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Seismic Data Interpolation with Graph Convolutional Networks

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Introduction

Seismic acquisitions with missing traces pose significant challenges to the construction of high-fidelity seismic images. The seismic interpolation techniques include frequency–space (FX) interpolation, prediction-error filtering, kriging, and more recently Machine Learning based methods, each aiming to reconstruct missing traces by exploiting spatial, spectral, or statistical properties of the seismic data. In this work we follow the Machine Learning approach, but we propose a novel strategy based on Graph Convolutional Networks (GCNs). The acquisition geometry is introduced in the GCNs framework in the following way: the nodes represent the seismic traces and edges are defined by the physical distances among traces. This representation enables the inference of missing traces by leveraging spatial relationships among neighboring traces.

Method and/or Theory

The strong point of the GCN formulation is that the spatial coordinates of receivers are naturally introduced in the graph structure of the network. The nodes with available traces are connected to nodes with missing traces, and edge weights are computed based on the inverse Euclidean distance among them. Binary masks are applied to simulate incomplete acquisition scenarios and are employed to simulate the absence of traces. These scenarios are used for training and testing the GCN in a self-supervised way. The edge weights guide the flow of information across the network, allowing the network to learn and infer missing traces from nearby ones. In this way, the GCN model is trained to minimize the reconstruction error of masked traces using their topological and spatial context.

Results and Conclusions

The results demonstrate that framing the seismic interpolation problem as a graph-based learning task is a promising tool. The GCN was able to reconstruct the masked traces while preserving spatial continuity and relevant seismic signal characteristics. The main limitation arises in regions with low connectivity or sparse neighborhoods, where interpolation is less accurate. Current improvements include refining the graph connectivity criteria, exploring new metrics in the graph, adding spectral information as new features in the graph, and tuning the batch size in the GCN learning process. The interpolated data used in this study are synthetic, but applying the method to real seismic datasets is one of the next steps in our research. As a perspective, the proposed graph-based approach shows strong potential in seismic preprocessing and data recovery under irregular acquisition conditions.