Accelerating Velocity Model Building in Frontier Exploration Using deep neural network

Jyoti Kumar, Mark Roberts, Oystein Korsmo; TGS

Introduction

Velocity Model Building (VMB) is a critical and time-intensive component of seismic imaging workflows, requiring significant expertise in Full Waveform Inversion (FWI), tomography, depth imaging, and geological interpretation. While FWI enables the construction of high-resolution velocity models, its effectiveness is strongly dependent on the quality of the initial model, which is often poorly constrained in frontier exploration settings and may rely on limited legacy data. This reliance on extensive manual intervention introduces inefficiencies and bottlenecks in the VMB process.

In this study, we present a pragmatic deep learning–based workflow designed to generalize across unseen field datasets and significantly reduce VMB turnaround time. The proposed approach targets three key components of the workflow: estimation of a robust initial macro-velocity model, automated picking of complex water-bottom horizons, and replacement of conventional tomography and interpretation steps to condition the initial FWI model. The deep learning approach, to obtain the initial FWI model, integrates Fourier Neural Operators (FNOs), convolutional neural networks (CNNs), and fully connected neural networks (FCNs) to estimate velocity errors in the image domain. We validate the approach using multiple field data examples from different sedimentary basins worldwide including the Agung area located north of Bali.

Methodology

The proposed strategy employs specialized Convolutional Neural Networks (CNNs) and hybrid deep learning architectures, incorporating both self-supervised learning and physics-based fine-tuning, to automate and accelerate key steps in the velocity model building (VMB) workflow.

In first step, to reduce the reliance on legacy velocity model a CNN is employed to estimate root-mean-square (RMS) velocity (Dix velocity) in a fully self-supervised manner, without the need for labelled training data, providing a robust initial model for subsequent tomography or migration velocity analysis (MVA). The loss function jointly minimizes differential semblance and maximizes stack power, with additional total variation and smoothness regularization to ensure geologically plausible results. In the next step, the proposed method employs a 3D convolutional neural network (CNN) to automatically interpret water-bottom by segmenting it from the subsurface, taking advantage of the enhanced spatial and contextual learning capabilities of 3D ML models to handle complex geological scenarios. Specifically, we utilize the same 3D-VNet architecture, input context, and data augmentation strategy described by Roberts et al. (2024).

The final challenge focuses on the iterative model updating phase required to obtain a velocity model sufficiently accurate for FWI. We implement a deep neural network as a tomographic operator, effectively replacing the conventional reflection tomography. The network combines FNOs with CNNs (Crawley et al., 2024; Korsmo et al., 2025) and is trained solely on migrated gathers, without reliance on residual moveout (RMO) or horizon picks. This enables the network to robustly identify both smooth and high velocity geo-bodies, streamlining the velocity model building workflow and improving initial FWI model quality.

Results

The example presented is from the Agung area, located north of Bali, a geologically complex region influenced by subduction of the Indo-Australian Plate. The basin is highly deformed and faulted, with carbonate units forming the primary reservoir targets. In this setting, reliable discrimination between volcanic rocks and carbonates in seismic data is critical for exploration. Figures 1a and 1b show the initial and updated velocity models with overlaid RTM images, while Figures 1e and 1f present corresponding depth slices at 3 km. The cumulative velocity updates are shown in Figures 1c and 1g, and the RTM images alone in Figures 1d and 1h. The workflow introduces high-velocity geobodies consistent with volcanic intrusions and sills (yellow arrows). Imaging beneath volcanic units is distorted in the initial model but significantly improved after updating, with enhanced basement focusing highlighted by the orange ellipse.

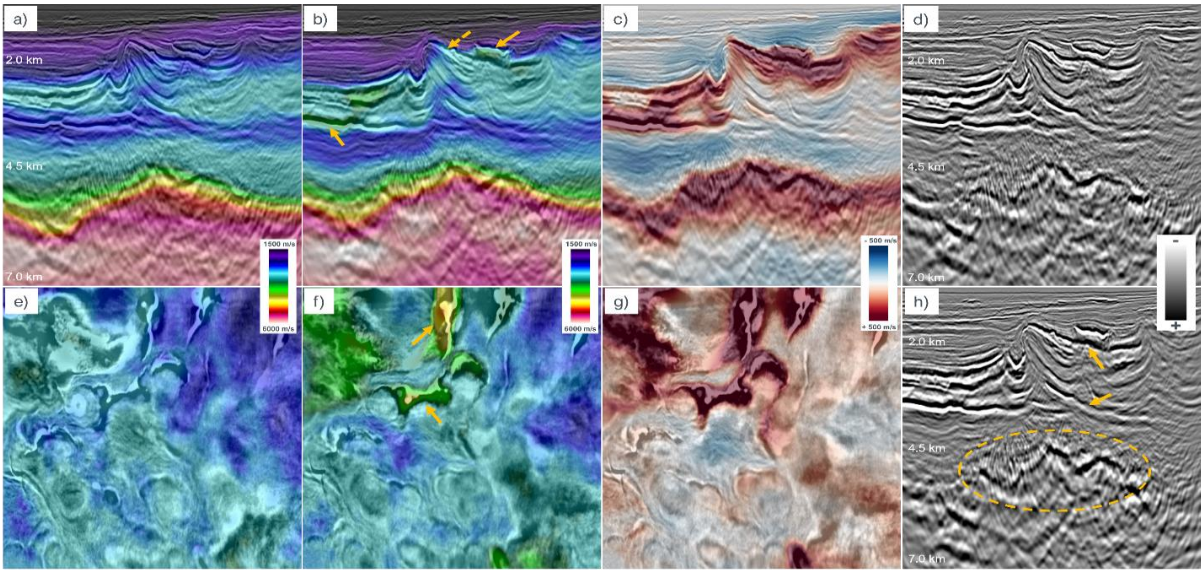

Figure 1. Cross section of initial a), updated model b) and accumulated velocity difference c) with image overlay. Depth slice at 3km using initial e), updated model f) and accumulated difference g). d) and h) are corresponding RTM image.

Conclusions

We address three key time-intensive challenges in the VMB —initial velocity estimation, water-bottom segmentation in complex settings, and iterative model updating—using advanced machine learning techniques. The integrated workflow rapidly delivers high-quality starting models for FWI. This methodology eliminates reliance on RMO picking, interpretive inputs, and special handling of sharp high-velocity contrasts for building initial model for FWI.

Acknowledgments

We would like to thank TGS for the permission to present this work and our colleagues at TGS for their valuable contributions and discussions.

References

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

Korsmo, Ø., Crawley, S., Pankov, A., Valler, V. and Chemingui, N. [2025]. Velocity model estimations with deep learning – field data examples with a Fourier neural operator network. 86th EAGE Annual Conference & Exhibition, Extended Abstracts.

Roberts, M., Warren, C., Lasscock, B., and A. Valenciano [2024]. 3D CNN for Salt Segmentation: Enhancing Continuity and Generalization. *85th EAGE Annual Conference & Exhibition, Extended Abstracts*.