Target-oriented time-lapse waveform inversion using a deep learning assisted regularization

Yuanyuan Li*, Tariq Alkhalifah and Qiang Guo, King Abdullah University of Science and Technology (KAUST)

Summary

Detection of the property changes in the subsurface during production is important, yet it is also very challenging considering that these changes are often very subtle. The quantitative evaluation of the subsurface property obtained by full waveform inversion (FWI) allows for better monitoring of these time-lapse changes. However, high-resolution inversion is usually accompanied with a large computational burden. Besides, the resolution of inversion is limited by the bandwidth and aperture of time-lapse seismic data. We apply a target-oriented strategy through seismic redatuming to reduce the computational cost by focusing our high-resolution delineation on a relatively small target zone. The redatuming technique enables retrieving time-lapse virtual data for the target-oriented inversion. Considering the injection and production wells are often present in the target zone, we can incorporate the well information to the time-lapse inversion by using regularization to complement the resolution and illumination at the reservoir. We use a deep neural network (DNN) to learn the mathematical relationship between the inverted model and the facies interpreted from well logs. The trained network is employed to map the property changes extracted from the wells to the target inversion domain. We then perform another time-lapse inversion, in which we fit the predicted data difference to the redatumed one from observation, as well as fit the model to the predicted velocity changes. The numerical results demonstrate that the proposed method is capable of inverting for the time-lapse changes effectively in the target zone by incorporating the learned model information from well logs.

Introduction

Time-lapse full waveform inversion (TLFWI) aims to quantitatively estimate the property changes in the subsurface induced by fluid injections using time-lapse seismic data (Hicks et al., 2016; Maharramov et al., 2016; Kazei and Alkhalifah, 2018). High-resolution delineation of the property changes is a major goal of time-lapse inversion. However, there are two primary issues that hinder the time-lapse inversion practice. On one hand, high-resolution FWI is computationally intensive, because fine discretization is required to stabilize the simulation of high-frequency wavefields (Routh et al., 2017). Its corresponding time-lapse applications require even more computational cost, because we need more simulations. On the other hand, due to the limitation we encounter with surface seismic data in terms of signal-to-noise ratio (SNR), frequency band and offset, seismic data often admit

incomplete subsurface information with limited space wavenumber (Alkhalifah, 2016; Li et al., 2018). In this work, we improve the performance of TLFWI by addressing these two issues.

The target-oriented approach has been developed to reduce the computational cost by inverting for a relatively small target zone of the subsurface (Ayeni and Biondi, 2010; Borisov and Singh, 2015; van Manen et al., 2007; Yuan et al., 2017). Redatuming techniques have been recently applied to target-oriented inversion by retrieving the Green's functions and generating virtual shot gathers at a desired datum level (Yang et al., 2012; Guo and Alkhalifah, 2019a). Besides, the redatuming is expected to improve time-lapse repeatability by suppressing 4D unrepeatability noise such as that induced by near-surface diurnal and seasonal weather cycles as well as small changes in acquisition geometry and shot coupling (Bakulin and Calvert, 2006).

Subsurface model building solely from seismic data is an underdetermined inverse problem, especially at high frequencies. Such inherent limitations of seismic data can be mitigated by integrating other geophysical data. Well logs show a promise in complementing seismic data to reduce the nonuniqueness of the inverse problem (Zhou et al., 2011; Asnaashari et al., 2013). Well logs provide reliable and detailed information of the subsurface, but only sample very limited areas laterally. The well information can be correlated to the inversion result from TLFWI using deep learning. Zhang and Alkhalifah (2019) and Li et al. (2020) employed deep neural networks (DNNs) to build the proper statistical connection that converts seismic estimates to facies interpreted from well logs. The derived prior information incorporating well logs is then added to waveform inversion as a regularization term.

To improve the performance of TLFWI for the target zone, we take advantage of the recently developed waveform redatuming (Guo and Alkhalifah, 2019b) and model regularization techniques (Li et al., 2020). The redatuming technique ensures reliable retrieval of target-oriented data for the following time-lapse inversion. The redatuming technique generates the target-oriented data for the following time-lapse inversion. To derive the prior model, we design and train the DNN to learn the mathematical relationship between the inverted model from time-lapse data and the facies interpreted from well logs. The prior model is expected to guide TLFWI toward a more accurate solution. Numerical tests on a time-lapse Marmousi and SEAM models are used to demonstrate the performance of the proposed method.

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Theory

Waveform redatuming

Based on the convolution-type representation of Green's functions (Wapenaar and van der Neut, 2010), the forward modeling for datuming (Guo and Alkhalifah, 2019b) is given by:

$$\mathbf{F}u_D(\mathbf{x}, \mathbf{x}_s, t) = \iint u(\mathbf{x}_{vs} - \mathbf{h}, \mathbf{x}_s, t) * \mathbf{V}(\mathbf{x}_{vs} - \mathbf{h}, \mathbf{x}_{vs}, t) \delta(\mathbf{x} - \mathbf{x}_{vs}) d\mathbf{h} d\mathbf{x}_{vs}, \quad (1)$$

where, $*$ refers to a convolution operator, $\mathbf{h}$ is the subsurface offset vector, $\mathbf{x}_s$ and $\mathbf{x}_{vs}$ are the source and virtual source location, respectively. The simulated wavefield (u_D) from the datum is generated from the secondary source given by the convolution of the source wavefield (u) with the redatumed virtual data ($\mathbf{V}$).

The redatumed virtual data $\mathbf{V}$ can be retrieved in an optimization problem by minimizing the data misfits (Alkhalifah and Wu, 2016; Li et al., 2019):

$$\min_{\mathbf{V}} J = \frac{1}{2} \|\Gamma(u + u_D) - d\|^2, \quad (2)$$

where, d is the observed data and Γ is used to map the simulated wavefield to the receivers. The gradient for the redatumed data $\mathbf{V}$ is expressed as:

$$\frac{\partial J}{\partial \mathbf{V}} = -\sum_s \langle u(\mathbf{x}_{vs}, \mathbf{x}_s, t), u^\dagger(\mathbf{x}_{vs} + \mathbf{h}, \mathbf{x}_s, t) \rangle, \quad (3)$$

where, $u^\dagger$ is the backward propagating wavefield from the adjoint source at the receivers. We can compute the gradient for virtual data $\mathbf{V}$ by multidimensional cross-correlating the forward and backward propagating wavefields at the datum level (Guo and Alkhalifah, 2019b). We will use equation 3 and the overburden inverted model to redatum both the base and monitor data of the time-lapse experiment.

Regularized TLFWI using deep learning

With the redatumed datasets prepared, we perform the double-difference waveform inversion (DDWI; Denli and Huang, 2009) to estimate the time-lapse changes in the target zone. Starting from the baseline inversion result ($\mathbf{m}_{ibase}$), the monitor model ($\mathbf{m}$) is updated by minimizing the objective function:

$$J_d(\mathbf{m}) = \frac{1}{2} \|\mathbf{u}(\mathbf{m}) - \mathbf{u}(\mathbf{m}_{ibase}) - \delta \mathbf{d}_{virtual}\|^2, \quad (4)$$

where, $\mathbf{u}$ is the simulated seismic data and $\delta \mathbf{d}_{virtual}$ is the data difference for virtual survey. The model updates are considered to be the model changes between monitor and baseline.

To incorporate the model information from wells, a model-space regularization term is also involved in the objective function, given by

$$J(\mathbf{m}) = J_d(\mathbf{m}) + \beta J_m(\mathbf{m}), \quad (5)$$

where,

$$J_m(\mathbf{m}) = \|\mathbf{W}_m(\mathbf{m} - (\mathbf{m}_{ibase} + \delta \mathbf{m}_{prior}))\|^2, \quad (6)$$

and β is a weighting parameter balancing the contributions from the data and model misfit terms, $\mathbf{W}_m$ is a diagonal weighting matrix, $\delta \mathbf{m}_{prior}$ is a prior model for model changes.

We derive a prior model by connecting the inverted model to interpreted facies from wells using a DNN (Li et al., 2020). The DNN consists of input and output layers, with fully connected hidden layers in between. The number of hidden layers and neurons in each layer can be adjusted according to the size of the training dataset. Here, we use 3 hidden layers and 64 neurons in each layer. The synthetic minority over-sampling technique (SMOTE) is applied to enlarge the training datasets and reduce the imbalance of different facies (Chawla et al., 2002). We also employ a random dropout of 30% to avoid over-fitting.

Both the baseline inverted model and the recovered velocity changes are used to discriminate the class of facies. Interpreted facies from the well logs are used as the labels in the training. After training, the DNN establishes a mathematical connection between the inverted model and facies classes. We can apply the network to the target inversion zone to predict the facies distribution. Considering the velocity changes for every facies are known in the well, the prior model for velocity changes can be obtained from facies distribution. Lastly, we implement the regularized DDWI by incorporating the prior model into the inversion workflow.

Examples

The Marmousi model

We test the proposed approach on the Marmousi model, which is shown in Figure 1a and is viewed as the baseline model. We implant velocity changes into the baseline model to construct the monitor model. Figure 1b shows the time-lapse changes of velocity in the target region. We generate seismic data for the baseline and monitor models using 92 shots near the surface and 461 receivers at depth 0.2km. Starting from the initial model (Figure 2a), we invert for the overburden model above the datum at 2.18 km depth using two frequency bands 3-12Hz and 3-30Hz, sequentially. Figure 2b shows the final inverted overburden model. Given the overburden model, we convert the seismic data recorded for both baseline and monitor to the virtual data at the new datum by waveform redatuming. Subtracting the baseline virtual data from the monitor virtual data, we obtain the time-lapse data difference for the virtual survey (Figure 3). The time-lapse velocity changes resolved from DDWI is shown in Figure 4a. We can see that the target-oriented inversion approach captures the velocity changes at the right position, but still is influenced

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by some artifacts and the amplitude of changes are underestimated. A vertical profile at 6.5 km represents well log information, which provides complementary high-resolution information to the target zone. Two facies, representing the injection and non-injection areas, are identified from the well and used as the labels for the training dataset. The deep neural network can learn a mathematical relationship between the inverted velocity and the facies to predict the facies distribution in the target zone. At last, we conduct a regularized TLFWI with the predicted prior model for the velocity changes, which delivers cleaner velocity changes (Figure 4b) than the standard inversion method (Figure 4a). For a more detailed comparison, we plot their vertical profiles at distance 6.8 km (Figure 4c). The inversion result using deep learning is closer to the true one, and the resolution is also improved.

Figure 1: (a) The true baseline model and (b) the true time-lapse velocity changes in the target region.

Figure 2: (a) The initial model and (b) the inverted overburden model using standard FWI.

Figure 3: The time-lapse data difference for the virtual survey.

Figure 4: The target-oriented time-lapse inversion results: (a) using a standard inversion scheme, (b) assisted by deep learning. (c) The vertical profiles of the velocity changes at $x = 6.8$ km.

The SEAM model

A 3D SEAM time-lapse model was constructed to simulate the changes in an oilfield reservoir. The model includes a water layer of 267.5 m depth on the top and four fault blocks across the reservoir with a thickness of about 500 m. The provided seismic dataset were simulated by the SEAM project assuming an isotropic elastic medium and recorded by ocean-bottom nodes (OBN). We extract a 2D line from the OBN dataset to further verify the feasibility of the proposed method. Its acquisition survey geometry includes 60 OBNs with 175 m interval at 267.5 m depth and 501 shots with 25 m spacing at 10 m depth. Figures 5a and 5b show the baseline P-wave velocity and the velocity changes caused by hydrocarbon production, respectively. A shot gather representing the pressure component for the baseline model is shown in Figure 6a. After production, both property changes and geometric shifts lead to the time-lapse seismic response (Figure 6b).

The smoothed version of the average of the baseline and monitor velocity models is used as the starting model (Figure 7), which potentially describes the kinematics of the medium accurately. Considering the target of interest is the reservoir between 3.5 km and 4.2 km depth, we set the datum at depth 3 km, which splits the whole model into the overburden and underlying model. Using the overburden from the starting model, we implement the redatuming process to retrieve the virtual datasets at the datum from the provided baseline and monitor datasets. Figure 8a shows the redatumed virtual shot gathers for baseline. The time-lapse difference between the redatumed monitor and baseline datasets is shown in Figure 8b. We then apply the DDWI method to the redatumed data. Figures 9a and 9b show the inverted baseline velocity and time-lapse velocity changes in the target zone, respectively.

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Two pseudo wells at 7.5 km and 8.125 km are used to boost the model information, and 3 facies can be interpreted from the wells representing two injection levels and the none injection area. After training, the deep neural network is applied to the target inversion region to generate the prior model (Figure 9c). The regularized DDWI method using the prior model provides a well-focused inversion result (Figure 9d), which facilitates interpreting time-lapse variations in the reservoir. Note that the inverted model somewhat identified the two injection levels separated by a none injection very thin layer at 3.4 km depth. The vertical profiles at distance 7.0 km (Figure 10), which was not used in the DNN training, also prove that the inversion quality is enhanced using the proposed method.

Figure 5: (a) The baseline P-wave velocity model and (b) the true time-lapse velocity changes.

Figure 6: (a) A shot gather of the pressure component for the baseline model and (b) the corresponding time-lapse data difference.

Figure 7: The starting model: a smoothed version of the average of the baseline and monitor models.

Figure 8: (a) The virtual shot gathers for baseline at the datum level and (b) the time-lapse data difference for the virtual survey.

Figure 9: (a) The inverted baseline model in the target zone. (b) The standard target-oriented time-lapse inversion result. (c) The predicted prior model using deep learning. (d) The final inverted velocity changes regularized by the prior model in Figure 9c.

Figure 10: The vertical profiles of the inverted and true velocity changes at $x = 7.0$ km.

Conclusions

We develop a regularized time-lapse waveform inversion scheme for a target zone. The target-oriented data are extracted from surface seismic data by waveform redatuming. Considering that the well logs provide prior information for model changes, a model-space regularization term is added to the objective function to enhance the resolution and illumination of seismic data. The required prior model is predicted from a trained deep neural network, which identifies connections between the inverted model and facies interpreted from well logs from a statistical perspective. The numerical examples show that the proposed method improves the inversion resolution and accuracy with better consistency with well logs.

Acknowledgements

We would like to thank the Shaheen supercomputing Laboratory in KAUST for their computational support. We thank KAUST for its support and SWAG for collaborative environment.

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