Removing Wavelet Effects from Seismic Data Through Deconvolution

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Abstract

To analyze and understand the deconvolution method in seismic processing, a code was developed in MATLAB to perform Wiener deconvolution and frequency-domain deconvolution on a noise-free and a noisy data. A function is built to determine the minimum phase wavelet of a wavelet. For noise-free data, the wavelet is known. In performing Wiener deconvolution, wavelet autocorrelation is needed, and it is easily found for noise-free data but for noisy data, it is estimated by windowing the data autocorrelation. Wiener deconvolution gave a good result in removing the wavelet effects from the data but not as good for noisy data.

Background / Theory

In seismology, the measured seismic data are regarded as the response of a convolution between the earth model that is represented by a series of reflections and a wavelet, which is generated from the seismic sources, such as explosives and vibroseis (Robinson and Treitel, 1980). An ideal source will produce a spike wavelet, but it is often a band-limited wavelet since a spiky wavelet is not achievable in practice (Sheriff and Geldart 1983). Therefore, the procedure of deconvolution is needed. Deconvolution is a filtering process which removes a wavelet from the recorded seismic trace by reversing the process of convolution.

Seismic deconvolution is most widely done using Wiener deconvolution method in which the optimum Wiener filter convert the seismic wavelet into any desired shape, usually into a spike (Robinson and Trietel, 1967). Wiener deconvolution uses the early part of autocorrelation of seismic trace as a representation of seismic wavelet and then try to achieve its inverse in the standard least square sense (Gharibi et al., 2015). The deconvolution filter is based on the least squares filter application and is performed in time domain (Equation 1).

$$f = (S^T S)^{-1} S^T y \tag{1}$$

Frequency domain convolution is deconvolution done in the frequency domain instead of time domain. Because of the frequency-domain implementation, the filter will have some key differences from its time-domain equivalent where a) it will always be the same length as the reflectivity estimate (it must have a value at every frequency), and b) there will be no edge effects (the filter will wrap in the time domain, so every coefficient is multiplying something).

The minimum phase wavelet can be determined from the zero-phase wavelet by defining the appropriate phase spectrum. A minimum phase wavelet has the phase spectrum, $\varphi(f)$, determined from the Hilbert transform, H, of the natural logarithm of the amplitude spectrum, $A(f)$ (Equation 2). The minimum phase wavelet, $F(f)$, then can be found using Equation 3.

$$\varphi(f) = \mathrm{H}(\ln[A(f)]) \tag{2}$$

$$F(f) = A(f)e^{i\varphi(f)} \tag{3}$$

Methods / Algorithm

The algorithm or code for this study is provided separately from the paper. For this study, the data file used to read by MATLAB contains measured noise-free data in “data1”, the associated times in “t1”, the associated wavelet in “w”, the associated wavelet times in “tw”, measured noisy data in “data2”, the associated times in “t2”.

A function is written to convert a wavelet into a minimum phase wavelet.

The Wiener deconvolution is performed with zero-lag and chosen time-lag on the noise-free and noisy data.

The frequency domain deconvolution is performed with zero-lag and chosen time-lag on the noise-free and noisy data.

Results

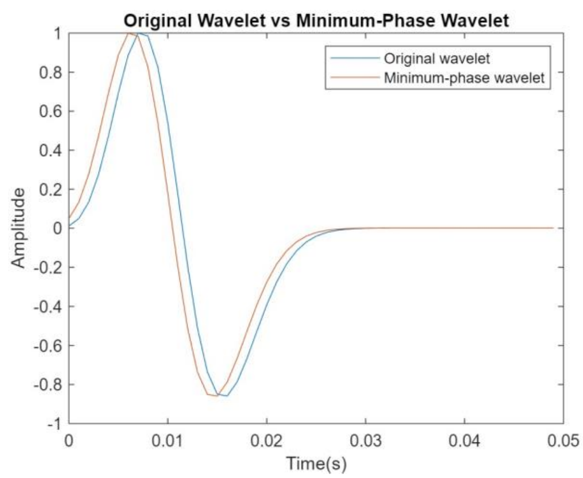

Figure 1 Original wavelet and its corresponding minimum-phase wavelet.

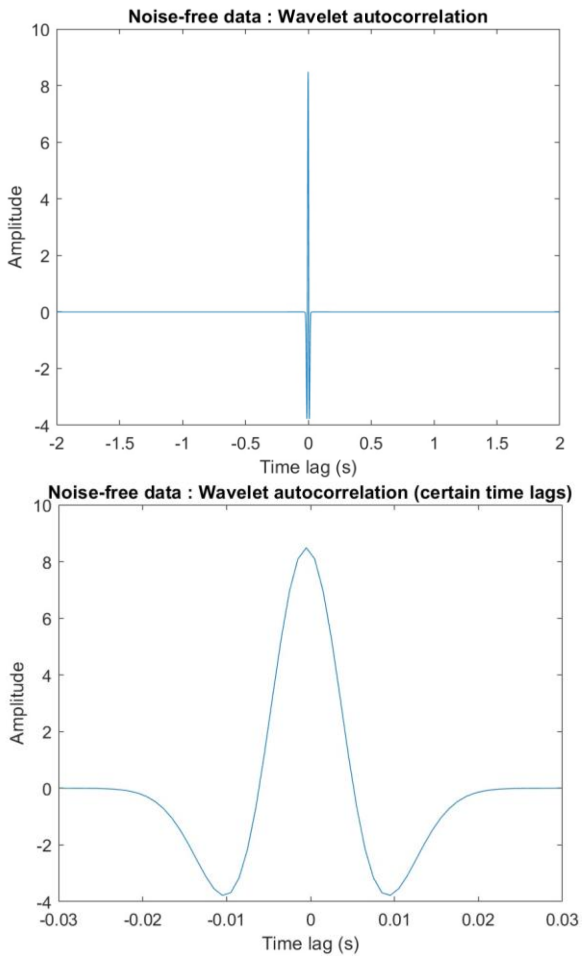

Figure 2 Wavelet autocorrelation for noise-free data.

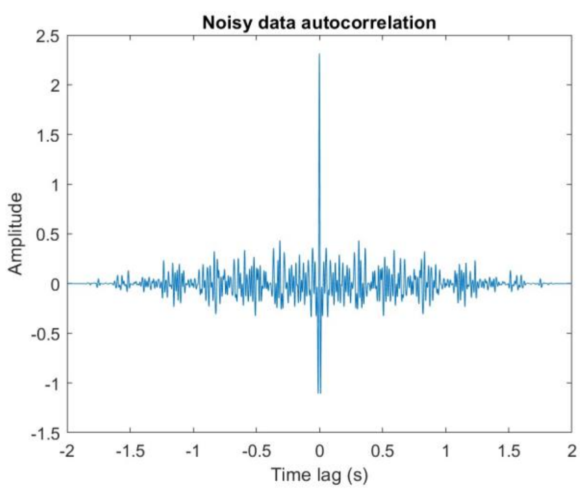

Figure 3 Noisy data autocorrelation.

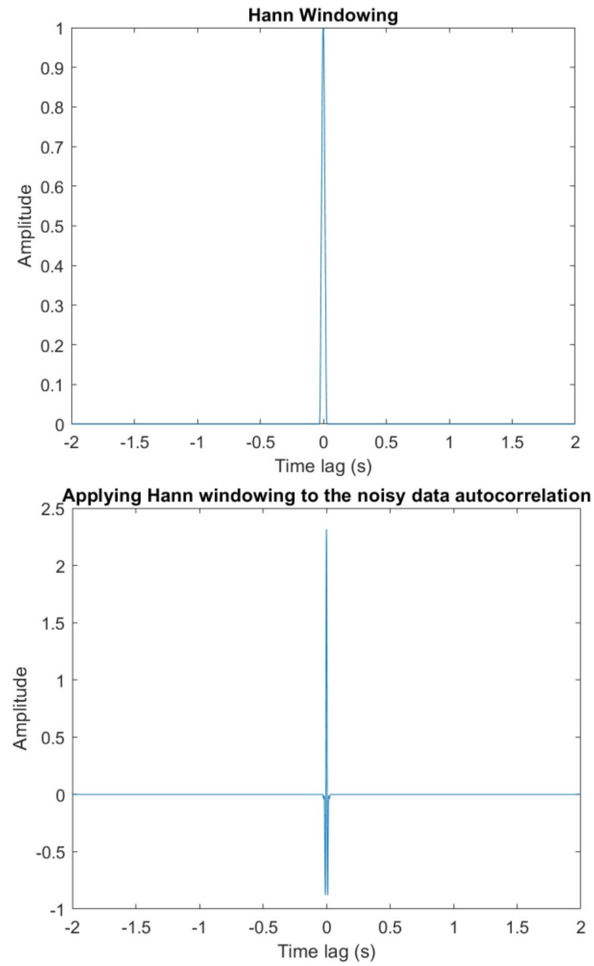

Figure 4 Hann window used to find noisy data wavelet autocorrelation.

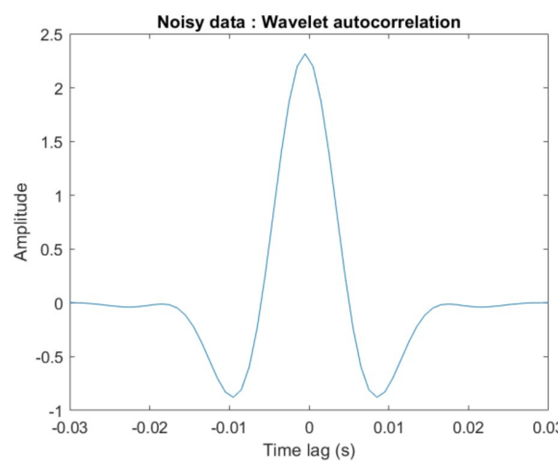

Figure 5 Wavelet autocorrelation for noisy data.

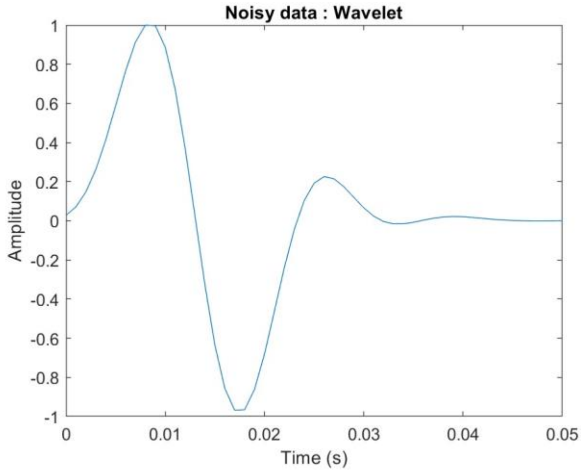

Figure 6 Wavelet for noisy data that is found from determining minimum phase of the wavelet autocorrelation.

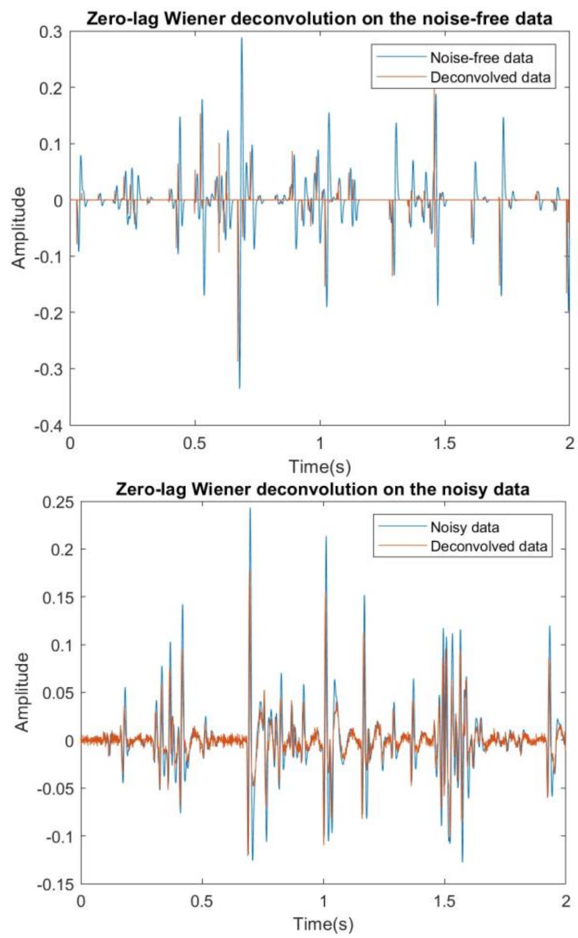

Figure 7 Zero-lag deconvolution on the noise-free and noisy data.

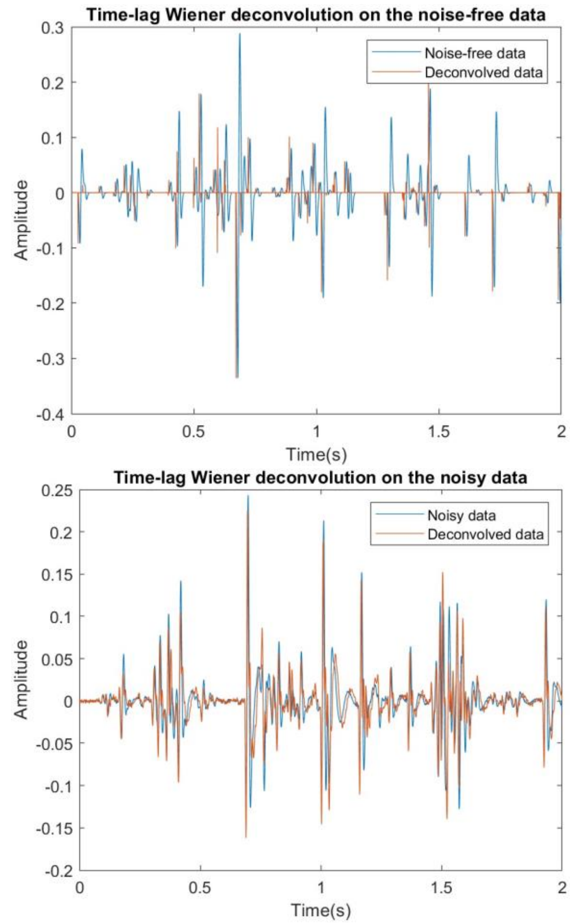

Figure 8 Time-lag deconvolution on the noise-free and noisy data.

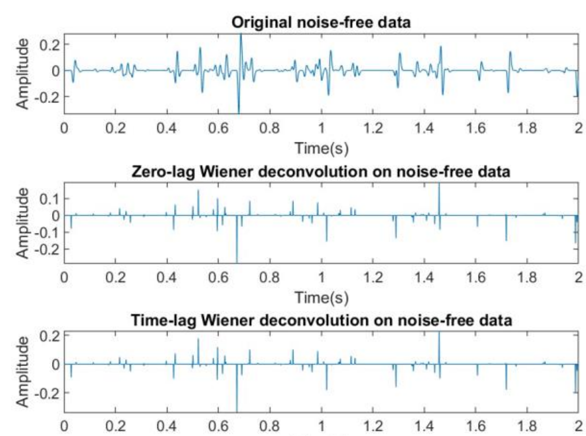

Figure 9 The original noise-free data and deconvolution results using zero-lag and time-lag Wiener deconvolution.

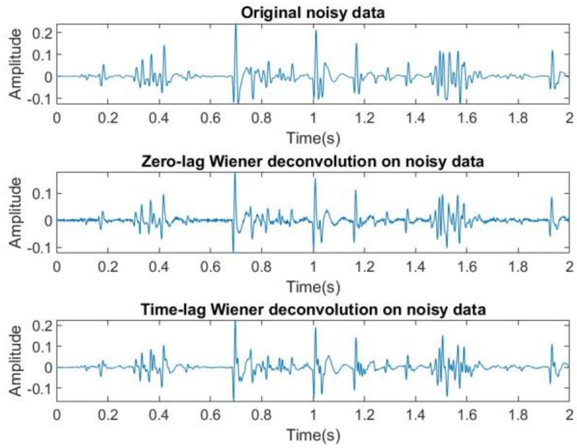

Figure 10 The original noisy data and deconvolution results using zero-lag and time-lag Wiener deconvolution.

Discussion

In Figure 1, the wavelet and its corresponding minimum-phase wavelet is shown. The shape of the minimum-phase is similar to the original wavelet. However, the original wavelet is lag behind the minimum-phase wavelet (by ~0.001 s).

In Figure 7, the noise-free and noisy data is plotted together with the results of the zero-lag deconvolution on the noise-free and noisy data respectively. The zero-lag deconvolution on the noise-free data gave us 'spiking' results whereas on the noisy data, no 'spiking' is seen, and the results follows the data approximately. This spiking can be interpreted as the reflectivity estimate. The deconvolution on the noisy data seems to amplify the noise in the results.

In Figure 9 and 10, the noise-free and noisy data is plotted together with the results of the time-lag deconvolution on the noise-free and noisy data respectively. The zero-lag deconvolution on the noise-free data gave us 'spiking' results whereas on the noisy data, no 'spiking' is seen, and the results follows the data approximately. The wavelet estimate for the noisy data set without a known wavelet is found using the autocorrelation of the data (Figure 3) where the wavelet autocorrelation (Figure 5) can be approximate by applying a window to the data autocorrelation (Figure 4). Then, by enforcing an assumption of minimum phase to the wavelet autocorrelation, the estimate of the wavelet can be generated (Figure 6).

Conclusion

The results of deconvolution for noise-free and noisy data are different. The deconvolution process on noise-free data can remove the wavelet effects nicely compared to noisy data deconvolution.

References

Gharibi M., Shadmanaman N., Kazemi K., and Mirzakhanian M. (2015) Wavelet Estimation and Seismic Deconvolution using Seprable Nonlinear Least Squares.

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