Velocity analysis and event estimation for passive seismic data using source focusing function

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SUMMARY

Attaining information corresponding to the passive seismic source location often helps in understanding the reservoir fracturing process. Time reversal based migration methods are widely used to find the source location directly. Such source locating methods share a fundamental weakness: The accuracy of source image depends highly on the accuracy of the velocity model. In order to solve this problem, we introduce a new objective function to optimize the velocity model and source image at a much higher quality. Since the source energy does not focus well when the velocity is inaccurate, we utilize a source penalty function, which is often used to measure the source focusing as an objective function. The source in the objective function is defined by the estimated source coordinates and source image. In order to get high-resolution source images, we use the geometric mean imaging condition. The simultaneous update of the velocity, source image and location allows us to fit the objective for all these attributes of the model and source. Applications on data generated using the 2D Marmousi and field data show that the proposed method can improve the velocity model and source image quality.

INTRODUCTION

Hydraulic fracturing is an important procedure in oil and gas extraction. In order to make dense rock crack, fluids or CO₂ are injected into the reservoir area to create high pressure conditions. The passive seismic events caused by the crack of the rock can be monitored through sensors in the well or on the earth surface. Locating passive seismic sources can help us understand the fracking impact, as we map the hydraulic fracturing, and monitor potential reservoir fluid migrations and production (Warpinski, 2009). Such information help the engineers make better injection decisions and strategies.

Over the years, researchers have developed many methods to locate passive seismic sources. Ray based methods rely on the traveltime picking accuracy of either P-wave or S-wave arrivals (Waldhauser and Ellsworth, 2000; Eisner et al., 2009). Though efficient and reasonably reliable, this category of methods tend to fail when the signal to noise ratio (SNR) is low, which results in inaccurate traveltime picking, and in complex velocity areas. In order to mitigate the uncertainty from the event picking, time reversal (Artman et al., 2010) based methods were developed. These methods adhere to the concept of wavefield reconstruction backward in time. By using an appropriate imaging condition, passive seismic source images are obtained. This category of methods requires denser acquisition scenarios compared to the traveltime methods. However, this kind of methods also has several limitations. The uncertainties of source wavelet and source origin time will make the wavefield reconstruction result unreliable, and such information is usually unavailable in passive seismic case. Velocity

accuracy is another key factor to the success of constructing the source image. In order to solve these problems, full waveform inversion (FWI) has recently been utilized to estimate passive seismic source locations. Kaderli et al. (2015) proposed to separate the wave equation source term into spatial and temporal components. They used FWI to invert for the source components. However, the computational cost and cycle skipping problems associated with FWI have limited its success.

In this abstract, we present a method to update velocity and calculate source image iteratively from a new perspective. The accuracy of velocity model is directly related to the focussing of the source image. Taking advantage of this physical feature, we propose to use a source energy focusing measurement function as the objective function instead of matching the observed and calculated data directly like conventional FWI. With the help of a new objective function, we no longer need to worry about the cycle skipping problem and bad initial source position guess in FWI. What's more, since we no longer need to invert for the source image over many iterations, this method is reasonably efficient. We use the geometric imaging condition to produce the source image at each iteration (Nakata and Beroza, 2016). This source imaging condition yields high-resolution source images even with sparsely collected data. As we update the velocity update through iterations with a conjugate gradient method, the source image quality is also improved gradually as part of the objective. Finally, we test proposed method on synthetic data generated from 2D Marmousi model and also we test the method on field data. The results show that the proposed method is valid and efficient.

THEORY

Wave propagation in isotropic acoustic media with constant density from a point source can be modeled by solving the following wave equation:

$$\frac{1}{v^2} \frac{\partial^2 u}{\partial t^2} - \nabla^2 u = f(t) \delta(x - x_s). \quad (1)$$

where v is velocity, $f(t)$ is wavelet function, $x = [x, y, z]$ are spatial dimensions, x_s is source coordinate, and $u(x, t)$ is the wavefield. In order to achieve a successful FWI using a point source wave equation, Huang and Symes (2016) proposed to use an extended source function to replace the point source. By doing this, nonphysical source energy away from $x = x_s$ can be penalized. This idea can also be used to quantitatively measure the source energy concentration property of the source image. By taking advantage of this property, the objective function for optimizing the source image is given as:

$$E(v, x_s) = \sum_x \frac{1}{2} \|(x - x_s) I(x, v)\|_2^2, \quad (2)$$

where $I(x)$ represents the source image. With the help of geometrical mean imaging condition, high-resolution source images can be calculated. First, we divide the recorded data to

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different receiver groups. Then, we construct the adjoint-state wavefields from the different receiver groups and correlate all these wavefields at each time step. Finally, we stack over time samples to obtain the source image.

$$I(x, v) = \int_t \prod_{i=1}^n \lambda_i(t, v) dt, \quad (3)$$

where index i represents the receiver group number, $\lambda_i(t, v)$ represents the adjoint-state wavefield calculated with background velocity v_0 , which follows:

$$\frac{1}{v_0^2} \frac{\partial^2 \lambda_i}{\partial t^2} = \nabla^2 \lambda_i + d_i(x_r, T - t), \quad (4)$$

with $d_i(x_r, T - t)$ as the recorded data of the i th receiver group at receiver locations x_r . According to Born theory, the perturbed wavefield $\delta \lambda_i$ can be written in an abbreviated form as: $L \delta \lambda_i = \frac{2\delta v}{v_0^3} \frac{\partial^2 \lambda_i}{\partial t^2}$, where $L = \frac{1}{v_0^3} \frac{\partial^2}{\partial t^2} - \nabla^2$ is the modeling/demigration operator. Using the adjoint-state method, we can perturb the objective function with respect to a perturbation in velocity, δv , as follows (R.E.Plessix, 2006):

$$\begin{aligned} \delta E &= \sum_x (x - x_s)^2 I(x, v) \int_t \prod_{i=1, i \neq j}^n \lambda_i(t, v) \delta \lambda_j(t, v) dt \\ &= \sum_{j=1}^n \sum_x \int_t \left\langle f(x), L^{-1} \left(\frac{2\delta v}{v^3} \frac{\partial^2 \lambda_j(t, v)}{\partial t^2} \right) \right\rangle dt \\ &= \sum_x \left\langle \sum_{j=1}^n \int_t L^{-T} \{f(x)\} \frac{2}{v^3} \frac{\partial^2 \lambda_j(t, v)}{\partial t^2} dt, \delta v \right\rangle \end{aligned} \quad (5)$$

where $f(x) = (x - x_s)^2 I(x, v) \int_\zeta \prod_{i=1, i \neq j}^n \lambda_i(\zeta, v) d\zeta$, n is the total number of receiver group. So the velocity gradient can be expressed as:

$$\frac{\partial E}{\partial v} = \frac{2}{v^3} \sum_{j=1}^n \int_t L^{-T} \{f(x)\} \cdot \frac{\partial^2 \lambda_j(t, v)}{\partial t^2} dt \quad (6)$$

As for x_s , we set $\frac{\partial E}{\partial x_s} = 0$ to obtain the following analytical solution:

$$x_s = \frac{\sum_x I(x, v)^2 x}{\sum_x I(x, v)^2}. \quad (7)$$

The workflow is shown in Figure 1.

EXAMPLES

We want to find out how much the accuracy of velocity model influences the source image quality. We use a simple homogeneous model with a velocity of 2000 m/s for this test. The size of the model is 200×200 . The horizontal and vertical grid spacing interval are both 25 m. We use a velocity that is lower by 88%, the same, and higher by 120% of the true velocity to compute the source images. We use one receiver group, which is also referred to as the autocorrelation source imaging condition to get the source image. The source images from the 88% of true velocity, true velocity, and 120% of true velocity are, respectively, shown in Figures 2(a), (b) and (c). We

Figure 1: The Marmousi model and the initial velocity model.

can see that only when we use the true velocity to get source image, the source energy is best focused, and the maximum energy point corresponds to the true source coordinate. When the velocity is lower than the true velocity, the source energy is poorly focused. By comparison, when the velocity is higher than the true velocity, the source energy is better focused than using the lower velocity. This is more apparent in the objective function value curve in Figure 3, where this source imaging condition is more sensitive to lower velocity perturbations.

Figure 2: Source images corresponding to using a velocity that is 88% of the true velocity (a), the true velocity (b) and 120% of the true velocity (c).

We set a homogeneous model of size 200×200 samples. The background velocity is 2000 km/s. We include a square anomaly with a velocity of 3000 km/s in the middle, which is shown in Figure 4(a). We place a 100 receivers at each of the four boundaries. The source image using 4 receiver groups for the background velocity is shown in Figure 5(a). Although the acquisition system is perfect, we still fail to get a well-focused source image. After 10 iterations of velocity update, the inverted velocity is shown in Figure 4(b), and one profile at 2500 m is shown in Figure 6. We can see that by using the proposed method the velocity anomaly can be recovered. Using the inverted velocity, the final source image is shown in Figure 5(b). From the final source image, we can see that the source energy is perfectly focused on the correct source position with reasonably high resolution.

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Figure 3: The objective function as a function of homogeneous velocity models.

Figure 7: The objective function as a function of iterations.

Figure 4: The true velocity (a) and the inverted velocity (b).

Figure 5: The source image from (a) the initial velocity and (b) the inverted velocity with 2 receiver groups.

Figure 8: The true velocity model.

Figure 6: The velocity profile of true velocity, initial velocity, and inverted velocity at location 2500 m from Figure 6.

Let us apply the proposed velocity update scheme on the Marmousi model. The true velocity model is shown in Figure 8. All the grid points on the surface will act like receivers. We use 2 receiver groups to calculate the source imaging. The initial model is a linearly increasing velocity model, shown in Figure 9(a). The source image corresponding to the initial model is shown in Figure 10(a). After 40 iterations of velocity update, the inverted velocity model is shown in Figure 9(b) and the final source image is shown Figure 10(b). We can see that the inverted velocity model has recovered the main structure of the true model with only one single source. Using the improved velocity model, the source energy focuses at its true location.

At last, we test our proposed method on one event captured in the field, which is shown in Figure 11(a). The field data is recorded in a borehole with only 15 receivers. The receiver positions are shown as a $\triangle$ sign in Figure 12(a). It is very obvious to find one event from the data. As the method we propose is based on acoustic wave equation, so we mute the S-wave and just utilize P-wave which is shown in Figure 11(b). We have very limited velocity information from the well log. In order to mitigate the influence from the reflection wave, we use the smoothed the well-log velocity as the initial velocity shown in Figure 12(a). Using 5 receiver groups, the initial source image is shown in Figure 13(a). We can see that the source energy is poorly focused. After 10 iterations velocity update, the inverted velocity is shown in Figure 12(b). Using the inverted velocity, the final source image is shown in Figure 13(b). It is clearly shown that the quality of final source image gets greatly improved, and the source energy is better focused.

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Figure 9: The initial velocity model (a) and final inverted velocity (b) using 2 receiver groups.

Figure 10: The source image from the initial velocity model (a) and final source image from inverted velocity model (b) using 2 receiver groups.

Figure 11: Recorded data (a) and data with S-wave muted (b).

Figure 12: Initial velocity from well log (a) and inverted velocity (b).

Figure 13: Source image from initial velocity (a) and inverted velocity (b) using 5 receiver groups.

CONCLUSIONS

We introduced a new objective function to optimize the velocity model and source image for passive seismic data. This formulation is immune to cycle skipping and a bad initial guess often impeding FWI implementations. It also mitigates uncertainties in the source wavelet and origin time. Using geometric mean source imaging condition, the resulting source image resolution is high even with sparsely collected data. After attaining the source image, we use the estimated source coordinates to calculate the velocity gradient. Using a conjugate gradient method to update velocity, the source energy focuses on the true source location with higher resolution. Applications to data generated from 2D Marmousi models yield reasonably good results. The application on field data also shows that the proposed method can provide more accurate velocity models and improved source image quality.

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