Case History

Seismic characterization of a carbonate reservoir in Tarim Basin

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ABSTRACT

Seismic characterization of carbonate reservoirs is a challenging task for geophysicists because of their special depositional environment and complex interior structures. We developed a case study of the seismic characterization of a karstified carbonate reservoir in the Tarim Basin, western China. The characterization procedure is sequential and includes fault and fracture detection, seismic facies classification, seismic impedance inversion, and lithofacies classification. We presented a dip-steered coherence algorithm for detecting faults and karst fractures in the carbonate reservoir. Incorporating the dip information improves the performance and robustness. We applied normalized seismic segments, rather than the amplitude values,

as the input to seismic facies classification, so as to reduce the impact of strong amplitudes, such as karst fractures, and to enable the analysis of weak amplitudes in the background strata. For the impedance inversion, we adopted a Fourier integral method for fast simulation in the stochastic inversion in this karstified carbonate reservoir. The algorithm honors the lateral variation based on the seismic trace similarity, instead of the lateral variogram that is commonly used in stochastic inversion. We conducted lithofacies classification, in which we used seismic coherence as a prior knowledge, so as to honor the fracture-associated local lithofacies with dolomitization and to distinguish it from limestone without dolomitization. Based on reservoir characterization described above, we determined three drilling wells for potential oil/gas exploration.

INTRODUCTION

It is a challenging task to characterize carbonate reservoirs based on seismic data (Lucia, 1983, 2007). Faults and fractures in carbonate reservoirs can have extremely high permeability, whereas their surrounding rock matrix may have very low permeability. Dolomitization may improve reservoir quality, but it is difficult to predict local dolomitization along faults and fractures. Although karst fractures in carbonate reservoirs can provide additional space for hydrocarbon accumulation, it is often difficult to determine the connectivity among neighboring karst fractures (Loucks, 1999; Zeng et al., 2011; Zhao et al., 2014). Therefore, it is important to apply advanced techniques for characterizing carbonate reservoirs (AlBinHassan and Wang, 2011; Al Mogbel and Wang, 2011; Karimpouli et al., 2013; Liu et al., 2015; Nouri-Taleghani et al., 2015; Parchkooi et al., 2015; Rao and Wang, 2015; Xu et al., 2016).

This paper presents a case study of carbonate reservoir characterization, based on 3D seismic data acquired from the Tarim Basin, western China. The research target is an Ordovician carbonate reservoir, lying on the slope between the Katake Uplift and the Manjiaer Depression (Figure 1a). The hydrocarbons were trapped in the carbonate formation with good cap rocks, while migrating upward from the adjacent Manjiaer Depression. A schematic structural profile through the study area is shown in Figure 1b, in which T is the top of the target reservoir.

The target Ordovician Formation was deposited in the open/restricted carbonate platform environment (Figure 1c). The shallow-water environment and high production rate produced a thick carbonate formation (Yun and Cao, 2014). Due to multiphase tectonic events and sea-level fluctuations, the Ordovician Formation experienced multiphase exposures and developed karst features.

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There are two major types of lithofacies in this area: limestone and limestone with dolomitization (Huang, 2014).

For the reservoir characterization, we have a 3D seismic cube covering 400 km² on the surface, consisted of 801 lines (inline numbers 2000–2800) oriented south to north, and 801 crosslines (crossline numbers 600–1400) oriented west to east (Figure 1d). The distance between adjacent lines is regularly spaced at 25 m. There are five boreholes available within this study area. Each of the existing boreholes, called B1–B5 (Figure 1d), contains six well logs: P-sonic, density, gamma ray, shallow, medium and deep resistivity, photoelectric effect, and spontaneous potential. We ex-

tracted a constant-phase wavelet and performed a seismic well tie (Figure 2). The correlation coefficients between the seismic traces and the wells at the five borehole locations ranged between 0.8 and 0.9.

Using this set of 3D seismic data to characterize the carbonate reservoir, we implemented the following four steps in sequence:

- 1) detecting faults and fractures in the target reservoir, using a dip-steered coherence algorithm,
- 2) performing seismic facies classification from normalized seismic segments to analyze the areas with hydrocarbon potential,
- 3) predicting the dolomitization in the target area, using a stochastic inversion, and
- 4) conducting coherence-constrained lithofacies classification.

Finally, we proposed several potential drilling wells for oil/gas exploration and production.

FAULT AND FRACTURE DETECTION

Faults and fractures are seismic discontinuities presented in the seismic cube. For detecting seismic discontinuities, we developed a dip-steered coherence algorithm. The information input to the coherence algorithm consists of seismic data $d(t, x, y)$, apparent dips along the inline direction $p(t, x, y)$, and apparent dips along crossline direction $q(t, x, y)$, where x is the crossline index, y is the inline index, and t is the time (Figure 3a). The apparent dips are estimated from seismic data based on the dip estimation algorithm by Marfurt (2006). The local analysis window is adjusted using preestimated reflector dips to flatten seismic data along local reflections (to eliminate the potential impact of dipping reflections on the coherence calculation). In the adjusted local analysis window, seismic coher-

Figure 1. (a) Location map of the study area (yellow square), indicating main tectonic units: Manjiaer Depression, Tazhong I fracture zone, and Katake Uplift. (b) Schematic structural profile through the study area, where T is the top of the target reservoir. (c) A cartoon showing the depositional environment. (d) Base map of seismic data set. The color on this map is the picked two-way times of reservoir top T. The dashed lines indicate two strike-slip faults. The circles are five available boreholes (B1–B5). The stars are three newly proposed well positions (P1, P2, and P3) resulting from this case study.

Figure 2. Seismic well tie. (a) Seismic two-way traveltime, reflectivity series, synthetic traces (red), and seismic traces (black). “T” is the top reservoir. (b) Constant-phase wavelet (-13°).

ence is a zero-lagged correlation coefficient, rather than the maximum correlation coefficient obtained among a set of time lags.

We used multiple traces to generate the average traces for a two-trace correlation (Bahorich and Farmer, 1995) whereby this algorithm is a pseudomultichannel calculation for improving the robustness. Hence, we compare its performance with a multichannel

Figure 3. Dip-steered coherence analysis. (a) Schematic diagram illustrating the dip-steered coherence algorithm. (b) Synthetic 2D seismic data. The S/N is five. (c) Seismic incoherence profile from the eigenstructure-based coherence algorithm. The dipping fault is not clear in this profile. (d) Seismic incoherence profile from the dip-steered coherence algorithm.

coherence method, the eigenstructure-based algorithm (Gersztenkorn and Marfurt, 1999). Figure 3b shows a synthetic seismic profile. Figure 3c shows the incoherence obtained from the eigenstructure-based coherence algorithm. The dipping fault is not properly detected, and the profile is noisy. Figure 3d shows the incoherence profile obtained using the proposed method. This final incoherence profile is clean, and both faults are detected.

Figure 4a displays an inline seismic profile across the 3D seismic cube. The time sampling interval is 2 ms. The reflection T is the top of the reservoir, which is the interface between the overlying siliciclastic deposits and the underlying carbonate deposits. The target interval in this study is 150 ms along the time axis. Figure 4b shows the seismic incoherence profile of inline 2218. A series of small faults and fractures below the top reservoir can be found from this profile. Areas near faults and fractures would have a high probability of dolomitization because fluids can cause dolomitization when migrating along these faults and fractures.

Figure 5a displays a seismic horizon slice at 30 ms below the top reservoir T. Figure 5b shows the associated incoherence slice. There are irregular circles on the top right corner, indicating the presence of karst features. Figure 5b evidences that there are two northeast strike-slip faults across the area, cutting through the target reservoir (Yun and Cao, 2014).

The role of these faults is twofold: the porous space for hydrocarbon accumulation and the migration pathway. When the fluids, such as meteoric water and those from deep earth, migrate through the faults, they can cause local dolomitization along the faults (Figure 6), which is one of the potential drilling targets in the area (Huang, 2014).

Figure 4. Fault and fracture detection. (a) A seismic profile (inline number 2218, referred to in Figure 1d). T is the top reservoir (top yellow line), which is the interface between the overlying siliciclastic deposits and the underlying carbonate deposits. The target interval is a 150 ms time interval below the top reservoir (between the two yellow lines). The black curve is the log acoustic impedance from well B4. (b) Seismic incoherence profile of the same line. Areas near faults and fractures would have a high probability of dolomitization.

SEISMIC FACIES CLASSIFICATION

Seismic facies classification attempts to identify major facies from seismic data or their numerical quantities so as to gain an intuitive understanding of the geology. A particular seismic facies represents an area with similar geologic characteristics, such as lithology, rock property, and fluid content (Saggaf et al., 2003; Qi et al., 2016). We applied seismic facies analysis to the karstified carbonate reservoir.

The top of the reservoir (T), a boundary between the overlying siliciclastic deposits and the underlying carbonate deposits, is a major reflection event. The strong amplitudes from this event may prevent facies classification from analyzing the variation in the target interval (weak amplitudes). In addition, the target carbonate reservoir (150 ms time window below T) has well-developed karst

Figure 5. Strike-slip faults across the area. (a) A horizon slice which is 30 ms below the top reservoir T. (b) The associated seismic incoherence profile, which clearly indicates two northeast strike-slip faults. Circular features in the top right corner indicate the presence of karst features.

fractures that are characterized by bead strings and strong amplitudes compared with their surrounding strata (Figure 7). Therefore, we perform facies classification based on normalized seismic segments, rather than the amplitude values. By removing the amplitude magnitude, variations in normalized segments from the karst fractures and their surrounding strata are all at the same level. Thus, it is easy for a classification algorithm to analyze variation patterns in weak and strong amplitudes.

In general, algorithms for seismic facies classification can be divided into two categories: supervised and unsupervised (Coléou et al., 2003; Marroquín et al., 2009). Following Wang (2012), we combine these two categories and perform self-organizing map (SOM), hierarchical clustering, and *K*-means classification sequentially. First, we select training data from the input 3D time interval, to train the weight vectors of the SOM. Then, we apply the hierarchical clustering to classify the trained weight vectors into a desired number of clusters, and the *K*-means classification to optimize the result generated by the hierarchical clustering. Finally, we classify each vector in the input 3D time interval into its closest weight vector.

We applied this classification strategy to generate a 3D volume of the seismic facies. Figure 8 displays a sample slice from this facies volume and a comparison with well-log data. Based on a

Figure 6. Fracture-associated dolomitization: A schematic illustration.

Figure 7. Comparison between seismic trace segments and normalized segments. The top panel is a group of seismic trace segments, with strong amplitudes of bead-string features. The blue lines in the top panel are karst related faults and fractures. The bottom panel is the group of normalized segments, i.e., amplitude variation patterns.

comparison of available well logs, facies “*f2*” (red color) best fits the “limestone with dolomitization” among the four facies clusters. In this profile, the dolomitization is mainly along one of the north-east strike-slip faults in the study area.

The classification result is only suitable for qualitative interpretation. This is because the variation pattern does not contain the amplitude-magnitude information, which relates to the lithology. Quantitative interpretation relies on seismic impedance information, described in the following section.

SEISMIC IMPEDANCE INVERSION

Reservoir characterization relies on seismic impedance data. Seismic impedance inversion involves two types of inversion: deterministic inversion and stochastic inversion.

For deterministic inversion (Wang, 2016), to compensate for the missing low-frequency components in seismic data, we extrapolated well-log data along picked horizons to build a low-frequency model, used as the initial model of the inversion. Then, we applied the inversion at five well locations to check the performance. The average residual energy at five well locations is 6.1%. Finally, we applied the inversion to the entire study area.

Figure 9a shows the inverted acoustic impedance of inline 2218. Due to the strong reflection (T) at the top of the reservoir, a 250 ms time interval, which starts 100 ms above the top reservoir T and ends 150 ms below T, is selected as the input time interval.

Once we have obtained the deterministic inversion result, we perform a stochastic inversion on the data set and use a Fourier integral method (FIM) to produce multiple acoustic impedance realizations (Appendix A). First, we build an initial low-frequency acoustic impedance model and estimate a vertical variogram model from the acoustic impedance difference between the initial model and the log acoustic impedance along five wells. Then, we generate

30 acoustic impedance realizations in total. Figure 9b and 9c compares a sample realization of the stochastic inversion and the mean of 30 realizations of the stochastic inversion. The stochastic realization and the mean have higher resolutions than the deterministic inversion (Figure 9a).

LITHOFACIES CLASSIFICATION

Once we had obtained seismic impedance realizations as in the previous section, we attempted to convert those impedance realizations into lithofacies realizations. We conducted this lithofacies classification, using coherence as a constraint, only within the 150 ms interval below horizon T.

As aforementioned, in the study area, fluids can cause local lithofacies variation (dolomitization) when migrating along faults and fractures. Figures 10 and 11 illustrate the relationship between the seismic incoherence and the lithofacies. Low seismic incoherence values mainly relate to limestone. Therefore, we used seismic coherence and the portion of lithofacies estimated from the five wells to build the prior probability, for honoring fracture-associated dolomitization and reducing the uncertainty of classification.

The portion of limestone from well data is 0.7. The calculated seismic coherence (not the incoherence) is smoothed using a median filter. The prior probability of limestone is calculated by combining seismic coherence $p(\text{coh})$ and the portion of lithofacies at well locations:

$$\text{prior}(\text{limestone}) = 0.7 \times p(\text{coh}). \quad (1)$$

The prior probability of limestone with dolomitization is calculated by

Figure 8. Seismic facies analysis. Top: a horizon slice at 30 ms below the top reservoir T. Bottom: comparison between the seismic facies analysis and well data. (a-e) are wells B1-B5. In the lithofacies column, the light blue color is the limestone, and red color is the limestone with dolomitization. Facies *f2* (red color) best fits the limestone with dolomitization among the four facies clusters.

Figure 9. Seismic impedance inversions. (a) Deterministic inversion result (inline number 2218). (b) Sample realization of the stochastic inversion. (c) Mean of 30 realizations of the stochastic inversion.

prior(limestone with dolomitization)

$$= 1 - \text{prior}(\text{limestone}). \quad (2)$$

Figure 12 gives two examples from the prior probability of limestone with dolomitization. The influence of seismic coherence is clear in these two examples. Areas near faults and fractures have higher prior probability compared with their surrounding areas.

Given the prior probability, we calculated the posterior probability for each type of lithofacies, by multiplying its prior probability with the likelihood function. The likelihood function is a Gaussian function that fits the histogram for each type of lithofacies, calculated based on well-log data. However, the likelihood functions alone cannot be used to distinguish these two types of lithofacies because the two histograms are overlapped (Figure 13).

Then, we converted each acoustic impedance realization into the lithofacies realization by comparing the two lithofacies probability values at each sample point. Finally, we calculated the lithofacies probability volume from the 30 lithofacies realizations.

Figure 14 shows two examples from the final probability volume of limestone with dolomitization. In the horizon slice, limestone with dolomitization is mainly distributed along one of the two northeast strike-slip faults and the intersection area of the two strike-slip faults.

Figure 10. The relationship between the seismic incoherence and the dolomitization: (a-e) gives wells B1–B5. In the lithofacies column, light blue color is the limestone and red color is the limestone with dolomitization.

DRILLING PROPOSAL

After accomplishing these sequential analyses described above, we made an effort ultimately to propose three potential drilling positions for oil/gas exploration and production.

In the study area, the key factors for determining potential wells are the reservoir quality and structure. The reservoir quality is mainly controlled by the dissolution of carbonate formation, as well as the modification by meteoric water and hydrothermal fluids that

Figure 11. Crossplot indicating the relationship between the seismic incoherence, acoustic impedance, and dolomitization.

Figure 12. The prior probability of limestone with dolomitization: (a) horizon slice, at 30 ms below the horizon T and (b) line example (inline number 2218).

have migrated along the large-scale faults. Areas near faults and fractures tend to have good reservoir quality. The nearby Manjiaer Depression, which is the source area, is lower than the target reservoir (Huang, 2014; Yun and Cao, 2014). Hydrocarbons can migrate upward easily along regional unconformity and large-scale faults to the target reservoir and be trapped in the structure high

Figure 13. Histograms of the two types of lithofacies: limestone (green) and limestone with dolomitization (blue).

Figure 14. Probability volume of limestone with dolomitization. (a) Horizon slice, at 30 ms below the horizon T. (b) Line example (inline number 2218). The lithofacies column from well B4 is for comparison.

Figure 15. Proposed well P1 at $(x, y) = (16.5, 14)$ km. Top to bottom: lithofacies probability map along with depth contour, seismic profiles, seismic facies classification profiles, and the probability of limestone with dolomitization.

Figure 16. Proposed well P2 at $(x, y) = (12.3, 11.0)$ km. The target interval should be in the range of 6530–6550 m.

of the study area. Therefore, a structure high such as a local anticline tends to have hydrocarbon accumulation.

In terms of the available wells, B1, B3, B4, and B5 are currently producing hydrocarbons from the target formation. These four wells were all drilled along the strike-slip fault zones, indicating that the areas near the faults and fractures tend to have great potential. Furthermore, B2 is not actually drilled at the high location of the structure but it is producing from shallower Silurian formations, which is probably drilled to locate the edge of the hydrocarbon-bearing zone.

According to quantitative results that are presented in the previous sections, we attempted to propose three potential wells.

Well P1 is at $(x, y) = (16.5, 14)$ km (Figure 15). The inline number is 2660, and the crossline number is 1160. The target is a local anticline. The nearby borehole B5 was drilled at the same anticline, indicating a good hydrocarbon potential along this anticline. There are two thin intervals of facies f_2 : 6330–6350 and 6430–6450 m. The lithofacies probability indicates that both intervals have a high probability of dolomitization (30%–50%), and the reservoir quality is better than surrounding areas.

Well P2 is at $(x, y) = (12.3, 11)$ km (Figure 16). The inline number is 2492, and the crossline number is 1040. This target is a small anticline, lying on the limb of the previous anticline. As the hydro-

carbon migrates upward, more hydrocarbon has to charge this small anticline to migrate further upward to charge the anticline in which borehole B5 was drilled. There are two intervals of facies f_2 : 6400–6430 and 6530–6550 m. The lithofacies probability indicates that the deep interval has a higher probability than the shallow interval, meaning that the target here should be at a depth of 6530–6550 m.

Well P3 is at $(x, y) = (15.5, 2.5)$ km (Figure 17). The inline number is 2620, and the crossline number is 700. The target is another local anticline. There are two intervals of facies f_2 : 6430–6460 and 6520–6550 m. The lithofacies probability indicates that the deep interval has a better reservoir quality (higher probability) than the shallow interval.

CONCLUSION

In this case study, we applied seismic discontinuities, seismic facies classification, stochastic inversion, and lithofacies classification for characterizing a carbonate reservoir. Two strike-slip faults and karst features can be identified from the seismic incoherence profiles. Seismic facies classification is implemented based on normalized seismic segments so as to reduce the influence of magnitude difference on the classification. Among all seismic facies clusters, the facies “limestone with dolomitization” matches these features best. The probability of dolomitization from the stochastic inversion and the coherence-constrained lithofacies classification further indicates that there is a high probability for the dolomitization to take place along one of the strike-slip faults.

The key factors affecting the hydrocarbon accumulation are reservoir quality and structure, considering the nearby source area and the good regional seal. Finally, we proposed three drilling locations that have hydrocarbon potential, according to the high probability of dolomitization.

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APPENDIX A

A FOURIER INTEGRAL METHOD FOR STOCHASTIC INVERSION

Stochastic inversion integrates seismic data, well data, and geologic information and produces a series of realizations of target reservoir attributes with high-frequency components (Bosch et al., 2010). The multiple realizations from stochastic inversion provide a basis for quantifying and assessing the uncertainty.

For characterizing carbonate reservoirs in this paper, we adopted the stochastic inversion based on the FIM, an efficient simulation method implemented in the frequency domain (Pardo-Iguzquiza and Chica-Olmo, 1993). The simulation target is the acoustic impedance difference

Figure 17. Proposed well P3 at $(x, y) = (15.5, 2.5)$ km. The target interval should be in the range of 6520–6550 m.

between the impedance calculated from the well logs and an initial model. Therefore, the final inversion solution is the simulated difference plus the initial model. The algorithm honors the lateral variation by incorporating the similarity among adjacent seismic traces into the inversion process. If adjacent traces are similar, a small amount of perturbation is applied.

Considering a discrete time series $z(k)$, its Fourier spectrum is $Z(j)$, and the spectral density is $|Z(j)|^2$. Assuming that $z(k)$ has zero mean and normalized unity variance, it leads to the coincidence of correlation function and covariance function. Based on the Wiener-Khinchin theorem, the spectral density $|Z(j)|^2$ is the Fourier transform of covariance function $c(h)$ (Anderson, 1971):

$$c(h) \leftrightarrow |Z(j)|^2. \quad (\text{A-1})$$

Only the power spectrum $|Z(j)|^2$ relates to the covariance function $c(h)$, and there is no phase term. Therefore, a realization that honors the covariance function $c(h)$ can be generated by combining the amplitude spectrum $|Z(j)|$ with a random phase spectrum and performing the inverse Fourier transform. This is called FIM.

Major steps of the FIM stochastic inversion are summarized as follows:

- 1) Initial model building — Build an initial acoustic impedance model AI_0 .
- 2) Vertical covariance function (variogram) estimation — Estimate a theoretical vertical covariance function $c(h)$ to capture the vertical variation of the residuals between the acoustic impedances from all the wells (containing all frequency components) and the corresponding acoustic impedances from the initial acoustic impedance model:

$$\text{AI}_{\text{residual}} = \text{AI}_{\text{well}} - \text{AI}_0. \quad (\text{A-2})$$

Treating $\text{AI}_{\text{residual}}$ as $z(k)$, $c(h)$ can be calculated based on the fitted variogram model $\gamma(h)$ from $\text{AI}_{\text{residual}}$:

Figure A-1. A 1D demonstration. (a) Acoustic impedance trace. (b) Seismic trace. (c) FIM inverted acoustic impedance (blue color) and deterministically inverted acoustic impedance (red color). (d) FIM inverted acoustic impedance (blue color) and original acoustic impedance (magenta color). (e) Synthetic seismic trace generated from FIM inverted acoustic impedance. (f) Residuals between the FIM synthetic trace and the input seismic trace.

$$c(h) = \sigma^2 - \gamma(h), \quad (\text{A-3})$$

where σ^2 is the variance. The amplitude spectrum $|Z(j)|$ can then be calculated from $c(h)$ based on equation A-1.

- 3) Inversion at the first trace (x_0, y_0) — At this first trace location, based on the amplitude spectrum $|Z(j)|$ and the random phase spectrum, a few candidate acoustic impedance realizations are simulated using FIM. Then, forward modeling is performed based on the combination of the simulated realizations and the initial model. Finally, the realization whose synthetic trace matches the input seismic trace is selected as the final result.
- 4) Determining the initial phase spectrum for the next trace (x_1, y_1) — Perform a correlation test between the seismic trace (x_1, y_1) and its adjacent traces in which the inversion process is complete. Select one of the adjacent traces having the maximum correlation coefficient C_{max} with trace (x_1, y_1) . Use the phase spectrum of this selected trace, ϕ_0 , as the initial spectrum of trace (x_1, y_1) .
- 5) Inversion at trace (x_1, y_1) by perturbing the initial phase spectrum by

$$\phi_1(j) = \phi_0(j) + (1 - C_{\text{max}})\Delta\phi(j). \quad (\text{A-4})$$

This ensures that the phase spectrum at the trace (x_1, y_1) is related to the phase spectrum of its adjacent traces through the correlation. Based on the amplitude spectrum $|Z(j)|$ and the perturbed phase spectrum ϕ_1 , a few candidate acoustic impedance realizations are simulated with FIM. Then, forward modeling is performed, and the realization whose synthetic trace matches the input seismic trace is selected as the final result.

- 6) Iteration over the rest of the traces.

Figure A-1 shows a 1D demonstration, in which Figure A-1a shows an acoustic impedance trace and Figure A-1b shows a synthetic seismic trace. The synthetic seismic trace is generated by convolving the acoustic impedance and a 30 Hz Ricker wavelet (Wang, 2015). The signal-to-noise ratio (S/N) is five. Figure A-1c compares the inverted acoustic impedance trace (blue) with the deterministically inverted acoustic impedance (red). Figure A-1d shows that the inverted impedance trace (blue) matches the original acoustic impedance (magenta). Figure A-1e shows a synthetic seismic trace generated by the inversion result. Figure A-1f shows that the residuals between e and b are small and random.

Next, we perform a 2D demonstration. Figure A-2a shows an impedance model, and Figure A-2b shows the corresponding synthetic seismic profile. The data in the previous 1D demonstration are considered as the only well. An inverted acoustic impedance realization (Figure A-2c) successfully inverts the layered structure. The associated synthetic seismic data (Figure A-2d) match the input seismic data.

It should be stated that the FIM stochastic inversion is performed over a regular grid (seismic time samples), rather than a stratigraphic grid. This is for the convenience of using the phase spectrums from adjacent locations during the inversion. With additional

modifications, it should work with the stratigraphic grid as well, which is one potential extension for future studies.

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Figure A-2. A 2D demonstration. (a) The original acoustic impedance. (b) Synthetic seismic data, generated based on panel (a); the S/N is five. (c) An inverted acoustic impedance realization by FIM stochastic inversion. (d) Associated synthetic seismic data.

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