Summary

This paper describes a Frequency Domain Smoothing (FDS) approach aiming to reduce random noise in seismic data in the frequency domain. Unlike time domain smoothing methods that tend to suppress high frequency components in the data, the FDS approach has little, if any, harm to high frequencies while reducing noise. Applying FDS before spectral balancing can significantly increase the resolution of seismic data without boosting high amplitude noise. The FDS does not need to be applied as a pre-processing step before spectral balancing, it is implicitly, as proved by this paper, imbedded in the short window Fourier transform, as well as the widely used Gabor transform.

Introduction

Conventional time domain smoothing methods are straightforward to implement and very robust in reducing random noise. In general, they suppress high frequencies and thus tend to reduce the effective resolution in the data making fault interpretation less precise. Edge preserving smoothing methods, recently published by many authors, tried to address this problem and several distinct algorithms have been reported in the literature (Luo et al., 2002; Marfurt et al., 2002; Taner, 2003a).

Ideally, we would like to remove random noise and simultaneously preserve the high frequency part of the spectrum in order to achieve the maximum possible seismic resolution. In practice, resolution is improved via deconvolution or spectral balancing-based methods which are often combined with a pre-processing step of noise suppression to avoid over boosting the noise, especially the high-frequency noise. Wang (2003), for example, suggested using FX-deconvolution as a pre-processing step before inverse Q filtering. Unlike the time domain smoothing, which can significantly damage the high frequency information, FX-deconvolution can preserve high frequencies well while reducing the noise. However, the FX-deconvolution approach depends on the predictability of the data, an assumption which is not always valid.

In this paper we present an alternative way to reduce noise without harming the high-frequency information. Unlike many conventional noise suppression algorithms, the FDS-based approach does not depend on the predictability of the signal and hence is more robust to noisy data. Moreover, as we will show, the FDS does not need to be applied as a separate pre-processing step. It is naturally and implicitly imbedded in the short window Fourier transform (SWFT) and the widely-used Gabor transform (Gabor, 1946; Margrave et al., 2002).

Theory

In this section, we describe the concept of FDS and its relationship with the SWFT. The study of FDS is inspired from Tury Taner’s new spectrum balancing approach (Taner, 2003b). Taner presented excellent results, where the resolution of the seismic data was enhanced by balancing the time-frequency spectrum (Figure 1).

Figure 1: Stacked sections before (top) and after (bottom) spectral balancing (after Taner, 2003b).

We show that Taner’s method can be conceptually divided into the following two steps. Firstly, it adopts the FDS to
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reduce noise without harming high-frequency components. In this step, an input trace is transformed into the frequency domain by the standard Fourier transform (FFT). The resultant spectrum (the complex-value Fourier transform of the trace, not the power spectrum) is then smoothed by some simple running-window or running-average smoothing, which is the so-called FDS procedure. As we will show, the FDS can reduce noise effectively. Secondly, the noise-reduced spectrum is balanced and transformed back to the time domain by a regular inverse FFT. We show that these two steps can be implemented simultaneously using short window Fourier transforms (SWFT) instead of the regular FFT. In other words, the FDS does not need to be carried out explicitly. It will be applied while performing the SWFT automatically.

Let us now see how the FDS works using some simple synthetic data. Figure 2a is a noise-free input signal and Figure 2b the same signal but with some noise added. Figures 2c and 2d are the power spectra of the standard Fourier transform of noise-free and noise-added data respectively. Clearly, the power spectrum of the noise-added data is quite different from the noise-free spectrum.

Comparison of Figures 2a and 3d reveals the key point of this paper: FDS (smoothing of the complex-value spectrum) can reduce noise while preserving the high frequency information. This statement will be further strengthened by the following discussion and examples.

The FDS was carried out by convolving a smoothing function in the frequency domain (Figure 4b) with the Fourier transform of the input trace. Since the convolution of two functions in the frequency domain is equivalent to multiplication in the time domain, the FDS can be exactly implemented in time by multiplying a time-window (Figure 4a) with the input trace. In practice, we can first apply the SWFT or the Gabor-Morlet decomposition to obtain the time-frequency spectrum, followed by a multiplication with a window function. If we aim to increase the resolution of the data, the power spectrum after SWFT can be balanced. A trace with higher resolution can thus be obtained after inverse Fourier transform of the balanced power spectrum.

Figure 2: (a) Noise-free signal. (b) Noise-added signal. (c) Power spectrum of noise-free signal. (d) Power spectrum of noise-added signal.

Figure 3a shows the results produced by smoothing the power spectrum shown in Figure 2d, while Figure 3b is the power spectrum created by smoothing the Fourier transform (not the power spectrum) of the noise-added data shown in Figure 2b. It is clear that Figure 3b is much closer to the right answer (i.e., the power spectrum of the noise-free data shown in Figure 2c) than Figure 3a. Figures 3c and 3d represent the inverse Fourier transform of Figures 3a and 3b respectively (both power spectra are flattened before the inverse FFT while their phases are kept intact).

Figure 3: Reducing noise by frequency domain smoothing (FDS). (a) Smoothed power spectrum. (b) Smoothed Fourier transform of the noise-added trace. (c) Inverse FFT of 3a after spectrum balancing. (d) Inverse FFT of 3b after spectrum balancing.

Figure 4: Window (Gaussian) functions used for FDS: (a) time domain and (b) frequency domain.
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Figure 5 illustrates the spectrum balancing in the time-frequency domain. The input trace and the resulted time-frequency spectrum are displayed side by side. The RMS amplitudes are computed for both the input trace and sub-band envelope within a user-defined time window. The ratio of the RMS amplitudes of the input trace over the one of the sub-band power spectrum is multiplied with the sub-band traces (note, the ratio is time-variant). A reconstructed trace is obtained by simply summing all the sub-band traces, which is equivalent to the inverse Fourier transform at zero time. The resultant trace should have improved resolution without too much noise, since the spectrum balancing has been performed on the noise reduced spectrum produced by the SWFT.

![RMS Amplitude Computed running time window](image)

Figure 5: Balancing power-spectrum in time-frequency domain.

Field Data Examples

In Figure 6 a stacked section from a land dataset is depicted before and after FDS-based spectral balancing. The corresponding frequency spectra are also shown in Figure 7. It is clear that the section after FDS balancing exhibits higher resolution along with a much broader spectrum bandwidth.

Figure 8 compares results after regular spectrum balancing (middle) versus the FDS spectral balancing (right). As expected, the result produced by the FDS spectral balancing approach is superior to the one made by regular spectrum balancing. The reason is that time-frequency balancing is applied on the data after FDS noise reduction while the regular one is applied to the raw data directly.

Conclusions

FDS can effectively reduce noise in the frequency domain without harming the high frequency part of the spectrum. Spectral balancing on the noise reduced data can significantly increase the seismic resolution without boosting overwhelming noise. The FDS is naturally included in the SWFT. This means that FDS will be applied to the data automatically whenever a window function is multiplied with the data in the time-frequency domain.

References


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Taner, M.T., 2003b, Auxiliary modules, Presentation at the Attribute Consortium of Rock Solid Images.


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Figure 6: Stacks before (left) and after (right) FDS spectral balancing.

Figure 7: Power Spectra before (a) and after (b) FDS spectral balancing.

(a)  
(b)  

Figure 8: Input stacked section (left) and results after regular (middle), and FDS (right) spectral balancing.