Chapter 3

3D field data applications - the Deimos Dataset

In this chapter, I apply least-squares reverse-time migration (LSRTM) to a three-dimensional ocean-bottom node dataset. Applying imaging algorithms onto 3D field datasets is often more challenging than applying on synthetic datasets. When applying least-squares migration (LSM) to a field dataset, a background data component must be subtracted from the observed data. I introduce salt-dimming data weighting to address some of the issues associated with a strong background data term for my study area. The Deimos data set has complex salt structure that obscures part of the image deep down. I use a target-oriented data-reweighting to emphasize deeper parts of the image near the salt. Oftentimes, a shortfall in the theory or challenges in pre-processing would generate unwanted noise in the LSRTM image. To make the algorithm more robust, I utilize the prestack extended-angle domain to filter some of the noise in the image space.

I will begin by introducing the 3D field dataset called Deimos. I will then illustrate some processing challenges associated with the dataset. I will discuss some methods I used to condition the LSRTM inversion with the field dataset. Finally, I will show
some of the RTM and LSRTM results, comparing between using primary-only, mirror-only, and joint datasets.

**DEIMOS 3D OCEAN-BOTTOM NODE DATASET**

The Deimos data set was recorded in an area south-east of New Orleans in the Gulf of Mexico. The field was discovered in 2002, with first oil production in 2007 (Burch et al., 2010; Smit et al., 2008; Stopin et al., 2008). In 2007, Shell Exploration and Production Company and their partner BP Americas commissioned Fairfield Industries to conduct a 3D ocean-bottom node survey over the Deimos field in the Mississippi Canyon protraction area. Prior to the 3D survey, 16 nodes were deployed on a single 2D line at their normal 3D grid locations (Hays et al., 2008). A swath of seven dual source sail lines nearest the node line were shot. There were fourteen source lines on the nominal 50x50 m grid with approximately 3300 shots. The ocean-bottom receiver was deployed by a remotely operated vehicle (ROV) at approximately 400 m spacing. Figure 3.1 shows the locations of the sources and receivers.

This was effectively a 2.5D survey where the horizontal (in-line) extent is much greater than the vertical (crossline) extent. As a result, inline dipping reflectors should be much better resolved than crossline dipping reflectors. Prior knowledge of this field suggests that there are fewer structural variations along the crossline direction compared to the inline direction. Figure 3.2 shows the migration velocity model used in this study.

Shell Exploration and Production Company performed some pre-processing of this ocean-bottom node dataset. Hydrophone and geophone recording were decomposed into up-going and down-going signal by PZ summation. Multiple removal were also performed using a modeled-based prediction and subtraction technique. Figure 3.3 shows the up-going and down-going data after pre-processing. Next, I will discuss some of the imaging challenges associated with this field dataset.
Figure 3.1: The acquisition geometry for the Deimos ocean-bottom data set. The 14 source lines span a 50x50 m grid. The 16 ocean-bottom node receivers were deployed on a 2D line with an approximate spacing of 400 m. [NR] chap3/. SouRecDeimos
Figure 3.2: The migration velocity model used for the Deimos ocean-bottom node survey. [ER] chap3/. veldeimos
Figure 3.3: One common receiver gather of the (a) up-going primary and (b) down-going mirror data after pre-processing.
CHAPTER 3. 3D FIELD DATA APPLICATIONS - THE DEIMOS DATASET

Imaging challenges

Incomplete removal of noise in the image

The conventional imaging scheme for ocean-bottom node datasets migrates only the down-going mirror signal (Ronen et al., 2005; Dash et al., 2009). More care is often given to the down-going mirror signal than the up-going signal. I observe that the down-going data is better separated than the up-going data. Figure 3.4a shows the crosstalk image, $m_{xalk}$, when we apply the down-going migration operator, $L_i^T$, onto the up-going data, $d_\downarrow$. It can be represented mathematically as:

$$m_{xalk} = L_i^T d_\downarrow.$$ (3.1)

Figure 3.4b shows the image produced from applying the down-going migration operator onto the down-going data, $d_\downarrow$. We can identify some of the events that are present in both of the two images. For example, the reflectors annotated in Figure 3.4 are in both images. This suggests that some residual down-going energy remains in the up-going data.

When wrongly attributed energy is present in the field dataset, it compromises both the RTM and the LSRTM results. When we migrate the down-going data with the kinematics of a primary reflection, the image will contain false reflectors at a depth that is deeper than the depth of the corresponding true reflectors. Similarly, when we migrate the up-going data with the kinematics of the mirror reflection, the image will contain false reflectors at a depth that is shallower than the depth of the corresponding true reflectors. Sometimes these false reflectors can be suppressed with LSRTM. However, the inversion can also adjust the solution to try to explain some of the wrongly attributed energy in the data. To alleviate this problem, I utilized the prestack extended-angle domain to discriminate some of the unwanted energy in the image space. I will discuss more about this noise filtering scheme in the next section.
Figure 3.4: (a) The image depicting crosstalk energy when applying the down-going migration operator onto the up-going data; $\mathbf{m}_{xalk} = \mathbf{L}_d^T \mathbf{d}_I$. (b) The image when applying the down-going migration operator onto the down-going data; $\mathbf{m}_{\text{RTM}} = \mathbf{L}_d^T \mathbf{d}_I$. The annotation is showing some of the events that are present in both images.

[CR] [chap3/. xtalkdeimos]
Incomplete theory

The wave theory we used might not adequately explain the entire physics of the subsurface. I assumed the Earth behaves as an acoustic isotropic medium. The assumption of an acoustic isotropic medium vastly simplifies the complexities happening within the Earth. In LSRTM, we hope to explain the entire wave-form of the observed data with the modeled data. In practice, it is naive to expect that the recorded data can be completely explained when the theory is over simplified.

The Earth is at least a visco-elastic medium with density variations. One can use more accurate wave theory in their LSRTM algorithm. It requires additional parameters such as the density or modulus to be estimated. In order for LSRTM to converge to a meaningful solution, the estimated parameters need to be sufficiently close to the true parameters, which can be challenging. To explore the algorithm in a robust way while obtaining useful subsurface information, I work with the acoustic isotropic wave equation.

**IMPROVING LSRTM RESULT IN FIELD DATASET**

With the imaging challenges described in the previous section, it is difficult to obtain desirable result using only the standard LSRTM objective function in field datasets. I introduce three ways to improve the LSRTM results, they are (1) salt-dimming, (2) target-oriented data reweighting, and (3) extended-angle domain noise removal.

**Salt Dimming**

The LSRTM objective function, $S(m)$, requires the background data term, $d_o$, to be subtracted from the observed data, $d_{obs}$.

$$ S(m) = \| d_{mod} - d_{obs} \|^2 = \| Lm - (d_{obs} - d_o) \|^2. $$

(3.2)
where \( d_{\text{mod}} \) is the modeled data. \( Lm \) represents the Born-modeled data and \( d_o \) is the background data. The modeled data is the sum of the Born-modeled data and the background data. In practice, \( d_o \) is the full-wave forward modeling using the migration velocity model. When the velocity varies smoothly, this term is usually negligible and we can ignore it in the inversion. The background data term is non-trivial when the velocity field has a sharp contrast such as a salt body. In the field data case, there are always errors in the background velocity, positioning, and reflectivity of the salt. As a result, an accurate estimation of the background data term is difficult. This makes following equation 3.2 impractical. Salt-dimming (Wong, 2013) is introduced as a way to bypass this problem.

Salt-dimming aims to down-weight the salt reflection energy in the data space so that the inversion can minimize other regions in the model. This corresponds to the objective function,

\[
S(m) = \| W_s(Lm - d_{\text{obs}}) \|^2,
\]

where \( W_s \) is the data weighting function that down-weights the salt reflection energy. This can be done by forward-modeling the salt reflection using the migration velocity. The next step is to calculate an envelope around the salt energy. The data weighting function can then be defined by assigning small values to the salt reflection envelope. The objective function with salt-dimming becomes:

\[
S(m) = \| W_s^\uparrow(L\uparrow m - d_{\text{obs}}^\uparrow) \|^2 + \| W_s^\downarrow(L\downarrow m - d_{\text{obs}}^\downarrow) \|^2. \tag{3.3}
\]

where the subscripts \( \uparrow \) and \( \downarrow \) represent the up- and down-going direction in OBN data. Figure 3.5a shows the forward modeling of one common-receiver gather in the synthetic Sigsbees model (Paffenholz et al., 2002). The salt reflection is then used to derive an envelope region to be down-weighted. One example of a weighting function is shown in Figure 3.5b, where the down-weighted region (blue) corresponds mostly to the salt reflector.
Figure 3.5: (a) Background data created by full-wave forward modeling using the migration velocity and (b) the corresponding salt-dimming weight ($W_s$) generated with the background data. [CR] chap3/. Vfig5wgt
Data reweighting to emphasize shadow zone

In addition to down-weighting the contribution from salt reflections, we can also use data weighting to emphasize an important part of the data. Due to geometric spreading and attenuation, reflection energy from the deeper part of the image is often significantly weaker than the reflection energy from the shallower part. In a least-squares inversion, the inversion algorithm often focuses on minimizing the strong energy in the data, which corresponds to the shallow reflection. This can be problematic when the deeper reflection energy is neglected. For the synthetic case, we have the exact operator that matches the physics of the recorded data. In this scenario, the strong shallow reflection energy can be fully explained by our modelling and migration operator. The deeper reflection in the data will subsequently be explained later. For the field data case, our operator might not exactly match the physics that generated the field data. As a results, it is impossible to expect the shallow reflection to be fully explained by the inversion. Often, the contribution to the objective function from the deeper part of the data will not be significant enough for some of the deeper reflector to be fully imaged.

I allow the inversion to fit the shallower part of the data for a few iterations and then reweight the entire inversion to focus onto the deeper part. The procedure to generates this weighting is relatively simple. The first step is to pick a few reflectors that are poorly illuminated in the RTM image (Figure 3.6). Next, perform Born modeling of the picked reflector (Figure 3.7a) and then extract an envelope around the forward modeled energy to produce a diagonal data weighting function (Figure 3.7b). The objective function then becomes,

\[
S(m) = \begin{cases} 
\|W_s^\dagger(L_im - d_{obs}^i)\|^2 + \|W_s^\dagger(L_im - d_{obs}^i)\|^2 & : I_{iter} \leq n_{rw} \\
\|W_B^\dagger W_s^\dagger(L_im - d_{obs}^i)\|^2 + \|W_B^\dagger W_s^\dagger(L_im - d_{obs}^i)\|^2 & : I_{iter} > n_{rw},
\end{cases}
\]

where \(W_B^{1/1}\) is the data weighting that emphasize picked reflectors. \(I_{iter}\) is the current iteration number in the conjugate gradient scheme. I use the objective function with
Figure 3.6: Reflector picks used to generate data reweighting. [CR]

chapt3/. Vreflpick
Figure 3.7: (a) Born modeled data of the picked reflectors in Figure 3.6 and (b) the associated data weighting. The weighting is extracted by an envelope around the prominent energy in the Born modeled data. [CR] chap3/. VbmDeiA8
salt-dimming for $n_{rw}$ iterations. The objective function is then reweighted at iteration $n_{rw}$ to include the new weighting to emphasize the deeper picked reflectors. I used $n_{rw} = 10$ as the reweighting limit for the Deimos field dataset.

Noise removal in the prestack extended-angle domain

The assumption behind extended-angle domain filtering is that noise and signal are formed at different angles. While this assumption is not true for all kinds of noise, it is useful as a way to alienate certain types of noise in the images. Figure 3.8a shows an OBN image gather generated by a single ocean-bottom node (OBN) at $x_{OBN} = 54150$ m and $y_{OBN} = 34800$ m. Figure 3.8b, c, and d are displaying the depth-angle panel of Figure 3.8a at 3 different inline locations of 53000 m, 54000 m, and 55000 m. These depth-angle panels are located to the left, around, and to the right of the ocean bottom receiver along the inline direction. There are several characteristics based on the image gather. Image points near the receiver are mostly illuminated by reflections with small aperture angles. On the other hand, image points located to the left of the receiver are predominantly illuminated by reflections with negative aperture angles as shown in Figure 3.8b. Similarly, image points located to the right of the receiver are predominantly illuminated by reflections with positive aperture angles as shown in Figure 3.8d.

We can identify areas of signal and noise in Figure 3.8 by slicing through the angle domain. Figure 3.9a shows the image extracted at an subsurface angle of 15 degrees. At this illumination angle, the image is predominantly signal (label 1). Figure 3.9c is showing an area (label 2) that is believed to be migration artifacts and is illuminated at -35 degrees.

It is important to highlight the benefit of filtering at each prestack OBN image gather instead of at a poststack image gather. This extra degree of freedom allows us to isolate noise that would have otherwise be buried with the signal in a poststack image gather. Given that we have identified an angular range to be signal for each OBN image gather, it is straight-forward to remove the noise. In two dimension,
Figure 3.8: An 2D RTM image generated with an ocean-bottom receiver located at $x_{OBN} = 54150m$ and $y = 34800m$. Depth-angle panels are taken at inline locations of (b) 53000 m, (c) 54000 m, and (d) 55000 m. The prominent energy in the depth-angle panel is shifted based on its relative position from the source. [CR] chap3/. dmDeiCbup-before
Figure 3.9: The same image gather from Figure 3.8. (a) is showing the image illuminated at an angle of 15 degrees. Label 1 highlights an area that is predominantly signal. (b) is showing the corresponding depth-angle panel extracted at midpoint $x = 55000$ m with a line indicating the slicing of the image cube at 15 degrees. (c) is showing the image illuminated at an angle of -35 degrees. Label 2 highlights an area that has conflicting dips with the sediment and is believed to be noise. (d) The same depth-angle panel as in (b) but with a line indicating the -35 degrees slicing.
filtering in the angle domain is equivalent to filtering the dips in the depth-offset domain. The relationship between the dips in the depth-offset domain to the aperture angle ($\gamma$) is,

$$\frac{k_{hx}}{k_z} = -\tan \gamma.$$  \hspace{1cm} (3.4)

where $k_{hx}$ and $k_z$ are wavenumber along the subsurface offset ($hx$) and depth $z$ directions. In practice, I apply the filter in the depth-offset domain by finding equivalent dips ranges based on the angle ranges using equation 3.4. Although equation 3.4 is only true in 2D, there is an equivalent expression in 3D that includes the reflector’s tilt. For this particular dataset, there is not enough crossline aperture to obtain a meaningful extended image gather in the crossline direction. An equivalent filtering procedure involving $k_{hy}$ can be applied in 3D.

Figure 3.10a shows the result of extended domain filtering on a prestack OBN image. Most of the noise is removed above the salt reflection at $z=4000$ m. Figure 3.10b, c, and d, are displaying the depth-angle panel of Figure 3.10a at $x=53000$ m, 54000 m, and 55000 m. The angle range are chosen to preserve the prominent energy in the image. Figure 3.11a shows the corresponding filtered noise. Figure 3.11b, c, and d, are displaying the depth-angle panel of Figure 3.11a at $x=53000$ m, 54000 m, and 55000 m. The original prestack RTM image (Figure 3.8a) is decomposed into the signal part (Figure 3.10a) and the noise part (Figure 3.11a).

**RESULTS**

**Imaging with a single mode**

In conventional imaging, the mirror signal is used for migration because it provides a wider illumination area. Often time, the primary signal is not used in imaging. This is because the illumination area of the primary reflections is often much narrower than that from the mirror reflections. In chapter 2, Figure 2.4 shows the relative illumination area (highlighted in yellow) of the primary and mirror events. The mirror signal can illuminate the sea-bottom region much better than the primary signal.
Figure 3.10: The same prestack RTM image as in Figure 3.8 after extended-angle domain filtering. Depth-angle panels are taken at inline location of (b) 53000 m, (c) 54000 m, and (d) 55000 m. [CR] /chap3/. dmDeiCbung-after1
Figure 3.11: The filtered noise from the same prestack RTM image as in Figure 3.8 after extended-angle domain filtering. Depth-angle panels are taken at inline location of (b) 53000 m, (c) 54000 m, and (d) 55000 m. The sum of Figure 3.10a and Figure 3.11a should be the same as Figure 3.8a [CR]
Figure 3.12 shows the RTM image using the primary-only signal and the mirror-only signal. The illumination area between Figure 3.12a and b is not as dramatically different as in Figure 2.4. This is because the lateral extent of the source grid is only slightly larger than the lateral extent of the receiver grid along the inline direction.

Although the illumination between the primary and mirror signals are similar for this survey, the angular coverage of the primary and mirror signals are different. Figure 3.13 shows the comparison of an angle-domain common image gather between the primary and the mirror signals. The side panel shows that the same reflector is illuminated at different angles by the primary and the mirror signals.

I ran LSRTM using the conjugate gradient method for 25 iterations. Figures 3.14 and 3.15 compares between the results of RTM with spectral balancing and LSRTM. In both cases, the LSRTM image is superior than the RTM image with higher resolution and better amplitude information. The improvements are more dramatic in regions that are 4000 m or deeper. Figure 3.16 shows the vertical wave-number amplitude spectrum for the primary-image between the RTM and the LSRTM case. The amplitude increases in both the higher end and the lower ends of the spectrum. With iterations, the LSRTM algorithm gradually recovered a banded white spectrum.

**Joint imaging of primary and mirror signals with LSRTM**

Figure 3.17a shows the joint-RTM image and Figure 3.17b shows the joint-LSRTM image. The joint-RTM image is essentially the first gradient of the joint-LSRTM algorithm. It can also be viewed as the sum of the primary-RTM image and the mirror-RTM image. In the joint image, we see similar improvement when using LSRTM as compared to using RTM.

Figure 3.18 shows a section of the Deimos image from Figures 3.14, 3.15, and 3.17; The four images are calculated using the mirror RTM with spectral balancing, primary LSRTM, mirror LSRTM, and joint LSRTM. I also observe better delineation of the dipping reflector in the joint-LSRTM image as highlighted by circle A. This is because the primary signal has a decreasing illumination aperture in region close to the
Figure 3.12: RTM image using (a) the primary signal and (b) the mirror signal. The front face shows the image slice located at a crossline location of \( y = 34450 \) m. [CR] chap3/. updownimagedeimos
Figure 3.13: (a) Angle domain common image gather for mirror RTM and (b) primary RTM. The angular coverage is different between the two signals. [CR]

chap3/. mDeiRTMang
Figure 3.14: A enlarged section of the (a) the mirror-RTM image with spectral balancing and (b) the mirror-LSRTM image after iteration 25. [CR] chap3/. downdeimosimage
Figure 3.15: A enlarged section of the (a) the primary-RTM image with spectral balancing and (b) the primary-LSRTM image after iteration 25. [CR]
Figure 3.16: Graph showing the amplitude spectrum of the vertical wavenumber for the primary-RTM (solid-line) and primary-LSRTM (dashed-line) images. With LSRTM, the amplitude information increases at both the higher and lower end of the spectrum. [CR] chap3/. spectrum
Figure 3.17: (a) Joint-RTM image with AGC and (b) joint-LSRTM image after iteration 25. [CR] chap3/. jointdeimosimage
ocean bottom node receiver. In chapter 2, the Cascadia field data result shows that information from the primary signal can help image dipping reflector better. Circle B shows a region where faulting is better recognized in the joint-LSRTM image than the mirror-LSRTM image. Circle C highlights a region where the sediment layers near the salt is better imaged with joint-LSRTM than the other three images.

Figure 3.19 shows a section of the Deimos image close to the left salt. The four images are calculated using primary RTM with spectral balancing, primary LSRTM, mirror LSRTM, and joint-LSRTM. Circle A highlights a region where the sedimentary reflector is better imaged with joint LSRTM (Figure 3.19d) than using primary signal ((Figure 3.19a and b). Circle B shows a region where the sedimentary layer truncate against a salt flank on the left. We can better delineate the reflectors in the joint-LSRTM image than the mirror-LSRTM image. Overall, joint LSRTM is consistently better as a whole than single-mode imaging. Besides studying the zero-subsurface offset image, we can also study the differences in angular illumination. Figure 3.20 and 3.21 shows the angular illumination of reflectors at two different lateral locations. The joint LSRTM image has the widest range of coverage.

**CONCLUSION**

Least-squares reverse time migration is an advanced imaging technique that can improve imaging with better relative amplitude information, fewer artifacts, and reduced noise. When applying to field data sets, the recorded data departs from the theory and assumptions of the LSRTM operator. A simple data-fitting objective function in LSRTM is insufficient. I used salt-dimming data weighting, extended domain noise filtering, and target-oriented data reweighting to improve the convergence of the LSRTM algorithm when applied to the 3D Deimos ocean-bottom field data set. The inverted LSRTM image has better relative amplitude balance for the reflectors and improved illumination near the salt than the conventional RTM image.

Instead of treating the primary image and the mirror image separately, I combine
Figure 3.18: A zoomed section of the Deimos image calculated using (a) mirror RTM with spectral balancing, (b) primary-LSRTM, (c) mirror-LSRTM, and (d) joint-LSRTM. The annotations highlight several areas where joint-LSRTM shows improvement over either mirror LSRTM or primary LSRTM.
Figure 3.19: The zoomed section of the (a) primary RTM with spectral balancing, (c) primary LSRTM, (c) mirror-LSRTM, and (d) joint-LSRTM. [CR chap3/. comparedemos2]
Figure 3.20: Angular illumination of reflectors at x=54000 m and y=34450 m from the (a) up-going LSRTM, (b) down-going LSRTM, and (c) joint LSRTM. The joint LSRTM has the widest range of coverage. [CR chap3/ CompareAng1]

Figure 3.21: Angular illumination of reflectors at x=57000 m and y=34450 m from the (a) up-going LSRTM, (b) down-going LSRTM, and (c) joint LSRTM. The joint LSRTM has the widest range of coverage. [CR chap3/ CompareAng2]
the information from the two sets of data coherently using joint least-squares reverse-time migration (LSRTM). The image calculated using joint-LSRTM of primary and mirror signals is superior than conventional single-mode imaging.

ACKNOWLEDGMENTS

I wish to thank Shell Exploration and Production Company, as well as BP Americas for permission to publish this work. I also thank Michael Merritt, Richard Cook, Colin Perkins, Vanessa Goh, and Alexander Stopin for their data processing, helpful suggestions and discussions.