An automated quantitative multi-stage approach to invert velocity models for microseismic event locations

Fernando Castellanos¹, Mike Preiksaitis¹, Ryan Nader¹, Vlad Shumila¹, Steve Falls¹, Dan Hook¹ and Doug Angus¹ discuss the development of an automated microseismic processing workflow for perforation shot detection and optimal velocity model inversion using particle swarm optimization.

Introduction

Complexity in hydraulic fracturing programmes has motivated microseismic service providers to innovate and propose creative methods to monitor drilling, completion and field development. Although microseismic analysis and interpretation have moved beyond the ‘dots-in-a-box’ solution, velocity model (VM) calibration using inversion plays a critical role in the initial phase of accurate microseismic event (event) locations to ensure the accuracy of subsequent higher-order microseismic attributes given data quality and monitoring geometry. Knowing that business decisions are, at times, required in real time, it is imperative to provide confident event locations efficiently through the construction of well-constrained VMs based on quantitative and objective methodologies. The most time-consuming aspects of microseismic data processing are optimal VM construction and inversion. In this paper, we demonstrate improved efficiency in microseismic data processing by developing and implementing an automated approach to perforation shot (perf) detection and VM inversion using Particle Swarm Optimization (PSO). These primary tasks (perf detection and VM inversion) are critical in the event location workflow and can benefit significantly from increased efficiency. Although more advanced Greens functions can provide more accurate solutions to the source location problem (e.g., Angus et al., 2014), we focus on ray-based approaches due to their high computational efficiency, especially for anisotropic media and hydraulic fracture monitoring where large volumes of microseismic data (commonly in excess of 100,000 events) must be processed.

In seismology, the VM represents a key uncertainty. In microseismic monitoring, seeking an accurate VM involves using well log data and perfs (control shots of known location) if they are available and/or 3D VMs from reflection seismic imaging. Well log data provide a starting point in VM construction, where a high-resolution log is converted into a ‘simplified’ 1D layered model with horizontal boundaries associated with impedance contrasts and lithological boundaries.

Since the locations of microseismic sensors and perfs are known (often within ±2 m uncertainty for high accuracy well surveys), perf signal arrival times allow for constrained VM inversion. Perfs are used in unconventional well developments to initiate pathways from the wellbore through the well casing, pipe or cement for direct contact with the target reservoir, using a bullet gun, abrasive water jets, or shaped charges. The explosion process generates a seismic signal that can be recorded on microseismic sensors and used for sensor orientation and VM inversion. The detection of perfs can be challenging since the recorded amplitude is a function of energy output of the charge and the source-sensor distance. The challenge is further compounded when adjacent wells are being stimulated during perf detonation. In the existing literature there are few studies that focus on automatic procedures to detect perfs. Partly this can be explained by the fact that some perforation technologies rely on the ‘time zero’ concept, which digitally records a spike-like electrical signal when a perf is detonated and allows for straightforward identification of perfs. Recording of auxiliary channels (i.e., time zero) is not available in many projects, which can increase the challenge of detecting perfs. Since perfs commonly have distinct signatures when compared to events, an automated approach based on waveform cross correlation (CC) should provide an alternative and objective tool in their detection for such cases.

Here, we demonstrate the automated workflow to detect perfs, invert and calibrate VMs and subsequently locate events. First, we briefly summarize the event location processing steps. Then, we describe the automated methodology to detect perfs using CC and azimuthal correction. Next, we discuss the automated VM inversion algorithm using perf locations and a parallelized PSO algorithm. Finally, combining these two approaches, we present event locations highlighting the robustness and efficiency of the method.

Data processing workflow

Presently, typical microseismic monitoring projects involve monitoring of multi-stage hydraulic fracture completions of multiple horizontal wells, using single array or more complex multi-array receiver geometries. Selection of optimal monitor-
ing configurations, usually via prior modelling studies, allow for increased event location accuracy, leading to confident interpretation of site characteristics, comparison of in-zone and out-of-zone fracture generation, and identification of overlap in potential production zones between wells and stages. Microseismic signals are commonly recorded using arrays of 3C 15 Hz geophones in vertical, deviated and horizontal array configurations, at fixed or variable inter-sensor separations.

Fracture growth is initially imaged using event locations and further refined using advanced attributes, such as seismic moment tensor and dynamic parameter analysis (e.g., Angus et al., 2019; Moradi et al., 2019).

A typical data processing workflow involves many steps, from validating sensor locations and orientations, checking well logs, pre-conditioning the triggered microseismic data and so forth (e.g., Eaton, 2018). Here we focus on what is generally the most time-consuming aspect of processing microseismic data for accurate event locations – VM inversion. The workflow consists of reliably detecting perfs within a volume of potential events (triggers), creating an initial VM from sonic logs and empirical information, defining VM checkpoints (multi-stage sections along treatment well) to evaluate model suitability, inverting for VMs using identified perfs, quantitatively evaluating the most suitable VM(s) for those checkpoints, and locating events (see Figure 1). Since VM inversion and general data processing workflows tend to be iterative, efficient measures in any of these steps significantly impact turnaround time, specifically in this workflow where these steps make up an estimated 60-80% of total processing time.

**Perf detection using CC**

Waveform CC techniques have been used to detect events, where it is expected that the events that rupture on the same fault segment or hydraulic fractures will have similar waveforms (e.g., Castellanos and van der Baan, 2015). Similarly, it is reasonable to assume that perfs for each stage have consistent source signatures that have sufficiently dissimilar characteristics to that of other nearby events. The perf detection approach we apply is based on a multiplet analysis method (Geller and Mueller, 1980; Arrowsmith and Eisner, 2006). First, we select all the triggers (i.e., time windows of potential events extracted from the continuously recorded data) within the expected perf time window (i.e., N triggers recorded within the approximate time window where a set of perfs have been detonated). For each trigger pair combination, we extract a portion of time span around the P-wave and evaluate waveform similarity by computing a weighted average of the CC coefficients across all three components for each sensor within the array. Weighting is determined by the maximum amplitude on each component, which reflects the signal-to-noise ratio in each trace. After calculating the averaged CC coefficient for all trigger pairs, we create an N×N upper triangular matrix containing the CC coefficients of all pair permutations. Next, we choose a minimum CC threshold that defines whether two triggers are considered highly correlated. This technique does not enforce mutual similarity among all triggers within the group but allows triggers to be correlated in a breadth-like fashion, so they can belong to the same group even if there is limited mutual similarity, mainly due to noise. If only one group is detected, it is likely the perfs belong to this group. However, if multiple groups are detected, we use hodogram analysis (e.g., Montalbetti and Kanasewich, 1970) to automatically find the group whose back-azimuth aligns with the perf zone. Although it is an imperfect assumption that perf signals will have strong similarity, we find the assumption is sufficient to discriminate between a strong isotropic (or volumetric) mechanism (i.e., perfs) and an event with constrained double-couple, tensile opening and closing, and CLVD type mechanisms.

We demonstrate the perf detection methodology on three datasets. The first dataset is from a multi-level vertical receiver array monitoring a horizontal stimulation in the Western Canadian Sedimentary Basin. The monitoring array was within 400 m from the treatment well. Figure 2a compares four perfs from one stage. Through a visual comparison of these perfs we expect high CC coefficients between them. To evaluate the variability of the perfs between stages, we focused on five consecutive stages, extracting a total of 310 triggers that occurred within ±2 minutes of the reported perf times. Figure 2b shows an upper-triangular CC matrix exhibiting strong perf similarity between stages. Figures 2c and 2d display the seismogram and spectrogram of a typical event and perf, respectively, highlighting differences in P- and S-wave amplitudes. The event has a characteristic P-wave arrival followed by a higher amplitude S-wave arrival (typical of shear dominated failures), whereas the perf contains the expected P-wave arrival, but also a weaker S-wave (generated either at the source or as a near-source P-to-S conversion). The spectrogram highlights differences in signal bandwidths, where the event has a higher frequency content.

The CC method alone is robust as a general tool, but not always sufficient to uniquely identify all perfs. The assumption that all perfs, particularly between adjacent stages along a treatment well, show high similarity is tested when events also share common signal characteristics (see Figure 2b); this results in occasional false positives. If only one spatial group is detected, it is likely the triggers are perfs or near wellbore events. If microseismic multiplets occur within the perf time window, the CC method will likely output more than one cluster. This is
correction identifies 97 perfs of the known 103; a success rate of 94% perfs detected but with 62 false detections.

The last dataset is from a multi-level Whip-array configuration, deployed simultaneously in horizontal and vertical positions of the monitoring well to monitor horizontal treatment wells targeting the Upper Devonian. The horizontal portion of the array was located within the mid-to-heel section of the well, with the vertical portion of the array located approximately 100 m above the treatment interval in the heel of the well. A total of 2492 triggers were recorded within the perf time window for all stages. CC reduced the number of triggers to 486 potential perfs. The number of spatial clusters per stage ranged between 1 and 4 (excluding doublets). After azimuth correction, the method identifies 100 perfs of the known 128; a success rate of 78% perfs detected but with 59 false detections. The success rate for the last two trials is not comparable to that of the first trial (e.g., > 99%) and is mainly due to increased coherent noise. However, we observe a significant reduction in potential triggers requiring manual QC (e.g., approximately 90% reduction in potential triggers).

Automated PSO VM inversion

It is well established that there exists strong natural vertical variation in rock properties and hence seismic velocities in unconventional reservoirs. On the other hand, for undeveloped plays, there is little evidence to suggest strong natural lateral variability of rock properties within individual lithological units. As such, dipole-sonic well logs are often used to determine an initial VM, where density and high frequency P- and S-wave vertical velocities are used to construct block type

![Figure 2](image)

**Figure 2** a) Waveforms from four perfs from one stage recorded at the same sensor. b) Upper-triangular CC matrix and detected perfs showing high similarity between all five stages. Comparison of waveforms corresponding to (c) an event (top is the waveform and bottom is the spectrogram) and (d) a perf (top is the waveform and bottom is the spectrogram).
VMs suitable for event location. In many situations economic constraints limit the dipole-sonic log to a single well and often this log can be a large distance (e.g., 10s km) from the target treatment and monitoring well locations. Subtle lateral as well as potentially significant vertical heterogeneity in the velocity structure could persist due to geological variation over distance ranges of 10s km. Furthermore, there are many subtle and dynamic factors that could induce local variations in the rock/velocity structure that require consideration in order to correctly locate events across multi-well fields. For instance, past and current completions activity could induce changes in the in-situ rock (i.e., velocity) properties, such as the introduction of large volumes of injected fluid and proppant (e.g., Sarout et al., 2019) and perturbations to the stress field due to changes in pore pressure (e.g., Price et al., 2017) from hydraulic fracture stimulation and subsequent depletion. As such, the VM needs to adapt to changes in the reservoir occurring throughout a stimulation program.

We use a ray-based Greens function to propagate the seismic wavefield between the source and receiver to fit various degrees of structural complexity. In many unconventional scenarios, the velocity structure can be generally represented as a horizontal or dipping layered sequence of lithological units alternating between shale, sandstone and limestone sedimentary packages. Therefore, we modified the two-point ray tracing approach (e.g., Yue and Xiao-Fei, 2005) to accommodate anisotropic media (e.g., VTI due to layering and intrinsic shale anisotropy as well as HTI due to the presence of fractures) as well as accounting for possible head waves arriving earlier than the direct arrivals.

For VM inversion, we use PSO, a population-based stochastic optimization technique used to efficiently invert for VM using perfs and early-stage events (Clerc and Kennedy 2002; Urbancic et al., 2006). PSO comes from a family of so-called genetic algorithms for global optimization that allows surveying a multi-dimensional parameter space to provide a constrained solution based on a priori geophysical bounds (e.g., the VM parameters can be constrained based on available sonic logs with some allowable deviation based on expected geological heterogeneity as well as measurement error). By varying the imposed constraints and target function, PSO can generate solutions suitable for a space and time evolving rock mass and/or changing configuration of the monitoring array. Thousands of VMs are automatically generated by PSO with varying layer seismic velocity and anisotropy, allowing for geologically constrained divergence from the input sonic log, resulting in tens to hundreds of final models to assess in determining the optimum model (Figure 4c). To exhaustively search the model space and evaluate potential models, we parallelize the two-point ray tracing algorithm by distributing each source-receiver pair. As an example, moving from the serial implementation for 1 CPU to the parallelized implementation using 48 CPUs results in an approximately 24 times decrease in compute time. The computation time depends on many factors such as the number of receivers, VM layers, resolution of the model as well as PSO model space set-up parameters (e.g., tribe size).

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Table 1: 138 out 139 (99%) of perfs were detected as part of CC-based perf detection using a fixed CC threshold of 0.8.
As a first pass, VM inversion using PSO can be applied for the entire treatment (multi-well) pad for all stages and perfs. However, if the local velocity is sufficiently variable, the resulting single VM may not be suitably accurate to locate the recorded events as required by the operator. One method of handling this potential variability is to allow for VM updates (or changes) across the treatment pad using defined checkpoints. Each checkpoint allows the VM to be updated if the target threshold is not met. Effectively, this allows the automated inversion approach to develop a discrete (or blocky) two-dimensional VM. For shorter wells (lengths < 2 km) with limited structural changes, two or three checkpoints per well may be sufficient and for longer wells (distances > 2 km), with potentially more variable or complicated structure, a greater number of checkpoints per well may be required.

There are many models that fit the resulting minimization of a target function misfit. By automating the VM inversion and calibration, we use multiple input seeds of varying model parameters to explore many geologically reasonable models. For each checkpoint, a quantitative criterion is used to identify the optimal model solution for that checkpoint. This criterion requires us to balance the desire to lower the observed versus modelled travel times (i.e., residuals) while ensuring that geologically realistic models are generated (not allowing drastic variations in velocity, anisotropy, impedance contrasts that is not supported by the data). The automated quantitative selection criterion considers key metrics such as maximum allowable perturbation of the velocity and anisotropy parameters, divergence from the sonic log and formation tops, and the difference between calculated and known perf locations. Figure 4a shows an initial starting VM derived from a sonic log. Figure 4b shows an example final VM for the whole treatment well. Figure 4c shows an example of PSO scoring, where the lowest score represents the optimum VM. Although combining this perf detection-checkpoint approach with anisotropic PSO VM inversion increases computational costs, this in practice allows for significant time savings and allows for a more accurate, quantitative and quicker delivery of microseismic imaging results with the optimum VM.

To illustrate the approach, we apply the automated PSO method on the first example dataset, where a conventional multi-level vertical receiver array monitors microseismicity from a multi-well stimulation (showing 1 of 5 horizontal treatment wells) targeting a formation in the Western Canadian Sedimentary Basin. We evaluate perf locations for three scenarios: an initial VM derived from the sonic log (see Figure 4a), a single PSO VM using all perfs along the well (see Figure 4b) and three PSO VM using the checkpoints for the toe, mid and heel sections of the well (e and f). The left column shows the map view of perf locations and the right column the cross-sectional view of perf locations. The vertical array is approximately 350-m long for scale.
sections of the well. Using the initial model, the perf locations show significant drift and noticeable depth arcing as offset increases (see Figure 5a and 5b). Locating the perfs using a single PSO model improves the locations by reducing the scatter but depth arcing, though less noticeable, is still apparent at far stages (see Figure 5c and 5d). Using three PSO models along the well removes the depth arcing (see Figure 5e and 5f). For most of the checkpoints, the automated PSO algorithm finds a best fitting model with location difference less than 25 m. The constrained PSO algorithm generally only deviates on the order of ±5% with respect to the P- and S-wave velocities and on the order of ±10% for anisotropy, which is consistent with lithological (Dewhurst and Siggins, 2006) as well as stress-induced anisotropy (Baird et al., 2013).

**Event locations**

Given the large number of recorded events, we use a ray-based coherency source scanning algorithm to locate as well as pick the theoretical P- and S-wave arrivals (e.g., Kao and Shan, 2004; Baig et al., 2015), see Figure 6a. Once optimal VMs are found along the treatment well(s), we calculate a brightness function for each event by summing the amplitudes observed on all sensors at their corresponding theoretical arrival times (see Figure 6). Then, the source locations (x, y, z and origin time) are identified by a search throughout the model space time for the maximum brightness (see Figure 6b-6d).

Figure 7 shows the results of locating events for 19 stages for the first dataset (see Figure 5). Comparison of the event locations from the standard workflow (Figure 7a and 7b) and the automated workflow (Figure 7c and 7d) demonstrate that the event locations and seismicity distribution for both approaches is similar. In Figure 7e, the events are colour-coded based on checkpoint VM. For this particular dataset, the time to generate the locations shown in Figure 7 for the standard approach required approximately six days’ effort whereas the automated approach required two days’ effort, a three-fold improvement.

Ultimately, the goal of any monitoring program is not to just collect data but rather to yield results that can be used for reliable interpretation of completions techniques and integration with other data streams. Therefore, in order to truly determine the viability of the automated processing workflow, it is necessary to try to assess its impact on interpretation. A key interpretive aspect of microseismic results is the estimation of fracture dimensions (height and half-length) estimates for each stage in a stimulation program. Figure 8 compares the estimated fracture dimensions for the standard processing and the automated processing workflows. The results show that fracture lengths and heights are consistent between both methods, with the few stages that show larger discrepancies (stages 5 and 6), being the farthest distances from the monitoring array. The similarities between the two datasets provides confidence that the final interpretation of results would not be negatively impacted by the automated methodology.
Conclusions
With the industry shift towards larger, simultaneous multi-well stimulations and strategic cube development, the volume of data collected on a given project has risen exponentially in recent years. Microseismic data volumes are no exception. To help address this dramatic increase in microseismic data, we have developed and demonstrated the use of an automatic approach consisting of perf detection using cross-correlation and velocity model calibration. This allows for a fast and quantitative assessment of optimal velocity models at different sections along the treatment well, aimed at significantly reducing the time an analyst would need to visually inspect potential perforations and apply quality control measures to finalized velocity models. To determine the benefit of the perf detection method, we recommend prior noise attenuation and filtering since low SNR perf would require lower cross correlation thresholds (<0.8), resulting in undesired false positives. As for PSO inversion, prior site information such as sonic and other logs, anisotropy, formation tops, presence of adjacent wells, are key to evaluating a feasible range of velocity perturbations and finding realistic velocity models based on a ‘score’ approach. These automatic methods require less manual work than standard workflows, allowing for faster, high-quality event locations that can be interpreted with high confidence.

References