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Quality Control of Microseismic Moment Tensors from Surface-Based Acquisitions

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Summary

Moment tensors from surface-based microseismic acquisition geometries are frequently used to infer the dynamics of hydraulic fractures. For example, these data yield estimates of the orientations of fractures in the subsurface, fundamental relationships on how hydraulic fractures relate to the seismicity they induce, and the orientations and dynamics of stress and strain. The nature of microseismic surface acquisition in low signal-to-noise environments and has necessitated different processing approaches to deliver moment tensors. We assess a couple of these approaches using synthetics and observe a bias towards so-called “bedding-plane slip” mechanisms when following our implementation of an imaging methodology. Using estimates of first motion amplitudes with signs recovers mechanisms without this bias, but may have a large sensitivity to noise. We describe how to assess the bias of the noise using first motions, and outline how to obtain a consistent dataset of moment tensors from such acquisitions. We outline the results of the implementation of our workflow.

Dataset

Our data and synthetic examples are from the near-surface acquisition of a zipper-frac in a North-American shale play during 4 days over which 20 stages were monitored. These data were recorded on a network of 69 shallow buried arrays, with stations deployed at four levels down to 27 m, as shown in Figure 1. Over the course of this time period, 14924 events were verified, of which 11200 were well-constrained and located. The majority of this activity was associated with slip on faults in an overlying formation, but a significant minority, 1396, could be associated with the growth of hydraulic fractures from the treatment. This association of frac- versus fault-related seismicity was done through an examination of the temporal and spatial relationships with the injection and reinforced through a template-matching based scheme to cluster events. The geometry from this array was also used in the simulations below to highlight the effects on methodology and numbers of stations on the biases and confidence of mechanisms.

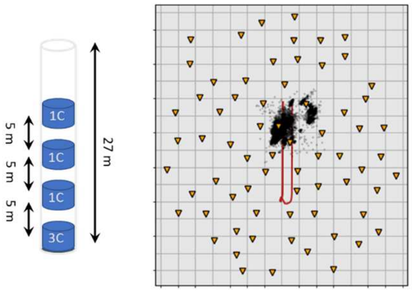

Figure 1 (left) Shallow borehole geometry and (right) of the treatment wells (red) and monitor wells (orange triangles) and event locations (black dots).

Imaging versus Inversion of Moment Tensors

Moment tensors from surface microseismic data (almost uniformly using only the first-arriving P-wave radiation on single-component geophones) can be determined through imaging-based (e.g. Chambers et al., 2014), template-matching (e.g. Diller et al., 2013), or more traditional inversions from measurements of polarities and amplitudes (e.g. Stanek and Eisner, 2013). This latter category of inversion is usually avoided as the signal-to-noise requirements of this particular datastream raise concerns on the impact of noise on the inversions.

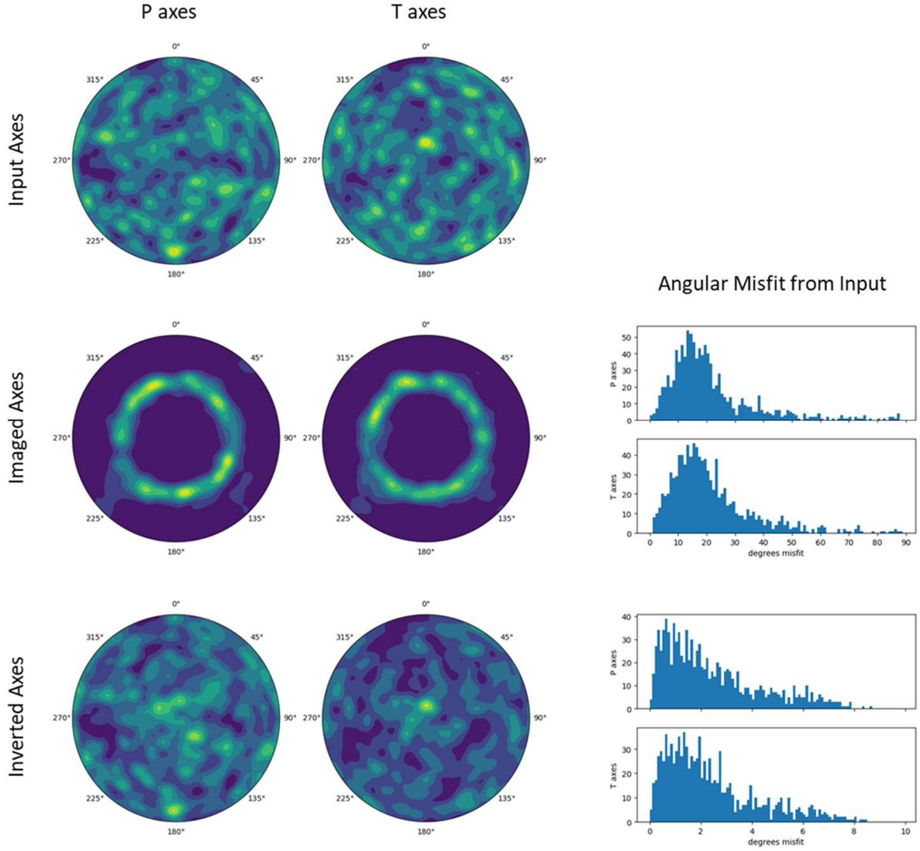

Figure 2 Lower hemisphere contour density plots of P and T axes from the 1000 input (left top), imaged (left middle) and inverted (left bottom) moment tensors. Note that the colourscale is independently assessed for each plot. Also show for the imaged (right middle) and inverted (right bottom) moment tensors is the angular difference between the input mechanisms. The horizontal scale differs on these plots, the imaged mechanisms show angular misfits up to 90º whereas the range for inverted mechanisms is restricted to 10º.

The choice of moment tensor processing methodology may introduce biases on the resultant mechanisms. We illustrate testing of a couple different approaches using synthetic data using the geometry shown in Figure 1, computed using a ray-theoretical approach, to show how biases may be detected in certain methodologies. Using a layered velocity model, we simulate 1000 moment magnitude 0, double-couple mechanisms with varying orientations, shown in Figure 2 through their compressional (P) and tensional (T) axes. A very small amount of white noise is added to each channel (RMS 1 nm/s) and the resulting data are imaged and inverted for moment tensors. We test two methods from the different families of moment tensor evaluation schemes mentioned above and adhere to the following nomenclature: “imaging”, referring to determination of the six components of the moment tensor in image space; and “inversion” indicating using measurements of polarities and amplitudes from the waveforms in a least-squares-based inversion for the moment tensor (following Strelitz, 1978). In both cases, the resulting moment tensors are forced to the best-fitting double couple for comparison (Strelitz, 1989), although the spurious non-double-couple components are usually negligibly small.

Figure 2 also shows the P and T axis from the imaged (middle) and inverted (bottom) moment tensors. While the recovery of the moment tensors is generally within a couple degrees from the inversions, the imaged mechanisms are biased towards P and T axes plunges of 45º, characteristic of the numerously-reported “bedding-plane slip” events described by a number of authors with a near-horizontal nodal plane complemented with a near-vertical nodal plane. We offer no direct refutation of these studies but we do note that the off-diagonal components of the moment tensor appear to be amplified resulting in the favouring of this kind of mechanism. We follow the suggestions of Chambers et al. (2014) to reweight the terms of the inversion but that does not suffice to reconcile this bias, and other, admittedly *ad hoc*, reweighting schemes introduce other biases that are similar in magnitude. Based on these results, we do find the biases in our implementation of the imaging-based moment tensor methodology to be unacceptable.

Amplitude and Polarity Estimation

Moving forward with an inversion methodology requires a large burden be placed on obtaining robust estimates of first motion. In our previous synthetic example, obtaining estimates of the first motion was trivially easy: 1nm/s is an extremely low RMS noise level and first motions for M0 events at normal treatment depths very frequently yield clear signals on overlying arrays. Enhancement of the first arrival therefore becomes extremely beneficial towards calculating the moment tensor. This enhancement can be accomplished through a combination of acquisition and processing steps. For example, Chambers (2018) describe an approach whereby semblance-weighted stacking across a “superstation” of hexagonally deployed geophone nodes in a local patch effectively attenuates the horizontally-propagating surface wave energy that is the main contribution to surface-recorded noise, while preserving vertically propagating signals from depth. However, such approaches need to be used with care, since the resultant mechanisms are sensitive to the relative amplitudes across stations (or superstations) and semblance-weighted stacking or field data does not necessarily preserve the amplitudes, even in a relative sense. Simple stacking will preserve the amplitudes, but not yield the added horizontal noise attenuation.

Additional information at our disposal to use for our moment tensor inversions is the time and location of the event, its moment magnitude, and the static corrections that optimally align our event. After applying some additional processing exploiting these data, we can measure amplitudes and enhanced signal-to-noise ratios corresponding to the time and location of the bright-spot in image space. We find that such procedures will align on the highest amplitude parts of the waveform associated with the first arrival, but not necessarily the peak associated with the first break. If this largest amplitude is opposite in sign to the direction of the first break, the recovered mechanisms is exactly opposite to the true mechanism. Knowledge of the source wavelet can help recover this sign ambiguity, but in its absence external constraints on the types of expected mechanisms or similarity with mechanisms with unambiguous first motions needs to be employed.

One of the primary advantages of using a least-squares inversion scheme for determining the mechanisms is that the stability and robustness of the mechanisms can be relatively well understood in terms of the inversion condition numbers. Additionally, the fit to the data can be very rapidly assessed using Pearson's R or other statistical measures. As such, confidence in the data can be estimated using standardized moment tensor parameters (e.g. Baig et al, 2016). Of particular interest in this low signal-to-noise environment is an assessment of how much significance can be assigned that a given mechanism is not explicable by noise. By running noise signals through the inversion, we can both assess the types of mechanisms that are represented by the noise as well as the (expected very poor) fit to the data. Using the distribution of Pearson's R from the noise allows for a confidence threshold to be related to a moment tensor based on its R value.

Moment Tensors Inversion Example

To highlight our workflow for mechanisms and the confidence that we can attach to the data, we return to the data from the hydraulic fracture shown in Figure 1. The locations of these data were determined through an imaging-based approach, described by Chambers et al., 2010, and their magnitudes were calibrated to moment magnitude following the procedure outlined in Baig et al., 2019. Inversions of noise data revealed that events with a Pearson correlation score above a threshold of R=0.34 can be considered to be statistically distinct from noise (see Figure 3): 8261 fault events and 769 frac events realized this bar. The fault related seismicity had remarkably consistent mechanisms, with high degrees of similarity observed on almost all events. Conversely, the frac-related seismicity featured a number of different mechanisms of families: one predominantly strike-slip and two normal mechanisms with different orientations (see Figure 4).

Discussion

We have presented how the result of our implementation of an imaging-based moment tensor methodology show a significant systematic bias to "bedding-plane slip" mechanisms. We show how such biases may be assessed and hope that such sensitivity analyses may be produced and diffused more routinely to help understand if there are indeed algorithmic biases that need to be accounted for.

By abandoning an imaging-based moment tensor inversion methodology, we need to have a detailed accounting for how noise influences the inverted moment tensors. The assessment of noise-based mechanisms allows us to assign confidence to field data based on the fits as measured through Pearson's R. We show how we have recovered a significant amount of data, slightly greater than 80% of the well-constrained locations, for the dataset that we examined.

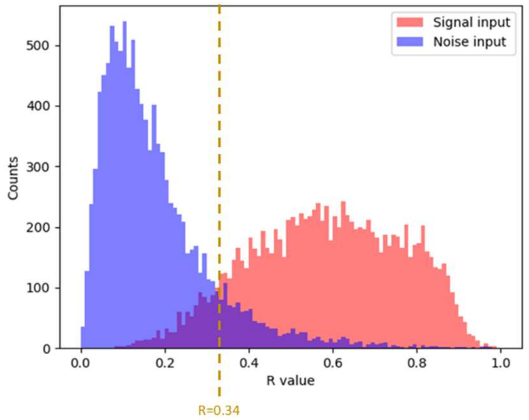

Figure 3: Determination of the significant moment tensors from comparison of the Pearson R values from signal and noise

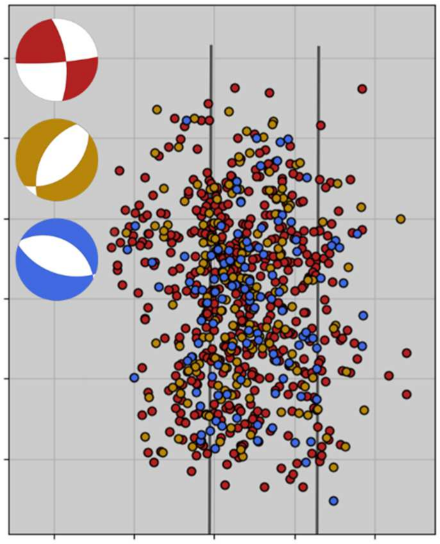

Figure 4. The distribution of frac-related seismicity coloured by the moment tensor family that they belong to. The average MT within the family is shown in the upper left

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