# Passive seismic event-classification techniques applied to heavy oil production from Cold Lake, Alberta

*Jeffrey Tan*, Henry Bland, and Robert Stewart, University of Calgary*

**Summary**

The CREWES Project at the University of Calgary is conducting research with Imperial Oil Limited concerning passive seismic monitoring of heavy oil production wells at Cold Lake, Alberta, Canada. This monitoring is required to proactively detect mechanical breakdowns in producing wells that can arise from the cyclic steam stimulation enhanced recovery process used to extract the viscous bitumen. These breakdowns induce microseisms that are recorded at the surface, resulting in the creation of a microseismic event file. Noise vibrations generated by pump rods or passing vehicles also trigger the passive seismic monitoring system and are recorded. Noise events comprise approximately 99% of all microseismic event files generated, but are generally not of interest and are usually discarded. The current classification software on this monitoring system incorrectly classifies a large portion of these files, resulting in many noise events being classified as microseisms worth further investigation.

The objective is to develop accurate passive seismic signal analysis and classification algorithms capable of precisely distinguishing between microseismic event files warranting further investigation, also referred to as "good" event files, from noise event files that are generally not of interest. Compared to noise events, many "good" events generally have lower frequency content, shorter P-wave event-lengths, and flatter time-domain characteristics. Based on these observations, methods involving frequency-filtering, event-length detection, and statistical analysis are developed and combined into a MATLAB graphical user interface.

Testing of this application on thousands of microseismic event files yields a classification accuracy between 96% and 99%, depending on the tested dataset. We aim to implement some of the developed algorithms on Imperial's passive seismic monitoring system at Cold Lake in the future, which would likely result in significant time-savings.

**Introduction**

Passive seismic monitoring listens for small earthquakes (microseisms) that occur when there are stress changes in a reservoir (Maxwell and Urbancic, 2001). The CREWES Project at the University of Calgary is involved in passive seismic research with Imperial Oil Ltd. regarding reservoir monitoring at Cold Lake, Alberta, Canada, where more than 120,000 barrels of bitumen are produced each day. The Cold Lake oil sands deposit, shown in Figure 1 (Imperial Oil Ltd., 2006) is one of three major oil sands deposits in Alberta.


Figure 1 (Imperial Oil Ltd., 2006): Alberta’s three major oil sands deposits.

Cyclic steam stimulation (CSS), an enhanced recovery technique, is required to extract the viscous bitumen that is buried over 400 meters deep at Cold Lake. The bitumen has an American Petroleum Institute (API) index of approximately 8° to 9°. This CSS process creates pressures and temperatures in the producing formation of approximately 320°C and 11 MPa, respectively (Campbell, 2005). Mechanical issues in the producing wells such as cement cracks or casing failures can result from these high pressures and temperatures. If undetected, these production issues could result in large cleanup costs, in addition to potential legal implications. For example, a casing failure could potentially cause environmental damage such as aquifer contamination. A microseismic earthquake with its focus near the damaged area is created when these mechanical issues occur. Imperial Oil Limited operates a passive seismic monitoring system at Cold Lake to proactively detect these microseisms so that prompt action can be taken if a production issue is detected.

The passive seismic monitoring system implemented at Cold Lake is present on approximately 75 production pads, each of which contain about 18 to 24 producing wells (Campbell, 2005). Each pad has a centrally located monitoring well that records ground vibrations (including microseisms). The monitoring well is instrumented by a down-hole array of five or eight 3-component (3-C) geophone sondes connected to seismic recorders at the surface (Tan et al., 2006). These seismic recorders listen for discrete seismic events and store them as microseismic event files to disk for later review. For an array of five (eight) geophones, these digital event files contain fifteen (twenty-four) traces that display 1.365 seconds (1.5 seconds) of microseismic activity recorded by the 3-component geophone sondes.

Vendor-supplied event-classification software analyzes each created microseismic file and assigns a classification. If a file is classified as "good", this indicates that the software has decided that the event file warrants further investigation; conversely, if a file is classified as "noise", it is supposedly an event that is not of interest (Tan et al., 2006). Approximately 99% of all detected events are noise. Examples of "good" events worth further investigation include cement cracks around the casing in the wells, and casing failures. Examples of noise events include noise created by pump rods and passing vehicles (Campbell, 2005). Noise events are usually discarded.

The current event-file classification software has been known to misclassify a large portion of the received files. This has resulted in many "good" events and noise events being incorrectly identified. These numerous misclassifications require extensive manual investigation. This time-consuming process of examining incorrectly classified files one-by-one can become very costly.

The purpose is to develop and combine microseismic analysis algorithms capable of precisely classifying the microseismic event files generated by the passive seismic monitoring system at Cold Lake. Frequency-filtering, event-length detection, and statistical analysis techniques are developed. An interactive graphical user interface (GUI) application is developed and tested. Depending on the tested dataset, it performs with approximately 96% to 99% accuracy, which is an encouraging result. We aim to implement some of the developed passive seismic event-classification algorithms on Imperial's system at Cold Lake in the future.

## Example Events

Figures 2 and 3 are two sample traces. Figure 2 shows a trace obtained from a "good" event, with the P- and S-wave arrivals indicated. Figure 3 shows a trace from a noise event. These two example traces do not characterize all of the possible detected events, but are a fairly reasonable representation of the characteristics pertaining to a fair number of "good" and noise events (Tan et al., 2006). These traces are normalized to the largest data value (in magnitude), and have any DC offset removed.

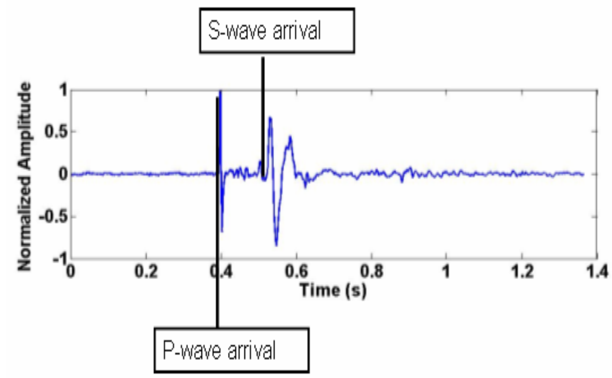


Figure 2: Example trace of a "good" event.

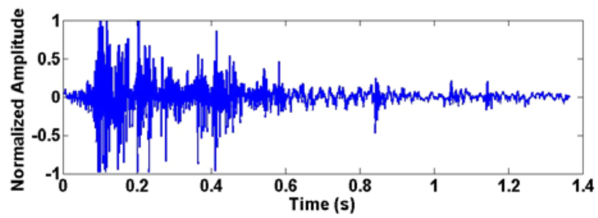


Figure 3: Example trace of a noise event.

## Algorithms

Compared to noise events, many "good" events generally have lower frequency content, shorter P-wave event-lengths, and flatter time-domain characteristics. Based on these observations, classification algorithms involving frequency-filtering, event-length detection, and statistical analysis are developed. Testing on microseismic event files is performed to decide algorithm details such as filter order, passband range, stopband range, and threshold settings.

Frequency Filtering

Many "good" events generally have lower frequency content than noise events. This set of classification algorithms filters incoming microseismic signals with low-pass, high-pass, and band-pass filters, followed by an amplitude analysis of the filtered signal**.** Chebyshev, Butterworth, and Inverse-Chebyshev frequency response approximations similar to those shown in Maundy (2005) as well as Zhou and McMechan (1999) are applied. Different filter responses are applied to provide balance and to capture the strengths of each response. As an example, for a given filter order, a Butterworth filter has a flat response in the passband (a desired characteristic), but provides less stopband frequency attenuation when compared to a Chebyshev filter. A Chebyshev filter, however, contains a small amount of frequency-domain ringing (an *equiripple* characteristic) in the passband. Filters with smooth cutoffs are applied to prevent Gibbs' Phenomenon (e.g. Sheriff and Geldart, 1995) from occurring, as a sharp cutoff in the frequency domain induces ringing in the time domain. An example application of a high-pass filter follows.

*High-pass example*

A fourth-order high-pass Butterworth filter with a 215 Hz upper stopband limit and 398 Hz lower passband limit is created. This filter provides at least 25 dB attenuation in the stopband and does not attenuate passband frequencies by more than 3 dB. Figure 4 shows the magnitude response for this filter.

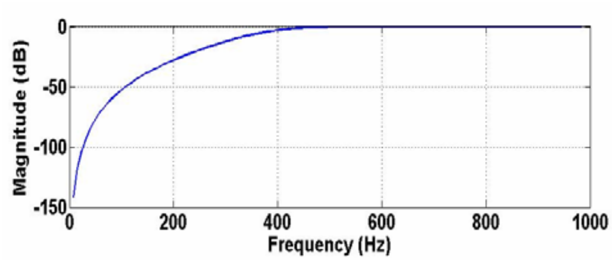


Figure 4: Amplitude response of high-pass Butterworth filter.

Figures 5 and 6 show the "good" and noise traces from Figures 2 and 3 after high-pass filtering. Note that the magnitude of the peak data value in Figure 5 (approximately 0.05) is much lower than that of Figure 6, which is approximately 0.7.

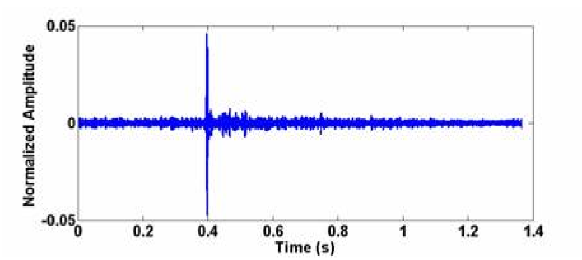


Figure 5: Result of high-pass filtering the "good" trace in Figure 2.

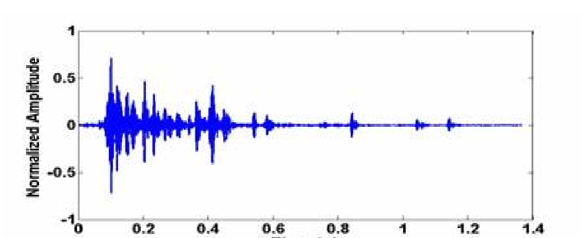


Figure 6: Result of high-pass filtering the noise trace in Figure 3.

<u>Event-length detection</u>

The P-wave event-length in many "good" traces is usually significantly shorter than noise event-lengths. This set of classification algorithms determines the first-arrival event-lengths.

*Time-domain*

An applied time-domain algorithm continuously calculates ratios of short-term averages (STA) to long-term averages (LTA) of microseismic energy. This is the STA/LTA technique (Ambuter and Solomon, 1974) demonstrated by Munro (2005). The STA/LTA ratio will often significantly increase at the onset of a microseismic event and decrease at its termination.

*Frequency-domain*

A second, frequency-domain, technique continuously analyzes frequency characteristics of a select number of points in a channel. The high-frequency content of many microseismic traces usually increases significantly at the onset of the event and decreases significantly at the event's termination. This technique is similar to the Gabor and S-transform techniques (e.g. Feichtinger and Strohmer, 1998) that are commonly used in signal processing.

If a time interval is defined from $t_1$ to $t_2$ in the channel, a continuous-time frequency analysis, using the discrete Fourier transform (DFT), can be performed by supplying a moving frequency transform window that exists between $t_1$ and $t_2$, with the limits $t_1$ and $t_2$ continually increased up until the end of the channel data. The resulting frequency power spectrum is then found for each time interval. There is a direct tradeoff between frequency and time resolution, as outlined by the uncertainty principle. If the time window is too small, the transformed output will have strong time resolution, but poor frequency resolution; conversely, if the window is too large, the output will have strong frequency resolution, but poor time resolution.

As an example, Figure 7 displays the "good" microseismic trace shown in Figure 2 with this continuous-time Fourier transform algorithm applied to it. The trace in Figure 2 has 4096 data points and was sampled at 3000 Hz. The moving frequency transform window contains 100 data points at each time interval. Thus, data in time intervals of length

$$\Delta t = \frac{100}{3000}\ \text{s} = 0.0333\ \text{s}$$

are frequency-transformed throughout the examined trace. The onset and termination points of the P-wave arrival are shown in Figure 7. The highest magnitudes are indicated with bright red and the lowest magnitudes are indicated with dark blue. There is a sharp increase in high frequency content at the onset of the event, and a sharp decrease in high frequency content at the event's termination. The length of the P-wave event is approximately 40 ms.

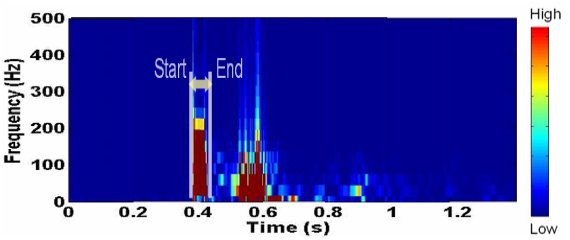


Figure 7: Continuous-time Fourier transform power spectral density plot of "good" trace in Figure 2.

Figure 8 shows the noise trace in Figure 3 with this transform applied. The noise event-length (approximately 550 ms) is much longer than the P-wave event-length in Figure 7.

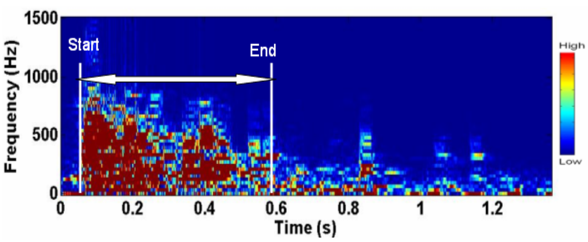


Figure 8: Continuous-time Fourier transform power spectral density plot of noise trace in Figure 3.

Statistical Analysis

Many "good" traces are generally much flatter than noise traces and usually contain a larger proportion of data points close to the time axis. Simple statistical analysis algorithms examine the concentration and distribution of trace data points to determine if these "good" characteristics are present. Algorithms that examine the fraction of data points outside a small threshold window, the concentration of points near the time axis, and the number of zero crossings after low amplitude noise is removed are applied.

## Multivariate Data Reduction

Principle Components Analysis

Initial tests suggest that algorithm output values from "good" and noise files cluster best when statistical analysis algorithms are used. To reduce the dimensionality of the data, a new set of variables that are linear combinations of statistical analysis results is created. This new group of variables forms the "principle components" of the data. Examples of applying this technique are outlined by Jackson (1991), and Jolliffe (2002), among many others. In essence, the concept is to rotate a matrix containing many observations of multiple variables by a transformation matrix. The transformation matrix is formed through determining the eigenvectors of the covariance matrix corresponding to the mean-corrected data. For a dataset containing *n* variables, there will be *n* corresponding eigenvectors, and *n* principle components. Each eigenvector represents the coefficients, or loadings, of a single principle component and occupies a single column in the transformation matrix, which is square. The dimensions of the transformation matrix will equal that of the covariance matrix. For detailed derivations, refer to the cited literature.

Currently, this analysis is being performed to examine if there is a single driving principle that can determine the classification of a microseismic file.

## Results

A graphical user interface (GUI) application is created that allows the user control of the deciding thresholds in the algorithms. This program correctly classifies approximately 96% to 99% of the thousands of files that it has been tested on, depending on the tested dataset**.** This is an encouraging result. We aim to implement some of the discussed passive seismic event-classification algorithms on the system at Cold Lake in the future, which would likely result in significant economic savings.

## Conclusions

Microseismic signal analysis algorithms are developed and combined into a graphical user interface application for classifying event files generated from the passive seismic monitoring system at Cold Lake, Alberta. Program tests suggest these algorithms are valid event-classification tools. We aim to implement some of the discussed algorithms on Imperial Oil's passive seismic monitoring system at Cold Lake, Alberta in the future. Should this occur, much time and money would likely be saved, as the average production rate at Cold Lake is over 120,000 barrels of bitumen per day. A potential shift in focus from manual microseismic file examining to other pertinent production issues could also occur for several Imperial Oil employees.

## Acknowledgements

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