Accelerating Velocity Model Building in Frontier Exploration through Self-Supervised and Physics-Based Deep Learning

Introduction

Velocity Model Building (VMB) is traditionally a complex and time-consuming process that requires highly experienced geophysicists skilled in technologies such as Full Waveform Inversion (FWI), various forms of depth imaging, geological interpretation and tomography. While FWI is a powerful tool for constructing accurate velocity models, its success is often heavily dependent on the quality of the initial velocity model. Furthermore, in frontier exploration areas, a robust initial model is generally unavailable, sometimes relying only on legacy 2D data. This reliance on extensive human intervention and the inherent difficulty of acquiring accurate initial models creates bottlenecks in the VMB sequence, which deep learning methods are well-positioned to address.

The application of Machine Learning techniques to the task of Velocity Estimation has a long history (e.g. Roth & Tarantola (1994), Calderon-Macias et al (1998) and Araya-Polo et al (2018)). This study seeks to close the gap between aspirational work and pragmatic steps to delivering workflows that generalize on real unseen datasets and focuses on leveraging deep learning techniques to significantly reduce the turn-around time for VMB. We focus on three key areas where considerable time is currently spent: estimating a robust initial macro-velocity model, accurately picking complex water-bottom horizon, and replacing tomography and interpretation steps for automating an accurate FWI initial model.

Dataset

The primary dataset utilized in this study is located offshore the north coast of Brazil, covering a vast area of approximately 20,000 square kilometers. The region presents a challenging environment for seismic imaging, with water depths ranging from 1,000 to 4,000 meters. The ocean floor has a complex landscape with many channels, canyons, and underwater mountains that create a varied

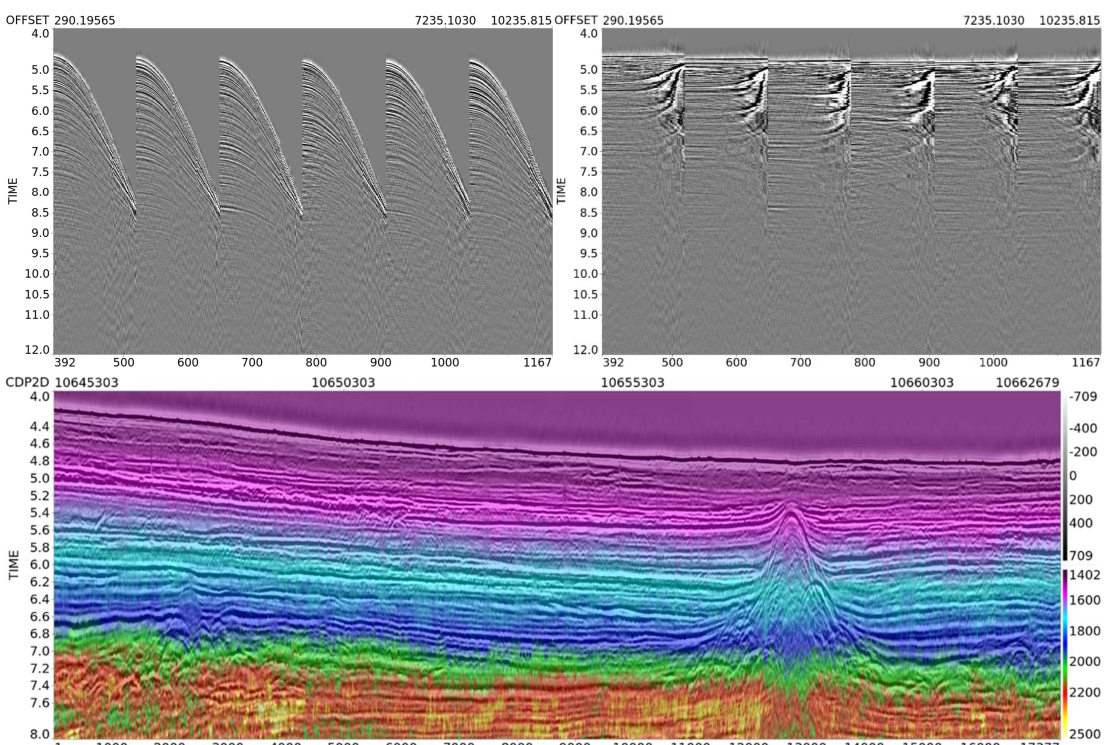

Figure 1111: Top left shows the input CMP gathers. Top Right shows the gathers after NMO with the estimated Vrms. Bottom shows the raw model output velocity model with the resulting stack as an overlay.

terrain.Geologically, the area is a rifted margin containing significant igneous rocks, such as volcanic sills and intrusions. These features: the complex water-bottom topography and the presence of high-velocity volcanic bodies, create substantial hurdles for traditional velocity model building. The data was acquired using multi-sensor streamer technology using 12 cables each with 804 channels at a 12.5 m group interval.

Method

The overall strategy employs specialized Convolutional Neural Networks (CNNs) and advanced hybrid architectures, utilizing both self-supervised and physics-based fine-tuning approaches, to automate and accelerate critical VMB steps.

1. Estimating an Initial Velocity Model

To provide a high-quality initial velocity model for subsequent tomographic or migration velocity analysis (MVA) steps, we utilize a CNN model to estimate a root mean square velocity (Dix's velocity). This estimation is achieved in a self-supervised manner, eliminating the need for any training data.

This loss function minimizes differential semblance and simultaneously maximizes the stack power. Crucially, the model incorporates additional regularization terms for Total Variation (TV) and smoothness to ensure geological plausibility and stability in the predictions. The model is trained in a self-supervised manner across an entire seismic line. This workflow is optimized for production use by implementing an approach similar to reinforcement learning, where the trained weights derived from processing a previous line are utilized to initialize the training for the current line. This weight transfer mechanism further reduces the training time and computational cost, making the initial velocity estimation highly efficient.

This self-supervised training technique was applied to the data in figure 1 with random weight and no pre-training. The top figures show a selection of unmigrated CMP gathers before and after NMO with the ML-estimated Vrms. Looking at the NMO-corrected gathers the combination of the differential semblance and stack power losses in combination with regularization terms were sufficient to converge to a robust solution. The bottom figure shows the raw ML result with no smoothing applied. The stack with the same model is used as an overlay. Looking at the resulting model in the 4-7 seconds range there is a very high level of continuity indicating the robustness of approach to low levels of noise. Towards the bottom of the section gather to gather inconsistencies can be seen indicating the need for some post-processing before calculating interval velocities is still needed.

2. Accurate Water-Bottom Picking

Accurate water-bottom interpretation is critical, but traditional auto-pickers frequently fail in areas exhibiting complex bathymetry, such as canyons, seamounts, and reefs. To overcome this challenge, we have adopted a workflow inspired by successful 3D machine learning applications in seismic interpretation, specifically the salt segmentation techniques explored in recent industry research.

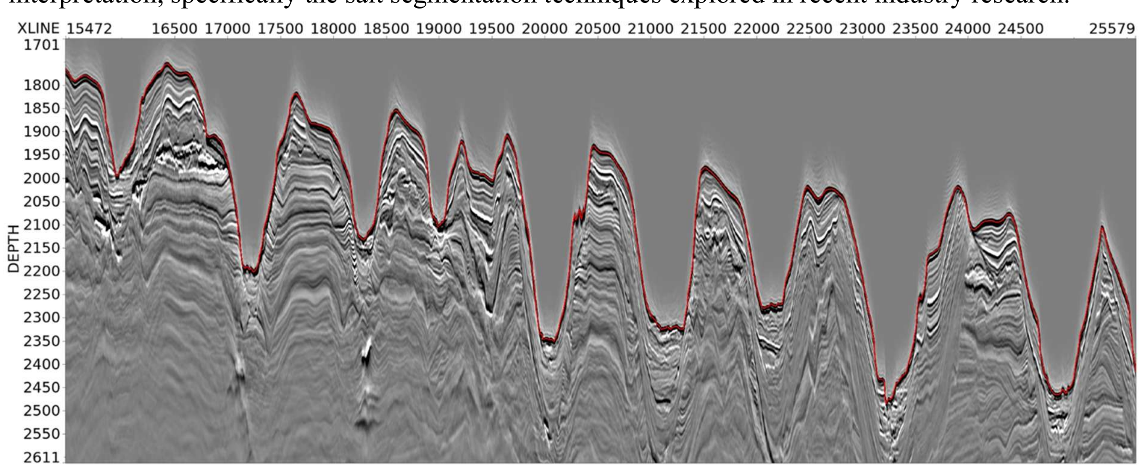

Figure 2222 Water-flood Kirchoff Depth Migration overlain with ML water-bottom pick

The approach employs a 3D CNN for the segmentation of water from earth. This technique capitalizes on the enhanced spatial and contextual capabilities of 3D ML models, which offer solutions to complex interpretation challenges. We use the same 3D-VNet, input context and data augmentation as used in Roberts, et al, (2024).

The 3D CNN model for water-bottom picking was trained using data from previous surveys located in both Brazil and West Africa. Figure 2 shows resulting ML pick from this dataset featuring highly complex canyons that render conventional auto-pickers ineffective. For this challenging area, it was estimated that human interpreters would require days to pick with conventional tools. Utilizing the trained ML model, this horizon can be performed in minutes while maintaining high accuracy.

3. Updating the Velocity Model for FWI

The final challenge addresses the iterative model updating phase necessary to achieve a sufficiently accurate velocity model for running FWI. While traditional MVA or tomography can flatten migrated gathers, improving image focus, they do not always provide the optimal starting models for FWI, which also requires matching refracted events. Furthermore, complex features like salt or igneous sills often necessitate manual insertion during model building.

Recent advancements have shown how ML (Korsmo, et al., 2025), can be used to incorporate these higher-resolution features, effectively replacing passes of reflection tomography. These ML networks, often trained on synthetic data, accelerate the VMB sequence and handle complex geobodies. Building upon these findings, our flow enhances the model updating capability through several key modifications. First, the input data domain is the velocity model and associated Kirchhoff Depth

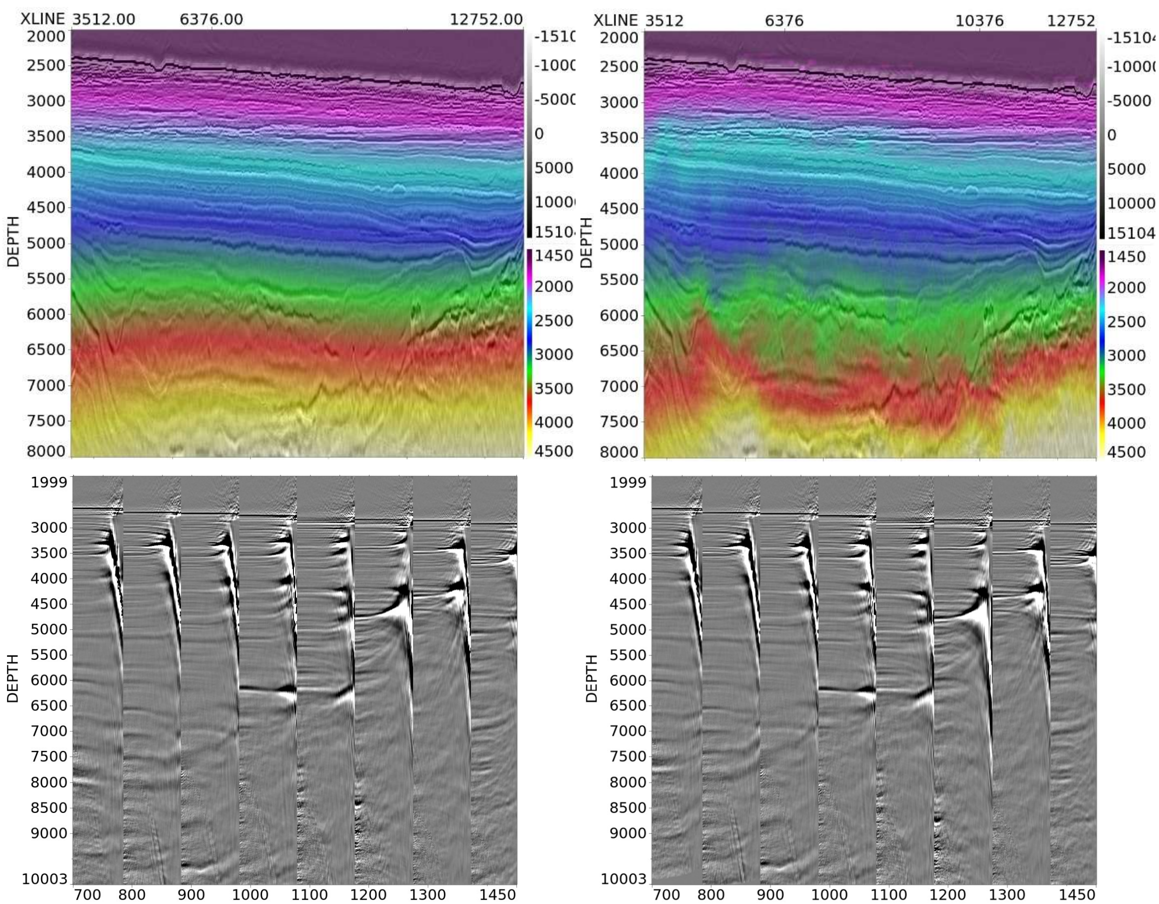

Figure 3333 Velocity model (top) and Kirchoff Depth gathers (bottom) before (left) an after (right) ML tomographic update.

Migrated offset gathers, aligning the approach with current model building best practices. Second, we generate significantly larger and more realistic synthetic training models including the detailed petrophysical analysis of over 60,000 offshore wells (see Roberts *et al* 2025 for details). Third, we have updated the model architecture to a hybrid-CNN-transformer model, specifically based on RAPUnet (Lee and Yoo, 2024) with an adapted convolutional head to handle the extra input channels. The model is trained with an input context of 512x512 with 81 input channels. Despite initial pre-training on this extensive synthetic dataset, issues with generalization to real seismic data can persist. To resolve this, we introduced a physics-based self-supervised fine-tuning approach. The model is fine-tuned using the entirety of the synthetic data combined with the specific target real data. During fine-tuning on the real data, we evaluate a loss function based on residual moveout (RMO). Similar to the initial estimation, the loss function comprises differential semblance, stack power, and regularization terms (TV and smoothness). Figure 3 shows the results of this flow on real data, fine-tuning in a self-supervised manner with a physics based loss was essential to allow the model to generalize on the real data and result in a model that flattened the gathers.

Conclusions

We have addressed three main, time-consuming challenges in the VMB sequence using advanced machine learning: initial estimation, accurate water-bottom segmentation in complex areas, and sophisticated model updating via physics-based fine-tuning. For complex, high-end projects, this integrated workflow can rapidly generate a high-quality starting model for subsequent FWI runs. Crucially, for many other applications in simple geological environments, such as 2D exploration datasets or Ultra-High Resolution (UHR) seismic surveys, these resulting velocity models have the potential to serve as the final models in significantly less time than traditional model building sequences.

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