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Full deghosting of Ultra-High Resolution seismic data with deep learning

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Summary

A good image of the seabed and shallow subsurface is crucial for activities such as windfarm site characterization. To generate a good image, it is usually necessary to attenuate the ghosts in early stage of the processing. However, deghosting of Ultra-High Resolution Seismic data (UHRS) is challenging. As the sea state continuously varies during acquisition, the actual source and receiver depths from the sea surface reflection point continuously fluctuate from the nominal depth leading to very high variability in the ghost arrival times relative to the original reflection. We present on real field data that a deep learning network can be used to simultaneously perform both source and receiver deghosting. The inversion based deghosting is used on a very small subset of data to create the training data for the network. We show that the performance of the trained network on unseen data from the same survey is robust and is suitable for both fast track and full integrity processing. We also discuss how trained network can very quickly be tuned if it encounters new data with, for example, unseen receiver depths. With such trained network, deghosting can be performed very fast and consistent.

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Introduction

A clear and sharp image of the seabed and shallow subsurface is crucial for windfarm site characterization. 3D Ultra-High Resolution Seismic data (UHRS) provides high-resolution 3-D images and potentially additional attributes such as velocities, diffraction images and some subsurface physical characteristics. In UHRS survey, seismic sources (e.g., sparkers, boomers) and receivers (hydrophones) are towed below the sea surface. The seismic sources emit acoustic energy which travels through the water and subsurface, and part of that energy is reflected upwards from the interfaces. There is also an undesired and very strong downward reflection from the sea surface called the ghost. Ghost reflections occur on both the receiver and source side, and they always have opposite polarity to the original reflection. The arrival times of the ghosts depend mainly on the depth of the source and receiver and the emergence angle of the reflected energy. In a UHRS survey, receivers are towed at very shallow depths (e.g. 3 m) compared to the oil industry acquisitions and sources are towed just below the sea surface (e.g. 0.5 m). The target vertical resolution for such surveys is a minimum of 0.25 ms leading to very high temporal sampling requirements. As the sea state continuously varies during acquisition, the actual source and receiver depths from the sea surface reflection point continuously fluctuate from the nominal depth leading to very high variability in the ghost arrival times relative to the original reflection. As the receivers are towed deeper than the sources, they naturally exhibit much higher variability.

To attenuate the ghost reflections, Bekara *et al*. (2024) proposed a data-driven inversion-based deghosting methodology that estimates the actual receiver depths and suppresses the receiver ghost by tracking and deconvolving the ghost in the (τ-p) domain. Deconvolution of the ghost operator is done via re-weighted iterative least squares which reduces ringing artefacts. The challenge with the proposed method is that it needs proper parameterization, and more processing hardware resources compared to conventional oil industry deghosting methods. This will increase both cost and turnaround time which are very restricting factors in windfarm surveys.

Researchers have recently successfully studied the application of Deep Learning (DL) in UHRS seismic deghosting (e.g. Farmani *et al*. 2024, Van Borselen and Vasconcelos 2024). Van Borselen and Vasconcelos (2024) showed on synthetic data with a source depth of 0.5 m and receiver depths in the range 0.3-1.1 m that a trained DL network can perform good source and receiver deghosting without any knowledge of the actual depth. Farmani *et al.* (2024) showed on real field data that a trained DL network can perform good receiver deghosting provided that the receivers' depth variation for the unseen data is close to range of receiver depths of the data used for training. Different network architectures have been used by these researchers. However, there has been a consistent practice of training the network in a supervised way either by using the synthetic data or through the use of input/output pairs prepared by other conventional processing methods. Both articles suggest that such trained DL networks are suitable for the fast track processing.

In this study, we extend the work of Farmani *el al.* (2024) and show on real field data that the same DL network used by authors to perform receiver deghosting can be used to simultaneously perform both source and receiver deghosting. We show that the performance of the network on unseen data from the same survey is robust and is suitable for both fast track and full integrity processing. The motivation behind this work is, first, to demonstrate that such a network can perform the full deghosting task much faster than the inversion-based method without requiring any user input parameters and, second, to demonstrate that both source and receiver deghosting can be performed by a single network.

Methodology

In our current approach, a small portion of the data in the acquired survey (e.g. one early sequence) is first fully deghosted using the method proposed by Bekara *et al.* (2024). Then, we train a convolutional neural network called real image denoising network (RIDNet) (Anwar and Barnes, 2019) to reproduce the fully deghosted output. RIDNet is a modular network comprising three main modules: feature extraction, feature learning residual module, and reconstruction. It has a sequence of modules called enhancement attention modules (EAM) which are sequentially connected to each other. Our RIDNet uses 4 EAM boxes. Compared to many other DL networks, RIDNet is a fairly small network with fewer learnable parameters. Therefore, training the model does not require large hardware resources. Once the model is trained, it is used to quickly deghost the other sequences in the survey. It is important that the training data encompasses the expected variation in source and receiver depths. We have observed that network can handle some deviations in source and receiver depth from the training data. However, as the deviation increases, the network performance becomes more and more suboptimal.

If, during the quality control of the deghosted data, data with suboptimal deghosting results are identified, due to, for example, a receiver depth that is not present in the training data, the network should be tuned for those data with re-training. However, there is no need for a full retraining. By using only a very small subset of the new, properly deghosted data, and freezing a large portion of the network, the network can be quickly re-tuned for the areas for which the original network performs suboptimally.

Example

The data used for this study are from a 3D UHRS survey acquired in 2024. The survey was conducted using 10 streamers, each 150 m long. The distance between receivers and streamers were 3.125 m and 12.5 m respectively. Four dual-stacked sparkers were used as seismic sources. The nominal receiver depth was 3 m, and source depth was 0.45 m. Temporal sampling was 0.125 milliseconds corresponding to a Nyquist frequency of 4 kHz. We first chose one of the early acquired sequences. The chosen sequence was fully deghosted using the inversion-based method for generating the desired output for supervised training. Apart from excluding the direct arrival, no additional pre-processing was applied to prepare the data for the training. The RIDNet network was then trained to learn the full deghosting task. The trained network was then ready to remove the source and receiver ghost from the other sequences in the survey.

Figure 1 shows the results of source and receiver deghosting of an inner cable from an unseen sequence in the survey in shot, channel, and stack domains. Both source and receiver ghosts are strongly attenuated by the RIDNet model. Figure 2 shows a zoomed section of the 2D QC stack before deghosting (2a), after inversion-based deghosting (2b), and after RIDNet deghosting (2c) for the same data in Figure 1. Note that inversion-based deghosting was applied with the same parameters used to generate the training data for RIDNet training and it was not tuned for the sequence. RIDNet deghosting appears to attenuate the residual ghost better and sharpens the dipping reflectors overlaid by the receiver ghost. One of the main strengths of DL networks is that they are trained on a large portion of data and, therefore, they are able to produce more consistent output compared to more locally applied algorithms. Figure 2d shows amplitude spectra of the images 2a, 2b and 2c. Figure 3 shows the results of source and receiver deghosting of an outer cable from the same unseen sequence in the survey in shot, channel, and stack domains. Again, both source and receiver ghost are strongly attenuated by the RIDNet model.

Conclusions

We present UHRS source and receiver deghosting using a convolutional neural network called RIDNet. The RIDNet model was trained using data deghosted by a data-driven inversion-based deghosting method. We showed that RIDNet can perform the full deghosting task on a new unseen sequence very well. We also discussed how the trained network can very quickly be tuned if it encounters new data with, for example, unseen receiver depths. Our methodology has been applied for both fast track and full integrity processing with good performance so far. The advantage of using such a method is removing the need for user parametrization, consistency in the performance and significant reduction in hardware usage and turn-around time.

Acknowledgements

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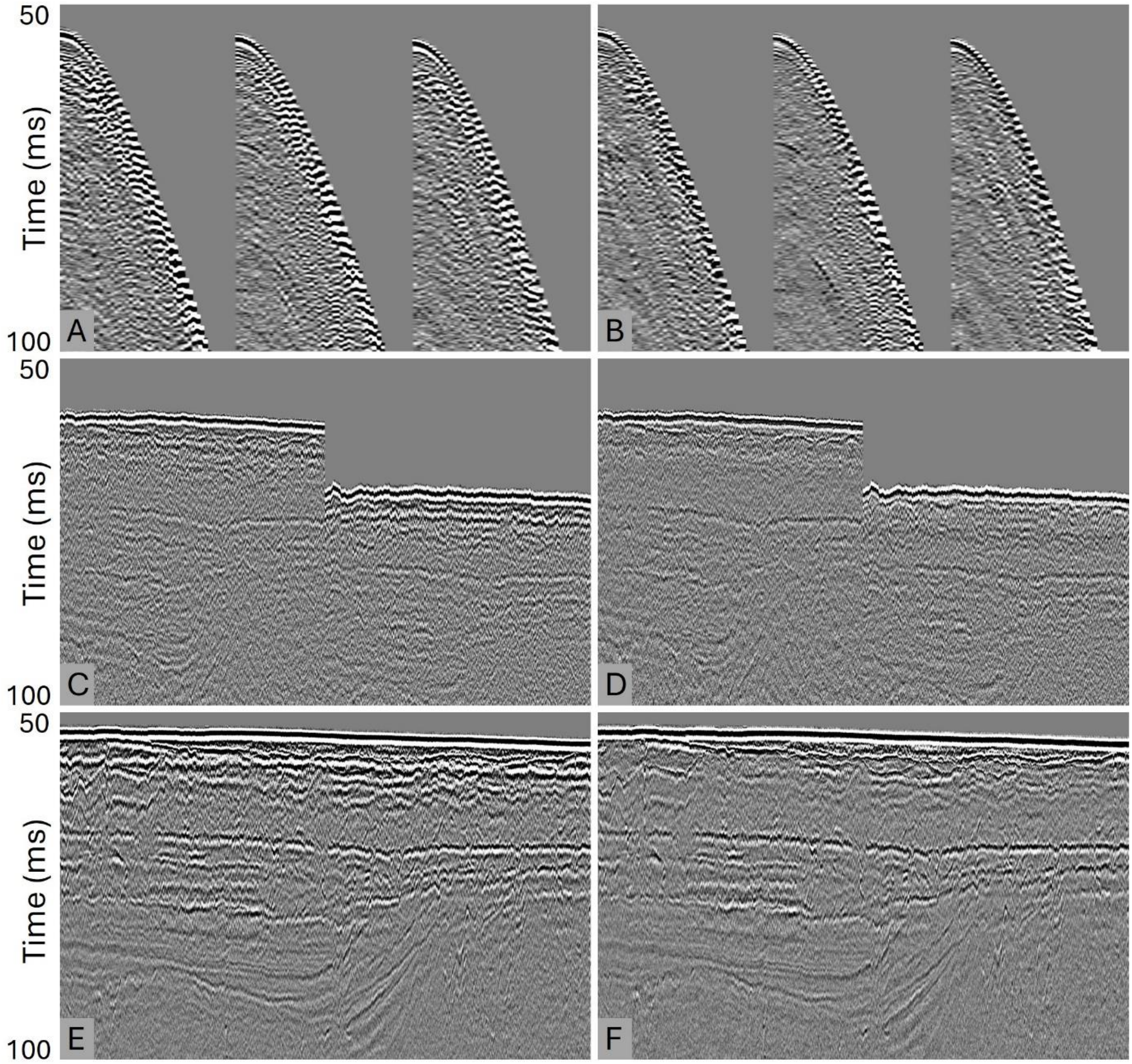

Figure 1 *Data example of an inner cable from an unseen sequence by the RIDNet network. Shot gathers a) before and b) after deghosting. Channel gathers c) before and d) after deghosting. 2D QC stack e) before and f) after deghosting. Images are scaled for display purposes.*

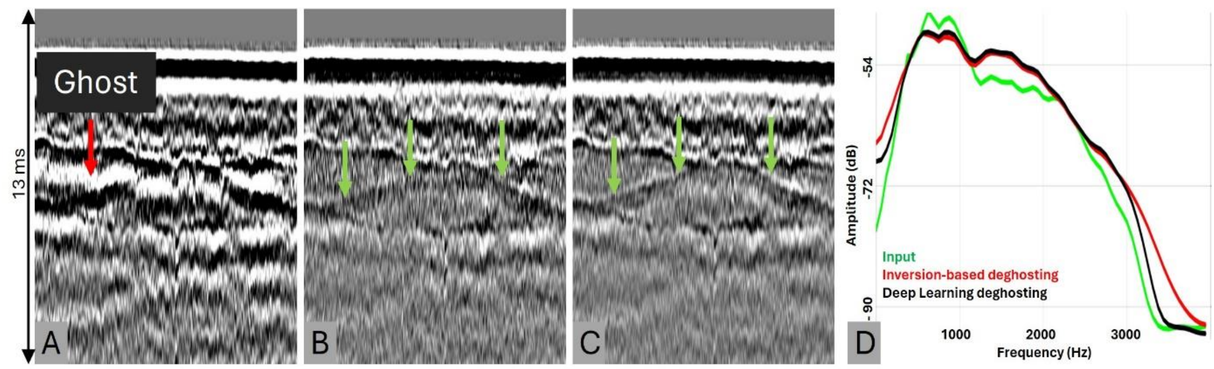

Figure 2 *Zoomed section of a 2D QC stack from the data example in Figure 1. a) Before deghosting with red arrow showing the receiver ghost. b) After inversion-based deghosting and, c) after RIDNet deghosting with green arrows showing dipping reflector overlaid by the ghost. RIDNet attenuates the residual ghost better and sharpens the dipping reflectors. d) Amplitude spectra of a, b and c.*

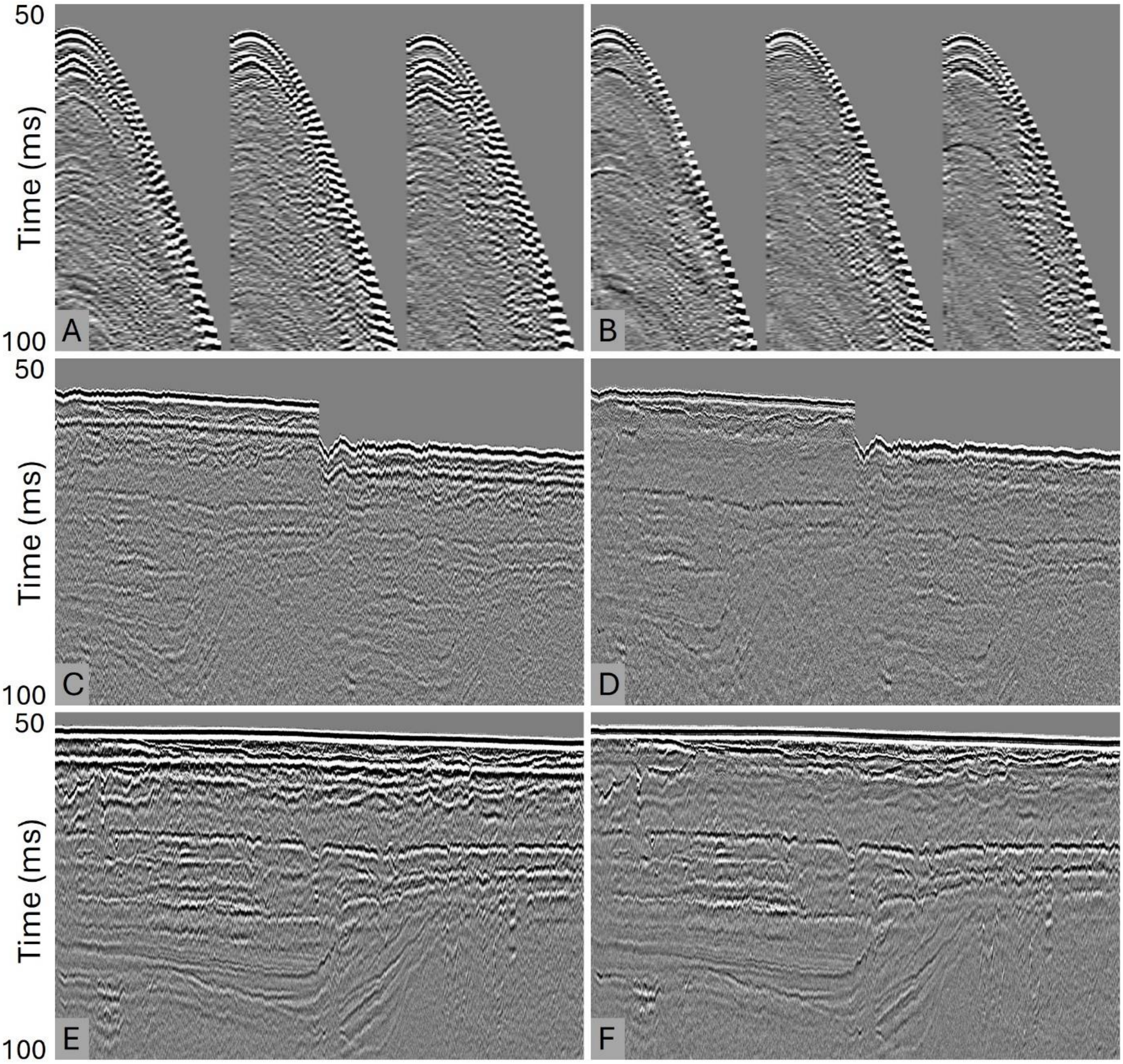

Figure 3 *Data example of an outer cable from an unseen sequence by the RIDNet network. Shot gathers a) before and b) after deghosting. Channel gathers c) before and d) after deghosting. 2D QC stack e) before and f) after deghosting. Images are scaled for display purposes.*

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