Optimum Seismic Resolution for Stratigraphic Imaging

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Summary

We present a technique for optimizing the seismic resolution in the presence of noise. We first discuss a simple anatomy of the seismic trace. The deconvolution operator which depends explicitly on an estimate of the SNR and wavelet spectra is then outlined with an insight into its effect on the data. Finally, we present a case study form the Rosemary basal quartz field in central Alberta which highlights various techniques, and propose an optimal enhancement processing flow.

1. Introduction

Consider the simple convolutional model illustrated in Figure 1. The model has three main constituents:

1- The reflectivity represents contrasts in the acoustic impedance of the earth, the information we strive to preserve and bring up as much as possible.

2- The wavelet represents the energy source and earth filtering effects. It masks the reflectivity making it difficult to resolve close reflection coefficients representing thin beds. To complicate the picture, the wavelet is non-stationary due to progressive earth filtering (attenuation and dispersion). In order to improve the resolution of seismic events, it is desired to compress the wavelet in time so that it would have less interference effects.

3- The noise is everything else recorded on the seismogram. It contains random components from acquisition source and array design as well as apparently random components due to back scattering from small inhomogeneous zones. It also contains coherent noise due to multiples, ground roll, converted waves and extraneous sources. The noise confuses the picture in two ways: it makes it difficult to visually detect primary reflections, and is amplified by wavelet compression filters. This sets a limit on how far one can compress the seismic pulse without irreparably altering the shape of the wavelet.

The power spectrum of the trace contains a composite of these effects, from which we hope to recover a representation of the reflectivity. In the absence of further assumptions, this seems to be an exercise in futility. Various spectral components can easily leak into one another, distorting our treasured reflectivity more after deconvolution.

Thus, out of convenience, we have the common assumption that the reflectivity is white, an assumption that has been invalidated by recent research indicating that the reflectivity is blue [2]. Most standard deconvolution algorithms totally ignore the noise term. In practice, a noise attenuation technique such as FX prediction filtering or Radon filtering is called upon to address the noise problem. This adds more implicit assumptions about the constituents of seismic data. When it comes to the wavelet, the convenient white noise reflectivity assumption is used to compute a scaled version of its power spectrum. The celebrated minimum phase assumption is used to estimate the shape of the pulse. Although there may be some physical grounds to justify a minimum phase wavelet in some situations (e.g. dynamite source), the minimum phase of a band-limited signal is quite unstable since it depends on the logarithm of the amplitude spectrum which is very high in absolute value at attenuated frequencies. Some sort of regularization in the minimum phase deconvolution process is needed to force some consistency on the phase.

Ignoring the noise term poses problems to most standard deconvolution techniques with no adequate mechanism to address them. This explains why surface-consistent deconvolutional operators work better in low noise environments.

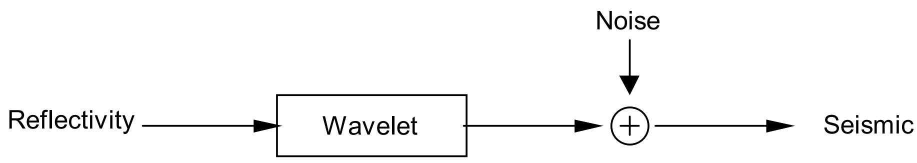


Figure 1: Convolutional Model for Seismic Data

2. The Operator

Given an estimate of the coherence spectrum c(f) and the wavelet spectrum W(f), it can be shown that [1] an optimal linear estimator of the reflectivity from the seismic trace is given by

$$A(f) = \frac{c(f)}{W(f)},$$

which implies that the desired wavelet amplitude spectrum is the coherence spectrum. The coherence spectrum is related to the SNR spectrum via:

$$c(f) = \frac{SNR(f)}{(1 + SNR(f))}.$$

Figure 2 shows the proposed operator as a cascade of a signal estimation filter and an inverse filter.

Clearly, the objective of this deconvolution is not to flatten the seismic spectrum but rather flatten the wavelet spectrum in a manner consistent with the SNR spectrum of the data. Flattening the seismic spectrum would be a geologic distortion with significant residual wavelet and distorted noise. Flattening the wavelet spectrum naively, would blow up the noise level at frequencies where wavelet amplitude spectrum is low, thus flooding the reflectivity with a lot of noise.

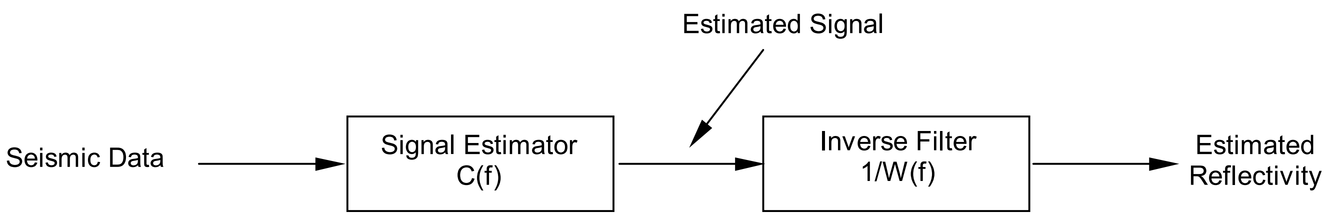


Figure 2: A block diagram of the operator

Although this operator was derived as the linear least squares estimator of the reflectivity sequence, it can also be interpreted in other ways.

1- Inverse filter applied to an estimated signal.
2- Wavelet shaping filter, where the input wavelet W(f) is shaped into the magnitude coherence spectrum.
3- Inverse filter with frequency-dependent prewhitening. Rewrite the operator as

$$A(f) = \frac{1}{W(f)\left[1 + \frac{1}{SNR(f)}\right]}$$

We can see the prewhitening level would be high at frequencies with poor SNR, which is effective for noise control. Notice here that different frequency components are handled differently in accordance with their SNR rather than using a fixed prewhitening level for all frequencies.

To estimate the SNR spectra, we use rational transfer function models that provide accurate spectral estimates using short time windows. Wavelet spectra are estimated from estimated signal spectra using a proprietary cepstral modelling technique. This technique does not require white reflectivity, which makes it useful for short time windows.

Thus, for non-stationary environments, the technique can be used to estimate many operators separated by a small time step. Such an approach would have the advantage of addressing both non-stationarity and additive noise issues when deconvolving seismic data.

The phase of the operator can be set to zero or minimum phase. The phase of the wavelet can be estimated after deconvolution from seismic data alone using a variety of techniques developed at SET. Such techniques are more stable for larger band-widths.

3. Examples

We now present a case study from the Rosemary basal quartz field in central Alberta. Figure 3 shows an inline from the unfiltered migrated stack. Figure 4 shows the inline after FXY filtering and signature deconvolution whereas Figure 5 shows the data processed through the proposed technique which is clearly a higher resolution image.

The next three figures are of the same geographic area, except overshot in a megabin design. Clearly, Figure 8 shows more details.

Figure 3: Unfiltered Migrated Stack

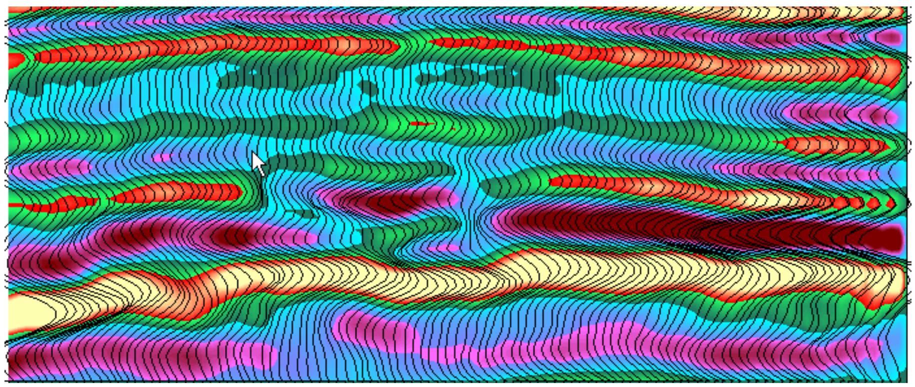


Figure 4: FXY Noise Attenuation and Signature Decon apllied to data in Figure 3

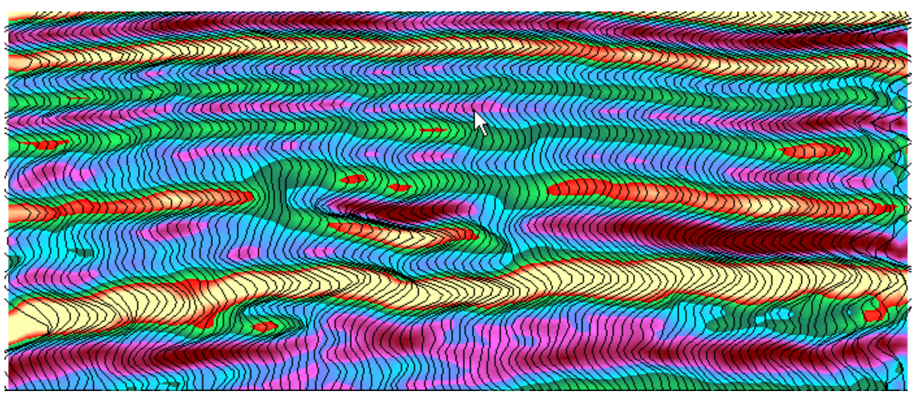


Figure 5: The data of Figure 3 after being processed by the outlined technique

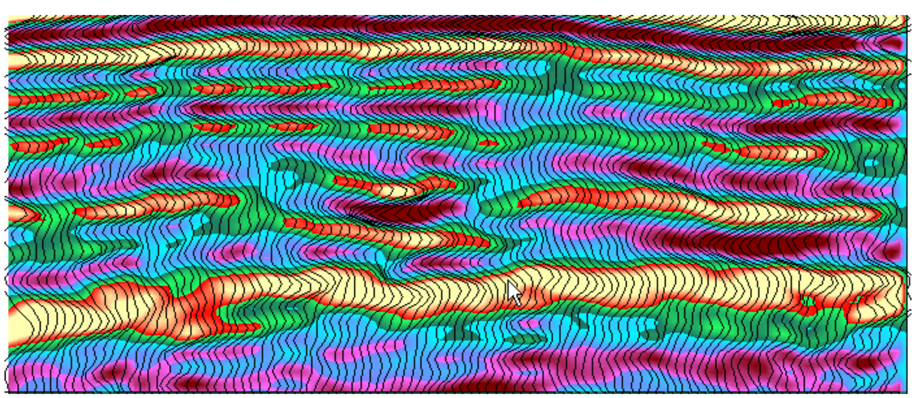


Figure 6: Unfiltered Migrated Stack Megabin Acquisition

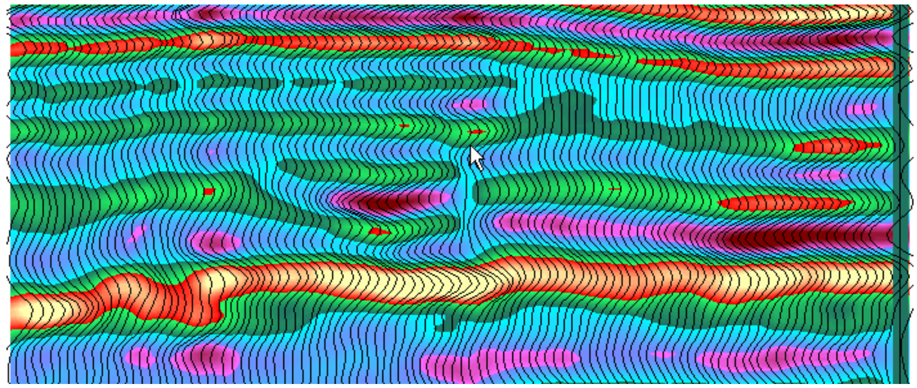


Figure 7: Data of Figure 6 after 2 Passes of Spectral Balancing and FXY Noise Attenuation

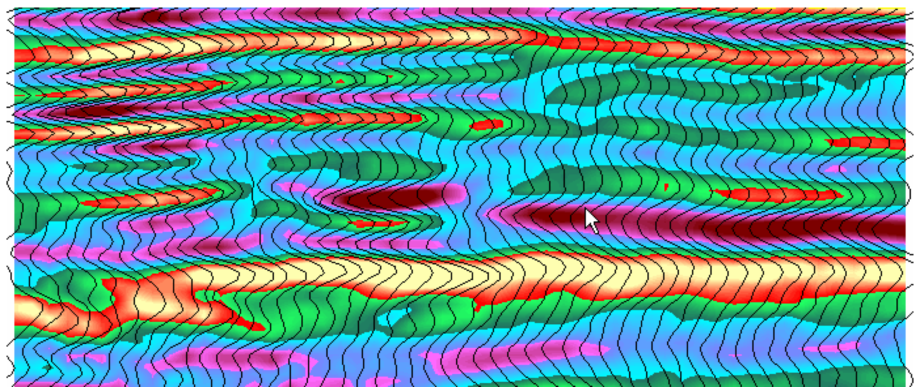
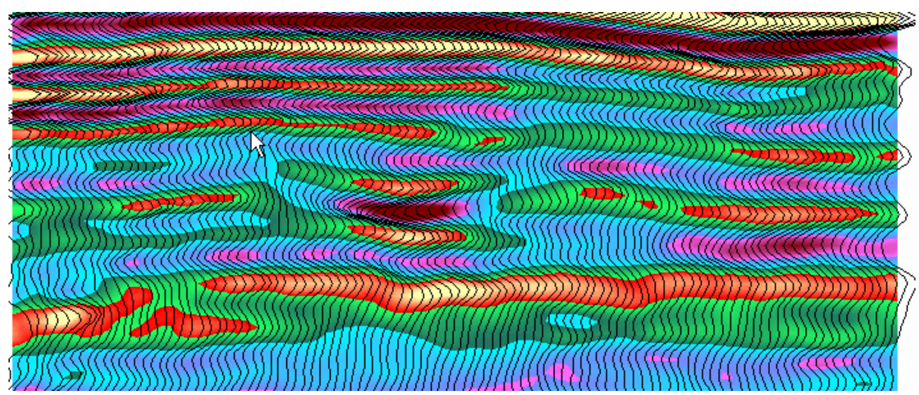


Figure 8: Data of Figure 6 after being processed by the outlined technique



4. Conclusions

We examined the problem of deconvolving noisy seismic data, and presented an optimal and practical approach based on basic estimation theoretic concepts. The technique is applicable in both stationary and non-stationary environment without making explicit assumption of the form of earth absorption. The performance of this technique is demonstrated on real seismic data and compared with industry standard techniques. The examples presented support the validity of the technique and demonstrate the improvement that is attained by employing estimation theoretic concepts for seismic data processing.

REFERENCES

(1) Maklad, M. S. *et,* "Optimal Seismic Resolution and SNR Estimation", SET Technical Report # 1986-01
(2) Walden, A. T. and Nunn, K. R. 1985, "Correcting for coloured primary reflectivity in deconvolution, presented at 47th EAEG Meeting, Budapest.