Distinguishing Operational Microseismicity in Western Canada from Induced Earthquakes

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Summary

The ToC2ME dataset provides a unique opportunity to investigate operational microseismicity and induced events in relation to a hydraulic fracturing experiment in a research-orientated project within Alberta. Previous efforts have identified ~25,000 microseismic events and located up to 18,500 of these using a stacked amplitude-envelope methodology, template matching and beam-forming techniques. However, most of the events identified are not thought to be directly associated with the operational fracturing procedure. Here, we use an STA/LTA algorithm and coincident trigger methodology to identify microseismicity. Our thresholds for detection are set reasonably low in order to detect as many events as possible, while minimising false alarms. We find many events with clear phase arrivals which have not been identified in previous catalogs of this seismicity. The amplitudes, inter-event times and frequency contents of the waveforms identified suggest a stable regime. Furthermore, we hope to use these events in a template matching procedure to further populate the catalog with low amplitude events which may be hidden by noise or temporal spacing, as some families of repeating seismicity have already been identified within this catalog by using this methodology.

Introduction

Hydraulic fracturing causes seismicity through the generation of tensile fractures by the injection of highly pressurised fluids into hydrocarbon-bearing reservoirs (e.g. Maghsoudi et al., 2018; Eaton, 2018; Schultz et al., 2017; Atkinson et al., 2016). Commonly, the term ``induced'' refers to any seismicity that is produced through anthropogenic activities (Keranen and Weingarten, 2018). Here, however, we use induced to mean seismicity which is generated due to increases in pore fluid pressure and stresses in close proximity to the reservoir (e.g. Ellsworth, 2013), and not that which is directly produced by operational fracturing within the geologic horizons of interest.

In recent years, the rates of large earthquakes (Mw>3) appears to have increased in relation to anthropogenic processes such as hydraulic fracturing experiments and waste-water injection (e.g. Atkinson et al., 2016). This not only has consequences for populations living in close proximity to these sites in terms of health and safety, but also for the large companies operating these stimulations, as regulations have now been bought in which force the shut-down of operations if seismicity exceeds certain thresholds. Typically, microseismic events associated with hydraulic fracturing have moment magnitudes of between -3 and +1, although most events occur with magnitudes less than zero (Warpinski et al., 2012). This makes them inherently difficult to monitor using sensors deployed at the surface.

The Tony Creek Dual Microseismic Experiment (ToC2ME) is a research-led project by the University of Calgary (UofC), in collaboration with a number of industry partners. The array consisted of 69 cemented shallow boreholes (only 68 produced viable data), each with one three-component geophone at 27 m, and three one-component geophones at 22 m, 17 m and 12 m respectively. These sensors continuously monitored a four-well hydraulic fracture experiment in the Kaybob-Duvernay region from 25 October to

15 December 2016 (Eaton et al., 2018). The Kaybob-Duvernay region is of particular interest as a number of large (> Mw 0) induced seismic events have been reported here, including one Mw 3.2 event during the period of acquisition.

Event detection using a stacked amplitude-envelope methodology across the entire array (68 boreholes) produced ~25,000 candidate events, which were visually inspected to identify events with high signal-to-noise ratios. From this, 15 template events were chosen and following Caffagni et al. (2016), a match-filtering detection algorithm was applied allowing the identification of ~14,000 microseismic events (Eaton et al., 2018). 4083 of these events showed clear P- and S- wave arrivals, with Mw -1 to Mw 3 and hypocenter locations in a number of distinct clusters. However, since only 15 template events were used for this identification, the results are inherently biased. Eaton et al. (2018) note that there are likely to be a plethora of events not identified using this technique, since many are likely to be low amplitude events embedded in noisy data. These events probably have small magnitudes (Mw < 0.5) and are most likely related to operationally induced seismicity during the completion stages (Eaton, 2018), which are notoriously more difficult to detect due to their small moment magnitudes (Warpinski et al., 2012).

In order to improve the available catalog, a beam-forming technique based on amplitude ratios (Verdon et al., 2017) was used on the ~25,000 detected candidate events, allowing the successful location of 18,472 events (Igonin et al., 2018). This represents approximately 60% increase in the number of located events from the original catalog, with these events clearly mapping a number of distinct linear subsurface features at depth. However, commercial processing of this dataset has identified >50,000 microseismic events, in comparison to the identification of ~25,000 by Eaton et al., 2018.

Identifying Operational microseismicity at Tony Creek

In order to reduce the effect of the template bias, we propose the use of a two-stage analysis whereby firstly microseismic events are detected using simple amplitude ratios across the entire borehole network, and secondly then use a template matching technique, with templates being based on all events detected in the first stage. REDPy uses a simple amplitude ratio algorithm to detect seismic events from the continuous record on a multiple station network and then determines whether any events are similar by identifying all events over a given cross correlation threshold (Hotovec-Ellis and Jeffries, 2016). In our case, we are interested in both the events which are classified into families, and events which do not (known as orphan events) as templates are be generate from both. REDPy allows us to identify both types of events.

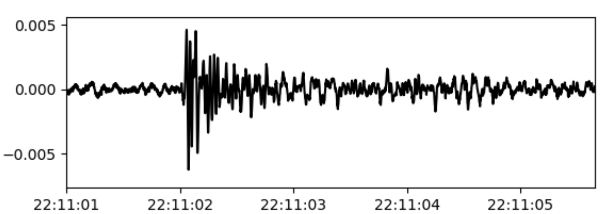

Figure 1a: Waveform identified by REDPy in this study that was also included in the previous ToC2ME catalog.

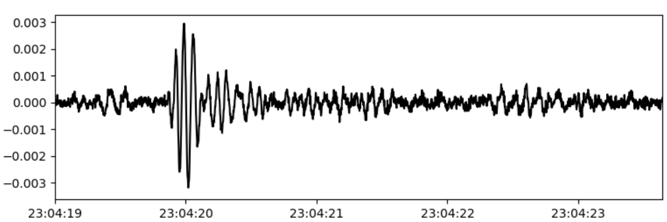

Figure 1b: Waveform identified by REDPy in this study that was not included in previous ToC2ME catalog. Clear phase arrivals can be identified in this waveform making it a good candidate for a successful location.

The REDPy algorithm for event detection consists of a trigger based on an short-term amplitude to long-term amplitude ratio (STA/LTA) algorithm and is better able to detect weak seismicity, compared to a simple amplitude-only trigger mechanism (Trnkoczy, 2002). We use an STA window of 0.2 seconds (100 samples), an LTA window of 1 second (500 samples), and a trigger threshold of 2.5, on only the Z-component of the 3-C sensors across the array, totalling 69 stations. The continuous data is bandpass filtered between 10 and 70 Hz to remove spurious noise, similar to Eaton et al. (2018), however we take lower frequencies into account than they do. In order for an event to be detected, we require a coincident trigger on at least 10 stations. This ensures that even small events which may only register on proximal stations are identified, but will allow us to keep errors small in the location analysis through a greater number of picks. An obvious trade-off exists between the length of the windows and the trigger thresholds, and in our case we have kept our parameters low in order to try and detect as many events as possible. Visual inspections confirms that values we have chosen appear to balance well between false triggers and missed events.

Results and Observations

Our methodology using a coincident trigger from multiple stations across the network identifies many microseismic events which have previously not been included in the ToC2ME catalogues of events (e.g. Eaton et al., 2018). Many of these events show clear P- and S- wave phase arrivals (Figure 1), and therefore would be good candidates for successful location analysis using conventional methods. There is some evidence of clustering of the microseismicity with time, with bursts of events interspersed with periods of quiescence lasting up to ~2 hours. Preliminary results of spectral and temporal characteristics of the microseismicity identified suggests that the RMS maximum amplitude, the inter-event time and the frequency content of waveforms remain fairly constant with time (e.g. Figure 2). Waveforms are dominated by high-frequency content (between 30 and 70 Hz, as indicated by values greater than zero in the lower panel of Figure 2), and the minimum inter-event time reported is 1.5 seconds.

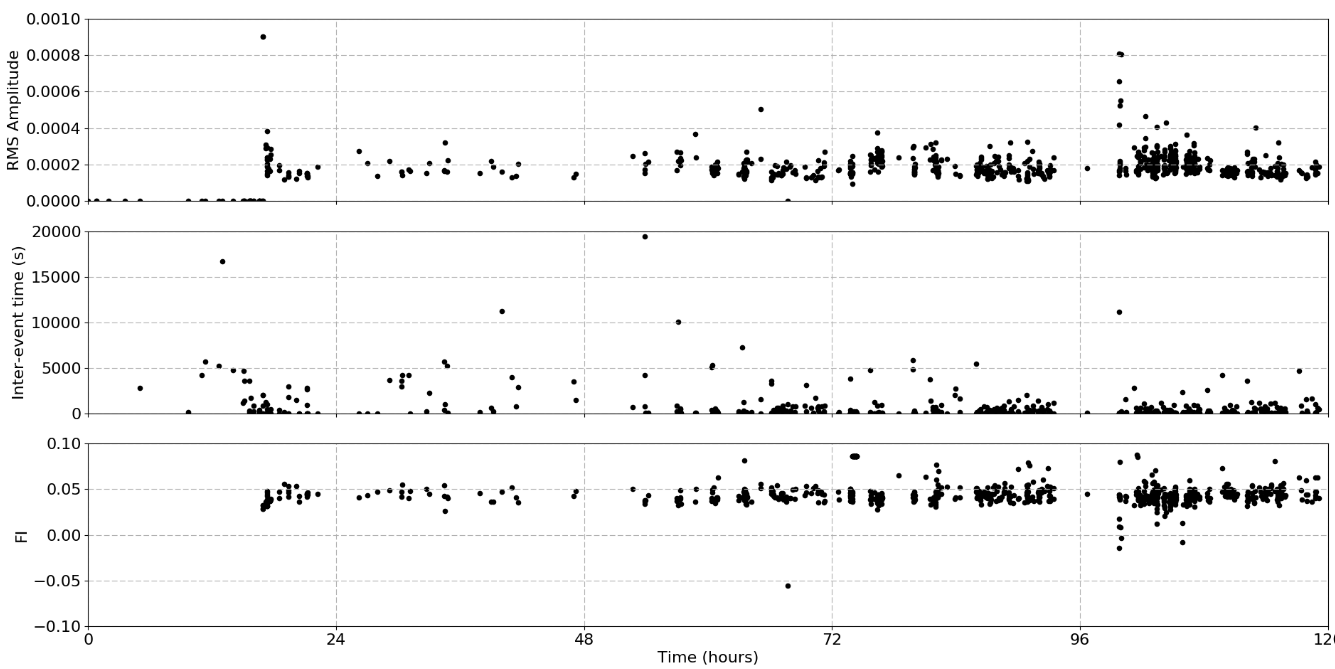

Figure 2: Waveform analysis across a 5 day period of 671 events. *Upper:* RMS maximum amplitude of events. *Middle:* Inter-event time (seconds). *Lower: Frequency content of the waveforms (Frequency Index). FI > 0 indicates events dominated by energy between 30 and 70 Hz, FI < 0 indicates events dominated by energy between 10 and 30 Hz.*

REDPy has the inbuilt capability to perform cross correlations on detected events in order to determine waveform similarity. This is advantageous as it allows us to speculate on different families of events and their durations without having to undertake a full template matching procedure. REDPy identified one dominant family, which contained over 100 similar events, in addition to two smaller families. Further analysis will be undertaken into the similarities of waveforms when we use template matching to further enhance the number of detected microseismic events.

Discussion, Conclusions and Future Work

The identification of microseismcity using a simple amplitude ratio algorithm with coincident triggers across at least 10 stations provides promising results into identifying microseismicity within this noisy environment. Coupled with a template matching technique using all the identified events as templates, we believe this is an excellent way in which to try and identify low amplitude events in low signal-to-noise environments. Although extensive location analysis will need to be carried out on the events identified by REDPy, the nature of the algorithm and visual inspection of a number of the candidate events suggests the high likelihood of location based on distinct phases in the waveforms (e.g. Figure 1). The candidate events identified by REDPy show very little variation in RMS amplitude, inter-event time or frequency content (Figure 2). Except for one larger amplitude event, RMS amplitudes remain constant. A subtle increase in the hours before the large amplitude event is not reflected in significant changes in either the inter-event time, the frequency index or the number of events identified. Further analysis across the entire dataset will reveal whether events are variable in relation to these parameters in either time or space.

A recent new addition to the REDPy algorithm is the ability to add a time offset to the recording sensors. This technique is similar to a beam-forming algorithm in which P-wave onsets are shifted based on theoretical P-wave travel times at depth. Due to the extensive distribution of geophones (approximately 56 km2 in the ToC2ME dataset, it is feasible that some events were not detected because the move-out between stations meant the REDPy algorithm did not consider them to be the same event. The time offset feature will compensate for this. However, one difficulty in implementing this is that only one time offset can be set within the algorithm. Determining the most appropriate time offset to minimise false detections will require a number of iterations.

Following the identification of microseismic events using REDPy, we propose to take the core event of each family identified across the entire ToC2ME sequence (from 25 October to 15 December), as well as all events identified as orphan events, and use these as templates to scan for more events within the continuous data. EQCorrScan (Chamberlain et al., 2017) is a template matching algorithm that has proved useful for identifying similar seismic events hidden in noisy environments, since events closely spaced in time and events with small amplitudes can be resolved (Salvage et al., 2018). A technique such as this will likely yield more events, since Eaton et al., 2018 have already shown that a template matching approach provides significant gains in event detection within the ToC2ME dataset.

We still cannot be certain that the events identified using REDPy are operational microseismic events until a thorough location analysis has been undertaken. In fact, since REDPy relies upon amplitude ratios, it is more likely that this algorithm will detect larger amplitude events and those with high signal-to-noise ratios. The use of the candidate events identified by REDPy as templates may allow us to identify those events hidden by greater noise, of low amplitude and those which are closely spaced in time. These are the most likely candidates to be the operationally induced microseismic events which have thus far eluded detection by other methods.

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