Passive seismic imaging of subsurface natural fractures: application to Marcellus shale microseismic data

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SUMMARY
Imaging and characterizing subsurface natural fractures that are common in the Earth crust has been a long-sought goal in seismology. We present an application of a 3-D passive seismic fracture imaging method applied to Marcellus shale microseismic data for mapping natural fractures. Unlike conventional seismic imaging methods that need source information, the proposed imaging method does not require source information and is flexible enough to apply to any passive seismic data where the source location is unknown or inaccurate. We first test our imaging approach using surface microseismic monitoring array data in 3-D synthetic examples. The finite-aperture fractures are designed by an open-source discrete fracture network software. Compared to conventional source-dependent fracture imaging, the proposed source-independent imaging approach produces superior images of fractures with less ambiguity. These tests also illustrate that the proposed method is less sensitive to the accuracy of background velocity and less affected by the sparse and irregular acquisition geometry which often cause acquisition-footprint issues in convention imaging methods. The final test in the field microseismic data from the Marcellus Shale (Pennsylvania) demonstrates the applicability of the proposed imaging method. Field data results indicate two clusters of east-northeast fractures existed above and below the hydraulic fracturing zone, which corroborates previous work that found two main types of faults in the study area.

Key words: Coda waves; Induced seismicity; Wave scattering and diffraction; Image processing.

INTRODUCTION
Natural fractures control much of the mechanical and transport properties (e.g. stress, flow pathways, permeability) of the rock system. It has been demonstrated that the presence of natural fractures in reservoir rocks significantly affect the process of hydraulic fracturing. Lamont & Jessen (1963) found that the capability of extending across pre-existing fractures with varying widths and orientations during hydraulic fracturing mainly depends on the direction of least-compressive stress and location of pre-existing fractures. In other words, natural fractures may likely contribute to the flow network or prevent the propagation of hydraulic fracture, and even potentially cause fluid leaking (Warpinski et al. 1998). Hence, accurate image of the natural fracture geometry is essential to help understanding the dynamics of the hydraulic fracturing process (Fig. 1).

One of the most powerful fracture imaging tools is seismic migration. Seismic migration cannot only delineate fractures in space and time, but also elucidate fracture properties from their effects on seismic wave propagation. When the scale of the fracture is smaller than the seismic wavelength, the scattering wave is relatively weak. Under this condition, equivalent anisotropic parameters of the fractured rock mass can be calculated using the effective medium theories, with which fracture density and orientation can be estimated from seismic reflection data (Tsvankin & Lynn 1999). When moderate or large size fractures in the subsurface are comparable to the seismic wavelength, the fractures most likely scatter the incident seismic waves and generate complex scattering coda waves, which has been observed in both the ultrasonic experiments (Groenenboom & Fokkema 1998; Groenenboom & Falk 2000; Pyrak-Nolte & Morris 2000) and field observations (Wills et al. 1992). To map such fractures in the subsurface, diffraction imaging methods, such as those developed in active-source seismic exploration, are promising as they are able to identify small subsurface objects, such as faults, fractures and sedimentary sequences.

The principle of the diffraction imaging method is that diffraction data, isolated from seismic reflection data, is applied to an imaging condition to reveal the diffraction edges. In the framework of traditional seismic migration imaging techniques (post- or pre-stack migration), various diffraction imaging methods have been developed...
In a companion paper, Zhu (2019) presents a concept of using primary transmitted and diffracted data to map fractures and proves its validity using 2-D synthetic and ultrasonic data sets. First, he advocates dealing with single phase $P$ wave (or $S$ wave) using the acoustic wave equation. Second, instead of processing converted $S$-wave data, he utilized diffraction data. This method is source-independent, i.e. no requirement of the source location. He shows that the proposed diffraction imaging gives results superior to that of source-dependent imaging even assuming that source information is exactly known. When source locations are inaccurate, fractures are missing (defocusing) in the source-dependent seismic image but mapped in the source-independent image. This is appealing for passive seismic data where source information is often not available or inaccurately estimated.

In this paper, we extend Zhu’s method to 3-D and formulate a 3-D source-independent fracture imaging method (referred as SIFI hereafter) which is applicable to sparse and irregular field microseismic data. We first test our approach using two 3-D synthetic examples to show the advantages of the proposed SIFI method on fracture imaging. We then investigate the defocusing issue when using inaccurate source locations as well as the footprint artefacts caused by the irregular and sparse acquisition in both methods. Finally, we examine a 3-D field microseismic data that was collected during a hydraulic-fracture stimulation of the Marcellus gas shale in Washington County, Pennsylvania, USA to map natural fractures in the studying area. We further compare the results with other studies and discuss the reasonableness of the obtained high-resolution fracture images.

**METHODOLOGY**

In this section, we briefly review the methodology of the conventional SDFI and SIFI. Then, we present the workflow of the SIFI method.

Seismic wave scattering is ubiquitous when waves propagate in the heterogeneous Earth media. The scattered wave data is generated by scatterers, e.g. faults/fractures, which act as the secondary sources according to Huygens’ principle (Fig. 1). In particular, when the seismic wavelength is comparable to the size of heterogeneous scatterers in the subsurface, the scatterers will generate complex scattering coda waves in the recorded seismograms. Therefore, the recorded seismic data at receivers can be decoupled as

$$d(r,t|s) = d_{\text{rec}}(r,t|s) + d_{\text{scat}}(r,t|s),$$

where $r$ stands for receiver locations, $s$ represents the source, $d$ is the recorded data, $d_{\text{rec}}$ is the recorded transmitted wave data propagated from the source to the receivers in the background medium, and $d_{\text{scat}}$ is the recorded scattered wave data.

To image the fractures (scatterers), the conventional SDFI procedure (e.g. reverse time migration) contains two steps of wave propagation simulations. One is the back-propagation of the scattered data $d_{\text{scat}}$ to reconstruct the scattered wavefield propagating from the fractures to receivers, which is referred as receiver-side wavefield; the other is the forward propagation wavefield from the source which is called as source-side wavefield (the source locations have to be known). The imaging condition $I(x)$ consists of zero-lag cross-correlation between the source-side and receiver-side wavefields at every image location in the subsurface space (Claerbout 1985), which can be expressed as

$$I(x) = \sum_s \int u_s(x,t|s)u_t(x,t|r)\,dt,$$

(Landa & Keydar 1998; Khaidukov et al. 2004; Popovici et al. 2015; Merzlikin et al. 2017), which potentially image subseismic-scale fractures (Popovici et al. 2015). All those seismic imaging methods require source locations. In post-migration procedure, source locations are used for common midpoint (CMP) gather sorting, while sophisticated pre-stack migration is to cross-correlate source-side wavefield and receiver-side wavefield to form a fracture image (Claerbout 1985). Hence, we name them source-dependent fracture imaging methods (referred to as SDFI hereafter). Given that the passive seismic source location is not directly available, application of such SDFI methods to microseismic data is not straightforward. One solution is to locate hypocentres of microearthquake events before migration (Zhang et al. 2009; Reshetnikov et al. 2010). However, accurate predictions of the source location in passive seismic applications (microseismic or earthquakes) are still challenging, and the errors of the source location are unavoidable, even with sophisticated source-location methods (Waldhauser & Ellsworth 2000; Zhang & Thurber 2003; Huang et al. 2017). Defocusing or missing imaging of the pre-existing fractures can be caused by the inaccurate source locations (Zhu 2019), which makes the existing SDFI methods not applicable to passive seismic data directly.

Recent development of using the interference between different types of wave phases (Nihei et al. 2000; Xiao & Schuster 2009; Shang et al. 2012; Shabelansky et al. 2017) may give us another solution. However, all those imaging approaches involving processing converted $S$-wave pose restrictions to demand not only $P$-wave velocity model but also $S$-wave velocity model which is rarely available for imaging. In addition, dealing with $P$ and $S$ waves by solving elastic wave equation requires a large amount of computational cost, especially in large-scale 3-D cases.

**Figure 1.** An illustration of surface microseismic monitoring in hydraulic fracturing and the existence of induced (blue lines) and natural fractures (black lines). Hydraulic fracturing induces microseismic events (red dots) which propagate outwards (red curves). Some passing through natural fractures will likely generate scattering waves (yellow curves).
where $u_s$ is the source-side wavefield propagating from source ‘s’ to each image point $x$ and $u_r$ is the receiver-side wavefield backpropagating from receiver ‘r’ to each image point $x$. If Kirchhoff pre-stack depth migration is applied, we need to replace the wave propagation simulation by ray tracing to compute ray paths. It is clear that both source and receiver information are required in eq. (2). Because the source–receiver geometry information is available in active-source seismic applications, it is very straightforward to implement the SDFI method. However, in passive seismic applications, the source information (including the source signature, origin time and source location) is usually unknown or inaccurately estimated. Best estimation of the source location may still suffer from errors of tens or hundreds of meters. Previous studies with 2-D synthetic models (Zhu 2019) show that the magnitude of 50 m of location error leads to defocusing of fractures in the seismic image. Consequently, the conventional SDFI technique may not be optimal to process passive seismic data.

As illustrated in Fig. 1, in passive seismic data, the scattered waves are generated by a scatterer when the transmitted wave is passing through the scatterer. Then the scattered waves propagate forwards following the transmitted wave. In terms of the reciprocity of wave propagation, both transmitted waves and scattered waves have spatial and temporal coincidence at the scatterer if we reconstruct the two wavefields by back-propagating (or ray tracing) the two data sets separately (Zhu 2019). Since the principle of seismic imaging is to find the spatial or temporal coincidence between two or more wavefields at each possible imaging location (Claerbout 1985), the scatters can be imaged by zero-lag cross-correlation of the two back-propagated wavefields expressed as:

$$I(x) = \sum_s \int_{t_1}^{t_2} u_{\text{dir}}(x, t | r) u_{\text{sc}}(x, t | r) dt,$$

where $u_{\text{dir}}$ is the back-propagation wavefield of transmitted wave data and $u_{\text{sc}}$ is the back-propagation wavefield of scattered (diffraction) wave data.

The main difference between two imaging conditions in eqs (2) and (3) is that, the SDFI method in eq. (2) requires both source-side forward propagation and receiver-side backward propagation while the SIFI method in eq. (3) only needs receiver-side backward propagation of transmitted wave data and scattered data. Thus, SIFI is source-independent and is free of source parameters (source signature, origin time and source location). By using only back-propagation wavefields from known receivers, the SIFI method helps to avoid the defocusing effect of source location uncertainty and is able to tolerate, to some degree, the inaccuracy of the imaging velocity model (Xiao & Schuster 2009; Zhu 2019). In addition, since $P$- or $S$-wave data is back-propagated using the acoustic wave equation, only the $P$- or $S$-wave velocity model is required and the computational cost is much lower compared to using the elastic wave equation.

To more clearly illustrate the procedure of the 3-D SIFI method, we briefly outline the workflow in Fig. 2(a). The first step is to extract the transmitted waves ($P$ and/or $S$ wave) and the corresponding scattered waves from seismic data. For simplicity, we use a simple subtraction in synthetic tests and manual picking in field data to accomplish data separation (detailed procedures are presented in numerical examples section). The median filtering (Zhu 2019) and plane-wave decomposition method (Taner et al. 2006) are alternative separation methods. The second step is to construct a smooth background ($P$ and/or $S$ wave) velocity model by using a priori information (e.g. obtained from sonic well logs or traveltomeography) for back-propagation of the prepared two data sets in step 1. The third step is to back propagate transmitted wave data and scattered data at receivers through the background velocity model, respectively. The last step is to apply the imaging condition (eq 3) to the two backpropagated wavefields derived from step 3 to construct an image of scatters, and then sum over all the event gathers to produce the final stacked image. For better comparison, we also outline the workflow of the SDFI method in Fig. 2(b). It is obvious that after data sorting, the SDFI uses scattered wave data to generate back-propagation wavefield and forward propagate the source to generate the source-side wavefield instead of back-propagating the transmitted wave data in SIFI. The computational cost of the proposed SIFI method and the SDFI method is about the same.

In post-processing, we apply the Laplacian filter to eliminate the low wavenumber noise and then normalize the image $I(x)$ by $\text{sgn}(I(x)) I^2(x)$ to enhance the imaged scatters, where the symbol ‘sgn’ is the sign function.

**SYNTHETIC EXAMPLES**

In this section, we show two synthetic examples to demonstrate the validity and effectiveness of the proposed 3D SIFI method on imaging natural fractures. In synthetic tests, the true velocity models are composed of two components: background velocity model and fractures. The background velocity model will be used for all imaging methods. Finite-aperture fractures with arbitrary azimuth are generated by an open-source discrete fracture network software (Fadakar et al. 2013). All fractures are produced with a thickness of one grid size, which is about 20 m and is much shorter than the seismic wavelength we used in simulations. We assume that seismic velocity of the filled material inside fractures is 2.5 km s$^{-1}$. We employ a 3-D finite-difference acoustic wave modelling scheme to generate the synthetic microseismic data. The finite-difference scheme is sixth-order accurate in space and second-order accurate in time. The same code is used to back-propagate the receiver-side wavefield from receivers in the time domain.

**Two-fractures model**

In the first test, the true velocity model consists of a constant velocity gradient (as the background model) and two fractures as inclusions (Fig. 3a). Fig. 3(b) shows the top view of the two fractures. To synthesize microseismic data, 81 microseismic events are regularly distributed in the subsurface at the depth of 0.8 km (purple dots in Fig. 3a). The source function is a Ricker wavelet with the dominant frequency of 15 Hz. A star-shape acquisition array is deployed on the surface to record the microseismic data (black dashed line in Fig. 3a). The acquisition survey consists of six lines and a total of 600 receivers. The size of the 3-D model is 2 km $\times$ 2 km $\times$ 1 km. The grid size is 20 m $\times$ 20 m $\times$ 10 m and the grid numbers are 100 $\times$ 100 $\times$ 100. Fig. 4 shows a gather profile for one of the synthetic microseismic events (red circle in Fig. 3a represents the source location). According to eq. (1), the data are divided into two components: the direct wave component (Fig. 4b) and the scattered wave component (Fig. 4c). In synthetic tests, since the background model is known, we run forward modelling with the background velocity model to generate transmitted wave data. Then we subtract the transmitted wave data from the observed data to acquire the scattered wave data. To visualize the 3-D imaging results, we show the isosurface image of fractures. The procedure of generating isosurface is that: we first scan the whole imaging domain and define a threshold with the value of 95 percent of the maximum amplitude.
in the image domain, then we use the defined threshold to form the isosurface. If the scanning results are not acceptable, we reduce the threshold value by 5 percent and scan again until the scanning results are meaningful to geological concept.

Fig. 5 shows the SDFI and SIFI imaging results overlaying on the true fracture shape denoted by black blocks. Both SDFI and SIFI methods are able to roughly image two fractures (red blocks). The SIFI imaged fractures with less spread-out have better agreement to true fractures. Two horizontal slices are also extracted from the two 3-D image volumes at different depths (Fig. 6). The image quality of the SIFI method is better than that of SDFI method, especially greater depths (Figs 6e–g). While there is only one fracture in the depth slice of 0.5 km (Fig. 6e) the SDFI result shows an artificial fracture (red dashed-line circle in Fig. 6f). This artefact is probably caused by inaccurate migration velocity. Since the migration velocity model contains no fractures, the forward wavefield from source and the backward wavefield from receivers both propagate at a higher speed than its original velocity when passing through the fracture zone. Hence, two wavefields still coincide but at a deeper zone in the SDFI image. In contrast, the SIFI imaging results show one fracture with very weak noise (highlighted in Fig. 6g). Since the proposed SIFI method simultaneously back propagates two data sets from receivers, the two corresponding wavefields always accompany each other even with an imprecise migration velocity model.

Note that the accurate microseismic source location is assumed in the SDFI test, which is an ideal situation. According to Zhu (2019), if the errors of the source location are introduced, the fractures are missing in 2-D SDFI results. What might happen in the 3-D case? To test the 3-D scenario, we rerun the SDFI imaging with perturbed source locations by adding a random perturbation into true source locations along depth direction (maximum 100 m). The results are shown in Figs 6(d) and (h). With source location errors only in the depth direction, the fractures are barely able to be identified in the
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Figure 4. (a) P-waveform gather profile from one microseismic event in two fractures model test; (b) the transmitted P-wave data; (c) the scattered P-wave data.

imaging results. The defocusing and artificial noise blur the image of fractures severely. The results show that the SDFI method is greatly sensitive to the accuracy of source locations in the 3-D case. However, the proposed SIFI method is immune to those location errors.

Multifractures model

In the second test, we increase the complexity of fracture network, e.g. multiple fractures, connected fractures, different sizes and dips, to better represent a realistic case. We choose a field microseismic monitoring survey in a hydraulic fracturing experiment in Marcellus shale. The microseismic monitoring array at the surface is shown as black lines in Fig. 7(a). The array consists of 10 lines and totally 1082 stations. The background velocity model is generated from a 1-D sonic well log (Fig. 7a). Six fractures are randomly generated and inserted into the background velocity. Again, seismic velocity of these fractures is set to 2.5 km s$^{-1}$. The zoomed-out fracture network model is shown in Fig. 7(b). The size of the velocity model is approximately $4.9 \text{ km} \times 5.66 \text{ km} \times 2.16 \text{ km}$. The grid size is $24.384 \text{ m} \times 24.384 \text{ m} \times 15.24 \text{ m}$ and the grid numbers are $201 \times 232 \times 142$. In total, 80 microseismic events are used in this test (red dots in Fig. 7a). All the events are located at the depth of $2.148 \text{ km}$ and equally distributed along nine horizontal wells. The source function is a Ricker wavelet with the dominant frequency of $15 \text{ Hz}$. Following the same strategy in the previous section, we divide the synthetic data into two components: transmitted wave data and scattered wave data.

Figs 8(b), (d), (i) and (k) show the horizontal slices of image results produced by both SDFI and SIFI methods. The SIFI imaging result shows a better and cleaner image of the fractures. Subwavelength fractures are visible in the horizontal slices. The SDFI
result show strong artificial noise that is possibly caused by relatively irregular and sparse microseismic data.

Not surprisingly, the acquisition geometry (whether it is regular/irregular and dense/sparse) influences the performance of the SDFI method. Sparse data will likely cause the incomplete wavefield stacking comparing to denser receivers. To test whether the proposed SIFI method is also sensitive to the acquisition survey, we test two scenarios: 1) sparser acquisition geometry. We reduce the total receiver numbers to 541 by picking one another receiver in each array in Fig. 7(a). 2) denser acquisition geometry. We use a regular acquisition geometry that consists of 100 receiver lines with 11 500 receivers (The receiver lines are evenly distributed along X direction with an interval of 48.768 m, and 115 receivers are evenly distributed along each receiver line), although this is not realistic in practical microseismic monitoring. The velocity model and sources are still the same as that in Fig. 7(a).

Figs 8(c), (e), (j) and (l) show the SDFI and SIFI image results for the sparse geometry. With irregular and sparser data, the acquisition footprint issues become more severe in SDFI results and the artificial noise largely blurs the image, especially in the deeper depth slice (Fig. 8j). In contrast, the SIFI results preserve high-quality images of fractures in the shallow depth slice. Slightly more artefacts appear in the deeper depth slice.

In scenario 2, we plot the traces of SDFI and SIFI results in Fig. 9. As expected, the SDFI results in Figs 9(a) and (b) have been greatly improved by the presence of dense and regularly spaced data. However, it is still clear that the SDFI result has some shifts to the accurate fracture position, especially at shallow depths. The SIFI results in Fig. 9 better image the true fractures and present the superior resolution of fracture images comparison to the SDFI results. One possible reason is that, due to the inaccuracy of the background velocity model (without fractures), the source-side wavefield (implemented
Figure 7. (a) The background velocity model derived from 1-D well log with six fractures and the acquisition survey system. The red dots stand for sources laying at the depth of 2.148 km, black lines stand for receiver arrays on the surface, and the blue thin slices represent fractures. (b) The zoomed fractures.

Figure 8. Horizontal slices at the depth of 1.0 km of (a) the velocity model, (b) the SDFI result and (c) the SDFI result with sparser data, (d) the SIFI result, (e) the SIFI result with sparser data. Horizontal slices at the depth of 1.38 km of (f) the velocity model, (i) the SDFI result and (j) the SDFI result with sparser data, (k) the SIFI result, (l) the SIFI result with sparser data.

Figure 9. Traces comparison of the velocity model (black), the SDFI imaging result (red) and the SIFI imaging result (blue) (a) at the depth of 1.0 km and (b) at the depth of 1.38 km using regular and dense data.
APPLICATION TO REAL MICROSEISMIC DATA IN MARCELLUS GAS SHALE

Lastly, we apply our method to a microseismic data set collected during a hydraulic-fracture stimulation of the Marcellus gas shale in Washington County, Pennsylvania, USA (Fig. 10a). The approximately 30 m thickness of Marcellus gas shale is at a depth of about 1.9 km. The hydraulic-fracturing experiment involves five wells drilled from a single pad. Surface receiver arrays are installed to monitor the stimulation job (the black dashed lines in Fig. 10b). The surface arrays consist of 10 ‘arms’ and a total of 1082 single-component geophones. Because of field permitting issues, the deployed array was not in an ideal symmetric star-shape. The microseismic data were recorded for one month during the stimulation at a sampling interval of 2 ms.

In the pool of approximately 16 000 microseismic events (Tan & Engelder 2016), 80 relatively strong events are selected to use for imaging the natural fractures. Preprocessing of the raw data occurred in Promax and included: normalization, amplitude compensation and AGC, and application of a bandpass filter (8–10–40–50 Hz) to eliminate low and high-frequency noise unrelated to microseismic signals (Fig. 11). Direct P and S waves as well as diffractions are identified. As mentioned above, the acoustic wave equation is used to back-propagate the recorded data. Hence, either P- or S-wave data can be used for back-propagation. Because S-wave velocities are not available, P-wave data are selected where the 1-D P-wave velocity model is derived from a well log (Fig. 10b). Then the direct P- and S-wave arrivals were picked. With these picks, we carefully window out direct P-wave data and extract data between direct P and S arrivals and treat them as diffraacted P-wave data. Although converted P−S waves likely exist in diffracted P-wave data, those converted waves should not be imaged or only produce some artefacts since P-wave velocity is applied to back-propagate the data.

We’ll demonstrate this in a synthetic example in the Discussion section.

Fig. 12 shows the 3-D image of natural fractures. Several vertical fractures are identified in two regions (Red blocks in Fig. 12a), one region is at the top of Marcellus shale (outside of green dashed-line box in Fig. 12a), the other is at the bottom of Marcellus shale to the extent of the underburden formation (see Fig. 12a). The length of single red blocks (imagined fractures) are varying from approximately 50 to 150 m. The major imaged fractures are interpreted as east-northeast (green lines in Fig. 12b). According to Engelder et al. (2009), the studying region of Appalachian Basin in Fig. 10(a) is well known for two sets of vertical joints: J1 in the east–northeast direction and J2 in the north–northwest direction. Therefore, we interpret the imaged east-northeast fractures possibly as J1. Another imaged fractures in the left-corner seem to be consistent with J2 (Purple line in Fig. 12b). Two fracture clusters appear to break out of the gas shales and populate the rock above those gas shales (or beneath those gas shales for J1). Those findings may provide seismic evidence on the existence of J1 and J2 fractures in the Appalachian Basin. We also plot horizontal slices of the results in Fig. 13. The high amplitude images circled by black ellipse again indicate the existence of fractures.

Microseismic events (grey dots in Fig. 12) from the first and last hydraulic fracturing stages are overlapped on the imaged fracture clusters. It is clear that many microseismic events inside or around the imaged fractures migrate upwards from the hydraulic fracturing zone (green dashed-line box in Fig. 12a). Such a spatial distribution of microseismic events could imply that hydraulic fracturing may reactivate natural fractures and cause microseisms. This consequence would likely influence estimates of stimulated reservoir volume and the future possibility of production (Downie et al. 2010).

NUMERICAL VALIDATION OF FIELD DATA RESULTS

To verify the results of imaged fractures with such a seismic acquisition, we set up a synthetic test. We use the imaged fractures in Fig. 14(a) and the 1-D well-log background model (Fig. 10b) to construct a synthetic velocity model. The wave speed of the fractures is 2.5 km s$^{-1}$. The locations of those 80 selected microseismic events are provided by Schlumberger and we synthesize the P-wave microseismic data. The dominant frequency of the filtered field data is about 25 Hz. To accommodate the velocity model (shown in Fig. 10b) to satisfy the numerical simulation stability conditions, we choose a Ricker wavelet with a dominant frequency of 20 Hz as the source function. The receiver array in Fig. 14(a) is kept the same as the field geometry setup in Fig. 10(b). Fig. 14(b) shows the synthetic data gather profile from one event. Diffractions are clearly modelled.

Fig. 15 shows the SIFI result. Most of the fractures are imaged with a slightly larger shape. We can identify two clusters of fractures and their locations are close to the ground truth in Figs 12(b) and 14(a). However, a few small fractures (small red blocks in Fig. 14a) are not mapped in Fig. 15, where the size of those fractures are less than 50 m (the wavelength is about 250 m). The possible reason is that the inaccurate source location information, the velocity model and low-frequency source wavelet for generating our synthetic data prevent from imaging of small fractures in such an acquisition geometry. Nevertheless, this result confirms that the SIFI method applied to field data without the availability of source locations seems to be able to map such small fractures (Fig. 12b).

DISCUSSION

Source distribution effects

We have presented a new 3-D SIFI fracture imaging technique to use microseismic full waveform data to map subsurface natural fractures. Although SIFI does not require knowledge of source locations, the image quality of SIFI still relies on the azimuth coverage and illumination of seismic acquisition with respect to the targeted area. In the two-fractures model example, all the sources are regularly distributed over the X–Y plan beneath natural fractures, which makes those fractures well illuminated. In real hydraulic fracturing monitoring, microseismic sources may be clustered into small areas along the hydraulic fracturing wells or induced fractures, which always cause inadequate or unbalanced illumination. To test the performance of SIFI method under such source-receiver geometry, we modify our first synthetic example by changing the distribution of sources. To be more practical to the field situation, we randomly...
Figure 10. (a) The map of the hydraulic fracturing site. Surface faults denoted by red arrows are visible in east-northeast direction; (b) The background velocity model and the receiver arrays represented by black lines.

Figure 11. Seismogram of one relatively strong event in the field data. Direct P and S waves and diffracted waves in most of the monitoring array are clearly observed.

Figure 12. Imaging results with (a) 3-D view and (b) top view. The red blocks stand for imaged fractures, grey dots represent the microseismic events that occurred at the first and last hydraulic fracturing stage using three wells, black dashed lines are the horizontal wells, the green box indicates the fracturing zone, green and purple lines label the primary directions of imaged fractures.

generate 80 sources to replace the regularly distributed sources (magenta dots in Fig. 16a, and the depth difference among sources is less than 200 m). All the sources are nearly linearly distributed along the line $X = 0.5$ km and are almost at one side of the two fractures (we mark them as fracture 1 and 2 in Fig. 17a). We test the sensitivity of the SIFI method to the source position by shifting all sources along depth direction in three scenarios: i) shifting all sources below the two fractures to a depth of $\sim$700 m; ii) shifting all sources
Figure 13. The horizontal slices of the SIFI result at depths of (a) 1.75 km, (b) 1.78 km, (c) 1.9 km and (d) 2.0 km.

Figure 14. (a) Synthetic test geometry. The black lines stand for the receiver lines, blue dots stand for the source locations for modelling synthetic data and the red blocks stand for the imaged fractures; (b) Synthetic seismogram of P-waveform from one event.

to a depth of ∼400 m beside the two fractures and iii) shifting all sources above the two fractures to a depth of about 150 m. Among tests, all other parameter settings are kept the same as those of the first two-fractures model example.

Fig. 17 shows the SIFI results of the three scenarios. Due to the linear distribution of sources in Fig. 16(a), the illumination quality is largely decreased. As anticipated, the image quality of Figs 17(b) and (g) is slightly reduced comparing to Figs 6(c) and (g). The image results (Figs 17b and c) are comparable in scenarios a and b. Although all sources are beside the fractures in the scenario b, most scattered waves can still be recorded by receivers at the opposite side of the sources. The image result in Fig. 17(b) is contaminated by high amplitude spots that are sources. A similarity between Figs 17(b) and (c) is that fracture 1 is better imaged than fracture 2. The reason may be that the dip angle of fracture 1 is larger and can be evenly illuminated by both sides of sources. The imaging result in scenario c is worse than that in scenarios a and b, but the two fractures can still be identified in the shallow region in Fig. 17(d). It is easy to imagine that when sources and receivers are both above natural fractures, to receive scattered waves needs downhole arrays or longer offset surface arrays. Hence, in scenario c, fewer scattered waves are recorded using the same source–receiver geometry.
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Converted-wave effects

In principle, using different types of wave phases (e.g. primary and converted-waves) is possible to map the discontinuity interface, which has been demonstrated by several authors (Nihei et al. 2000; Xiao & Schuster 2009; Shang et al. 2012; Shabelansky et al. 2017). This is because the fracture serving as secondary sources can generate converted waves when primary waves pass through the fracture. Here we argue that several difficulties may limit their applications. For example, identifying different phases (in particular, converted waves) in real microseismic data is not trivial; S-wave velocity model is rarely available in practice; and using an elastic propagator is inefficient for imaging problems. Instead, SIFI based on the acoustic propagator can use either P waves or S waves with the corresponding coda waves to produce a fracture image (Zhu 2019). In the codas, since S waves are not considered in SIFI, it may impact more or less the fracture image. To illustrate the converted wave effects, we design a synthetic test. We take the same source–receiver geometry and P-wave velocity model as that in the two-fractures model example. The S-wave velocity model is generated by multiplying 0.6 to P-wave velocity. Then, we apply the elastic wave modelling to simulate the three-component data using P- and S-wave velocity models. Fig. 16(b) shows the vertical component of a gather profile for one of the microseismic events. We separate the direct P- and S-wave data from the scattered data (converted waves are embedded) by subtracting the transmitted P- and S-wave data by running the elastic wave modelling using the corresponding background P- and S-wave velocity models without fractures. After separation, scattered data still includes P waves, S waves and converted P and S waves. The SIFI results are shown in Figs 17(e) and (j). The results confirm our argument that the presence of S waves in the scattered data slightly affects the fracture image with a few artefacts. The possible reason is that the usage of P-wave velocity for SIFI imaging defocuses S-wave data so as to only produce a few artefacts.

Comparison with other microseismic methods and potential applications

SIFI differs from the state-of-art microseismic imaging methods that use direct P- and/or S-wave traveltimes or full waveforms to determine microseismic event locations to infer the geometry of induced fractures (Grechka & Heigl 2017). SIFI is based on observations of scattered data after direct waves from which we have derived an imaging condition of cross-correlating direct waves and diffractions. As a result, SIFI would only manifest the diffractors. SIFI also differs from the tomographic fracture imaging method (Geiser et al. 2012) which back projects the summation of trace over time to image very weak events to identify natural and induced fractures. They hypothesize that the weakness of natural (pre-existing) fractures/cracks under small stress variations and fluid pressure perturbation can cause these pre-existing fractures to fail. This tomographic method is similar to the state-of-art microseismic imaging method to search microseismic locations.

Wave-equation imaging methods to process full waveforms often pose restrictions on the dense source–receiver geometry that is rarely available for passive seismic experiments, in particular earthquakes. In our tests, we found that the proposed SIFI method is less sensitive to the sparseness of receivers. The SIFI imaging results are nearly identical between dense regularly spaced data and sparse irregularly spaced data when imaging multiple fractures. With the recent deployment of relatively dense seismic arrays to study fault zones (e.g. Ben-Zion et al. 2015), we anticipate the proposed method’s application to microearthquake events for mapping local faults. Because our proposed method does not require knowledge of the locations of microearthquake events, the proposed SIFI should lead to a better imaging and understanding of faults than previous passive seismic methods (Zhang et al. 2009; Reshetnikov et al. 2010).

Conclusions

We have presented a 3-D fracture imaging technique to use microseismic full waveform data to map subsurface natural fractures. The proposed SIFI method is data-driven and source-independent. Through a series of numerical tests using both synthetic and field microseismic data, compared to SDFI methods, we draw the following conclusions: (1) Natural fractures can be better imaged by the proposed SIFI method using passive seismic data without any source information. (2) The SIFI imaging method is less sensitive to the acquisition footprint issue in realistic 3-D geometry. The star-shape receiver arrays and microseismic sources should be sufficient enough to image natural fractures above or beside the sources. Wide-azimuth acquisition can help increase the illumination area, thus improve the image quality. (3) The field microseismic data example shows the feasibility and capability of the SIFI method. Our field data results may provide seismic evidence about two clusters.
of natural fractures J1 and J2 in the Marcellus shale formation. Besides microseismic monitoring data, this method can be potentially applied to local earthquakes with dense arrays for imaging faults.

ACKNOWLEDGEMENTS

The authors thank Range Resources, Microseismic Inc., Schlumberger and Gas Technology Institute for providing the field data set. The authors would like to thank Terry Engelder (PSU) and Natalie Accardo (PSU) for reading the draft to help eliminate all errors. We thank Yunhui Tan (PSU) for help on field data processing. We also thank Editor R. Plessix, A. Shabelansky and another anonymous reviewer for their constructive comments and suggestions that helped to improve the manuscript significantly. Funding for this project is provided by the startup funds from Department of Geosciences and Institute of Natural Gas Research at Penn State University. C. Huang was financially supported by the U.S. Department of Energy’s (DOE) National Energy Technology Laboratory (NETL) under Award No. DE-FE0031544.

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