AVA simultaneous inversion of partially stacked seismic amplitude data for the spatial delineation of lithology and fluid units of deepwater hydrocarbon reservoirs in the central Gulf of Mexico

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ABSTRACT

This paper describes the successful application of amplitude-versus-angle (AVA) inversion of prestack-seismic amplitude data to detect and delineate deepwater hydrocarbon reservoirs in the central Gulf of Mexico. Detailed AVA fluid/lithology sensitivity analysis was conducted to assess the nature of AVA effects in the study area based on well-log data. Standard techniques such as crossplot analysis, Biot-Gassmann fluid substitution, AVA reflectivity modeling, and numerical simulation of synthetic gathers were part of the AVA sensitivity analysis.

Crossplot and Biot-Gassmann analyses indicate significant sensitivity of acoustic properties to fluid substitution. AVA reflectivity and angle-gather modeling indicate that the shale/sand interfaces represented by the top and base of the M-10 reservoir are associated with typical Class III AVA responses caused by relatively low-impedance gas-bearing sands. Consequently, prestack seismic inversion provided accurate and reliable quantitative information about the spatial distribution of lithology and fluid units within the turbidite reservoirs based on the interpretation of fluid/lithology-sensitive modulus attributes. From the integration of inversion results with analogous depositional models, the M-series reservoirs were interpreted as stacked, progradational lobes within an overall fan complex. The massive and planar stratified sands exhibit moderate sorting and excellent interparticle porosity. Rock-core measurements indicate excellent intrinsic properties: 20–30% porosity and several hundred to thousands of millidarcies of nominal permeability.

In an effort to improve reservoir development of the study area, we resorted to amplitude information of prestack seismic data to quantify the vertical and lateral extent of the main turbidite reservoirs. We first conducted amplitude versus angle (AVA) sensitivity analysis based on well-log data, and subsequently applied AVA simultaneous 1D seismic inversion to generate 3D spatial distributions of lithology/fluid-sensitive modulus attributes.
AVA FLUID/LITHOLOGY SENSITIVITY ANALYSIS

We used well-log measurements to assess the A VA behavior of the M-series sand reservoirs, and to determine the sensitivity of modulus attributes to variations of lithology and fluid content. This methodology involves crossplot analysis, Biot-Gassmann fluid substitution, A VA reflectivity modeling, and numerical simulation of synthetic gathers.

Crossplot analysis

P- and S-impedance (Ip and Is, respectively) being the product of the density times P- and S-velocity, respectively, were calculated from dipole-sonic and density logs. Subsequently, we applied the lambda-mu-rho method introduced by Goodway et al. (1997) to generate fluid and lithology-sensitive modulus attributes lambda-rho (λρ) and mu-rho (μρ), which are defined as the product of the Lamé elastic parameters (λ and μ) times the bulk density (ρ), respectively. These modulus attributes were computed and crossplotted with P- and S-impedance logs using

\[ λρ = I_P^2 - 2I_S^2, \] (1)

and

\[ μρ = I_S^2. \] (2)

The effectiveness of this crossplotting technique is based on the fact that λρ is primarily sensitive to fluid content, and secondarily, to lithology and porosity, whereas μρ is primarily sensitive to lithology. Figure 2 shows a lambda-rho versus mu-rho crossplot constructed with well-log data acquired along the M-series sands. Hydrocarbon-bearing sands are associated with relatively low values of λρ and μρ whereas shales exhibit a completely opposite behavior characterized by relatively high values of λρ and μρ. Water-bearing sands, on the other hand, exhibit the low values of μρ characteristic of sands, whereas λρ values (mostly fluid sensitive) are similar to those of shales.

Biot-Gassmann fluid substitution

We performed fluid substitution analysis to quantify the influence of saturating fluids on the acoustic properties of the M-series reservoir sands. This was accomplished using Biot-Gassmann’s theory (Biot, 1956; Gassmann, 1951) and assuming constant porosity values of 20%, 25%, and 30%. Results in Figure 3 indicate that P-velocity, P-impedance, and lambda-rho decrease with an increase of hydrocarbon saturation. This behavior is corroborated by the petrophysical analysis of well-log data, specifically from the M-series vertical interval (including embedding shales) and gathered from multiple wells (Figure 4).

AVA reflectivity modeling

Well-log data in combination with Zoeppritz equations were used to simulate variations of PP reflectivity with angle of incidence at the top of the M-10 reservoir. The latter interface is a shale/gas-sand contact. Results from this exercise are shown in Figure 5a. The simulated A VA reflectivity is negative at normal incidence (R0), and its absolute value increases with angle. This behavior corresponds to the characteristic AVO response of Class III sands as defined by Ru-
therford and Williams (1989). Class III AVO sands are usually undercompacted and unconsolidated and, consequently, are associated with impedance values lower than those of the embedding shale as well as with larger negative values of $R_0$.

**Numerical simulation of synthetic gathers**

We simulated 1D, NMO-corrected synthetic gathers using well-log data acquired in an oil-producing well. Simulated gathers are the result of the convolution between a previously extracted wavelet and the well-log AVA reflectivity series. These reflectivity series were computed from Vp, Vs, and density logs using the Knott-Zoeppritz equations (Aki and Richards, 1980). Figure 5c shows results from the simulation of 1D NMO-corrected synthetic gathers. Consistent with the results of AVA reflectivity modeling, the synthetic gather simulated at the top of the M-10 reservoir sand exhibits a clear increase of amplitude with angle of incidence. This typical Class-III AVO behavior is corroborated by the measured-angle gathers shown in Figure 5b.

**AVA SIMULTANEOUS INVERSION**

We refer to the inversion procedure as 1D to emphasize that each CMP gather is separately assumed to be the result of two-layer plane-wave reflections of a local stack of homogeneous and isotropic horizontal layers. We do not enforce horizontal smoothness constraints on the inverted vertical distributions of elastic parameters between adjacent CMP gathers. Thus, 3D distributions of elastic properties are the result of displaying together the independently inverted vertical distributions of elastic parameters. Our inversion methodology consists of partial-angle stacking and time alignment, low-frequency modeling, angle-dependent wavelet estimation, 1D AVA-constrained sparse-spike (CSSI) simultaneous inversion, quality control of inversion parameters, and extraction of petrophysical attributes.

**Seismic amplitude data**

Seismic amplitude measurements were sampled at 4 ms and have a frequency band of 6–70 Hz, with a central frequency of 20 Hz. For an average P-velocity of 2500 m/s, the expected vertical seismic resolution is approximately 18 m. The 3D survey from the Marco Polo Field consisted of 254 crosslines spaced at 25-m intervals (6.35 km) and 320 inlines spaced at 20-m intervals (6.4 km). This acquisition amounted to 81,280 traces over an area of approximately 40.64 km². The measured CMP gathers were migrated and corrected for NMO using Kirchhoff prestack time-domain migration. In this

Figure 3. Biot-Gassmann fluid substitution exercise indicating that Vp, Ip, and $\lambda\rho$ decrease with an increase of hydrocarbon (oil/gas) saturation; the rate of decrease is a function of porosity. $\lambda\rho$ is considered an excellent fluid discriminator because of its relative change from 100% water saturation to 100% hydrocarbon saturation is larger than the corresponding relative change of either Vp or Ip.

Figure 4. Crossplots of water saturation and Vp, Ip, and $\lambda\rho$, generated from well-log data. Sample points are color coded based on the corresponding value of volumetric shale concentration. This exercise corroborates Biot-Gassmann predictions: Oil-bearing sands are associated with relatively low values of Vp, Ip, and $\lambda\rho$.
paper, we assume that the migrated and NMO-corrected CMP gathers are devoid of multiple and transmission effects and can be accurately described as the superposition of two-layer responses of a stack of horizontal layers. Further, we consider only PP reflectivity events in the analysis of prestack seismic amplitude variations. These assumptions are justified by the quality control performed on the migrated and NMO-corrected CMP gathers.

Partial-angle stacking and time alignment

The version of the 1D inversion algorithm implemented in this paper assumes input-seismic amplitude data organized into partial-angle stacks (PAS). Therefore, special processing of the prestack seismic-amplitude data was performed prior to 1D inversion.

We used a ray-tracing algorithm to transform the prestack seismic amplitude data from the offset domain to the incidence-angle domain, and generated four partial-angle stacks using the NMO-corrected and migrated offset gathers and the migration-velocity field. The angle range available from the seismic amplitude data was 6–46°; each partial-angle stack was generated using a 10° constant range. Final partial stacks included the following near, mid, far, and ultrafar angle ranges: 6–16°, 16–26°, 26–36°, and 36–46° (Figure 6a). In addition, small time-shift corrections were applied to the partial-angle stacks in order to reduce event misalignment caused by processing errors such as residual NMO corrections.

Low-frequency modeling

Low-frequency volumes of P-Impedance, S-Impedance, and density are required for 1D trace-based inversion because the low-frequency information needed to include the compaction trend (0–6 Hz in our case) is not available from the seismic amplitude data. Additionally, low-frequency volumes are used to guide the soft-trend constraints imposed by the 1D inversion algorithm. We generated these volumes with the weighted lateral interpolation of well logs using the geological model as guiding framework (Figure 6a). The geologic model was constructed based on the horizon interpretation of the tops of the main geologic formations. Finally, the interpolated models were low-pass filtered with a cutoff frequency of 6 Hz to generate the final low-frequency property volumes.

Angle-dependent wavelet estimation

The estimation of AVA wavelets within the target time interval was performed with deterministic techniques (Figure 6a). We combined well-log data with the partial-angle stacks to estimate the corresponding angle-dependent wavelets using Knott-Zoeppritz equations. In so doing, the angle-dependent reflectivity was derived from P-sonic, S-sonic, and density well logs, using the angle range assigned to a particular partial-angle stack. Subsequently, a best least-squares wavelet was estimated from the calculated reflectivity and the seismic amplitude data following the method described by White (1980).
1D AVA-CSSI simultaneous inversion

The 1D deterministic inversion of partially stacked seismic amplitude data used in this paper is based on the amplitude-versus-angle-constrained sparse spike inversion (AVA-CSSI) algorithm developed by Fugro-Jason. As described in Appendix A, the inversion algorithm minimizes an objective function that combines l1-norms of seismic-amplitude data misfit, subject to value-range constraints (Debye and van Riel, 1990; Pendrel and van Riel, 1997). The AVA-CSSI inversion algorithm combines all the available CMP gathers to estimate the corresponding 1D time-domain distributions of P-impedance, S-impedance, and density. This trace-based inversion algorithm is an extension to nonzero time-domain distributions of P-impedance, S-impedance, and density.

This inversion algorithm simulates the seismic amplitude measurements with 1D convolution based on the Zoeppritz equations for two-layer AVO reflectivity.

The main CSSI inversion parameters include a stabilization parameter alpha (α) which enforces a trade-off between data misfit (low seismic amplitude residuals) and sparsity of reflectors (and associated reflectivities), and the merge frequency cutoff, which is used to merge the band-limited inversion results with the low-frequency component interpolated from well-log data. These inversion parameters were chosen based on a sensitivity analysis of inversion results that include high crosscorrelation between synthetic (inversion derived) and measured seismic amplitude data, and high model-space crosscorrelation between inverted and measured elastic properties at well locations.

The aligned partial-angle stacks (corresponding to near, mid, far, and ultra-far angle ranges), were simultaneously inverted via AVA-CSSI making use of the previously estimated angle-dependent wavelets and the low-frequency volumes of elastic properties. Inversions focused exclusively on PP reflectivities (incident-reflected P-waves). Final products were volumes of Is, Is, and Ip obtained from separate 1D inversions of CMP gathers (Figure 6).

AVA-CSSI generated acoustic impedances (Figure 7) that are very similar to those obtained from previous poststack inversion tests (Z0-CSSI); however, an improvement in the accuracy of the estimated P-impedance (compared to well-log AI) is achieved with AVA simultaneous inversion (Figure 8). This relative gain in vertical resolution is attributed to the fact that prestack (or partially stacked) seismic amplitude data include AVA information that is not preserved in the fully stacked seismic amplitude data.

Figure 7. AVA-CSSI acoustic impedance results: (a) Acoustic impedance (Ip) section intersecting the exploratory well and one of its side-tracks. Hydrocarbon-bearing sand units coincide with the lowest values of Ip; (b) enlarged view around the vertical well, with overlying Ip (low-pass filtered) and gamma-ray logs (wiggle) included to emphasize the degree of vertical resolution obtained with AVA-CSSI inversion.

Figure 8. Comparison of poststack (black) and prestack (red) inverted acoustic impedance (Ip) and well-log Ip (blue).
Quality control of inversion results

The accuracy and reliability of the 1D inversion results was quantified in four ways: (1) with a sensitivity analysis of inversion residuals, (2) with a perturbation analysis of all of the inversion parameters, (3) with inversion exercises performed on multiple combinations of angle ranges, and (4) with tests on blind wells (wells not included as part of the input data for the inversions).

Extraction of petrophysical attributes

During this final phase, the two main inversion products, P- and S-impedance, were used to generate volumes of the fluid and lithology-sensitive modulus attributes $\lambda p$ and $\mu p$ using equations 1 and 2. Figure 9b is a 3D view of the rms attribute of $\lambda p$ for the M-10 reservoir overlaying a structural map in seismic time at the top of the same reservoir (Figure 9a). In this project, the $\lambda p$ attribute, which is primarily sensitive to the rock’s fluid component, is extremely valuable in the delineation of hydrocarbon-bearing rocks. As indicated by the Biot-Gassmann fluid substitution exercise, replacement of water by hydrocarbon in water-saturated sands decreases the values of $V_p$, $I_p$, and $\lambda p$. Accordingly, wells with confirmed hydrocarbon presence (shown with green lines in Figure 9b) are located within the boundaries of low $\lambda p$ anomalies, whereas dry or water wells (shown with blue lines in Figure 9b) coincide with high $\lambda p$ anomalies. Figure 9c is a 3D graphical rendering of low-$\lambda p$ geobodies associated with the best hydrocarbon-producing areas across the M-series sands. Such low-$\lambda p$ geobodies were extracted from the previously computed $\lambda p$ volume using a cutoff of 16 GPa × g/cm³.

High-porosity geobodies associated with the best hydrocarbon-prospective areas were extracted from an AI-derived porosity volume. A linear relationship between porosity and AI inferred from well-log data was applied to transform the inverted AI volume into a pseudoporosity volume (Figure 10a); subsequently, a cutoff of porosity $>28\%$ (Figure 10b) was applied to the volume in order to isolate high-porosity geobodies associated with the best hydrocarbon-prospective areas across the M-series sands. Figure 10c is the final 3D rendering of the high-porosity geobodies resulting from this exercise.

Integration and geologic interpretation of inversion results

Previous interpretations from regional stratigraphic/depositional studies (Galloway et al., 2000; Combellas, 2003), indicate that the M-series turbidite deposits of the Marco Polo Field are genetically linked to the western submarine fan of

Figure 9. (a) Structural map in seismic time of the top of the M-10 reservoir; (b) rms map of $\lambda p$ for the M-10 reservoir overlaying the same structural map shown in (a); (c) Geobodies captured with low values of $\lambda p$ correspond to M-series sands (different colors identify non-connected geobodies). Most hydrocarbon-prospective areas coincide with zones of low $\lambda p$ values. Blue lines represent well trajectories. The spatial coverage considered in the figures is approximately 8 km².

Figure 10. Porosity from P-impedance ($I_p$): (a) Porosity volume calculated with a linear relationship between porosity and $I_p$ inferred from well-log data. (b) Histogram of computed porosity values indicating the range of porosity values considered for reservoir delineation (porosity $>28\%$). (c) 3D visualization of geobodies captured from zones that exhibit low values of $I_p$ within the M-series reservoirs (different colors are used to indicate nonconnectivity between geobodies). The spatial coverage considered in the figures is approximately 8 km².
the Miocene MCA VLU Submarine Fan System. Accordingly, initial geologic interpretation of core data indicated that the depositional environment consisted of deepwater turbidites associated with terminal lobes.

By integrating the information rendered by core data, the characteristics of the channel/lobe depositional model introduced by Galloway and Hobday (1996); and (b) Deterministic inversion results. From integration of the above information, the M-series reservoirs can be interpreted as stacked turbidite lobes within an overall fan complex.

CONCLUSIONS

AVA fluid/lithology sensitivity analysis indicates significant sensitivity of acoustic properties to fluid substitution and corroborates the existence of Class III A AVA responses associated with the shale/hydrocarbon-sand interface at the top of the M-series reservoir sands. Accordingly, 1D prestack seismic inversion products in the form of fluid/lithology sensitive modulus attributes provided accurate quantitative information about the spatial continuity of lithology and fluid units within the turbidite reservoirs.

From integration of 1D deterministic inversion results with deepwater analog-depositional models and previous rock-core studies, the M-series reservoirs have been interpreted as stacked terminal-turbidite lobes within and overall fan complex. This interpretation is consistent with the channel-lobe depositional model, previous interpretations of rock-core measurements, and regional stratigraphic/depositional studies. Finally, by combining fluid/lithology sensitivity analysis techniques with 1D A AVA simultaneous inversion and awareness of inversion pitfalls, it is possible to substantially reduce the risk in the exploration and development of the M-series reservoirs.

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APPENDIX A

Even though the inversion algorithm developed by Fugro-Jason considers several variants for data conditioning, model parameterization, model constraints, and stabilization, here we explain only the specific version and features of the algorithm implemented to obtain the results described in the paper.

One-dimensional inversion of A AVA surface seismic amplitude measurements yields distributions of P-impedance ($I_p$), S-impedance ($I_s$), and bulk density ($\rho$) as functions of normal-incidence seismic traveltime.

The algorithm used in this paper for the 1D inversion of NMO-corrected A AVA seismic amplitude measurements is based on a sparse-spike regularization strategy. This procedure emphasizes PP reflectivity models that exhibit a prescribed degree of sparsity (or clustering) of reflectors. P- and S-impedances and density are further constrained to remain within upper and lower bounds inferred from well logs (thus the name A AVA constrained sparse-spike inversion, or A AVA-CSSI, used when referring to this inversion algorithm). The inversion of 1D A AVA seismic amplitude measurements is performed by minimizing the constrained objective function $F(I_p, I_s, \rho)$ given by
\[
F(I_P, I_S, \rho) = \alpha \sum_{i,j} (S_{ij}^{data} - S_{ij}(I_P, I_S, \rho))^2 + \sum_{i,j} |R_{ij}(I_P, I_S, \rho)| \\
+ \sum_j (I_P^{low} - I_P^{low}) + (I_S^{low} - I_S^{low}) \\
+ |\rho^{low} - \rho^{low}|, \quad (A-1)
\]

subject to

\[
I_{Pmin} \leq I_P \leq I_{Pmax},
I_{Smin} \leq I_S \leq I_{Smax}, \quad \text{and}
\rho_{min} \leq \rho \leq \rho_{max}.
\]

In the above expressions, \(I_P, I_S, \rho\) designate functions sampled at discrete values of normal seismic traveltime; \(i\) is the partial angle-stack index; \(j\) is the sample (time) index; \(R_{ij}\) identifies the angle-dependent PP reflectivity coefficients; \(S_{ij}(I_P, I_S, \rho)\) is the 1D numerically simulated AVA seismic amplitude data, and \(S_{ij}^{data}\) is the measured AVA seismic amplitude data. The variables \(I_P^{low}, I_S^{low}\), and \(\rho^{low}\) designate low-frequency components of P-impedance, S-impedance, and density, respectively, previously interpolated and low-pass filtered from available well-log measurements, and the variables \(I_P^{high}, I_S^{high}, \rho^{high}\) designate the corresponding high-pass filtered components of the inverted models. Moreover, the functions \(I_{Pmin}, I_{Pmax}, I_{Smin}, I_{Smax}, \rho_{min}, \rho_{max}\) identify time-dependent value-range constraints enforced by the inversion.

The first additive term (\(\ell_2\)-norm) of the cost function, \(F\), given by equation A-1 enforces a prescribed degree of misfit between the numerically simulated and measured prestack seismic amplitude data. The second additive term (\(\ell_1\)-norm) of the objective function biases the estimation of P-impedance, S-impedance, and density to render sparse and amplitude-constrained time sequences of angle-dependent PP reflectivity coefficients. Finally, the third additive term of the objective function (\(\ell_0\)-norm) biases the low-frequency components of the estimated P-impedance, S-impedance, and density toward the corresponding pre-defined volumes of low-frequency properties. The second and third additive components of the cost function are included to stabilize the inversion in the presence of noisy and inadequate AVA seismic amplitude measurements. Therefore, the user-defined scalar \(\alpha\) in equation A-1 is chosen to control the sparsity and amplitude of the estimated angle-dependent reflection coefficients when decreasing the data misfit (Debye and van Riel, 1990; Oldenburg et al., 1983). Unaccounted presence of noise in the input AVA seismic amplitude data may cause the inversion to yield spurious reflectors (associated with spurious reflectivities). Thus, the adjustment of \(\alpha\) prevents the inversion from mapping noisy AVA seismic measurements into non-existing reflectors. The use of mixed norms in the cost function \(F\) is intended to reduce Gibb’s-type oscillations in the inverted 1D distribution of elastic parameters that could be mistakenly associated with non-existing reflectors (Oldenburg et al., 1983).

In the inversion exercises considered in this paper, we enforced wide-open value-range model constraints. The enforced value of \(\alpha\) was estimated from trial-and-error by best-fitting existing well logs. Finally, we generated the low-frequency model components from low-pass filtered versions of the 3D volumes of properties interpolated from well logs.

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