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Streamlining Marine Seismic Preprocessing with AI

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Abstract Summary

In seismic imaging, reducing the turnaround time of imaging projects is essential. Machine learning solutions offer the potential of reduced turnaround time without the loss of data quality that comes with traditional fast-track solutions. These are achieved through faster execution times and the elimination of parameter testing. Machine learning solutions have been used to reduce turnaround in the VMB (Velocity Model Building) steps (Crawley, 2024) and in the preprocessing steps (Brusova, 2021; Roberts, 2024). Here, we leverage machine learning (ML) to accelerate and improve the efficiency of preprocessing, focusing on three key steps: swell noise removal, deghosting, and designature. We demonstrate these results on data from a recent 3D project from the Niger Delta, offshore Nigeria.

Introduction

Reducing seismic imaging turnaround time is critical, but progress is offset by increasing algorithmic complexity (e.g., deblending, deghosting, demultiple, 5D regularization) and data volumes, shifting bottlenecks from production to testing and impacting project timelines. Traditional 'fast-track' solutions offer speed but compromise data quality. Machine learning (ML) provides a path to reduced turnaround without this quality loss through faster execution and minimized parameter testing, with applications in VMB (Crawley, 2024) and preprocessing (Brusova, 2021; Roberts, 2024). This work leverages ML to accelerate swell noise removal, deghosting, and designature, demonstrated on a recent 3D project from the Niger Delta.

Designature is not typically a computationally intensive process. However, parameterization and QC for removing the source wavelet, including the bubble and the subsequent conversion to zero-phase, can often be time-consuming. It requires an accurate estimate of the source wavelet from

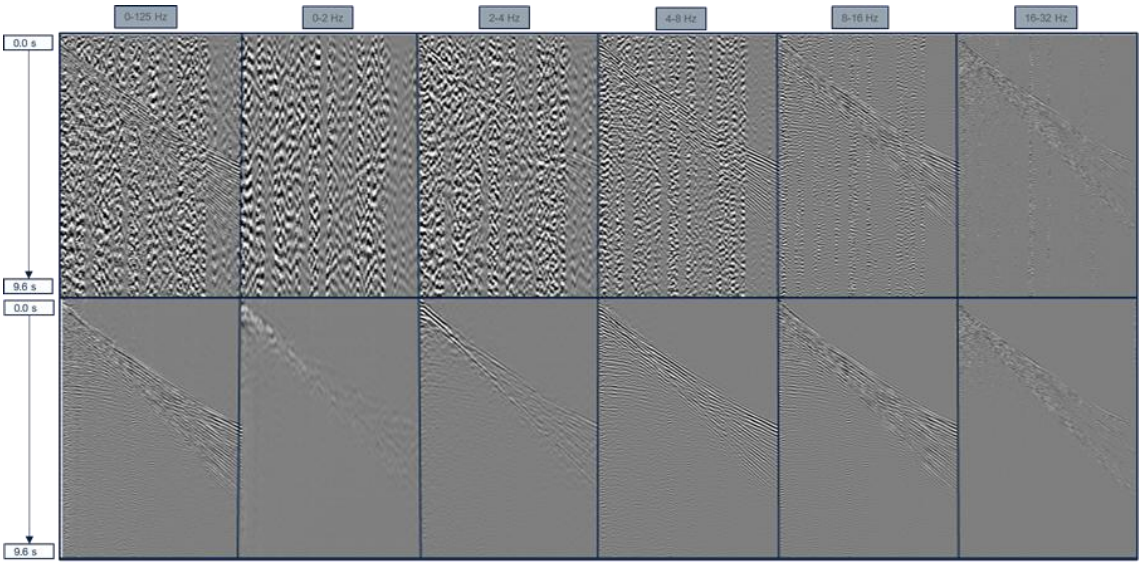

Figure 1:Octave panels: a) before ML deswell; b) after ML deswell.

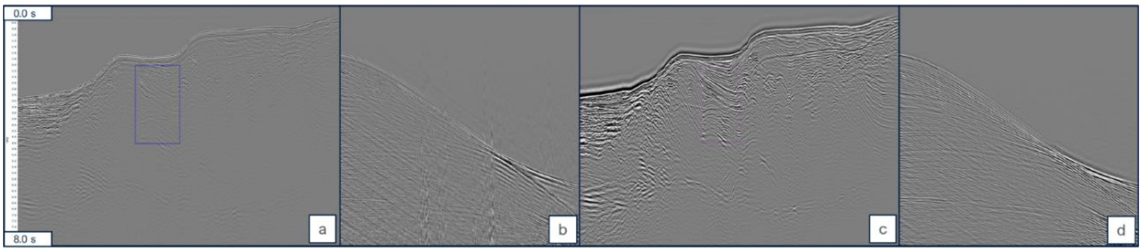

Figure 2 Comparison of data before and after the ML fast track flow: a) and b) stack and shot gather before deswell; c) and d) the same stack and shot data after ML deswell, deghost and designature.

the data or Near Field Hydrophones (NFHs). The machine learning solution was trained using data from a dual-source streamer survey that performed designature through a two-step debubbling and zero-phasing process with a far-field signature derived from NFH data. This model was applied with reasonable success to the Awele triple-source acquisition, although there are some difference in the low frequencies, which are thought to come from the difference in source configuration between the dual and triple source acquisition. Further work is necessary to understand how generalizable the model is to source configurations and source volumes that different to the training data.

Method

Swell noise removal, traditionally needing manual tuning (Masoomzadeh et al. 2017), is addressed using deep neural networks (DNNs) per Brusova et al. (2021). A deep convolutional U-net, trained by combining noise recorded during acquisition with clean data from a comprehensive global library, effectively performs pixel-to-pixel noise removal and generalizes well to unseen field datasets.

Deghosting traditionally employs methods like 3D sparse tau-p (Seher et al., 2024), requiring accurate but often elusive source/receiver depth information, increasing costs and potential inaccuracies. Our ML model, trained on precise 3D sparse tau-p deghosting results in areas with known depths, combined with synthetically ghosted data generated with varied source/receiver depths, eliminates the need for explicit depth information, reducing computational costs while achieving comparable results.

For designature, typically not computationally intensive, ML streamlines time-consuming parameterization and QC. An ML model trained on dual-source streamer survey data (using a far-field signature derived from NFH data) was applied to a triple-source acquisition. While largely successful, observed low-frequency discrepancies, thought to stem from source configuration differences, indicate further investigation is needed regarding generalization across different source configurations and volumes.

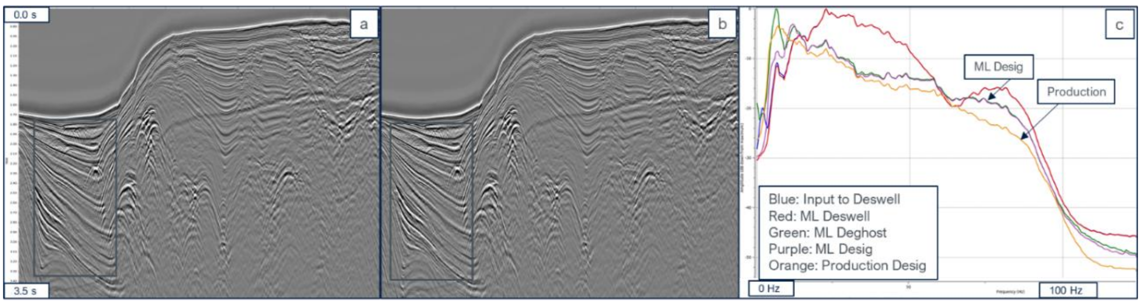

Figure 3 Comparison of a) stack of conventional flow, b) stack of ML flow and c) amplitude spectra spectra comparisons (blue rectangle shows the approximate analysis window).

Results

The Awele project is a deepwater 3D survey acquired in the Niger Delta, offshore Nigeria, in 2023. The full survey size is 11,430 km^{2,} and the data were acquired with a single vessel towing 12 streamers, which were 10,050 m long and separated by 150 m. A triple source was used with an array volume per source of 3,250 cu. in. The final bin size and fold were 6.25 m x 25 m and 89, respectively.

The Niger Delta developed during the Late Cretaceous to Quaternary and is characterised by an extensive progradational sequence of deltaic clastics overlying pro-delta marine shales. Multiple structural domains are present, including an extensional domain, shale diapir zone, inner/outer fold, and thrust belts. The Akata formation pro-delta shales form a thick over-pressured shale section which has been proven to contain at least one high-quality source rock in the inboard part of the delta. In addition, the presence of seabed pockmarks and Bottom Simulating Reflectors (BSRs) across large parts of the survey area provides further evidence for fluid escape and recent hydrocarbon generation.

This significant level of geological complexity creates a high degree of spatial heterogeneity in the data, making the task of parameterisation a time-consuming one while also increasing the risk of parameters falling outside of optimal ranges for lines other than the selected test lines. Furthermore, large variations in receiver depth were encountered during acquisition, which required accurate estimation of receiver depths to effectively deghost the data. Here we present the results of applying ML processing solutions together with a comparison to a conventionally processed data set.

Figure 1 shows octave panels before and after ML deswell. On this line, the swell noise is strong, extending up to at least 32 Hz. In addition, at lower frequencies, swell noise covers a significant percentage of the shot, making removal using frequency and amplitude discrimination methods challenging. Figure 1b shows the data after swell noise removal. The ML deswell technique has successfully attenuated the swell noise at all frequencies. This result was achieved with no parameter testing and no additional training of the global model, representing a considerable time saving over conventional methods.

Figures 2a and 2b show a stack (Figure 2a) and shot gather (Figure 2b) before deswell, and the Figures 2c and 2d show the same stack (Figure 2c) and shot (Figure 2d) after applying ML solutions for deswell, deghost and designature combined into a single ‘job step’ for one swath of data. These three processes were applied without prior testing or additional training. Extrapolated over the full survey, this represents a significant saving of time and effort over the cumbersome testing strategies, test line selection, and complex processing flows associated with the traditional route.

Figure 3 shows a stack comparison of the conventional flow (Figure 3a) with the ML flow (Figure 3b). Visually, the two images are very similar. This conclusion is supported by the amplitude spectra (Figure 3c), in which the combined ML flow is shown by the purple curve (labelled ML Desig) and the conventional flow by the orange curve (labelled production). As already noted, the two curves are different at low frequencies, but similar at higher frequencies.

Conclusions

ML can transform marine seismic data preprocessing by automating key tasks like swell noise removal and deghosting, leading to reduced processing times and enhanced data quality. The use of global ML models is pivotal for achieving time savings through simplified parameterization and reduced testing. However, some models, as noted for designature, may require refinement for broader applicability, a time and resource consideration. Ongoing work aims to optimize model updates within production project constraints and extend this ML approach to other preprocessing steps, such as demultiple.

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