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# Detection and analysis of microseismic events using a Matched Filtering Algorithm (MFA)

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### SUMMARY

A new Matched Filtering Algorithm (MFA) is proposed for detecting and analysing microseismic events recorded by downhole monitoring of hydraulic fracturing. This method requires a set of well-located template ('parent') events, which are obtained using conventional microseismic processing and selected on the basis of high signal-to-noise (S/N) ratio and representative spatial distribution of the recorded microseismicity. Detection and extraction of 'child' events are based on stacked, multichannel cross-correlation of the continuous waveform data, using the parent events as reference signals. The location of a child event relative to its parent is determined using an automated process, by rotation of the multicomponent waveforms into the ray-centred co-ordinates of the parent and maximizing the energy of the stacked amplitude envelope within a search volume around the parent's hypocentre. After correction for geometrical spreading and attenuation, the relative magnitude of the child event is obtained automatically using the ratio of stacked envelope peak with respect to its parent. Since only a small number of parent events require interactive analysis such as picking P- and S-wave arrivals, the MFA approach offers the potential for significant reduction in effort for downhole microseismic processing. Our algorithm also facilitates the analysis of single-phase child events, that is, microseismic events for which only one of the S- or P-wave arrivals is evident due to unfavourable S/N conditions. A real-data example using microseismic monitoring data from four stages of an open-hole slickwater hydraulic fracture treatment in western Canada demonstrates that a sparse set of parents (in this case, 4.6 per cent of the originally located events) yields a significant (more than fourfold increase) in the number of located events compared with the original catalogue. Moreover, analysis of the new MFA catalogue suggests that this approach leads to more robust interpretation of the induced microseismicity and novel insights into dynamic rupture processes based on the average temporal (foreshock-aftershock) relationship of child events to parents.

**Key words:** Time-series analysis; Microseismic; Computational seismology; Statistical seismology; North America.

#### INTRODUCTION

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Hydraulic fracturing (HF) is a process, widely used in unconventional shale and tight-sand oil–gas reservoirs, which consists of injecting fracturing fluids into a rock formation at a pressure exceeding the fracture pressure of the rock, thus inducing a network of fractures through which oil or natural gas can flow into a wellbore (CCA 2014). During a HF treatment, microseismic events occur due to deformations associated with fluid and pressure changes in reservoir and may be related to activation of pre-existing fractures or the creation of new fractures (Maxwell & Urbancic 2001; Eaton *et al.* 2014c). Microseismic monitoring can be achieved by installation of receivers at the surface or in a wellbore, providing an effective technology to analyse and map brittle deformation processes associated with fracture development (e.g. Rutledge & Phillips 2003; Warpinski 2009; van der Baan *et al.* 2013).

In practice, downhole microseismic monitoring is often undertaken using an array of geophones within a single monitor well (e.g. Eaton *et al.* 2014a,b; Caffagni *et al.* 2015). For this acquisition geometry, event hypocentres are typically computed by picking P- and S-wave arrival times, obtaining a least-squares fit to the picked times based on a site-specific velocity model, and estimating the azimuth from the receiver to the event by polarization analysis of the P wave (Oye & Roth 2003). Although some automation of this process can be achieved, it nevertheless requires a significant level of user interaction, and is prone to missing events for which only a single-phase (e.g. the S-wave) is readily discernible.

Various template-based techniques have been developed to detect and localize small events using matching signals recorded on an array (e.g. Got et al. 1994; Roux et al. 2014). In earthquake studies, template-based approaches have been employed for automated detection of events by cross-correlation (e.g. Van der Elst et al. 2013). Also known as Matched Filtering Analysis (MFA), this approach evolved from studies of repeating earthquakes (Nadeau & Johnson 1998; Igarashi et al. 2003; Schaff & Richards 2004), in which high waveform similarity for different events observed using the same sensor implies similarity in source radiation patterns and path effects, and thus similarity in terms of both focal mechanism and location. These approaches extend the notion of cross-correlationbased waveform similarity (e.g. van Decar & Crosson 1990; Dodge et al. 1995; Rowe et al. 2002). The key step that separates MFA from waveform cross-correlation (WCC) is that WCC determines similarities between triggered (detected) events, whereas a matched filter correlates a template waveform against a continuous data stream to detect occurrences of that waveform (e.g. Van Trees 1968).

A number of versatile MFA techniques have been developed in recent years. Gibbons & Ringdal (2006) showed that an MFA approach with a master signal immersed in seismic noise could detect signals approximately 0.7 orders of magnitude lower than triggering based on ratios of short-term to long-term averages (STA/LTA) (Trnkoczy 2009). Harris (2006) developed a technique based on subspace correlation defined by the Principal Component Analysis of array data, which operates in specific source regions, matching the fine temporal and spatial structure of the signal. Van der Elst *et al.* (2013) developed a matched filtering technique to detect small earthquakes by cross-correlation of raw continuous waveform data using reference events, demonstrating enhanced remote triggering of seismicity caused by fluid injection. Skoumal *et al.* (2015) identified 77 earthquakes in Poland Township, Ohio using an optimized multistation cross-correlation template-matching routine.

Correlation-based MFA techniques have also been applied in passive-seismic monitoring contexts. At the In Salah carbon capture and storage project (Algeria) Goertz-Allmann *et al.* (2014) detected more than 5000 microseismic events using a single 3-C receiver at a pilot monitoring well, enabling correlations between clusters of microseismicity with injection rates and wellhead pressures.

We remark that our method should not be confused with the wellknown MFP technique, classically described as 'Matched-Field Processing' (see Jensen *et al.* 1994, for an extended review), widely developed in underwater acoustics and seismic exploration. The MFP is a high-precision source-localization technique based on phase match between data and a computed model-based synthetic field (the replica vector) generated by a point source at each candidate point in a search grid of the medium, which has its phase and/or amplitude matched (Corciulo *et al.* 2012). Recently these techniques have been applied successfully for location of sources of hydrothermal activity (e.g. Vandemeulebrock *et al.* 2013).

In this paper, we develop and test a novel MFA method that is designed for application to downhole microseismic monitoring of HF using an array of multicomponent sensors. By exploiting both the beam-forming capabilities and directional sensitivity of the downhole array, our approach facilitates automated detection and analysis of microseismic events that might otherwise be difficult to locate by means of a standard detection procedure.

The paper is organized as follows. First, the basic elements of the MFA theory are described. Parameter sensitivity and capabilities of the MFA method are investigated using synthetic tests to evaluate its effectiveness for suppressing false detections, detection of low S/N events and reliable location of detected events. Next, the method is applied to a data set recorded during an HF treatment program in central Alberta, Canada. In comparison with the original event catalogue obtained with traditional downhole processing, in this example the MFA approach yields a more than fourfold increase in the number of located events. Our analysis also shows that this approach leads to more robust interpretation of the microseismicity and new insights into dynamic rupture processes.

#### METHOD

The essence of the MFA approach is a multicomponent crosscorrelation between a long time-series  $u_{ij}(t)$  with a reference signal  $p_{ij}(t)$ ,

$$c_{ij}(t) = p_{ij}(t) \otimes u_{ij}(t) = \int_{-\infty}^{+\infty} p_{ij}(\varsigma) u_{ij}(\varsigma + t) d\varsigma, \qquad (1)$$

where  $u_{ii}(t)$  represents continuous raw data for the *i*th component and the *j*th receiver level, and  $p_{ij}(t)$  is a parent event containing P- and S-wave arrivals (Eaton & Caffagni 2015). Positive peaks in the cross-correlation function  $c_{ii}(t)$  represent short segments of the continuous data where a high degree of waveform similarity exists with the reference signal. The onset time of a correlation peak represents the time lag between the parent and the child event. Fig. 1 shows an illustrative example of two microseismic events (a, b) with very similar waveform characteristics, including nearly identical moveout (change in arrival time across the array) of the P and S arrivals, in addition to very similar pulse shape and relative amplitude at each receiver level. These similarities provide a strong indication that the two events are approximately co-located and have similar focal mechanisms. We infer that the two events experienced similar path effects from the source to the receiver and are also characterized by similar P- and S-wave radiation patterns, which determines the relative amplitude and polarity of the phase arrivals at each receiver level. Due to these characteristics, particularly the moveout, we expect that the cross-correlation peak will exhibit approximately the same lag time for all receiver levels. For this reason, a stacked time-series, s(t) is obtained from the three-component (3C) cross-correlation,

$$s(t) = \sum_{i=1}^{3} \sum_{j=1}^{N} c_{ij}(t), \qquad (2)$$

where *N* is the number of receiver levels. The correlation-stacking process represents an implicit beam-forming operation, since it makes use of the arrival times and polarization information contained in the parent waveform. We do not make use of independent weighting factors for *P*- and *S*- wave, as implemented in the multiplet analysis of Kocon & van der Baan (2012). Here, only parent-child doublets with similar S - P times are considered, and inclusion of both *P* and *S* waves within the cross-correlation time window for the parent is an important element of our method, as the 3C cross-correlation approach is formulated such that the relative amplitude



Figure 1. Two microseismic events (a, b) with similar waveforms, representative of approximately co-located events with similar focal mechanisms. *P* and *S* arrivals are marked for the higher-magnitude event. Only one waveform component is plotted.



Figure 2. Workflow for the MFA method.

and moveout characteristic of both P and S waves contributes to the computed degree of similarity represented by eq. (2).

The basic workflow for the MFA method is shown in Fig. 2. The main inputs are: (1) continuous microseismic recordings from a multicomponent downhole array, and (2) a suite of high signal-to-noise ratio (S/N) parent events that represent short time windows (less than 1.0 s) extracted from the continuous data. Magnitudes and hypocentres of parent events are required prior to further analysis and can be obtained using existing methods (e.g. Oye & Roth 2003).

#### Selection and processing of parent events

As with any matched-filtering process, parent events provide template waveforms for event detection. In the case of hydraulicfracture monitoring, microseismic events typically occur in distinct spatial and temporal clusters near the injection site for each treatment stage (Eaton et al. 2014c). For a given event cluster, parent events are selected on the basis of two criteria: S/N ratio, and distinctive waveform characteristics such as P- and S-wave moveout and time separation. Under the assumption that background noise is random, the selection of parent events with high S/N will optimize the cross-correlation based detection process. The choice of parent events with distinctive waveform characteristics will tend to reduce the occurrence of duplicate child events (i.e. those that correlate with multiple parents). In practice, hypocentre information is often available for a subset of the highest S/N events. For potential parent events that are approximately co-located, the event with the highest S/N is chosen. For the data sets considered here, both parent and child event waveforms are extracted from the continuous recordings within time windows that are less than 1.0 s in duration. Time windows are centred on the detected arrival times.

The choice of a sufficient set of parent events is critical. As elaborated below, parent events can be viewed as basis functions for the detected microseismicity; consequently, if the set of parent functions used for MFA processing is insufficient or limited, then by definition they will not span the output space of recorded microseismicity. Although it is not possible, in general, to be certain that all detectable microseismic events have been extracted from a given data set, we have developed strategies for optimal selection of parent events. In the absence of existing processed data, potential events are obtained from the continuous raw data using an STA/LTA algorithm (Trnkoczy 2009), a well-established approach for downhole microseismic processing (e.g. Oye & Roth 2003) (see Supporting Information). If previous processing has been performed, then the original catalogue of microseismic events, obtained by downhole standard detection techniques, is considered. It is important to ensure that a sufficient number of parent events is obtained for each treatment stage, excluding potential parent events that are too close in space or time ( $\sim 20$  m and 0.5 s). In our experience, four parent events for each treatment stage are generally sufficient; this parameter choice reflects an unavoidable trade-off between computation time and catalogue completeness. For the field data considered here, our tests indicate that inclusion of more than four parent events for each cluster yields only a small increase in the number of detections,

Onset times of parent events are automatically re-picked via the Akaike Information Criterion (AIC) algorithm (Ove & Roth 2003), as this method is generally more accurate than STA/LTA techniques (Leonard 2000; Akram 2014). Polarization analysis is then carried out, followed by rotation of 3-C traces into ray-centred co-ordinates (Cerveny 2001), thereby separating P,  $S_{\text{fast}}$  and  $S_{\text{slow}}$  signals into distinct components. Arrival time picks are refined using the iterative cross-correlation approach of De Meersman et al. (2009), including time-shifts and polarity checking. If previous processing has not been performed, hypocentres are determined by minimizing the least-square misfit between observed and calculated times based on a local velocity model, which should be calibrated using sources with known locations (e.g. perforation shots). This is combined with event azimuth information derived from the polarization direction of P wave to estimate the hypocentre (Oye & Roth 2003; Akram 2014). Finally, moment magnitude  $M_{\rm w}$  is determined by fitting the observed displacement spectrum with the Brune model (Eaton et al. 2014b).

After each parent event is processed, one of the phase arrivals (typically the  $S_{\text{fast}}$  wave or the *P* wave) is chosen as a reference phase for future processing of child events. As elaborated below, this choice of reference phase is incorporated into the processing of child events, resulting in a source-localization procedure that is effective even for single-phase events.

#### Detection of child events

To account for large variability in the amplitudes of microseismic events arising from the large range in both hypocentral distance and seismic moment, we apply an Automatic Gain Control (AGC; e.g. Yilmaz 2001) procedure that preserves polarization information:

$$u_{ij}(t) = \frac{u_{ij}^0(t)}{\bar{A}(t) * \Delta(t, t_{\Delta})},$$
(3)

where  $\Delta(t, t_{\Delta})$  is a triangular smoothing operator of unit peak amplitude and duration  $t_{\Delta}$ , and \* denotes the convolution product. In this expression, in eq. (3),  $u^{0}_{ij}$  is the raw input data, before preconditioning, of the *i*th component and *j*th receiver level, and *A* is defined by

$$\bar{A} = \frac{1}{3} \max \left| \sum_{i=1}^{3} u_{ij}(t) \right|.$$
 (4)

This method has the desirable characteristic that it preserves event polarization information. For our data set, 3C-AGC provides comparable results to widely used matched filtering analysis based on normalized cross-correlation (e.g. Shelly *et al.* 2007; van der Elst *et al.* 2013), due to the varying length and amplitude of parent waveforms. However the latter approach requires visual inspection of the detections and is nevertheless prone to detect noisy events, such as tube waves (see Sections Synthetic Tests and Supporting Information).

After preconditioning, each parent event is cross-correlated with the continuous raw data (eq. 2). In practice, a time window (e.g. several hours before or after the parent event time) can be applied to speed up this process. Detections (child events) coincide with local maxima of s(t) (eq. 2) that exceed an empirically determined multiple (denoted as  $\xi$ ) of its standard deviation value. Similar to STA/LTA (e.g. Jones & van der Baan 2015), there are trade-offs in the choice of  $\xi$ : a value that is too low could result in detecting child events with multiple parents, whereas a value of  $\xi$  that is too high could result in missed events. In our experience,  $6 < \xi < 11$ provides a suitable range for the array aperture and noise characteristics of the microseismic recordings that we have analysed (see the Appendix for further details on the acquisition geometry). This detection threshold is based on a summed, multicomponent crosscorrelation function and is not a direct measure of the similarity of individual waveforms; thus, comparison of this empirically derived range for  $\xi$  with Gaussian measures from multiplet-derived analysis (Kocon & van der Baan 2012) is not meaningful.

Overlapping of child microseismic events may occur, especially during intervals of high seismicity rate; therefore the code automatically discards detected child events with a minimum time separation of approximately  $0.38^*T_{\rm C}$ , where  $T_{\rm C}$  is the child signal window.

After detection of child events, it is necessary to check for duplicate child events and discard them. The procedure is simple; each detected child event is associated with a parent event, and in the case of multiple detections of the same child event, only the parent-child pair with the highest cross-correlation value is retained.

#### Location and magnitude of child events

The first step in the location procedure is to transform the threecomponent waveforms for each child event into ray-centred coordinates of the corresponding parent. This is achieved by projecting the three-component recorded waveforms for the child event onto the polarization directions for the *P*,  $S_{\text{fast}}$  and  $S_{\text{slow}}$  arrivals of the parent event. This step has the effect of approximately isolating the *P*,  $S_{\text{fast}}$  and  $S_{\text{slow}}$  waves of the child event. The previously chosen reference phase is then selected, denoted by  $q_j(t)$ , where *j* is the receiver level.

After isolation of the reference phase, hypocentre locations of child events are determined by maximizing the stacked (beamformed) amplitude value, by searching within a region centred in the parent hypocentre (Fig. 3a). As part of this process, a moveout correction (i.e. time shift) is applied to each trace, to account for the differential arrival times across the receiver array (Fig. 3b). Moveout corrections are applied using a lookup table that is parametrized using 2-D cylindrical co-ordinates, defined by radial distance (r) and depth (z).

The moveout correction is determined based on the picked arrival times for the parent event using a grid-based search approach. Parent-specific lookup tables are constructed by calculating the ray theoretical differential time and then adding it to the time picks for the parent, that is,

$$t_{\text{lookup}} (\Delta r, \Delta z) = t_{\text{parent}} + dt (\Delta r, \Delta z)$$
  
=  $t_{\text{parent}} + t_{\text{ray}} (r_0 + \Delta r, z_0 + \Delta z) - t_{\text{ray}} (r_0, z_0),$   
(5)

where  $\Delta r$  and  $\Delta z$  represent the radial distance and depth coordinates relative to the parent event at  $r_0$  and  $z_0$ . By incorporating the picked times for the parent events, this approach implicitly accounts for small scale velocity heterogeneity that is not accounted for in the background velocity model. It also assures that child events with moveout that is identical to its parent will be co-located with the parent hypocentre.

In order to estimate the relative azimuth of each child event, a series of trial rotations is applied in ray-centred co-ordinates (Fig. 4). Consider a trace  $q'_i(t, \Delta r, \Delta z, \Delta \theta)$ , obtained by applying a moveout



Figure 3. (a) Geometry of the search region centred on the hypocentre of a parent event, denoted by a star. The radial distance r is measured from the nearest geophone, shown by triangles. (b) Schematic illustration of the moveout correction used to search for optimum relative location of child events.

correction and rotation to  $q_j(t)$ . The amplitude envelope is then calculated using:

$$\operatorname{env}\left(q_{j}^{'}\right) = \left[\left(q_{j}^{'}\right)^{2} + \left(H\left(q_{j}^{'}\right)^{2}\right)\right]^{\frac{1}{2}},\tag{6}$$

where H is the Hilbert transform (Kanasewich 1981). The amplitude envelope is applied in order to mitigate the effects of small variations in source radiation pattern and path effects, which can lead to changes in phase and polarity of traces. The stacked amplitude is computed by summing, over all N receivers, the transformed amplitude-envelope traces:

$$E\left(\Delta r, \Delta z, \Delta \theta\right) = \max\left\{\sum_{j=1}^{N} \operatorname{env}\left[q_{j}^{'}\left(t\right)\right]\right\}.$$
(7)



**Figure 4.** Ray centred co-ordinate system, showing sense of rotation applied during search for child hypocentre location.

Optimal values of  $\Delta r$ ,  $\Delta z$  and  $\Delta \theta$  are determined by selecting max(*E*) using an exhaustive search procedure. These obtained values are used to determine the child hypocentre with respect to its parent. Only solutions that are in the interior of the search region are retained, by omitting maxima that fall on any edge of the pie-shaped region. Finally, the child hypocentre location is obtained by transforming the location co-ordinates into the original Cartesian reference system. Our method for source-location involves a reference phase rather than multiple phases, namely, *P*, *S*<sub>fast</sub>, *S*<sub>slow</sub>, since child locations are reliably obtained relative to the parent hypocentre. Therefore, the integration of the other phases may result in less accurate child location estimates.

Relative magnitudes for child events can be derived from the Brune formula for seismic moment. Following Eaton *et al.* (2014b), the estimated seismic moment  $M_0$  is related to the measured low-frequency amplitude of the radiated seismic waves, *A*, by (Abercombie 1995):

$$M_0 = \frac{4\pi\rho c^3 Ar}{R} e^{-\frac{\omega r}{2cQ}},\tag{8}$$

where  $\rho$  is density, *c* is the wave velocity of the reference phase, *r* is the hypocentral distance,  $\omega$  is the angular frequency, *R* is the average radiation pattern for the reference phase and *Q* is the seismic quality factor for the reference phase. The moment magnitude  $M_w$  is related to the seismic moment by (Stein & Wysession 2009):

$$M_{\rm w} = \frac{2}{3} \log_{10} \left( M_0 \right) - 6. \tag{9}$$

Child moment magnitude,  $M_{\text{child}}$ , is related to the corresponding parent moment magnitude,  $M_{\text{parent}}$ , by

$$M_{\rm child} = M_{\rm parent} + dM. \tag{10}$$

The difference dM is obtained using eqs (8) and (9):

$$dM = \frac{2}{3} \left[ \log_{10} \left( A_{\text{child}} d_{\text{child}} e^{\frac{\pi f_0 d_{\text{child}}}{cQ}} \right) - \log_{10} \left( A_{\text{parent}} d_{\text{parent}} e^{\frac{\pi f_0 d_{\text{parent}}}{cQ}} \right) \right], \tag{11}$$

where  $d = (r^2 + z^2)^{1/2}$  is the distance from the nearest receiver to the hypocentre, for both parent ( $d_{parent}$ ) and child ( $d_{child}$ ) events,  $f_0$  is the dominant frequency of the event, c is the average wave velocity for the reference phase along the source-receiver path, Q is the quality factor for the reference phase, and  $A = \max(S(t))$  denotes the peak value of the beam-formed and stacked amplitude envelope function,



**Figure 5.** First synthetic test. (a) Left: synthetic data set containing a reference event (highlighted), a strong event with different waveform characteristics and a weak event that is similar to the reference event. (b) Traces are then aligned, beam-formed with a time shift and cross-correlation computed. After stacking (bottom trace), the strong event produces a false detection. (c) The same test data set as in panel (a) after the application of AGC function. (d) Cross-correlation results after AGC. This pre-conditioning process reduces the likelihood of false detections.

calculated using waveforms with no AGC applied. This approach is analogous to time-domain calculation of magnitude discussed by Stork *et al.* (2014). This formulation implicitly accounts for effects that arise from differential geometrical spreading and attenuation. From these relationships, it follows that

$$M_{\rm child} = M_{\rm parent} + \frac{2}{3} \log_{10} \left[ \frac{d_{\rm child}}{d_{\rm parent}} e^{\frac{\pi f_0 \Delta d}{cQ}} \frac{A_{\rm child}}{A_{\rm parent}} \right],\tag{12}$$

where  $\Delta d$  is the difference in distance between the parent and child event.

The magnitude of child events is obtained from the parent, based on a relative, rather than absolute, magnitude calculation. Any systematic error in parent magnitudes (e.g. due to erroneous application of instrument response) would therefore also apply to the child magnitudes, although relative magnitude information remains unaffected. Furthermore, in the absence of an existing contractor catalogue, as aforementioned, parent magnitudes must be computed based on eqs (8) and (9).

#### SYNTHETIC TESTS

A set of synthetic tests was performed with the objectives of formulating the preconditioning procedure, evaluating the detection capability of the cross-correlation procedure and validating the search procedure for source-localization.

The first synthetic test (Fig. 5a) involves three events with typical moveout characteristics of microseismic field data. The signals consist of an initial parent event, a second high-amplitude event with discordant characteristics in terms of moveout, frequency content and P-S amplitude radiation patterns, and a subsequent child event that has reduced amplitude but is otherwise a direct copy of the parent event. For each event, the source waveform is a Ricker wavelet and the signals were computed using far-field



Figure 6. Second synthetic test. 3-C section of the first of three reference events from different treatment stages recorded during the HFME experiment (Eaton *et al.* 2014a).

elastodynamic Green's functions for a homogeneous medium (Aki & Richards 1980) using a tensile-crack opening for the parent/child event and a double couple shear faulting for the second event. The two different source types chosen guarantee completely different characteristics in signals. In the absence of any preconditioning, the application of correlation and stacking (eqs 1 and 2) results in high correlation amplitudes for the strong event (Fig. 5b). Despite its discordant waveform characteristics, this spurious correlation occurs because the strong event is sufficiently similar to the parent waveform to generate a high correlation. Fig. 5(c) shows the same data set as in 5a but traces are AGC scaled, in a 50 samples triangular window length. Fig. 5(d) shows the cross-correlated AGC scaled traces and at the bottom, the stacked trace. It is clear that this approach suppresses the false detection (stronger event) while enhancing the detection of the corrected child event. As shown in the Supplementary Data, the use of normalized cross-correlation as suggested by some previous studies (e.g. Shelly et al. 2007; van der Elst et al. 2013) is less effective than the AGC approach used here and nevertheless requires visual inspection of the detections.

A second synthetic test was undertaken to evaluate the sensitivity of the method for detection of weak events under realistic S/N conditions. Three distinct parent events are considered, from downhole microseismic monitoring of an HF treatment in a tight sand reservoir, (Eaton et al. 2014a). The 3-C section of the first of the three parent events is displayed in Fig. 6. We consider continuous waveform data constructed using 15 min of pre-treatment noise recordings. The three parent events along with ten scaled copies of each (for a total of 33 events) were added to the background noise. A random time shift, as well as a random amplitude-scaling factor between 0.01 and 0.6, were applied to each synthetic child event prior to summation with the noise record. The 3-C synthetic data set that was constructed in this manner (Fig. 7, for sensor 12 and one horizontal component) contains events with S/N as low as 0.1. Parent events (three numbered peaks) and their copies (unnumbered peaks) are plotted respectively in the synthetic trace.

Fig. 8 shows the stacked cross-correlation function, s(t) (eq. 2) obtained using the first reference signal as a parent event. The thick horizontal line shows the detection threshold corresponding to  $\xi = 11$  [i.e. eleven times the standard deviation of s(t)]. The method successfully detected all ten child events (10 unnumbered peaks)



**Figure 7.** Single horizontal component trace from a 3-C synthetic data set including the three reference events (numbered peaks) and 10 randomly scaled and time-shifted weaker copies (unnumbered peaks) of the three reference events, summed with 15 min pre-treatment noise.



**Figure 8.** Stacked function s(t) (eq. 2) of the synthetic time-series in Fig. 7. The synthetic trace is AGC scaled and the three parent events normalized with respect to the 3-C maximum, then the cross-correlation computed. In this case, a detection threshold of  $\xi = 11$  returns only the first parent event and all of the 10 weaker copies (child events), with no false detection.

of the first parent event and the parent itself (numbered peak), as indicated by peak values of s(t) that exceed the threshold level. Note the exact correspondence in time between parent events and copies in Figs 7 and 8. The overall performance of the method is summarized in Table 1, showing that 29 out of 30 child events were detected, with no false detections. This test indicates that for

 
 Table 1. Results of the second MFA synthetic test. Parent events are detected but not included in the number of detections.

	Number of detections	Number of missed events	False detections
Event 1	10	0	0
Event 2	9	1	0
Event 3	10	0	0



**Figure 9.** (a) Velocity model and receiver depth, used for both the third synthetic test and the Garrington data set, obtained by adjusting the initial model with calibration source points. (b) Example synthetic event with random noise added. Histogram of horizontal and vertical location error for 150 random mislocated child events, respectively without (c, d) and with (e, f) random noise added to the waveforms. Mean errors and standard deviations are indicated in the figure.

a typical downhole monitoring geometry, with a vertical array of equispaced geophone aperture ( $\sim 230$  m, Fig. 6) and noise levels such as those that characterize this example, the MFA procedure is capable of detecting weak events with S/N << 1.

A third synthetic test was undertaken to evaluate the reliability of our search-grid procedure for source-localization. Fig. 9(a) shows the velocity model and receiver depths which are identical to the real-data example in the next section. The star indicates the depth of the parent (970 m) used for the synthetic test. Fig. 9(b) shows an example synthetic event, obtained by ray tracing the direct P and S waves. A double-couple source is used with horizontal and vertical nodal planes. Noise is added to this example, taken from the previous field data. Note that the P wave is barely visible above the noise. Figs 9(c) and (d) show a histogram of the horizontal and vertical location error for 150 random child events without noise. The actual child locations are displaced from the parent location by uniform random values that are up to  $\pm 75$  m laterally and vertically from the parent event, and up to  $\pm 25$  m out of the plane. The mean horizontal and vertical error in estimated hypocentre locations is respectively 12.9 and 1.5 m (for the vertical the absolute error is computed), with a standard deviation of 10.1 and 3.9 m. Location errors exist,

even without any noise, because the approximate traveltimes diverge from the actual traveltimes with increasing distance. Figs 9(e) and (f) show a histogram of the horizontal and vertical location error for the same 150 random child events, with random noise added to the waveforms. In this case, the mean horizontal and vertical errors are respectively 15.5 and 1.3 m, with a standard deviation of 11.2 and 3.1 m. The vertical error is much smaller than the horizontal error, which reflects the fact that the receiver array straddles the source zone. There is negligible change in the vertical error in the presence of noise, whereas the horizontal uncertainty increases. Based on this synthetic test, we conclude that for the receiver geometry, velocity model and expected noise characteristics of our data, the MFA algorithm developed in this study provides hypocentre locations with positional uncertainties on the order of ~15–20 m for the horizontal and much smaller for the vertical (~5–6 m).

#### APPLICATION TO A REAL DATA SET

In this section, we show the application of the MFA method to a field data set. Data were recorded on 2011 August 26 during the first four stages of a multistage HF treatment of the upper Cretaceous



Figure 10. Location map of the study area showing Garrington and other Cardium pools (from Mossop & Shetsen 1994).

Cardium formation within the Garrington field in Alberta (Duhault 2012), Canada (Fig. 10). Commercial processing of this part of the data set yielded a complex spatial distribution of microseismicity with 346 microseismic events ranging in magnitude from -4.01 to -1.29 (Duhault 2012). The HF completion was carried out using an open hole wellbore assembly, which makes use of fracture ports activated using an engineered ball-drop system together with packers for localization of the injection during each stage (Duhault 2012). The initial velocity model used to locate the microseismic events was constructed using well-log data from the vertical monitor well. The final velocity model (Fig. 9a) was obtained by adjusting the initial model to ensure that calibration source points, consisting of sleeve opening events observed with the microseismic array, were located at their correct positions. The treatment made use of slickwater fracturing fluid, which represents a low-viscosity solution of fresh water mixed with sand and minor amounts (<1 per cent) of chemical agents for friction reduction (CCA 2014).

Four events from each treatment stage were chosen as parent events, based on criteria of high S/N and avoidance of parent events in the same parent-child family. The locations and magnitudes of the parent events and the velocity model are based on the original contractor processing of the data. Parameter choices for MFA processing were guided by the results of the synthetic tests. For example, we selected  $\xi = 7$  by visual inspection of the child events and considered trade-offs between the number of detected child events and the number of duplicate children. AGC triangular length window was set up at 100 samples (0.05 s).

Fig. 11(a) shows the 3-C trace  $(h_1, h_2, z)$  of a parent event, with a catalogue magnitude  $M_w -1.94$ , projected (b) onto the ray-centre components (*P*,  $S_{\text{fast}}$ ,  $S_{\text{slow}}$ ), according to the reference phase (*S* wave), and one of its child events (c) projected onto the same polarization components of the parent event (d). The child magnitude obtained with the MFA method is -2.46. The similarity in moveout

between these events is consistent with the principle that the two events are approximately co-located. Fig. 12(a) shows the stacked amplitude envelope of the *S* component of the child traces in Fig. 11 for the rotational angles  $\Delta\theta$ . The stacking procedure (eq. 2) accounts for the traces moveout removing also the mean across the array, and makes use of the values of  $\Delta z$ ,  $\Delta r$  and  $\Delta\theta$  that maximize the *E* parameter as in eq. (7). Fig. 12(b) shows a look-up radial distance vs depth plot and the parent location is indicated by a block cross whereas its child event with a white circle; this child event is located 52 m from the parent.

Application of the MFA method to this data set yielded 1530 unique child events (Figs 13 and 14). Table 2 shows the performance of the MFA method in comparison with the number of events found in the contractor catalogue and by direct inspection of the raw data, by using a standard STA/LTA algorithm. Details of STA/LTA analysis, number of detections, compared to MFA and contractor catalogue are presented in the Supporting Information section. Visual inspection of all the events detected with the STA/LTA algorithm indicated that this method is too sensitive to noise bursts and tube waves. In addition, the majority of detections using STA/LTA were not locatable using conventional methods since only one phase (typically the S wave) was discernible above the noise (i.e. single-arrival events). The number of the events detected with the MFA method refers to child events after removal of duplicates (1822), while 1530 are events for that we can 'trust' the location. It is important to highlight that the MFA method enables to locate all the detected events, opposite to a standard STA/LTA (see Supporting Information).

The temporal relationship of microseismic activity to the treatment program can be discerned by comparing seismicity rate with the pump curves, which consist of surface treatment pressure, injection rate and proppant concentration (Fig. 13). The beginning and end of each treatment stage is marked by a pressure buildup and drop-off, respectively. Within a given stage the injection rate is maintained at a relatively constant level whilst the proppant concentration is progressively increased. While the MFA results and the original catalogue exhibit generally similar trends, it is notable that the rate of seismicity inferred using the MFA method is more than 4 times greater than obtained during the original commercial processing (Fig. 13, lower panel). Four local peaks in seismicity rate are evident: near the beginning of stage 1 roughly synchronous with the peak (breakdown) pressure, near the end of stages 2 and 3 at approximately the same time as the proppant concentration peaks, and in the next stage 4. Rather than following the common practice of attributing microseismic events to each stage based on the treatment data, the rise and fall of seismicity rate is used as the basis for subdividing the microseismic events into four distinct temporal clusters, each separated by a local minimum (Fig. 13, lower panel).

Fig. 14(b) shows the spatial distribution of microseismicity in map view, broken down by temporal clusters that are delineated in Fig. 13, lower panel. Each event cluster has distinct characteristics, probably indicative of reservoir heterogeneity along the treatment wellbore (Eaton *et al.* 2014c). The first cluster (indicated by red dots) contains 137 events and 302 events, respectively, in the original (Fig. 14a) and MFA (Fig. 14b) catalogues. To a first approximation, these events define an NE trending feature that is roughly parallel to the regional direction of the maximum horizontal stress axis (Heidbach *et al.* 2010). The second cluster (indicated by blue dots) contains 58 and 358 events, respectively, in the original and MFA catalogues. The distribution of events in the original catalogue is scattered and sparse, but the MFA results exhibit a relatively tight distribution of events aligned at N60°E, slightly oblique to the maximum horizontal stress axis. Activity commenced along this oblique



**Figure 11.** Three-component record sections for an M – 1.94 parent [panels (a) and (b)] and M – 2.46 child event [panels (c) and (d)]. In panels (a) and (c), traces are plotted using the original geophone orientations without rotation (h<sub>1</sub> = red, h<sub>2</sub> = green, z = blue). In panels (b) and (d), traces are projected onto the polarizations of the parent event (P = blue, S<sub>1</sub> = red, S<sub>2</sub> = green). This projection results in approximate separation of P and S<sub>1</sub> wavefields. For this example, the S1 phase was used to estimate the hypocentre location of the child event.

trend during the development of the first cluster. The third cluster (indicated by green dots) contains 119 and 691 events, respectively, in the original and MFA catalogues with a complex spatial distribution. Finally, the fourth cluster (indicated by magenta dots) contains 34 and 179 events, respectively, in the original and MFA catalogues. No clear trend is evident in the original catalogue, but comparison of the MFA data in Fig. 14 with the temporal evolution in Fig. 13 shows that a pressure buildup after stage 4 resulted in reactivation of a distal region of the distribution from cluster 3.

#### DISCUSSION

Our method for locating child events is based on amplitude envelope-stacking across the sensor array. As discussed by Gharti *et al.* (2010), averaging of trace envelopes reduces the influence of noisy traces/receivers. Our MFA approach exhibits some similarities also with beam-forming techniques used to locate long-period volcanic signals (e.g. Almendros *et al.* 2002) and amplitude-based

techniques used to locate non-volcanic tremor (e.g. Wech & Creager 2008). An important distinction of our method is the choice for each parent event of a reference phase, which enables the detection and analysis of child events with a single-phase arrival, whereas the mentioned methods in volcanic studies necessarily assume the same seismic phase dominates the wavefield across the entire array. Our procedure can be compared to the method of pattern recognition of earthquake detection proposed by Joswig (1990), which is a standard noise adaptation technique. In the latter, one would select the template event and treat child events such as noise floor. However our method works in the opposite way, namely, it extracts child events by virtue of waveform similarity between selected parent events and raw data.

The distribution of microseismic events in Fig. 14 shows that all of the clusters, especially for the MFA results, exhibit a clear asymmetry towards the NE with apparent bias in the direction of the monitor well (Fig. 14). This asymmetry may largely reflect velocity heterogeneity (Eisner *et al.* 2009) or acquisition bias towards the



**Figure 12.** (a) Stacked envelope amplitude versus rotation angles  $\Delta \theta$  for the child event in Fig. 11(c). Look-up radial distance versus depth plot (b); the white circle shows the child location at the maximum stacked value, and the black cross shows the parent. The child is located 52 m from the parent.

monitor well (Rutledge & Phillips 2003; Fischer *et al.* 2008). On the other hand, results of microseismic monitoring from this area indicate that hydraulic fracture growth appears to occur preferentially towards the NE (updip) irrespective of the location of the monitor well (Duhault 2012). If asymmetric fracture growth can be validated by additional work, it may be indicative of the geomechanical influence of the driving role of strong lateral stress gradients (Fischer *et al.* 2008; Dahm *et al.* 2010).

Fig. 15(a) shows a histogram of the time difference between child events and the corresponding parent events. In this figure the occurrence of all the child events detected for all the 16 parent events, are considered. This type of diagram is enabled by the association between parent and child events and thus cannot be produced from conventional processing of microseismic data. A negative time difference implies that the child event preceded the parent, and vice versa. In addition to the main peak in the histogram, an interesting feature in this diagram is secondary peaks that separated by 35–38 min in time, both before and after the primary histogram peak. These secondary peaks reflect the underlying cyclic rate of seismicity that is evident in Fig. 13, and represent child events that occur during a different stage than the parent. Such events may occur during an earlier stage, such as events during cluster 1 that are west of the main distribution and that follow an oblique trend that becomes fully active during cluster 2, or after a stage is completed, such as cluster 4 events that appear to reactivate a distal part of the cluster 3 seismicity distribution. The occurrence of these early and late child events, located far from the injection point or locus of hydraulic fracture growth, suggest that stress activation of microseismicity may be occurring in addition to commonly assumed fluid activation (Maxwell & Urbancic 2001; Rutledge *et al.* 2004; Shapiro & Dinske 2009).

Fig. 15(b) shows an enlargement of the main peak of the histogram from Fig. 15(a), which covers parent-child temporal relationship within a single treatment stage. The shape of this histogram before the occurrence of the parent event is strikingly different from the shape afterwards. Before the occurrence of a parent event, the histogram shape is suggestive of a uniform probability of precursory child events over a time period of about 10 min. For greater times in advance of parent events the probability of occurrence is significantly reduced. On the other hand, we observe a spike in the occurrence of child events immediately following the parent, with a subsequent diminishing occurrence rate. For any given parentchild event set in this diagram, the magnitude of the parent event is greater than any of the child events. Thus, the diminishing occurrence rate is reminiscent of an Omori distribution. Taken together, this distribution is strongly suggestive of a dynamic process that consists of a ~10-min precursory sequence of microseismicity that is terminated by a larger magnitude (parent) event and followed by a typical aftershock decay sequence. The resolution of this type of dynamic behaviour of microseismicity during HF stimulation of a reservoir holds promise for further studies, with potential to provide new insights on rupture dynamics that could be used to refine models of crack propagation.

Figs 15(c) and (d), similarly to Figs 15(a) and (b), show a test conducted on the sensitivity of the parent-child temporal relationship. All the child events obtained by four randomly selected parent events, are removed. This test confirms the previously obtained trends, providing greater confidence in the robustness of the method. The sensitivity test, as well as, can give some insights to the selection of parent events in the MFA method and to what extent it could span the detected microseismicity in the stage.

The MFA approach developed here, perhaps used in combination with other techniques for estimating the Stimulated Reservoir Volume (SRV) holds promise for interpretation of induced seismicity processes in an oil–gas reservoir. Improved location obtained with our method may help to 'illuminate' fracture networks and/or buried faults, with application to mitigation strategies.

#### CONCLUSIONS

We have designed an MFA that is tailored for application to downhole microseismic monitoring using an array of multicomponent sensors within a single monitor well. Our procedure is based on cross-correlation between reference events (parent) and continuous raw data, generating additional (child) events. Amplitude normalization of the data is required as a preconditioning step to enable detection of weak child events and reduce false detections. A new technique based on the projection of child events onto ray-centred co-ordinates of the corresponding parent facilitates estimation of relative magnitudes and locations, including single-phase events. Hypocentre locations of child events are obtained by maximizing the amplitude of stacked envelope functions within a 3-D annular region centred on the parent hypocentre.



Figure 13. Comparison between pump curves (upper panel) with seismicity rate (lower panel) determined using both the MFA approach (blue) and the original catalogue (red). The rise and fall of seismicity rate is used as the basis for subdividing the microseismic events into four distinct temporal clusters, each separated by a local minimum.



Figure 14. Map view of event locations from the original catalogue (a) and the MFA results (b). The monitor well is indicated by the black circle with a cross. The approximate injection point is indicated by a magenta circle with a cross inside. The black line shows the trajectory of the lateral treatment well. Coloured dots indicate clusters 1 (red), 2 (blue), 3 (green) and 4 (magenta). Grey dots show locations of events from previous clusters.

Application of our MFA procedure to four stages from an HA treatment in western Canada yielded promising results, with an approximate 4.4-fold increase in the number of located events relative to recent commercial processing. On the basis of comparison with treatment curves, we divided the microseismicity into temporal

clusters. The spatio-temporal evolution of clusters of seismicity can be more readily interpreted using MFA results. Finally, the MFA approach enables analysis of the distribution of time difference between child and parent events. The inferred distribution shows evidence for far-field (stress related?) triggering of microseismicity

**Table 2.** Summary of detections using an STA/LTA algorithm, the MFA and the original catalogue (see Supporting Information for details on STA/LTA analysis). Noisy events refer to noise bursts and tube waves. The STA/LTA revealed to be too sensitive to noisy events.

Catalogues	Number of detection	Percentage noisy events
STA/LTA	2674	>60 per cent
MFA	1822	0 per cent
Contractor	346	0 per cent

during previous and later stages, as well as dynamic behaviour of microseismicity characterized by a  $\sim 10$  min precursory sequence that is terminated by a larger event and followed by an Omori-like aftershock decay trend.

On the Cardium data set, the MFA method extends considerably the potential of events detection in comparison to standard STA/LTA

techniques, which are too sensitive to noise bursts and tube waves.

The MFA method may hold promise in combination with techniques to estimate the SRV and interpretation of deformation processes in induced seismicity.

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Figure 15. (a) Histogram of relative time of child events with respect to their corresponding parent events. (b) Enlargement of the histogram in panel (a), showing the occurrence of child events during the same treatment stage as the parent event. Distribution suggests that a precursory sequence of child events, lasting  $\sim 10$  min, precedes most parent events. After the parent event, which has the highest magnitude in each sequence, the distribution resembles an Omori decay suggesting that child events that occur after the parent behave as aftershocks. Panels (c) and (d), similarly to panels (a) and (b), are constructed removing four selected randomly parent events, confirming the previously obtained trends.

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#### SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this paper:

**Figure S1.** Potential detection of AGC (a) and NCC (b). Detection threshold is fixed at 2.2 times the standard deviation of the stacked trace. In this example, using AGC results in two good detections and no false positives; using NCC results in two good detections and one false positive.

**Figure S2.** Stacked cross-correlation function obtained with the two approaches: (a) AGC, (b) NCC, using the first parent event as a detection template. Detection threshold is fixed at 7 times the standard deviation of each stacked trace.

**Figure S3.** Representative example of a tube wave (noisy event) detected by NCC at 13:31:42. This approach is prone to detect noisy events.

**Figure S4.** Representative example of a tube wave (noisy event) detected by the STA/LTA algorithm at 12:45:23.

**Figure S5.** Representative example of a potential event detected by the STA/LTA algorithm at 14:32:52.

**Figure S6.** Representative example of a good event detected by the STA/LTA algorithm at 13:19:13.

 Table S1. Comparison among the detection obtained using AGC and NCC. Noisy events were determined by visual inspection.

 Table S2 CTM (CTM)

Table S2. STA/LTA parameters.

**Table S3.** Detections using STA/LTA and MFA compared with the Contractor event catalogue for the same time period.

**Table S4.** Child detection obtained by varying the number of parent events for stage,  $N_{\rm P}$ .  $N_{\rm D}$  and  $N_{\rm C}$  refer to the number of child events obtained with the MFA method, prior to and after removal of duplicates, respectively.

(http://gji.oxfordjournals.org/lookup/suppl/doi:10.1093/gji/ggw168/-/DC1).

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#### APPENDIX: ACQUISITION GEOMETRY FOR THE SYNTHETIC AND REAL EXAMPLES

Data used in this work for the second of the two synthetic tests presented are extracted from the full data set recorded during the Hoadley Flowback Microseismic Experiment (HFME). This experiment and all the technical details are described by Eaton *et al.* (2014a); the vertical downhole acquisition geometry consisted of a vertical monitoring well where a 12 sensor array of triaxial geophones (corner frequency 15 Hz) was installed. Inter-pod spacing varied from 30.5 m for the top four units to 15.25 m for the bottom eight, representing a total array aperture of 229 m.

Data used for the application example of the MFA method shown are taken from the microseismic experiment discussed in detail by Duhault (2012). The monitoring system, similar to HFME, was composed of 12 3-C geophones straddling the reservoir target with a sensor spacing of 30 m for a total array aperture of 330 m.