Velocity model estimations with deep learning – field data examples with a Fourier neural operator network.

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Summary

We have trained a deep neural network based on Fourier Neural Operators (FNOs) to replace the traditional tomographic inversion engine and successfully performed velocity predictions on field datasets. Our implementation does not require residual move-out picking, masking, or interpretation work. We demonstrate how FNO network predictions can condition the initial Full Waveform Inversion (FWI) model by reducing cycle-skipping, building a structurally consistent model directly from a 1-D function, and effectively replacing passes of reflection tomography. The results suggest that this could be a powerful tool in accelerating the velocity model building (VMB) sequence.

The key elements of this work include the operator training, iterative image domain implementation, and the considerably large dataset seen by the network. We also discuss why this approach could potentially converge faster, utilize more information than traditional tomography engines, and mitigate limitations of ray-based methods in high-contrast environments.

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Introduction

Velocity model building is a complex and time-consuming process that often requires highly experienced geophysicists with several years of expertise in technologies such as Full Waveform Inversion (FWI), various forms of depth imaging, and tomography. While FWI is a powerful tool for constructing accurate velocity models, its success heavily depends on the quality of the initial velocity model, as well as the presence of rich low frequencies and long offsets in the data

In this paper, we explore the potential of utilizing deep learning to condition the initial FWI model and to reduce the reliance on conventional tomography in a model building project. The network is based on Fourier neural operators (FNOs), connected with convolutional neural networks (CNNs). The FNOs facilitate global representation and non-local feature detection, which are attractive properties in a Velocity Model Building (VMB) context. Using field data examples from different basins, we demonstrate the potential of this technology to accelerate and improve the VMB sequence.

Motivation

Although the motivation for this work is mainly to assist and accelerate the VMB sequence, deep learning also has the potential to understand and handle the data differently and mitigate limitations with conventional model building tools like reflection tomography and FWI.

In reflection tomography we use residual move-out picks (RMO) combined with a priori information to guide the velocity updates, but we know that flat gathers do not guarantee a correct velocity model. Information like un-collapsed diffractions and event crossings in the common angle/offset domain also carries important information about the velocity errors. We also know that ray-based methods are not suitable in high contrasts mediums, so standard methods may require special handling and/or interpretation work to deal with geobodies or other non-smooth features. On the other hand, FWI is general enough to handle these complexities, but it comes with a high compute cost when high-frequency elastic modeling is a requirement. In addition, both FWI and tomography linearize the highly nonlinear inversion problem by taking small steps in the direction of the gradient. Consequently, many iterations will be required before the inverse problem has been resolved.

In this work, we utilize a deep neural network trained as a tomographic back projection operator, effectively replacing the traditional tomographic inversion engine. The network is trained with the migrated gathers alone, without using any RMO or horizon picks, salt masks, etc., to find a wide variety of smooth and sharp velocity features. Because the network is tuned to recover the true velocity model from various incorrect model realizations, it has the potential to convergence faster and to introduce larger velocity updates compared to reflection tomography and FWI. In addition, it opens the possibility to train the model with different types of data, etc. data with multiples, to further accelerate the VMB sequence.

Methodology

The network comprises a series of integral operator blocks (IOBs) connected with CNNs. Unlike CNNs, IOBs facilitate the learning of long-range dependencies in the data. The introduction of FNOs has enabled non-local feature detection, global representation and mesh independence. These neural operators have shown significant promise in solving complex and computationally expensive equations, such as partial differential equations (Li et al., 2021).

Initially, our training process aimed to map velocity errors directly from data to the image domain (Huang et al., 2023). More recently, we have focused on: 1) modifying the network to map velocity errors within the image domain, and 2) extending the training process by generating and processing more labeled data. These modifications have resulted in a solution that inputs depth migrated gathers along with the corresponding velocity model and outputs the required predicted velocity update (Crawley et al., 2024). Figure 1 illustrates the micro and macro network design.

The first step in the forward propagation of the IOB is to lift the data, increasing its dimensionality through a fully connected network (v(x)). This is followed by a forward Fourier Transform (FT) and an inverse transform of the most energetic wave modes. A version of the data is also passed outside the FT path and added before an activation function completes the FNO layer. The data is then normalized and passed to another fully connected network, the Multilayer Perceptron (MLP). We use dropout and skip connections as regularization strategies, enabling us to increase the depth of the trainable neural network, which is essential to learn these complex operators. A series of IOBs are connected with CNNs before the final predictions are made with another MLP.

The image-to-image domain mapping reduces the data dimensionality that the network must handle, potentially simplifying the learning process. The network has been trained on synthetic 2-D data from approximately 50,000 different velocity models of various geologies, including salt bodies and slow velocity anomalies of different shapes and sizes. Data augmentations have been applied to introduce variations in water depth, velocity ranges, and different degrees of velocity errors. Our strategy has been to build this as an interactive workflow. This approach aims to minimize the impact of variations in acquisition design on the gathers and reduce the geological variations the network must process. In our implementation the predicted velocity model from the first pass is used in a new migration process, forming the input for the second pass of predictions. The number of iterations required depends on the complexity of the problem, but experience shows that 2-5 iterations are sufficient to resolve the macro model.

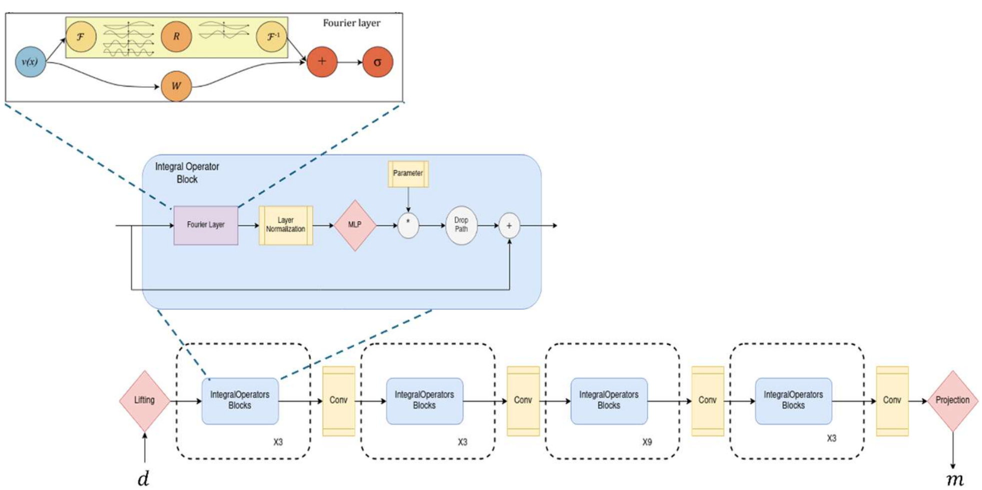

Figure 1 *This shows the network architecture, consisting of a series of IOBs and CNNs. The FNOs facilitate the learning of long-range dependencies in the data.*

Field data examples

The first field data example is from the Norwegian Sea over the Outer Vøring basin. This area has large velocity variations, but it also generally provides a good seismic reflectivity response. We selected an area of 800 km² from a newly acquired multi-component streamer acquisition for the FNO network predictions. The starting velocity model was a simple 1-D gradient hanging from the water bottom. Figure 2a and 2b shows the initial velocities and the corresponding migrated angle gathers. Figure 2c and 2d show the results after two iterations of FNO network predictions. One can clearly see the overall improvements in gather flatness as well as a good structural consistency with the updated model, shown with the image overlaid. The deeper high-velocity features are volcanic intrusions and sills that been recognized by the FNO network. Figure 3 shows the validation in the data-domain at 9Hz. In this case make use of a vector-reflectivity modeling engine (Whitmore et al., 2020) to generate the full wavefield from the two models and interleave the results with the observed data. The events are overall kinematically better aligned after the FNO network predictions and illustrates the potential of this tool to condition the initial velocity model for FWI. In practice, the FWI process would start much lower in frequency than 9Hz.

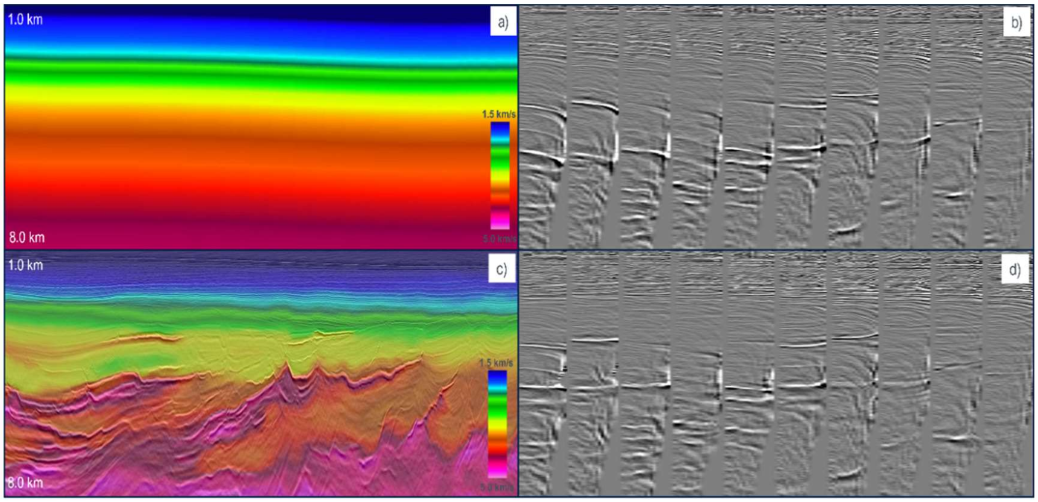

Figure 2 *Initial velocity model with corresponding migrated angle gathers in a) and b). Results after two iterations of FNO network predictions in c) and d). Notice the overall improvements in gather flatness achieved with the deep neural network and the structural consistency of the updated velocity mode, highlighted with stack overlay.*

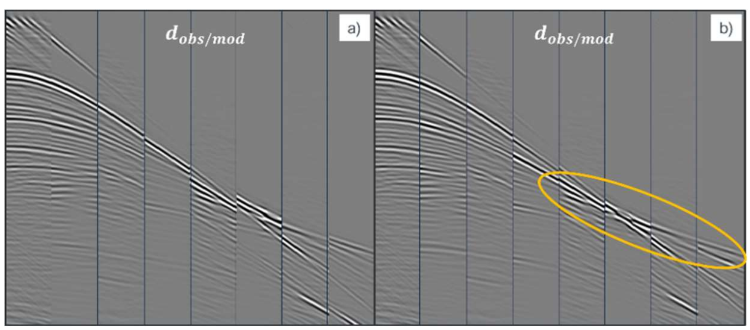

Figure 3 *Forward modeling QC of interleaved observed and model data with the initial velocity model a) and after two iterations of FNO network predictions in b). Notice the improvements in the data-domain, with better kinematic alignments (yellow ellipse).*

The next example is from the Agung area, a geologically complex region north of Bali influenced by the subduction of the Indo-Australian Plate. This area is part of the Sunda volcanic arc and is characterized by significant tectonic activity, including compressional thrust faulting and volcanism related to subduction. The basin is highly deformed and faulted. Carbonates are the primary reservoir rocks in the Agung area, and the ability to identify volcanic rocks from carbonates in seismic data is crucial for exploration. In 2023, a newly acquired marine streamer dataset (10 km offset) provided a high-quality seismic dataset to improve the imaging of carbonate reservoirs and distinguish them from the volcanic rocks present in the area. Figures 4a and 4b show the initial and updated models after two iterations of FNO network predictions. The initial velocity model was partially derived from a multi-client VMB sequence, which included tomography, low-frequency (8 Hz) acoustic FWI, and an initial basement interpretation. This model began to identify higher velocities where volcanic sills are present, however the FNO-predicted model significantly improves the insertion of considerably higher velocities where expected. The yellow arrow indicates a possible sill, delineating it from the underlying structure, and the velocities (yellow dashed arrow) now more accurately follows the thrust structure. At the black arrow, the updated model delineates possible volcanics more effectively. Figures 4c and 4d show the RTM imaging of the initial and updated velocity models. The area beneath the volcanic activity causes distortions in the initial image, while the basement structure becomes better focused after the FNO predictions (orange ellipse).

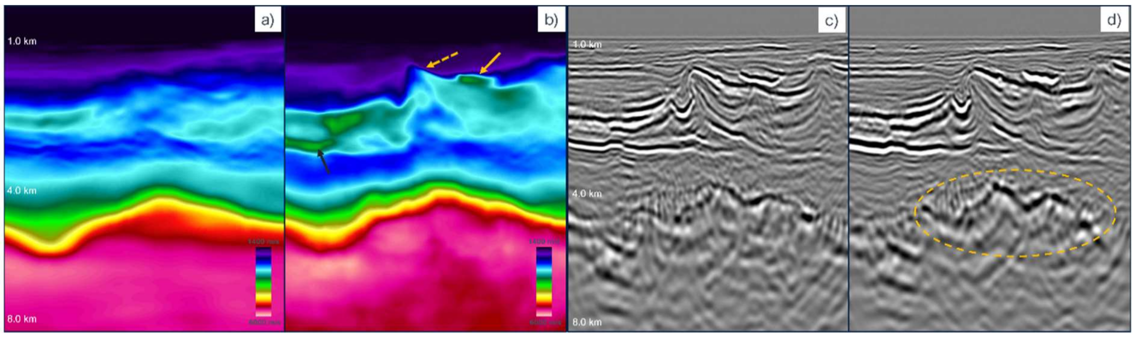

Figure 4 *Initial a) and updated b) velocity model from the FNO network prediction. Notice the structural consistency and the large-scale velocity updates (+/-800 m/s) achieved in only two iterations. The arrows points at sills and volcanic intrusions introduced with the FNO network predictions. RTM images of the initial and updated model can be seen in c) and d). The yellow ellipse in d) shows how the basement structure starts to come through after resolving more of the overburden complexity.*

Conclusions

In this work, we have demonstrated how deep learning can be utilized in VMB projects to condition the initial FWI model by reducing cycle-skipping and constructing a geologically consistent and sensible velocity field. Furthermore, we have shown that just a few iterations of network predictions can assist tomographic updates and significantly improve the image. The process does not require any RMO picking, interpretations, or special handling of sharp high-velocity contrasts. The network is based on FNOs, which facilitate the learning of long-range dependencies in the data, enabling it to map velocity errors independently of where the effects of the velocity error are observed. Although the results are encouraging, the prediction process should not be treated as a black box. Model validation remains critical, and it is important that predictions are made on datasets within the distributions seen by the network.

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References

Crawley, S., G. Huang, R. Djebbi, J. Ramos-Martinez, and N. Chemingui, 2024, Shortening turnaround time for high-resolution velocity model building with deep learning: 85th Annual International Conference and Exhibition, EAGE, Extended Abstracts.

Huang, G., S. Crawley, R. Djebbi, J. Ramos-Martinez, and N. Chemingui, 2023, Deep learning velocity model building using Fourier neural operators: 84th Annual International Conference and Exhibition, EAGE, Extended Abstracts.

Li, Z., N. Kovachki, K. Azizzadenesheli, B. Liu, K. Bhattacharya, A. Stuart, and A. Anandkumar, 2021, Fourier neural operator for parametric partial differential operators: arXiv preprint, doi:https://doi.org/10.48550/arXiv.2010.08895.

Whitmore, N., Ramos-Martinez, J., Yang, Y. and Valenciano, A.A. [2020] Seismic modeling with vector reflectivity. *81st Annual International Meeting, SEG, Expanded Abstracts.*