geoconvention
Calgary • Canada • May 7-11 2018

Energy-stack and Kurtosis: the dynamic duo for microseismic event identification

Atila S. Paes[ab] and David W. Eaton[ac]
[a]Dept. of Geoscience, Univ. of Calgary, [b]paesa@ucalgary.ca, [c]eaton@ucalgary.ca

Summary

Event detection, validation and arrival-time picking are critical components for processing microseismic monitoring data. The energy-stack has been developed as a fast and efficient scanning method for potential microseismic events. Among a large number of tested metrics used in arrival-time picking, the use of kurtosis stands out due its accuracy and the onset sharpness of either P- and S-waves in real-world noisy datasets. This paper combines energy stacking and kurtosis as the core of a new workflow based on: 1) building a potential-event catalog based in energy-stack and peak properties; 2) analysis of the signal of each peak to refines the initial catalog; and 3) quality-control for removal of false and poor quality events. Benchmarking of the potential-event detector shows excellent results compared with several other existing methods. In particular, the energy-stack approach collects all quasi-simultaneous perturbations in the geophone array, while the kurtosis approach collects a higher number of fair picks and removes erroneous picks in all tested cases.

Introduction

In practice, microseismic monitoring may last from hours to weeks. Consequently, a post-acquisition event detection software must pre-process the raw data pack in order to reduce it to a limited set of potential-events that deserve closer attention. Among dozens of detection methods, none of them performs optimally under all situations (Sharma et al.,2010). Even the most used ones demand adjust of several sensitive variables to locate low amplitude events.

The way data is inputed in characteristic function (CF) is not a consensus among authors. Pursuing signal to noise ratio (SNR) increase and noise damping in STA/LTA algorithms, Saari (1991) uses the absolute value of the product of amplitudes from a 3-c geophone. Likewise, Oye and Roth (2003) use the stack of absolute values of 3-c signal. Finally, Akram and Eaton (2016) use the absolute amplitude stack, arguing it is more effective for data with low SNR. Following a different direction, the CF proposed in this work uses the stack of the squared signal for a 3-c geophone and over the array. The overall idea is to sum energy in a non-destructive interference and analyses not a single geophone but a collection in a certain vicinity. The signal delay between adjacent geophones (that defines the shape of the final CF) is used as a feature to confirm the nature of the event (Paes et al., 2016).

Li et al. (2014) proposed the use of kurtosis in a STA/LTA algorithm to identify the transition from Gaussian to non-Gaussian behavior that coincides with the onset of the microseismic event in the presence of noise. Baillard et al. (2014) has introduced a intricate CF that includes slope evaluation. The CF proposed in this work for robust arrival-time picking is a simplification of Baillard et al. (2014) method that uses the positive part of the kurtosis derivative in a narrow data window.

For large datasets, the automation of tasks such as event-detection and arrival-time picking is essential. This paper intends to fill a gap in the used workflows for fast detection and robust arrival-time picking with two original characteristic functions that focus on the balance between effectiveness and speed. The limitations of both methods rely in the evaluation of excessive low SNR events. For detecting these events and picking its arrival-times, it is recommended the use of Matched Filtering Algorithms (Caffagni et al., 2016).

Theory and Methods

This section consists of three topics. The first discusses the energy stack method to detect potential microseismic events, while the second is about the use of kurtosis to detect onsets of P- and S- waves. The software currently in development uses booth techniques to complement each other.

The stack of the energy for fast dataset scanning and event detection was initially developed as a simple and light-weight method to identify perforation shots in a dataset (Paes et al., 2016). Later, the method was refined to be also applied for detection of low SNR microseismic events. The main features are: first, drastically reduction in the signal dimensionality once just a single time series is evaluated, allowing the analysis of massive amounts of raw data in a fast and uncomplicated algorithm. The second is to dilute the influence from noisy or dead geophones, once their influence become a shift in the final signal instead a shape change.

The energy-stack characteristic function (defined by Equation 1) is developed in three steps. First, the signals of three mutually perpendicular channels of each geophone are squared, normalized and then element-wise summed over the three components. The resulting curve is proportional to the seismic-wave kinetic energy through the geophone. Second, the curves representing each geophone are stacked as shown in Figure 1 (E.S). As result, there is an increase of the SNR as more significant as higher the number of geophones used. The event presence is highlighted from the background, which is fundamental for low SNR datasets. Finally, the resulting curve is smoothed by a moving average filter, Equation 2. This method is a practical and lightweight substitute to STA/LTA for the presented characteristic function.

$$\mathrm{ES}_i = \sum_{g=1}^{n}\left(\left(Z_g\right)_i^2 + \left(H1_g\right)_i^2 + \left(H2_g\right)_i^2\right), \qquad (1)$$

where ES_i is the Energy-Stack in the i-th element in the time serie. $(Z_g)i$, $(H1_g)i$ and $(H2_g)i$ are the i-th component of the vertical and two horizontal components of the g-th geophone. The total number of geophones used is 'n'.

$$\mathrm{MAVG}_I = \begin{cases} \sum_{j=i-s/2}^{i+s/2} ES_j \ \text{ if } s/2 \le i \le l - s/2 \\ 0 \text{ otherwise} \end{cases}, \qquad (2)$$

where $MAVG_i$ is the moving average function at the i-th index, ES is the Energy-Stack function, s is the (even) number of samples around the index 'i' and 'l' is the length of the ES time serie.

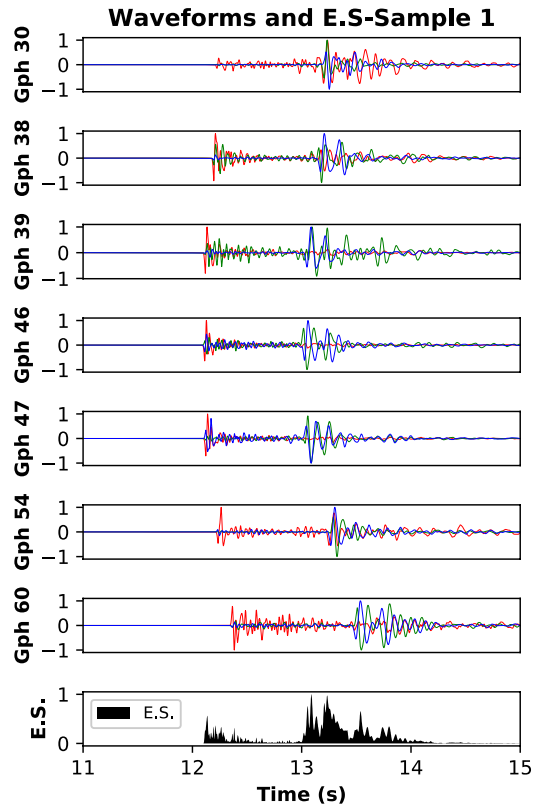

Figure 1: Waveform and energy stack for 7 out of 69 geophones in Sample 1.

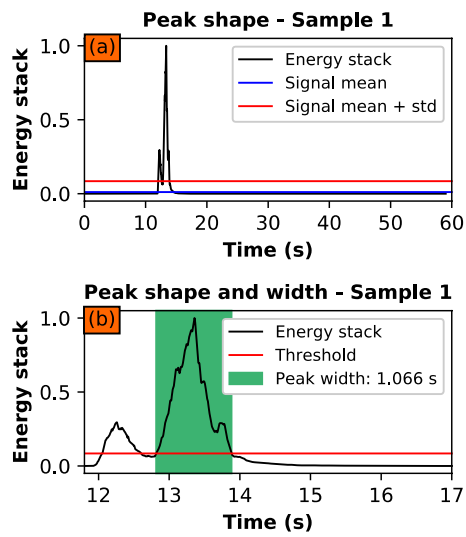

Figure 2: Typical energy-stack peak shape after smoothing. (a) E.S. time series for single MS event in a 60 s range. (b) Zoom in the peak shape with threshold definition and peak width.

The Energy-Stack has three main properties: the peak level, width and the m-shape. All of them are considered in the manual and automatic quality control of the method. The peak level is the main responsible for event identification and directly related with the number of geophones used in processing.

Sample 1 (Figure 2-a and b) shows a single and very distinct peak. During the potential-event identification, the function peak (black) is compared to the signal mean plus one standard deviation (red). The second property is the peak width, that is measured at the higher peak (normally the second one for non-explosive sources) and is caused by the stack of S-waves and its coda. Although it varies amoung different datasets and the spatial geophone distribution, this parameter is about 1 second. The case presented in Figure 2-b shows a width (green) based in a threshold of the signal mean plus one standard deviation (red). Finally, m-shape is caused by the stack of P- and S-waves, with the second hump being higher than first one. This particular shape is used as the first item in visual quality control and troubleshooting.

Akram and Eaton (2016) review more than a dozen arrival-time picking algorithms. Among the methods discussed, the one based in kurtosis stands out due its accuracy and the sharpness in the arrival of either P- and S-waves in real-world noisy datasets. Kurtosis is a statistical value that characterizes the shape of the analyzed distribution. It is largely determined by the distribution tail and can bee seen as a measure of the tailedness of the probability distribution of a sample. In this context, it can be interpreted as a measure of Gaussianity. The kurtosis is a positive scalar defined as the standardized forth moment about the mean. It is 3 for a Gaussian distributions and normally increases for non- Gaussian distributions. Seismic-waves onsets generate a temporary non-Gaussian wavefield that increase kurtosis. This localized perturbation can be used to accurately pick the onset times (Westfall, 2015), (Baillard, 2014) and (Li, 2014).

For an temporal series of n elements, in which each of them are represented by x_i, one can define the four basic statistic moments: the mean (1st), the variance (2nd), skewness (3rd) and kurtosis (4th). Kurtosis is defined by Equation 3 (Li et al., 2014).

$$\mathrm{kurt} = \frac{\frac{1}{n}\sum_{i=1}^{n+1}(x_i-\bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n+1}(x_i-\bar{x})^2\right)^2} - 3, \qquad (3)$$

where $\bar{x}$ is the mean over n samples.

The term '-3' was introduced in Fisher's notation in order to attribute the value zero to a normal distribution (Zwillinger and Kokoska, 2000), which is useful in the definition of characteristic functions used in seismic signal processing.

Akram and Eaton (2016) have build the characteristic function based on the application of STA/LTA to the Kurtosis of the seismic trace. Also, the paper suggests the use of the picking in the curve maximum slope of the CF instead of a local maximum. Similarly, Baillard (2014) has build a complex CF that, in short words, extracts and analyses the positive gradients of the kurtosis curve. The characteristic function proposed in this paper merges both methods and is calculated in four steps: 1) Potential-event time identification (by enegy-stack), data slice and and filtering. 2). Calculation of Kurtosis derivative (diff(kurt)). 4) Extract just the positive values and spot the maximum as the onset of the seismic wave, Figure 3-f at 'Kurt Range 2'.

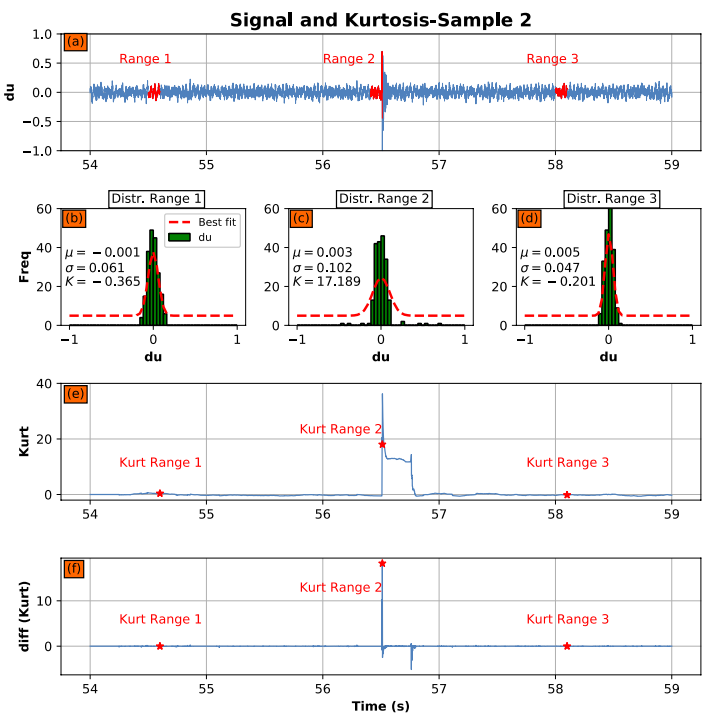

Figure 3: Example of microseismic signal and calculated CF. (a) Filtered seismic trace. (b, c and d) Histograms of the three evaluated signals with mean, variance and kurtosis. (e) Seismic trace kurtosis (200 samples). (f) Kurtosis derivative with max at range 2.

Examples

For benchmarking the energy-stack method, the official project catalog (based in MFA) and the continuous waveform from a single day were used. The parameters were loose in order to detect a wider

range of potential-events. Due the large number of available geophone (total of 69) and the distance between the well tracks and the array periphery, only a third part of the geophones was used in the event detection software. As result, a total of 8196 potential-events were detected in the period, Figure 4. The official project catalog reports 120 identified and specified events plus 58 files containing events. Only the specified events catalog was used for the benchmark. From the total of 120 events, 72 were identified simultaneously by the Energy-stack method, Figure 5. The ES method has detected 465 potential events with SNR higher than 10 as show in Figure 5.

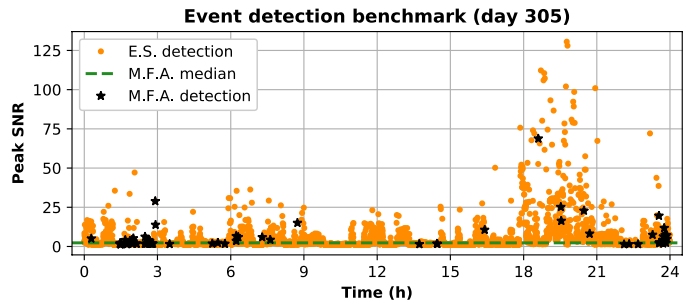

Figure 4: Potential-event detection benchmark by comparing the SNR with events in the official catalog.

Based in the nature of MFA, one could infer that the higher number of potential events located by ES had a low cross-correlation coefficient with the standard events, meaning they are different enough to be considered distinct. The events detected by both methods presented a relatively low ES SNR (5 ±9).

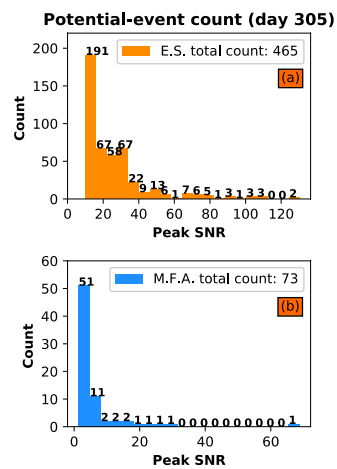

Figure 5: Potential-event detection count for (a) the energy-stack method (event SNR>10) and (b) MFA simultaneously with ES.

Conclusions

The energy-stack method has been used effectively for microseismic data analysis and creation of potential-event catalogs. Its key advantages rely in its remarkable speed, low sensitivity to missing or noisy geophones, significant increase of the SNR and not sample-event-based detection. The main caveat is the shallowness of the signal analysis that is partially suppressed by setting appropriate software parameters. The use of a characteristic function based in kurtosis for arrival-time picking has demonstrated robustness in a wide range of event SNR as the ones from the official catalog. Once it is based in the amplitude sample distribution instead of localized amplitude, the arrival-time picking are either accurate and resilient. Although the characteristic function is a bit time consuming (Intel I5 2.6 GHz , single-core processing time of 0.5 s for each monitoring second in a 69 3-c geophone array), the software is parallelized over an undefined number of cores. Another noteworthy topic is the use of basic statistics in the quality control module that filtered mispickings from final results (Paes and Eaton, 2017).

The core methods for potential-event location and arrival-time picking have been successfully developed, tested and benchmarked against the official catalog and a skilled-picking human. Subsequently, the future works must include improvements of the embryonic quality-control module for both event-detection and arrival-time picking, where software intelligence would bring unprecedented advance in information quality.

Acknowledgements

Sponsors of the Microseismic Industry Consortium are sincerely thanked for their support of this initiative. This work was supported by funding to DWE for the NSERC/Chevron Industrial Research Chair in Microseismic System Dynamics. Additionally, the first author would like to thank the program Science Without Borders (CAPES/Brazilian Ministry of Education) for the opportunity to pursue a PhD program at the University of Calgary as well as financial support. The software used for this work comprises part of the open-source project OpenMicroseismic, available at https://github.com/atilapaes/OpenMicroseismic.

References

Akram, J. and Eaton, D. (2016). “A review and appraisal of arrival-time picking methods for downhole microseismic data”. In: GEOPHYSICS 81.2, KS71–KS91. DOI: 10.1190/geo2014-0500.1.

Baillard, C. et al. (2014). “An Automatic Kurtosis-Based P- and S-Phase Picker Designed for Local Seismic Networks”. In: Bulletin of the Seismological Society of America 104.1, pp. 394–409. ISSN: 0037-1106. DOI: 10.1785/0120120347.

Caffagni, E. et al. (2016). “Detection and analysis of microseismic events using a Matched Filtering Algorithm (MFA)”. In: Geophysical Journal International 206.1, ggw168. ISSN: 0956-540X. DOI: 10.1093/gji/ggw168.

Li, F. et al. (2014). “Automatic event detection on noisy microseismograms”. In: SEG Technical Program Expanded Abstracts 2014. Society of Exploration Geophysicists, pp. 2363–2367. DOI: 10.1190/segam2014-1605.1.

Oye, V. and Roth, M. (2003). “Automated seismic event location for hydrocarbon reservoirs”. In: Computers & Geosciences 29.7, pp. 851–863. ISSN: 00983004. DOI: 10.1016/S0098-3004(03)00088-8.

Paes, A., Uesato, A. and Eaton, D. (2016). “Energy-Stack: A simple method to detect potential events on downhole microseismic”. In: Microseismic Industry Consortium – Annual Research Report - Vol. 7. Calgary AB, Canada: University of Calgary.

Paes, A. and Eaton, D. (2017). “Energy-stack and Kurtosis: the dynamic duo for microseismic event identification”. In: Microseismic Industry Consortium – Annual Research Report - Vol. 8. Calgary AB, Canada: University of Calgary.

Saari, J. (1991). “Automated phase picker and source location algorithm for local distances using a single three-component seismic station”. In: Tectonophysics 189.1-4, pp. 307–315. ISSN: 00401951. DOI: 10.1016/0040-1951(91)90503-K.

Sharma, B., Kumar, A., and Murthy, V. (2010). “Evaluation of seismic events detection algorithms”. In: Journal of the Geological Society of India 75. March, pp. 533–538.

Westfall, P. H. (2015). “Kurtosis as Peakedness, 1905 - 2014. R.I.P.” In: The American statistician 68.3, pp. 191–195. ISSN: 0003-1305. DOI: 10.1080/00031305.2014.917055.

Zwillinger, D. and Kokoska, S. (2000). CRC Standard Probability and Statistics Tables and Formulae. New York: Chapman & Hall/CRC. ISBN: 1-58488-059-7.