Time-frequency sparse Gabor transform for detecting microseismic events

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Summary

Event detection is a challenging and time-consuming step in microseismic processing because microseismic signals usually have low amplitudes and are often embedded in high-amplitude noise. This study proposes a fast, automatic, and promising method to detect microseismic arrivals using a time-frequency sparse Gabor transform. First, we perform time-frequency denoising based on an automatic noise-level estimation and a neighboring block thresholding technique. Then, we estimate the spectrum of the denoised data using the Gabor transform via a sparsity constrained inversion scheme. Microseismic events are detected based on a characteristic function calculated from the resulting Gabor spectrum. This study uses a robust sparse inversion to obtain high-resolution Gabor spectra and automatically detected events based on abrupt changes in the energy distribution in the time-frequency representation. We test the algorithm on a real microseismic data set in a Montney reservoir. The results show that the proposed method can automatically detect potential microseismic events with an increased precision rate and works well with noisy data.

Theory / Method

Time-frequency sparse Gabor transform

The Gabor's expansion for a time series s(t) is defined as (Sacchi et al., 2009)

$$s(t) = \sum_m \sum_k a_{mk} g(t - mL) e^{\frac{i2\pi kt}{K}}, \qquad (1)$$

where a_{mk} are the Gabor coefficients corresponding to the amplitude of the elementary signal, the kernel $g(t - mL)$ is the synthesis window (known as the elementary signal). The Gabor coefficients can be retrieved through a Gabor transform as

$$a_{mk} = \sum_t s(t) w^*(t - mL)\, e^{-\frac{i2\pi kt}{K}}, \qquad (2)$$

where $w^*(t)$ is the analysis window. The Gabor transform is a windowed Fourier transform that uses the Gaussian window as a window function. A robust way to obtain the Gabor coefficients is from a sparsity constrained inversion scheme using an iteratively reweighted least-squares algorithm, which is accelerated by the preconditioned conjugate gradient method (Sacchi and Ulrych, 1996; Sacchi et al., 1998; Sacchi et al., 2009). The inversion algorithm finds the sparse solution by minimizing the following cost function that is the combination of (i) the misfit between the data, $\vec{s}$, and the estimated data, $G\vec{a}$, in a least-squares L2 sense and (ii) a model coefficient norm in a Cauchy norm

$$J = \|T(\vec{s} - G\vec{a})\|_2^2 + \mu^2 \sum_{m,k} ln\left(1 + \frac{a_{mk} a_{mk}^*}{\beta^2}\right), \qquad (3)$$

where μ determines the importance of the regularization term relative to the data misfit, and β is the Cauchy scaling constant, which controls the amount of sparseness attained by the inversion and also depends on the noise level.

Detecting events using the estimated Gabor coefficients

This study employs TF denoising that combines an automatic noise level estimation and a neighboring block thresholding technique in the STFT domain (Mousavi and Langston, 2016a). Then, we compute the Gabor coefficients using the TF sparse Gabor transform. The Gabor transform has a compact representation that produces high resolution and consequently enhances noise sensitivity in signal detection and extraction (Auslander et al., 1990). After that, we can automatically detect the microseismic arrivals using a CF computed from the resulting Gabor coefficients (Mousavi et al., 2016)

$$CF(m) = \sum_{k=1}^{n_f} |a_{mk}|, \quad (4)$$

where m is time sample and k is frequency sample in equation (2). The CF can capture the abrupt energy changes associated with microseismic arrivals in the TF domain (Mousavi et al., 2016). A potential event will be detected when the CF value is higher than a user-defined threshold.

A Field Example

We apply the detection algorithm to a one-hour single-channel microseismic data set in a single stage (stage 16) in a hydraulic-fracturing well 2 in a Montney reservoir, northeastern BC (see Bui and van der Baan, 2020 for more details about the data). We also compare the results with the results from the fast matched filter (MF) (Bui and van der Baan, 2020) and the STA/LTA method (Trnkoczy, 2009). First, we denoise the data in the TF domain using the automatic noise level estimation and neighboring block thresholding technique. The data length should be long enough to include both signal and noise. The past spectral power values of noisy measurements are used to estimate the variance of the noise-level. A weighting factor of 0.92 is used to obtain the tradeoff between noise reduction and signal distortion. The TF plane is segmented into disjoint macroblocks of length L = 8 in time and width W = 16 in frequency. In each block, an attenuation factor is computed and used to modify the TF coefficients for the denoising purpose. Then, we compute the Gabor spectrogram of the denoised signals using the TF sparse Gabor transform. The Gabor window width is 25 samples, with a shift of 4 samples between Gabor windows. A threshold of 10^{-10} is set for the misfit. Figure 1 shows a 0.9 s denoised signal with the corresponding Gabor spectrogram and the CF plot computed from the Gabor coefficients. By looking simultaneously at the spectrogram and the CF plot, we can determine the onset of the microseismic events, which is indicated by a vertical black line in the bottom panel of Figure 1.

Table 1 shows the detection results, including the number of excellent microseismic events (events with clear P- and S-phases) and the number of noise records detected from the proposed method, MF, and STA/LTA. Noise records include both false alarms and true microseismic events but without both clearly identifiable P- and S-wave onsets. The proposed TF method, with a threshold of 1.5, detects a total of 123 potential events, and among these, there are 104 excellent events and 19 noise signals. With a threshold of 2, it detects 103 potential events with 93 excellent events. The STA/LTA is applied using the same parameters described in Bui and van der Baan (2020). With a threshold of 2 and a criterion of at least half of the number of receivers (15 receivers) must see the events, we detect a total of 227 potential events, and only 103 events have visible P- and S-phases. The MF with a threshold of 0.25 detects 155 potential events, and 101 are excellent events. To evaluate the detection performance, we use a precision rate, the ratio between the number of true events and the total number of true events and noise records (Bui and van der Baan, 2020). From Table 1, the proposed method gives an increased precision rate of 84.55% (with the threshold of 1.5) compared with the MF with 65.16% and the STA/LTA with only 45.37%. The TF algorithm detects almost the same number of excellent events as the other methods with much fewer noise records.

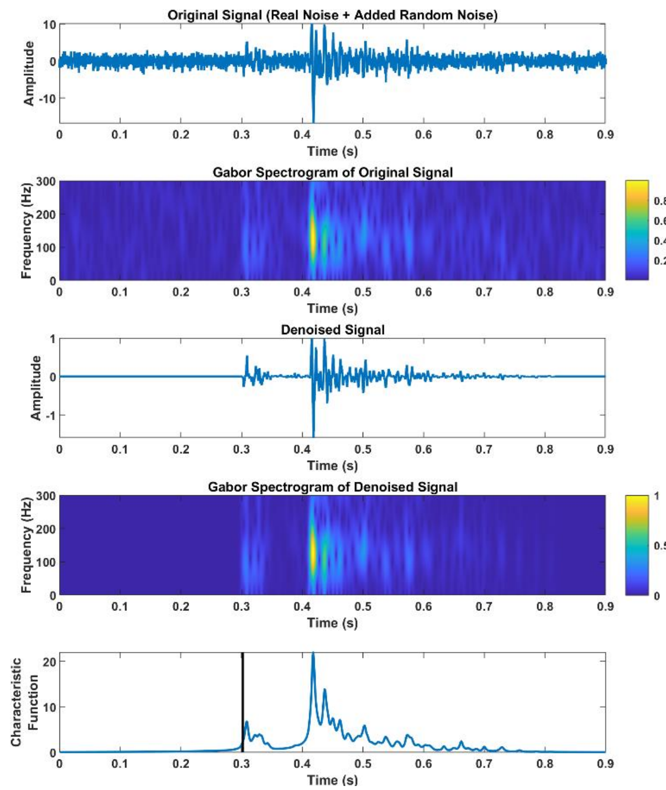

Figure 1 - A 0.9 s original signal and its Gabor spectrogram (the top two panels), denoised signal and its Gabor spectrogram (the middle two panels), and CF plot (the bottom panel). The vertical black line represents the event onset.

Table 1: Detection results.

Detection method	Number of excellent events	Number of noise records	Precision rate (%)
STA/LTA (threshold = 2)	103	124	45.37
MF (threshold = 0.25)	101	54	65.16
Proposed TF method (threshold = 1.5)	**104**	**19**	**84.55**
Proposed TF method (threshold = 2)	93	10	90.29

Figure 2 shows the detection results of the proposed TF detection algorithm on a single-channel data example. We plot the original signal, the denoised signals obtained from two methods (band-pass filter with cut-off frequencies [60 300] Hz and TF denoised method and the corresponding CFs with a detection threshold of 2). As can be seen, the algorithm performs well with noisy data. Most of the high-amplitude background noise has been attenuated, and more weak events can be detected (e.g., event at 8.4 s).

Conclusions

The sparse Gabor transform provides an efficient TF representation for microseismic events, which is applicable in event detection. This study has successfully retrieved the TF Gabor coefficients through a robust inversion using a sparsity constraint in the form of a Cauchy norm and automatically detected potential events in single-channel data sets using the CF computed from the Gabor coefficients. The proposed TF Gabor transform workflow for event detection gives a higher precision rate than the STA/LTA and the MF method. It can also work well with weak events in data sets having high-amplitude noise. Real examples of microseismic events in HF treatments have shown that events in noisy data sets can still be triggered and detected. Therefore, the algorithm is a promising technique for detecting microseismic events.

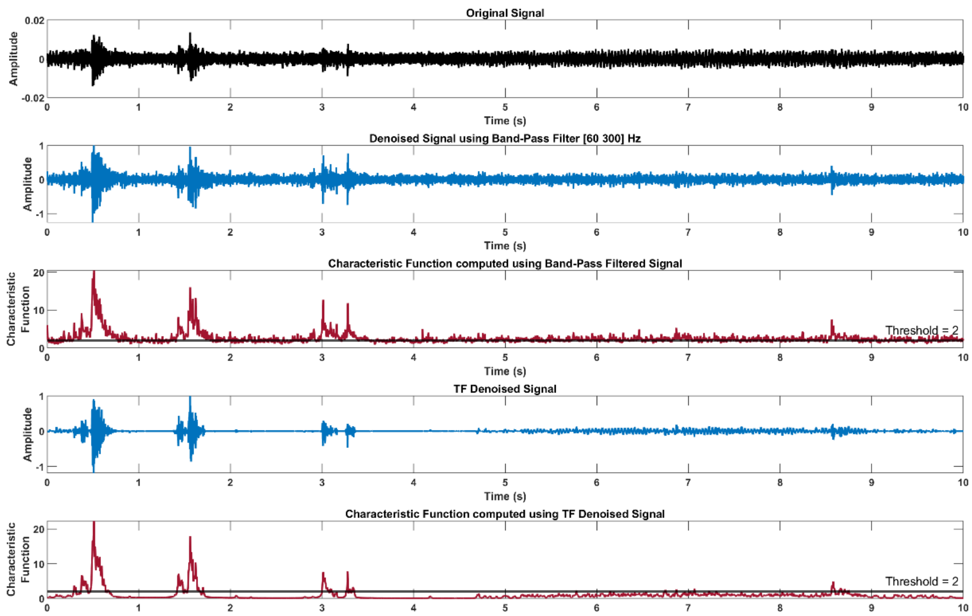

Figure 2 - The detection results of the proposed method with a threshold of 2 on an example recording. The original data, denoised data (using a band-pass filter and TF denoising technique), and the corresponding CF plots.

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