An integrated processing tool for microseismic data analysis

Athanasios Lois, Seismotech sltd, Konstantinos Leontarakis, Seismotech sltd, Paraskevas Paraskevopoulos, Univeristy of Patras, Nikolaos Martakis, Seismotech sltd, Katerina Polychronopoulou, Seismotech sltd and G-Akis Tselentis, Univeristy of Patras.*

Summary

By this work, a new approach is proposed for the solution of the microseismic event detection problem, as well as the accurate estimation of P- and S- arrival times. This technique consists of an event detection algorithm based on the polarization attributes of the seismic signal on the time-frequency domain, further analysis on the detection results in order to obtain the optimal parameters' values for the picking procedure and an automatic picker relying on the statistical characteristics of the seismic signals. The performance of the proposed technique is evaluated using real seismic data recorded during passive seismic tomography surveys as well as an acid fracing experiment and compared to the well known sta/lta algorithm.

Introduction

During enhanced hydrocarbon recovery operations such as hydraulic fracturing (fracing) or high resolution passive seismic tomography surveys (PST), small-magnitude earthquakes are used to increase our knowledge of reservoir characteristics.

In such applications, the greatest possible number of small-magnitude events, which can be treated as point sources, is necessary. However, event detection and accurate arrival time picking from the recorded seismograms constitutes a hard and challenging task due t,o the generally low signal-to-noise ratios (S/Ns) of the recorded events, especially if they are acquired in urban areas characterized by high-energy anthropogenic noise.

Furthermore, as the stations recording during each survey increase in number and sampling frequency, data sets become too large for manual processing to be effective. Thus, a robust automatic methodology is required, that allowing a reliable identification of the microseismic events as well as accurate P- and S- arrival times estimation, without losing important information.

Methodology

a. <u>Event Detection</u>

The problem of the seismic event detection, namely the segmentation of a seismic record into separate parts that include the microearthquakes and the seismic noise, constitutes a very important and challenging task, since its solution provides the input for the automatic picking algorithms. When applying a robust event detection algorithm to experiments such as PST and hydraulic fracturing, the desirable output is primarily the detection of a significant number of microseismic events and then the selection of accurate intervals from the seismic record, corresponding to the real "length" of the recorded events. Based on the polarization attributes of seismic signals in time-frequency domain (Leontarakis et al, 2014), a new approach is followed in the work presented herewith.

i) Time - Frequency Analysis

In the first step of the proposed technique, the 3C seismic record is filtered by a band-pass Butterworth filter, in a specific number of frequency subzones corresponding to equal periods, according to record's the sampling rate. Moreover, the envelope function of the absolute values of each filtered signal, corresponding to each frequency subzone, is estimated. For each subzone we evaluate the differences of the aforementioned envelopes among the three components (vertical, north-south and east-west). Hence, three matrixes D_{vn}, D_{ne} and D_{ve} are formed, representing the recorded polarization differences among the three components, in time-frequency domain. In Figure 1, the polarization differences between the NS and EW records through matrix D_{ne}, in time-frequency domain are depicted.

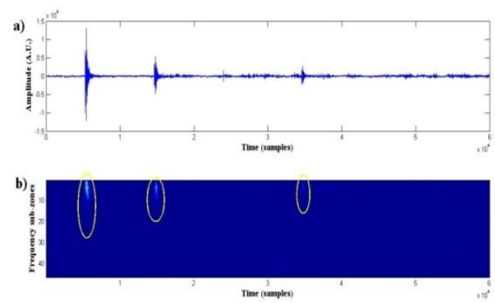

Figure 1: Example of seismic record (vertical component) a) and the corresponding image containing the polarization differences between the NS and EW records b). The recorded seismic events are indicated in red ellipses.

ii) Corrections

It is evident (Figure 1) that during a seismic event, the polarization differences are presented to occupy a wider range of frequencies and exhibit higher values than those corresponding to seismic noise. Nevertheless, there are cases, where a specific subzone appears to present higher values than the average level of each subzone's values,

possibly due to sensor's interference. In such cases, a regression analysis technique is applied in order to substitute the undesirable values with the ones corresponding to the expected average level of the specific subzone.
Additionally, a simple smoothing filtering procedure is applied over the rows (frequency) and columns (time) of the aforementioned matrixes, in order to remove single-frequency anomalies and high-frequency spikes, which apparently do not correspond to a seismic event.

iii) Characteristic Function

In the next step of the proposed algorithm, the three matrixes D_i, $i=\{vn, ne, ve\}$, are summed over their rows resulting to three time series y_{vn}, y_{ne} and y_{ve}. These new sequences are standardized by their median value, which represents the average "noise" level of each curve y_i, $i=\{vn, ne, ve\}$ and transformed by the function:

$$f_i = mtan^{-1}\left\{\frac{\frac{1}{a_i}{y_i}^2}{\frac{1}{a_i}y_i + a_i^3\left(tan^{-1}\left(\frac{1}{y_i^3}\right)\right)}\right\},$$

where the parameter m controls the maximum value of each sequence f_i and α_i is automatically estimated, based on the maximum "noise" level of each curve y_i. Finally, for the detection of seismic events, the following characteristic function is formed:

$$CF = \left(\prod_{i=1}^{3} f_i\right)^{1/3}$$

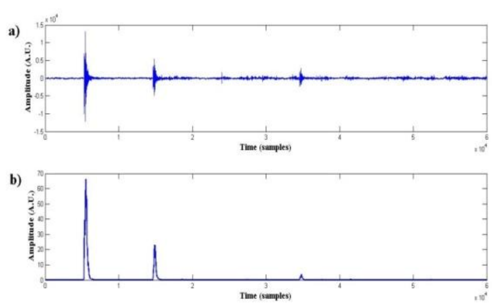

Figure 2: Example of seismic record (vertical component) a) and the corresponding proposed characteristic function b).

The choice of the specific characteristic function is based on the fact that it suppresses the noise under a constant level (the unity which now corresponds to the maximum "noise" level) and enhances the useful seismic information. Thus, unity constitutes a "safe" choice for threshold value, in order to discriminate the microseismic events from the seismic noise. An example of the aforementioned characteristic function is given in Figure 2.

iv) Analysis on the event detection results

The application of the proposed algorithm on several seismic data sets, recorded on different regions, resulted in sufficiently good results, even in very low S/Ns. In comparison with the well known STA/LTA method, in moderate and low levels of seismic noise the two approaches presented almost the same performance, while in records with high noise levels, the proposed technique exhibits higher detection rate. The commonly used STA/LTA algorithm appears to fail to detect microearthquakes with low S/Ns (S/N<3 dB) and, at the same time suffers from a high number of false alarms (see Figure 5). Moreover, the detected time intervals that the proposed technique provides as output are proportional to the real "length" of the recorded events; thus a "rough" estimation of the magnitude of these events can be provided by single station analysis and a more accurate by a multi-station analysis.
The results obtained by the application of the detection algorithm, provide useful information for the automatic picking parameter setting. In particular, the maximum value of the characteristic function corresponding to each detected segment of the record lies always on the neighborhood of the S-arrival. Thus, the time that corresponds to this value is analogous to the distance from the hypocenter (Figure 3). Based on this fact, the picking algorithm is fed with a specific time interval which includes both P- and S- phases for further processing. Furthermore, for a specific event, a ratio os evaluated ("active ratio"), based on the maximum polarization difference and the detected time interval, which constitutes an estimation of the distance between the hypocenter and the station that recorded the particular event (Figure 4). In this way the picking algorithm is able to reject teleseismic events, as well as to choose the appropriate window lengths, in order to estimate accurate P- and S- onset times.

a. <u>P- and S- arrival time estimation</u>

Once the desired segments of the record including the seismic information have been obtained, an automatic picker is applied in order to estimate the arrival times of P- and S- seismic waves. Concerning the picking procedure, it is essential to mention that the lengths of the moving windows utilized herewith, have been automatically selected, based on the aforementioned analysis.

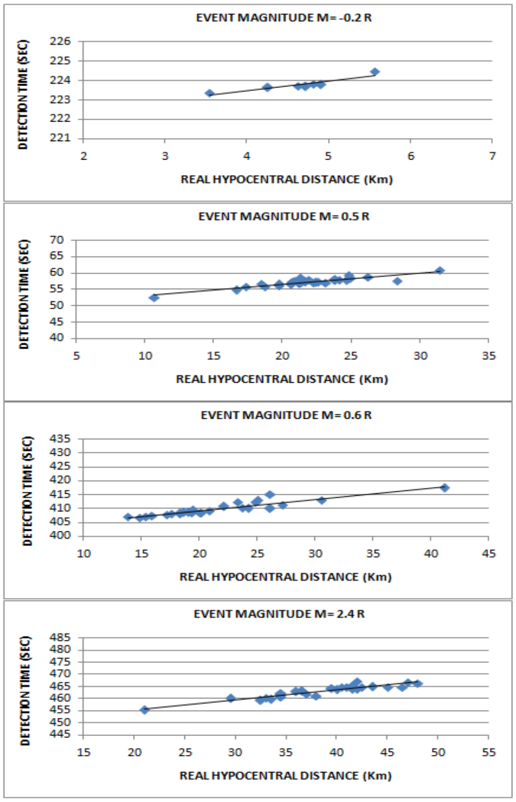

Figure 3: Detection time (time corresponds to the maximum value of characteristic function) versus the real hypocenter distances as estimated by expert analysts, for four different seismic events. The corresponding regression lines are indicated with black lines.

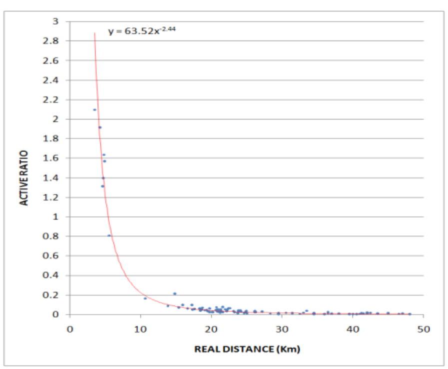

Figure 4: "Active" ratio for the above four seismic events in relation with the real distance of each hypocenter. The corresponding regression curve in red is used for a "rough" distance estimation.

i) P-arrival time estimation

The estimation of the first arrival of a seismic signal is based on the properties of a higher order statistic parameter, kurtosis which constitutes the fourth order zero lag cumulant (Saragiotis et al, 2002, Lois et al, 2010). In particular, kurtosis is evaluated on the seismic record, by means of an N-length moving window, using the estimator:

$$kur(X) = \frac{\sum_{i=1}^{N}\{(X(i)-\hat{m}_x)^4\}}{(N-1)\hat{\sigma}_x^{\,4}}$$

where X is the time series of the record, $\hat{m}_x$ the mean value and $\hat{\sigma}_x$ the standard deviation of the record within the moving window. Kurtosis is a measure of heaviness of the tails of a distribution and its use is based on the fact that during transition from the ambient noise to the seismic signal, high values of the signal occupy the tails of the distribution, causing a steep increment on kurtosis values. As a result, kurtosis presents maxima in the neighborhood of the P-onset and the point that corresponds to the maximum slope of the kurtosis curve is assigned to the P-onset time.

ii) S-arrival time estimation

The S-arrival time is evaluated using a time domain technique, based on the statistical processing of a specific characteristic function, which is obtained by eigenvalue analysis on the three component seismic record (Lois et al., 2013). Initially, the algebraic eigenvalue problem of the data covariance matrix is solved by means of an M-sample time moving window and three sequences of eigenvalues $\lambda_1(t) > \lambda_2(t) > \lambda_3(t)$ are obtained. The characteristic function that is used for further processing is the sequence:

$$r(t) = \sqrt{\lambda_1(t)}$$

The next step is to apply the kurtosis criterion on a specific part of *r(t)*, corresponding to the interval between the estimated P-arrival and the coda of the seismic signal and thus a first S-onset time estimation is provided. In order to reduce the algorithm's dependence on the moving window's length, a multi-window approach is followed, combined with an energy-based weighting scheme.
In particular, the same algorithm is applied, using different window lengths and on each S-arrival estimation a weight is assigned, based on the change of energy that takes place during this arrival. The final S-onset time estimation is given by the weighted mean of the set of S-arrival times:

$$S_{final} = \frac{\sum_{i}^{w} S_{on}^{i} q_i}{\sum_{i}^{w} q_i}$$

where the index i=1,2,..,w indicates the number of the different time-windows used.

Application on real seismic data

The proposed method was applied on various different real seismic data sets, recorded during a passive seismic tomography survey in Silchar (India), during the monitoring of an aftershock sequence in Kefalonia (Greece), as well as an acid fracing experiment in Delvina (South-West Albania). In Figure 5 an example of a good quality seismic signal recorded in Silchar and the results from the implementation of the proposed technique (red dots) and the STA/LTA algorithm (green lines) are depicted.

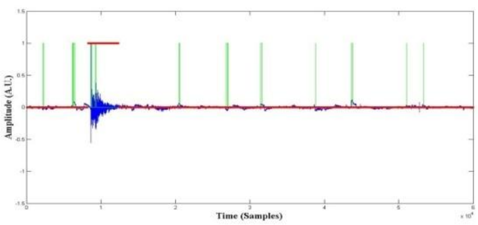

Figure 5: Example of the implementation of the proposed event detection algorithm (red dots) and the STA/LTA algorithm (green lines) on a good quality signal recorded in Silchar, India .

It is evident that the proposed technique succeeds to detect the record segment that corresponds to almost the entire "length" of the seismic signal, while the STA/LTA algorithm detects a part of it and particularly the time interval between the first arrival and the S-wave onset. Furthermore the STA/LTA suffers from a significant number of false alarms, contrary to the proposed methodology which only detects the useful seismic information.

Figure 6 shows a seismic signal, recorded during the monitoring of the aftershock sequence of M_w 6.2, January 26, 2014, seismic event at Kefalonia, Greece. In the upper plot, with red dots the detected segments of the record are presented, while the bottom plots illustrate P-(red lines) and S-(green lines) arrival times estimation for the selected events in the black rectangles.

It is understood that the picking results are strongly dependent on the intervals that the event detection algorithm provides as output.

Figure 7 presents an example of seismic data obtained during an acid fracing experiment that took place in Delvina, Albania. In the specific example, there is only one seismic event "buried" on noise (indicated in black rectangle), whose existence was verified by crosschecking the seismic data from nearby stations. The effectiveness of the proposed methodology is confirmed, as even in seismic records characterized by extremely high noise levels, the algorithm succeeds to extract the desirable information.

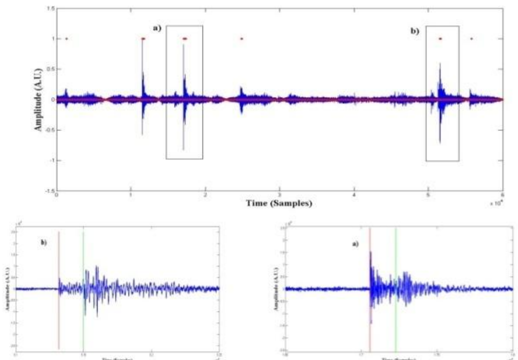

Figure 6: Example from the implementation of the proposed methodology on seismic data recorded in Kefalonia, Greece (upper plot), as well as P- and S- arrival times estimation for the selected events in the black rectangles (bottom plots).

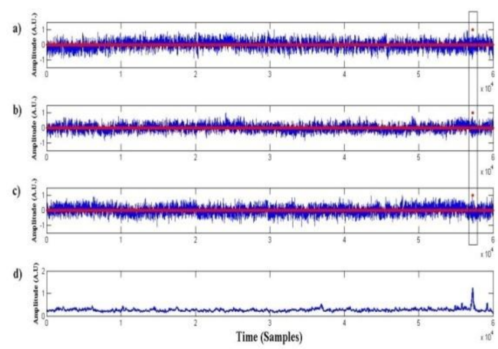

Figure 7: Example of the implementation of the proposed methodology on poor quality seismic data recorded in Delvina, Albania, during a hydraulic fracturing experiment. The 3C seismic record with the detected segment (red dots), a),b) and c) and the corresponding characteristic function d).

Conclusions

By this work, a new strategy is proposed for automated analysis of microseismic data, obtained during passive seismic tomography and hydraulic fracturing experiments. The identification of the microearthquakes is achieved, using a new technique, based on signal's polarization characteristics on the time-frequency domain. Moreover, a thorough analysis of the results, obtained by the implementation of the proposed event detection technique, provides useful information regarding the parameters setting related to the automatic picking procedure. Finally, the P- and S- arrival times are estimated, using algorithms that exploits the statistical characteristics of the examined seismic record. In general this hybrid method is straightforward to implement, demands low computational resources and requires minimum user intervention.