Time-lapse full waveform inversion with non-local shaping regularization: Toward integrated reservoir monitoring

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ABSTRACT

We present a regularization strategy to integrate geomechanical modeling results into the time-lapse full waveform inversion (FWI) workflow. The method constructs a non-local shaping regularization based on the time-lapse attributes change from geomechanical modeling linearly correlated with the seismic velocity change. The regularization pushes the velocity change to have similar shape as the geomechanical attributes, overcoming the challenge of unknown scaling factors between different attributes. We show the potential of the proposed methods on synthetic models with both noise free data and noisy data.

INTRODUCTION

Successful reservoir management requires the integration of knowledge from seismic imaging, reservoir simulation and geomechanical modeling to understand the reservoir production process (Biondi et al., 1998; Johnston, 2013). The conventional methods for analyzing time-lapse data are based on interpretation such as picking changes in travel time for seismic images. While effective in practice, the interpretation relies on highly specialized skills and the process is not fully automatic. In addition, quantitative comparison of attributes is challenging because of the scale of different reservoir data types, which increases the difficulty of integrating optimization-based seismic imaging methods such as wave equation migration velocity analysis and FWI.

Full waveform inversion estimates the high-resolution subsurface models by minimizing the mismatch between the observed seismic data and the synthetic data (Tarantola, 1984; Virieux and Operto, 2009). FWI is a useful tool for time-lapse (4D) seismic imaging problems (Denli and Huang, 2009; Routh et al., 2012; Maharramov and Biondi, 2014). Time-lapse FWI faces the challenge of detectability and non-repeatability from the seismic surveys. Different inversion strategies, including parallel difference, sequential difference, and joint inversion have been proposed to reduce the impact of the acquisition footprint. Regularization techniques, such as total variation (TV) (Maharramov and Biondi, 2014) and L1 norm optimization methods are used to recover production-induced changes from noisy seismic data.

In this paper, we propose a regularization strategy to integrate the geomechanical modeling results into the time-lapse FWI objective function. We assume a linear relation exist between production-induced attribute changes, such as velocity and strain, while the exact relation is assumed to be unknown. A non-local shaping regularization is constructed, forcing the attributes to be visually similar.

We test our methods on a synthetic model based on the Marmousi model, with time-lapse changes simulating reservoir compaction and overburden dilation, inspired by previous field data studies (Hodgson et al., 2007; Herwanger and Horne, 2009). In the absence of noise, time-lapse FWI captures the velocity changes even without regularization, and the use of regularization improves the accuracy of the inversion. When noise is present in the data, minimizing the data residuals alone cannot recover the time-lapse change properly, especially the low amplitude changes in the overburden. Our proposed methods improve the inversion results with non-repeatable noise in the surveys.

METHODS

Time-domain full waveform inversion can be formulated as an optimization problem with the following objective function (Tarantola, 1984; Virieux and Operto, 2009)

$$J(\mathbf{m}) = \frac{1}{2}\|\mathbf{S}\mathbf{u}\left(\mathbf{m}\right) - \mathbf{d}\|_2^2, \tag{1}$$

where $\mathbf{m}$ is the subsurface model (velocity, anisotropic parameter, etc), $\mathbf{S}$ is the measurement operator, $\mathbf{u}$ is the synthetic wavefield and $\mathbf{d}$ is the observed data. For isotropic acoustic wave equation with $\mathbf{m}$ being the velocity model, the wavefield is computed by solving the following:

$$\left[\frac{1}{v^2}\partial_t^2 - \nabla^2\right]\mathbf{u} = \mathbf{f}, \tag{2}$$

where v is the acoustic velocity, $\mathbf{f}$ is the source function.

We estimate the subsurface model $\mathbf{m}^*$ by minimizing the following objective function

$$\mathbf{m}^* = \text{argmin}_{\mathbf{m}} J(\mathbf{m}). \tag{3}$$

Time-lapse FWI estimates the production-induced change in the subsurface using seismic data from a survey before production (baseline survey), and repeated surveys during production (monitor survey). Common Time-lapse FWI strategies include parallel difference (estimating baseline and monitor model separately), sequential difference (using baseline model as the starting model for monitor model estimation), double difference (inverting the differential data) and joint inversion approach (estimating baseline and monitor model simultaneously).

We use a the joint inversion approach with the following objection function:

$$J(\mathbf{m}_\mathrm{b}, \mathbf{m}_\mathrm{m}) = \frac{1}{2}\|\mathbf{S}_\mathrm{b}\mathbf{u}_\mathrm{b}\left(\mathbf{m}_\mathrm{b}\right) - \mathbf{d}_\mathrm{b}\|_2^2 + \frac{1}{2}\|\mathbf{S}_\mathrm{m}\mathbf{u}_\mathrm{m}\left(\mathbf{m}_\mathrm{m}\right) - \mathbf{d}_\mathrm{m}\|_2^2 + \frac{\alpha}{2}\|\mathbf{W}\mathbf{R}\left(\mathbf{m}_\mathrm{m} - \mathbf{m}_\mathrm{b} - \Delta\mathbf{m}_\mathrm{prior}\right)\|_2^2, \tag{4}$$

where b is a substript indicating baseline variables, m is a subscript for monitor variables, α is the strength of the regularization term, $\mathbf{W}$ is a weighting function, $\mathbf{R}$ is regularization on the model difference $\mathbf{m}_\mathrm{m} - \mathbf{m}_\mathrm{b}$ and $\Delta\mathbf{m}_\mathrm{prior}$ is the a prior time-lapse model change. In practice $\mathbf{R}$ can be an identity operator, promoting minimum norm solution. $\mathbf{R}$ can also be the gradient operator for the recovery of blocky time-lapse change.

The estimation of model prior $\Delta\mathbf{m}_\mathrm{prior}$ is challenging for integrated reservoir monitoring. In principle we can estimate $\Delta\mathbf{m}_\mathrm{prior}$ from reservoir simulation results, based on the relation between velocity and differential pressure (Johnston, 2013)

$$v = v_\mathrm{inf}(1 - Ae^{-P/P_0}), \tag{5}$$

where v_inf, A and P_0 are fitting constants. We can also estimate $\Delta\mathbf{m}_\mathrm{prior}$ from geomechanical modeling (Landr and Stammeijer, 2004) using the following:

$$\frac{dv}{v} = -R\varepsilon_\mathrm{zz}, \tag{6}$$

where $\frac{dv}{v}$ is the fractional change in velocity and ε_zz is the vertical strain. The ratio R depends on the rock properties. Without sufficient data to fix the value of those fitting parameters, we cannot effectively integrate reservoir simulation or geomechanical modeling results into our time-lapse FWI objective function.

In this paper we propose a non-local, non-convex regularization term on the time-lapse model change. We assume a linear relation between time-lapse velocity change and the prior information from geomechanical modeling as follows:

$$\Delta\mathbf{m} \propto \Delta\mathbf{p}_\mathrm{prior}, \tag{7}$$

where $\Delta\mathbf{p}_\mathrm{prior}$ can be vertical strain, pressure change, etc. We formulate a shaping regularization term as

$$\|\frac{\Delta\mathbf{m}}{\|\Delta\mathbf{m}\|_2} - \frac{\Delta\mathbf{p}_\mathrm{prior}}{\|\Delta\mathbf{p}_\mathrm{prior}\|_2}\|_2^2, \tag{8}$$

where the scaling factor between velocity change and attribute change is eliminated by the normalization.

The regularization term in Equation 8 promotes time-lapse change $\Delta\mathbf{m}$ to have the same shape as the prior $\Delta\mathbf{p}_\mathrm{prior}$. As long as the linear relation in Equation 7 holds, the regularization term in Equation 8 goes to zero.

With our proposed regularization strategies, we modify the time-lapse FWI objective function as follows:

$$\begin{aligned} J(\mathbf{m}_\mathrm{b}, \mathbf{m}_\mathrm{m}) = & \frac{1}{2}\|\mathbf{S}_\mathrm{b}\mathbf{u}_\mathrm{b}\left(\mathbf{m}_\mathrm{b}\right) - \mathbf{d}_\mathrm{b}\|_2^2 \\ & + \frac{1}{2}\|\mathbf{S}_\mathrm{m}\mathbf{u}_\mathrm{m}\left(\mathbf{m}_\mathrm{m}\right) - \mathbf{d}_\mathrm{m}\|_2^2 \\ & + \frac{\gamma}{2}\|\frac{\mathbf{m}_\mathrm{m} - \mathbf{m}_\mathrm{b}}{\|\mathbf{m}_\mathrm{m} - \mathbf{m}_\mathrm{b}\|_2} - \frac{\Delta\mathbf{p}_\mathrm{prior}}{\|\Delta\mathbf{p}_\mathrm{prior}\|_2}\|_2^2, \end{aligned} \tag{9}$$

where each term in the objective function is nonlinear, non-convex.

The non-convex nature of the FWI objective could potentially lead to the convergence to a local minimum (the cycle-skipping issue), and adding another non-convex regularization term could be problematic. However for time-lapse FWI, where cycle-skipping issue can be avoided even when applied to field data, the objective function in Equation 9 has the potential of integrating the geomechanical results with the seismic data.

NUMERICAL EXAMPLES

We tested our method based on the Marmousi model. The Marmousi velocity model in Figure 1a is used as the baseline model. The production-induced changes are shown in Figure 1c. On the right side of the model the velocity increases and is localized in space, thereby simulating fluid substitution by water injection. On the left side of the model, the velocity decreases near the reservoir and also in the overburden area, thereby simulating fluid extraction, reservoir compaction and overburden dilation, inspired by recent studies in the Gulf of Mexico (Hodgson et al., 2007; Herwanger and Horne, 2009).

Figure 1b shows the starting velocity model. The starting model does not contains a high contrast except for the water bottom.

For this synthetic study, we build the prior model based on the true time-lapse change of the velocity model. We multiply the velocity change by a random factor as follows:

$$\Delta\mathbf{p}_\mathrm{prior} = \kappa\left(\mathbf{m}_\mathrm{m} - \mathbf{m}_\mathrm{b}\right), \tag{10}$$

where κ is the fitting parameter and is supposed to be unknown during the optimization process. The prior model in Equation 10 cannot be directly used in the regularization for objective function 5; however, it provides valuable information for our proposed objective function 9.

For the first numerical test, no noise is added to the observed data. For the second numerical test, we add noise to the observed data, thereby simulating the non-repeatability issues for the time-lapse problem.

We use a hierarchical multiscale approach for the optimization process. We start from data centered at 5 Hz, and increase the frequency up to 20 Hz. The same starting velocity model is used for both the baseline and the monitor model. For our proposed objection function 9, the regularization is added only after the inversion with data at 5 Hz. The reason is that our objective function goes to infinity when $\mathbf{m}_{\mathrm{m}} - \mathbf{m}_{\mathrm{b}} \to 0$.

In Figure 2, we see the inversion results for noise-free data. We can see that even without regularization we recover both time-lapse changes without difficulty. Artifacts below the reservoir are expected because we update the whole domain before having built an accurate model for the shallow part. Using our proposed methods, the estimated time-lapse change approaches the true production induced change as we increase the regularization strength from Figure 2b, Figure 2c to Figure 2d. Result in Figure 2d exhibits features beyond the resolution of seismic data, showing that the regularization is too strong and that we are not estimating the time-lapse change mainly from the seismic data.

Figure 3 shows the results with noisy data. In this case, inversion without regularization is contaminated by the noise. The time-lapse change on the right is still observable; however, we cannot recover the overburden dilation induced change on the left. With our proposed method, we get better results shown in Figure 3b, Figure 3c and Figure 3d, with increasing regularization strength. Similar to the clean data study, results in Figure 3d suggest improper regularization. The optimal choice of regularization strength is still under investigation.

CONCLUSIONS AND DISCUSSIONS

In conclusion, we propose a regularization strategy to combine geomechanical modeling results into the time-lapse FWI objective. Assuming linear relation between attributes from different types of reservoir data, we construct a non-local shaping regularization. The shaping regularization forces the attributes to be visually similar without knowing the exact scaling factor between them.

We study the shaping regularization with a simple synthetic example based on the Marmousi model. The numerical results suggest that the shaping regularization improves the inversion results for the production-induced change, especially in the presence of noise in the data.

Ideally we would like the regularization term to provide guidance for the shape of the time-lapse change, and use the seismic data to recover the amplitude of the change. Therefore we can effectively combine different types of reservoir data for integrated reservoir monitoring.

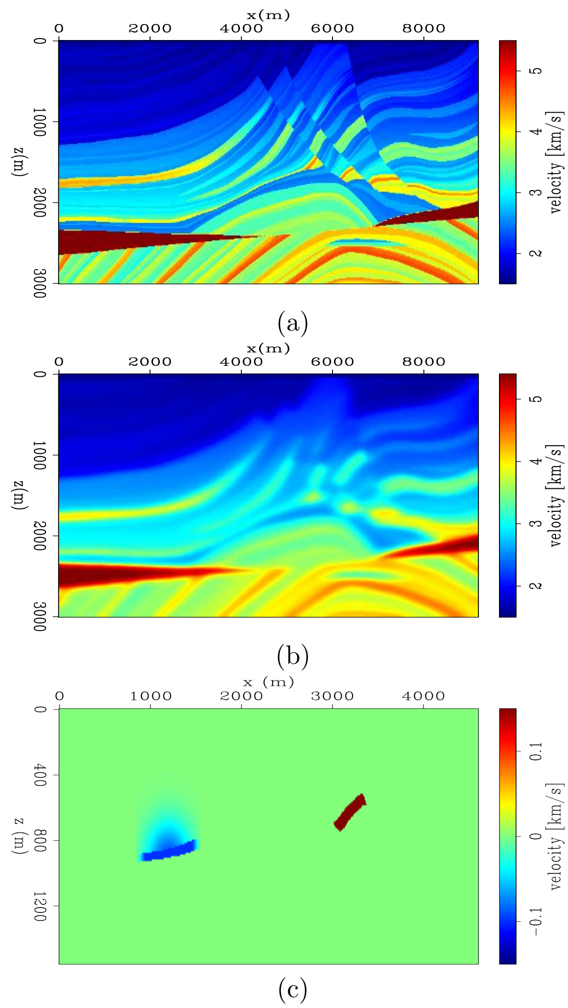


Figure 1: (a) true baseline velocity model. (b) starting velocity model. (c) time-lapse velocity change. [**CR**]

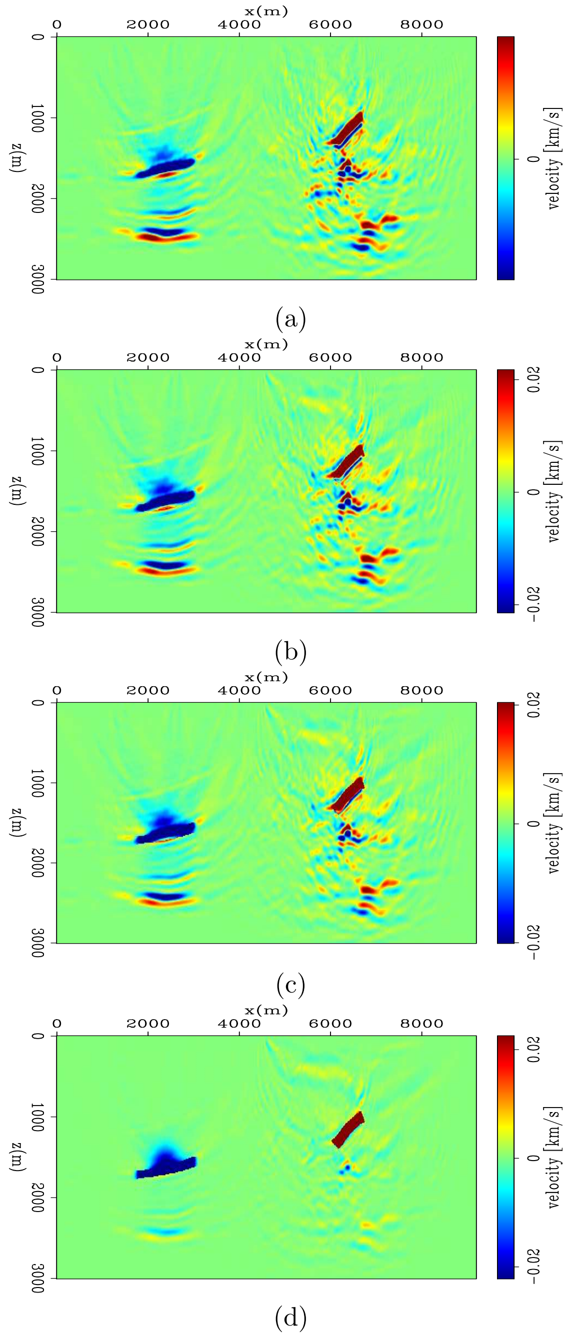
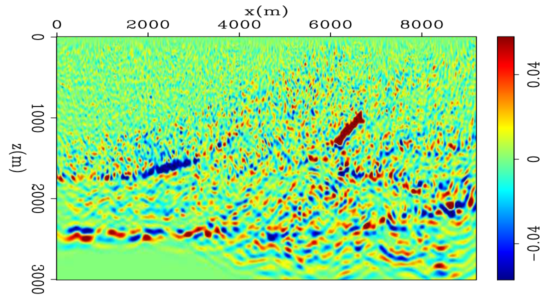
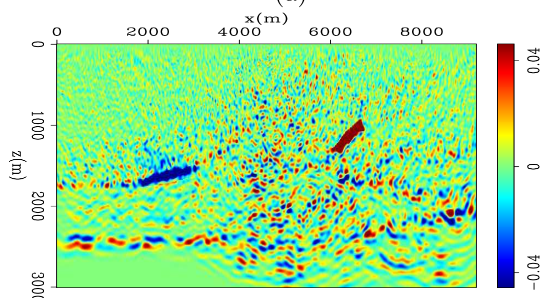


Figure 2: Estimated time-lapse change with noise-free data. (a) is the inversion result without regularization. (b) (c) and (d) are the inversion results using our proposed regularization method, with increasing regularization strength. [**CR**]



(a)



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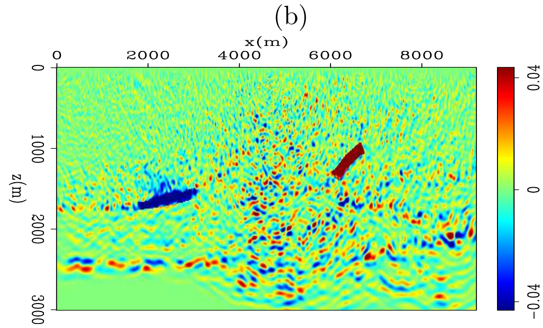

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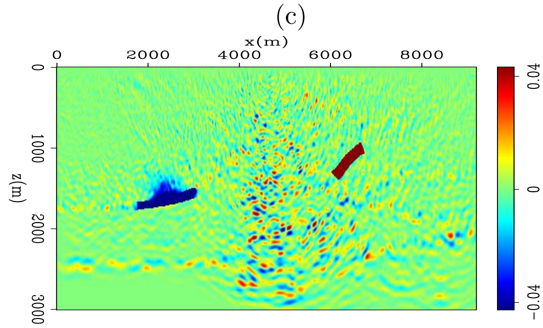

(d)

Figure 3: Estimated time-lapse change using data with noise. (a) is the inversion result without regularization. (b) (c) and (d) are the inversion results using our proposed regularization method, with increasing regularization strength. [**CR**]

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