Fluid property discrimination by AVO inversion
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Summary
Bayesian AVO inversion method is the developed prestack inversion technique for inverting seismic elastic parameters (p-wave velocity, s-wave velocity and density). The method is included AVO processing and analysis, well-log editing and calibration, and prestack seismic inversion. This analysis draws rock physics and Bayesian AVO inversion to discuss the fluid discriminator based on Bayesian inversion scheme. The fluid discriminator is calculated by Gassmann’s equation. The uncertainty is analyzed in the inversion procedure for elastic parameters and modulus. The rock physics relationship and gain function are also used to calculate the fluid modulus. This method is applied to seismic data from the Gulf of Mexico. The result is inverted at the target horizons for the small 3D cubes around two wells. The fluid discriminator inverted from prestack seismic data is sensitive to the pore fluid content.

Introduction
AVO equations have been derived that the variation in amplitude with offset in seismic data can help to discriminate the fluid content. The lamda-mu-rho method was proposed to identify the fluid content using the prestack seismic data.(Goodway, 1997) The fluid-factor discrimination calculated from p-wave and s-wave impedance was put forward to differentiate between the pore fluid and the rock matrix. (Brian H. Russell et al., 2003) AVO gradient and intercept inversion is developed by the weighted stacking method to identify the fluid anomalies. (Foster. Et al., 1993; Castagna, et al., 1998) Bayesian linearized AVO inversion method was applied in the prestack seismic inversion using angle gather. (Arild Buland and Henning Omre, 2003) In the previous papers, those methods didn’t make the prediction about the uncertainties on the inverted modulus. This work address the weak by inputting Bayesian inversion scheme into the uncertain analysis for the elastic parameters and modulus and use the simplified Gassmann’s equation to invert the fluid discriminator by the maximum a posterior model(MAP) solution of the modulus.

Methodology
Bayesian AVO inversion

The three term reflectivity approximation of Aki and Richards (1980)

\[ R(θ) = \frac{1}{2} (1 + \tan^2 θ) \frac{ΔV}{V_p} - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 θ \frac{ΔV}{V_s} \]

Where \( V_p \) is the P-wave velocity, \( V_s \) is the S-wave velocity, and \( ρ \) is the density. The quantities with \( Δ \) in front are the contrasts and the quantities with bars on the top are the average or the background values. The following relationship:

\[ \frac{Δx}{x} = Δln(x) \]  

is substituted into the parameters in equation (1), when \( Δx \) is very small. The equation (1) becomes:

\[ R(θ) = \frac{1}{2} (1 + \tan^2 θ) Δln(V_p) - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 θ Δln(V_s) \]

\[ + \frac{1}{2} (1 - 4 \left( \frac{V_s}{V_p} \right)^2 \sin^2 θ) Δln(ρ) \]

The parameters \( Δln(V_p), Δln(V_s), \) and \( Δln(ρ) \) are inverted from the prestack seismic angle gathers. These parameters are integrated and exponentiated by the following equation:

\[ x = \exp\left(\int Δln(x)\right) \]

The low frequency components are extracted from the well log data and merged into the inverted elastic parameters. This inversion result is band-limited.

Rock physics relationship

The basic equations for P-wave velocity and S-wave velocity in elastic isotropic nonporous media can be written as:

\[ V_p = \sqrt{\frac{M}{ρ}} \]
\[ V_s = \sqrt{\frac{μ}{ρ}} \]

Where \( M \) is the P wave modulus, \( μ \) is the shear modulus, \( ρ \) is the density.

The Gassmann’s equation provides the simple model for the fluid substitution effect in the rock. The formula can be simplified as (De-hua Han and Michael L. Batzle, 2004):

\[ K_i = K_d + ΔK = K_d + G(φ) × K_f \]
\[ μ_i = μ_d \]
\[ M = M_d + ΔK \]
\[ G(φ) = D^2 × φ × (2 - D × φ) \]

Where \( K_f, K_d, K_i \) are the bulk modulus of the fluid, dry rock and saturated rock frame, respectively; \( φ \) is the porosity; \( μ_d, μ_i \) are the dry rock and saturated...
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rock frame shear modulus; $G(\phi)$ is the gain function; D is the coefficient; $\Delta K$ is the fluid discriminator or bulk modulus increment in the fluid substitution.

To calculate the dry $P$ wave modulus, the crossplot between dry $P$ wave modulus and dry shear modulus is drawn again, and the relationship between dry $P$ wave modulus and dry shear modulus can be calculated as Figure 1 (De-hua Han and Micheal L. Batzle, 2005):

$$M_d = \mu_s \cdot 2.3083$$  

$$V_p^2 \rho = 2.3083 \cdot V_s^2 \rho + \Delta K$$  

$$\Delta K = V_p^2 \rho - 2.3083 \cdot V_s^2 \rho$$  

$$K_f = \Delta K / G(\phi)$$  

For shaly sandstone and porosity is 0.3, $D=1.450$, and $G(\phi)=2.5$

Uncertainty analysis:

Baye’s theorem provides a theoretical framework to estimate the posterior probabilities of the unknown model parameters from uncertain data and a priori information. In this analysis, the elastic parameters are assumed to be lognormal distribution. Figure 3 shows that this assumption is acceptable despite some curvatures in these plots.

The posterior expectation and covariance for elastic parameters can be written as (Arild Buland and Henning Omre, 2003):

$$\mu_{\text{post,mod}} = \mu_n + (S\sum_{\text{mod}})^{-1}(d_{\text{obs}} - \mu_{\text{obs}})$$  

$$\sum_{\text{post,mod}} = \sum_{\text{mod}} - (S\sum_{\text{mod}})^{-1}(d_{\text{obs}}^T S\sum_{\text{mod}} S_{\text{obs}})^{-1} S_{\text{obs}}$$

S is the wavelet matrix; $A$ is the coefficient matrix of the reflection coefficient equation; $\sum_{\text{mod}}$ is the covariance matrix for $\Delta \ln(V_p)$, $\Delta \ln(V_s)$, and $\Delta \ln(\rho)$; $\sum_{\text{data}}$ is the covariance matrix for the data; $\mu_n$ and $\mu_{\text{obs}}$ are the expectation matrix and covariance matrix for the model parameters; $\mu_{\text{post,mod}}$ and $\sum_{\text{post,mod}}$ is the posterior expectation matrix and covariance matrix for the model parameters $M$ - $\mu_M$, and $M_d$ are the lognormal distribution, the posterior expectation and covariance matrixes for $M$, $\mu_M$, and $M_d$ can be calculated based on the relationship of modulus, velocity, and density.

Example

The data set is from the Gulf of Mexico and used to test the method of the fluid discrimination. In this survey, the water depth is about 4100 feet and the reservoir depth is about 11200 ft. Only two 3D small patch seismic data are available for this work. Each seismic data has one well in the middle. In well A the commercial gas reservoir is discovered and the low gas reservoir in well B. (Figure 2) (O’Brien, 2004; Xin-gong Li et al., 2005) Both of two patch seismic data show the strong amplitude anomalies at the reservoir depth. From seismic amplitude, it is difficult to tell the fluid property difference between two reservoirs. In the inversion, the background $vp/vs$ ratio is extracted from the well log. The main inversion steps are the following:

1 invert $p$-wave velocity, $s$-wave velocity and density by angle gather  
2 calculate $P$ modulus and shear modulus and analyze the uncertainty  
3 calculate fluid discriminator using MAP solution of modulus

Figure 4 provides the final inversion result scaled to the fluid modulus range for sand 1A and 1B on the top of the target horizons.(sand 1A and 1B) In the inversion, the gain function value is 2.5 which is the value for shaly sandstone. The inverted fluid discriminator in the vicinity of well A shows the gas saturated zone and the inversion in the vicinity of well B shows low possibility of gas saturation.

In this work, we still assume that:

1 wavelet is consistent across different incident angles  
2 frequency losses caused by NMO stretch and amplitude losses caused by attenuation are compensated before doing the inversion  
3 tuning effect caused by thin layer is removed before doing the inversion  
4 seismic is the convolution of wavelet with reflection coefficient

Conclusions

Bayesian linearized inversion method can invert the elastic parameters from the seismic angle gathers. It is easy to be handled and costs less time than conventional inversion method.

The uncertainties analysis for elastic model parameters and modulus can be done in this work using Bayesian inversion scheme. The inversion results show that in patch A, the reservoir has low fluid modulus values than in patch B, which means patch A with low fluid modulus is gas reservoir and patch B with high fluid modulus possibly is low gas saturated reservoir. The inversion result also shows the distribution of the gas zone in patch A.

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Figure 1 the relationship between dry P modulus and dry shear modulus is:

\[ M_p = \mu_p \times 2.3083 \]

Figure 2 (a) shows the locations of two small patch seismic data
(b) shows the ties between seismic and well A and B (Xin-gong Li et al., 2005)
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Figure 3 Gaussian probability plot of the logarithm of the P-wave velocity (left), S-wave velocity (middle), and density (right). (a) well A; (b) well B

Figure 4 the fluid factor inverted by modulus. The black points in the middle are the well locations; (a) the inverted fluid modulus in the well A, the low value zone (dark blue) means the possibility of the gas distribution; (b) the inverted fluid modulus in the well B, the high values (red) means the low gas saturation zone.
EDITED REFERENCES
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