Introduction

Monitoring microseismic is very important to geosciences and has several applications, for example, in oil and gas industry to the monitoring of hydraulic fracturing (Maxwell, 2011) and in reservoir stimulation (Williams-Stroud et al., 2013). In fact, high-quality monitoring requires a robust detection of microseismic events. However, detecting microseismic is a great challenge. The main reasons are seismic signals with poor signal-to-noise ratio (SNR) due to the strong noise scenarios and/or data recording with reasonable quality (e.g. by using distributed acoustic sensing systems (Mateeva et al., 2013)), and low energy of these events which requires filtering techniques to extract the correct information.

The classical method to seismic phase detection was introduced by Allen (1978) and it is known as Short Term Average/Long Term Average (STA/LTA). This method consists of calculating the average energy for two time-windows: a short-term and a long-term window. The ratio between these two windows (STA/LTA ratio) is employed as a criterion for detection. However, this method has several free parameters (Trnkoczy, 2002) which, when misused, can lead the method to find false positives and/or false negatives microseismic detection. In addition, the STA/LTA method is very sensitive to signal energy, making it unenforceable to use this technique for strong ground motion noisy and/or low SNR data.

In this study, we present the Instantaneous Spectral Entropy Detection (ISED) algorithm, which is a robust algorithm for detection of seismic waves in noisy environments without the requirement for filtering. Our proposal consists of two steps: in the first one, we compute the time-frequency power spectrogram and then calculate the Shannon entropy for each time-window, resulting in a time series: The Instantaneous Spectral Entropy. In the second step, we use the STA/LTA detector on the Instantaneous Spectral Entropy to detect the microseismic phase. Our methodology was validated with synthetic data (not presented in this study) and with a moderate magnitude earthquake field data (presented in this study). Then, to demonstrate the potential of our proposal to microseismic event detection, we used field data of microseismic events with low SNR. We conclude that our scheme outperforms the classical STA/LTA in a complicated noisy environment.

Instantaneous Spectral Entropy Detection (ISED)

The Instantaneous Spectral Entropy is defined as:

\[ E(t) = -\sum_k P(t,f_k) \log(P(t,f_k)) \]  

(1)

where \( P(t,f_k) \) is the instantaneous probability distribution of the time-frequency power spectrogram \( S(t,f) \) at time \( t \) and frequency \( f \), in which:

\[ P(t,f_i) = \frac{S(t,f_i)}{\sum_k S(t,f_k)} \]  

(2)

Note that the entropy is calculated for each time window of the time-frequency power spectrogram. Thus, instantaneous spectral entropy gives a measure of the homogeneity of the frequency composition for each time window, revealing peaks in times of the most energy-containing time windows, that is, emphasizing the seismic signal rather than noise. Finally, the instantaneous spectral entropy time-series is used as input to the STA/LTA algorithm for automatic detection of the maximum entropy and other seismic phases. The proposed method makes the application of STA/LTA more efficient since the seismic phases are related to high-amplitude of the \( E(t) \). Figure 1 shows a summary of this procedure.
Application to microseismic detection case study

We applied the method outlined in the previous section to real data obtained from Incorporated Research Institutions for Seismology (IRIS), which is available on the site of the IRIS University Consortium (http://www.ds.iris.edu). We extracted the waveforms of three seismic events: the first one corresponds to the waveforms of a moderate earthquake to illustrate a simple situation; Then, we extracted the waveforms of microseismic events for two low magnitude natural earthquakes. Table 1 shows the main information about the seismic sources.

<table>
<thead>
<tr>
<th>Event ID</th>
<th>Date (yyyy/mm/dd)</th>
<th>Time UTC (hh:mm:ss)</th>
<th>Latitude (°)</th>
<th>Longitude (°)</th>
<th>Depth (km)</th>
<th>Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>2019/03/22</td>
<td>12:50:30</td>
<td>12.64 S</td>
<td>76.59 W</td>
<td>48.14</td>
<td>4.6 m&lt;P&gt;</td>
</tr>
<tr>
<td>02</td>
<td>2019/03/23</td>
<td>07:34:18</td>
<td>37.30 N</td>
<td>117.50 W</td>
<td>7.0</td>
<td>3.0 m&lt;s&gt;</td>
</tr>
<tr>
<td>03</td>
<td>2019/06/27</td>
<td>17:00:07</td>
<td>37.23 N</td>
<td>117.68 W</td>
<td>0.96</td>
<td>1.9 m&lt;s&gt;</td>
</tr>
</tbody>
</table>

Table 1 Main information on earthquakes used in this study.

The waveform of the event 01 (see table 1) recorded near the coast of Peru is used in the first test, specifically from the vertical channel of the Nana station (NNA) located in Peru, depicted in Figure 2(a). This earthquake was chosen due to the ease of identification of the P- and S-waves. The green and magenta colour lines represent the detection of P and S-waves performed automatically by the STA/LTA method. Figure 2(b) shows the time-frequency power spectrogram. Note that the part of the signal spectrogram is most strongly seen (colours closer to red). Figure 2(c) shows the instantaneous spectral entropy obtained from the spectrogram and the travel-time approximately estimated (red and blue colour lines). Note that the STA/LTA algorithm with or without entropy influence can identify seismic phases.

Figures 3(a) and 4(a) shows the unfiltered seismograms recorded at Columbia College station (CMB) located in Columbia, CA, USA (event 02) and at NVAR Array Site 31 station (NVAR) located in Mina, NV, USA (event 03), respectively. The STA/LTA algorithm was unable to identify P and S-waves due to

Figure 2 Event 01: (a) Original waveform and visually easy identified events are shown with coloured vertical lines for each method. (b) Spectrogram and (c) Instantaneous Spectral Entropy for event 01.
strong noise for both cases. Figures 3(b) and 4(b) shows the spectrograms for events 02 and 03 and figures 3(c) and 4(c) respective Instantaneous Spectral Entropy. Unlike of classical STA/LTA, the proposed method was able to identify the events, in which the STA/LTA detector has been able to identify major ISED peaks and thus automatically pick the seismic phases. To validate our results, the seismograms (Figures 3(a) and 4(a)) were filtered between 2 and 20 Hz by using Butterworth filter for visual identification of seismic waves, as depicted in Figures 3(d) and 4(d). Using filtered waveform, we apply the STA/LTA method and compare with our strategy, validating the detection performed by ISED applied to the unfiltered data.

Conclusions

The ISED is a promising automatic detection strategy of microseismic under strong noisy circumstance. Although the data is obscured by noise, the proposed method successfully identifies the presence of seismic waves in unfiltered seismograms. The success of the proposed strategy is related to the quantification of frequency content in time-frequency domain using information entropy (or Shannon entropy), in which the seismic signal energy information is concentrated in a certain region of the spectrogram while the noise energy is spread out. Satisfactory results obtained on the low magnitude natural earthquakes prompts us to apply this strategy on a large-scale multi-channel dataset, which will be the matter of future studies. To conclude, the ISED method is an excellent alternative for monitoring microseismic due to its ability to identify weak signals in noisy environments, outperforming the classical STA/LTA technique.
Figure 4 Event 03: (a) Unfiltered waveform; (b) Spectrogram; (c) Instantaneous Spectral Entropy; (d) Data with processing.

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References