Noise Attenuation in Seismic Data
Iterative Wavelet Packets *vs* Traditional Methods

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Summary

In this document we expose the ideas and technologies behind GeoEnergy's noise attenuation services. GeoEnergy's patented adaptive Wavelet Packets (WP) technology is contrasted with commonly used filtering tools, and the ability to extend adaptive WP technology through iterative methods is described.

Ideas & Technology

Adapted Waveform Analysis

Wavelet packets are a powerful, flexible and computationally cheap form of adapted waveforms. Since its inception, analysis with adapted waveforms, AWA, has enabled many new applications in signal processing in domains such as image, radar, or audio signal processing. In seismic data processing, however, AWA-based methods have not yet achieved a very broad deployment. This is not entirely surprising, since a fair amount of engineering is needed to scale tools from research up to production. The sheer size of a typical seismic data set poses a serious deterrent to the application of any method that is computationally more costly than the simplest of transforms. With the availability of better tools and faster computers with multi-gigabyte memories, as well as low-cost clusters, AWA methods now become increasingly more practical in seismic data processing as well.

Our approach generalizes wavelet analysis and is based on wavelet packets analysis with best-basis search [Coifman 1997]. In wavelet analysis, we decompose a signal using a library of adapted, compactly supported waveforms, wavelets, to obtain a multi-scale representation of the signal's components. The basic building blocks of a wavelet analysis are obtained from a compactly supported function or "mother wavelet" $\psi(x)$ by scaling *b* and translation *a.* A wavelet transform decomposes the function $f(t)$ into a set of such basis functions, and the inverse wavelet transform reconstructs it perfectly:

basis wavelet function, wavelet transform (continuous), inverse transform

$$\psi^{a,b}(x) = |a|^{-1/2}\psi\left(\frac{x-b}{a}\right)$$

$$W_{\psi}(f)(a,b) = \frac{1}{\sqrt{a}}\int f(t)\psi\left(\frac{t-b}{a}\right)dt$$

$$f(x) = C_{\psi}\iint \left\langle f,\psi^{a,b}\right\rangle \psi^{a,b}(x)a^{-2}dadb$$

Wavelet packets analysis generalizes wavelet analysis by yielding a redundant set of signal decompositions from which many different bases may be selected, each representing the same signal from a different perspective. A best-basis is then one which, upon some sparsifying operation on its coefficients, provides the best signal reconstruction for a given purpose. For example, if the purpose is (lossy) signal compression then a basis would be selected that provides the lowest bit-cost of coding the most energetic wavelet packet coefficients. The construction of the best-basis proper is driven by a function measuring that bit-cost [Averbuch et al 2001].

Adaptive vs Fixed Decomposition Space

As a spatial grouping of echoes, seismic data is well suited to spectral methods. Because of the difficulty in picking an adapted tiling of the time-frequency plane (basis), most seismic denoising is performed in a fixed basis. Denoising tools are arguably more often chosen for the underlying decomposition basis they impose on the data (i.e. Fourier, Radon, Wavelet) than on the actual computations performed in that basis.

We define "denoising" as the removal of "noise" from a "signal", and we also coin the word "designaling" as the removal of "signal" from "noise" – where "noise" and "signal" are respectively undesired and desired components of the data. Removal requires separation of "signal" and "noise"; given that along a single trace in the original time domain, "signal" and "noise" are usually inseparable, denoising requires the coordination of both a mathematical domain in which separation can be achieved and mathematical tools that can be successfully applied in that domain. Except for the attenuation of multiple reflections, the signal is always geologically meaningful and the noise is not.

The importance of data representation cannot be underestimated. A simple example is shown in *Figure 1* where a seismic trace is decomposed with a short-time window Fourier transform and a best-basis WP transform, respectively. A tight representation of the data, one where few values hold most of the signal's energy, offers a clear view of the set of spatiotemporal events that make up a seismic trace. By finding an optimal time-frequency tiling of the signal (best basis), the adapted WP decomposition is far more efficient at collecting such events, and building a model of the signal, than are traditional, non-adaptive methods.

Fixed window Fourier transform TF-plane tiling *vs* Adaptive WP decomposition TF-Plane tiling

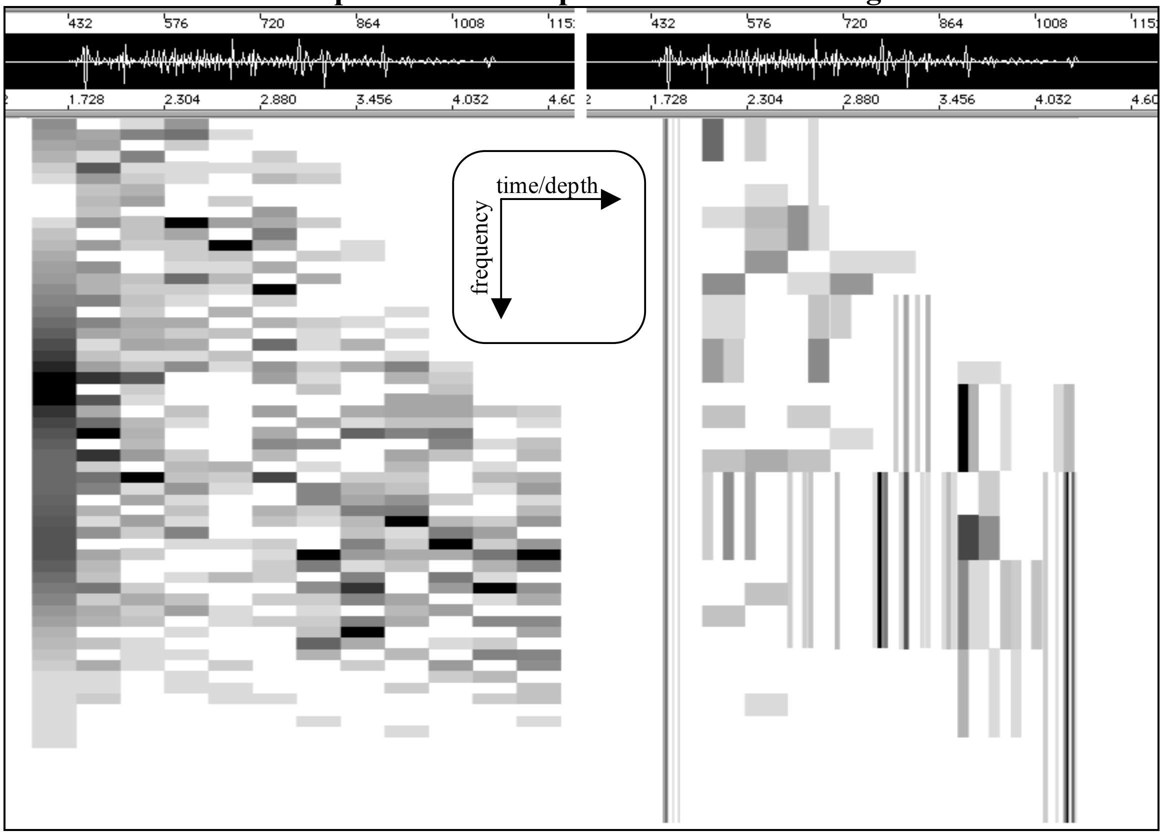


Figure 1

Local vs Global Approach

GeoEnergy's tools leverage the multi-dimensional space-spanning nature of physical structures present in seismic data. Thanks to the computationally moderate cost of using multi-dimensional wavelet packets, it is feasible to seek the separation of signal and noise using all available information along every axis. The swell noise example Figure 3 visibly depicts this concept; 1D trace-based mathematical tools cannot compete with 3D WP in lifting energetic swell noise from fine geological structures.

The ability to iterate

The ability to perform iterative separation of signal and noise is arguably the greatest strength of GeoEnergy's tools. We shall hence explain the method, philosophy and requirements of the procedure.

As depicted in *Figure 2* the iterative process is performed as follows:

1. An initial signal c_0 is over-denoised so as to generate a completely noise-free s_0 with maximal signal energy.
2. The result is subtracted from the original to obtain the residual r_0, where the SNR is lower (and hence the NSR higher) than in c_0. We can consider r_0 to be "noise heavy" relative to c_0, it has a higher proportion of noise than the original signal and is hence a good candidate for the next step.
3. r_0 is designaled to generate a completely signal-free n_0 with maximal noise energy.
4. A new signal c_1 can be generated by subtracting n_0 from c_0. Because n_0 was entirely signal-free, there is no loss of signal in c_1, only a loss of noise. By the same token, comparing r_1 to r_0 we can state that there has been no loss of noise in r_1, only a loss of signal. As long as each iteration can pull additional noise-free signal and signal-free noise at each iteration, both the signal and the noise models will improve until the data is fully separated as shown in *Figure 4*.

As stated above, this procedure requires (a) that one can always find a noise-free version of the signal and signal-free version of the noise and (b) that additional signal and noise must be retrievable with each iteration. If condition (a) is not met, whatever noise is left in the signal (or signal in the noise) will be irretrievably lost, and if condition (b) is not met the procedure will not converge to a full separation.

We are currently unaware of any tool other than WP that allows for both those conditions to be met, and hence for an iteratively improving denoising to be achieved on seismic data.

Iterative process

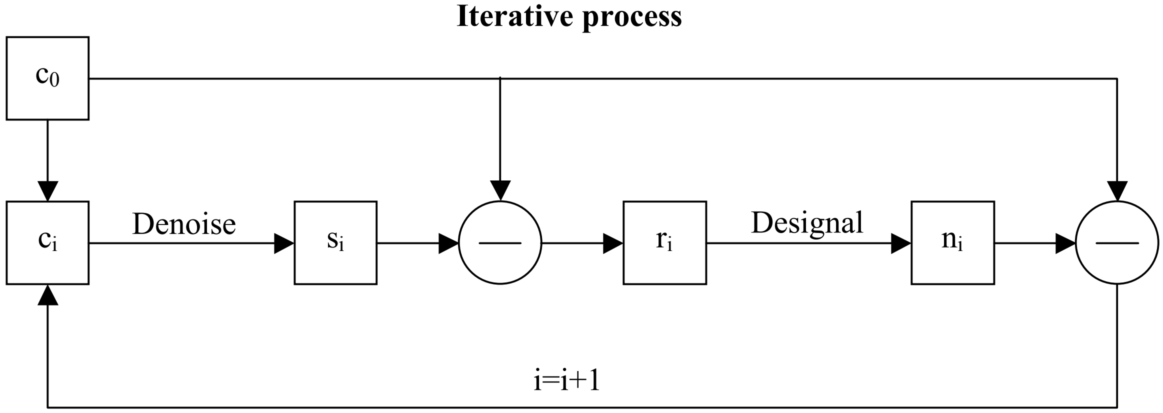


Figure 2

Multiple types of noise - Peeling layers

The noise in seismic data is rarely homogeneous in nature (e.g. swell noise is often accompanied by cable jerk noise and/or seismic interference). Thanks to the adaptability of wavelet packets and GeoEnergy's approach, both denoising and designaling can be parameterized so as to separate one type of noise at a time. In this manner, each type of noise can be peeled from the signal until none remains.

Conclusion

A core objective of all seismic data processing is to increase the signal-noise ratio in the data. It is a fact of life that the achievement of an optimal image of the subsurface is hindered by a broad range of noise types. Noise may occur at one or more stages, from acquisition to interpretation, defying a general solution to the problem. Without claiming to have found such a general solution, GeoEnergy has developed a practical methodology to address a great variety of noise problems and to provide results that are superior to any one of the existing common practice methods.

Swell noise denoising comparisons

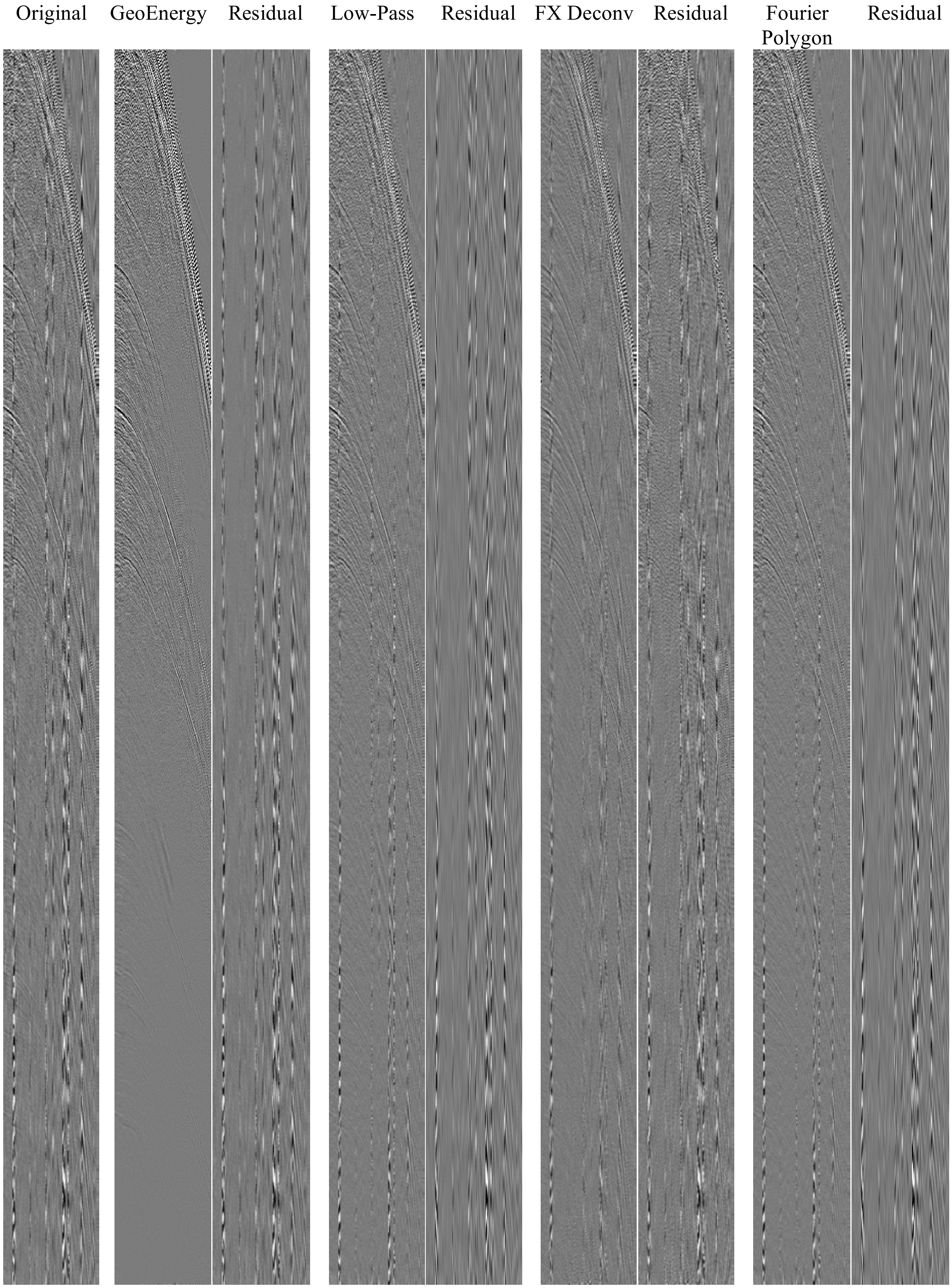


Figure 3

Some swell noise iteration results

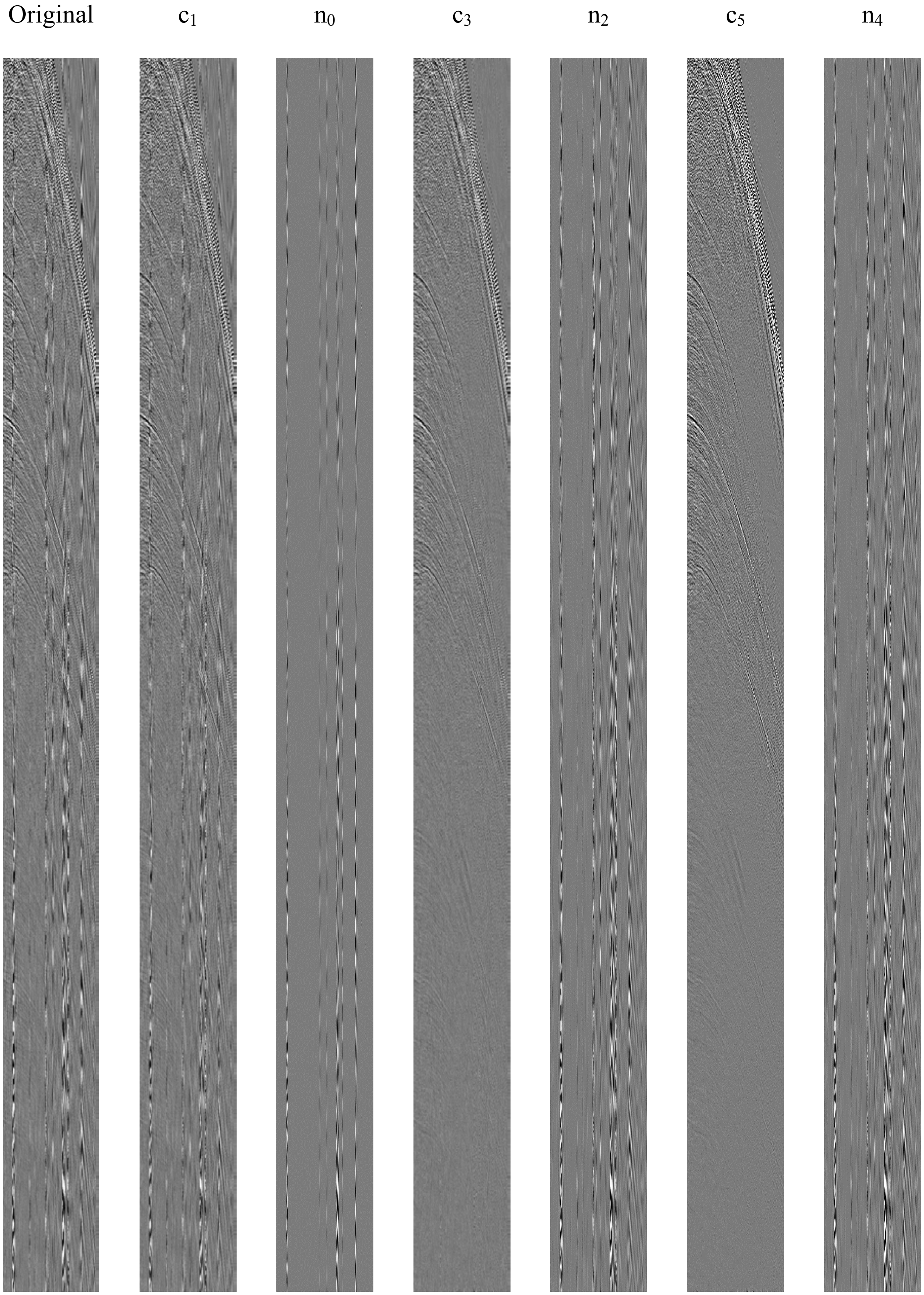


Figure 4

Examples

Apex-shifted multiples

Apex-shifted multiples are not surface related. This type of coherent noise can not be attenuated by Radon transform, SRME or any other noise attenuation method. Attempts to modify the Radon transform to compensate for the apex shifting have not been successful. The wavelet packet iterative adaptive denoising provides a completely new and different alternative into the apex shifted multiple reflection attenuation

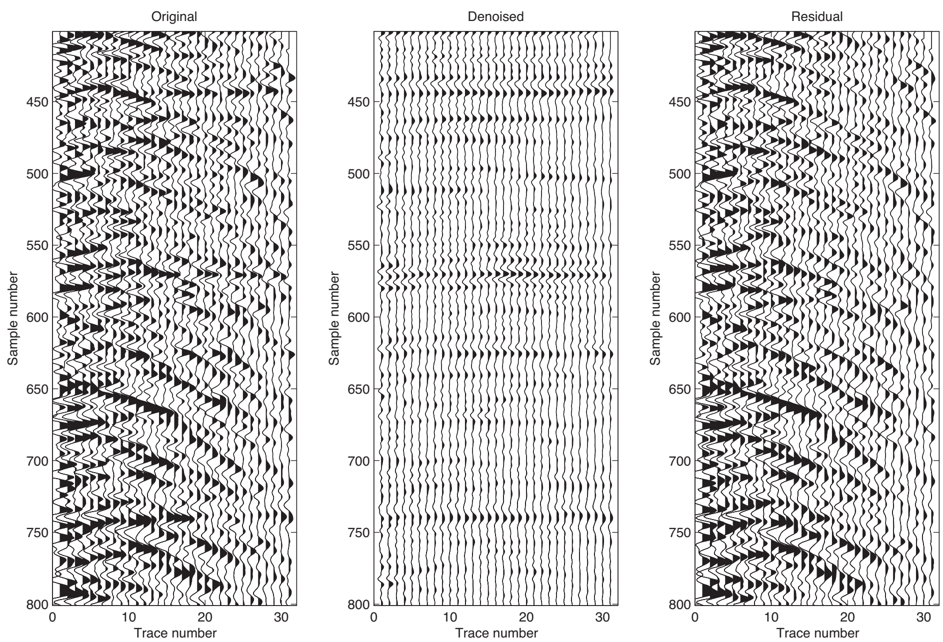
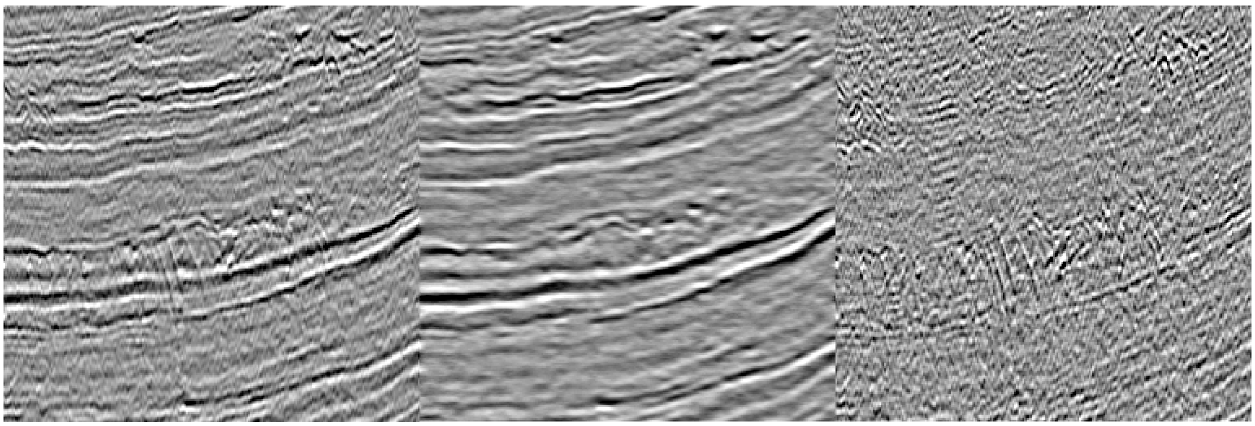


Figure 5

Migration noise

In this example, clearly non-geological artifacts created by the migration process can be seen intersecting geological layers. With each iteration (denoising shown in *Figure 6, Figure 7*), the amount of signal left in *r* diminishes until no geologically meaningful signal is left in the residual.

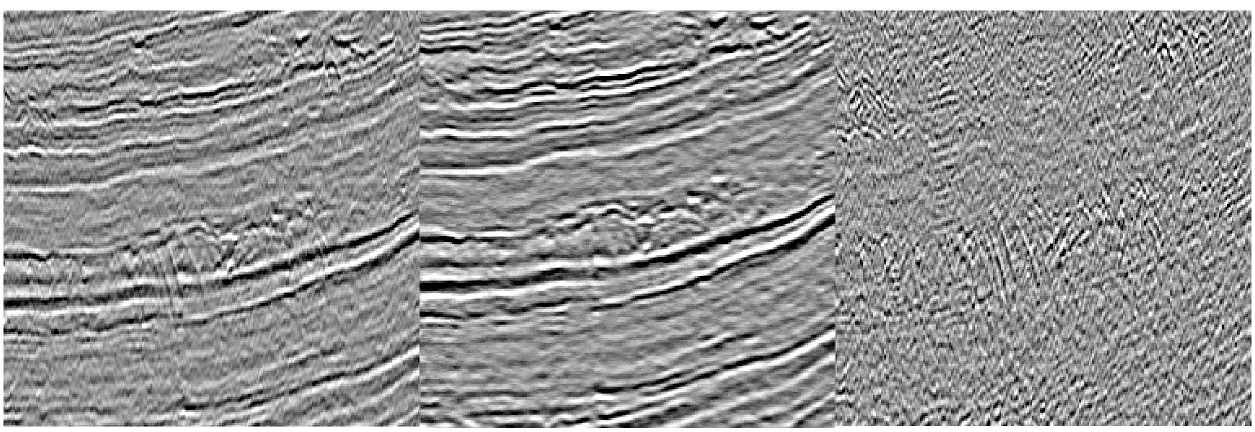
Initial signal-noise separation



Original s_0 r_0

Figure 6

Signal-noise separation after 3 iterations



Original s_2 r_2

Figure 7

Land Data

In this 3-D land seismic data example we show raw prestack time migrated gathers. The objective was to perform amplitude versus offset (AVO) computations using these PSTM gathers. The SNR of the gathers was very low, yielding unreliable AVO intercept and gradient volumes.

Application of the multidimensional denoising led to much higher SNR and therefore to useable AVO intercept and gradient volumes.

GeoEnergy Denoising, pre-stack land data

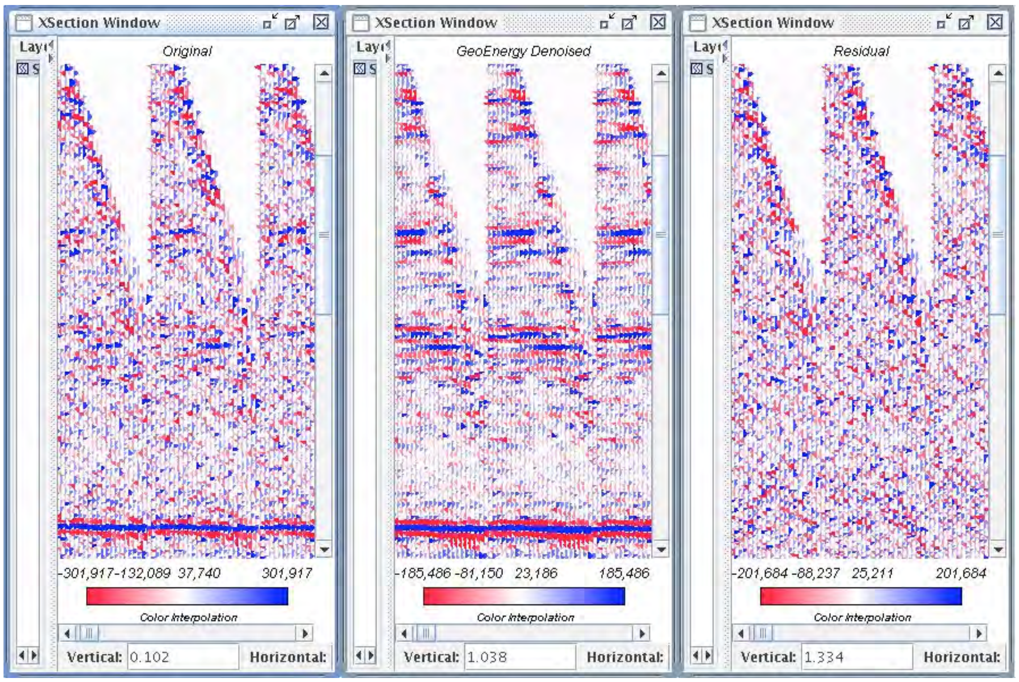


Figure 8

FX Deconvolution Denoising, pre-stack land data

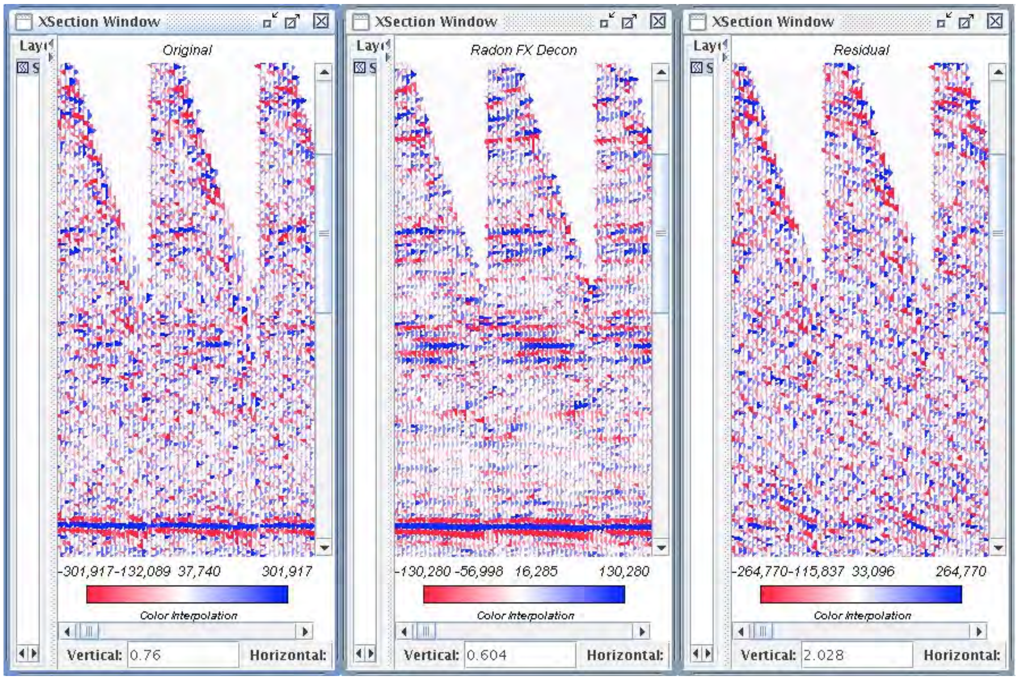


Figure 9

Radon Denoising, pre-stack land data

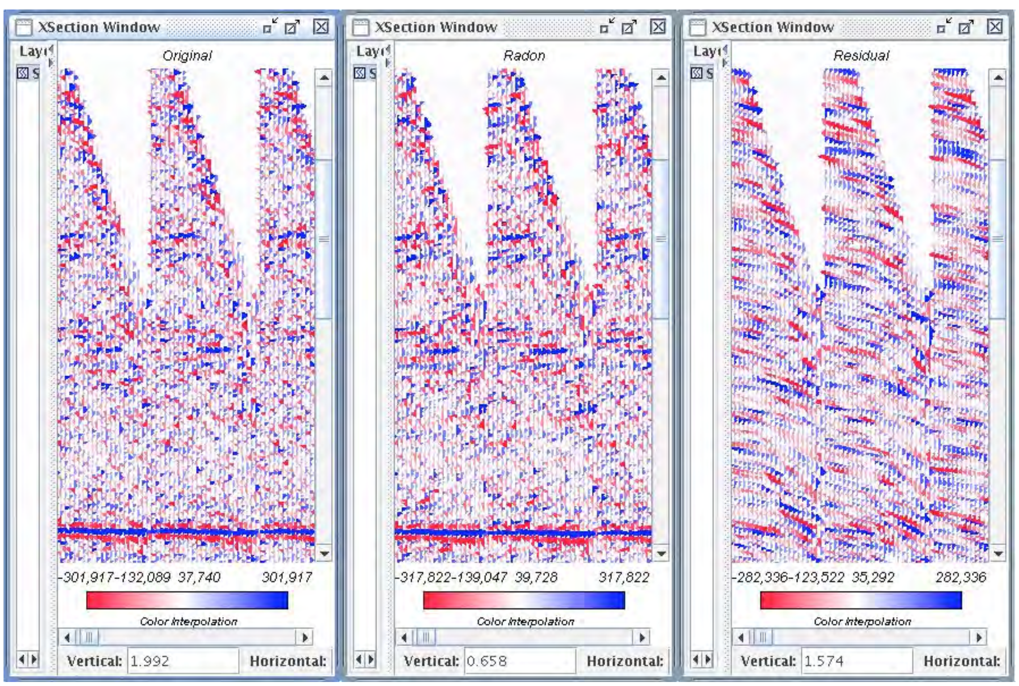


Figure 10

GeoEnergy denoising, pre-stack land data

Original

Denoised

Residual

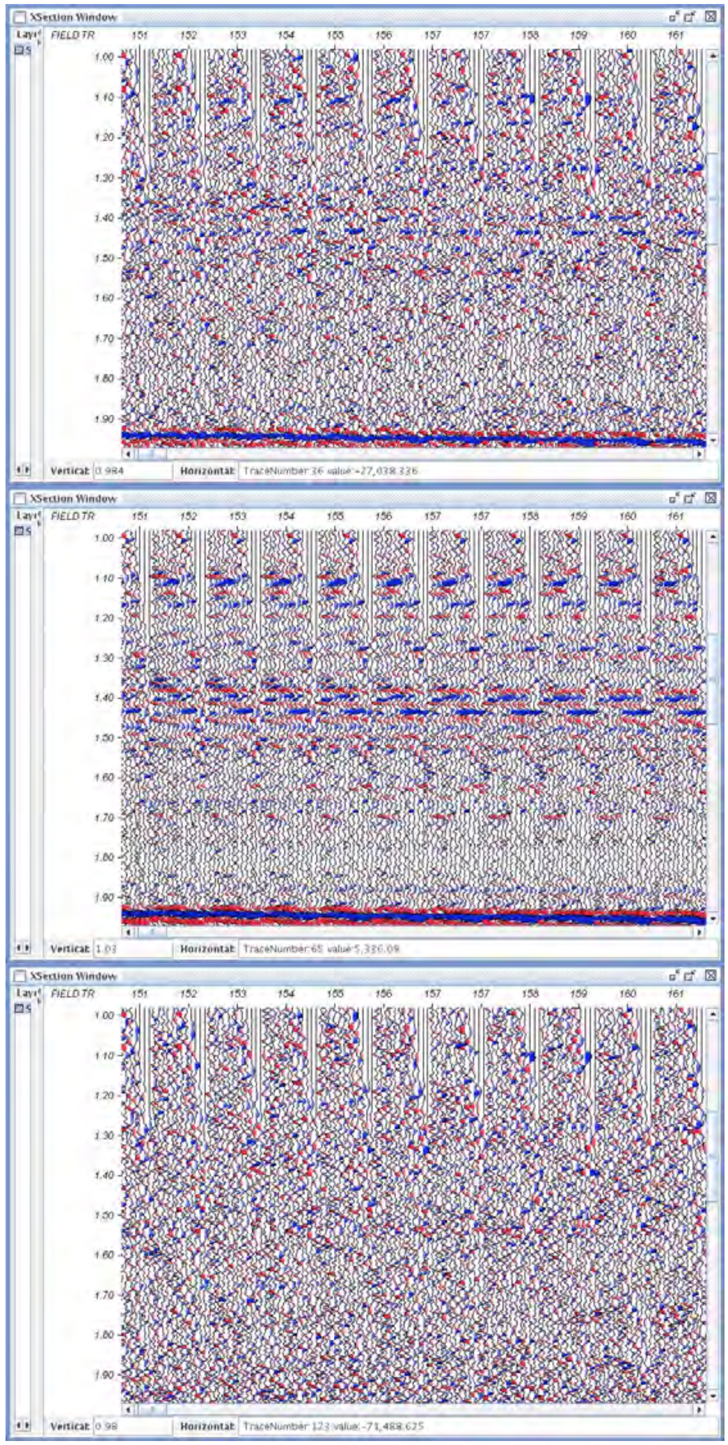


Figure 11

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