Accelerating and Enhancing 3D UHRS Data Processing Through Machine Learning Innovations

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Summary

Machine Learning (ML) is transforming 3D ultra-high-resolution seismic (UHRS) data processing, offering faster, consistent, and high-quality results. This study highlights ML applications in denoising, deghosting, and velocity model building. Tools like RIDNet and Fourier Neural Operator (FNO) deliver efficiency and accuracy by leveraging supervised learning on high-quality training datasets. RIDNet excels in tasks such as deghosting, significantly reducing computational demands compared to traditional inversion methods. Meanwhile, FNO generates high-resolution velocity models with geological conformity, providing an efficient alternative to Full Waveform Inversion (FWI).

A proof-of-concept demonstrated ML’s ability to integrate multiple processing steps—such as deghosting, denoising, and demultiple into a single operation, paving the way for near-real-time 3D fast-track workflows. However, challenges persist, including the need for proprietary training data for UHRS-specific scenarios. Synthetic datasets offer a promising solution, particularly for velocity models, though validation for other processing steps is needed.

ML’s efficiency in handling UHRS’s ultra-high-frequency content, combined with its potential to rethink traditional workflows, positions it as a critical tool for future geophysical applications. By addressing processing challenges and accelerating timelines, ML enables scalable solutions for increasingly complex and larger 3D UHRS datasets.

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Introduction

Machine Learning (ML) has gained widespread acceptance in seismic processing and imaging of the subsurface in the oil and gas sector (Oukili *et al*., 2023). Its primary advantage lies in significantly faster processing times compared to traditional geophysical methods. This work explores the application of ML techniques for 3D ultra-high-resolution seismic (UHRS) data. Beyond accelerating turnaround times, ML often offers simpler parameterization (no testing) and consistency in quality across surveys.

While turnaround time is often perceived as a minor concern in UHRS processing due to smaller data volumes, the scale of 3D UHRS surveys has grown significantly. Caselitz *et al*. (2024) highlighted the challenge posed by processing data from surveys exceeding 500 sqkm. Even for 2D or smaller 3D UHRS surveys, machine learning offers the potential to dramatically accelerate the testing phase, a common bottleneck that can delay project timelines.

Currently, the main ML applications for UHRS data are in denoising and deghosting. For denoising, ML eliminates the need for a high-order interpolation process. In deghosting, it resolves challenges related to unknown (and variable) receiver and source depths. For velocity model building of UHRS data, ML offers a new opportunity by enhancing the resolution and accuracy of velocity models, achieving results unattainable with traditional velocity picking or tomographic methods. These high-resolution models could provide insights for soil interpretation and input to future stratigraphic inversion works.

ML technology proves highly effective in overcoming the challenges associated with 3D UHRS data. It delivers high-quality outputs and ensures timely production of the results, making it a valuable addition to the seismic processing toolkit. This technology should also provide opportunities to rethink data processing by combining multiple processing steps into one.

Methods

The ML methods employed in this study are all supervised and depend on high-quality training data to ensure optimal output. Figure 1 illustrates the supervised learning workflow. The steps in the green box cover the machine learning model generation, an essential foundation for accurate predictions.

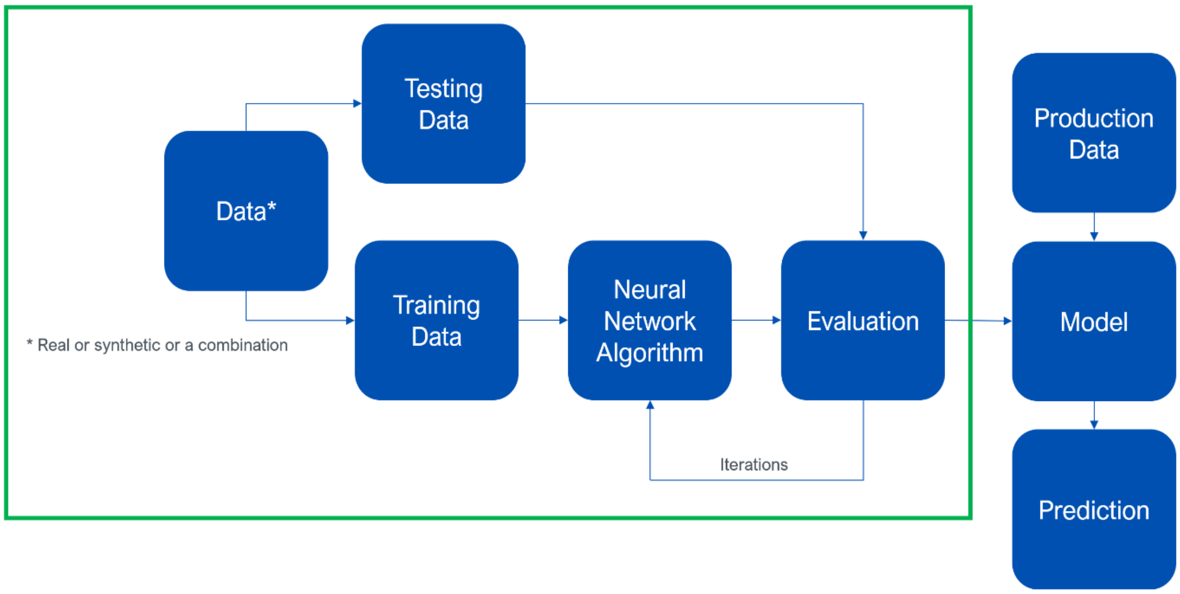

***Figure 1**: Supervised learning workflow diagram. The green box highlights the model generation part of the workflow.*

We utilized the RIDNet Deep Neural Network (DNN), as detailed by Farmani *et al*. (2023), and the Fourier Neural Operator (FNO), described by Crawley *et al*. (2023). RIDNet excels in signal processing tasks such as denoising and deghosting, while FNO has shown its capability to build velocity models in complex geological settings, including salt provinces. This study marks the first application of FNO to UHRS data. The technique has demonstrated its ability to produce very high-resolution velocity models on conventional seismic data, comparable to high-resolution Full Waveform Inversion (FWI) models but with significantly reduced turnaround times. RIDNet is widely used in production settings for denoising and receiver deghosting of UHRS data, with networks trained for each specific UHR project. Conversely, FNO operators are derived from extensive synthetic datasets representing diverse geological and acquisition scenarios. For this study, the FNO method was tested on UHRS data using operators trained exclusively on conventional seismic setups. A new model incorporating synthetic data reflecting 3D UHRS acquisition geometries and near-surface geological settings is planned for future developments.

Other machine learning applications are used in the UHRS processing sequence such as U-Net CNN to attenuate post-migration noise. A similar ML algorithm separates reflections from diffractions helping at identify hazardous objects such as boulders.

Examples

The first application example focuses on receiver deghosting. Due to the significant uncertainty in UHRS streamer depth, geophysical deghosting techniques must be inversion-based and include receiver depth estimation steps. The method described by Bekara *et al*. (2024) achieves high-quality results but demands substantial computational resources. A faster alternative is the RIDNet DNN, trained using the inputs and outputs of inversion-based geophysical deghosting applied to one acquisition sequence. Once trained, this model processes all sequences much faster than geophysical methods. Figure 2 compares 2D stack of receiver deghosting using geophysical and ML methods, showing that both achieve high-quality results, but ML operates significantly faster. The line shown is a QC line not used to train the ML model.

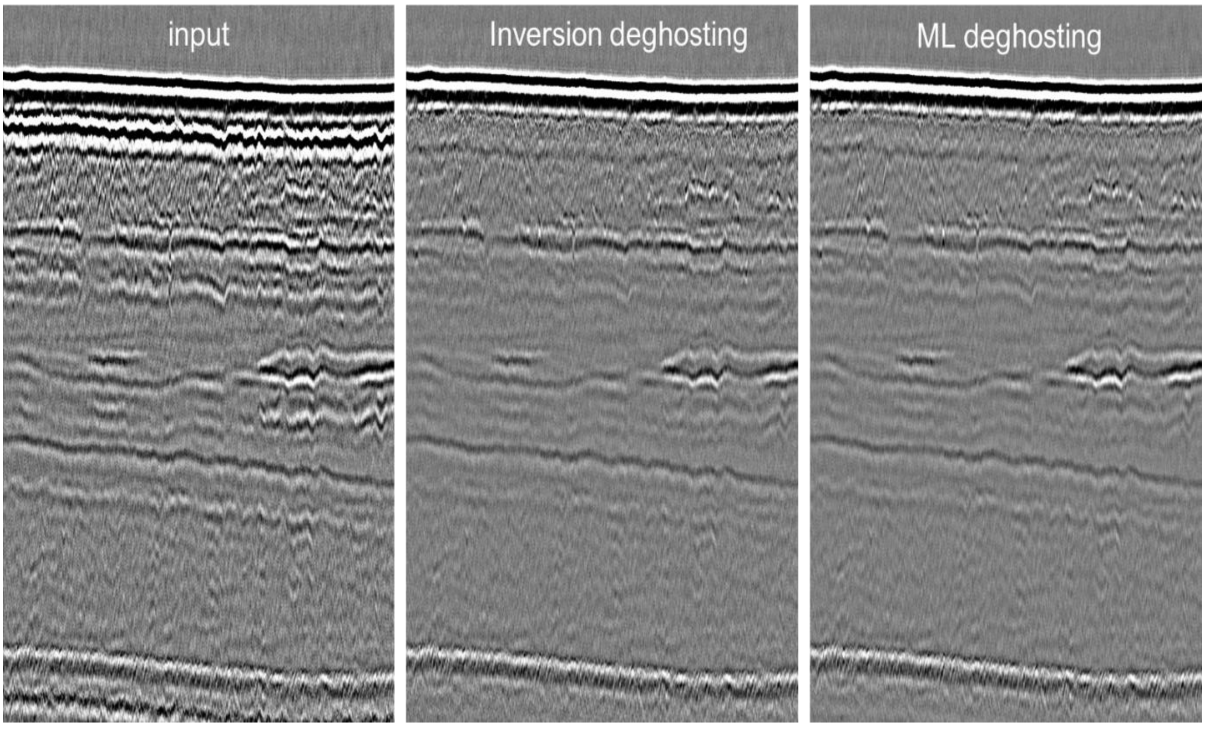

Figure 2*: 2d stack comparison QC. Input to receiver deghosting (left), inversion deghosting (center), ML deghosting (right). Both methods produce a high-quality output.*

The second application involves velocity model derivation. As noted earlier, the trained model used here was generated using synthetic data from 15 Hz RTM angle gathers with typical oil and gas acquisition geometries and geological settings. Although this model does not specifically account for UHRS acquisition configurations and near-surface geological settings, it successfully produces a velocity model (in m/s) showing geological conformity. Figure 3 displays the initial and ML velocity model overlaid on their respective migrated stack. The migrated images are similar, but the ML velocity model has much higher resolution highlighting shallow channels filled with slower velocity sediments. This demonstrates ML's potential to build ultra-high-resolution models efficiently, providing a computationally efficient alternative to high frequency full waveform inversion (FWI).

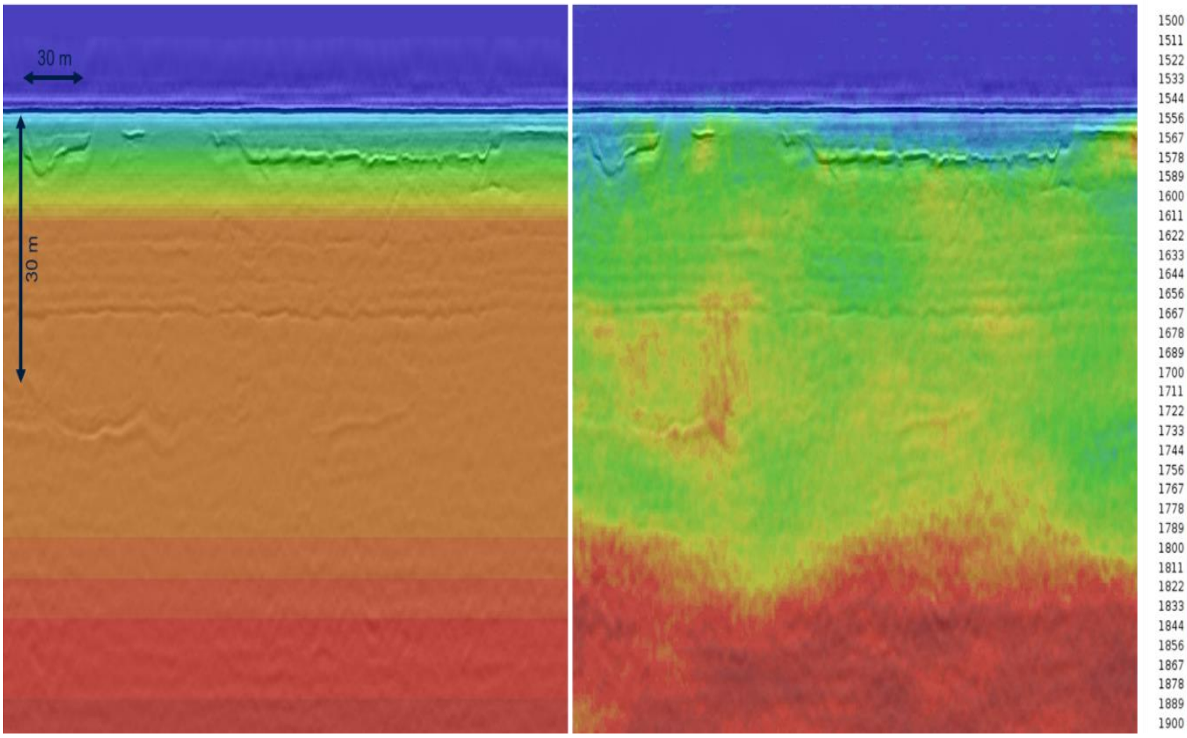

Figure 3*: Migrated stack with overlaid velocity model (m/s) – Initial model and stack (left), ML model and stack (right). The ML algorithm is able to capture low velocity related to shallow channels just beneath the seabed.*

The final example highlights broader applications of ML. Unlike traditional workflows, where separate processes handle individual processing steps, this ML approach integrates multiple processes into a single operation. Figure 4 illustrates a proof-of-concept for a "one-pass" ML-based post-stack process, applied to a raw stack with statics and NMO corrections. The ML solution is evaluated against the conventional workflow where denoise, deghosting, designature and demultiple are applied pre-stack. The displayed line is a verification line excluded from the ML model's training data. A RIDNet DNN model was trained on stacks to simultaneously perform deghosting, designature, denoising, and demultiple corrections. While it is likely that the current result could be substantially improved, this proof-of-concept demonstrates ML's ability to transform seismic data processing. It could enable efficient workflows by generating inputs for post-stack migration in near-real time, offering 3D ultra-fast-track products within hours instead of days.

Conclusions

Machine learning methods can revolutionize UHRS data processing, offering the ability to deliver high-quality results quickly. Applications like denoising and deghosting are already widely adopted in production workflows. However, a significant challenge is the need for training datasets derived from geophysical methods applied to real UHRS data. Since these projects are proprietary, training must be conducted for each production project, as data cannot be reused to train generic models without data owner consent. Experience indicates that building the ML model adds little to project turnaround, since it requires only a small training dataset. An alternative is to use synthetic datasets, as demonstrated with the velocity model FNO method, though this approach has not yet been validated for processing steps such a deghosting. Machine learning also introduces novel possibilities, such as combining multiple processing steps into a single workflow, enabling 3D UHRS data processing to be conducted with time efficiency. Additionally, ML methods are particularly adept at handling the ultra-high-frequency content of UHRS data, which often demands substantial computing resources when processed using conventional geophysical techniques.

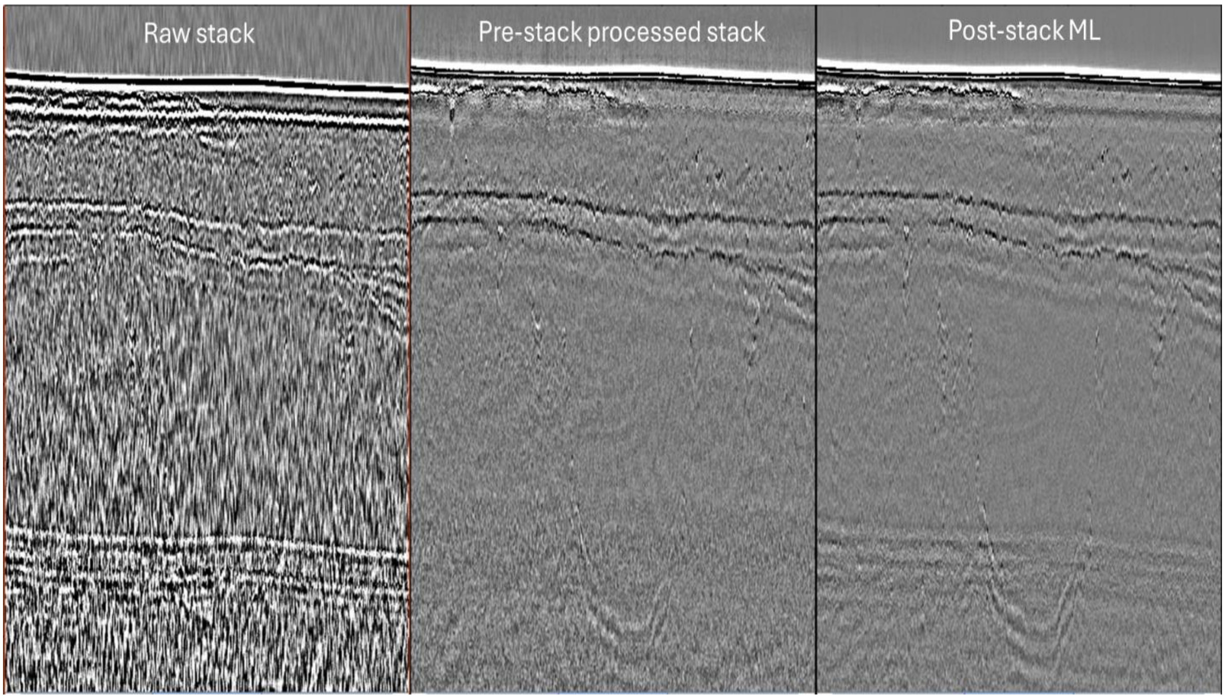

***Figure 4**: Unmigrated stack comparison QC. Raw stack (left), pre-stack processed stack (center), post-stack ML (right). The ML solution provides a better signal-to-noise ratio but leaves more multiples energy.*

Acknowledgements

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References

Bekara M., Davison C., Lange M., Limonta L. (2024). Deghosting of UHR seismic data via dynamic ghost tracking, EAGE 2024.

Caselitz B., Limonta L., Oukili J., Tegnander J., Catterall V. (2023). 3D Ultra High resolution seismic processing – A case study from Offshore USA. IMAGE 2024.

Crawley S., Huang G., Djebbi R., Ramos J., Chemingui N. (2023). High resolution angle gather tomography with Fourier neural operators. IMAGE 2023.

Farmani B., Lesnes M., Pal Y. (2023). Multisensor noise attenuation with RIDNet. EAGE 2023.

Oukili J., Kumar J., Burren J., Cochran S., Bubner M., Nasyrov D., Farmani B. (2023). Large-scale industrial deployment of machine learning workflows for seismic data processing. First Break, Volume 41.