

# We B3 12

# Full Waveform Inversion for Reservoir Characterization - A Synthetic Study

E. Zabihi Naeini\* (Ikon Science), N. Kamath (Colorado School of Mines), I. Tsvankin (Colorado School of Mines), T. Alkhalifah (King Abdullah University of Science & Technology)

# Summary

Most current reservoir-characterization workflows are based on classic amplitude-variation-with-offset (AVO) inversion techniques. Although these methods have generally served us well over the years, here we examine full-waveform inversion (FWI) as an alternative 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 explained using the theoretical radiation patterns produced by perturbations in the medium parameters.



## Introduction

The current reservoir characterization workflows are based on 'classic' seismic inversion techniques. The term 'classic' refers to methods that make use of the amplitude variation of reflected waves with offset or angle (AVO/AVA) to invert for elastic or reservoir properties in deterministic or stochastic fashion (Russell, 1988). Also, these techniques are typically applied to migrated data and often based on 1D convolutional modelling. Nonetheless, such classic AVO-based techniques have been used to obtain geologically plausible models by constraining the inversion using well log data. These types of constraints are often included in the form of linear rock-physics relationships between the elastic properties (e.g., between acoustic impedance and density). This approach, however, inevitably imposes the same linear trend for all facies in the model, which is often violated for different lithologies (e.g., shales and sands). To address this issue, a natural solution (which is more difficult to implement) is to impose rock-physics constraints for each facies type, as shown in Gunning et al. (2013).

Although these classic techniques have generally served us well over the years, here we examine FWI as an alternative reservoir-characterization tool. The critical advantage of FWI is the modelling of the full wavefield (not only the amplitudes), which makes it possible to operate with unprocessed (raw) data. Hence, one might argue that FWI handles the physics more accurately. As proposed in Zabihi Naeini et al. (2016), it makes sense to implement facies-based constraints adapted from the classic methods for FWI as well. With FWI being a highly nonlinear optimization tool, such constraints should help to converge towards a more geologically plausible and higher-resolution model by properly honoring the well data. In this paper we introduce a practical approach to implement such facies-based constraints by adding extra regularization terms focused on the desired facies. We show numerical examples of this approach for both isotropic and VTI elastic media and explain the results based on the theoretical radiation patterns.

## FWI for Reservoir Characterization

FWI is an inversion method that operates with the raw recorded data (shot records) and aims to use the entire waveforms (e.g., traveltime, amplitude, and phase). The output depends on the specific formulation of the problem and the objective of the study (which also determines the choice of forward modelling) and can include acoustic or elastic (isotropic or anisotropic) model parameters. To apply FWI as a reservoir-characterization tool, one can follow the process depicted in a concept diagram in Figure 1.



Figure 1 Concept diagram for anisotropic elastic reservoir-oriented FWI (Zabihi Naeini et al., 2016).

At the heart of FWI is a measure of how well the simulated data fit the observed data; that is the objective function. Such a measure is usually given by the *l2 norm* of the data misfit which is the basis of least-squares optimization. Developing the workflow in Figure 1 requires taking smaller steps to prove the required concepts. With that in mind, we implement one of such steps by incorporating facies-based rock-physics constraints in the form of extra regularization terms in the objective function as follows:

$$\boldsymbol{E}(\mathbf{m}) = \boldsymbol{E}_{d}(\mathbf{m}) + \beta \boldsymbol{E}_{prior}(\mathbf{m}), \qquad (1)$$



where  $E_d(\mathbf{m})$  represents the data misfit and  $E_{prior}(\mathbf{m})$  includes the rock-physics constraints for each facies, with  $\beta$  determining the overall impact of prior information. The constraints are in the form of linear relationships between different elastic or anisotropy parameters.  $\beta$  is set to a small value to weight  $E_{prior}(\mathbf{m})$  relative to  $E_d(\mathbf{m})$ . In the following sections, by referring to standard FWI, we mean the contribution only from the data misfit  $E_d(\mathbf{m})$  (e.g.,  $\beta=0$ ). Depending on the number of representative facies (to be obtained from well data in practice) in the model, we run FWI sequentially by incorporating the facies information (i.e., by adding  $E_{prior}(\mathbf{m})$ ) at each step. This is acceptable for simple synthetic examples in this paper but would require more sophisticated methods for complex geology and real data. We plan to incorporate image-guided steering filters and Bayesian classification methods in future work.

### Data Example – Elastic Isotropic Model

First, we apply the method to an elastic isotropic model (Figure 2). A thin reservoir is located at a depth of 1.6 km with some lateral and vertical variation in the elastic properties representing oil sand, gas sand and brine sand facies. There are also three non-reservoir facies. The layer around the reservoir has the characteristics of encasing shale (between 1.1 to 2.3 km; yellow color AI).



The choice of acoustic impedance (AI), Vp and Vs (P- and S-wave velocities) to represent the model in FWI follows the analysis of radiation patterns (Operto et al., 2013) and should reduce the cross talk between parameters. Figure 3 shows the initial models used for FWI and the results of standard elastic FWI for comparison. Facies-based regularization is applied in two stages for this model. At first we impose rock-physics constraints for the encasing shale layer around the reservoir and then the corresponding constraints for the reservoir only. Note that the constraints are facies-based (i.e., the relationship between AI and Vp, and AI and Vs for sand and shale in the model), and are weighted substantially lower than the data misfit. There is a visible improvement after FWI in AI and Vp, especially for the encasing shale. At the reservoir level the inverted AI is more accurate than the inverted Vp. This can be explained by the radiation patterns: AI is most sensitive to near-offset data whereas Vp can be best resolved by diving waves and long-offset reflections. The lateral variation of AI and Vp at the reservoir level could not be captured in any case due to trade-off with density. The inverted Vs is similar for both methods and is most sensitive to P-wave energy incident at intermediate angles. The resulting density obtained by dividing the inverted AI by Vp (not shown here) is generally not accurate although it shows some improvement with the constraints. Generally the accuracy of estimating the density from elastic FWI is questionable and more work is required to fully explain the results in different scenarios.

### Data Example – Elastic Anisotropic Model

It is generally well understood that if one desires to perform elastic FWI then considering anisotropy is a must (although it is also useful for acoustic media) so that the physics is captured more accurately (Zabihi Naeini et al., 2016). We, therefore, extend the proposed method to elastic VTI media as the first step towards incorporating realistic anisotropic models. The parameterization we adopt for this case is  $V_{hor}$  (P-wave horizontal velocity),  $V_{s0}$  (S-wave vertical velocity),  $\eta$  and  $\epsilon$  (anellipticity coefficient  $\eta$  is related to Thomsen coefficients  $\eta \equiv (\epsilon - \delta)/(1 + 2\delta)$ ). This choice is suggested by radiation pattern analysis to optimize the inversion and reduce parameter trade-offs.



*Figure 3 Top*) Initial models, and the output of the (*middle*) standard elastic FWI, and (*bottom*) facies-based elastic FWI.

The radiation patterns for this parameterization are shown in Figure 4. The expectation is to obtain a good estimate of  $V_{hor}$  due to its even radiation pattern constant for all angles and accurate  $\epsilon$  from near-offset data.  $\eta$  is sensitive to P- and SV-waves propagating at intermediate opening angles, and hence, the updates in this parameter should be the smallest. Although the P-wave radiation pattern of  $V_{s0}$  is similar to that of  $\eta$  (and is the same as in isotropic media), the sensitivity of SV-wave energy incident at small opening angles to  $V_{s0}$  helps obtain better results for  $V_{s0}$  compared to  $\eta$ . There are more parameters to invert for even after ignoring the density in VTI media (in the example in this section the density is assumed to be known).

However, this parameterization may help estimate  $V_{p0}$  with higher accuracy as it is related to  $V_{hor}$  and  $\epsilon$  via  $V_{hor} = V_{P0}\sqrt{1+2\epsilon}$ . Another potential advantage of incorporating anisotropy is specific to our proposed facies-based approach: we can better separate the different facies (for example, it is reasonable to assume reservoir sands to be isotropic and shales anisotropic) and constrain the inversion (we only constrain  $\eta$  here). Also, we could obtain more reservoir attributes, by inverting for VTI parameters. The model we used to examine elastic VTI inversion has the same vertical velocity and density as the model in Figure 1. However, we consider the encasing shale to be VTI, while the reservoir sand is isotropic. The resulting  $\eta$ - and  $\epsilon$ -sections are shown in



*Figure 4 P*-wave radiation patterns for the VTI parameters.

Figure 5 along with their smoothed versions which have been used as the initial models for the inversion. The inverted models using the standard and facies-based FWI are shown in Figure 6. It can be observed that the estimated  $V_{p0}$  obtained from the inverted  $V_{hor}$  and  $\epsilon$  is more accurate compared to the isotropic case (Figure 3). The resolved lateral variations are in part due to a known density model, although our tests show that we can get better results even with a smooth density model. The coefficient  $\epsilon$  is also well-



estimated with vanishing values at the reservoir and non-zero values for the shale. As expected, the key observation is that  $\eta$  is not well resolved by the standard FWI at the reservoir level. This is improved by the facies-based FWI in which reservoir facies is constrained to be isotropic.



Figure 6 Output of the (top) standard and (bottom) facies-based elastic anisotropic FWI.

# Conclusions

With the objective to extend FWI to reservoir characterization, we introduced a practical approach to add facies-based rock-physics constraints through regularization terms. The method was tested on synthetic isotropic and anisotropic elastic models with lateral heterogeneity. The results show the benefits of this new approach in resolving fine structural details. Interestingly, including the anisotropy may be an advantage (depending on the availability of tight constraints) in a facies-based approach as it allows more degrees of freedom to classify the facies and constrain the inversion. The algorithm is currently being applied to more complex models and will be tested on field data.

### References

Gunning, J., Kemper, M., Saussus, D., Pelham, A. and Fitzgerald, E. [2013] A Tour of Optimization Methods for Facies Estimation in AVO Seismic Inversion Using Markov Random Fields. 75th EAGE Conference & Exhibition, Extended Abstract, Tu 10 10.

Operto, S., Gholami, Y., Prieux, V., Ribodetti, A., Brossier, R., Metivier, L. and Virieux, J. [2013] A guided tour of multiparameter full-waveform inversion with multicomponent data: From theory to practice. *The Leading Edge*, **32**(9), 1040–1054.

Russell, B. H., 1988, Introduction to seismic inversion methods: Society of Exploration Geophysicists.

Zabihi Naeini, E., Alkhalifah, T., Tsvankin, I., Kamath, N. and Cheng, J. [2016] Main components of full-waveform inversion for reservoir characterization. *First Break*, **34**(11), 37–48.