

# White Noise Suppression in the Time Domain – Part II

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## Summary

In Part I an algorithm for removing white noise from seismic data using principal component decomposition in the time domain was presented (Jones, 1985). This works well with signal to noise ratios near 1.0. Now you will be shown the loss of signal and frequency content under high noise conditions ( $S/N \sim 0.14$ ). We will demonstrate the use of this algorithm for data clean up, velocity analysis, selected clean up, and data whitening. For the latter application it is very important to adjust the phase of the data.

In short the time-space domain has proven to be both a robust and useful domain for processing seismic data. If you respect that the seismic data "wobbles" in time and space and changes in amplitude then the signal may be extracted relatively easily.

## Introduction

In Part I you heard some of the reasons why we chose to work in the time domain – most importantly, that all frequencies of the wavelet are moved together and that amplitude and statics variations in space are handled easily. You were shown how to construct the basis functions and you were shown that we were able to extract most of the signal (down to 30 dB) with only three of these basis under conditions of moderate ( $S/N \sim 1.0$ ) noise. Now you will see the high noise limitations and applications of this algorithm.

## High Noise Limitations

A stacked section which already contains some noise is combined with white noise band limited to match the data. The RMS level of this noise is about 7x the amplitudes on the strongest events on the section. I use 41 traces x 300 ms to create the basis functions (about 6.4x noise reduction). Signal is lost when the  $S/N$  ratio is about 30 dB (Figure 1).

This result may be enhanced by applying smoothers to the amplitude and statics matches – shown in Figure 2. Note that the statics smoothers produce the typically wormy appearance of a mix. Even the strong events have a "jitter" due to the high amplitude noise. Notice that where the section is too noisy, high dip events are created. This is actually an advantage as they can be easily seen and removed. If the programs were to create low dip events from the noise, these could easily be confused with signal.

## High Noise Limitations

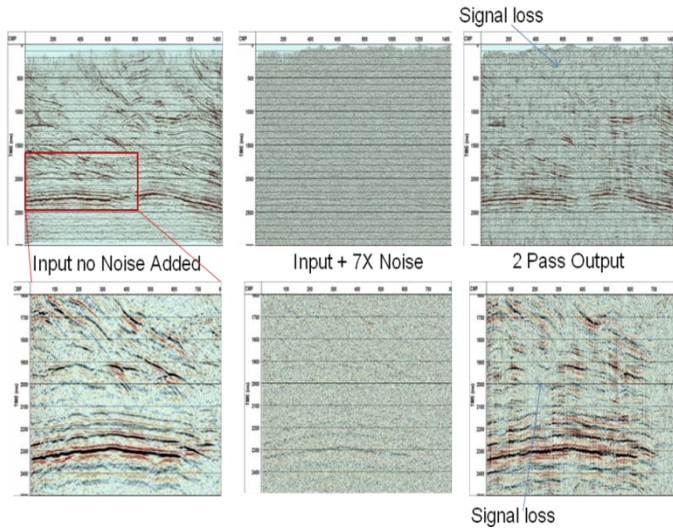


Figure 1: effect of algorithm on very noisy data

## Limits - Smoothing

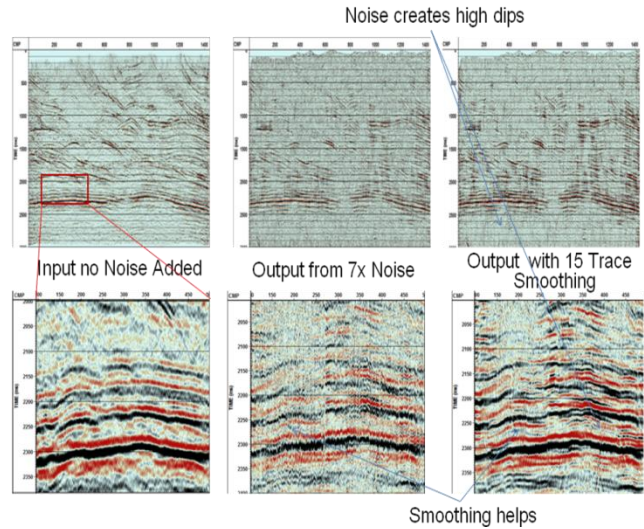
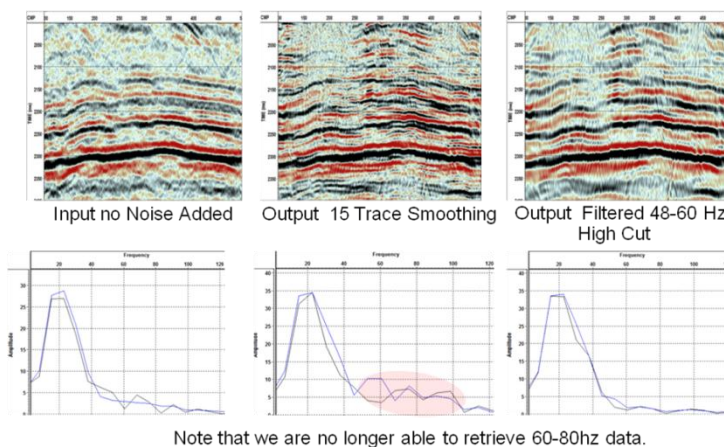


Figure 2: effect of smoothers

Figure 3 shows that the smoothed events are higher frequency than the original input without added noise. This is a result of the statics we used ahead of the stacks used to create the basis functions. The statics have lined up noise and whitened the wavelet. We can remove this by applying a 48 - 60 high-cut filter. This is a problem to be aware of (we are losing the 60 - 80 Hz data) but considering the section that we started with it is a small price to pay.

Notice also that the diffraction patterns have been lost. This is a combination of the smoothers and the signal to noise.

## Limits - Frequency Content



Note that we are no longer able to retrieve 60-80hz data.

Figure 3: effect of noise on high frequencies

## Applications

Most of the signal can be extracted – even when it is badly contaminated with white noise. Here are some possible applications.

We can clean up the section (see Figure 4) and improve our ability to interpret it but prestack migration most of the time is a good noise suppressor too. If the prestack is noisy the white noise algorithm can be run on that. It may also, for example, be run on gather data sorted by offset and thus may be enhance AVO. In Figure 5 if the section looks like the middle panel some analyzable data may still be recovered.

### Cleanup - Character Changes

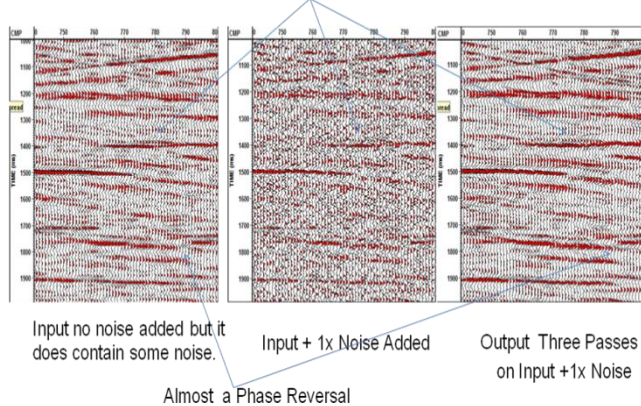


Figure 4: example of cleanup

### Strong White Noise

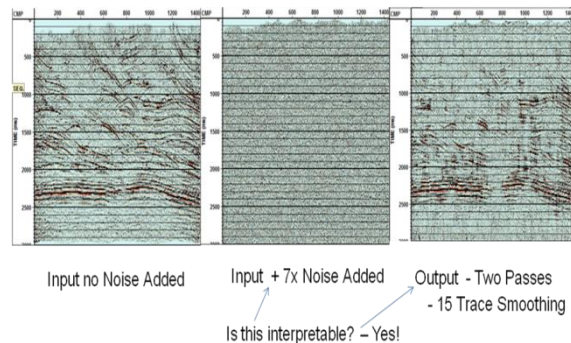


Figure 5: strong white noise

Because the algorithm preserves the original signal amplitudes we can pick velocities in movie mode. The amplitudes on the result (Figure 6) match the amplitudes on the input data so we preserve amplitudes section to section and can see which percent step-outs are brightest and most coherent.

### Velocity Analysis –strong noise

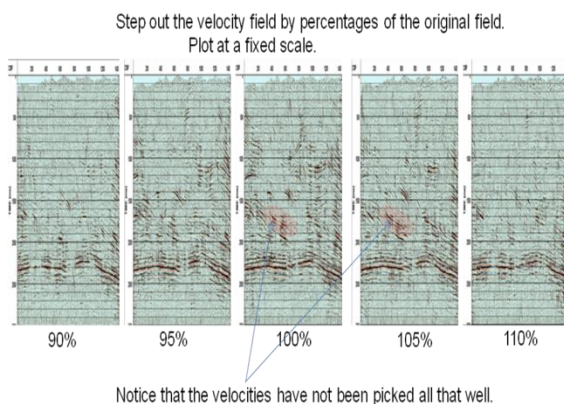


Figure 6: Velocity analysis after removal of strong

### Nonlinear Add Back Model

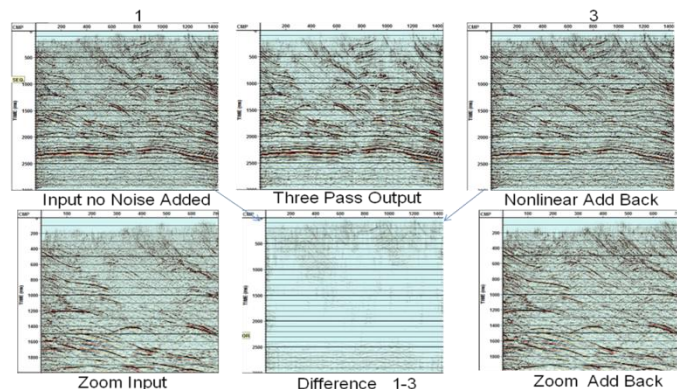


Figure 7: example of non-linear add back white noise

As shown in Figure 7, we can clean up the section but where the data was noisy often the signal is still weak. If we can assume that the scalars are being affected by the higher noise in these areas, then it makes sense to add back the model nonlinearly into the original section bringing these areas to a

minimum signal to noise ratio and adjusting the total amplitude to match the original amplitude. Places where the signal to noise ratio exceeds the minimum are left untouched.

If the noise is not too extreme the algorithm can extract most of the signal with the high frequencies intact. This process can be used before say spectral balancing is applied to flatten the high frequencies. Since the white noise is reduced, spectral balancing will work harder and the result will be a broader flat spectrum. Note that the old chestnut FXDECON and many other frequency domain programs cannot do this because they are unable to determine dips with the little signal we have at the high frequencies.

Unfortunately the phase of the high frequency data is unlikely to be correct. There is both DECON (the high end is way below noise) and NMO stretch to consider.

This has been analyzed by applying the algorithm and looking at the phase spectra of a number of events on the section – as shown in Figure 8. To flatten the spectra a phase ramp of 0 degrees up to 60 Hz rising to 90 degrees at 80 Hz has been applied. Notice that on the section with zero phase shift the whitening has not really helped the resolution while the section with the phase shift is sharper and has not really changed the original event. Thus to broaden the spectrum one must consider the phase of the data being boosted.

Thus to whiten the data these steps should be followed – as shown in Figure 9:

- Phase correct the data
- Apply the white noise removal algorithm
- Subtract it from the phase corrected data
- Apply Spectral balancing
- Add back noise, if desired

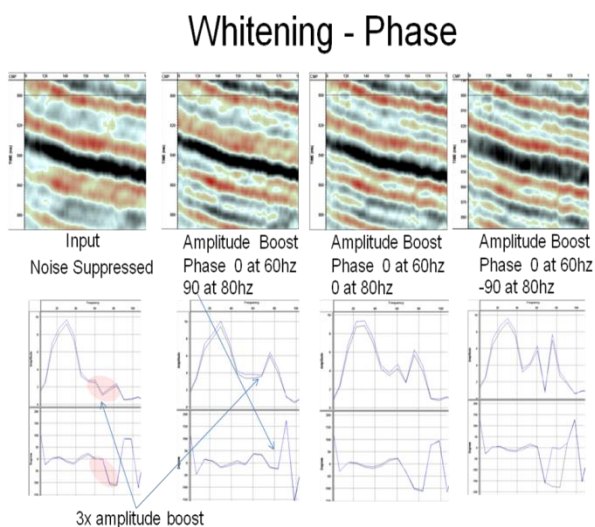


Figure 8 – effect of phase

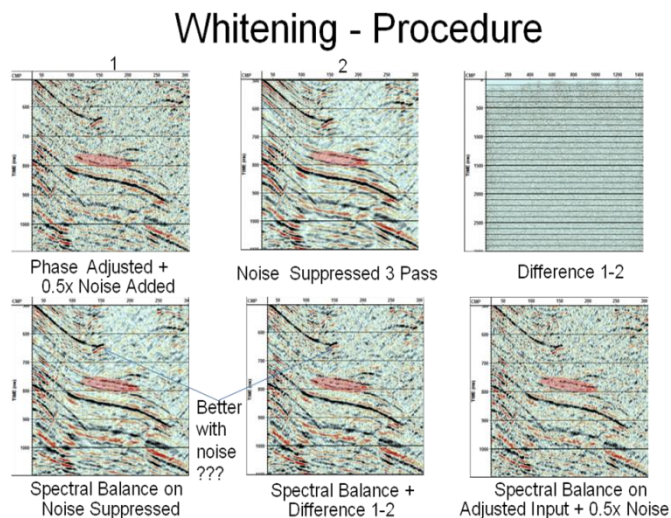


Figure 9 – whitening procedure

Notice that, as promised, the spectral balance with the white noise removal algorithm has worked a lot harder than just spectral balance on the phase adjusted input. Also the plain spectral balance has boosted the noise in the input.

## **Conclusions**

It has been shown that the algorithm can retrieve signal in the time domain even when the signal to noise ratio approaches 30 dB. It can be used for velocity analysis, section cleanup and enhancement and spectral whitening.

In practice, the time domain principal component decomposition has proven to be a robust and effective technology. Almost the entire signal is preserved and only a few principal components at any time and place are needed.

If you respect that seismic data "wobbles" in space and time and changes in amplitude, then the seismic signal may be extracted relatively easily.

## **Acknowledgements**

Thanks to GEDCO for allowing me to present this material – modules 4,5DDEC from the seismic processing package VISTA<sup>®</sup> from GEDCO.

## **References**

Jones, I.F., 1985, Thesis, Applications of the Karhunen-Loeve transform in reflection seismology: University of British Columbia