Shortening turnaround time for high-resolution velocity model building with deep learning

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Summary

We introduce a method using Fourier neural operators to rapidly generate a high-quality starting model for FWI or joint inversion. Instead of directly moving from field shot gathers to velocity, we migrate the data to produce angle gathers. Our approach leverages the simplicity of mapping within the model space and the reduced variety of data features in migrated angle gathers, making it easier to train a neural network. This gather-based migration velocity analysis is valuable for quickly estimating a starting velocity, leading to fewer FWI iterations in finalizing the velocity model. We showcase a successful inference derived from 3D, full azimuth field data collected offshore Brazil using ocean-bottom nodes. A few iterations of low-frequency RTM were sufficient to go from a featurelessly smooth model to one which had the 3D structure of the salt mostly defined, and shallow and deep sediments approximately corrected. In complex settings (e.g., salt), this could be a valuable tool for rapidly generating a model suitable for input to FWI.

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Introduction

In recent years, there has been an increasing interest in the application of deep learning-based algorithms for estimating seismic velocity models. This includes the direct conversion of input shot gathers into high-resolution velocity models, as discussed by Araya-Polo et al (2018) and Shibayama et al (2021), among others. Alternatively, background models, designed for use in Full Waveform Inversion (FWI), can be obtained directly from shot gathers, as indicated by Farris et al (2018), or through a combination of data attributes and well information, as explored by Mohamed et al (2023).

Several approaches in this domain leverage convolutional neural network (CNN) architectures, incorporating local convolutional operators. Notable alternatives include transformers (Wang et al., 2023) and Fourier neural operators (FNOs) (Huang et al., 2023). This study specifically focuses on Fourier neural operators (FNOs), initially introduced as a machine learning method for solving partial differential equations (Li et al., 2021). Unlike CNNs, which utilize local operators, FNOs employ global convolutions efficiently computed with Fast Fourier Transforms (FFTs). FNOs are recognized for their capability to represent non-linear, non-local operators more effectively than CNNs. Moreover, they demonstrate mesh independence, allowing flexibility in performing inferences on grids different from the training grid. Previous works by Yang et al. (2021) and Konuk and Shragge (2021) applied FNOs to solve the acoustic wave equation, while Huang et al. (2023) used them for velocity estimation from input shot gathers. Given their ability to capture non-local effects and mesh independence, FNOs are well-suited for Machine Learning-based Migration Velocity Analysis (MVA). This suitability arises from the fact that errors in a migration velocity model typically manifest elsewhere in the migrated image, rather than directly at the location of the error itself.

One of the common challenges in working with neural networks is ensuring their effective generalization from training data to real-world field data. Neural networks often struggle when faced with input data features that are not present in their training set. Synthetic training data is employed to ensure accurate labels during training. However, field data introduces complexities such as noise, irregular acquisition geometry, and unmodeled physics. To enhance the realism of training data, Park et al. (2023) and others employ neural style transfer, particularly focusing on noise content. In contrast, our approach takes a different path by migrating the data before feeding it into the neural network. Migration serves to regularize and filter the data, potentially narrowing the disparity between training data and field data. Naturally, we continue to introduce diverse types of noise to the migrated training datasets, alongside augmenting the data through filtering and scaling, similarly to the approach employed by Klochikhina et al. (2021). Moreover, migration involves mapping the data into identical physical coordinates as the velocity model, incorporating additional aspects like angles and extended image axes, providing a natural lifting effect. A neural network aiming to derive an earth model directly from seismic data must understand the mapping between data space and model space. We anticipate that keeping the mapping within the model space, utilizing defocused images and residual moveouts to generate velocity updates, presents a more manageable task for the neural network to perform.

We introduce a method using Fourier neural operators to rapidly generate a high-quality starting model for FWI or joint inversion. Instead of directly moving from field shot gathers to velocity, we migrate the data to produce angle gathers. Our approach leverages the simplicity of mapping within the model space and the reduced variety of data features in migrated angle gathers, making it easier to train a neural network. This gather-based migration velocity analysis is valuable for quickly estimating a starting velocity, leading to fewer FWI iterations in finalizing the velocity model.

First, we provide a brief overview of the adapted FNO architecture and the workflow for creating synthetic datasets employed in the training process. Then, we showcase a successful inference derived from 3D, full azimuth field data collected offshore Brazil using ocean-bottom nodes. The inherent redundancy in the data allows for effective ensembling of the 2D inferences.

Method

The basic workflow and architecture are described in Crawley et al (2023). The original architecture introduced by Li et al. (2021) is modified by the addition of convolutional layers between integral operator blocks, as shown in Figure 1. Lara-Benitez et al. (2023) present the mathematical proof of a similar architecture used to solve the Helmholtz equation.

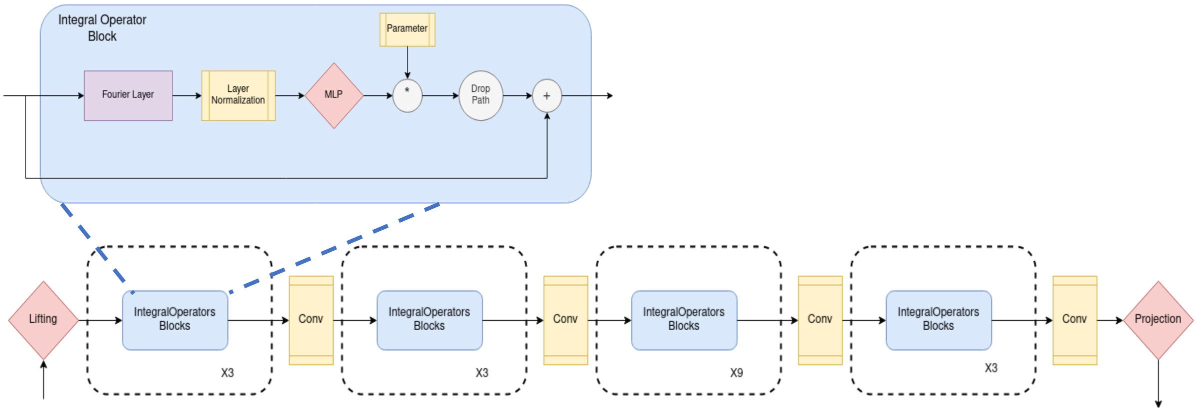

Figure 1 *Macro design of adapted FNO architecture.*

To train the network, we first generated 10,000 synthetic surveys with randomly generated background velocity models and density models based on Hamilton's and Gardner's relations. Some of the models were augmented with randomly shaped geobodies to simulate salt. Errors of various types and magnitudes were introduced to each model. The synthetic surveys were subsequently migrated using the resulting incorrect velocity models, producing gathers. We augmented the gathers by adding noise, filtering, and scaling in depth. We then trained an FNO-based network to determine the correct velocity based on the initial model and migrated gathers as input. Each input sample comprised a set of migrated gathers and a velocity model, while each target sample represented an updated velocity model.

The trained network lends itself to iterative use. When provided with a set of migrated gathers, it generates a new velocity model. This updated model is then employed to generate a fresh set of migrated gathers, creating a recursive process. Furthermore, applying the trained model to additional synthetic data yields a velocity estimate, which may still be inaccurate to varying degrees. Migrating with these estimates generates additional training samples, contributing to the refinement of the network.

3D offshore Brazil example

We applied the trained model to an ocean bottom node survey conducted offshore Brazil in the Santos Basin area. Leveraging a high-quality legacy velocity model for the region, we generated a starting model through extensive smoothing, retaining only the water bottom. Consequently, the resulting starting model resembles a v(z) model hanging from the water bottom. Subsequently, three iterations of Reverse Time Migration (RTM) and velocity model updates through inference were conducted. Figure 2 displays a crossline slice from the starting model (Figure 2a), the inferred result (Figure 2b), and the legacy model (Figure 2c), alongside the corresponding portion of the image. The initial model exhibits significantly higher velocities in the shallow regions compared to the legacy model (Figure 2c) and lacks fine details. After a few iterations, our result (Figure 2b) largely corrects the shallow velocities and captures the salt formations. It deviates from the legacy model in the very deep section, beyond the last events captured in the image (Figure 2d), where gathers lacked any informative content.

The field data consisted of 3D OBN data, whereas the training data were fixed spread 2D data. Consequently, we selected inline and crossline images, along with angle gathers from the appropriate azimuth, and input them into the trained network. This yielded two volumes of inferences, exhibiting some expected differences, and displaying noise perpendicular to the slicing direction of the inference. Employing total variation denoising to combine azimuths during each iteration resulted in a single updated model. Depth slices through the top of salt are presented in Figure 3. The merger of multiple azimuths and iterative denoising successfully reconstruct structures in the velocity that are diagonally oriented relative to the imaging grid. While there is room for further improvement, the inferred velocity model is very suitable for input into FWI. The compute cost of the exercise was very modest—only one low-frequency RTM per iteration. Inference and denoising processing incurred negligible costs. However, the implicit assumption in updating a 3D model through 2D slices remains a topic for future work.

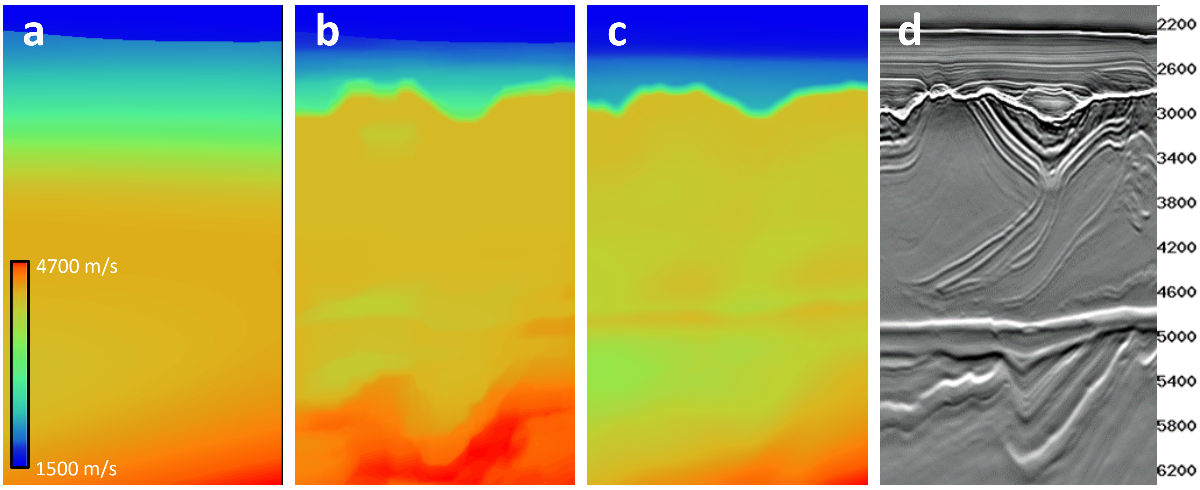

Figure 2 *Crossline slice showing performance of the neural network on the 3D Brazil example. The starting model (a, with the velocity scalebar overlaid) is an aggressively smoothed version of the legacy model (c). The result after three iterations (b), is partially though not perfectly corrected in the shallow sediments and salt. The deepest part of the section diverges somewhat, but this occurs below the bottom-most significant events in the migrated data (d).*

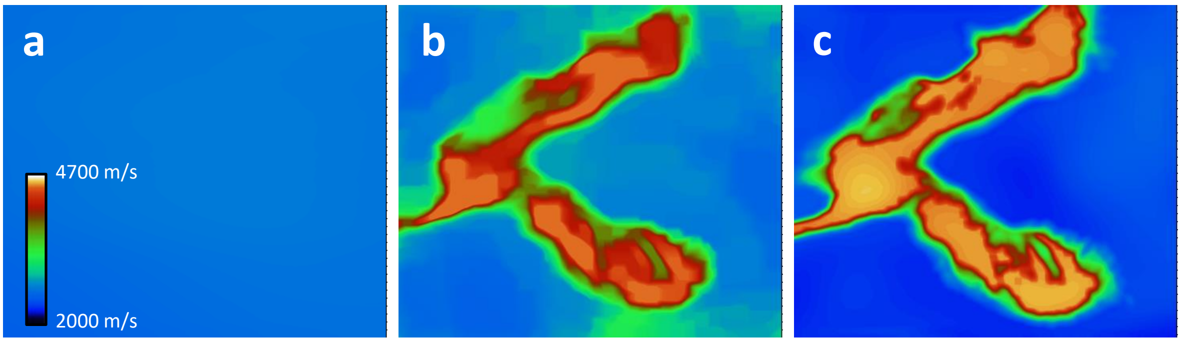

Figure 3 *Depth slice showing performance of the neural network on the 3D Brazil example. The starting model (a, with the velocity scalebar overlaid) is nearly v(z) and doesn't contain any detail. The result after three iterations (b) is imperfect but has the structure and approximate values of the legacy model (c). The next step is to refine this model with FWI.*

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 field data, our method leverages the shared domain between migrated data and velocity models. This facilitates generalization from training with synthetic data to field data inferences. Moreover, the extended domain (e.g., angle) provides a natural lifting, incorporating additional physical information that enhance the robustness of the velocity estimation. We demonstrate the effectiveness of our approach on field data acquired in offshore Brazil. A few iterations of low-frequency RTM were sufficient to go from a featurelessly smooth model to one which had the 3D structure of the salt mostly defined, and shallow and deep sediments approximately corrected. In complex settings (e.g., salt), this could be a valuable tool for rapidly generating a model suitable for input to FWI.

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