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Seismic application of quality factor estimation using the peak frequency method and sparse time-frequency transforms

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Summary

The attenuation of seismic waves during their propagation, often quantified by the quality factor Q, is connected to various medium properties such as rock types, fracture density or fluid content. This is also an important parameter for seismic data correction. Quality factors are commonly measured in the frequency domain using the spectral ratio method or the frequency shift method. These methods require spectra with large, uncorrupted continuous frequency bands at different locations on the ray path to estimate reliable quality factors. However, these methods cannot be used with high-resolution time-frequency techniques which show highly localized, sometimes discontinuous, time-frequency representations. Sparse time-frequency representations are focused around the dominant frequency components of a signal. For these representations, we demonstrate that quality factors can nonetheless be estimated with the peak frequency method which is based on the changes in peak frequencies during seismic wave propagation. We here apply three sparse time-frequency transforms, namely basis pursuit, the synchrosqueezing wavelet transform and complete ensemble empirical mode decomposition to a seismic trace. Instead of using peak frequencies which show large scattering, we use frequency centroids to estimate quality factors. The effective quality factors estimated are consistent among the different techniques, ranging mainly from 20 to 80. This application shows that sparse time-frequency transforms can be still be used to measure seismic wave attenuation.

Introduction

Seismic waves lose energy due to anelastic attenuation during their propagation. This attenuation is related to intrinsic losses, corresponding to the transformation of waves energy into heat or fluid flow (Muller et al. 2010), and apparent attenuation which includes different physical mechanisms (Reine et al. 2012). Considering that intrinsic attenuation is linked to some properties of rocks and pore fluids like fluid content and permeability (Best et al. 1994), attenuation measurements can be employed for monitoring (e.g., Schurr et al. 2003; Blanchard and Delommot 2015). Attenuation is often quantified using the quality factor Q which corresponds to the loss of wave energy per cycle.

Common methods to measure attenuation in the frequency domain, such as the spectral ratio method and the frequency shift method (Quan and Harris 1997), are based on the earlier disappearance of high frequencies during seismic waves propagation. This leads to a reduction of the frequency bandwidth and a decrease of the dominant frequency of a wavelet over time/distance. These methods need large uncorrupted frequency bandwidth in order to reliably estimate attenuation. Conventional spectral estimation techniques such as the Fourier transform and the Wavelet transform provide continuous spectra that are appropriate for these attenuation measurement methods.

On the other hand, high-resolution time-frequency techniques exhibit highly localized spectra (Tary et al. 2014) that are incompatible with these attenuation measurement methods. Other methods, solely based on the decrease in peak frequency (Zhang and Ulrych 2002) or the estimation of instantaneous frequencies (Engelhard 1996), are more adapted in this case. We here employ three sparse time-frequency transforms: basis pursuit, the synchrosqueezing wavelet transform and complete ensemble empirical mode decomposition, and the peak frequency method of Zhang and Ulrych 2002 to estimate the variations in frequency content and quality factors of a seismic trace.

Peak frequency method

Assuming that the amplitude spectrum of a seismic signal $A_R(t,f)$ is the superposition of contributions coming from the source amplitude spectrum $A_S(f)$, a transfer function $G(t,f)$ including instrument, source and medium responses, and attenuation as

$$A_R(t,f) = G(t,f)\,A_S(f)\,e^{-\frac{\pi f t}{Q}},$$

where t is the propagation time, f frequency, and Q the quality factor including both apparent and intrinsic losses. We further assume that the transfer function $G(t,f)$ has negligible influence on the frequency content of the seismic signal, and that the source spectrum can be approximated by a Ricker wavelet with peak frequency f_0.

Using these assumptions, the quality factor Q for a seismic signal characterized by a peak frequency f_p is given by (Zhang and Ulrych 2002)

$$Q = \frac{\pi t f_p f_0^2}{2\left(f_0^2 - f_p^2\right)}.$$

To estimate quality factors for multiple layers, the contribution of quality factors from shallower layers can be removed using layer stripping (Zhang and Ulrych 2002). Quality factors estimations for shallower layers are then influencing those of deeper layers. Here we estimate peak frequencies on successive signal windows with 30 % overlap. Also, we do not compensate for quality factors from earlier layers by layer stripping and present the effective quality factors for each signal window.

Sparse time-frequency transforms

Instead of the conventional spectral estimation methods which are characterized by smearing, we employ three very different sparse time-frequency transforms: basis pursuit, the synchrosqueezing wavelet transform and complete ensemble empirical mode decomposition (Tary et al. 2014). Basis pursuit decomposes a signal in a set of time-frequency atoms, which are Ricker wavelets in the present case, coming from a user-defined dictionary (Chen et al. 2001). The time-frequency distribution is optimized through an inversion scheme using a mixed norm (Vera Rodriguez et al. 2012). The final distribution is obtained by minimizing both the data misfit (least square norm) and the number of time-frequency atoms, favoring a low number of high-amplitude time-frequency atoms.

The synchrosqueezing wavelet transform is based on the continuous wavelet transform (Daubechies et al. 2011). From the time-frequency representation of the continuous wavelet transform, instantaneous frequencies are calculated for each time-frequency coefficient. After removing low-amplitude coefficients by thresholding, the remaining coefficients are then reassigned on the instantaneous frequencies.

Complete ensemble empirical mode decomposition is a variant of empirical mode decomposition (Huang et al. 1998; Torres et al. 2011). Empirical mode decomposition extracts recursively intrinsic mode functions from the time domain signal. These functions correspond to the different oscillatory components of the signal. The signal can be reconstructed by summing all the intrinsic mode functions. The time-frequency distribution corresponding to these functions is obtained by calculating the instantaneous frequencies of each function with the Hilbert spectrum (Huang et al. 1998).

For the following application to a seismic trace, we use the three sparse time-frequency techniques described above plus the short-time Fourier transform.

Application to a seismic trace

The seismic trace is extracted from a seismic profile crossing a Canadian sedimentary basin (see Herrera et al. 2014). This trace is sampled at 1000 Hz and crosses a paleo-channel at 0.42 s (Figure 1).

The peak frequencies are estimated for windows of 0.16 s with 0.05 s overlap. In the case of the short-time Fourier transform, the spectrum of each window is smoothed using a low-pass filter prior to the computation of peak frequencies.

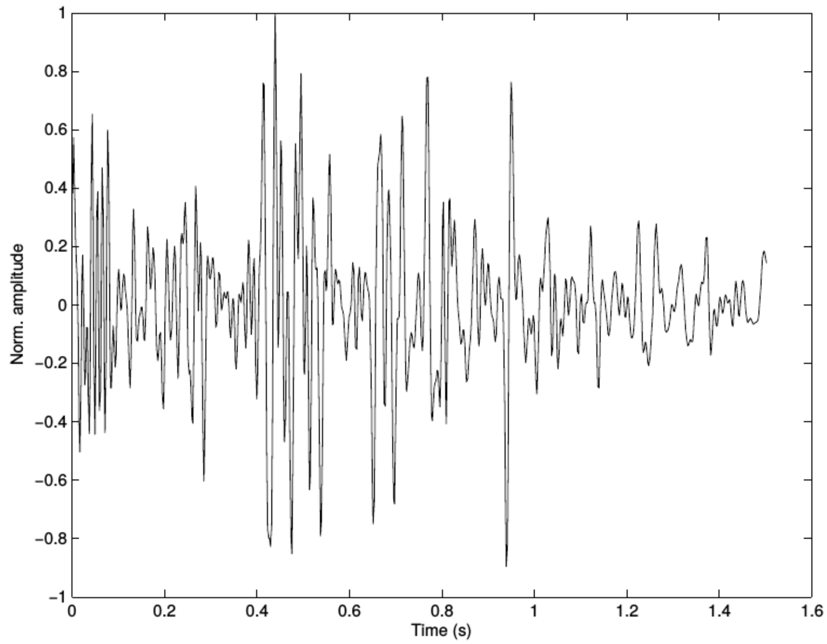

Figure 1. Normalized seismic trace. A paleo-channel is located at 0.42 s.

The peak frequencies estimated using the four time-frequency techniques show a strong scatter between 10 and 100 Hz (Figure 2), especially the synchrosqueezing wavelet transform and complete ensemble empirical mode decomposition. Quality factors calculated using such scattered values would not be reliable. Instead of using peak frequencies and in order to smooth their estimation, we then use frequency centroids f_c given by

$$f_c = \frac{\int_0^\infty f A(f)\,\mathrm{d}f}{\int_0^\infty A(f)\,\mathrm{d}f}.$$

The frequency centroids estimated show less scatter and are consistent for the four time-frequency techniques (Figure 2). They range between 50-70 Hz at the beginning of the signal and 10-40 Hz at the end of the signal. The frequency centroids estimated using the short-time Fourier transform are significantly higher by around 10-15 Hz while showing the same pattern as the other transforms. The quality factors computed using the frequency centroids range mainly between 10 and 80 for the sparse time-frequency transforms, and between 40 and 100 for the short-time Fourier transform. The quality factors show a slight increase at around 0.38 s, near the time of the paleo-channel, and at 1 s, near the time of large amplitude arrival (Figure 1).

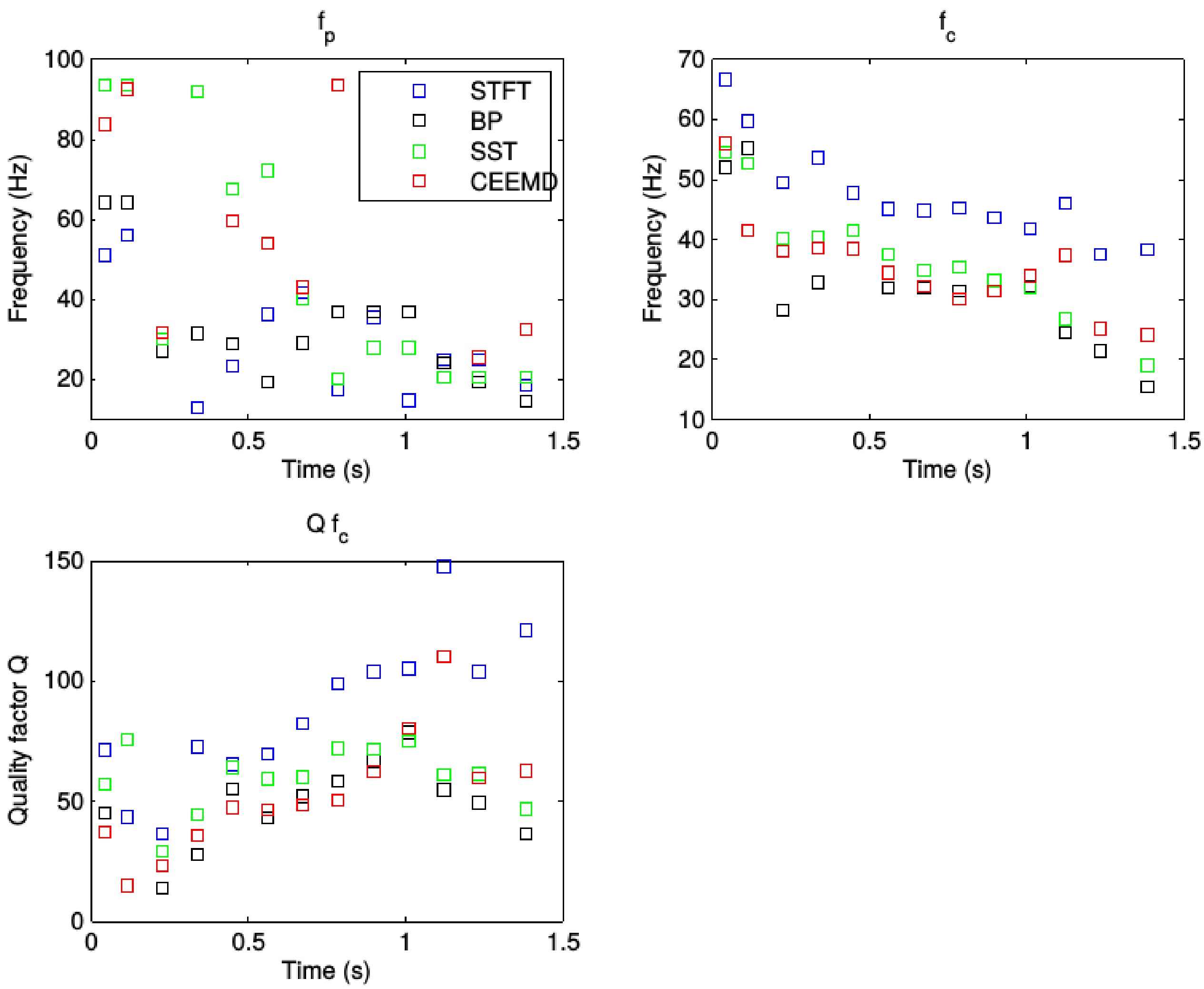

Figure 2. Peak frequencies f_p, frequency centroids f_c and quality factors Q estimated on successive windows of 0.16 s with an overlap of 0.05 s, using the four time-frequency transforms (STFT: short-time Fourier transform, BP: basis pursuit, SST: synchrosqueezing wavelet transform, CEEMD: complete ensemble empirical mode decomposition). The quality factors are estimated using the frequency centroids.

Conclusions

Despite their highly-localized time-frequency distributions, sparse time-frequency transforms can be used to estimate quality factors using the peak frequency method. For the present application to a seismic trace frequency centroids extracted from these time-frequency distributions show smooth and consistent patterns for all time-frequency transforms. Quality factors are here calculated assuming a single layer. The complete seismic profile or the pattern in peak frequencies and frequency centroids could be used to determine the number and position of different layers, in order to compute interval quality factors.

Sparse time-frequency transforms, characterized by a reduction in smearing and a higher resistance to background noise, constitute then another strategy to improve the estimation of quality factors.

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