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Using image warping for time-lapse image domain wavefield tomography

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ABSTRACT

Time-lapse seismic data are widely used for monitoring subsurface changes. A quantitative assessment of how reservoir properties have changed allows for better interpretation of fluid substitution and fluid migration during processes such as oil and gas production and carbon sequestration. Full-waveform inversion (FWI) has been proposed as a way to retrieve quantitative estimates of subsurface properties through seismic waveform fitting. However, for some monitoring systems, the offset range versus depth of interest is not large enough to provide information about the low-wavenumber component of the velocity model. We evaluated an image domain wavefield tomography (IDWT) method using the local warping between baseline and monitor images as the cost function. This cost function is sensitive to volumetric velocity anomalies, and it is capable of handling large velocity changes with very limited acquisition apertures, where traditional FWI fails. We described the theory and workflow of our method. Layered model examples were used to investigate the performance of the algorithm and its robustness to velocity errors and acquisition geometry perturbations. The Marmousi model was used to simulate a realistic situation in which IDWT successfully recovers time-lapse velocity changes.

INTRODUCTION

Time-lapse seismic monitoring is often applied for reservoir management in the oil industry to obtain information about reservoir changes. It helps identify bypassed oil to be targeted for infill drilling, which extends the economic life of a field (Lumley, 2001). It is also capable of monitoring the progress of fluid fronts, providing information for injection optimization in enhanced oil recovery and long-term fluid storage such as carbon sequestration (Bickle et al., 2007). Generally, one baseline survey and subsequent monitoring surveys are acquired over time. Analysis and comparison of the data sets provide an estimate of changes in seismic velocity and mass density. These changes are related to changes in dynamic reservoir properties such as pore pressure and fluid saturation (Dadashpour et al., 2008), which are important in reservoir simulation and interpretation.

For a time-lapse seismic data set, information about the changes in model parameters in the target zone can be categorized into two groups: amplitude changes and time shifts. Amplitude changes could be induced by new scattering in the target interval or differences in reflectivity at the interfaces. Time shifts are the response to a physically shifted geologic interface (e.g., a compacting reservoir) or a velocity perturbation along the signal's raypath. To better link the changes in measured signals to inferred reservoir responses, it is essential to quantify the changes from different mechanisms. In some time-lapse seismic analysis, the time shift information is omitted because the monitor data or images are aligned with the baseline to compare the amplitudes. In other studies, time shifts picked at certain horizons are used to study the reservoir velocity changes or the strain field changes above the reservoir (Landrø and Stammeijer, 2004; Barkved and Kristiansen, 2005). However, these analyses are conducted on poststack data, which have already lost some information during the stacking process. In this study, we focus primarily on time shifts in prestack data and velocities in model space. We do not consider amplitude changes, which can be better inverted or interpreted after the inversion for a corrected time-lapse velocity model.

To recover the seismic velocities, full-waveform inversion (FWI) (Tarantola, 1984; Virieux and Operto, 2009) has been applied to individual surveys. The application of FWI to time-lapse data seems straightforward; however, in practice it is constrained by the survey design, data quality, and the nonlinear nature of FWI. Inversion strategies tailored for time-lapse data have addressed issues such as repeatability, computation efficiency (Yang et al., 2012), and

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local minima (Watanabe et al., 2005; Denli and Huang, 2009; Asnaashari et al., 2011; Yang et al., 2011). Traditional FWI requires low-frequency data and large survey offsets to invert for the low-wavenumber component of the velocity model (Virieux and Operto, 2009). However, seismic surveys with large offsets are expensive particularly when the region of interest is relatively small. Small-offset reflection data do not provide constraints on the model from a wide enough range of different angles to allow for the estimation of low-wavenumber structures. With small offsets, FWI functions more like least-squares migration, which only finds reflectivity. Image-domain methods, often involving velocity analysis, have been proposed to obtain the low-wavenumber part of the velocity model from reflection data (Biondi and Almomin, 2012; Sun and Symes, 2012). Some image-domain methods are computationally expensive because they require the calculation of angle gathers or offset gathers, which require many sources and receivers. These methods are more suitable for initial model building. Shragge et al. (2013) extend an image-domain tomography method to 4D; however, the inverted velocity changes can be smeared.

When a seismic reflection is shifted in time, there is ambiguity as to whether the reflector has shifted or there is a velocity change above the reflector. However, in many cases, the changes in the depths of the structures are not expected to be as significant as the depth shifts of the reflectors in the images due to velocity changes. For example, the physical displacement of the reservoir boundaries caused by compaction may be only a fraction of a sampling interval of the migration image (e.g., half a meter per year in the North Sea [Barkved and Kristiansen, 2005]). However, volumetric strain in the overburden due to compaction may cause changes in its seismic velocities. Velocity in the reservoir itself might also change due to depletion or fluid substitution. In cases such as CO_2 sequestration, large amounts of fluid are injected into the subsurface, without significant changes in pore pressure. Compared to physical structure changes, velocity changes are expected to be the dominant effect on time-lapse images from these settings (Arts et al., 2004). In this paper, we assume that seismic reflectors do not shift over the period during which time-lapse surveys are collected. We also assume that the waveforms reflected from interfaces in the targeted area do not change significantly. Based on this assumption, successive acquisitions that illuminate similar areas should produce similar images without depth shifts if correct velocity models are used.

In this paper, we present an image-domain wavefield tomography (IDWT) method specialized for time-lapse reservoir monitoring. With a baseline velocity model, migrated images for baseline and monitor data can be produced with a reverse time migration (RTM) algorithm. With the assumptions above, depth differences between images should be primarily caused by time-lapse changes in the velocity and not by physical changes in reflector position. Dynamic image warping (Hale, 2013) is used to measure the image shifts in a way that is robust to cycle skipping and amplitude differences between images. By minimizing the warping function (the shifts between baseline and monitor images), we invert for velocity changes iteratively using the adjoint-state method (Plessix, 2006). The inversion is only sensitive to low-wavenumber velocity perturbations that control wavefield kinematics. The inverted velocity changes are found to be localized between reflectors, which aids interpretation of fluid migration such as gas leakage. Yang et al. (2014) apply this method to time-lapse data sets from a CO_2 injection field. In this paper, we describe the theory and workflow of the IDWT approach. Synthetic examples are used to demonstrate its capability and limitations. The robustness of the method to baseline velocity errors and survey geometry nonrepeatability is also investigated.

THEORY

Iterative inversion methods such as FWI are designed to estimate model parameters by fitting observed data with simulated data. In the time-lapse IDWT method, the model parameters are seismic velocity changes and the observed data are the migrated images that are constructed from baseline and monitor seismic surveys. We estimate velocity changes by matching monitor migrated images with baseline migrated images. The cost function here can be written as the L-2 norm of some measure of dissimilarity between two images. The simplest measure is the amplitude difference:

$$E_{\text{subtract}}(m) = \frac{1}{2}\sum_{x_s}\int_x\int_z |I_1(x,z,x_s) - I_0(x,z,x_s)|^2 \mathrm{d}x\mathrm{d}z, \tag{1}$$

where I_0 is the baseline image, I_1 is the monitor image, x and z are spatial coordinates, and x_s is the source index. We derive all the equations here in 2D for simplicity, but the extension to 3D is straightforward with one additional integral over the third spatial dimension. This cost function has the same drawback as the traditional FWI cost function. When reflector shifts are too large (> a half-wavelength, measured normal to the reflector), cycle skipping makes the cost function insensitive to local velocity perturbations. The direct subtraction $I_1 - I_0$ also causes problems when the images have different amplitudes. These differences could be related to effects other than velocity perturbations. In these cases, even if the velocity model is correct, the cost function may not be minimized.

As described by Hale (2013), a migration image I based on the incorrect velocity can be considered a warped version of the true image $\tilde{I}$ based on the correct velocity. In equation 1, $h(x,z)$ and $l(x,z)$ are warping functions that specify how much the image point at (x,z) in $\tilde{I}$ is shifted from the same image point in I in the horizontal (h) and vertical (l) directions:

$$I(x,z) = \tilde{I}(x + h(x,z), z + l(x,z)). \tag{2}$$

Here, we assume that the monitor image based on the baseline velocity model is a warped version of the baseline image. For images with reflection data, vertical and lateral shifts can be measured (Cox and Hatchell, 2008; Hale et al., 2008). In this study, we only measure the vertical warping $l(x,z)$ for simplicity. The amount of vertical warping can be calculated by solving an optimization problem. Specifically, we compute

$$w(x,z) = \arg\min_{l(x,z)} D(l(x,z)), \tag{3}$$

where

$$D(l(x,z)) = \int_x\int_z (I_1(x,z) - I_0(x,z+l(x,z)))^2 \mathrm{d}x\mathrm{d}z. \tag{4}$$

We use the dynamic warping algorithm (Hale, 2013) to solve the optimization problem above for the warping function $w(x,z)$.

Because the warping function decreases in magnitude as I_1 and I_0 become well aligned, we use the L-2 norm of $w(x,z)$ as the cost function:

$$E(m) = \frac{1}{2}\sum_{x_s}\int_x\int_z |w(x,z,x_s,m)|^2 \mathrm{d}x\mathrm{d}z, \tag{5}$$

where m is the squared slowness used for migrating monitor data and x_s is the source index. We invert for velocity $\frac{1}{\sqrt{m}}$ by minimizing $E(m)$ with a gradient-based method.

To calculate the gradient G, we use an adjoint-state method (Plessix, 2006). In FWI, the gradient is calculated by crosscorrelating the forward-propagated source wavefield and the back-propagated residual wavefield (the adjoint wavefield). In IDWT, the gradient can be similarly written as a correlation between wavefields:

$$G(x,z) = -\sum_{x_s}\int_{t=0}^{T}\left(\frac{\partial^2\lambda_s(x,z,t,x_s)}{\partial t^2}u_s(x,z,t,x_s) + \frac{\partial^2\lambda_r(x,z,t,x_s)}{\partial t^2}u_r(x,z,t,x_s)\right)\mathrm{d}t, \tag{6}$$

where $u_s(x,z,t,x_s)$ and $u_r(x,z,t,x_s)$ are the source and receiver fields from forward and backward propagation, respectively. The associated adjoint wavefields are $\lambda_s(x,z,t,x_s)$ and $\lambda_r(x,z,t,x_s)$. The adjoint wavefields λ are obtained by solving the wave equation:

$$m\frac{\partial^2\lambda(x,z,t)}{\partial t^2} - \Delta\lambda(x,z,t) = d, \tag{7}$$

where m is the squared wave slowness and d is the adjoint source. The adjoint sources for solving for $\lambda_s(x,z,t,x_s)$ and $\lambda_r(x,z,t,x_s)$ are, respectively,

$$d_s(x,z,t,x_s) = \alpha(x,z,x_s)u_r(x,z,t,x_s) \tag{8}$$

and

$$d_r(x,z,t,x_s) = \alpha(x,z,x_s)u_s(x,z,t,x_s), \tag{9}$$

in which

$$\alpha(x,z,x_s) = \frac{w(x,z,x_s)\frac{\partial I_0(x,z+w(x,z,x_s),x_s)}{\partial z}}{\left(\frac{\partial I_0(x,z+w(x,z,x_s),x_s)}{\partial z}\right)^2 - \frac{\partial^2 I_0(x,z+w(x,z,x_s),x_s)}{\partial z^2}(I_1(x,z,x_s) - I_0(x,z+w(x,z,x_s),x_s))}. \tag{10}$$

The derivation is similar to the formula in differential semblance optimization (Plessix, 2006). The details are presented in Appendix A. The wavefield mask $\alpha(x,z,x_s)$ is oscillatory due to the term $\frac{\partial I_0(x,z+w(x,z,x_s),x_s)}{\partial x}$ in the numerator. The denominator in $\alpha(x,z,x_s)$ acts as an amplitude normalizer; in practice, we add a water-level term to the denominator to avoid dividing by zero. The warping function $w(x,z,x_s)$ tells us where α should be nonzero, and it determines the sign of the adjoint source, which determines the sign of the velocity update. The implementation of the inversion process consists of the following steps:

1) given a baseline velocity model m_0, and a baseline migration image I_0
2) for each shot x_s, migrate the monitor data with the velocity model m_0 used to produce $I_1(x,z,x_s)$
3) compute the vertical shifts $w(x,z,x_s)$ using dynamic warping
4) evaluate the cost function $E(m)$ after the summation over shots x_s, stop (if small enough) or go to the next step
5) for each shot x_s, compute the adjoint wavefields λ_s, λ_r, and the partial gradient $G(x,z,x_s)$
6) sum $G(x,z,x_s)$ over all shots to form the gradient $G(x,z)$
7) update the velocity model with $G(x,z)$ to get m_{i+1}
8) remigrate the monitor data with the updated model m_{i+1} and go to step 2.

EXAMPLES USING SYNTHETIC DATA

In this section, we will use synthetic data to show how the method works and investigate its performance under different scenarios. First, a simple three-layer model is used to demonstrate IDWT's ability to recover low-wavenumber velocity changes. The performance of IDWT with respect to the number of shots is tested with the same model. A model with six layers is used to study the relation between IDWT resolution and the layer spacing. The robustness of IDWT to errors in the baseline velocity model is tested with two cases in which one large and one small Gaussian velocity errors are introduced. The robustness of IDWT to source-receiver geometry discrepancies between surveys is investigated for correct and incorrect baseline velocity models. Finally, the Marmousi model is used to show how IDWT performs for a complicated velocity structure.

Three-layer model

The three-layer model has a constant velocity ($V_\mathrm{P} = 3000$ m/s) but a different density in each layer (Figure 1a). A velocity anomaly is placed in the middle of the time-lapse model as shown in Figure 1b. The shape of the anomaly is Gaussian with a maximum velocity increase of 800 m/s. We place 300 receivers (blue triangles in Figure 1a) at an interval of 10 m, and five sources (red stars in Figure 1a) at an interval of 600 m on the surface. The source is a Ricker wavelet with a center frequency of 25 Hz. We use a finite-difference acoustic wave equation solver to generate the data sets. In this example, we assume that the constant baseline velocity is known.

Imaging and warping

RTM (Baysal et al., 1983; McMechan, 1983) is used to produce all the migration images during the inversion. The baseline and initial monitor images obtained using a single shot gather (the third shot in Figure 1a) are shown in Figure 1c and 1d, respectively. The position of the deeper reflector in the monitor image (Figure 1d) is shifted vertically due to the velocity change in Figure 1b. We compute $w(x,z)$ using the dynamic image warping algorithm (Hale, 2013) to describe how much I_1 is shifted from I_0, as shown in Figure 2. The maximum vertical shift is four grid points (40 m). As in equation 10, $w(x,z)$ is used to calculate a spatial weighting function $\alpha(x, z, x_s)$, to mask the wavefields u_s and u_r to form adjoint sources (equations 8 and 9).

Inversion results comparison

Figure 3a shows the velocity model change recovered from IDWT with the five sources shown in Figure 1a. The recovered anomaly is centered at the correct location, but it is smeared vertically due to the acquisition geometry. This vertical smearing is bounded by the two reflectors. If the inversion attempts to put any perturbation above the first reflector, the entire image will be shifted. IDWT will subsequently reduce this shift by reversing that perturbation. Some of the changes are positioned along the raypaths due to limited source and receiver coverage. Within the area of the recovered anomaly, the amplitude is not correctly distributed, and the maximum velocity increase is only 50% of the true value.

Although the inverted velocity is not perfect, the monitor migrated image based on it (Figure 3b) shows reflectors at the same locations as in the baseline image (Figure 1c). The model from IDWT has the correct background kinematics, and it is a good starting model for FWI. Figure 3c shows the velocity change determined with the application of a standard FWI (Tarantola, 1984) for the same monitor data using the velocity model obtained from IDWT as a starting model. The amplitude of the anomaly and the distribution of the velocity are improved as FWI inverts more phase and amplitude changes.

For comparison, we compute a standard FWI on the monitor data starting from the correct baseline velocity and density models. Figure 3d shows the result. The inversion gives poor recovery of the velocity anomaly because of several issues. First, the velocity change is large enough to cause cycle skipping in the data domain. Second, FWI with this narrow-offset survey geometry reduces to least-squares migration, so that the volumetric velocity change is barely resolved. Instead, a reflector that does not exist in the true velocity model is generated to fit the data.

Figure 4 shows cost-function curves for IDWT, FWI, and FWI after IDWT. IDWT converges within 10 iterations, while FWI converges much slower, after IDWT and for FWI alone. The cost function for FWI alone plateaus after 10 iterations because the residual is insensitive to velocity perturbations, due to cycle skipping. FWI after IDWT converges with a lower cost than does FWI alone, but remarkably slower than does IDWT. However, IDWT requires

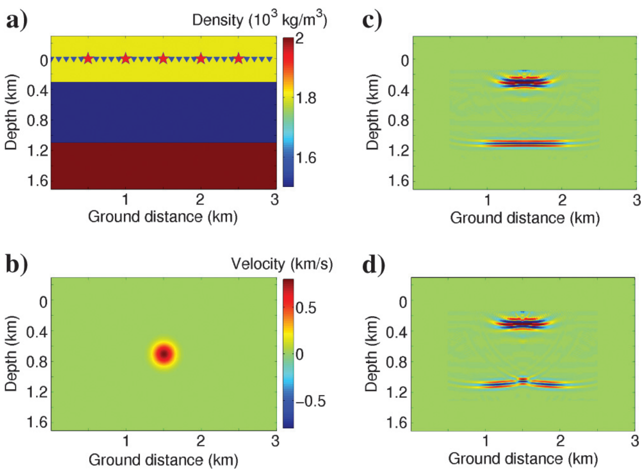

Figure 1. (a) The three-layer density model for baseline and monitor surveys. Red stars denote the locations of the shots, and blue triangles denote the receiver locations. (b) Differences in the P-wave velocities between baseline and monitor surveys. The maximum velocity change is 800 m/s. (c) The baseline image I_0 obtained using one shot gather and the constant velocity model. (d) The monitor image I_1 obtained using one shot gather and the constant velocity model. The center part of the second reflector is vertically shifted due to the absence of the velocity anomaly in (b).

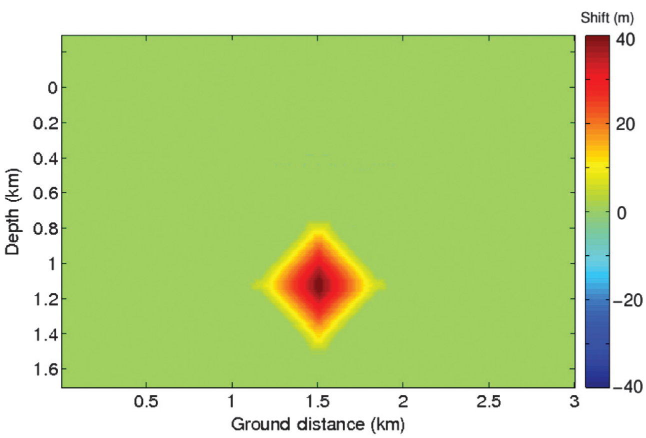

Figure 2. The image warping function $w(x, z)$ calculated from Figure 1c and 1d. Units on the color scale are meters. Positive values indicate upward shifts. The maximum warping is four grid points (i.e., 40 m).

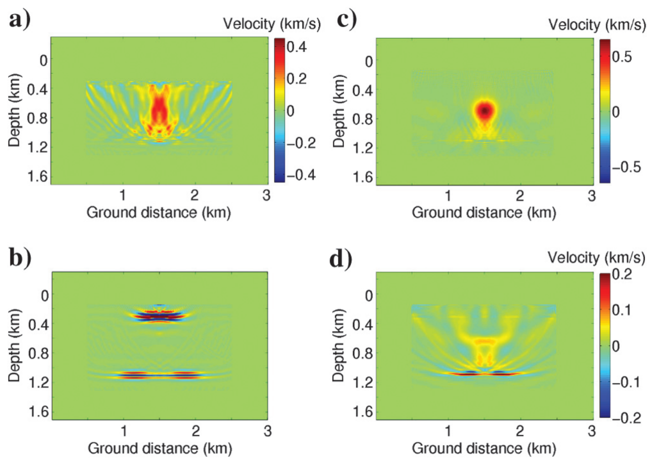

Figure 3. (a) The velocity changes found by IDWT with five sources. The anomaly is correctly positioned. However, the limited aperture of the acquisition makes the waves travel primarily in the vertical direction, so the recovered velocity anomaly is smeared vertically. (b) The monitor migration image obtained using one shot gather and the velocity model inverted by IDWT. The second reflector is correctly positioned. (c) The velocity changes refined by FWI after IDWT. The amplitude differences and subtle phase shifts between data and simulation are minimized to resolve the fine details in the velocity model. FWI has significantly reduced the vertical smearing observed in Figure 3a. (d) The velocity changes obtained with standard FWI applied to the monitor data, starting from the baseline constant background velocity model. The Gaussian anomaly is barely visible. An artificial reflector is erroneously created to account for data differences. This failure is due to the combined effects of cycle skipping and limited survey geometry.

four wavefield calculations to obtain the gradient in each iteration, and two wavefield calculations are required for one migration. Assuming each wave propagation calculation takes time T and each line search takes 3 migrations, the actual computational cost of IDWT is 10 times that for computing N wavefields, where N is the number of IDWT iterations. Similarly because it requires three forward models per line search, one FWI iteration takes $5T$. In this example, to get the final model in Figure 3c, we used 10 IDWT iterations and 20 FWI iterations. Thus, the total computation time is $200T$, of which 50% is used in IDWT.

Multilayer model

As shown in the three-layer model example, the smearing of the time-lapse velocity change is bounded by the reflectors. We expect that smaller reflector spacing will lead to a better determined anomaly. To investigate this, we use a multilayer model to simulate the case in which time-lapse changes span several layers. A constant velocity ($V_P = 3000$ m/s) is used for the baseline model. The time-lapse velocity model is the same as that in Figure 1b. A six-layer density model as shown in Figure 5a is used to generate reflections. Layer thicknesses in the center of the model are smaller than the size of the velocity anomaly in Figure 1b.

Figure 5 shows the velocity changes resolved by IDWT using different numbers of shots. Only one single shot placed in the center on the surface is used in Figure 5b. Compared with the results in Figure 3a, the anomaly is much better constrained vertically by the second and fourth reflectors in the model. Correspondingly, the magnitude of the velocity anomaly is better recovered; 10 and 20 shots are used evenly spaced at intervals of 265 and 125 m in Figure 5c and 5d, respectively. The shape and relative magnitude distribution are improved with additional shots.

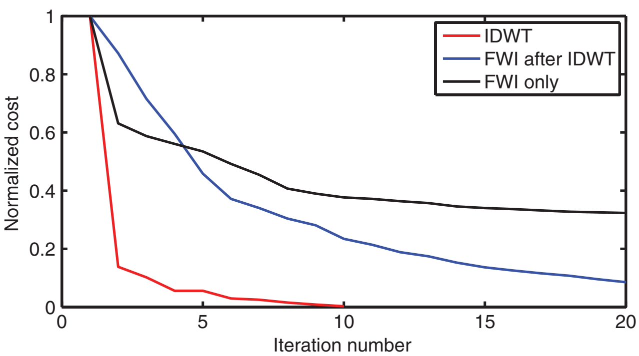

Figure 4. Cost function curves for IDWT, FWI after IDWT, and FWI only. The cost functions are normalized by their values before the first iterations. IDWT converged within 10 iterations. FWI after IDWT converged much slower. The cost function of FWI starting from the constant velocity plateaued after 10 iterations.

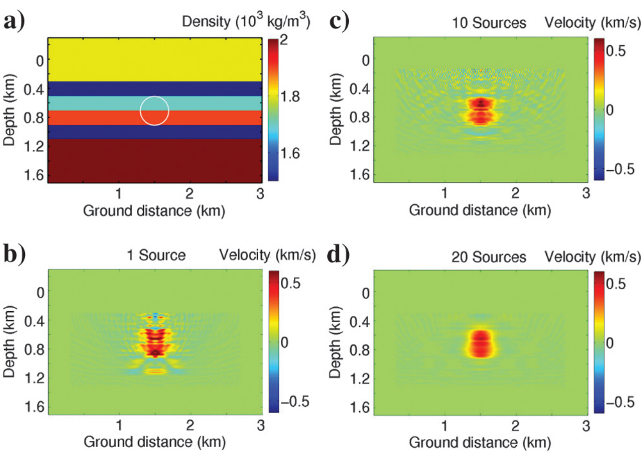

Figure 5. (a) The six-layer baseline and time-lapse density model. Layers in the center are smaller in thickness than the size of time-lapse velocity anomaly (white circle). Panels (b-d) show the IDWT results with one shot, 10 shots, and 20 shots, respectively. As we include more shots, the amplitude distribution within the anomaly is corrected. The vertical smearing is well constrained by the reflector. The maximum velocity change is closer to the true value as the changes are confined to a smaller area.

Baseline velocity errors

For all the previous examples, we assumed that the baseline model was exactly known. In practice, it is more likely that the baseline velocity model we build is inaccurate. To study the robustness of IDWT to errors in the baseline velocity, we use the model in Figure 6a, which contains a Gaussian-shaped low velocity zone,

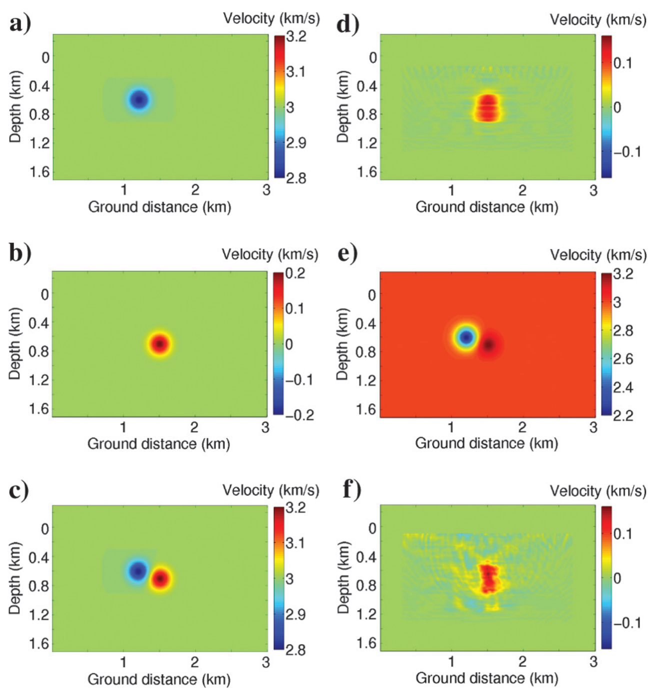

Figure 6. (a) True baseline velocity model with a Gaussian anomaly with peak velocity change of 200 m/s. We assume the anomaly is not known, and we use a constant velocity model for the baseline migrations. (b) True time-lapse velocity changes with peak value of 200 m/s. (c) True time-lapse velocity model I with two Gaussian anomalies (a plus b). (d) The time-lapse velocity changes found using IDWT. (e) True time-lapse velocity model II. We increase the peak amplitude of the Gaussian anomaly in the baseline velocity model to 800 m/s, and we use the same time-lapse velocity changes as in (b). (f) The time-lapse velocity changes inverted by IDWT. The shape of the anomaly is distorted because of the large error in the baseline velocity model, but the basic location and amplitude are preserved.

as the true baseline velocity model. We assume the anomaly is not resolved by the baseline velocity model building and so a constant velocity model is used for the baseline migration. We use the density model in Figure 5a with 20 shots evenly spaced at an interval of 125 m on the surface to generate synthetic data. The true time-lapse velocity model (Figure 6c) has an additional high-velocity Gaussian-shaped anomaly, which is the net change between the baseline and time-lapse models (Figure 6b). The peak magnitude of both anomalies is 200 m/s.

Figure 6d shows the IDWT result obtained when using 20 shots. Compared with the result obtained using the correct baseline model (Figure 5d), the resolved time-lapse anomaly maintains the same quality in shape and magnitude. More importantly, there are no negative velocity changes apparent in the result. The baseline velocity model error (the negative Gaussian-shaped anomaly) is not carried over to the time-lapse inversion. In other words, IDWT detects only the relative changes in the models. A close scrutiny of Figures 5d and 6d reveals that the shape of the resolved change is slightly distorted because of the kinematic error induced by the unknown Gaussian anomaly in Figure 6a. We expect the distortion to get stronger with bigger errors in the baseline velocity model. We test this with the model shown in Figure 6e, in which we increase the maximum amplitude of the low-velocity error in the baseline model to 800 m/s. The IDWT result with 20 shots, shown in Figure 6f, is severely distorted in shape, but the amplitude and position are still accurately recovered.

Source geometry nonrepeatability

Seismic survey repeatability is a key factor in achieving successful time-lapse monitoring. One common issue is the discrepancy of source-receiver geometry between surveys. A small deviation of the source position in the monitor survey from that of the baseline can lead to large differences in waveforms, which makes direct comparison between data sets difficult. Time-lapse FWI methods, such as double-difference waveform tomography, which requires data subtraction (Watanabe et al., 2005; Denli and Huang, 2009), must carefully coprocess the baseline and monitor data sets. In IDWT, instead of data, we compare images, which are less sensitive to shot position deviations. With the correct velocity model, neighboring sources should give very similar images. As a result, when they are migrated with the same baseline velocity, differences between a monitor image for shot position $x + \delta x$ and a baseline image for shot position x should still relate to time-lapse velocity changes. We expect IDWT to be robust to this type of source geometry difference between surveys.

We employ the baseline velocity models used in previous examples, with the constant velocity, weak Gaussian anomaly (200 m/s), and strong Gaussian anomaly (800 m/s). The maximum value of the time-lapse change is 200 m/s. The density model is the same as that in Figure 5a. For the baseline survey, 15 sources are evenly spaced at an interval of 170 m, and 300 receivers are evenly spaced at an interval of 10 m. For the monitor survey, we only consider source positioning errors. Because IDWT is conducted with shot gathers, the effects from receiver positioning errors should be negligible as long as they cover the same area. Two types of source positioning errors are commonly observed in practice: random perturbations (e.g., limited global positioning system (GPS) precision) and systematic perturbations (e.g., feathering effects in acquisition).

For random perturbations, we randomly perturbed each source either one grid point left or one grid point right from its baseline position. The grid spacing is 10 m in our tests, which is large compared to position errors observed in some well-repeated surveys in practice (Yang et al., 2013). In addition, position errors in reality would not be uniformly ± 10 m. However, we do not expect this to have a large effect on the results.

Figure 7 shows the IDWT results with different levels of baseline velocity errors but with the same randomly perturbed source positions. There is no baseline velocity error in Figure 7a. The baseline velocity models used in Figure 7b and 7c have Gaussian-shaped errors of 200 and 800 m/s peak value, respectively. The one-to-one comparison among Figure 7a–7c and Figures 5d, 6d, and 6f shows that the random source position perturbations have little effect on the performance of IDWT.

To study the effect of systematic perturbations, we move the monitor survey source positions uniformly toward the right. Three levels of shot position error are studied: δx equals 10, 20, and 50 m. The monitor data sets are generated and migrated using the perturbed source locations. Figure 8a–8c shows the IDWT results with the known constant baseline velocity model. The time-lapse velocity anomalies are resolved with the same quality in all three cases with increasing shot positioning error. Artifacts near the sources result from illumination differences between baseline and monitor surveys. As we discussed for the three-layer model, when the shot positions are the same in both surveys, the smeared updates near the sources are diminished by iteratively correcting the image of the shallower reflector. However, when the shot positions are different, as illustrated in Figure 9, parts of the monitor image have no corresponding parts in the baseline image (dashed circles). As a result, part of the velocity update cannot be constructed because the unconstrained parts of the image marked by arrows in Figure 9 are insensitive to that velocity change. At greater depths, this effect is mitigated by stacking shots, but the effect of stacking is weak near the sources. If the targeted area is deep in the subsurface, these artifacts will not affect the interpretation. If the monitor image is compared to the entire image formed by all the baseline shots, this effect will be eliminated because the shadowed areas in Figure 9 will be covered by baseline images of neighboring shots.

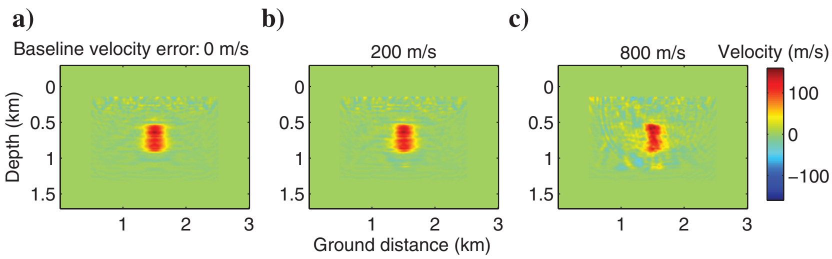

Figure 7. This figure shows robustness tests of IDWT to random source positioning errors and baseline velocity errors. The sources in the monitor survey are randomly shifted ± 10 m from their baseline positions. The baseline velocity error for each case has a maximum value of 0 (a), 200 (b), and 800 m/s (c). Compared to the case where there is no mispositioning in Figures 5d, 6d, and 6f, the random source positioning error has little effect on the performance of IDWT.

Figure 8d–8f shows the IDWT results with a weak Gaussian velocity error (200 m/s) in the baseline model. As the shot positioning error increases, the error induced by the incorrect baseline velocity model, marked by black circles, gets stronger. The principle that neighboring shots should give similar images is violated because the baseline velocity is incorrect. As a result, differences between baseline and monitor images are caused by the baseline velocity errors and the time-lapse velocity changes. The difference caused by baseline velocity error is bigger when two shots are further apart. Accordingly, the velocity error increases as the shot positioning error increases. In addition, the velocity error is inverted with a reverse sign because the monitor image is aligned with the incorrect baseline image. For example, if the low-velocity region in the baseline model is unknown (i.e., not included in the model for migration), the reflectors imaged by a source that illuminates the anomaly will be deeper than their true positions. Regardless of the time-lapse changes, IDWT would assume the baseline image is correct and perturb the velocity to make monitor image reflectors deeper, leading to a high-velocity update.

Figure 8g–8i shows the IDWT results with the strong Gaussian velocity error (800 m/s) in the baseline model. As expected, the larger error induces bigger false changes (located inside the black circles) in the time-lapse inversions. In Figure 8i, the false changes already have the same order of magnitude as the time-lapse changes when the source positioning error is 50 m. In this case, an interpretation would likely be affected by the velocity error. However, an 800 m/s velocity error in the baseline model is significant, and source positioning errors of 50 m are excessive in a well-repeated 4D seismic survey. Based on the tests shown in this section, we conclude that for relatively large errors in the baseline velocity model, and for random and systematic source geometry discrepancies between surveys, IDWT is robust and expected to be capable of delivering useful inversion results.

Marmousi model

For a more realistic synthetic test, we apply IDWT using the Marmousi model (Versteeg, 1994). As shown in Figure 10a, only part of the original Marmousi model with complicated geologic structures is used to better simulate narrow-offset acquisition. Five shots evenly spaced at an interval of 200 m (red stars) are used to generate the synthetic data sets, and 400 receivers are deployed on the surface at an interval of 5 m. Figure 10b shows the true time-lapse velocity model with a velocity decrease in the layers at around 1900 m depth. The actual boundary of the velocity anomaly is outlined by the black dashed line. The density is constant throughout the model.

We smooth the Marmousi model to generate the baseline model for migration as shown in Figure 11a. Figure 11b shows the migrated image with one shot gather of the baseline data sets. Due to the limited aperture of the acquisition, some of the structures (marked by arrows in Figure 11b) are not illuminated. The layers in these areas are completely missing in the image. The reflectors above and below the layer containing the time-lapse changes (dashed line in Figure 11b) are clearly imaged.

The IDWT result obtained using these five shots is shown in Figure 12b. The resolved anomaly is localized within the area enclosed by the dashed line. The shape and amplitude of the anomaly are well recovered. The true change, as shown in Figure 12a, has small values near the boundary of the anomaly (dashed line). In

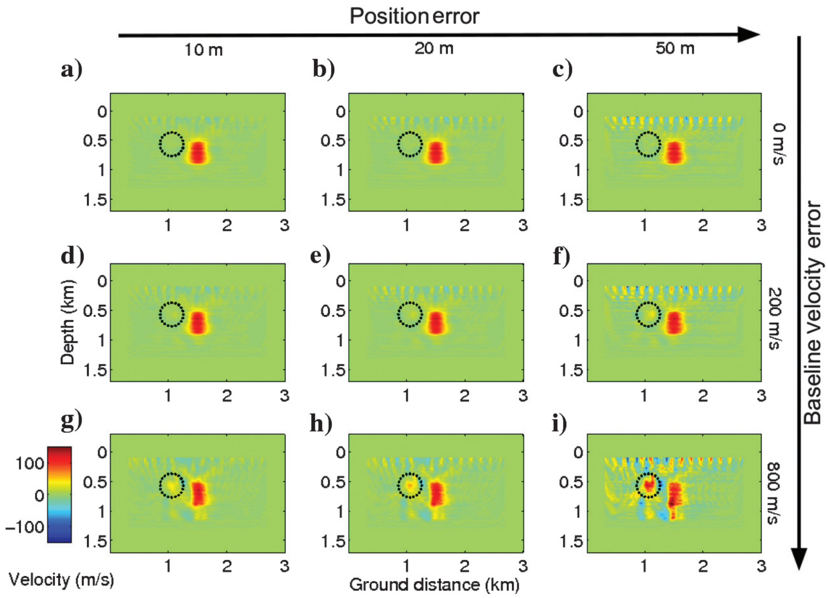

Figure 8. Robustness tests of IDWT against source positioning error plus baseline velocity error. In the 3×3 plot, the monitor survey sources are systematically shifted 10, 20, and 50 m from their correct positions for each column, respectively. The baseline velocity error for each row has maximum value of 0, 200, and 800 m/s. Black dotted circles mark the areas where false velocity changes are resolved due to the baseline velocity error, which is at the same location as shown in Figure 6e.

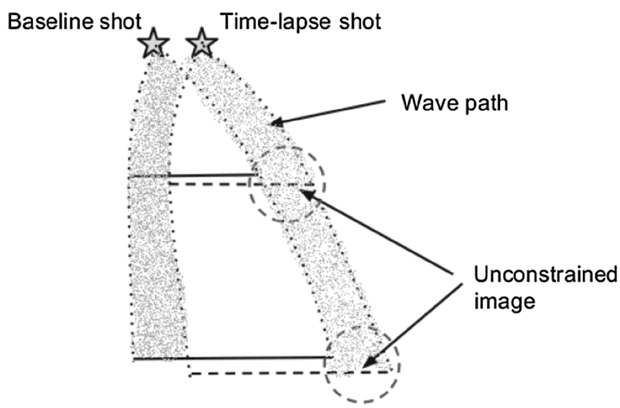

Figure 9. Migrated images for one baseline shot and one shifted monitor shot. Dotted lines show the wave paths along which velocities are updated. Portions of the monitor migrated image marked as unconstrained image (dashed circles), have no corresponding image points from the baseline image.

contrast, the inverted change appears to be larger in size due to vertical smearing between reflectors. The arrow in Figure 12b points to a location where the inverted anomaly spreads beyond the boundary of the actual anomaly but is well constrained by the reflector below. The smearing occurs because the boundary of the true time-lapse change, marked by the arrow in Figure 10b, is in the middle of the layer. As we observed for the layered-model examples, velocity changes within a single interval are vertically smeared throughout the layer but bounded by the reflectors. With this limitation, IDWT is again effective in recovering the local time-lapse velocity change.

DISCUSSION

From synthetic examples, we see that IDWT is able to robustly recover time-lapse velocity changes, with acquisition limitations such as narrow offsets and survey nonrepeatability. As with most tomography methods, IDWT smears velocity changes along wavepaths. However, the smearing effect is clearly bounded by reflectors above and below the changes. This effect is important for leakage monitoring when the ambiguity between the smearing and real leakage must be removed. Smaller differences between the boundary of the changes and the reflector boundaries lead to more reliable estimates of velocity changes. Better estimates of the velocity changes lead to more reliable interpretations of the changes.

In time-lapse inversions, we are interested in the relative changes between the surveys at different times. However, the data residuals due to the uncertainty in the baseline inversion are likely to contaminate the final result of time-lapse FWI. Tailored FWI schemes have been developed to suppress these sources of noise (Denli and Huang, 2009; Yang et al., 2011). In IDWT, errors in the baseline model affect the baseline and monitor images. Because the monitor images match the baseline ones, any perturbation in the velocity model is caused by the kinematic difference between the monitor and baseline data sets. Even with large baseline velocity errors, IDWT recovers the correct magnitude and position of velocity changes.

Another concern for time-lapse monitoring is the repeatability of surveys. In practice, shot and receiver locations are not identical between surveys, even for high-quality ocean bottom cables (Beasley et al., 1997; Yang et al., 2013). In some cases, after the initial large survey for exploration, specialized local surveys for

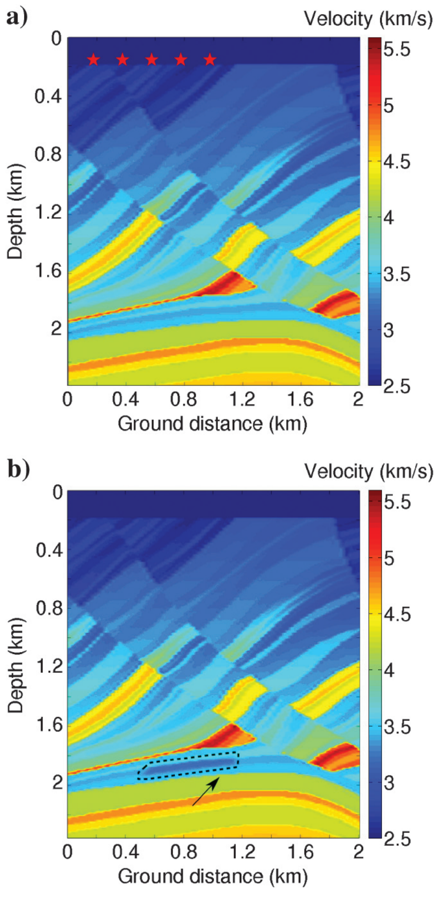

Figure 10. (a) The center part of the original Marmousi model is used as the true baseline velocity model. The maximum source-receiver offset is 2 km. Five shots (red stars) are used to generated synthetic data. (b) True time-lapse velocity model with a negative velocity change marked with a black dashed line. The black arrow points to the area where the boundary of the changes is located in the middle of the layer. We designed this half-layer velocity change intentionally to show how IDWT would smear the changes within a layer.

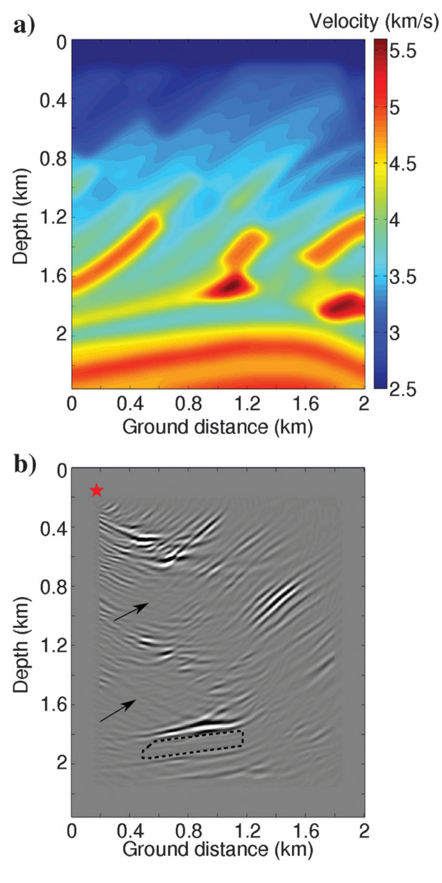

Figure 11. (a) A smoothed version of the Marmousi model is used as the baseline model for migration. (b) Migrated image for one shot (red star). Areas pointed to by arrows are poorly imaged due to the limited receiver aperture. Dashed lines mark the boundary of the velocity changes. The interfaces above and below the anomaly are well imaged.

monitoring are more economical and efficient (Hatchell et al., 2013). Deviations between survey geometries cause problems in time-lapse FWI methods that require data subtractions (Watanabe et al., 2005; Denli and Huang, 2009). In contrast, IDWT depends only weakly on the survey geometry. With a good baseline model, IDWT delivers accurate results, as long as the monitor survey illuminates an area of interest that is also well imaged with the baseline survey. When large errors (e.g., 800 m/s) exist in the baseline model, IDWT still produces reasonable results when differences in survey geometries are considerable (e.g., 50 m).

From a computational point of view, IDWT requires two wavefield extrapolations for each migration. With the same wave equation solver, it takes twice as much time as FWI for each iteration. However, it is not necessary to simulate the full wavefield to form the images. The image warping cost function is sensitive only to misalignments, and it is robust to inaccuracy in simulated waveform amplitudes. In contrast, traditional FWI needs accurate amplitudes so that differences between waveforms are reliable. We could potentially use a faster traveltime solver such as ray tracing to speed up IDWT. Another possible concern is the memory requirement for IDWT. Whereas RTM or FWI needs to store two wavefields for calculating the gradient, IDWT needs to store four wavefields, which could be too demanding in a 3D application. Symes (2007) presents an optimal check-pointing method that trades floating point operations for most of the storage in general adjoint computations. Although the memory requirement is still going to be twice that of FWI, it should be manageable in practice.

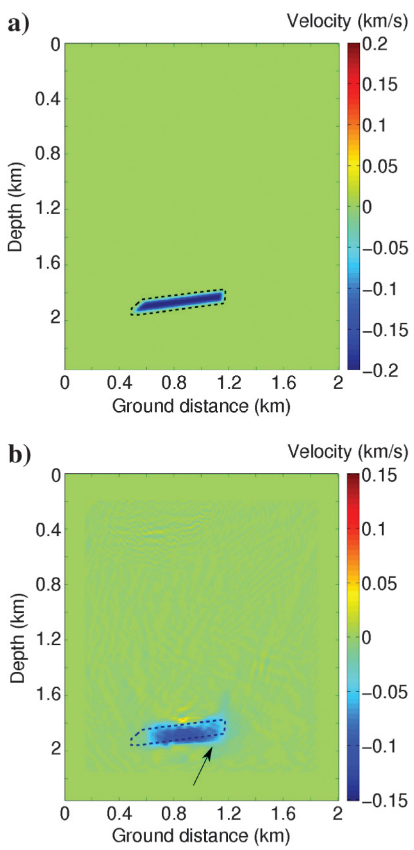

Figure 12. (a) The true time-lapse velocity changes. The anomaly is smooth at its boundary (dashed lines). (b) The inverted time-lapse changes using IDWT with five shots. The black arrow points to the area where the inverted velocity changes diffuse across the boundary of the true changes (dashed lines) and are smeared toward and bounded by the lower interface of this layer.

Although the time per iteration is twice that of FWI, IDWT appears to converge more quickly. Therefore, when using IDWT before FWI to resolve velocity anomalies with high resolution, the actual computation of IDWT does not dominate the cost of the overall process. As in the first synthetic example in this study, IDWT takes only 50% of the total CPU runtime of the process. When large velocity changes exist, the cycle-skipping effect makes the regular FWI cost function insensitive to velocity updates. IDWT using image warping helps to find a good starting model with correct large-scale kinematics for FWI. For initial velocity model building, ideas similar to image warping can be implemented in the data domain to avoid cycle skipping. However, with reflection geometries, FWI fails to invert for volumetric changes in velocity and the result tends to be like that of a least-squares migration. Ma and Hale (2013) successfully overcome this problem. However, to extend their method to time-lapse applications requires further study.

Beyond the theory and numerical studies presented here, we have applied IDWT to field data sets (time-lapse walkaway vertical seismic profiles) that were collected from a CO_2 sequestration testing site and successfully recovered P-wave velocity changes that cannot be resolved by FWI (Yang et al., 2014). With very limited survey apertures and the presence of strong noise in real data, stacking images of neighboring shots would increase the signal-to-noise ratio and mitigate imaging artifacts without losing much angle information if the source distribution is dense. Studies with more field data sets of different acquisition conditions and different time-lapse mechanisms (e.g., water flood, gas leakage) are planned for the near future.

CONCLUSION

We have proposed a time-lapse wavefield tomography method in the image domain for reflection data. The warping between baseline and monitor images is used as a cost function that is sensitive to smooth velocity perturbations and robust to cycle-skipping errors. The method is accurate and wave-equation based, and it requires no linearization or assumptions about the smoothness of the model. It is computationally efficient with fast convergence, and it does not require the computation of angle gathers. Even with limited acquisitions, such as narrow offsets and small numbers of sources, and for complex subsurface structures, IDWT delivers reliable time-lapse inversion results. It is also robust with respect to baseline velocity errors and survey geometry discrepancies between surveys. With IDWT, kinematic effects are distinguished from other time-lapse effects, thereby providing a good foundation for subsequent analysis of amplitudes and reservoir characterization.

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APPENDIX A

ADJOINT METHOD FOR IDWT

Here, we present the mathematical derivation of the adjoint wavefields and the gradient for IDWT using the associate Lagrangian in the time domain. Following the approach of Plessix (2006), the steps of the derivation are: for model parameter m and cost function $J(m)$:

1) list all the state equations $F_i = 0$
2) build the augmented functional L by associating the independent adjoint state variables λ_i with the state equations F_i
3) define the adjoint-state equations by $\frac{\partial L}{\partial \lambda_i} = 0$
4) compute the gradient by $\frac{\partial L}{\partial m} = \frac{\partial J}{\partial m}$.

To make the process less complicated, we derive everything based on a single shot in a 2D space. A more general derivation can be easily achieved by summing over all the shots. The extension to 3D is straightforward by applying an integral over y. The least-squares functional is

$$J(m) = \frac{1}{2}\int_x \int_z |w(x,z)|^2 \mathrm{d}x\mathrm{d}z, \tag{A-1}$$

where $w(x,z)$ is the warping function that minimizes

$$D(w(x,z)) = \frac{1}{2}\int_x \int_z |I_1(x,z) - I_0(x, z + w(x,z))|^2 \mathrm{d}x\mathrm{d}z, \tag{A-2}$$

where $I_0(x,z)$ is the baseline image that stays invariant throughout the process and $I_1(x,z)$ is the monitor image based on the slowness model m. The first derivative of the function with respect to $w(x,z)$ should be close to zero at the minimum point:

$$\frac{\partial D}{\partial w}(x,z) = (I_1(x,z) - I_0(x, z + w(x,z)))\frac{\partial I_0(x, z + w(x,z))}{\partial z} \approx 0. \tag{A-3}$$

The value of $I_1(x,z)$ is obtained from the imaging condition:

$$I_1(x,z) = \int_0^T u_s(x,z,t)u_r(x,z,T-t)\mathrm{d}t. \tag{A-4}$$

The source wavefield u_s is obtained by solving the following wave equations:

$$\begin{cases} m\frac{\partial^2 u_s(t)}{\partial t^2} - \Delta u_s(t) = f_s \\ u_s(x,z,0) = 0 \\ \frac{\partial u_s(x,z,0)}{\partial t} = 0 \end{cases}. \tag{A-5}$$

The receiver wavefield u_r is obtained by solving the following equations:

$$\begin{cases} m\frac{\partial^2 u_r(t)}{\partial t^2} - \Delta u_r(t) = d(T-t) \\ u_r(x,z,0) = 0 \\ \frac{\partial u_r(x,z,0)}{\partial t} = 0 \end{cases}. \tag{A-6}$$

For simplicity, the spatial boundary conditions are left unspecified because any condition that guarantees a unique solution is acceptable. In our numerical examples, we use absorbing boundary conditions.

Using the Lagrangian formulation, we associate the adjoint states $\tilde{\mu}_s^0, \tilde{\mu}_s^1, \tilde{\mu}_r^0$, and $\tilde{\mu}_r^1$ with the initial conditions in equations A-5 and A-6, respectively. Adjoint states $\tilde{\lambda}_s$ and $\tilde{\lambda}_r$ are associated with the wave equations in equations A-5 and A-6. Adjoint states $\tilde{\phi}_I$ and $\tilde{\phi}_w$ are associated with equations A-4 and A-3. With the operations above, the augmented functional is defined by

$$\begin{aligned} &L(\tilde{\phi}_I, \tilde{\phi}_w, \tilde{\lambda}_s, \tilde{\lambda}_r, \tilde{\mu}_s^0, \tilde{\mu}_s^1, \tilde{\mu}_r^0, \tilde{\mu}_r^1, \tilde{u}_s, \tilde{u}_r, \tilde{I}_1, \tilde{w}, m) \\ &= \int_x \int_z \frac{1}{2}|\tilde{w}(x,z)|^2 \mathrm{d}x\mathrm{d}z \\ &- \int_0^T \left\langle \tilde{\lambda}_s, m\frac{\partial^2 \tilde{u}_s(t)}{\partial t^2} - \Delta \tilde{u}_s(t) - f_s \right\rangle_{x,z} dt \\ &- \langle \tilde{\mu}_s^0, \tilde{u}_s(0)\rangle_{x,z} - \left\langle \tilde{\mu}_s^1, \frac{\partial \tilde{u}_s(0)}{\partial t}\right\rangle_{x,z} \\ &- \int_0^T \left\langle \tilde{\lambda}_r, m\frac{\partial^2 \tilde{u}_r(t)}{\partial t^2} - \Delta \tilde{u}_r(t) - d(T-t) \right\rangle_{x,z} dt \\ &- \langle \tilde{\mu}_r^0, \tilde{u}_r(0)\rangle_{x,z} - \left\langle \tilde{\mu}_r^1, \frac{\partial \tilde{u}_r(0)}{\partial t}\right\rangle_{x,z} \\ &- \left\langle \tilde{\phi}_I, \tilde{I}_1(x,z) - \int_0^T u_s(x,z,t)u_r(x,z,T-t)\mathrm{d}t \right\rangle_{x,z} \\ &- \left\langle \tilde{\phi}_w, -(\tilde{I}_1(x,z) - \tilde{I}_0(x, z + \tilde{w}(x,z)))\frac{\partial \tilde{I}_0(x, z + \tilde{w}(x,z))}{\partial z} \right\rangle_{x,z}. \end{aligned} \tag{A-7}$$

with $\langle \tilde{\lambda}_s, \tilde{u}_s \rangle_{x,z} = \int_x \int_z \tilde{\lambda}_s(x,z)\tilde{u}_s(x,z)\mathrm{d}x\mathrm{d}z$ being the real scalar product in space. By two integrations over t by parts, we switch the second-order time derivative operator from $\tilde{u}_s$ to $\tilde{\lambda}_s$:

$$\begin{aligned} \int_0^T \left\langle \tilde{\lambda}_s, m\frac{\partial^2 \tilde{u}_s(t)}{\partial t^2}\right\rangle_{x,z} \mathrm{d}t = &\int_0^T \left\langle m\frac{\partial^2 \tilde{\lambda}_s(t)}{\partial t^2}, \tilde{u}_s \right\rangle_{x,z} \mathrm{d}t \\ &+ \left\langle \tilde{\lambda}_s(T), m\frac{\partial \tilde{u}_s(T)}{\partial t}\right\rangle_{x,z} - \left\langle \tilde{\lambda}_s(0), m\frac{\partial \tilde{u}_s(0)}{\partial t}\right\rangle_{x,z} \\ &- \left\langle m\frac{\partial \tilde{\lambda}_s(T)}{\partial t}, \tilde{u}_s(T)\right\rangle_{x,z} + \left\langle m\frac{\partial \tilde{\lambda}_s(0)}{\partial t}, \tilde{u}_s(0)\right\rangle_{x,z}. \end{aligned} \tag{A-8}$$

The same operation is applied to similar terms: $\int_0^T \langle \tilde{\lambda}_r, m\frac{\partial^2 \tilde{u}_r(t)}{\partial t^2}\rangle_{x,z}\mathrm{d}t$, $\int_0^T \langle \tilde{\lambda}_s, \Delta \tilde{u}_s(t)\rangle_{x,z}\mathrm{d}t$, and $\int_0^T \langle \tilde{\lambda}_r, \Delta \tilde{u}_r(t)\rangle_{x,z}\mathrm{d}t$.

With equations A-7 and A-8, we can compute the derivatives with respect to the adjoint states and evaluate them at

$(\lambda_s, \lambda_r, u_s, u_r, \phi_I, I_1, \phi_w, w)$ to obtain the adjoint-state equations. With respect to $\tilde{u}_s$, we have equations

$$\begin{cases} m\frac{\partial^2 \lambda_s(t)}{\partial t^2} - \Delta\lambda_s(t) = \phi_I(-u_r(T-t)) \\ \lambda_s(T) = 0 \\ \frac{\partial \lambda_s(T)}{\partial t} = 0 \end{cases}. \tag{A-9}$$

With respect to $\tilde{u}_r$, we have equations

$$\begin{cases} m\frac{\partial^2 \lambda_r(t)}{\partial t^2} - \Delta\lambda_r(t) = \phi_I(-u_s(T-t)) \\ \lambda_r(T) = 0 \\ \frac{\partial \lambda_r(T)}{\partial t} = 0 \end{cases}. \tag{A-10}$$

With respect to $\tilde{I}_1$ and $\tilde{w}$ we have equations

$$\begin{cases} -\phi_I - \phi_w\left(-\frac{\partial I_0(x,z+w(x,z))}{\partial z}\right) = 0 \\ w - \phi_w(-\Pi) = 0 \\ \Pi = \left(\frac{\partial I_0(z+w(x,z))}{\partial z}\right)^2 - \frac{\partial^2 I_0(z+w(x,z))}{\partial z^2}(I_1(x,z) - I_0(x,z+w(x,z))) \end{cases}. \tag{A-11}$$

By taking the derivative of L with respect to the model parameter m, we have the gradient of the cost function:

$$\frac{\partial L}{\partial m} = \frac{\partial J(m)}{\partial m} = -\int_0^T \frac{\partial^2 \lambda_s(x,z,t)}{\partial t^2} u_s(x,z,t) + \frac{\partial^2 \lambda_r(x,z,t)}{\partial t^2} u_r(x,z,t)\mathrm{d}t. \tag{A-12}$$

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