Broadband FWI through alternating restoration and inversion of missing frequencies

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Summary

Acquired seismic data are always bandlimited. In typical seismic datasets, low frequency components are often absent, imposing big challenges for full waveform inversion (FWI) due to the cycle skipping phenomenon. In this work, we developed a novel method, FWI through alternating restoration and inversion (ARI-FWI), to restore the missing bandwidths in the recorded seismic data. The ARI-FWI method includes three modules: 1) Data Inversion Module; 2) Bridging Module; 3) Data Restoration Module. In the Data Inversion Module, a synthesized low frequency dataset is inverted by a conventional FWI engine to produce a low resolution velocity model. This velocity model serves as the starting model in the Bridging Module to invert the high frequency measurement data, outputting a high resolution velocity model to the Data Restoration Module, where a forward modeling simulator synthesizes a dataset consisting of the low frequency components that are absent in the measured data. After that, this synthetic dataset is injected back into the Data Inversion Module to start a new iteration. Within the ARI-FWI workflow, these three modules are implemented alternatingly to restore the missing low frequency components, gradually increasing the restoration accuracy as the iteration proceeds. After each ARI-FWI iteration, the Data Inversion Module provides an enhanced low resolution velocity model for the high frequency FWI in the Bridging Module. On the other hand, the Data Restoration Module always reconstructs the low frequency components with improved accuracy over the previous iteration. Eventually, the restored low frequency data tends to converge to the true low frequency data and the final velocity model is expected to contain broad and continuous bandwidth wavenumber, eliminating the cycle-skipping artifacts. The numerical experiments are presented to validate that this novel approach accurately restores the missing frequency components within a few iterations without any *a priori* information of the geological structures. The velocity models reconstructed by the ARI-FWI method in the numerical experiments are immune to the cycle-skipping phenomenon even in complicated geological environment with complex salt domes.

Introduction

Because reliable low frequency components below 5 Hz do not practically exist in most acquired seismic datasets, FWI, an advanced velocity model building technology, often suffers from the cycle-skipping issue, inducing strong artifacts in the inversion results and causing misinterpretation of the subsurface geophysical properties and geological structures. In recent years, many research efforts were devoted to overcome this challenge, i.e., suppressing the cycle-skipping phenomenon without acquiring low frequency data. Many of these research works were reviewed and summarized by Hu et al. (2018). One category of these approaches is to synthesize artificial low frequency data using high frequency data via some nonlinear transformations (Shin and Cha 2008; Wu et al., 2014; Li and Demanet, 2016). Although the limited numerical testing shows some positive potential, the inherent high sensitivity to noise and some questionable assumptions made in these approaches prevent them from being applied to industry production. More recently, some researchers embraced the powerful deep learning neural networks to predict the absent low frequency data from the acquired high frequency seismic data (Jin et al., 2018; Sun and Demanet, 2018; Ovcharenko et al., 2018). While the early stage work on these pure data driven methods are very encouraging and imply great potential of this research direction, some major questions of this category of methods need to be addressed. For example, how to design the training datasets to yield unbiased training result? How to reduce the number of training datasets to make the algorithms computationally manageable? How to quality control the network training process?

All of these research efforts help mitigating the cycle-skipping issue to some extent. However, till today, direct restoration of the missing low frequency components from acquired high frequency seismic data remains as an extremely challenging task. In this work, after a feasibility study of this topic, we propose a novel methodology for iterative restoration of the missing bandwidth in the recorded seismic data with high accuracy and robustness. This new method, the so-called Alternating Restoration and Inversion FWI (ARI-FWI), initiates the low frequency data restoration by inverting a set of pseudo low frequency data derived by the Beat Tone technique (Hu, 2014). After that, in every iteration of ARI-FWI, a high frequency FWI (using measurement data) is implemented to produce a high resolution velocity model even it is severely contaminated by cycle-skipping induced artifacts. This velocity model is input into a forward modeling simulator to generate a set of synthetic data containing the missing frequency components in the acquired seismic data. Next, the synthesized low frequency data are fed into the FWI engine to produce a low resolution velocity model, serving as the starting FWI velocity model for the next ARI-FWI iteration. To summarize, the ARI-FWI method performs the low frequency data restoration and inversion alternatingly in an iterative manner with additional information generated by the high frequency data FWI continuously streaming into the process, thus steadily increases the data restoration accuracy as the iteration proceeds.

Nonlinear Link between Low and High Frequency Data

For general random signals, there is no meaningful relationship between the low frequency components and the high frequency components. Consequently, the low frequency data reconstruction is impossible. However, in exploration geophysics, acquired seismic data are not random signals. Instead, they are the earth response to a wideband excitation deployed on the earth surface. Therefore, there is an implicit tunnel connecting the low frequency components and the high frequency components and this tunnel is established through the wavenumber components of the subsurface geological and geophysical properties. According to the diagram shown in Figure 1, there are two important observations: 1) low frequency data are mainly contributed by the subsurface low wavenumber information; 2) high frequency data are dominantly contributed from the high wavenumber structures but also carry some information of the low wavenumber structures due to the various offset setting in a seismic data acquisition survey.

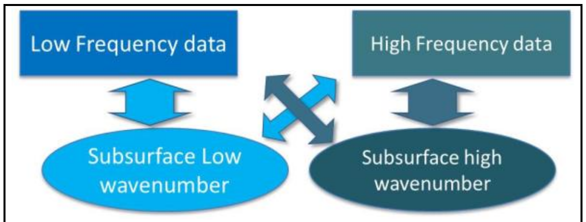

Figure 1: Diagram of relationship between low frequency and high frequency components through subsurface wavenumber.

Based on these observations, there is an established route connecting high frequency data – subsurface wavenumber – low frequency data. Our task is to study the high frequency data and predict the low frequency data by retrieving the subsurface low wavenumber information, which acts as the link connecting these two data bandwidths. Unfortunately, although direct inversion of high frequency data is able to reconstruct some valuable low wavenumber information, the reconstructed low wavenumber information in this way is only partially correct if there is no low frequency component participating in the FWI process. Furthermore, this partially recovered low wavenumber information is buried in the overwhelming high wavenumber information, and is contaminated by the cycle-skipping-induced artifacts. In order to perform a successful FWI immune to the cycle-skipping artifacts, we need to amplify the proper low wavenumber information, remove the incorrect low wavenumber information, and suppress the high wavenumber during the restoration of low frequency data.

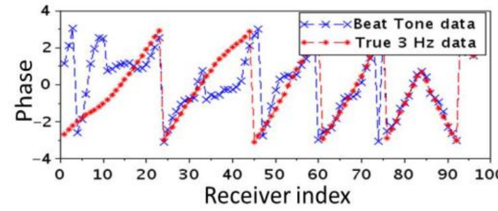

Figure 2: Comparison between pseudo 3 Hz data derived from 10 Hz and 13 Hz data using Beat Tone technique and true low frequency 3 Hz data.

A simple method of low frequency data prediction is the Beat Tone technique (Hu, 2014). The pseudo-low-frequency data calculated by the Beat Tone method share some spatial variation patterns as the true low frequency data. As shown in Figure 2, the pseudo 3 Hz data (phase only) calculated from the 10 Hz and 13 Hz exhibit similar patterns to the true 3 Hz data, but they are not identical. In other words, the Beat Tone technique is capable of amplifying the low wavenumber information while suppressing the high wavenumber. However, the Beat Tone method is unable to completely eliminate the high wavenumber components contained in the high frequency data unless the scenarios are extremely simple. Moreover, the accuracy and reliability of the low wavenumber information amplified by the Beat Tone technique is highly dependent on the geological structures, survey geometry, data quality, and many other factors.

ARI-FWI Method

In this work, we developed a more advanced approach for robust and accurate low frequency data restoration. The flowchart of this approach is shown in Figure 3. There are three modules in the workflow: 1) Data Inversion Module; 2) Data Restoration Module; 3) Bridging Module. In the Data Inversion Module, the synthesized low frequency data are fed into an FWI engine to produce a low resolution velocity model with partially recovered low wavenumber information. In the Data Restoration Module, a high resolution velocity model (might be contaminated by cycle-skipping-induced artifacts) is input into a forward modeling simulator to produce a set of synthetic data with the frequency components that are absent in the measurement data. The Bridging Module connects the Data Inversion Module and the Data Restoration Module through an FWI process inverting the high frequency measurement data.

Next, a simple numerical example (the lowest frequency used in this example is 10 Hz) is presented to describe the ARI-FWI workflow and show the performance.

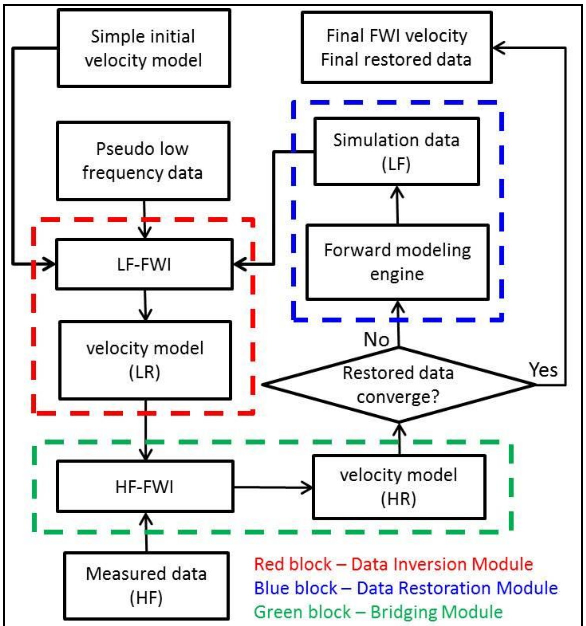

Figure 3: Workflow of ARI-FWI.

LF – low frequency; HF – high frequency; LR – low resolution; HR – high resolution.

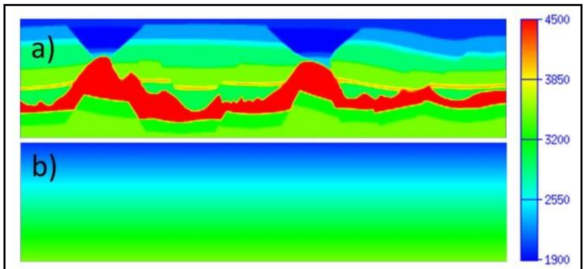

Figure 4: a) True velocity model; b) simple intial velocity model.

In this example, the true velocity model and the simple initial velocity model are shown in Figure 4a and 4b, respectively. The ARI-FWI process is initiated by an FWI inversion of the pseudo 3 Hz data calculated from the 10 Hz and 13 Hz using the Beat Tone technique. The resulting low resolution velocity model is sent to the Bridging Module for the high frequency FWI (10 Hz – 30 Hz measurement data). Within this module, some of the improper low wavenumber information produced by the pseudo 3 Hz data is corrected as a byproduct while the FWI engine attempts to invert the high frequency measurement data. However, at this early stage, the corrected low wavenumber information is buried under the large amount of high wavenumber information. This partially recovered low wavenumber information is very valuable but is far from sufficient to avoid the cycle-skipping and eliminate the corresponding artifacts as observed in Figure 5.

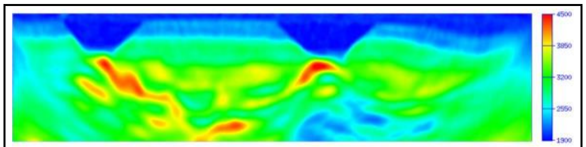

Figure 5: FWI inversion of pseudo 3 Hz data, followed by high frequency FWI inverison of measurment data (10 Hz – 30 Hz). Cycle-skipping induced artifacts are strong.

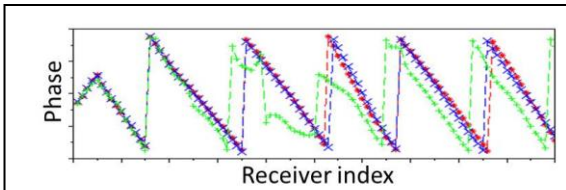

Figure 6: True 3 Hz data (blue), pseudo 3 Hz data (green), and reconstructed 3 Hz data (red) after one iteration of ARI-FWI.

The next step is to retrieve the valuable low wavenumber information buried in the artifact contaminated velocity model shown in Figure 5, and convert the retrieved low wavenumber information to the data domain. We designed the Data Restoration Module to accomplish this task. In the Data Restoration Module, a forward modeling is performed to produce a low frequency synthetic dataset. This completes the first ARI-FWI iteration. The reconstructed 3 Hz data after the first ARI-FWI iteration are significantly improved over the pseudo 3 Hz data. As shown in Figure 6, they are almost identical to the true 3 Hz data with slight deviation at far offsets.

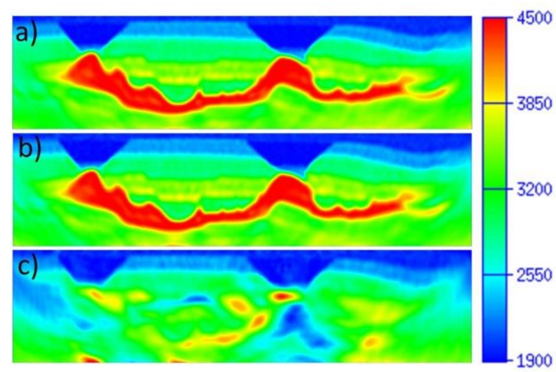

Figure 7: a) reference solution (conventional FWI using full bandwidth data from 3 Hz to 30 Hz); b) ARI-FWI result after 3 iterations using lowest frequency of 10 Hz; c) conventional FWI using high frequency data from 10 Hz to 30 Hz.

In the Data Restoration Module, any low frequency components can be reconstructed as needed. In this example, we restore 3 Hz, 5 Hz, and 7.5 Hz. After 3 iterations of ARI-FWI, both the restored low frequency data and the velocity model converge. The final velocity model of ARI-FWI (Figure 7b) is nearly identical to the reference solution in Figure 7a (conventional FWI inversion of true full bandwidth data 3 Hz – 30 Hz). The conventional FWI using only the high frequency data (10 Hz – 30 Hz) gives severely artifact-contaminated velocity model as shown in Figure 7c.

ARI-FWI of BP-2004 Model

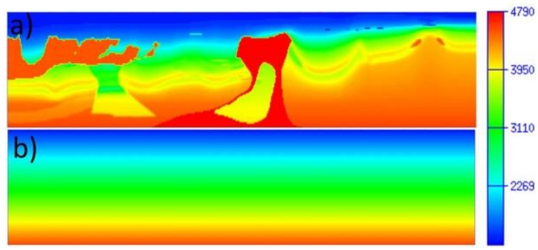

Figure 8: a) true velocity model; b) simple intial velocity model.

To further verify the robustness and accuracy of the ARI-FWI method, we tested the approach on a more complex velocity model. The true velocity and initial velocity are shown in Figure 8a and 8b.

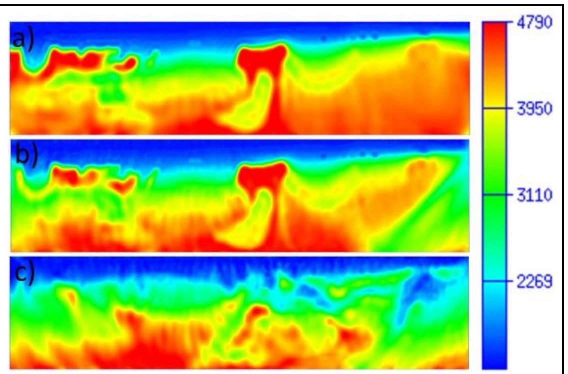

Figure 9: a) reference solution (conventional FWI using full bandwidth data from 3 Hz to 25 Hz); b) ARI-FWI result after 5 iterations with lowest frequency of 10 Hz; c) conventional FWI using only high frequency data from 10 Hz to 25 Hz.

We performed 5 iterations of the ARI-FWI, starting from the simple initial velocity model shown in Figure 8b. Again, the lowest frequency components used for the ARI-FWI is 10 Hz. The final result is shown in Figure 9b. For comparison, the reference solution (obtained by implementing conventional FWI using full bandwidth data from 3 Hz to 25 Hz) is presented in Figure 9a. Except for the regions near the edges of the inversion domain, the ARI-FWI result is in excellent agreement with the reference solution. On the other hand, the conventional FWI using 10 Hz to 25 Hz data failed to resolve the salt structures and produced strong artifacts. Similar to the previous numerical example, not only 3 Hz, but also 5 Hz and 7.5 Hz data are restored accurately. This capability implies that the ARI-FWI approach is not only an effective method for the cycle-skipping suppression, but also a powerful algorithm for reconstructing velocity model covering broad and continuous wavenumber spectrum. The 3 Hz and 5 Hz data restoration effect is plotted in Figure 10a and 10b.

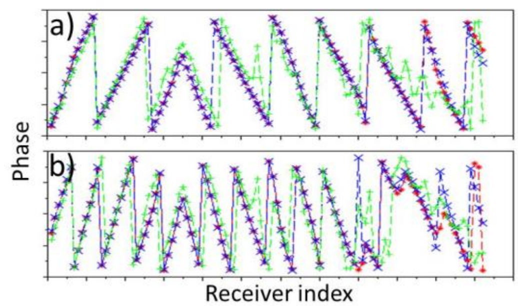

Figure 10: True low frequency data (blue), pseudo low frequency data (green), and reconstructed low frequency data (red) after 5 iteration of ARI-FWI on BP-2004 model: a) 3 Hz; b) 5 Hz.

Conclusions

A novel ARI-FWI method was developed and its effectiveness of cycle-skipping suppression was validated. The ARI-FWI method alternatingly performs the Data Inversion Module, the Bridging Module, and the Data Restoration Module in an iterative manner to progressively restore and correct the low wavenumber information in the reconstructed velocity model, retrieve this gradually enhanced low resolution structural information that is buried in the overwhelming high wavenumber components, and convert it to the data domain, thus successfully restoring the missing bandwidth in the acquired seismic data with high accuracy. The robustness of this approach is verified by the two numerical experiments. Without any frequency components below 10 Hz in the measurement data, this method successfully eliminated the cycle-skipping artifacts. It is worth mentioning that the ARI-FWI method is potentially a very powerful tool for high quality subsurface velocity model building covering broad and continuous wavenumber spectrum because it is able to restore any missing low frequency components as needed.

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