Ultralong Offset OBN: Path to better subsalt image

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Summary

Ocean Bottom Node (OBN) acquisition provides ultralong offset and full-azimuth (FAZ) illumination for better model building and imaging. A blended-source, sparse-node deep water OBN survey can achieve a notable balance of acquisition cost and imaging quality. We applied Dynamic Matching Full Waveform Inversion (DMFWI) to obtain a more accurate velocity model to mitigate model uncertainty for imaging. An image-domain Least-squares Reverse Time Migration (LSRTM) with nonstationary matching filters was conducted on top of the model update to further improve imaging results. Although we only used preliminary deblending hydrophone data to run mirror RTM, our study shows that LSRTM combined with FWI can unlock the potential of the ultralong offset OBN survey for complex subsalt imaging even with a large amount of residual noise presented.

Introduction

In summer 2019, a large multi-client blended OBN survey was completed in the Mississippi Canyon and the Atwater Valley, Gulf of Mexico (GOM). Previous 3D conventional streamer data starting from narrow-azimuth to multiwide-azimuth (Baldock, 2009) have been acquired and processed in this area, but challenges remain to obtain a clear image to uncover the hidden deep salt features and delineate the details within the complex overburdens. With the newly added OBN data, we can further explore the potential solutions to the remaining imaging challenges.

Reverse time migration (RTM) is a preferred migration algorithm for imaging of complex geology with large velocity contrast. It forms the subsurface image by cross-correlating the forward propagating source wavefield and the backward propagating receiver wavefield. Theoretically, RTM can image complex structures without dip limitation However, RTM still has difficulties in correctly representing the subsalt reflectivity due to illumination issues such as acquisition imprints or salt-related illumination distortions. Additional problems can arise from model errors and the noise remaining in the input data. Typical RTM image imperfections often include migration artifacts, uneven amplitudes, and limited resolution.

Conventional LSRTM was introduced into the industry to obtain a better reflectivity image from seismic data by minimizing the misfit value between observed data and synthetic data (Dong et al., 2012; Zeng et al., 2014). The iterative data domain approach can compensate for illumination loss, attenuate migration artifacts and produce higher image resolution by reducing source signature and ghosting effects. However, it suffers from its slow converging rate, high computational cost and potential add-in artifacts due to biased data fitting from an inaccurate velocity model and residual noise. In recent years, various single-iteration image-domain LSRTM methods have been proposed to reduce the computational cost and make LSRTM more feasible (Fletcher, et al., 2016; Wang, et al. 2016; He, et al. 2018). We calculated inverse Hessian operator which obtains matching filters for different dipping and frequency components to better compensate frequency and angle-dependent illumination differences. Additional benefits include migration swing attenuation and artifacts reduction. Extending it from the stack domain to the common-offset RTM (COR) gather domain, can produce a cleaner image and more importantly, amplitude versus offset (AVO) friendly output.

FWI using FAZ, ultralong-offset data with rich low frequency can provide a more accurate velocity model for LSRTM. We apply our DMFWI algorithm to the simultaneous-shooting ultralong-offset OBN data and successfully invert for a much better velocity model from shallow sediment to salt and subsalt. The FWI algorithm focuses on inverting the kinematic difference and suppressing the noise impact (details in Huang et al., future publication SEG Extended Abstract, 2020). With the upgraded velocity model, we can better investigate the LSRTM benefits.

Method

Ray-based methods, such as ray tomography, provide a gross impedance trend in conventional processing to image the sediment reflectors. But it usually fails in salt areas due to the high-velocity contrast. FWI can break the tomography limit in salt-model building but requires a robust algorithm to avoid common issues such as cycle-skipping, noise contamination.

A multichannel local correlation reflection FWI algorithm (Mao et al., future publication SEG Extended Abstract, 2020) is proposed to provide high fidelity and high-resolution model parameters through minimizing the phase difference between the observed and synthetic datasets with correlation based objective function. By focusing on the kinematic mismatch of information and downplaying the noise impact, we allow the signal rather than the noise to win in FWI. It is essential that the ultralow-frequency signal is used to avoid cycle-skipping.

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The sparse node FWI-oriented survey with about one square kilometer node spacing helps to build a good velocity model in the presence of complex salt features. On the other hand, the sparse layout brings challenges in structural imaging. To mitigate the migration artifacts and heal amplitude distortions, we used LSRTM to further improve the RTM image.

Image-domain least-squares migration estimates the inverse Hessian operator with the equation $\mathbf{m^*} = (\mathbf{L}^T\mathbf{L})^{-1}\mathbf{L}^T\mathbf{d}$ and $\mathbf{H}=\mathbf{L}^T\mathbf{L}$. Here, $\mathbf{d}$ is the data, $\mathbf{L}^T$ is the migration operator, $\mathbf{L}$ is the demigration operator, $\mathbf{H}$ is the Hessian operator and $\mathbf{m^*}$ is the inverse Hessian compensated image. $\mathbf{H}^{-1}$ can be considered as a deconvolution filter which conduct image focusing, amplitude compensation and bandwidth expansion. It consists of two operators, the demigration and migration operators, which fundamentally are determined by the model, the underlying wave propagation method and the acquisition geometry. We can approximate $\mathbf{H}^{-1}$ by a bank of nonstationary filters estimated from the initial migration and remigration of the demigrated data. Then such filters can be applied to the original migration image to generate a compensated image.

Field Example

The large multi-client blended OBN survey is in the Gulf of Mexico (Figure 1). Presurvey acquisition studies, which were driven by FWI requirements, indicated survey design with nominal node spacing of 1000 m by 1000 m (except a dense infill area) and source spacing of 50 m by 100 m. A minimum 40 km offset for each node location was acquired to honor enough deep penetration for an FWI subsalt update. The reliability of 18 km depth penetration is verified by an RTM based diving-wave illumination study. Aiming to

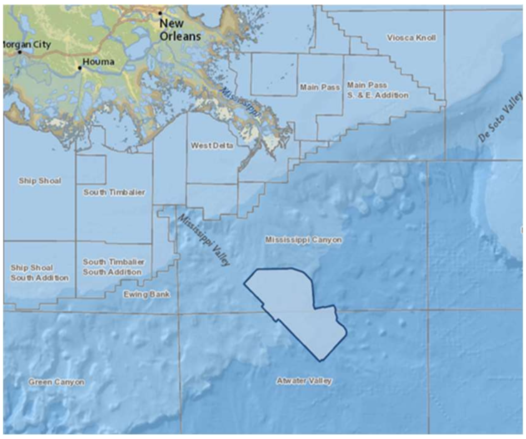

Figure 1: Amendment Phase I survey in GOM. The solid blue polygon defines the node coverage.

acquire all shots within the battery life of the node to reduce the operational cost, the survey was acquired in a blended style with three dual-source vessels. The two sources on each vessel were fired within a plus-minus one second time dither from the pre-plot source location.

The study area contains large-scale structures such as salt feeders, salt canopies, and small-scale structures such as rafted carbonate carapaces. Although the legacy model set was obtained from many iterations of high-resolution tomography work and intensive human salt interpretation effort, it still struggles to reveal the accurate velocity details in such a geologically complex environment, especially where velocity variation is rapid.

Our FWI initial models were built by smoothing the salt boundaries in legacy models to reduce the interpretation and tomography uncertainties. Aiming for a complete update of the velocity model, we applied our DMFWI algorithm with raw hydrophone data from ultralow frequency and with the full offset range included. Although this minimum intervention approach seems quite ambitious, we successfully obtained a velocity model that significantly improved the RTM image and flattened RTM common imaging gathers globally.

The shots within each common node were divided into different offset classes with 600 m increment up to 20 km. For each individual node, a wavefield from a mirrored node position was convolved with the wavefield from the shots within each offset group. COR gathers were generated by stacking the partial images offset by offset and across all the nodes. A COR gather-based curvelet domain Hessian filter was approximated by a bank of nonstationary filters estimated from the initial migration and remigration of the demigration data. Then these filters were applied to the initial migration results to generate the inversion result.

For a quality check, we first compare RMS amplitude extraction on different migration images along water bottom. Figure 2a shows the water bottom amplitude extraction from the image volume of conventional RTM. It clearly shows the acquisition shot line footprints and node pattern due to the sparse layout. On the other hand, the water bottom amplitude extraction on LSRTM image (Figure 2b) reduces the footprint with less amplitude variation and improves geological features.

Then, we demonstrate how the images were evolved through DWFWI and LSRTM in Figure 3. Raw OBN data with blended noise is used in DWFWI and the velocity update is from top down without any constraint. Migration is performed using mirror node migration and hydrophone data with preliminary deblending. Velocity models before and after FWI are compared in Figure 3a and Figure 3b. It can be

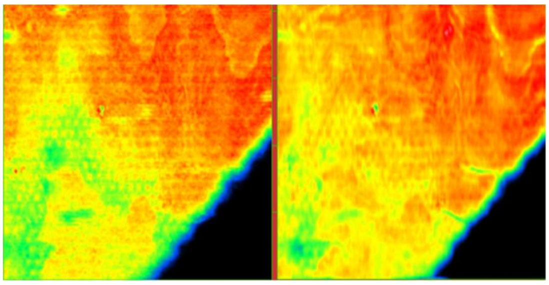

Figure 2: The amplitude map extracted along the water bottom in the image volume of a) RTM and b) LSRTM. Image-domain inverse Hessian operator reduces footprints and improves geological features.

seen from the figures that the updated model fine tunes the salt exit velocity and has better definition of velocity between Cretaceous and Louann salt. The RTM image (Figure 3d) from the legacy model has strong migration swing contamination and unbalanced amplitude along the displayed QC line. The distorted Cretaceous suggests the inaccuracy of the subsalt velocity. The RTM image (Figure 3e) from the (DM) FWI model has a simpler subsalt structure and improved coherence. However, obvious migration swings cutting through the primary structures and weak amplitude zone can be still be observed. With LSRTM (Figure 3f), both swing noise attenuation and amplitude balancing are improved.

Another QC line is demonstrated in Figure 4. From Figure 4a to Figure 4b, we observed the uplift from the FWI model by simplifying the geology and focusing the faults. Combining with LSRTM, the image continuity is further improved and the swing noise is reduced while the faults were preserved.

Discussion

FWI is a nonlinear inversion method which tries to utilize all information in the seismogram to build the earth model. It aims at finding the model that generates the best fitting of the real data. However, when the modeling process is based on an acoustic assumption, it is reasonable to match the phase instead of the amplitude. Once the model matches the kinematic information from the data, it is time to turn to LSRTM to make sophisticated use of the data, allowing it to partially compensate for the uneven subsurface illumination and sparse acquisition. The amplitude information from the data is mapped to structure by RTM followed by an image-domain filter as LSRTM to further improve the illumination and image quality. It leads to a possibly more accurate structural interpretation and prospect reading.

Conclusions

A simultaneous-shot, ultralong offset, full azimuth and sparse-node OBN survey fulfilled its original designed objectives: imaging and FWI velocity model update. Two components from the seismic data: phase and amplitude play essential roles to invert modeling and image. DMFWI with the raw sparse node data helped to reduce the velocity uncertainties for imaging a geologically complex area, which can potentially reduce interpretation effort and speed up the processing cycle. Image-domain LSRTM can further improve the image quality by attenuating migration artifacts, removing the illumination shadow and working toward true amplitude preservation.

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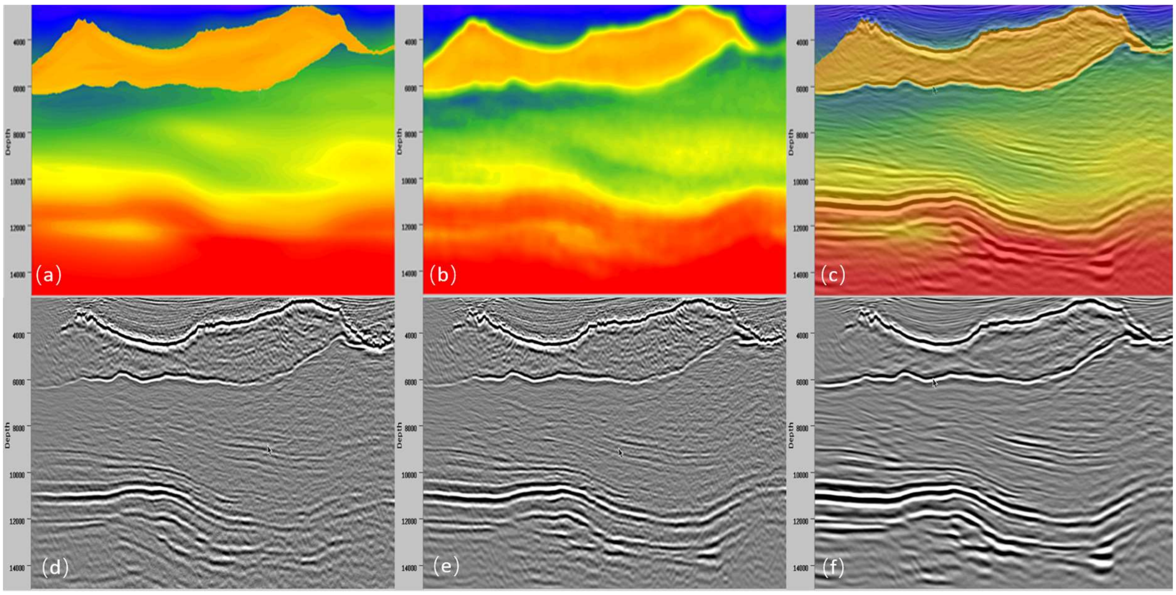

Figure 3: a). The legacy velocity model with hard salt boundary. b). FWI updated velocity model. c). FWI velocity model overlaid with image. d). The legacy RTM image. e). RTM image for FWI model. f). LSRTM for FWI model. The FWI model improves the coherence of the subsalt events at 12km depth. With LSRTM, the image continuity and S/N are further improved with less swing noise.

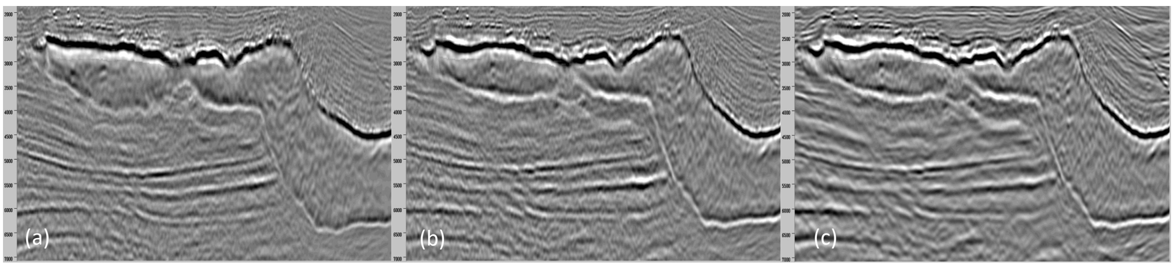

Figure 4: a). The legacy RTM image. b). RTM image for FWI model. c). LSRTM for FWI model. The FWI model improves the coherence of the subsalt events. With LSRTM, the image continuity is improved with faults preserved.

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