International Petroleum Technology Conference 2025

IPTC-24841-Abstract

A Study into Deep Learning-based Seismic Deghosting Using Multi-Component Measurements

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Summary

In this abstract, we explore the potential use of multi-component measurements towards deghosting using Deep Learning (DL). Using multiple wavefields, sufficient data diversity can be obtained to employ a generalized supervised Deep-Learning approach to map the recorded wavefields into deghosted pressure wavefields. The application of DL-based solutions to handle acquisition uncertainties, such as variable recording- and / or source depths is also investigated.

Method

The presence of ghosts is known to deteriorate the seismic image, as these ghosts are constructively and destructively interfering with the primary wavefields. In literature, several deterministic solutions have been developed to address the problem. Such methods require detailed information about several acquisition parameters, such as the source depths, the receiver depths along the recording cables, the state of the water surface and the reflection coefficient of the free surface, hampering user-friendliness and computational efficiency.

An alternative is to use supervised Convolutional Neural Networks (CNNs), where a network is trained to map the recorded wavefields into deghosted pressure wavefields. To ensure that such network can deal with uncertainties, data diversity during the training stage is critical.

Using an analytical modelling, the pressure wavefield (*Psct*), the vertical- and crossline horizontal component of the particle velocity (*Vz* and *Vy*) and the upgoing, receiver ghost-free data (labelled *Pup*) were created. Three synthetic well-logs with different water-depths were used, modelled at various source- and receiver depth configurations to ensure sufficient diversity of the training data.

Using the modelled data, a 12-layer deep feed-forward CNN was trained, where no encoding / decoding or skip-connections were used. The modelled data were split into a number of patches of 120-time samples and 50 traces, from which 80% was used to train the CNN, and the remainer to validate the network.

Results

Application of the CNN to perform the receiver deghosting using only the crossline component *Vy* leads to satisfactory results. Utilizing both the *Vy* and the scattered pressure wavefield *Psct* during the training stage, further improvements were obtained. This explained by the increased diversity of the data used during the training of the CNN.

The application of the same CNNs to a variable receiver depth inference data set, where the receiver depths varied linearly between 10 meters and 20 meters, also leads to satisfactory results, indicating the robustness of the Deep-Learning approach proposed.

Conclusions

This paper demonstrates the novel use of crossline particle velocity measurements in a Deep-Learning based approach to deghosting. By including additional measurements, such as the vertical component of the particle velocity and/or the pressure wavefield, the robustness of the trained neural network can be increased further. The method is also capable to deal with variable source / receiver depths during data acquisition.