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Model regularization strategies in multi-parameter timelapse FWI

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Summary

Seismic full-waveform inversion (FWI) has great potential for subsurface monitoring, however, the non-uniqueness of the FWI solution requires strategies to overcome this ambiguity. One of them is to constrain the model space through the introduction of a model regularization term, which promotes certain characteristics in final models. Especially within timelapse FWI, which often involves separated inversions of baseline and monitoring data, the model regularization can have drastic influence on the resulting timelapse differences. In this work different regularization strategies for multi-parameter timelapse FWI are illustrated using a synthetic carbon sequestration model. The results indicate that constraints acting on the model entropy outperform conventional minimum length regularization as they can help isolate timelapse differences related to the fluid plume and improve timelapse analysis.

Introduction

An important task within subsurface energy projects, like carbon capture and storage (CCS), is the cost-effective and reliable monitoring, measurement, and validation (MMV) of the injected or extracted fluid within the reservoir. Seismic time-lapse imaging techniques are proven to be suitable for the MMV task, as the elastic property changes induced by fluid replacement in the pore space could be exploited to localize reservoir changes (Kolkman-Quinn et al., 2023). In particular, seismic full-waveform inversion (FWI) (Tarantola, 1984a, b) emerged as a promising approach for the subsurface monitoring task due to improved resolution compared to conventional post-stack seismic images. A big drawback of the FWI technique is the inherently non-unique solution, i.e. infinite models explain the observed data equally good. This is especially problematic in the case of timelapse analysis, where baseline and monitoring data is inverted independently. Then the non-uniqueness of each inversion result can have considerable influence on the analysis as calculated timelapse differences are contaminated related to imaging artifacts rather than the reservoir fluids.

To tackle the non-uniqueness of the FWI solution some decisions can be made to limit the solution space to a suitable or optimal model based on certain constraining criteria on the model space, generally referred to as model regularization (Zhdanov, 2015). Depending on availability of prior knowledge and needs, functions can be designed to promote models with desired properties, for example models close to a reference model, laterally continuous models or models with structural similarity in case of multi-parameter FWI. Timelapse model reconstruction can be improved by applying different regularization approaches at different stages of the timelapse FWI procedure, such that more value is added to the MMV task of subsurface operations. This work will explore this approach using synthetic imaging examples.

Theory

Seismic FWI is an imaging technique that can be used to reconstruct elastic properties more accurately, as the entirety of the recorded waveform is considered in the model reconstruction.

FWI can be defined as an optimization problem that seeks a set of model parameters $\mathbf{m}_{\mathbf{min}}$ which minimizes the data residuals between the resulting simulated data and some observed data $\mathbf{d}$ (Tarantola, 1984a; Virieux and Operto, 2009). This optimization problem is commonly formulated in terms of the objective functional ϕ:

$$\mathbf{m}_{\mathrm{min}} = \min_{\mathbf{m}} \phi(\mathbf{u}(\mathbf{m}), \mathbf{d}, \mathbf{m}), \tag{1}$$

where $\mathbf{u}$ is the simulated wavefield based on the elastic parameter set $\mathbf{m}$ and fulfills the 2D isotropic elastic wave equation in the frequency domain. The objective functional consists of two distinct parts, namely the data objective functional ϕ_{D}, which ensures that data residuals are minimized, and the model regularization term ϕ_{M}, which constrains the model space. It can be expressed as follows:

$$\phi(\mathbf{u}(\mathbf{m}), \mathbf{d}, \mathbf{m}) = \phi_{\mathrm{D}}(\mathbf{u}(\mathbf{m}), \mathbf{d}) + \lambda \cdot \phi_{\mathrm{M}}(\mathbf{m}). \tag{2}$$

As seen, a trade-off parameter λ, also referred to as regularization factor, is applied to the model regularization term to ensure that model constraints are weighed optimally. Within this work, four different regularization approaches are applied, namely the cross-gradient (CG), the minimum length (ML), the joint minimum entropy (JME) and the minimum entropy (ME) regularization. The ML regularization minimizes a squared difference between the model and some reference model $\mathbf{m}_{\mathrm{ref}}$, such that the parameter distribution is damped towards the reference model throughout the inversion. The CG approach is a structural coupling concept originating from multi-physical inversions and is defined following Gallardo and Meju (2004):

$$\phi_{\mathrm{CG}}(\mathbf{m}) = \sum_{\mathrm{i,\ j}}^{V_P^{-2},\ V_S^{-2},\ \rho} \left\| \nabla\mathbf{m}^{(\mathrm{i})} \times \nabla\mathbf{m}^{(\mathrm{j})} \right\|. \tag{3}$$

where $\nabla\mathbf{m}^{(\mathrm{i})}$ refers to the gradient field of the three elastic parameter distributions density (ρ), squared P-slowness (V_P^{-2}), and squared S-slowness (V_S^{-2}). Structural coupling between different parameters is promoted through enforcing parallel or antiparallel gradients in the multi-parameter images. ME and JME regularizations are relatively novel concepts that promote models which keep the model entropy or joint model entropy small. They are defined via pseudo-probability density functions p on the modelling domain Ω (Zhdanov et al., 2022; Ziegon et al., 2024):

$$\mathrm{p}_{\mathrm{ME}}(\mathbf{r}) = \frac{|\mathbf{m}(\mathbf{r}) - \mathbf{m}_{\mathrm{ref}}(\mathbf{r})|^{\mathrm{q}} + \beta}{\mathrm{Q}_{\mathrm{ME}}}, \tag{4}$$

$$\mathrm{p}_{\mathrm{JME}}(\mathbf{r}) = \frac{\sum_{\mathrm{i}}^{V_P^{-2},\ V_S^{-2},\ \rho} \left(\left| \mathbf{m}^{(\mathrm{i})}(\mathbf{r}) - \mathbf{m}_{\mathrm{ref}}^{(\mathrm{i})}(\mathbf{r}) \right|^{\mathrm{q}} + \beta \right)}{\mathrm{Q}_{\mathrm{JME}}}. \tag{5}$$

Here, $\mathbf{r}$ is the position vector (i.e. a grid cell) within Ω, q the order of the expression, β a numerical stabilizer, and Q a normalization factor. The ME and JME regularization terms ϕ_{ME} and ϕ_{JME} are then calculated through:

$$\phi_{[\mathrm{J}]\mathrm{ME}}(\mathbf{m}) = -\int_{\mathbf{r}\in\Omega} \mathrm{p}_{[\mathrm{J}]\mathrm{ME}}(\mathbf{r}) \cdot \ln \mathrm{p}_{[\mathrm{J}]\mathrm{ME}}(\mathbf{r})\, \mathrm{d}\mathbf{r}. \tag{6}$$

Note that ϕ_{ME} and ϕ_{JME} are holding the same focusing properties, but the JME approach provides additional weak structural coupling.
In this work the parallel timelapse FWI strategy is applied, which consists of a baseline and a monitoring inversion based on the same starting model. Afterwards, timelapse changes can be visualized by subtracting the monitoring FWI results from the baseline FWI result. In this environment we propose the following strategies to constrain the model space in a meaningful way: (1) During the baseline inversion no regularization approaches are applied that require an accurate reference model. Instead, structural similarity is constrained via the CG method as the geologic structure of the subsurface should generally be consistent in all three elastic parameter distributions. (2) In the monitoring inversion we seek a model that is close to the baseline results in a sense that the timelapse difference between the models only reflects changes due to fluid extraction or substitution. Therefore, ML, ME and JME appear to be naturally suited for this stage as they all require an accurate and meaningful reference model, which in this scenario is the baseline inversion result.

Method

This timelapse regularization strategy is tested on a synthetic timelapse imaging scenario of a fictional geologic CCS play inspired by the synthetic models of Hu et al. (2023). As seen in Figure 1, CO_2 is injected into clean sandstone reservoirs at approximately 450 m and 700 m (Units 3 and 4). Reservoirs are delineated by shale-rich layers (Units 1 and 2) that contain the CO_2 within the desired layers. Petrophysical properties are converted using the stiff-sand model to obtain elastic baseline and timelapse models that are used to create synthetic data.

Data is generated using 26 surface sources and 50 surface, multi-component geophones alongside a straight DAS fiber cemented to the deviated injection well (Figure 1). Acquisition and frequency parameters are kept constant for the simulated baseline and time-lapse studies. Starting models and inversion parameters are kept identical for all baseline and timelapse FWIs except for the regularization factor λ, as its value depends on the regularization approach that is applied.

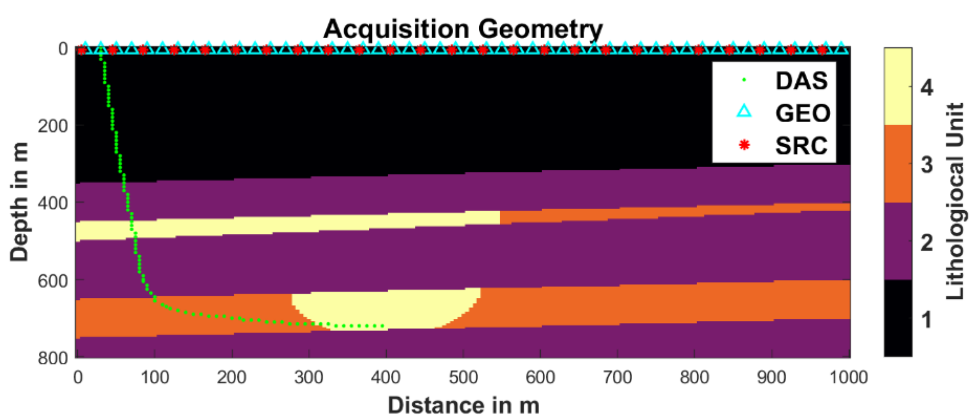

FIG. 1. Acquisition geometry superimposed on petrophysical zones of the synthetic time-lapse CCS model. Shown are sources (red), multi-component geophones (cyan), and straight DAS fiber channels along a deviated well path (green). Note that unit 4 resembles the CO_2-plume.

Results

Figure 2 shows the elastic timelapse differences based on the CG-regularized baseline inversion and timelapse inversions for different regularization approaches. As seen, all timelapse differences show differences outside the plume regions which can be ascribed to the non-uniqueness of the solution and imaging artifacts. Comparing the results obtained from ML regularized inversion and ME as well as JME inversion, there appears a great improvement in terms of reduced background variation and focusing of the true fluid-related timelapse anomaly. Data fit is comparable for all inversions, but model reconstruction shows clear qualitative and quantitative discrepancies for different model space constraints. In this scenario the focusing properties of the model entropy formulations enhance the plume delineation in all elastic parameters and therefore provide more accurate plume monitoring.

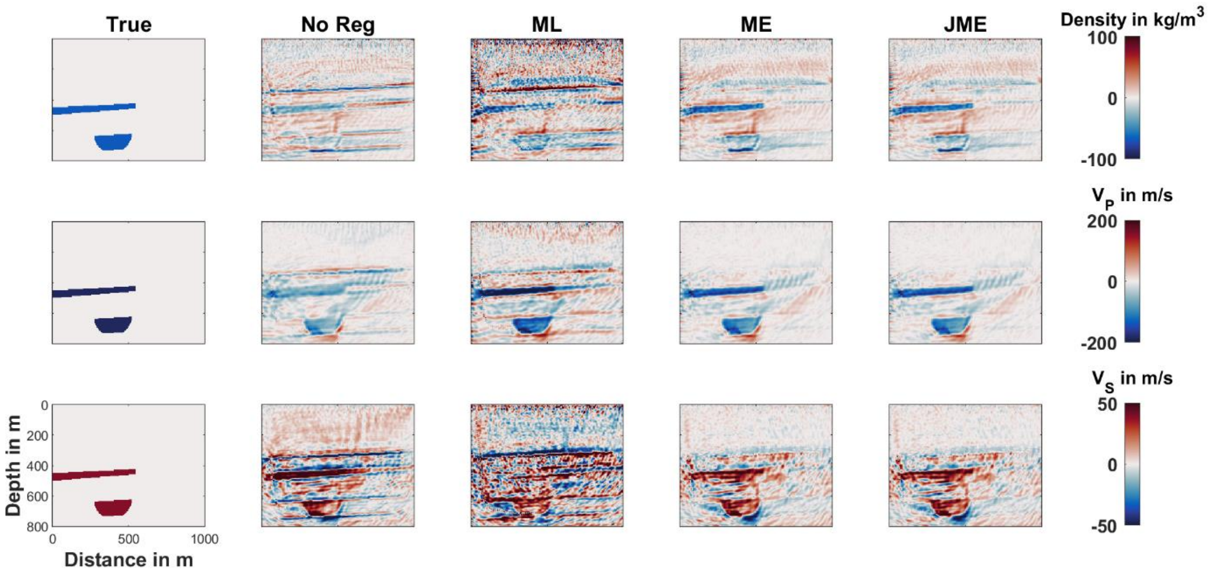

FIG. 2. True and inverted time-lapse differences. The latter is created by differencing CG-regularized baseline inversions and timelapse inversion regularized with no regularization as well as with ML, ME, and JME constraints. Note that all differences share the same baseline model which was used as the reference model in the time-lapse inversion.

Conclusions

The results illustrate that model regularization can be a valuable tool in timelapse FWI when applied in a suitable strategy. In this synthetic imaging scenario, the ME- and JME-regularized monitoring inversions seem to outperform the more conventional ML regularization in all aspects, which makes these entropy-based approaches a promising tool for future studies. Note that this report cannot cover all regularization approaches and model constraints must be designed and applied based on needs as well as prior knowledge, and their introduced biases in the inversion must be justifiable. Furthermore, it is important to realize that model regularization does not quantify the uncertainty of the solution and therefore other approaches like probabilistic FWI or nullspace-shutteling should be considered for these analyses.

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