample was an updated velocity model.

Naturally, a single model can be incorrect in many different ways. Any number of different salt bodies (including none) can be added to a given background velocity. Additionally, testing a trained model produces a (sometimes slightly, sometimes rather severely) incorrect estimate of the velocity, especially when complex salt bodies are included. Each of these tests can also become future training samples. So hypothetically we have an endless supply of training samples. Figure 3 shows an example of a test sample not seen by the network during initial training. A large salt body, missing from the migration velocity model, causes large errors in the initial migration and a poor stacked image. The model is not fully recovered in one pass through the neural network, but the resulting model is much closer to the correct one, and the image is much better. Additionally, the more subtle remaining velocity error forms part of the next generation of training data.

The trained network can naturally be used iteratively. Given a set of migrated gathers, the trained network produces a new velocity model. The updated model can then be used to produce a fresh set of migrated gathers, and so on (Figure 2). Gather-based MVA has its limits, especially when velocities are very complex, but potentially this workflow can provide a relatively inexpensive means to reduce the amount of work left for FWI to do.

Field data inference

We tested the trained network on a portion of a field survey which was acquired offshore Newfoundland, Canada, using multi-sensor streamer technology. The maximum inline offset is about 8.1 km. Standard pre-processing is applied to the data, including multiple suppression. The data were migrated (with a wavelet and frequency band similar to the original synthetic training data) to generate input gathers for the trained network and remigrated a few times after subsequent model updates.

The initial model, and the model after three iterations, are shown in Figure 4. The initial model is converted from a time migration model. It is very smooth and not very accurate, judging from the residual moveout, which is ubiquitous and strong. After three iterations of migration and update, the model is much more detailed and the gathers flatter. The updates were masked in the water column at each iteration.

Conclusions

We introduce a novel approach to estimate high-resolution velocity models from migrated gathers using Fourier neural

operators. In contrast with deep-learning algorithms that estimate velocity directly from shot gathers, our approach takes advantage of the fact that migrated data and velocity models share the same domain. This facilitates generalization from training with synthetic data to field data inferences. Moreover, the extended domain (e.g., angle) provides a natural lifting, which contains extra physical information that eventually improve the robustness of the estimation of velocities. We demonstrate the effectiveness of our approach on field data acquired in offshore Canada. This approach might be an alternative approach to FWI or in complex cases (e.g., salt settings) a provider of a good starting model for FWI.
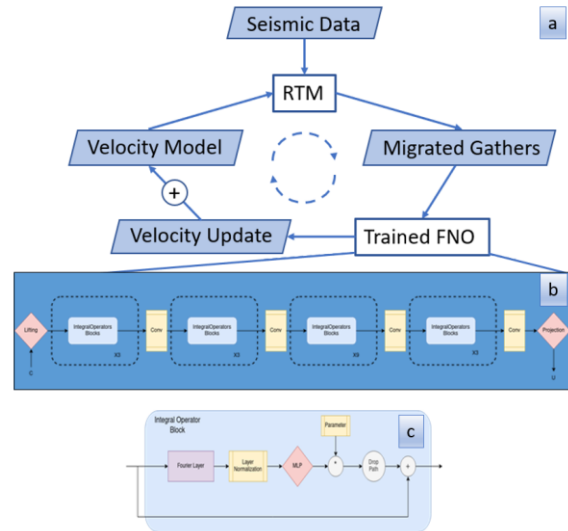

Figure 1: Migration velocity analysis (MVA) loop (a), with velocity update performed by a trained FNO-based neural network (b), rather than back projection of picked residual moveouts, or similar traditional gather-based MVA operations. The macro design (b) of the network is adapted by the addition of convolution blocks between integral operator blocks.
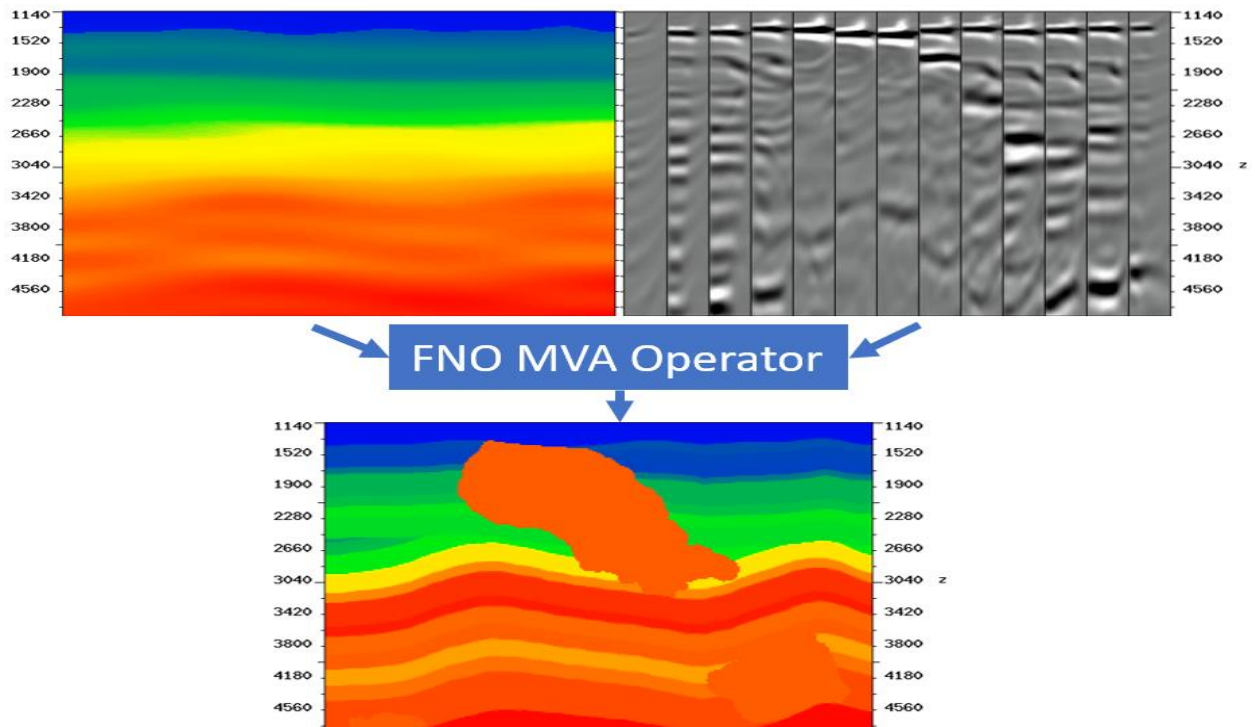
Figure 2: During training, erroneous velocity models and resulting gathers are input, with correct velocity models as the targets
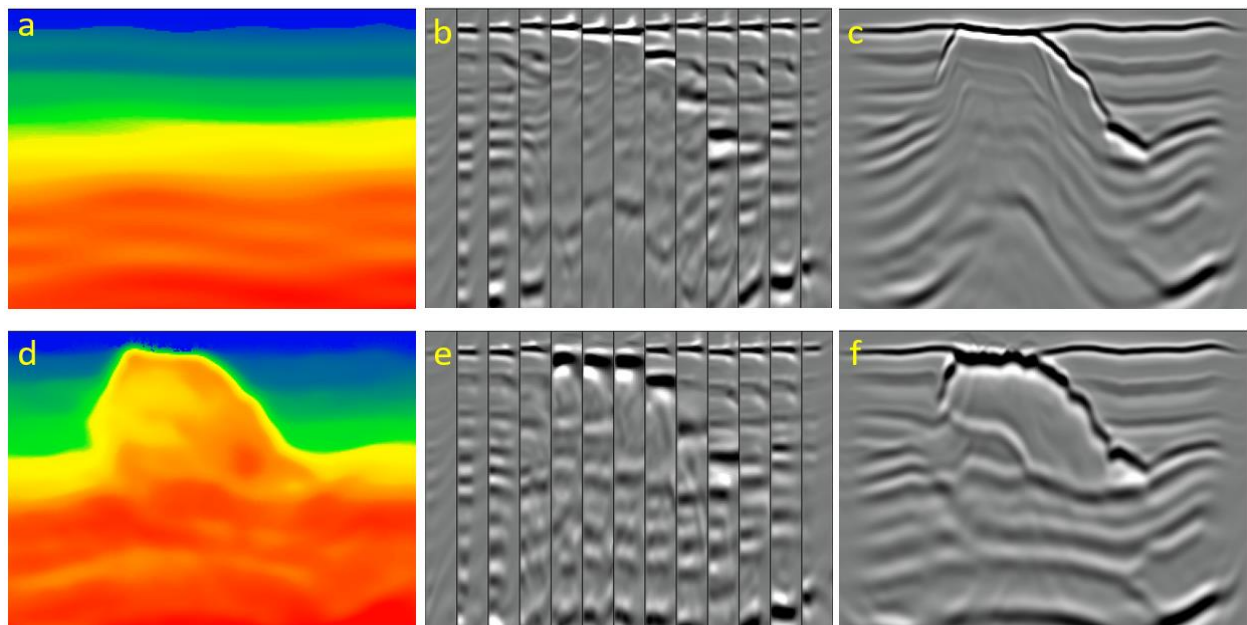

Figure 3: Evaluation sample not included in training. Initial velocity (a) and gathers (b) are inputs to the network. The stack (c) is for illustration. The trained network produces model estimate (d). Migration with the estimated model produces much improved (though still not perfect) gathers (e) and stack (f), included for comparison. Model (d) and gathers (e) may become part of additional training.
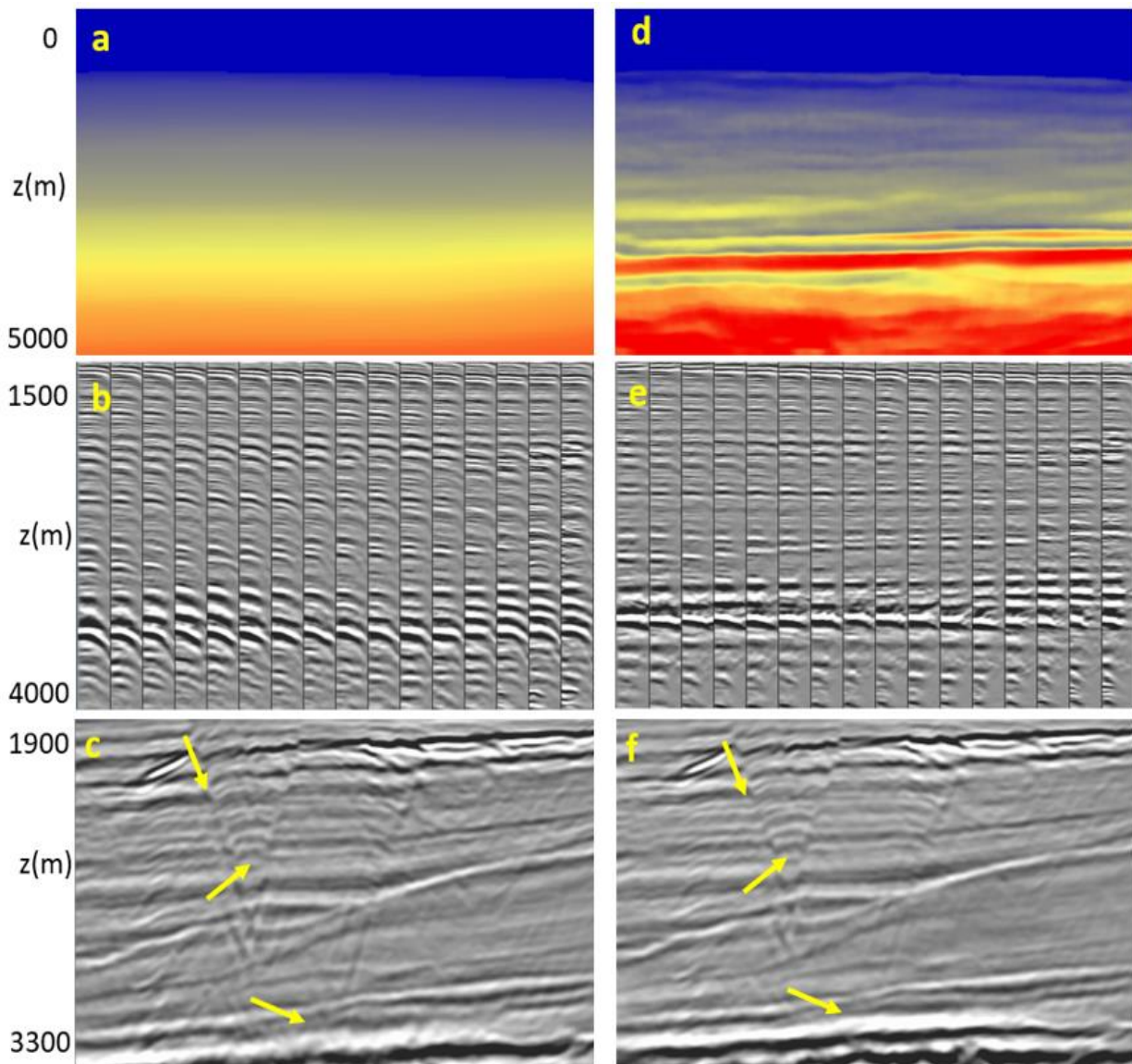
Tomography with Fourier neural operators

Figure 4: Field data test. Starting model (a), zoomed portion of initial migrated gathers (b), and stack (c); updated model after 3 iterations (d), and corresponding zoomed gathers (e) and stack (f). Arrows indicate layers and faults that appear better focused after the update.