Full-waveform inversion for reservoir characterization: A synthetic study
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SUMMARY

Most current reservoir-characterization workflows are based on classic amplitude-variation-with-offset (AVO) inversion techniques. Although these methods have been widely used over the years, full-waveform inversion (FWI) represents a potentially powerful tool for higher-resolution reservoir characterization. An important step in developing reservoir-oriented FWI is the implementation of facies-based rock-physics constraints adapted from the classic methods. We show that such constraints can be incorporated into FWI by adding appropriately designed regularization terms to the objective function. The advantages of the proposed algorithm are demonstrated on both isotropic and VTI (transversely isotropic with a vertical symmetry axis) models with pronounced lateral and vertical heterogeneity. The inversion results are in agreement with published theoretical radiation patterns produced by perturbations in the medium parameters.

INTRODUCTION

Conventional AVO-based inversion of migrated data is usually constrained by well logs to obtain geologically plausible models (Russell, 1988). Although such classic techniques have generally served us well over the years, FWI represents an attractive alternative tool for reservoir characterization. An important advantage of FWI is modeling of the full wavefield (not only amplitudes), which makes it possible to operate with unprocessed (raw) data and avoid well-known limitations of migration algorithms. As proposed in Zabihi Naeini et al. (2016), facies-based constraints adapted from the classic methods can be incorporated into FWI as well. With waveform inversion being a highly nonlinear optimization tool, such constraints are essential in ensuring convergence towards a geologically plausible, higher-resolution model by properly honoring available well data.

Here we introduce a practical approach to implement such facies-based constraints by supplementing the objective function with extra regularization terms focused on the desired facies. We apply the algorithm to isotropic and VTI elastic media and explain the results using the theoretical radiation (sensitivity) patterns.

FWI FOR RESERVOIR CHARACTERIZATION

FWI is an inversion method that usually operates with raw seismic data (shot records) and aims to use the entire waveforms. The output depends on the specific formulation of the problem and the study objectives (which also determine the choice of

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E(m) = E_d(m) + \beta E_{\text{prior}}(m),
\]

where \(m\) is the vector of model parameters, the term \(E_d(m)\) represents the data misfit, \(E_{\text{prior}}(m)\) includes the rock-physics constraints for each facies, and \(\beta\) determines the relative contribution of prior information. The constraints are in the form of linear relationships between different elastic or anisotropy parameters. By referring to the “standard” FWI below, we mean the result of minimizing only the data misfit \(E_d(m)\) (e.g., \(\beta = 0\)). Representative facies are supposed to be identified from well data. We incorporate model constraints \(E_{\text{prior}}(m)\) into FWI one facies at a time. This approach is acceptable for the synthetic examples here but treating complex geology

Figure 1: Concept diagram for anisotropic elastic reservoir-oriented FWI (Zabihi Naeini et al., 2016).
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Figure 2: Elastic isotropic FWI of diving P- and SV-waves. The actual velocities (a) $V_P$ and (b) $V_S$, the initial (c) $V_P$ and (d) $V_S$, and the inverted (e) $V_P$ and (f) $V_S$.

and field data would require more sophisticated techniques. We plan to employ image-guided steering filters and Bayesian classification methods in future work.

EXAMPLE 1: ELASTIC ISOTROPIC MODEL

First, we apply the method to the elastic isotropic model in Figure 3. A thin reservoir is located at a depth of 1.6 km with lateral variations in the elastic properties representing oil sand, gas sand, and brine sand facies. The layer around the reservoir has the characteristics of encasing shale (between 1.1 to 2.3 km); there is a total of three nonreservoir facies. The choice of acoustic impedance (AI), the P-wave ($V_P$) and S-wave ($V_S$) velocities to represent the model follows the analysis of radiation patterns (Operto et al., 2013) and should reduce the crosstalk between the parameters.

Facies-based regularization is applied in two stages. First, rock-physics constraints are imposed only on the shale layer around the reservoir. Next, the model constraints are applied just to the reservoir itself. Note that the constraints are facies-based (i.e., they are in the form of the relationships between AI and $V_P$ and AI and $V_S$ for the sand and shale facies in the model), and have a much lower weight than the data misfit (i.e., $\beta \ll 1$). There is a visible improvement in AI (compare Figures 3(g) and 3(j)) and $V_P$ (Figures 3(h) and 3(k)) after including the model constraints in the facies-based FWI, especially for the encasing shale. At the reservoir level the inverted AI (Figure 3(j)) is more accurate than the velocity $V_P$ (Figure 3(k)). This is because AI is most sensitive to near-offset data whereas $V_P$ in the employed parameterization can be best resolved by diving waves and long-offset reflections (Operto et al., 2013). The lateral variation of AI and $V_P$ at the reservoir level could not be properly captured due to their trade-off with density. The velocity $V_{S0}$ obtained from the facies-based approach is slightly closer to the actual model compared to that produced by the standard FWI, especially at the reservoir level. The resulting density obtained by dividing the inverted AI by $V_P$ (not shown) is generally inaccurate, although it shows some improvement after application of the constraints. Density estimation even from elastic FWI is known to be questionable and more work is needed to better estimate $V_P$, $V_S$, and $\rho$ for realistic reservoir models.

EXAMPLE 2: ELASTIC VTI MODEL

It is generally well recognized that reservoir-oriented FWI has to take anisotropy into account (Zabihi Naeini et al., 2016). We extend the proposed method to elastic VTI media as the first step towards incorporating realistic anisotropic symmetries. The parameterization includes $V_{hor}$ (the P-wave horizontal velocity), $V_{S0}$ (the S-wave vertical velocity), and the anisotropy coefficients $\epsilon$ and $\eta \equiv (\epsilon - \delta)/(1 + 2\delta)$. This choice is suggested by radiation pattern analysis (Alkhalifah and Plessix, 2014; Kamath et al., 2016) to optimize the inversion and reduce parameter trade-offs.

The VTI model in Figure 4 has the same vertical velocities $V_{P0}$ and $V_{S0}$ and density as the isotropic model in Figure 3. However, we consider the encasing shale to be VTI, while the reservoir sand is isotropic, which helps differentiate them in the inversion. The density is assumed to be known, and we invert for the four parameters ($V_{hor}$, $V_{S0}$, $\epsilon$, and $\eta$) compared to three for the elastic isotropic medium in the previous example (Figure 5). The velocities $V_{hor}$ and $V_{S0}$ are generally well constrained; our facies-based approach leads to a slight improvement over the standard FWI in the reservoir. The coefficient $\epsilon$ is well-estimated with positive values for the shale, and the reservoir being practically isotropic ($\epsilon = 0$) for both the standard and the facies-based approaches. Although $\eta$ is not well resolved by the standard FWI at the reservoir level (Figure 5(c)), its estimates are improved by our algorithm in which the reservoir facies is constrained to be isotropic. Note that the velocity $V_{P0}$ computed from the inverted $V_{hor}$ and $\epsilon$ obtained by the facies-based FWI is more accurate compared to the isotropic case (Figure 3), most likely because the density of the VTI model is assumed to be known.

To evaluate the influence of density errors, we smooth the actual density field with the same filter used to generate the initial velocity models. Even for this distorted density field, facies-based FWI yields better results than for the isotropic model, probably because of the constraints imposed on the sandstone reservoir layer.
Figure 3: Elastic isotropic model described by the (a) acoustic impedance (AI) and the velocities (b) $V_P$ and (c) $V_S$. The initial parameters (d) AI, (e) $V_P$, and (f) $V_S$. The parameters (g) AI, (h) $V_P$, and (i) $V_S$ obtained from the standard FWI. The parameters (j) AI, (k) $V_P$, and (l) $V_S$ from the facies-based FWI. The AI is in $10^{-6}$ Kg/(m$^2$s), and velocities are in km/s.
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Figure 4: Anisotropy parameters (a) $\varepsilon$ and (b) $\eta$ of an elastic VTI model. The initial parameters (c) $\varepsilon$ and (d) $\eta$.

Figure 5: VTI parameters (a) $\varepsilon$, (b) $V_{P0}$, and (c) $\eta$ obtained from the standard FWI. The parameters (d) $\varepsilon$, (e) $V_{P0}$, and (f) $\eta$ obtained from the facies-based FWI.

CONCLUSIONS

With the goal of extending FWI to reservoir characterization, we introduced a practical approach to add facies-based rock-physics constraints through regularization terms in the objective function. The method was tested on isotropic and VTI elastic models that include a thin laterally heterogeneous reservoir. The results demonstrate the benefits of the new approach in resolving fine details of the parameter fields for a wide depth range. Interestingly, including anisotropy may represent an advantage (depending on the availability of parameter relationships) in a facies-based approach because there are more degrees of freedom in classifying the facies and constraining the inversion. The algorithm is currently being applied to more complex synthetic models and will be tested on field data.

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REFERENCES


