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Accelerating Marine Seismic Preprocessing with Machine Learning

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Summary

In seismic imaging, reducing the turnaround time of imaging projects is essential. Although advances in computer power have shortened the processing time of the standard marine sequence, this progress has been offset by an increase in the algorithmic complexity of processing steps, such as deblending and deghosting. Furthermore, the critical path of many projects has shifted from production to testing, resulting in turnaround times remaining static. A traditional solution to turnaround reduction is the 'fast-track' product: a reduced processing sequence that can be applied to the data quickly to give the interpretation team a product to work with as early as possible. However, this product, by its nature, often has increased noise levels, residual multiples, or other artefacts that can hamper interpretation. Machine learning solutions offer the potential of reduced turnaround time without the loss of data quality that comes with fast-track solutions. These are achieved through faster execution times and the elimination of parameter testing. 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.

Accelerating Marine Seismic Preprocessing with Machine Learning

In seismic imaging, reducing the turnaround time of imaging projects is essential. Although advances in computer power have shortened the processing time of the standard marine sequence, this progress has been offset by an increase in the algorithmic complexity of steps like deblending, deghosting and 4D and 5D regularization. When combined with increasing volume sizes, this has resulted in turnaround times remaining static for several years. Furthermore, the critical path of many projects has shifted from production to testing, meaning that turnaround times cannot be reduced by compute power increases alone. Cutting turnaround time is crucial because imaging projects are often scheduled around license round decisions or drilling timelines. When projects overrun, this can lead to time allocated for data interpretation being lost to data processing, potentially jeopardizing drilling decisions or prospect evaluations.

A traditional solution to turnaround reduction is the ‘fast-track’ product: a reduced processing sequence that can be applied to the data quickly to give the interpretation team a product to work with as early as possible. However, this product, by its nature, often has increased noise levels, residual multiples, or other artefacts that can hamper interpretation.

Machine learning solutions offer the potential of reduced turnaround time without the loss of data quality that comes with 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.

Method

Swell noise is common in marine seismic data. It manifests as low-frequency vertical stripes on shot records, masking seismic signals and hindering data quality. Traditional methods (Masoomzadeh et al., 2017) require manual parameter tuning and extensive quality control (QC), which can lead to delays in the creation of the fast track product.

Using the method developed by Brusova et al. (2021), we employ deep neural networks (DNNs) for efficient and automated swell noise removal. Our approach tackles the challenge of training data scarcity by combining noise recorded during acquisition with clean data from a comprehensive global library. A deep convolutional U-net architecture effectively performs pixel-to-pixel image translation for noise removal. The trained model exhibits excellent generalization capabilities, successfully removing swell noise from diverse field datasets not included in the training process. This global model reduces testing and production times and enhances data quality significantly.

Deghosting is another critical preprocessing step. It removes ghost events caused by reflections from the sea surface. Traditional deghosting techniques use multidimensional transforms such as 3D sparse tau-p (Seher et al., 2024) and often require accurate source and receiver depth information. This information can be challenging to obtain accurately and varies significantly in real-world scenarios. This increases computational costs and produces inaccuracies, particularly when there are uncertainties in the depth of sources and receivers.

To address these challenges, we employ a machine-learning solution for deghosting. Our ML model effectively eliminates the need for source and receiver depth information. It achieves this by leveraging a large dataset, and by learning from accurate 3D sparse tau-p deghosted data from areas with known source and receiver depths. This data is combined with synthetically ghosted data generated with a wide variety of source and receiver depths. The solution significantly reduces computational costs and testing time, compared to the 3D sparse tau-p method, while achieving comparable results.

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 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 has been applied with reasonable success to triple-source acquisition, although there are some difference in the low frequencies, which are thought to come from differences 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 are different to the training data.

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 comparisons to a conventionally processed data set.

Figures 1a and 1b show stacked data after conventional 3D sparse tau-p deghosting and ML deghosting. The amplitude spectra are shown in Figure 1c. The conventional deghost spectrum (red curve) shows a peak at just over 60 Hz. This corresponds to the notch frequency associated with the receiver ghost and is indicative of an inaccurate receiver depth in the deghosting. The ML technique is free of the need for accurate receiver depths and the corresponding spectrum (green curve) shows the ML technique delivered an improved result.

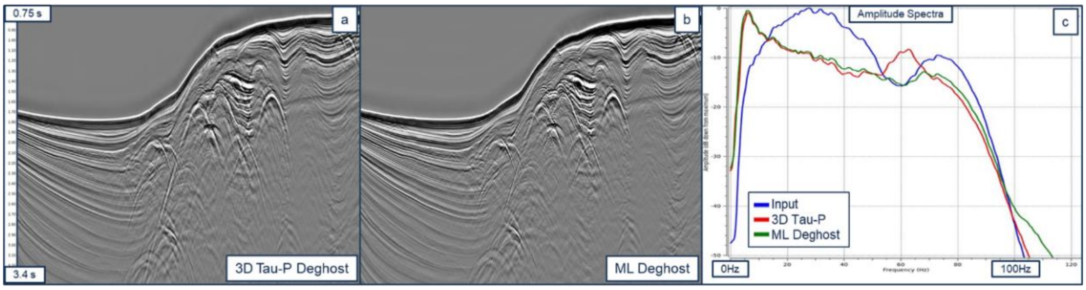

***Figure 1** Comparison of conventional and ML deghosting: a) 3D sparse tau-p deghost; b) ML deghosting; c) amplitude spectra.*

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.

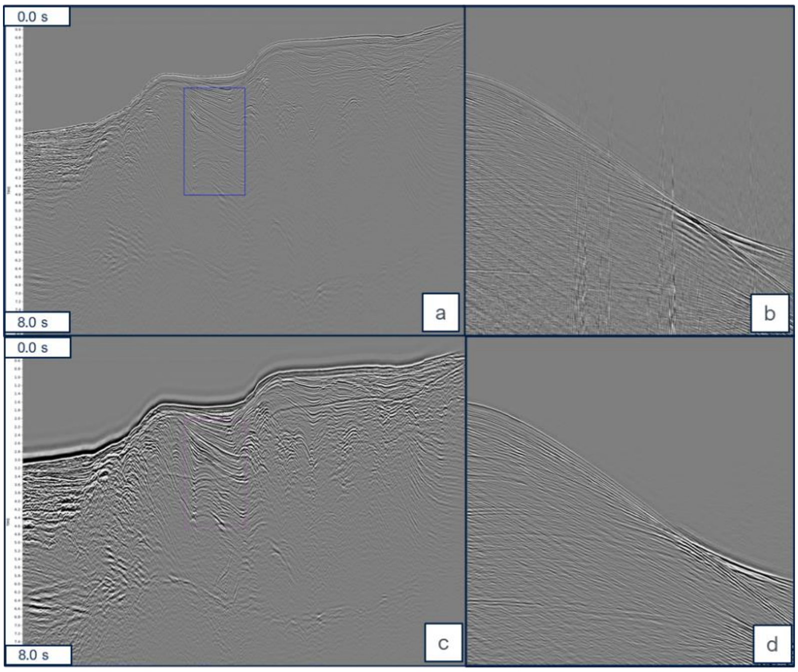

Figure 2 *Comparison of data before and after the ML fast track flow: a) and b) stack and shot gather before deswell; c) and d) the same stack and shot data after ML deswell, deghost and designature.*

Figure 3 shows a zoomed-in view of the 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.

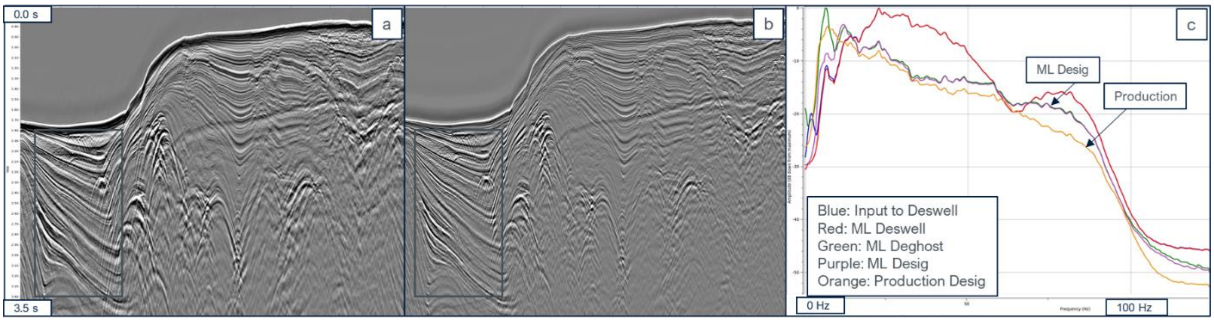

Figure 3 *Comparison of a) stack of conventional flow, b) stack of ML flow and c) amplitude spectra comparisons (blue rectangle shows the approximate analysis window).*

It is important to ensure the spatial consistency of the ML methods; therefore, the QC of the results is as important for ML solutions as it is for conventional processing. Taking the ML deghost flow as an example, we show a bespoke deghost QC to estimate the width of the wavelet before and after deghosting. We expect successful deghosting to shorten the wavelet width by removing sidelobes associated with source and receiver ghosts. This QC was run on a subset of the data before and after ML deghost in a one-second window following the water bottom. The results are shown in Figures 4a and 4b. The maps show a shift toward narrower wavelengths (more red colours), indicating good deghosting. A close analysis of the results reveals valuable information on localized variations in deghosting, making this a useful QC tool.

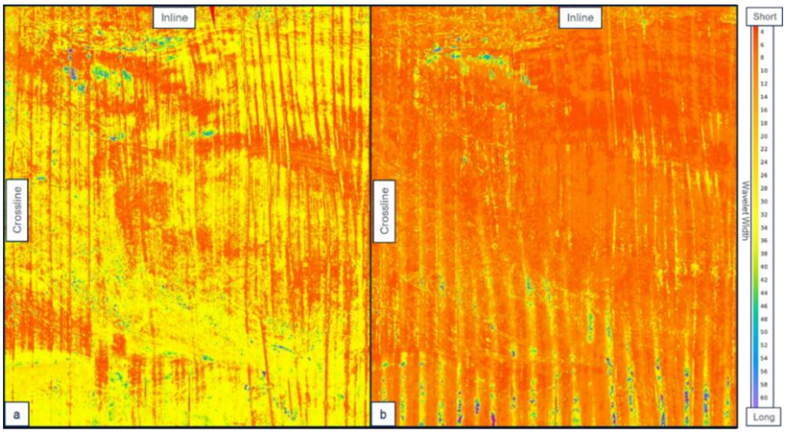

Figure 4 *Wavelet Width Deghosting QC: a) before ML deghosting; b) after ML deghosting*

Conclusions

This research demonstrates the transformative potential of machine learning in accelerating and improving marine seismic data preprocessing. ML offers a fast-track solution by automating key tasks like swell noise removal and deghosting, reducing processing time and enhancing data quality. One of the keys to the success of the method is the use of global models in the ML solution since they make possible the time savings associated with easier parametrization and reduced testing. However, as described here, some models need to be refined before use, which has a time and resource cost. Further work can be done to understand when to update models and how to do this efficiently within the time constraints of a production project. Work is ongoing to extend this approach to other preprocessing steps, such as demultiple.

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