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COMPRESSION DENOISING: USING SEISMIC COMPRESSION FOR UNCOHERENT NOISE REMOVAL

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Summary

Wavelet related techniques have been proved successful in many seismic processing applications, such as filtering or compression. While seismic data compression is not yet widely accepted, we propose a compression based on filter banks as a means to remove uncoherent noise from seismic data, and thus improve the SNR. Results are demonstrated on synthetic data.

Introduction and overview of time-frequency techniques

If we let data analysis aside, two main applications have demonstrated the power of the wavelet transform:

- seismic data compression [Chen, 1995, Donoho et al., 2000];
- coherent or uncoherent noise attenuation [Miao and Cheadle, 1998].

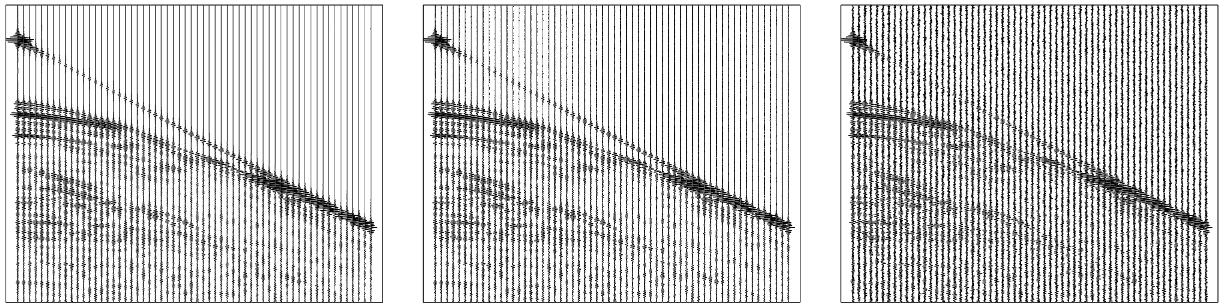
Several authors, e. g. Vermeer et al. [1996], have recently recognized that wavelets may not be the best fit for seismic data since they present large-scale oscillations. They have therefore investigated for instance wavelet packets, local cosine or Gabor transforms. We focus here on filter banks (FB), which can be regarded as a multichannel generalization of wavelets [Duval and Røsten, 2000]. Instead of iterating one low-pass and one high-pass filter, we directly use a FB composed of $M > 2$ band-pass filters. The signal is decomposed into localized time-frequency coefficients, which are processed according to the target purpose (i. e. denoising or compression).

Noise attenuation and data compression require analogous qualities from a transform. One of the main benefits of time-frequency representations is that one can act on local frequency features of the signal without disturbing frequency features located elsewhere, as opposed to the global effect of band-pass filtering in the Fourier domain.

The compression program employed here uses two different FBs along the space and the time directions, instead of the traditional wavelet decomposition. Filter banks used in this study are the Walsh-Hadamard transform and a 8-channel 16-tap biorthogonal FB that together yield good compression performance. The transform coefficients are then parsed from the biggest to the smallest ones (in magnitude), while taking care of the coefficient time-frequence dependency. We refer to Duval and Røsten [2000] and its references for a more detailed treatment on filter banks and a description of the compression algorithm.

Why may compression cancel uncoherent noise?

Figure 1 represents a shot gather resulting from elastic modeling based on an actual well log. The synthetic model signal $m_{t,x}$ being free from uncoherent noise (up to modeling and computational uncertainties), we add a gaussian white noise $n_{t,x}$ with various levels, resulting in a noisy signal $s_{t,x} = m_{t,x} + n_{t,x}$. The



(a) (b) (c)

Figure 1: Noise free model shot gather (a), with SNR$_n$ = 17.8 dB (b), with SNR$_n$ = 2.3 dB (c).

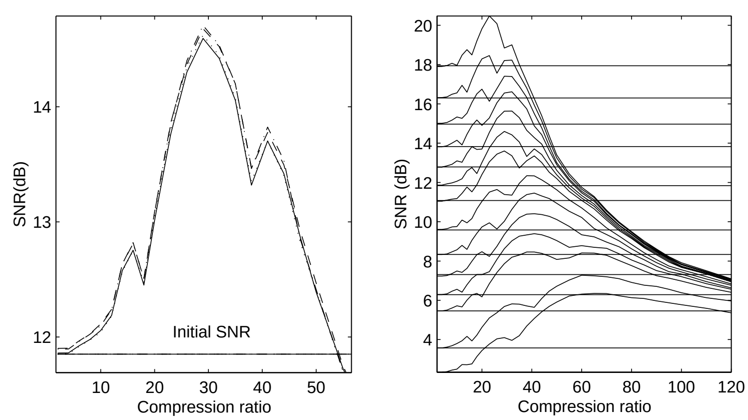
corresponding noisy signal-to-noise ratio (SNR$_n$) is calculated using the classical formula:

$$\mathrm{SNR}_n = 10\log_{10}\frac{\sum m_{t,x}^2}{\sum n_{t,x}^2}.$$

Two noisy versions of the shot gather are depicted in Fig. 1 (b–c).

In classical data compression applications, one usually considers the compression induced error $e_{t,x}$ added to the original signal $s_{t,x}$, which already contains more natural uncoherent noise. The SNR for the compressed signal $c_{t,x} = s_{t,x} + e_{t,x}$ is defined as $\mathrm{SNR}_c = 10\log_{10}\sum s_{t,x}^2/\sum e_{t,x}^2$. It generally decreases as the compression ratio (CR) increases. But since noise attenuation and data compression generally share similar features, we hope that careful data compression could serve as a denoising tool. From a very simple point of view, let us assume that $s_{t,x}$ is decomposed by a linear time-frequency transform T: $T(s) = T(m) + T(n)$. Compression generally quantizes and thresholds some time-frequency coefficients. Uncoherent noises are difficult to compress, since they are mostly unpredictable. Instead of trying to represent them faithfully in the time-frequency domain, we can discard them during compression. As a result, the quantity $T(n)$ could be reduced and the compressed signal $c_{t,x}$ will look like the underlying signal $m_{t,x}$ a little more. We now define the SNR to model as $\mathrm{SNR}_m = 10\log_{10}\sum m_{t,x}^2/\sum(c_{t,x} - m_{t,x})^2$, and try to reach the unequality $\mathrm{SNR}_m \geq \mathrm{SNR}_n$, via compression.

Results: reproducibility on different noise realizations



(a) (b)

Figure 2: (a) Denoising realizations for a SNR of 11.8 dB. (b) Distorsion curves at various SNRs.

The first experiments test the reproducibility of noise removal. Four realizations of a gaussian white noise are added to the model data, with a constant SNR$_n$ of 11.8 dB. The noisy shot gather then undergoes compression at various ratios, defined as the number of signal samples (e. g. 60) represented by a single compressed sample. CRs vary here from $1:1$ (no compression) to $60:1$.

The horizontal straight line from Fig. 2 (a) represents the initial noise level. The four other curves represent realizations of denoising, the y-axis representing the SNR_m between the model and the compressed signal at several compression ratios (on the x-axis). The first observation is the four experiments show similar behaviour. Between CRs of 1 and 50, the distorsion curves lie above the initial noise level. This means that in a least square sense, the compressed signal is closer to the underlying model signal, i. e. a little compression improves the quality of the recorded signal, since some uncoherent noise has been canceled out by the compression.

Nevertheless, for CR > 50, SNR_m becomes lower than the noisy SNR_n. SNR_m reaches a maximum, which could be a compression target, since it provides an optimum in a least-square sense.

Results: compression behaviour at different noise levels

Figure 2 (b) displays the results of compression denoising from several initial SNRs. Each curve pair may be read as follows, in a similar way as in the preceeding chapter: a straight line denotes the initial SNR_n and the curves sharing the same origin represent the SNR_m calculated at several compression ratios.

Observations are somewhat similar to the former example: between low (near to 1) and moderate CRs, compression usually results in an improvement over the initial noisy signal. The compression range where $\text{SNR}_m \geq \text{SNR}_n$ tends to broaden as the initial noise variance increases: the CR at which SNR_m becomes lower than SNR_n increases as SNR_n decreases.

These observations are supported by Fig. 3. It displays the compression result for near (left panel) and far offset (right panel) traces for initial SNR_n of 17.8 dB (top) and 2.3 dB (bottom), cf. Fig. 1. The chosen compression ratios correspond to the maximum of the SNR_m curve. Fig. 3 can be read as follows, from top to bottom: model trace, noisy trace, noisy trace after compression, initial noise, noise after compression. The two later noise plots share the same amplitude scale. We observe that after compression, ambient noise added to the data has been partialy reduced by compression, thus enhancing the data quality.

Conclusions

Common knowledge states that lossy compression generally adds noise to the data. In contrast, we have shown that, when ambient uncorrelated noise is present, careful compression may improve the signal-to-noise ratio to the underlying data, providing guidelines for seismic compression on acquisition.

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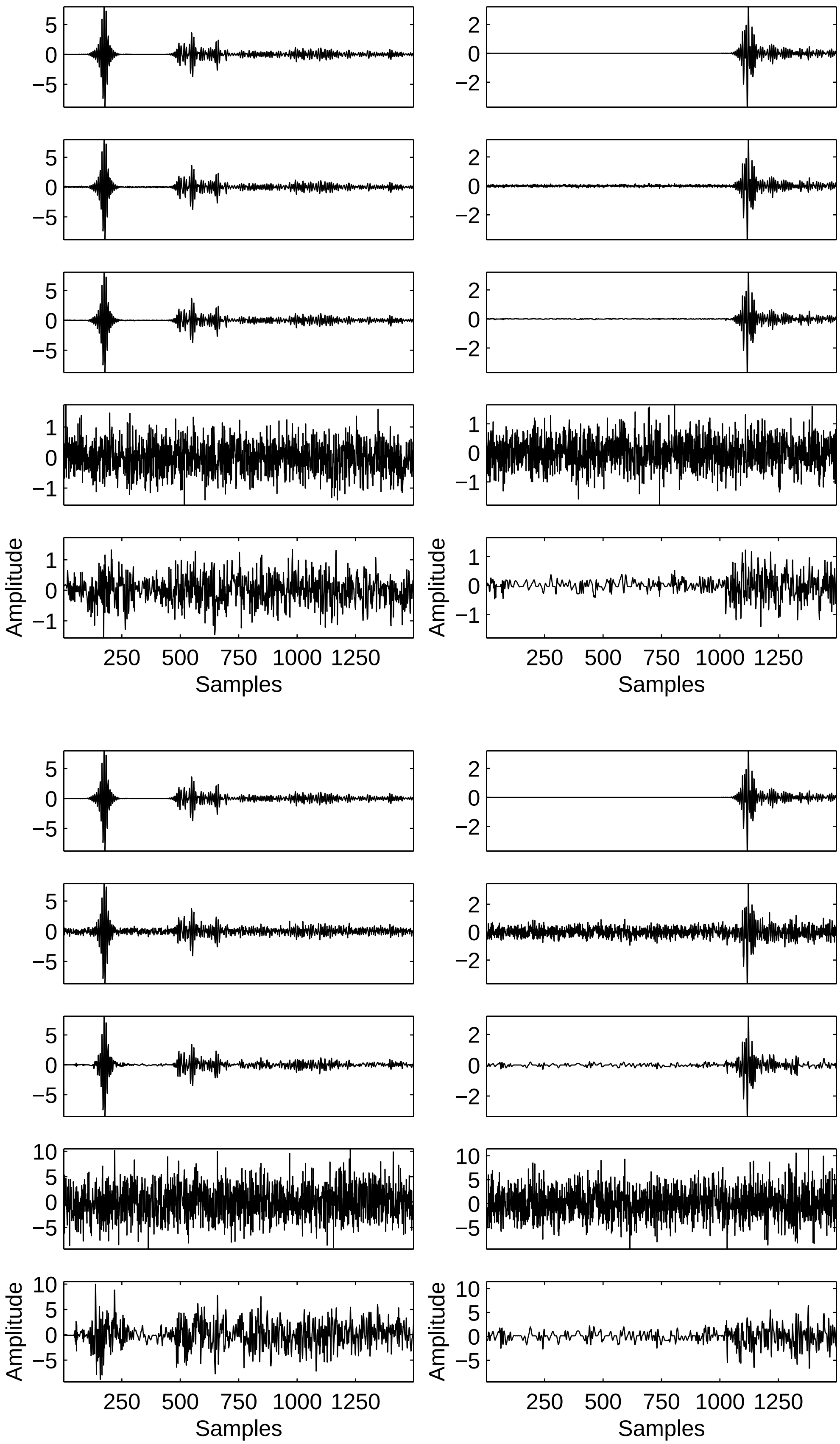

Figure 3: Compression denoising with $\mathrm{SNR}_n = 17.8$ dB and CR = 23 (top) and $\mathrm{SNR}_n = 2.3$ dB and CR = 65 (bottom) for a near offset (left panel) and a far offset trace (right panel).