Passive Seismic Event Classification Techniques Applied to Heavy Oil Production from Cold Lake, Alberta

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Overview

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, where more than 120,000 barrels of bitumen are produced each day (Imperial Oil Ltd., 2006).

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 (twentyfour) 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 MATLAB graphical user interface (GUI) application, entitled Event_Analyzer, is developed and tested. The developed application is tested on 7697 microseismic files. It correctly classifies 99.4% of these files, which is an encouraging result. With continued testing, development, and optimization, we aim to implement this GUI on Imperial's passive seismic monitoring system at Cold Lake in the future, which would likely result in significant economic savings.

Example Events

Figures 1 and 2 are two sample traces. Figure 1 shows a trace obtained from a "good" event, with the P- and S-wave arrivals indicated. Figure 2 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.

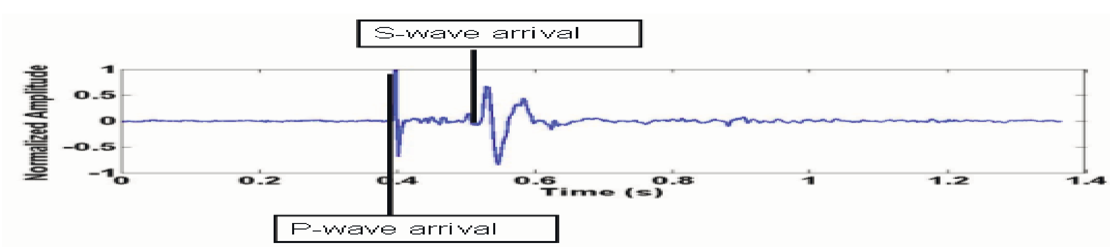

Figure 1. Example trace of a "good" event.

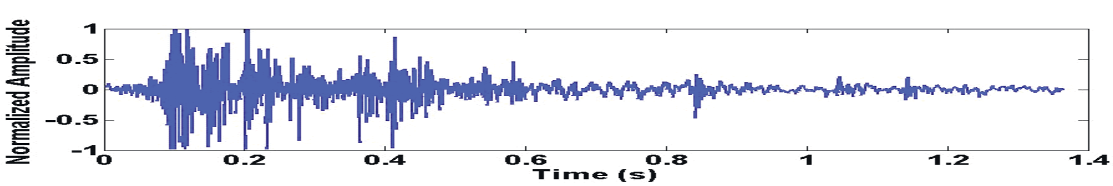

Figure 2. Example trace of a noise event.

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. A preliminary available dataset of 7032 microseismic event files is used 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.

Event-Length Detection

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. 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. 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.

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 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.

Results

Crossplots suggest that “good” and noise files cluster best when statistical analysis algorithms are used. Thus, *Event_Analyzer* has been recently updated to classify files as either “good” or noise based on a function dependent on the results of the statistical algorithms pertaining to a microseismic file.

Two major test datasets are examined to measure the accuracy of Event_Analyzer. The first tests pertain to an initial dataset of 7024 noise and 8 “good” files, which mostly come from a limited number of production pads. These first tests are used to perform initial program optimization. The second, most recent, tests correspond to 407 noise and 258 “good” files from a wide range of pads. These secondary tests measure the robustness of the application. As an example, Figure 3 depicts the deciding function’s output corresponding to files from the second test dataset. Each grey triangle (black square) marker represents a noise (“good”) file. The dashed line represents a chosen deciding threshold value based on the results. If the function output from an examined microseismic file is below the dashed line, the file is classified as “good”; otherwise, it is classified as “noise”. The threshold shown for the dashed line in this case is 0.75.

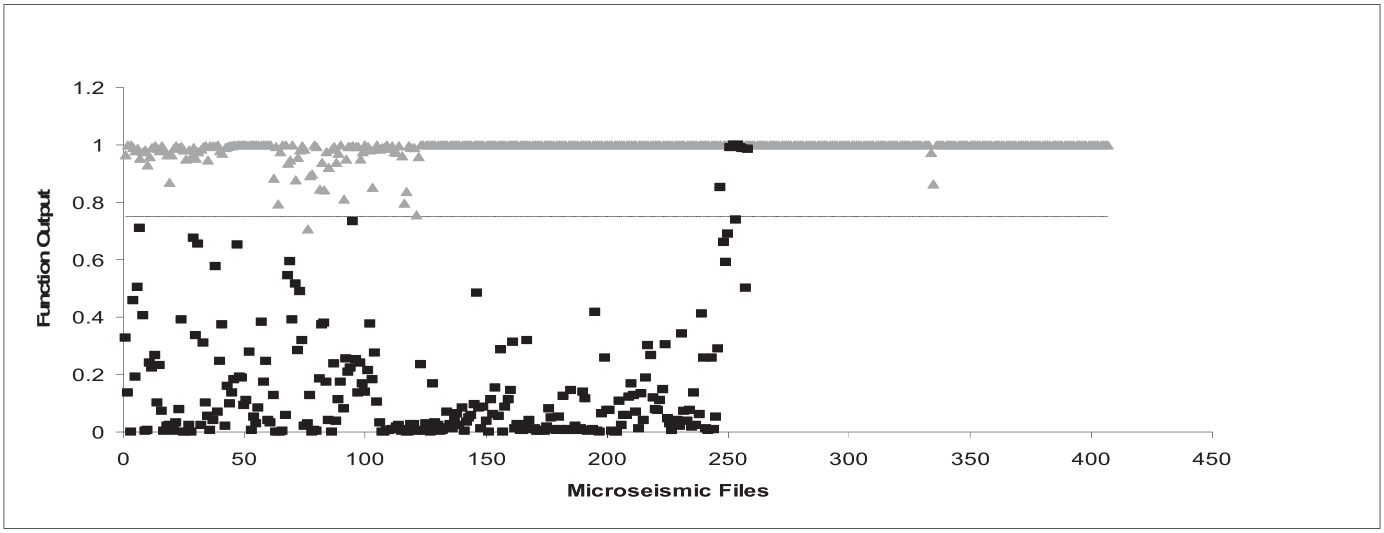

Figure 3. Function output corresponding to files from second test dataset. Each grey triangle represents a noise file, and each black square represents a “good” file.

The application correctly classifies 99.5% and 98.8% of the files from the first and second test datasets, respectively. These results are encouraging. With continued testing, development, and optimization, we aim to implement this GUI on Imperial's passive seismic monitoring system at Cold Lake in the future, which would likely result in significant economic savings.

References

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