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| Please fill in your manuscript title. | A Label-Free Deep Learning Method for Cycle-Skipping Suppression in Seismic Full-Waveform Inversion |

Please fill in your author name(s) and company affiliation.

| Given Name | Surname | Company |
|---|---|---|
| Wenyi | Hu | Advanced Geophysical Technology, Inc. |
| Yuchen | Jin | University of Houston |
| Xuqing | Wu | University of Houston |
| Jiefu | Chen | University of Houston |
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## Abstract

### Objective

To effectively prevent the cycle-skipping phenomenon in FWI when low frequency seismic data are unavailable, we developed a novel deep learning method integrated with a physics-based module to reconstruct the low frequency phase information from the high frequency components. Numerical experiments validated the accuracy and robustness of this approach. Without any frequency components below 10 Hz, this approach is able to successfully invert complicated velocity models without being contaminated by cycle-skipping-induced artifacts.

### Methodology and Workflow

Unlike standard deep learning method that requires a large amount of labeled training datasets to exhaustively learn the underlying relationship between the high frequency (HF) and low frequency (LF) data, this label-free deep learning approach retrieves the HF-LF relation iteratively by progressively evolving a single training dataset to generalize the deep learning network, as shown in Figure 1. Furthermore, the initial training velocity model is automatically generated through a bandwidth extension algorithm and the LF prediction is implemented in a semi-supervised manner.

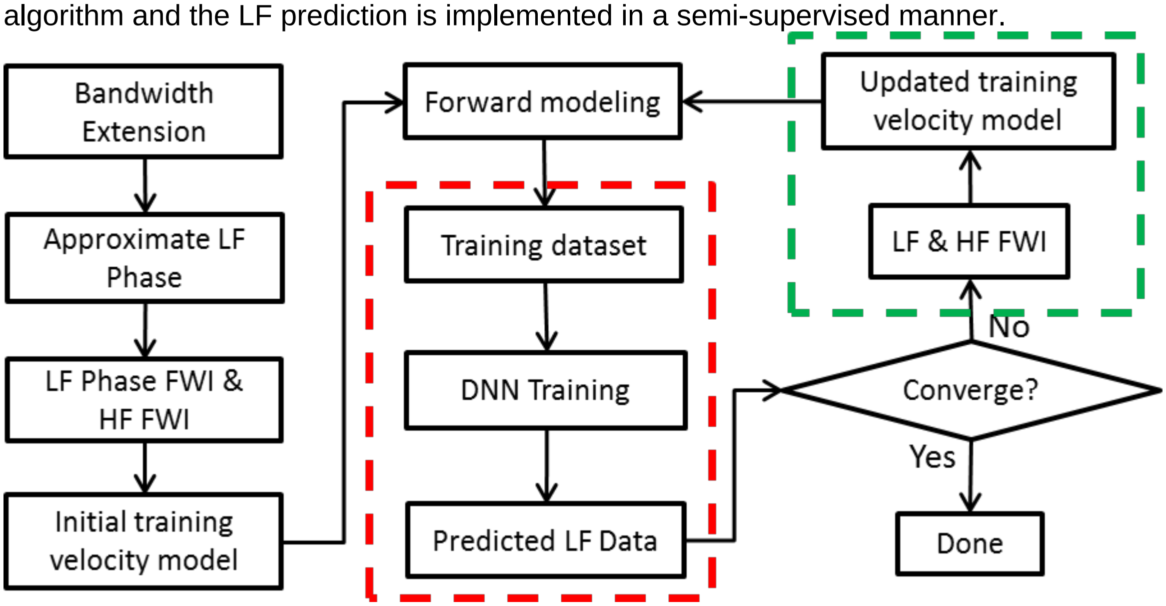


Figure 1. Workflow of the label-free physics-driven deep learning method for LF data reconstruction.

## Numerical Results

A numerical experiment is conducted to reconstruct the BP2004 velocity model (Figure 2a), assuming only 10 Hz and higher frequency data are acquired and a simple 1D linear velocity model is available as the FWI initial model (Figure 2b). The data in the frequency range 10 Hz – 25 Hz are input into the deep learning network to predict the 3 Hz – 9 Hz data. Figure 3 shows the comparison between the true 3 Hz and the deep learning predicted 3 Hz data. The FWI result using the predicted 3 Hz – 9 Hz data and the measured 10 Hz – 25 Hz data is shown in Figure 2c, where the salt structures are resolved properly without being affected by the cycle-skipping issue. On the other hand, the FWI using 10 Hz -25 Hz measurement data (Figure 2d) only fails to recover the salt and produces a completely wrong subsurface structure.

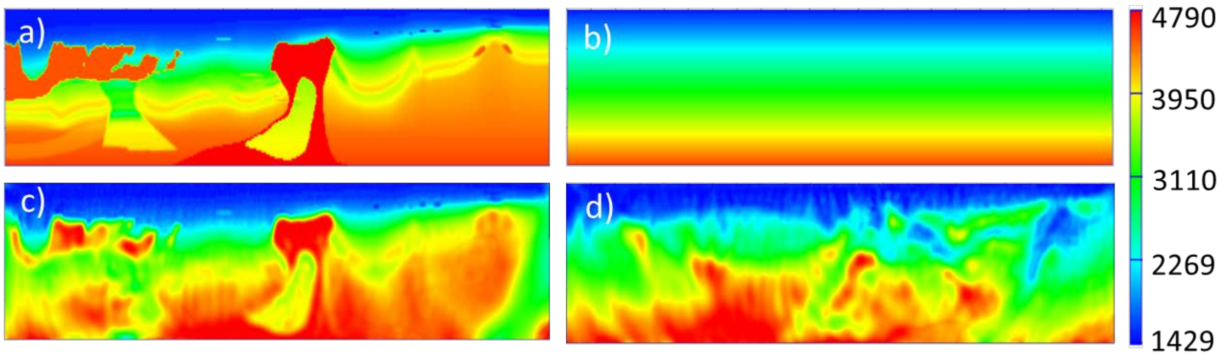


Figure 2. a) True model; b) initial FWI velocity model; c) FWI result using predicted 3 Hz – 9 Hz and measured 10 Hz – 25 Hz data; d) FWI result using measured 10 Hz – 25 Hz data.

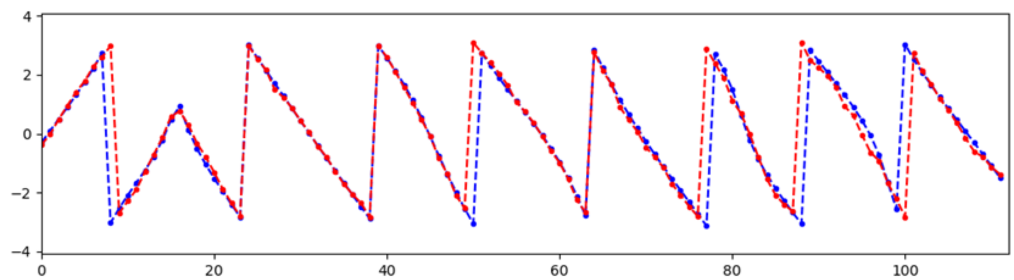


Figure 3. Blue – true 3 Hz data; red – deep learning predicted 3 Hz data.

## Novel and Additive Information

The deep learning-based method developed in this work has the following novel features: 1) a progressive transfer learning strategy to generalize the deep learning network without being overwhelmed by large quantity of training data; 2) a bandwidth extension algorithm to automatically initiate the label-free learning process; 3) a semi-supervised learning workflow to reliably fill large bandwidth gap.

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## Disclaimer