Low frequency data reconstruction for Full Waveform Inversion

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Summary

Overcoming cycle-skipping in Full-Waveform Inversion (FWI) is important for the automation of this technology and key for its success to build high-resolution velocity models. Cycle-skipping arises from the nonlinearity of the cost function used in the FWI formulation. A simple solution to mitigate the cycle-skipping problem, without reformulating a new objective function, is to use the low frequency content of the seismic data and/or to start from an accurate initial velocity model. However, the Signal-to-Noise-Ratio (SNR) at low frequencies is often bad and it is not always possible to improve it with conventional noise attenuation approaches. In this work, we show that by properly reconstructing the low frequency content of seismic data we can effectively mitigate cycle-skipping and not only reduce the dependency on an accurate initial model but also improve the quality of the final model. We apply FWI to a multi-sensor field dataset, acquired offshore Angola, and we compare its performance with and without low frequency reconstruction. The frequency reconstruction was done below 4 Hz and the chosen starting model was not accurate enough to avoid cycle-skipping. Results demonstrate the effectiveness of the proposed approach to mitigate cycle-skipping and to improve the accuracy of the final model. Low frequency reconstruction is a powerful and cost-effective data conditioning step in our proposed FWI workflow that can help reduce the turnaround time for the velocity model building process.

Introduction

Full waveform inversion (FWI) aims to recover a high-resolution velocity model using least-squares minimization of the difference between field and numerically modeled seismic data. To reduce the nonlinearity of the objective function and minimize potential cycle-skipping, good quality low frequencies and/or an accurate initial velocity model are required. Alternative objective functions have been proposed to improve the convexity of the FWI cost function. Attributes, such as time-lag (Luo and Schuster, 1991), seismic data envelope (Wu et al., 2014), or phase derivative (Choi and Alkhalifah, 2013), have been used to describe the data misfit. Domain extension (Symes, 2008) in the model or data domains has also been shown to reduce the non-linearity but adds computational cost.

A different solution is to enhance the quality of the low frequency content in the data. Low frequencies with good SNR are not only crucial to reduce cycle-skipping but also are needed to build an accurate background (low wavenumbers) for the inverted velocity model. Acquiring data with good SNR below 3 Hz, is still challenging due to environmental noise and physical limitations of the seismic sources. To address this issue, Li and Demanet (2016) extrapolated the low frequencies by decomposing the data into frequency-dependent amplitude and phase atoms. The method was applied mainly to synthetic data and helped improve the background velocity model. Recently, alternative approaches, driven by advances in Machine Learning (ML), have been proposed. Various network architectures have been tested and, in most cases, the extrapolation models are trained using synthetic data (Ovcharenko et al., 2017; Sun and Demanet, 2020). However, generalization to field data and possible bias towards the training models are issues that still need to be addressed.

As an alternative solution, a signal-processing-based approach for Low Frequency Reconstruction (LFR) was proposed by Bekara et al. (2022). This solution was used to condition field data for FWI application and shown to improve the quality of the inverted final model (Djebbi et al., 2022). In this work, we apply the proposed method to a field dataset acquired in offshore Angola and demonstrate its benefits in assisting FWI to minimize cycle-skipping. We briefly describe the LFR approach and the FWI algorithm, then we show the low-frequency reconstruction and FWI results.

Method

The low frequency reconstruction is performed using an autoregressive filter estimated from the data itself at higher frequencies. It is based on the concept that a sequence of spikes in the time domain maps into a superposition of linear harmonics in frequency domain, which can accurately be modeled using autoregressive filters. The method transforms the data locally over sliding data windows, from the time-space to the frequency-slowness domain where the reconstruction is performed. The data transformation is important to enforce the sparsity assumption of the signal and limit the deviation from the linear harmonic assumption. Furthermore, the reconstruction is naturally constrained within the data "signal cone" and is performed in a stepwise fashion and the recursive model is re-estimated after the reconstruction of each frequency sample (Bekara et al., 2022).

To demonstrate the benefits of the reconstruction of the low frequencies in FWI, we use an inversion algorithm based on the $\boldsymbol{L_2}$ objective function. We apply a multiscale approach starting from the lowest available frequencies to achieve optimal convergence to a good model. At the early stages of inversion (low frequencies), we use an FWI kernel that removes the reflection isochrones from the gradient and enhances the long wavelengths (Ramos-Martinez et al., 2016). At the final stage of the multi-scale strategy (higher frequencies), a conventional cross-correlation gradient kernel is used to incorporate more details into the recovered model.

Low frequency data reconstruction

We demonstrate the performance of our low frequency reconstruction approach using synthetic data. We numerically modeled the seismic response for a source/receiver geometry that mimics a typical streamer acquisition with a maximum offset of 8 km and using the Marmousi II velocity model. The source wavelet is a Ricker wavelet with 16 Hz peak frequency. Figure 1-a shows the modelled data (noise free) in the 1-4 Hz frequency band. In Figure 1-b, we added low-frequency noise extracted from typical field data. The noise is very strong and the SNR equals -46dB at 2 Hz, and -18dB at 4 Hz which makes conventional denoising processes ineffective. Figure 1-c shows the result of the application of a sequence of F-X projection and F-X prediction filters in various data sorting domains. The LFR result is shown in Figure 1-d. Frequencies below 4 Hz are reconstructed using higher frequencies (4-8 Hz). The quality of the data is considerably improved and most of the events are recovered with high accuracy. With this controlled experiment we showed that the reconstruction, although not perfect, is able to recreate useful signal for FWI.

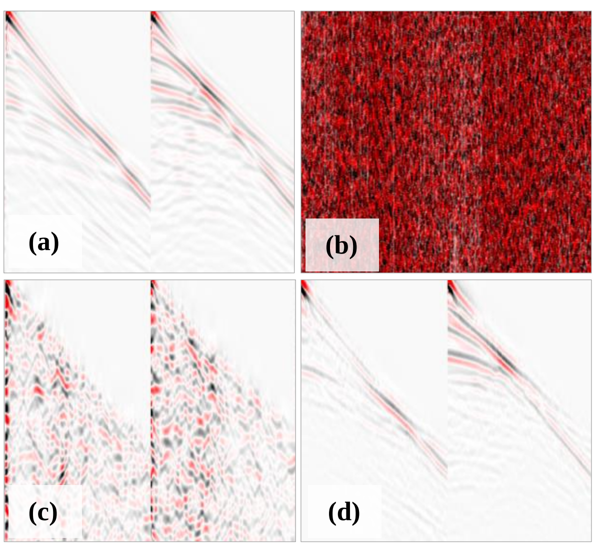

Figure 1: Synthetic data example. Input shot gathers for a 1 to 4Hz frequency bandwidth. (a) Noise-free gathers; (b) gathers after adding actual field data noise; (c) gathers after conventional denoising; (d) gathers after applying LFR.

We apply the proposed method to re-build the low frequency content of marine seismic data as an alternative conditioning to conventional denoising. The data corresponds to a shallow water setting acquired with multi-sensor technology in offshore Angola, with a maximum 8 km inline offset. Figure 2-a shows two shot gathers at 1-3 Hz frequency bandwidth after conventional denoising. The SNR in the data is poor at this frequency band and most of the events are discontinuous and contaminated with noise. It is common that frequencies below 3 Hz are challenging to exploit when performing FWI and the inversion may converge to a local minimum when the initial model is not accurate. We have applied the proposed method in the shot domain, to reconstruct the signal below 4 Hz. Results are shown in Figure 2-b. The LFR process provides clean and coherent events which suggests a sensible reconstruction.

Full waveform inversion application

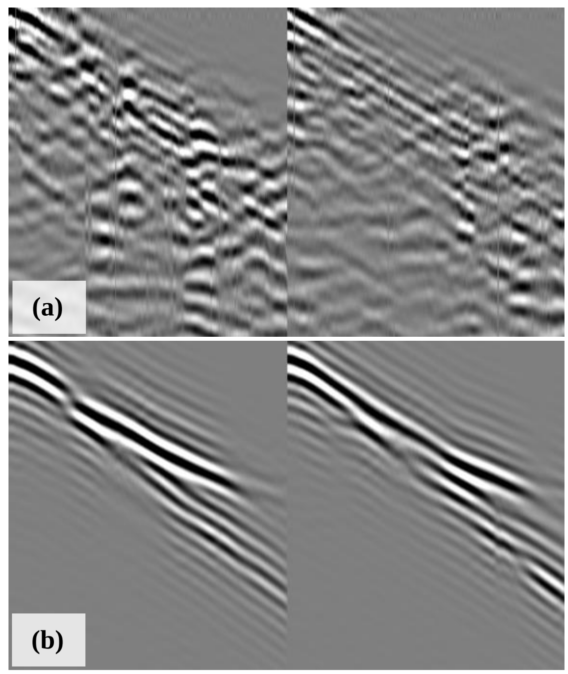

Figure 2: Angola multi-sensor field data. Two sample shot gathers at a 1 to 3Hz frequency bandwidth after, (a) conventional denoising and (b) LFR.

We use the low-frequency reconstructed data for FWI and compare the inverted model with that obtained from the original data without LFR. The initial velocity model (Figure 3-a) is a smooth simple model which produces cycle-skipping in several areas, given that the subsurface is complex with the presence of carbonates and salt bodies. In this scenario, low frequencies are very important, not only to avoid cycle-skipping, but also to reconstruct these complex geobodies. For the LFR data, we performed FWI in a multi-stage approach up to 8 Hz (at stages of 1-3 Hz, 2-4 Hz, 2-6 Hz, 2-8 Hz, and the maximum inversion frequency is ~12 Hz). For the test without LFR data, the first two stages were not possible because of the poor SNR at those frequency bandwidths. The final FWI results are shown in Figures 3-b and 3-c illustrating a clear difference between the two models. The inversion with LFR successfully managed to recover the high velocity geobodies and update the velocity model below them. In both shallow and deep areas, a higher resolution is observed as result of a more accurate background obtained at the early stages of the inversion strategy.

To assess the quality of the inversion, we carried out modeling using the initial, and the two FWI models. Figure 4 shows the modeling results. The field and modeled data are interleaved to show how well they are fitting. Modeling with the initial model (Figure 4-a) shows a mismatch between

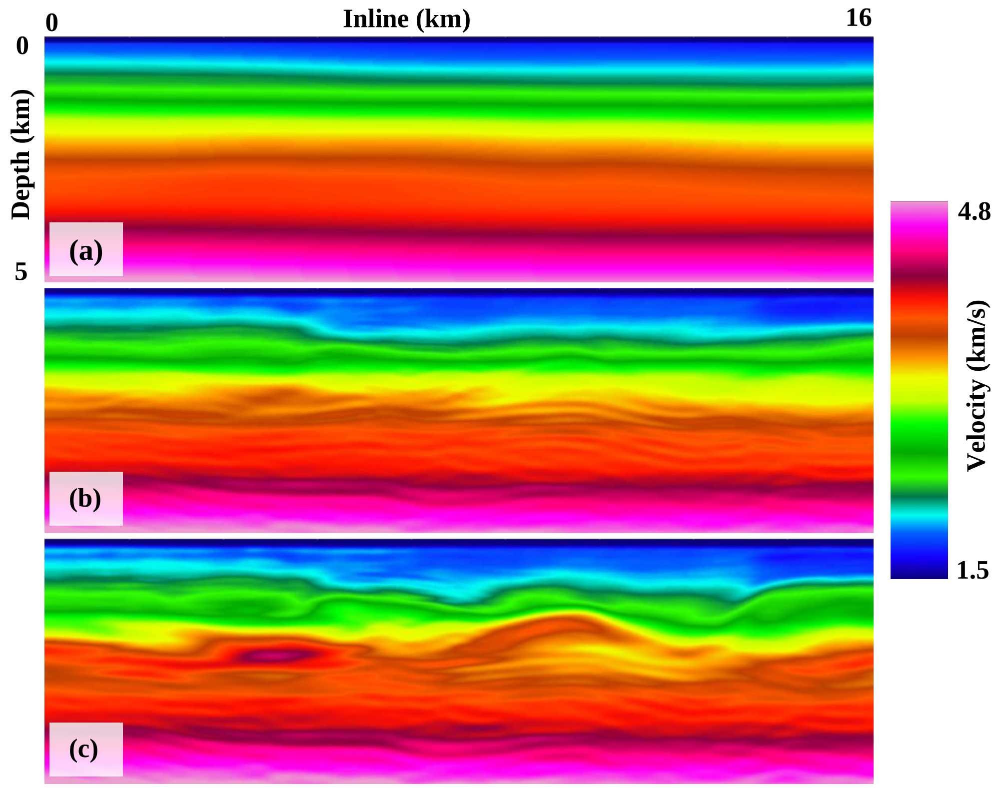

Figure 3: Angola field data example. (a) the initial velocity and FWI models (b) without and (c) with LFR.

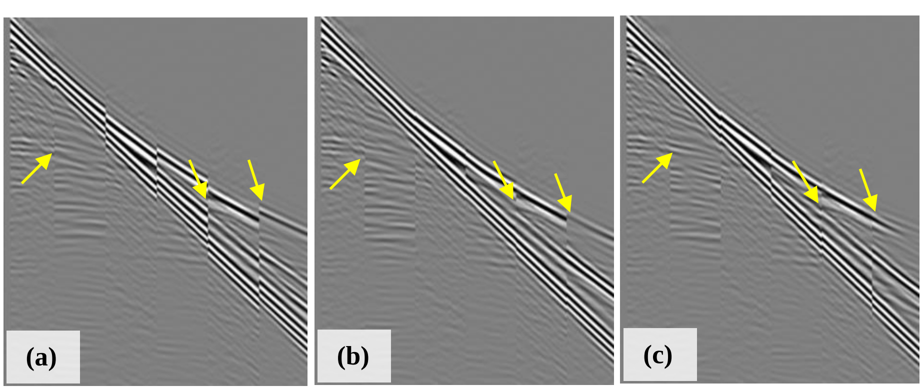

Figure 4: Angola field data example. Comparison of field and modelled data at 2-8Hz frequency bandwidth from the (a) initial and the FWI models (b) without and (c) with LFR. Offset panels show the data matching improvements after inversion with LFR.

field and synthetic data. The inversion without LFR (Figure 4-b) improved the data fitting at some offsets, however, some arrivals still suffer from cycle-skipping. With the LFR model, the modeled data is matching the recorded traces very well.

We also performed Reverse Time Migration (RTM) using the initial and both FWI models. The images overlaid to the velocity models are shown in Figure 5. Around the geobodies, the migration using both the initial and the FWI without LFR were distorted. With the LFR data, the base of the geobodies is better defined. Also, there is a clear uplift of the image quality below the high velocity bodies in many areas as indicated by the arrows. The depth slices at 2 km depth, shown in Figure 6, confirm the benefits of the use of LFR data in FWI, with better resolution and alignment between the velocity model and the RTM image.

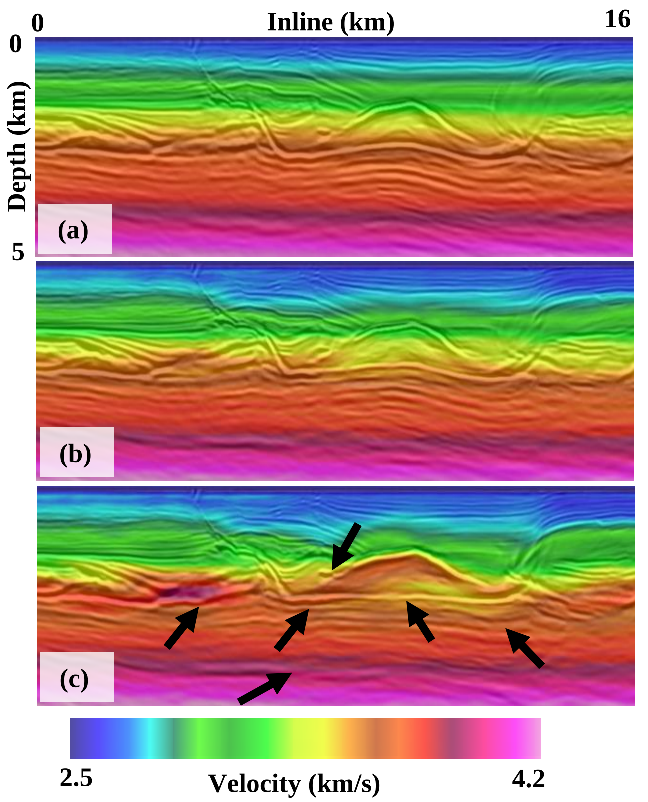

Figure 5: Angola field data example. Reverse time migration using the (a) initial velocity and FWI models (b) without and (c) with LFR.

Conclusions

We have proposed a novel and an effective data conditioning solution to improve the performance of FWI. The solution reconstructs the low frequency contents of the seismic data from its high frequencies where the SNR is generally good. One can see this step as a form of "regularization" or initial FWI model improvement achieved through data low frequency conditioning. Application of the proposed solution to field data showed that the reconstructed low frequencies improved the accuracy of the background velocity model as well as the image below the salt/carbonates. In addition, it allows us to be less dependent on a highly accurate starting velocity model and this will have a direct impact on reducing the turnaround time of velocity model building using FWI.

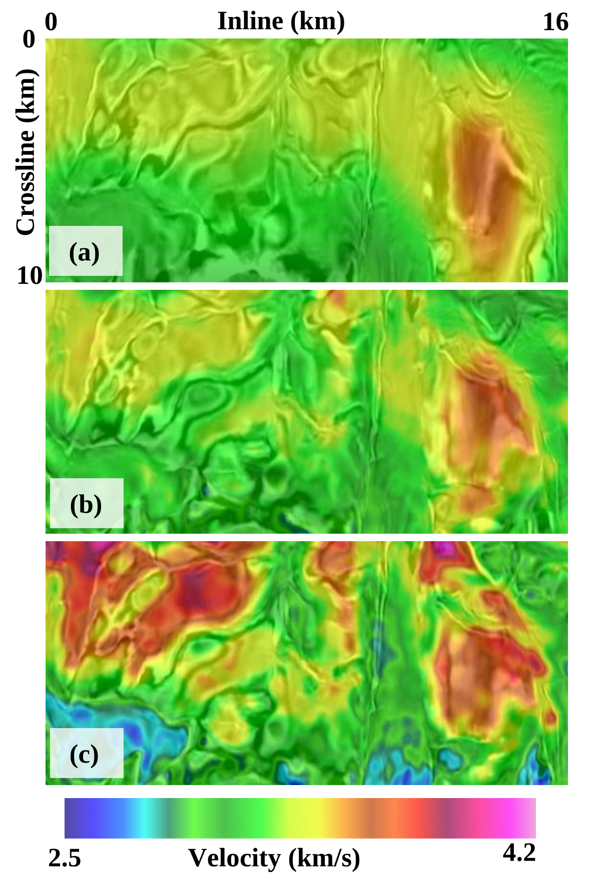

Figure 6: Angola field data example. Depth slice at 2 km depth with the RTM images overlaid to the velocity models. (a) initial and FWI models (b) without LFR and (c) with LFR.

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