Rapid Turnaround for Multi-Sensor Data: An ML-Driven Workflow

Mark Roberts, Olga Brusova, David Brookes, Leandro Gabili and Alejandro Valenciano*
TGS

Introduction

In offshore seismic imaging, reducing turnaround time is critical for project success. While computational power has increased, the rising complexity of algorithms like deblending and deghosting has kept production timelines static. Traditionally, "fast-track" products sacrificed quality for speed. This work presents a hybrid workflow that integrates Machine Learning (ML) with physics-based foundations, extending previous hydrophone-only successes to multi-component (geophone and hydrophone) streamer data. By targeting the most parameter-sensitive stages, such as denoising, and deghosting, this approach eliminates weeks of manual effort while maintaining high-fidelity results.

The implementation of a Deep-Learning based velocity estimation allows the rapid generation of stacked seismic sections to provide an initial look at the data and facilitate the QC process.

Theory and/or Method

The workflow consists of four primary ML-enhanced stages designed to handle the complexities of multi-sensor data:

Enhanced ML Denoising: Utilizing an expanded dataset of raw noise and denoised signals, four models were developed for hydrophone and geophone components. The training pipeline uses "pseudo-synthetic" examples—adding real noise to clean records—and robust data augmentation to ensure model stability. A secondary model is employed to monitor and mitigate potential signal leakage.

ML-Assisted Deblending: Rather than replacing robust iterative inversion methods (POCS/FISTA), this workflow uses a "blind-trace" ML model to generate an initial estimate or "seed." This hybrid approach accelerates the inversion process significantly without compromising the quality of recovered diffractions or weak events.

Multi-Sensor ML Deghosting: Leveraging the complementary nature of pressure and particle velocity, a modified DuckNet architecture (utilizing ConvNext v2 blocks) was trained to perform wavefield separation. To overcome the lack of low-frequency geophone data, the model was trained on "pseudo-synthetic" ghosted data alongside real production lines.

Velocity Model Building (VMB): To further accelerate the project, a self-supervised CNN was implemented to estimate RMS velocity. By minimizing differential semblance and maximizing stack power, the model

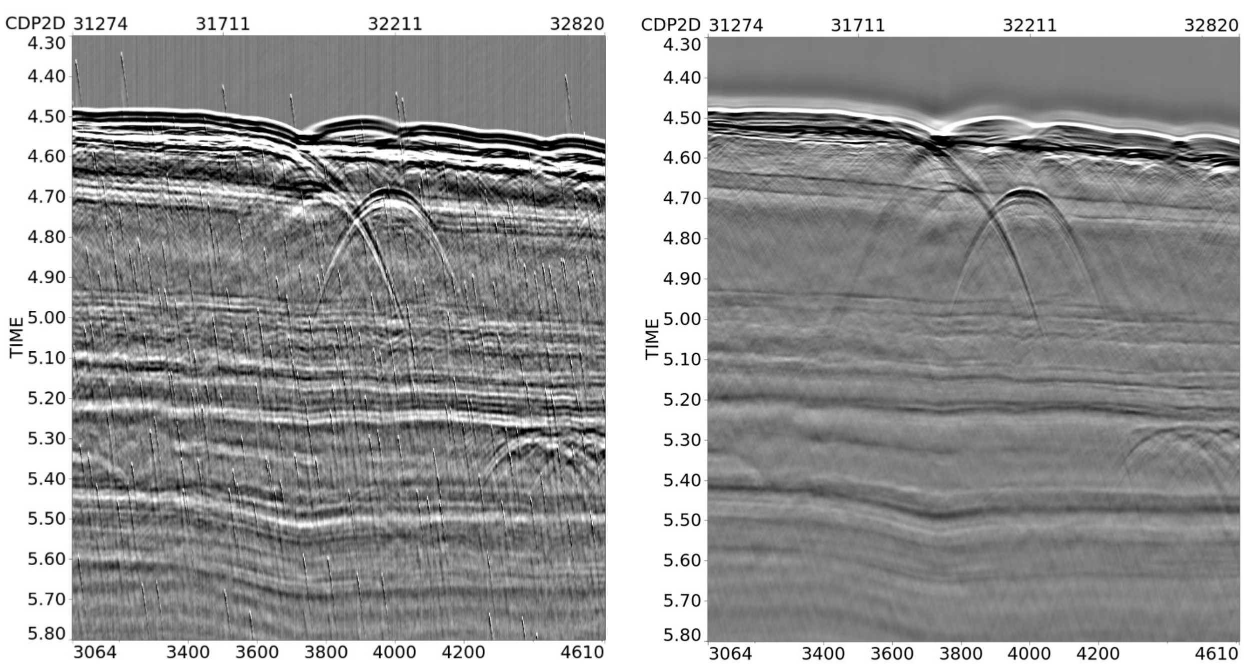

Figure 1: *A close up of the water-bottom for the example line. Left, the raw stack. Right, stack with ML-based processing*

converges to a robust NMO solution without requiring manual training data. Weight transfer, using weights from previous lines to initialize new ones, further optimizes production speed.

Examples

The workflow was validated by testing on some test data from the Pama 3D survey, a 20,000 km^2 deepwater project offshore Brazil. Figure 1 shows the result of a test line showing the improvement and quality of the ML based workflow. One key finding was that quantitative analysis showed that a two-channel ML model (hydrophone + geophone) achieved a validation loss of **0.017**, compared to **0.025** for a hydrophone-only model, proving the observation of the enhanced deghosting performance of multi-component data holds for data-based approaches.

Figure 2 shows the results from the ML based velocity estimation. The top right figure shows the faltness of the gathers after NMO with the derived velocity. The bottom image shows the lateral continuity of the raw ML velocity output as well as the raw stack with the ML-processing and ML-based velocity estimation.

Conclusions

By combining ML with physics-based constraints, this workflow delivers a high-resolution product that facilitates faster initiation of Velocity Model Building. The integration of geophone data provides a superior baseline for deghosting that exceeds conventional single-component results, offering a path toward near-real-time, production-quality seismic imaging.

Key words

Machine Learning, Seismic Processing

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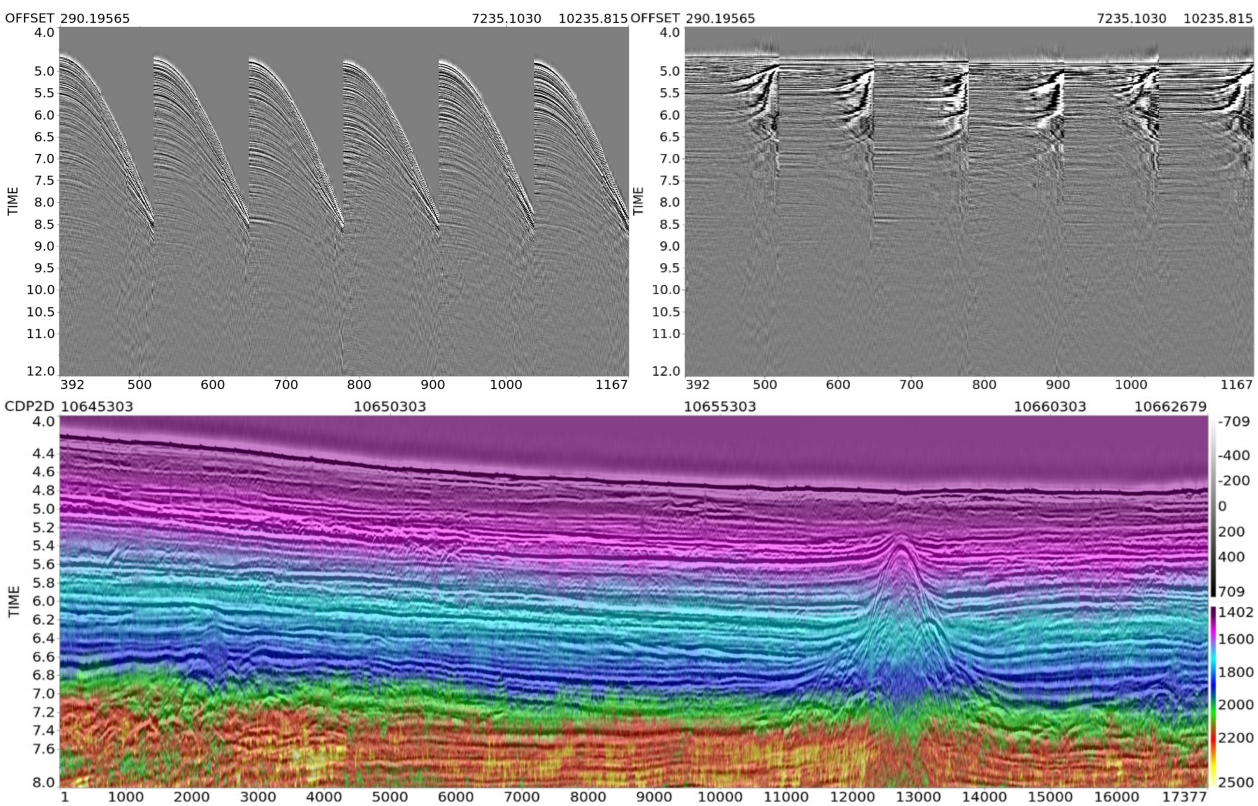

Figure **2**: Top left shows the input CMP gathers. Top Right shows the gathers after NMO with the estimated Vrms. Bottom shows the raw model output velocity model with the resulting stack as an overlay.