For two to three decades, microseismic monitoring has been popular in the development of unconventional resources, because the fracture network generated by hydraulic fracturing mainly controls the productivity, and microseismic monitoring enables direct measurements for imaging the fracture network. Nevertheless, some refinements are required to make this method more practical. One challenge is to quantify the effects of pre-existing natural fractures for generating microseismic events. We determine the hypocenters of microseismic events occurring in a shale gas play in the Horn River Basin, Canada, and report several interesting spatial and temporal features of the hypocenter distributions. Automatic phase-picking is applied to waveform data recorded at 98 shallow buried three-component geophones, and phases thought to be from the same event are associated. The initial hypocenters of events are determined by iterative linear inversion algorithm then relocated using a double-difference algorithm, where relative travel time measurements are obtained with the waveform cross-correlation. We group events into many clusters based on fracking stages and their hypocenters, and then define the best-fitting plane of hypocenters for each cluster. Most strikes of the best-fitting planes are consistent with the direction of local horizontal stress maximum, indicating that hydraulic fracturing induces most microseismic events. However, the best-fitting planes of several clusters have strikes similar to those of pre-existing faults or fractures, indicating that pre-existing natural faults or fractures can affect the generation of microseismic events. In addition, some observations suggest that natural fractures can affect the temporal evolution of the spatial occurrence pattern of microseismic events. We observed specific migration patterns of microseismic events around known faults in the study area. Although further work is required for complete understanding of this phenomenon, our observations help elucidate the nature of microseismic generation.
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Characteristics in hypocenters of microseismic events due to hydraulic fracturing and natural faults: A case study in the Horn River Basin, Canada

Running title: Characteristics of microseismic events due to hydraulic fracturing

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ABSTRACT

For two to three decades, microseismic monitoring has been popular in the development of unconventional resources, because the fracture network generated by hydraulic fracturing mainly controls the productivity, and microseismic monitoring enables direct measurements for imaging the fracture network. Nevertheless, some refinements are required to make this method more practical. One challenge is to quantify the effects of pre-existing natural fractures for generating microseismic events. We determine the hypocenters of microseismic events occurring in a shale gas play in the Horn River Basin, Canada, and report several interesting spatial and temporal features of the hypocenter distributions. Automatic phase-picking is applied to waveform data recorded at 98 shallow buried three-component geophones, and phases thought to be from the same event are associated. The initial hypocenters of events are determined by iterative linear inversion algorithm then relocated using a double-difference algorithm, where relative travel time measurements are obtained with the waveform cross-correlation. We group events into many clusters based on fracking stages and their hypocenters, and then define the best-fitting plane of hypocenters for each cluster. Most strikes of the best-fitting planes are consistent with the direction of local horizontal stress maximum, indicating that hydraulic fracturing induces most microseismic events. However, the best-fitting planes of several clusters have strikes similar to those of pre-existing faults or fractures, indicating that pre-existing natural faults or fractures can affect the generation of microseismic events. In addition, some observations suggest that natural fractures can affect the temporal evolution of the spatial occurrence pattern of microseismic events. We observed specific migration patterns of microseismic events around known faults in the study area. Although further work is required for complete understanding of this phenomenon, our observations help elucidate the nature of microseismic generation.
Keywords

Induced seismology, principal component analysis, Horn River Basin, fracture propagation, microseismic event location
1. INTRODUCTION

Microseismic monitoring is a widely used seismic tool for imaging fracture networks induced by hydraulic fracturing. Hydraulic fracturing induces cracks by injecting fluids under high pressure into an impermeable media, thereby enhancing the permeability of the media. Enhanced permeability can be long lasting because, along with fluids, proppants are injected to inhibit crack closure and enable economic recovery of natural gas. Thus, monitoring microseismic events generated by the crack-opening process can give useful information on the development of fracture networks (Warpinski et al., 1998; Sasaki, 1998; Anikiev, 2014). However, it is well known that not only those fractures generated by hydraulic fracturing but also pre-existing natural fractures can affect the final productivity of natural gas. Therefore, an important current question is how to distinguish between events directly related to hydraulic fracturing and those somehow associated with pre-existing natural fractures. The first step to resolve this issue is to compile well-analyzed results from different situations.

In this study, we determined the hypocenters of microseismic events occurring in a shale gas play in the Horn River Basin, Canada. Since the number of microseismic events to be located is usually very large, we automatized the entire procedure. A phase-picking algorithm based on STA/LTA was used to measure P- and S-wave arrival times, and an association algorithm using a Wadati diagram was utilized to identify events. The association process applied conservative thresholds for identifying events in order to prevent potential bias caused by false event detections. The absolute hypocenters were determined by a widely used iterative linear inversion scheme and then relocated by double-difference algorithm to improve the precision of their relative locations. For relocation, the waveform cross-correlation method was applied to improve relative travel-time measurements. We grouped events into many clusters, mainly based on their hypocenters, and found the best-fitting plane
of hypocenters for each cluster by means of principal component analysis (PCA). The spatial distributions of strike and size of the planes were analyzed to investigate effects due to hydraulic fracturing and pre-existing natural faults or fractures. Our observations show that the spatial and temporal distributions of microseismic events can be affected by natural fractures. Although it is difficult to quantify their effects based solely on these observations, our findings can contribute to improving the knowledge of microseismic generation.

2. DATA AND METHODS

2.1. Data Acquisition

Hydro-fracturing was implemented at two tight shale gas formations (Muskwa and Evie), located in the Horn River Basin, Canada. The Evie Formation is shallower than the Muskwa. Four and three horizontal wells were drilled at the Muskwa and Evie formations, respectively (Fig. 1). For observing microseismic activities at the two formations, a shallow buried array was operated for a total of 70 days. Ninety-eight three-component geophones (center frequency 10 Hz, sampling rate 500 Hz) were deployed. The average interstation distance between two adjacent geophones was only several hundred meters. The aperture of the whole array was approximately 6 km and was sufficiently large to cover the lateral extent of all horizontal wells. Surface monitoring of microseismic events is cheaper than monitoring at depth, and can efficiently detect events occurring across a broad area. However, a significant scattering of waves near the surface can reduce signal-to-noise ratio (SNR). A surface buried array used in our case is designed to mitigate this issue by reducing the noise level and enhancing SNR.

2.2. Data Processing
For P- and S-phase detection, we applied the short-term average to long-term average (STA/LTA) method to 5–50 Hz bandpass filtered data. The STA/LTA method, which is widely used in weak-motion seismology, takes advantage of the characteristics that a short time window can capture transient change due to seismic signal whereas a long time window mostly changes with background noise (Trnkoczy, 2012). In the STA/LTA method, raw data are usually transformed into characteristic functions (CFs) containing the energy information.

The STA and LTA values of the $i^{th}$ windows are described as:

$$\text{STA}(i) = \frac{1}{n_s} \sum_{j=i-n_s}^{i} CF_j,$$

$$\text{LTA}(i) = \frac{1}{n_l} \sum_{j=i-n_l}^{i} CF_j,$$

Equations (1a) and (2a) average-out a series of traces of a characteristic function. Then, the ratio of STA and LTA

$$\frac{\text{STA}(i)}{\text{LTA}(i)}$$

becomes high when a signal arrives. However, the value of STA/LTA in Equation (2) can vary from case to case, requiring some experience in selecting appropriate $n_s$, $n_l$, and threshold of event detection (Trnkoczy, 2012). We use the characteristic function of Grigoli et al. (2013), in which the P characteristic function ($\text{CF}^P$) is defined as a squared vertical component of seismic traces, as represented in Allen (1978). The method used to define the S characteristic function ($\text{CF}^S$) is more complex. Initially, analytic traces are introduced by two horizontal components and Hilbert transform, $H$:

$$X(j) = x(j) + iH\{x(j)\},$$

$$Y(j) = y(j) + iH\{y(j)\}.$$
\[ Q(j) = \begin{pmatrix} X(j)\hat{X}(j) & X(j)\hat{Y}(j) \\ Y(j)\hat{X}(j) & Y(j)\hat{Y}(j) \end{pmatrix}, \] (4)

Where \( \hat{\cdot} \) represents the conjugate transform. Then, the S characteristic function (CF^S) is defined as in Equation (5):

\[ CF^S = \lambda_1(j)^2 + \epsilon. \] (5)

Here, \( \epsilon \) is a small positive number preventing STA/LTA from having an infinite value.

The basic algorithm of Equations (1a) and (1b) is modified in Grigori et al. (2013) into the recursive STA/LTA algorithm of Withers et al. (1998, 1999), described as follows:

\[ STA(j) = K_s[CF(j)] + (1 - K_s)STA(j - 1), \] (6a)

\[ LTA(j) = K_l[CF(j - n_l - 1)] + (1 - K_l)LTA(j - 1), \] (6b)

Here, \( K_s \) and \( K_l \) are set to \( 1/n_s \) and \( 1/n_l \), respectively. Following multiple trials, we fixed \( n_s \) and \( n_l \) to 20 and 60, and P and S detection thresholds to 5 and 10, respectively.

As the STA/LTA method detects the maximum value of each pick, the measured phase arrival time can be delayed with respect to the actual phase arrival time. To improve the picking accuracy, a correction procedure was applied as follows. We set a 0.4-second time window before the measured phase arrival time and aligned data points by order of amplitude. We then selected data points belonging to a low 20% rank and identified intervals within which more than five consecutive samples (0.01 sec in this case) were selected. The corrected phase arrival time was defined as the end of the last interval within the 0.4-second time window. (Figure 2 is about here.) Figure 2 shows an example of the phase-picking correction discussed above. The approach was utilized to overcome the inherent drawback of STA/LTA algorithms, which is the delay phenomenon of the measured arrival time.
2.3. Microearthquake Association

Before locating the events, it is necessary to associate the phase arrival times from the same event. (Figure 3 is about here.) First, the P- and S- arrivals at each station were paired if their time difference was 0.4–1.5 s, thereby eliminating many false detections. Then, the number of P-arrivals paired with corresponding S-arrivals was counted for all stations within a moving window of 0.5 s interval and 0.1 s increment (Fig. 3a). If the number of counts was >7, it was classified as an event detection. Due to the possibility of false detection and inaccurate picking, some phase arrival data for each event can lower the quality of the location result. To resolve this, we used a Wadati plot, which shows the relationship between P arrivals and P–S times. For the velocity model with homogeneous Vp/Vs ratio, the time difference of P- and S-arrivals is proportional to P-travel time. Thus, points plotted on the Wadati diagram should have a linear trend if there is no false detection and all points are correctly measured. To discard erroneous phase arrival time data, we drew a Wadati plot for each event and reselected the pairs lying between two parallel trend lines. Here, two trend lines have the same slope of 1, which means that Vp/Vs is 2, but shifted by 0.1 s along the P–S time axis. An average Vp/Vs value can be estimated from the well logging data (Fig. 4) (Figure 4 is about here.) and the value is similar to the previous study (Zeng et al., 2014). In Zeng et al. (2014), the Vp/Vs ratio was set to 2.2 for shale and 1.8 for limestone, based on the results of Castagna et al. (1985). We identify trend line positions that maximize the number of pairs located between the two lines. An example Wadati diagram is shown in Figure 3b. By the series of association procedures, we detect the phase arrival time sets of more than 8000 microseismic events.
2.4. Microearthquake Location

For each phase arrival time set, we determined its hypocenter using HYPOELLIPSE (Lahr, 1989), linear, iterative inversion software that was developed to determine the locations and origin times of shallow earthquakes by minimizing the differences between theoretical and observed phase arrival times. The algorithm requires the calculation of theoretical travel times for a one-dimensional (1D) velocity model shown in Figure 4. (Figure 5 is about here.) The inversion results of the hypocenters are plotted in Figure 5.

To investigate the detailed spatial distribution of hypocenters, they were relocated using hypoDD software adopting a double-difference algorithm (Waldhauser and Ellsworth, 2000; Waldhauser, 2001). This method corrects relative hypocenters by using travel time differences between two adjacent events or stations. The time differences can be measured by the waveform cross-correlation rather than direct phase picking, which can significantly reduce measurement errors (Friberg, 2014). Since the double-difference algorithm is applicable to events having similar hypocenters, all the microseismic events were grouped according to the fracking stage and the events were relocated group by group. (Figure 6 is about here.) As a result, 174 groups were relocated, as shown in Figure 6. The velocity model for the relocation procedures is shown in Figure 4.

2.5. Pattern Analysis for Microearthquakes

Since the spatial and temporal distribution of all hypocenters is too complex to interpret as a whole, we divided most hypocenters into 194 clusters. Here, we attempted to gather hypocenters associated with the same local fracture network as one cluster. It would be expected that the hypocenters of events generated by hydraulic fracturing would align on a plane, as reported by many previous studies (Yost II, 1988; Fisher et al., 2002; Gale, 2007;
Assuming that the events will be on a specific plane, we determine the best-fitting plane from the hypocenters for each cluster by means of principal component analysis (PCA). The PCA algorithm finds independent unit basis vectors that maximize the data variance (Jackson, 1991). The detailed processes are represented in the following steps. For the hypocenters in a three-dimensional space, the first unit bases vector \( w_1 \), which maximizes the variance of the hypocenters, is expressed as:

\[
 w_1 = \arg\max_{\|w\|=1} \left\{ \sum_{i=1}^{N} (x_i - x_{\text{mean}}, w)^2 \right\}, \tag{7a}
\]

Here, the inner product and the number of the hypocenters are represented by \( \langle, \rangle \) and \( N \), respectively. The second unit bases vector \( w_2 \) can be obtained likewise after removing the \( w_1 \) component from the hypocenters as:

\[
 w_2 = \arg\max_{\|w\|=1} \left\{ \sum_{i=1}^{N} (x_i - x_{\text{mean}} - w_1, x_i, w)^2 \right\}, \tag{7b}
\]

Using the above equations, we defined the fitting plane as that containing the average location of hypocenters and perpendicular to both unit vectors, \( w_1 \) and \( w_2 \).

For the best-fitting plane of each event cluster, we calculated strike and projected area based on the method proposed by Woo et al. (2016).

3. RESULTS

3.1. The Muskwa Formation

The Muskwa Formation contains four horizontal wells termed (from northeast to southwest) M1, 2, 3, and 4 (Fig. 1). The total number of events occurring in the Muskwa...
Formation is 3512. Approximately 1000 events occurred due to hydraulic fracturing at each well except for M1. The number of events associated with Muskwa is only 189. At well M1, three clusters were found, and all strikes are different from the local maximum stress direction of N60°E. Since there are only three clusters and the event location data are of low quality, we are unable to reach any conclusions for this well. However, the results from the other three wells provide more information. The most prominent feature of clusters for wells M2, 3, and 4 is that the pre-existing faults seem to control the spatial occurrence pattern of the events. (Figure 7 is about here.) Figure 7 shows that many clusters are located at the south-eastern and north-western parts of the site, with few clusters in the south-western part bounded by faults. This feature is also recognized in the map showing the distribution of individual epicenters (Fig. 6). Although it is likely that faults can affect the spatial pattern of hypocenters, most strikes in the Muskwa clusters are well matched with the local maximum stress direction of N60°E. Quantitatively, 61.1% of clusters have strikes ranging from N40°E to N80°E.

3.2. The Evie Formation

The Evie Formation contains three horizontal wells, termed (from northeast to southwest) E1, 2, and 3 (Fig. 1). In this formation, 3512 events were recorded (2100, 1975, and 910 at wells E1, 2, and 3, respectively). The total number of clusters for the Evie Formation is 120, which is more than at the Muskwa Formation. The number of events associated with E1 (located directly below M1) exceeds that of M1 by more than one order of magnitude. The E1 clusters are uniformly distributed from toe to heel, and most of their strikes are consistent with the local stress maximum direction, similarly to the clusters of the Muskwa Formation. However, some clusters have strikes of about N45°E. For wells E2 and E3, the cluster
locations are uneven, and variations in strike are not negligible. Particularly, we found a group of clusters showing NW–SE trend, with locations several hundred meters away from E3. Clusters with strikes ranging from N40°E to N80°E account for 52.2% of cases, which is less than that for the Muskwa Formation.

### 3.3. Other Characteristics of Microseismic Cluster

To quantify the size of the fracture hosting microseismic events for each cluster, we calculated the length and area of the cluster. The length is calculated by (1) finding two hypocenters in each cluster, which maximize the apparent distance in direction of the vector \( w_1 \), (2) projecting corresponding two hypocenters on the surface, and (3) measuring the distance between the two projected points on the surface. The lengths of the clusters are plotted as bars in Figure 7. The average lengths of clusters in the Muskwa and Evie formations are 381 m and 201 m, respectively. This indicates that hydraulic fracturing generated longer fractures in the Muskwa Formation, if the powers of hydraulic fracturing are uniform. A similar trend is observed for the projected area, which is defined as an area of the polygon containing the projected hypocenters on the fitting plane (Woo et al., 2016). The average projected areas for the Muskwa and Evie formations are \( 3.94 \times 10^6 \text{m}^2 \) and \( 2.03 \times 10^6 \text{m}^2 \), respectively, i.e., the average projected area for the Evie Formation is only about 51% of that for the Muskwa Formation.

### 4. DISCUSSION

Several previous studies have used the same data. Rahimi Zeynal et al. (2014) applied the beam-steering processing technique of Lakings et al. (2006) as an imaging tool based on beam forming, which is applicable to the surface array. Their method stacks highly attenuated
signals generated by microseismic events, and they detected more than 11200 events at the same site. Snelling et al. (2013b) discussed the uncertainty of detected microseismic events: approximately 10 m horizontally and 20 m vertically. For each hydro-fracking well, Snelling et al. (2013a) analyzed the b-value, which shows the relationship between the event frequency and magnitude, and focal mechanism solutions. Since the Muskwa and Evie formations are dominated by non-double-couple and double-couple events respectively, they reported that the events in the Muskwa Formation might be induced by hydro-fracturing, whereas those of the Evie might be related to the structure-controlled rock failure due to change of stress. In addition, they insisted that the generation of higher-magnitude events is related to fault reactivation, because most occur near known faults.

The number of events located in this study is approximately 8500, which is slightly less than in the previous studies discussed in the above paragraph. This is because we applied conservative thresholds for event detection and association. Especially, we declared event detection only if both P- and S-arrival data were available. In doing so, we attempted to obtain more reliable images of microseismic hypocenters, free of distortion by false events. Although we used a different method from previous studies for locating events, our results are consistent with those of Snelling et al. (2014), thereby validating our result. In addition, since the double-difference method applied in our study can precisely determine the relative locations of the events, our results well depict the nature of the microseismic events.

To investigate the spatial variations in strike and the possible effects of natural fractures, we divided the clusters into two groups. Clusters with strikes ranging between N40°E and N80°E are represented as white bars and others are indicated with black bars (Fig. 7). For both formations, it is clear that the black bars are located near the known natural faults whereas the white bars are more scattered across the entire area (Fig. 7). This observation is
natural, since we would expect that the locations of clusters directly induced by hydraulic
fracturing will be less affected by the faults or fractures compared with those clusters
associated with re-activation of the faults. Some black bars, showing a linear trend in the map
view, are located in the north-west part of the site. Although there is no known fault in this
area, the trend of clusters is completely different from the direction of local stress maximum.
Therefore, it is likely that they are related to unknown local faults. Our results indicate that
the proposed cluster analysis might distinguish between events directly induced by fracture
generation and those related to re-activation of the faults even in cases where there is no
information on the natural faults.

We also investigate whether there are characteristic migration patterns of microseismic
events. For each cluster, we examine the relationship between relative origin times and
locations. Relative origin time is measured from the origin time of the first event in each
cluster, and the relative location (L) of each hypocenter is measured by dot product of the
vector, defined from the center of the cluster to the hypocenter, and another vector \( \mathbf{w}_1 \)
defined in Equation (7a). After investigating all clusters, we found two distinct unilateral and
bilateral migration patterns (Fig. 8). (Figure 8 is about here.) As shown in Figure 8, in some
clusters the hypocenters seem to propagate in one direction with increasing time, whereas
others propagate in two directions. These phenomena have been reported by several case
studies (Maxwell and Cipolla, 2011; Neuhaus et al., 2012). In Neuhaus et al. (2012),
sequential and lateral migration of events usually appeared in the initial state of hydro-
fracturing, when there were only a few cracks near operated wells. As the fracture system
becomes more complex due to hydro-fracking, the sequence of hypocenters becomes
disorderly. We found only 23 and 6 clusters clearly showing unilateral and bilateral patterns,
respectively, representing only a small fraction of all clusters.
(Figure 9 is about here.) Figure 9 plots the hypocenters with their relative origin time on a color scale. For comparison, the relative origin times of all clusters are normalized such that 0 and 1 indicate the origin times of the first and last events in each cluster, respectively. The light-gray and dark-gray circles represent the clusters of unilateral propagation and bilateral propagation, respectively. The clusters with unilateral propagation seem to be found near the well, meaning that the unilateral pattern may be mainly related to hydro fracturing rather than regional effects, whereas those with bilateral pattern are located in limited regions, suggesting stronger association with regional environments. It is noteworthy that the migration velocities of the four cases in Figure 8 are approximately uniform at 0.16 meters per minute (see the red lines in Fig. 8). Although this value does not apply to all clusters and the values differ case by case, this may reflect the physics of stress transfer or fluid flow, which are not well understood.

5. CONCLUSION

We located more than 8000 microseismic events within one shale gas play in the Horn River Basin by using a series of automatic processes including STA/LTA algorithm and linear inversion methods. We then analyzed the spatial and temporal characteristics of hypocenters, and the influences of local stress environment and pre-existing faults. For quantitative investigation of the effects of the two different mechanisms, we grouped hypocenters into clusters and extracted parameters characterizing each cluster. In addition, we divided the clusters into two groups: one directly induced by hydraulic fracturing, the other related to reactivation of the faults. The distributions of the two groups of clusters show specific patterns, which can be predicted by hydro-fracking and fault reactivation theories. We also observed interesting unilateral and bilateral migration patterns of the events, and the
migration velocity is estimated at approximately 0.16 m/min. At this stage, it is difficult to associate this velocity with any specific physical mechanism. Additional case studies and various models of fracture generation will be necessary to better understand the general characteristics, including this interesting observation, of microseismic events.

Acknowledgements

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**Figure Captions**

**Fig. 1.** Layout of shallowly buried array (a–c) and hydro-fracturing wells (a–d). The coordinate origin is at the center of hydro-fracking wells. Location of subsurface array is marked as triangles and the lines of horizontal hydro-fracturing wells are distinguished by different colors. Well log data for making the one-dimensional (1D) velocity model were obtained from the three regions, marked by purple, yellow, and green stars in panel (a). Locations and names of hydro-fracking wells in the Muskwa and Evie formations are shown in (b) and (c). Note that the locations of M1 and the M4 are the same as E1 and E3 on the map view, but the Muskwa Formation is at shallower depth than the Evie Formation. Panel (d) shows the depth profile of the seven hydro-fracking wells. It is projected along the E2 line, located at the center of the seven wells.

**Fig. 2.** An example of phase-picking correction for improving measurement accuracy. Each column is separated by stations. The first row is the waveform of the vertical component. The second row is the STA/LTA of P characteristic function in the case of \( n_s = 20 \) and \( n_l = 60 \). The third and fourth rows are the waveforms of two horizontal components. The fifth row is the STA/LTA of S characteristic function in the case of \( n_s = 20 \) and \( n_l = 60 \). The blue ‘+’ marks indicate automatically determined P-arrival times (first and second rows) and S-arrival times (third, fourth, and fifth rows) before correction; the red ‘+’ marks indicate automatically determined P-arrival times (first and second rows) and S-arrival times (third, fourth, and fifth rows) after correction.

**Fig. 3.** Example of automatic association process. Panel (a) shows a primitive automatic association process. Ordinates indicate the counts of P arrivals during cumulative 0.5-seconds time window, and abscissae indicate the end of the 0.5-seconds time window. Counts >7 are classified as an event detection. Panel (b) shows the use of Wadati diagrams for pair
reselection. The gradient of the underlying red line is 1 and the overlying line is shifted by 0.1 seconds along the P–S time axis. Pairs are chosen for the location inversion when the red lines are positioned to maximize the pairs captured between them.

**Fig. 4.** Data for the three well logs and the 1D velocity model for the location inversion. The sites for well logging data are shown in Figure 1a. At each depth interval, the velocity model utilizes median values of Vp and Vs. The blue and red lines indicate P-wave and S-wave velocity models, respectively. The depths of the Muskwa and Evie formations are denoted by two arrows.

**Fig. 5.** Map view (a) and depth profiles (b) of microseismic event locations via HYPOELLIPSE software. Solid black dots and open white circles represent events occurring during the fracking stages of the Muskwa and Evie wells, respectively. The thick green lines in the map view indicate known regional faults. The description of the seven hydro-fracking wells is the same as in Figure 1.

**Fig. 6.** Map view (a) and depth profiles (b) of microseismic event locations via HypoDD software. All symbols match those described in Figure 5.

**Fig. 7.** PCA analysis for each cluster of the Muskwa (a) and Evie (b) formations. The length of each rectangle represents the range of the principal component in the map view, such that it matches the linear trend of each cluster. White bars denote clusters with strike between N40°E and N80°E; other clusters are denoted as black bars. All other symbols match those described in Figure 1.

**Fig. 8.** Four examples showing relationships between the relative origin time and the relative location, L (the score of principal component, w1 of Equation (7a)). Open circles shown in each window represent the events of each cluster. The origin of each window is based on the first origin time and the mean location of the events. The top panels show
unilaterally propagating migration patterns and the bottom panels show bilaterally propagating migration patterns. The red lines approximate the migration velocity (0.16 m/min). The sites for the four examples are shown in Figure 9.

Fig. 9. Map view for the relative origin time in each cluster. For every cluster, the event origin times are linearly normalized based on the first and last event origin times. All the basic symbols are equal to those in Figure 1. Clusters with unilateral- and bilateral-propagating migration patterns are indicated as light and dark circles, respectively. The four sites (a–d) are denoted for the description of Figure 8.