Submission code: A8VNB0GK8L

Enhancing low-frequency data for FWI through Self-Supervised Learning

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Introduction

A high signal-to-noise ratio (SNR) on the low-frequency (LF) band of the seismogram is essential for Full-waveform inversion (FWI) to be robust against uncertainties in the initial velocity model. Due to the importance of LF, numerous engineering efforts are focused on developing sources and receivers capable of acquiring data with a high signal-to-noise ratio (SNR) in the LF band. Despite these efforts to obtain better LF seismograms, a large amount of vintage data lacks high-quality LF content. Reprocessing these data with new techniques can improve the geological understanding of specific regions and expedite some business decisions.

Various formulations were proposed to map the non-linear relationships between the frequency bands of the seismic data for reconstructing the low-frequency (LF) component. The range of solutions encompasses predictive filters to deep learning (DL), given their ability to learn patterns and infer missing information from images.

Method and/or Theory

The use of deep learning methods to optimize and improve seismic processing still faces several challenges, primarily related to generating suitable data for training. In this work, we evaluated a self-supervised low-frequency (LF) reconstruction method called Low2Lower, which eliminates the data generation problem. This method trains a neural network to increase the LF content of the input data using the real data itself as input for training. The self-supervised pipeline employs a modified version of classical U-Net architecture. A key modification to the original U-Net is the concatenation of the input data with the final convolutional layers, ensuring the preservation of high-frequency details in the seismogram.

The self-supervised nature of the training arises from the neural network receiving high pass filtered versions of the real data as input, with the original real data serving as the label. The data is prepared by selecting 2D patches from the seismic shots. The loss function combines two L1 norms: the first computes the difference between the output and label in the time domain, and the second computes the misfit in the amplitude spectra.

Results and Conclusions

We tested the method over two different datasets from the Santos Basin. The first dataset is from a legacy streamer acquisition with an initial peak frequency for inversion of approximately 5 Hz and a low SNR. The second dataset is from a modern Ocean Bottom Node (OBN) acquisition, which, despite presenting useful information down to approximately 1 Hz, exhibits a high level of noise and some artifacts in this initial frequency band. For both datasets, we observed an increase in signal coherence, even when analyzing the data in regions orthogonal to the inference direction for the OBN case. The FWI tests on the streamer data demonstrate the potential for higher convergence and a more detailed final model, which could lead to improved FWI imaging results.