



An Enhanced FWI Scheme using Machine Learned Low Frequency Signals

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Full waveform inversion (FWI) has been extensively used in ground penetrating radar and seismic imaging. Ideally, FWI exploits full bandwidth data with both low frequency and high frequency signals. In reality, the obtained GPR or seismic signals are usually band-limited without reliable low-frequency components due to sensor limitation. The missing low frequency data may lead FWI to be trapped in local minima and present strong artifacts in the inversion results, which is also called the cycle skipping phenomenon.

We propose an enhanced FWI scheme with machine learned low frequency signals using a deep neural network (DNN). A DNN is constructed for learning a fast forward non-linear mapping from the high frequency data to the low-frequency data. After well-trained, the network serves as a fast and accurate low-frequency data predictor. The machine learned low frequency signals will be integrated into the FWI framework to enhance the subsurface imaging results [1].

To improve the performance of the DNN, we proposed a progressive transfer learning workflow as shown in Figure 1. The progressive transfer learning starts from an initial guess of the geophysical model, which is used for generating the initial training set. Each loop of the progressive transfer learning is described as the following steps: (1) Train the network with the current training set; (2) Use the trained network to predict the low-frequency data from the high-frequency data; (3) Perform the inversion using the predicted results; (4) Use the predicted geophysical model for the progressive transfer learning, we propose to construct the initial geophysical model for training using a bandwidth-extension (BWE) dataset obtained by a supervised learning strategy. First, we perform the conventional sparsity-promoted bandwidth-extension algorithm on a small part of the raw data to yield a labeled training dataset. After that, the fully trained network makes the wideband data prediction on the remaining raw seismic data (band-limited). With this strategy, we are able to cut the computational cost substantially. We have tested this workflow using seismic and GRP data, the results show that the proposed approach can significantly improve inversion performance with predicted low-frequency data.

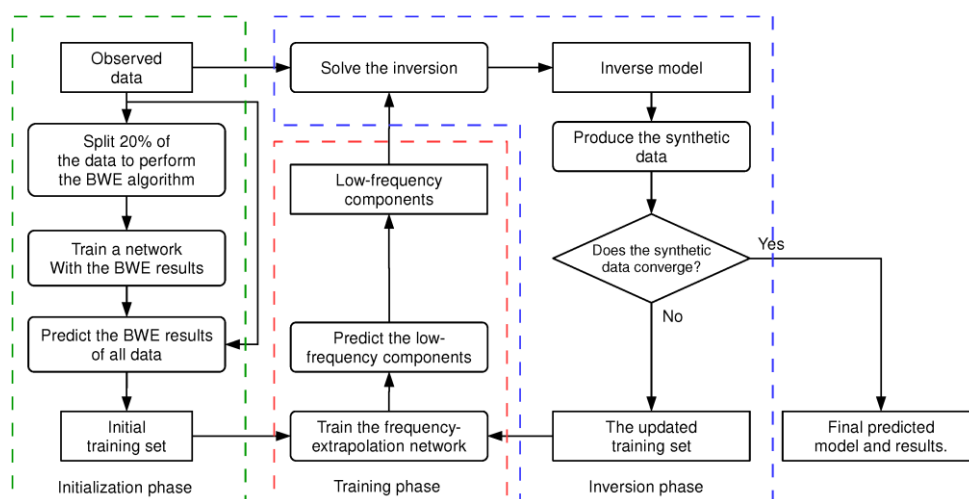


Figure 1. Workflow of enhanced FWI with machine learned low frequency signals.