Data-driven diffraction imaging of fractures using passive seismic data
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SUMMARY
We present a workflow of seismic imaging for passive seismic data. Unlike conventional diffraction imaging that often adopts reflection-type seismic imaging with known source, our approach relies on the data without the need for passive source information. We use two types of information from passive data: transmitted waves and scattering (coda) waves. The imaging formula states that direct waves should coincide with coda waves at scatterer points at the time of scattering. Instead of generating source wavefields in the conventional imaging method, we back propagate transmitted and scattered data from known surface or borehole receiver arrays. Then we apply zero-lag crosscorrelation imaging condition to produce an image. We can apply this processing for both P- and S-waves. In our numerical examples, we evaluate surface and borehole acquisition scenarios. We found that our approach performed well compared with conventional seismic imaging when assuming exact source information is known. When we perturbed source location, fractures were missing in the conventional seismic imaging map but our approach was not influenced.

INTRODUCTION
Most shale formations contain natural (preexisting) fractures. Because of their effects on permeability and the further stimulation volume in hydraulic fracturing shale formation, it is desirable to map natural fractures. Yang and Zoback (2014) observed that unusual microseismic patterns result from fluid channeling dominated by preexisting fractures and faults, which are also critical for refracturing.

Faults and fractures may generate apparent scattering waves when seismic waves pass through them. Full wavefield data contains more fruitful information, for example, P and S waveforms, reflections, conversions, and scattered waves. Using full wavefields information, with less reliance on phase picking, promises to provide a more complete and reliable monitoring. Recent studies have shown that using waveform information could yield better constraints of microseismic sources, and thus induced fractures (Duncan and Eisner 2010; Song and Toksz 2011; Sun et al. 2015). In addition, the frequency content of microseismic data is often high, above 200 Hz, which implies the ability to image small-scale structures.

Passive seismic imaging usually adopts conventional reverse-time seismic imaging for mapping such targets. For example, Reshetnikov et al. (2010) used migration of passive reflections to construct a high-resolution image of faults in the San Andreas Fault region. Their approach needs to generate source wavefields from the hypocenter of the microseismic event, which must be located before migration. However, with either traveltime based or waveform based location approaches, passive source location is most likely to be uncertain and inaccurate. When the source wavefield is extrapolated from such poorly known source, the uncertainties of source location will be translated into focusing/defocusing in the seismic image. This makes conventional migration difficult to use for passive seismic data.

In this study, we present a data-driven diffraction imaging approach without the need for source information. Our study is inspired by Nihei et al. (2000) who used the directed and converted PS waves of VSP data for back propagation in the reverse-time migration to locate fractures. They implemented the elastic reverse-time migration. Shabelansky et al. (2015) developed a method using reflection/transmission waves and converted waves for velocity analysis. Wang et al. (2014) presented an autocorrelation of primary and multiples for imaging subsalt. Here we use passive data and back propagate transmitted wave and scattering waves that can be significant in microseismic data. Our approach back propagates both transmitted waves and the rest of data from receivers into the medium. A zero-lag crosscorrelation imaging condition is applied to construct images of fractures as the source of scattering.

METHODOLOGY
Passive seismic data usually exhibit clear P- and S-wave phases, which are transmitted waves from passive sources to surface or borehole receiver stations. P- and/or S-wave phases are used to infer seismic sources and subsurface structure. Here we consider that the recorded seismic data for a passive source consists of transmitted waves \(d_f(x_s, t)\) and scattered waves \(d_s(x_s, t)\), which can be expressed as:

\[
d(x_s, t) = d_f(x_s, t) + d_s(x_s, t)
\]

where \(x_s\) denotes the spatial coordinates of receivers and \(t\) is the recording time. When a point source emits a wave, the wave hits a scatterer which acts as a secondary source and produces scattering (diffraction) waves, shown schematically in Figure 1a. Diffractions may accompany transmitted waves but propagate in different directions. Figure 1a shows the coming transmission wave interacting with scatterers that produce scattered wavefields accompanying transmission wavefield. In surface receivers arrays, all these waves can be recorded.

Consider an acoustic Green’s function \(G(x_s, t)\) which represents an impulse response observed at \(x_s\), due to a source at \(x_s\). The back propagation of seismic data \(d(x_s, t)\) can be written mathematically as \(W_G(x_s, t) = G(x_s, -t) * d(x_s, t)\), where the symbol ‘*’ represents the convolution. A conventional imaging condition for shot-record migration consists of time crosscorrelation at every image location between the source and receiver wavefields, followed by image extraction at zero time.

\[
G(x_s, t) = \int_{-\infty}^{\infty} G(x, t) \delta(t - t_0) dt
\]

where \(G(x, t)\) is the Green’s function, which depends on the spatial coordinates of receivers and \(t\) is the recording time. The spatial derivatives of Green’s function \(G(x_s, t)\) can be written as:

\[
\frac{d}{dx} G(x_s, t) = \int_{-\infty}^{\infty} \frac{d}{dx} G(x, t) \delta(t - t_0) dt
\]

where \(\delta(t - t_0)\) is Dirac’s delta function.
(Claerbout, 1985). Thus, the image \( I(x) \) is expressed as
\[
I(x) = \int_0^T W_s(x,t) \ast W_d(x,t) dt \quad (2)
\]
Here, \( W_s(x,t) \) is the source wavefield, \( T \) is the total time length of recorded data, and the symbol \( \ast \) denotes cross-correlation in time. Considering the reciprocity of wave propagation, during the back propagation, the transmitted and scattered wave fronts should meet at the scatterers’ location. Figure 1b schematically shows back propagation of two separated data into the same medium. At a time, two wavefields meet and then focused scattering waves diverge. Transmitted waves finally converge to the source location. During back propagation we apply a zero-lag crosscorrelation imaging condition. We can represent this process by the relation:
\[
I(x) = \int_0^T W_{dp}(x,t) \ast W_{ds}(x,t) dt \quad (3)
\]
The imaging condition does not require the propagation of the source wavefield. We can reconstruct those two back propagated wavefields from data using any type of extrapolation.

We repeat steps 1-5 for each time step during the backpropagation of the data from the receiver array into the subsurface model. The image of the scatterers is produced by summing the results of step 5 for all the time steps. At points in space where there is no scattering, the product of \( W_{dp}(x,t) \) and \( W_{ds}(x,t) \) will vanish. When the deconvolution condition is applied, the value of the image can represent the transmission coefficient at that point. This imaging scheme does not require any knowledge of the source properties, such as location, radiation patterns, or source time functions, which makes the proposed method preferable for passive seismic data. In conventional imaging, we need to forward and backward propagate data for \( N_S \) sources. With the imaging method that is independent of source, we only need to propagate the data once. Thus, the computational cost is \( N_S \) times less than standard reverse-time imaging scheme.

SYNTHETIC EXAMPLES

We present synthetic surface and borehole passive seismic monitoring examples to show the possibility of an effective detection of faults and fractures. Figure 2 shows the geometry of the layered model. Hydraulic fracturing is operated in the fourth layer at the depth of \(-1200 \) m. Natural fractures in the above layer are denoted by black solid lines. We have 70 point-sources randomly distributed in the fourth layer, where the P-wave quality factor \( Q_p = 20 \). The above and below layers are \( Q_p=50 \). In the first two layers \( Q_p=200 \).

Surface arrays

In the first demonstration, we generate acoustic data with attenuation effects generated by solving the viscoacoustic wave equation (Zhu and Harris, 2014). Following the proposed work flow, we separate recorded data into transmission and scattering data. For simplicity here we run forward models twice with the background velocity with and without fractures. So they are full data and transmission data, respectively, shown in Figure 3a and 3c. Figure 3b show coda data that is obtained by subtraction between full and transmission data.
Figure 2: P-wave velocity model. Down-triangles denote surface receivers. Red stars denote point sources randomly distributed in the layer. In the above natural fractures are plotted in thin white polygon.

Figure 3: Acoustic shot gather data (a). Scattering (Coda) data (b). Transmission data (c).

Figure 4: Fracture imaging of acoustic data by using our proposed method (a), autocorrelation (b), standard RTM (c).

Figure 4a shows the final image using the proposed method. For comparisons, we also conduct two experiments with autocorrelation imaging condition (Artman et al., 2010) and standard reverse-time migration (RTM) with the assumption of known source information. Results are shown in Figure 4b and 4c. The proposed approach yields better imaging of fractures. If we perturb source location with small random errors, fractures become difficult to identify in the standard RTM image (not shown here).

For a more realistic scenario, in the second test, we generate a viscoelastic data set with both P- and S-wave attenuation effects (Zhu and Carcione, 2014). We set $V_s = V_p/1.7$ and $Q_s = Q_p$. Again, we run forward modeling twice using background velocity with and without fractures. Full data and transmission data, respectively, are shown in Figure 5a and 5c. In this case, we extract S-wave data by windowing and removing the energy before direct S-wave. Figure 5b show coda data that is obtained by subtraction between full and transmission data. Figure 6a shows the final image. For comparisons, we also conduct two experiments with autocorrelation imaging condition and standard reverse-time migration (RTM) with the assumption of known source information. Results are shown in Figure 6b and 6c.

Figure 5: Elastic shot gather data (a). The dashed line represents the direct S-wave arrivals. Scattering (Coda) data (b). Transmission data (c).

**Borehole arrays**

We adopt a P-wave velocity model (Figure 7) in the San Andreas fault observatory at depth (SAFOD) project for monitoring micro-earthquakes using a borehole array (Sava, 2011). Sources are randomly distributed along the San Andreas fault. The goal is to map the small fractures close to the well.

Figure 8 shows the results from our proposed approach (b,e), autocorrelation method (c,f), and standard RTM imaging (d,g). In the first row, we use a shorter receiver array. The images in Figure 8b and 8c are slightly worse than conventional RTM. However, Figure 8b has less artifacts. To improve the overall image quality, we increase the receiver array. Results are correspondingly shown in Figures 8e–8g. Again, our proposed approach gives us satisfied images with the agreement to standard RTM imaging. In the above tests source information are assumed to be perfectly known. Then, we randomly perturb our sources with the maximum variation of $\pm 130$ m. Standard RTM has difficulty locating fractures as shown in Figure 9b.
Figure 6: Fracture imaging of elastic data by using our proposed method (a), autocorrelation (b), standard RTM (c).

CONCLUSIONS

We present a workflow for diffraction imaging of passive seismic data. The main feature of this imaging method is that it is data-driven without the need for source information. We have shown two synthetic examples: surface and borehole passive monitoring cases. We found that our approach performed well compared with standard RTM imaging when assuming source information is exactly known. When we randomly perturbed source location with maximum 130 m, fractures were missing in the standard RTM imaging map but our approach was not influenced. This makes our approach appealing for passive seismic fracture imaging where source information is often not available or inaccurately estimated.

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Figure 7: P-wave velocity model. Red star denotes sources and black triangles are receivers.

Figure 8: Fracture imaging by using our proposed method (b,e), autocorrelation (c,f), standard RTM (d,g).

Figure 9: Fracture imaging with random errors of source location.