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A Deep Internal Learning Coordinate-Based Method for Seismic Interpolation in a Marine Survey

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Introduction

The analysis of seismic data rely heavily on densely sampled data. However, physical and economic constraints result in sparse data possesing few seismic traces, complicating subsequent accurate imaging. The most common approach is interpolating missing traces of a shot gather, at the expense of large amounts of training data to adequately represent typical seismic events. A more advanced strategy is based on deep internal learning methods. It focuses on interpolating complete missing shot gathers in irregularly sampled data, which offers significant economic, environmental, and implementation benefits in land survey acquisitions. In this regard, we employ a method termed coordinate-based seismic interpolation (CoBSI), which employs a continuous coordinate-based representation of the seismic wavefield, parameterized by a neural network. In this work, we adapt the CoBSI method to a two-dimensional acquisition geometry. Our objective is to reconstruct missing shot gathers from irregular marine surveys using a simple, but effective multilayer perceptron (MLP) trained solely based on the available seismic data.

Method and/or Theory

The core idea of the CoBSI method consists of mapping a given coordinate $\boldsymbol{v} = [t, x_r, x_s]$ into a wavefield amplitude r using a neural network M_θ, i.e., $r = M_\theta(\boldsymbol{v})$. The elements of $\boldsymbol{v}$ denote time, receiver, and source positions, respectively. Moreover, we include in the MLP architecture nested Fourier features mapping functions γ acting on the coordinates set $\boldsymbol{v}_i$, where i index the elements of the training set. The MLP is trained in a self-supervised fashion by minimizing the mean squared error between the known amplitudes and the model predictions. After training, the acquired and interpolated amplitudes are mapped back to their respective coordinates to reconstruct the complete seismic dataset.

Results and Conclusions

Our results indicate that the CoBSI method can accurately restore seismic data with different missing shot gathers ratios, including regularly, and irregularly source sampling. A limitation of CoBSI lies in the fact that it requires training an MLP for each new seismic dataset. In our future work, we will explore this limitation by enhancing the MLP's generalization ability on different data sets. Additionally, we plan to investigate the performance of CoBSI on a three-dimensional acquisition geometry and explore alternative strategies for tuning the positional encoding frequencies.