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Target-oriented Time-lapse Imaging Using FWI with Prior Model Information

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SUMMARY

We propose a target-oriented time-lapse imaging using regularized full waveform inversion (FWI) including prior model and model weighting. The scheme applies strong prior model constraints outside of the expected areas of 4D changes, and relatively less prior constraints in the 4D target zones. In application to the Marmousi model, the local resolution analysis with spike tests shows that the target-oriented inversion prevents the apparition of artifacts outside of the target areas, especially in the sequential difference method where these artifacts could contaminate and compromise the reconstruction of the real time-lapse changes. In noisy case, the target-oriented prior model weighting ensures a same behavior for both time-lapse strategies, the differential and the sequential difference methods, and leads to a more robust reconstruction of the time-lapse models.

Introduction

Full waveform inversion (FWI) is a promising approach for time-lapse applications that delivers quantitative and high resolution images of physical parameter changes. For monitoring purposes, where different kinds of non-seismic data are available in the target zone, such prior information should be included to the inversion so as to increase the accuracy of reconstructed baseline, and also to recover the time-lapse changes in a robust way. Recently, Asnaashari et al. (2013) have proposed a regularized FWI scheme based on including a priori model information into the misfit function. Adding a prior model misfit term is one way for the introduction of the prior information into FWI. This term can drive the inversion optimization toward a given direction and reduce the ill-posedness of the inverse problem.

Once the baseline reconstruction is achieved, two different strategies can be used for recovering the time-lapse changes. The differential FWI (double-difference) focuses on inverting the differential data set (difference between baseline and monitor data sets) starting from the reconstructed baseline model (Watanabe et al., 2004; Denli and Huang, 2009). A second approach, called the sequential difference method, uses the final baseline model as a starting model for inverting the monitor data set. Then, the time-lapse changes will be produced by subtracting the baseline model from the recovered monitor model.

It has been shown that the differential approach is more robust than the sequential difference method in low-noise environment and is less sensitive to the inaccuracy of the recovered baseline model, when used as the initial model (Asnaashari et al., 2012). However, the main advantage of the sequential difference strategy is it lesser dependency on the repeatability of acquisition geometry between baseline and monitor surveys, while the differential method demands a perfect match of, the receiver and source positions between the two surveys. On the other hand, the sequential difference method cannot focus naturally on the target areas and on the time-lapse changes during inversion. Is there a way to make the sequential difference inversion to focus on the target zones? In addition, could we reduce effects of image noises outside of the expected target zones? These are the questions that we want to address in this study.

Time-lapse methods with regularized FWI including prior model

We use the time-domain regularized FWI algorithm with prior model penalty introduced in Asnaashari et al. (2013). The misfit function $\mathscr{C}(\mathbf{m})$ can be expressed using the ℓ_2 norm as

$$\mathscr{C}(\mathbf{m}) = \frac{1}{2}\Big\{ (\mathbf{d}_{obs} - \mathbf{d}(\mathbf{m}))^T \, \mathbf{W}_d^T \mathbf{W}_d \, (\mathbf{d}_{obs} - \mathbf{d}(\mathbf{m})) \Big\} + \frac{\lambda_1}{2}\{\mathbf{m}^T \mathbf{D} \mathbf{m}\} + \frac{\lambda_2}{2}\Big\{ (\mathbf{m} - \mathbf{m}_p)^T \, \mathbf{W}_m^T \mathbf{W}_m \, (\mathbf{m} - \mathbf{m}_p) \Big\}, \quad (1)$$

where vectors $\mathbf{d}_{obs}$ and $\mathbf{d}(\mathbf{m})$ are the observed and calculated data at receiver positions, respectively. The matrix $\mathbf{W}_d$ is a weighting operator on the data misfit. The second term of the objective function corresponds to the Tikhonov regularization, where the first spatial derivatives of the model in x and z directions are minimized. Practically, they can be reduced to the application of the second-order Laplacian operator $\mathbf{D}$. The third term is related to the prior model $\mathbf{m}_p$ designed from available prior information. The matrix $\mathbf{W}_m$ is a weighting operator on the model space. This matrix contains the prior uncertainty information and will be used for target-oriented imaging. In our misfit function, the prior-model variance information is included in the diagonal $\mathbf{W}_m$ matrix and the covariances are implicitly accounted for by the Tikhonov term. The two regularization hyper-parameters λ_1 and λ_2 allow each penalty term to be weighted with respect to each other and to the data term. The quasi-Newton procedure using the L-BFGS-B scheme (Byrd et al., 1995) is used for the optimization for the determination of the model parameter vector $\mathbf{m}$.

Differential FWI method

In differential method, instead of minimizing the difference between the observed and the calculated data, we can minimize the difference of the differential data (double-difference) between two data sets (Watanabe et al., 2004; Denli and Huang, 2009),

$$\Delta\mathbf{d} = (\mathbf{d}_{obs_m} - \mathbf{d}_{obs_b}) - (\mathbf{d}_{calc_m} - \mathbf{d}_{calc_b}), \quad (2)$$

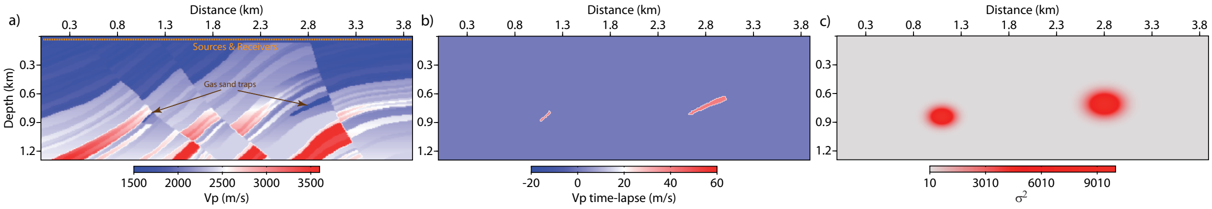

Figure 1 *(a) The true V_p baseline model selected from Marmousi model and the acquisition geometry; (b) the true time-lapse model; (c) the target-oriented σ model.*

where $\mathbf{d}_{obs_m}$ and $\mathbf{d}_{obs_b}$ are the monitor and baseline observed data respectively, and $\mathbf{d}_{calc_m}$ and $\mathbf{d}_{calc_b}$ are the calculated data for these experiments. For the differential analysis, we first need the construction of a composite data set defined as

$$\mathbf{d}_{composite} = \mathbf{d}_{obs_m} - \mathbf{d}_{obs_b} + \mathbf{d}_{calc_{rec-b}}, \tag{3}$$

which is composed of (a) the time-lapse differential observed data $(\mathbf{d}_{obs_m} - \mathbf{d}_{obs_b})$ and (b) the simulated data $\mathbf{d}_{calc_{rec-b}}$ computed using forward modeling in the reconstructed baseline model. This composite data set $\mathbf{d}_{composite}$ can be used as a new observed data set $\mathbf{d}_{obs}$ in equation (1), which is equivalent to minimizing the differential residual (2) with a standard regularized FWI algorithm. Finally, the time-lapse model change $\delta\mathbf{m}_{time-lapse} = \mathbf{m}_{composite} - \mathbf{m}_{rec-b}$ is obtained. The method relies on the fact that the events, common to both surveys, unexplained at the baseline reconstruction step do not contaminate the time-lapse reconstruction.

Sequential difference FWI method

The baseline model should be a good candidate for a starting model, because of weak time-lapse changes between two data sets. The sequential difference method uses the recovered baseline model as a starting model for the monitor data inversion. The time-lapse response can be obtained by making a subtraction between the recovered monitor and baseline models. The main advantage of this approach is its applicability to acquisition geometries that do not match exactly between the two surveys. Nevertheless this method attempts to recover the parts of baseline model which have not been fully reconstructed during baseline reconstruction step. Therefore, there is a potential risk of spurious time-lapse variations.

Target-oriented FWI

As the baseline model is close to the monitor model, since the time-lapse variations are small and localized, the recovered baseline model could also be a good candidate for the prior model in both strategies. Therefore, we can constrain the inversion outside of the area of changes through the prior-model misfit term in the objective function. In other words, we give strong weights to the prior model (here, recovered baseline model) for those parts of model where the time-lapse variations are not expected, and relatively less prior weights in the target areas. By doing so, the inversion tries to recover the monitor model mostly inside the target areas: the smaller prior constraints allow to give more relative weight to the data-misfit term in the objective funcion in these parts of model.
To identify the areas of time-lapse changes, in addition to the non-seismic information, one can also use the migrated image of the differential data set. We can migrate the differential data set $(\mathbf{d}_{obs_m} - \mathbf{d}_{obs_b})$ with the reconstructed baseline model using Reverse Time Migration (RTM). This migrated section highlights the area of changes and helps to design the $\mathbf{W}_m$ matrix. The diagonal model weighting matrix is computed based on $diag(\mathbf{W}_m^T \mathbf{W}_m) = 1/\sigma^2(\mathbf{m})$, where $\sigma^2(\mathbf{m})$ is related to the prior uncertainty (Figure 1c).

Application on the Marmousi model

A selected target zone of the Marmousi P-wave velocity (Martin et al., 2006) and a homogeneous density model are considered as the true baseline model (Figure 1a). The true monitor velocity model is created

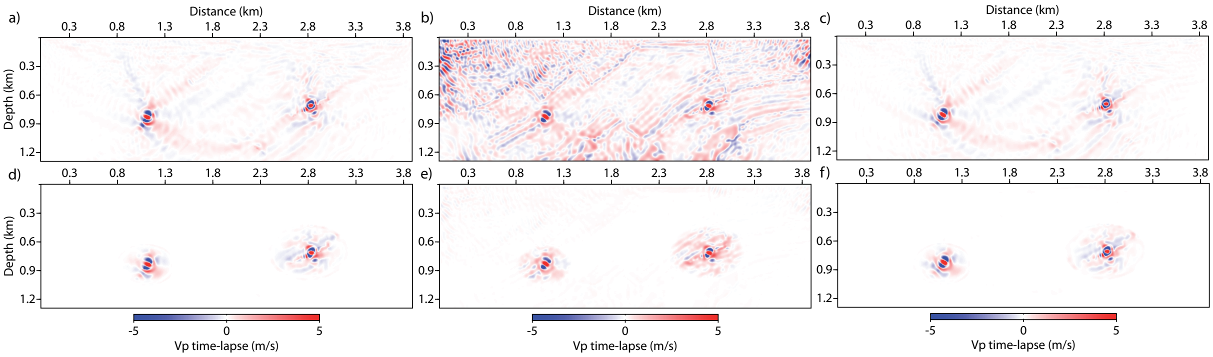

Figure 2 *Local resolution analysis with the spike tests, top panel without target-oriented inversion: (a) inside the true baseline model; (b) sequential difference method starting from the recovered baseline model; (c) differential method starting from the recovered baseline model; (d), (e), and (f) same as (a), (b), and (c) in case of using the target-oriented model weighting.*

from the baseline model with a relative ($40\ m/s$) variation of velocity inside the two gas reservoirs (Figure 1b). The surface acquisition geometry with free-surface condition is used to generate the synthetic data, using 77 isotropic pressure sources, located along a horizontal line at 16 m depth, each 50 m and a horizontal receiver line at 15 m depth with a 10 m sensor interval. A Ricker wavelet source with a central frequency of 10 Hz is used, for both surveys. The noise-free time seismograms are generated using finite-difference modeling in the time domain. In the following, noise-free and noisy cases, the baseline model is recovered by dynamic regularized FWI, using a prior model constrained by well logs (Asnaashari et al., 2013).

Local resolution analysis

First, we can study the local resolution analysis of both time-lapse strategies, in conventional and target-oriented modes for the noise-free data set. The Hessian is related to the point-spread functions (PSFs) or spike tests that are commonly used as a diagnostic tool for resolution analysis in linearized tomographic problems (Menke, 1984). In this test, the true monitor model contains only two spike functions inside the two reservoirs.

In a first investigation, without any target-oriented prior weighting, the time-lapse images (two spike functions) are recovered starting from the true baseline model (Figure 2a), from the recovered baseline model (not shown here) using the sequential difference method (Figure 2b), and from the recovered baseline model using the differential method (Figure 2c). When the true baseline model is used (Figure 2a), both time-lapse approaches are equivalent. The results are shown after 10 iterations. The recovered spikes by the differential approach appear to be very similar to the ones obtained using the true baseline model, showing the robustness of the differential method with respect to the starting model. In addition, the total energy of the time-lapse perturbations is better localized and better focalized at their positions for the differential method, as compared to the sequential difference method.

In a second investigation, the same tests are performed, using this time the initial model as a prior model and applying the target-oriented prior model weighting (Figure 1c). The results are shown in Figure 2, bottom panel. The target-oriented inversion prevents the artifacts to be produced outside of the target areas, especially for the sequential difference method. For both time-lapse strategies, the target-oriented approach can significantly improve the results compared to the conventional method (compare top and bottom panels of Figure 2).

Noisy data

An artificial Gaussian noise in the range of $0-30\ Hz$ (the bandwidth of the source wavelet) has been added to the true noise-free data. The signal-to-noise ratio is around 4.5 dB (strongly noisy). The conventional and target-oriented inversions, differential and sequential, are performed from the recovered

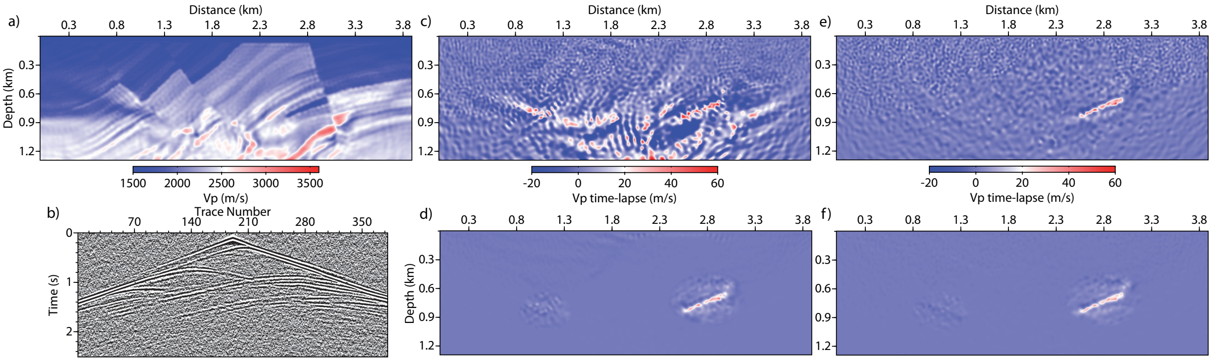

Figure 3 *In noisy case: (a) the recovered baseline model; (b) monitor seismograms for center shot; time-lapse models using: (c) the conventional sequential difference; (d) the target-oriented sequential difference; (e) the conventional differential; (f) the target-oriented differential method.*

baseline model (Figure 3a) in this noisy environment (Figure 3). In conventional mode, the result of differential is more robust than the sequential one, however for both, the whole recovered domain is dominated by the uncorrelated image noises. The target-oriented inversions can prevent the apparition of perturbations outside of the expected target zones: most of the image noise artifacts are removed. Although, the significant achievement is that the target-oriented weighting matrix $\mathbf{W}_m$ allows to reproduce a same behavior for both strategies. Therefore, in some applications where the differential method is not applicable (for example, non-perfectly matched acquisition geometries), the target-oriented sequential difference can provide the same robust result as the differential method. Clearly, the smaller reservoir change is missed in all inversions because of high level of noise, small size of perturbation area, and baseline model inaccuracy.

Conclusions

We propose a target-oriented time-lapse imaging using regularized FWI including prior model. The approach applies, in the misfit function, strong prior model constraints outside of the areas of expected 4D changes and gives relatively smaller prior constraints in the target zones. The target-oriented inversion steers the recovery of the monitor model towards the target areas, where the smaller prior model constraints give more relative weight, in the misfit function, to the data-misfit term. In the application to the Marmousi data set, the local resolution analysis with the spike tests shows that the target-oriented inversion prevents the production of artifacts outside of the target areas. In noisy case, the target-oriented $\mathbf{W}_m$ leads to a same behavior for both time-lapse strategies and delivers more robust images.

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