Modeling the Seismic Wavelet with Model-based Wavelet Processing

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Summary

Model-based Wavelet Processing is a technique for modeling the seismic wavelet. However, it is more than a wavelet modeling technique since it explicitly includes terms that account for random noise in the data. As a result, Model-based Wavelet Processing can account for the effects of noise on predictive deconvolution. Using the model of the deconvolved seismic wavelet one can derive a filter that will shape the wavelet to zero phase.

Introduction

Connelly and Hart (1985) introduced a technique to model the seismic wavelet that they called Model-based Wavelet Processing or MBWP. The core notions of the MBWP technique are a set of convolutional models aimed at analyzing the components of a seismic acquisition system and the processing applied to the data. These models not only contain components of the seismic wavelet, but also contain information about the noise in the data. As such they can account for the degrading impact of noise on predictive deconvolution. Additionally, it is possible to account for the effects of non-white reflectivity and non-white noise on predictive deconvolution using these modeling techniques.

In this paper we describe the MBWP modeling technique and discuss the procedures one might use to verify that the model produces an accurate estimate of the seismic wavelet. Furthermore we show how to accurately determine the parameters (a *Q* value and a signal-to-noise ratio) for the MBWP model using a nonlinear, least-squares technique. Since these parameter estimates are derived trace-by-trace, it is possible to produce map displays of the values of these parameters for a 3-D seismic survey.

The MBWP Technique

Figure 1 contains a schematic representation of the components in the seismic experiment that form the basis of the MBWP model of the seismic trace. The procedure starts with a seismic source, *S(t)*. This source propagates to acoustic impedance interfaces in the earth and is reflected back to a detector. Denote the reflectivity of the earth as *R(t)*. During propagation between the source and detector the seismic wavelet undergoes Q-like absorption, which is denoted as *Q(t)*. At the detector, both the signal from the earth and noise, *N(t)*, are received and filtered with its response, *D(t)*. The signal and noise recorded by the detector are then filtered by the instrumentation in the field, whose response is *I(t)*. Combining these terms, as shown in Figure 1, produces the MBWP model of the seismic trace, *x(t)*,

$$x(t) = \{[S(t)*R(t)*Q(t)] + N(t)\}*D(t)*I(t) \qquad (1)$$

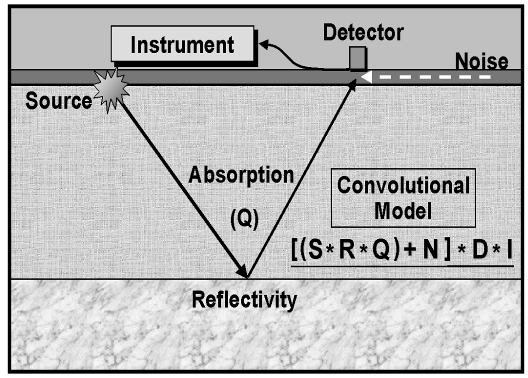

Figure 1. A schematic representation of the seismic experiment. The resulting convolutional model forms the basis of MBWP.

Using Equation 1, one can directly account for the effects of non-minimum-phase or mixed-phase components in the seismic acquisition system. In particular, mixed-phase sources can be directly modeled. Also, random noise is a fundamental part of the MBWP model.

By carrying out the convolutions in Equation 1 the MBWP model can also be written as

$$\begin{aligned} x(t) &= S(t)*Q(t)*D(t)*I(t)*R(t) \\ &\quad + D(t)*I(t)*N(t) \end{aligned} \qquad (2)$$

or more compactly as

$$x(t) = \sigma_s W_s(t)*R(t) + \sigma_n W_n(t)*N(t) \qquad (3)$$

Here σ_s and σ_n are the strength of the signal and noise, respectively. $W_s(t)$ is the seismic wavelet: the collection of terms convolved with the earth's reflectivity. $W_n(t)$ includes the effects of filtering the noise in the seismic data with the field instrumentation.

Modeling the seismic wavelet with MBWP

In the convolutional model, by definition, the seismic wavelet is what is convolved with the reflectivity function. For the MBWP model in Equation 2 the seismic wavelet is

$$W_s(t) = S(t)*Q(t)*D(t)*I(t) \qquad (4)$$

This model contains terms for the source, detector, and instrument that are either accurately modeled or are recorded in the field. They represent deterministic components of the wavelet and consequently the model may contain any of their mixed-phase characteristics. Absorption is explicitly included with its frequency-decay of amplitude and its minimum-phase filtering action.

Verifying the MBWP model of the seismic wavelet

The wavelet in seismic data is generally difficult to directly observe. However, three procedures for confirming the MBWP models of the seismic wavelet exist. First, one can compute models for different acquisition systems and use the models to design filters that shape the wavelet in the data to zero phase. Comparisons of data from the two acquisition systems at overlapping CMP locations can indirectly verify whether the MBWP model of the seismic data is correct. Hootman and Hart (1998) discuss this procedure for processing mixed-source 3-D seismic surveys. Additionally, one can compare synthetic seismograms to data whose phase has been corrected using the MBWP technique.

A more direct observation of the seismic wavelet is the first arrival in a VSP experiment. Figure 2 shows a comparison of MBWP models of the seismic wavelet with a dynamite source, shown as the solid blue line, with the first arrival, shown as a dashed red line, for four separate dynamite sources. There is good agreement between the MBWP model of the wavelet, especially at the earlier times.

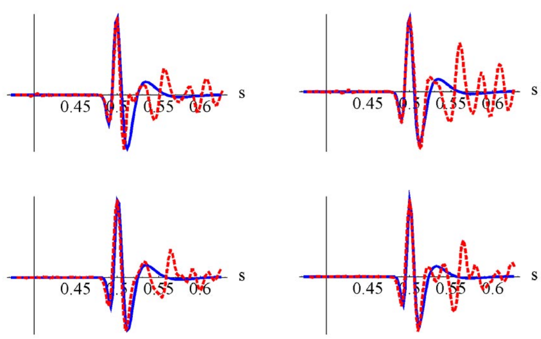

Figure 2: MBWP models of the seismic wavelet for dynamite acquisition, shown as the solid blue line, overlain on the first arrival from a dynamite source in a VSP experiment, the dashed red line.

Figure 3 is the same type of comparison except with MBWP models that contain a Vibroseis source and the VSP data recorded from four different Vibroseis sources. Again, there is good agreement between the model of the seismic wavelet and the VSP first arrival.

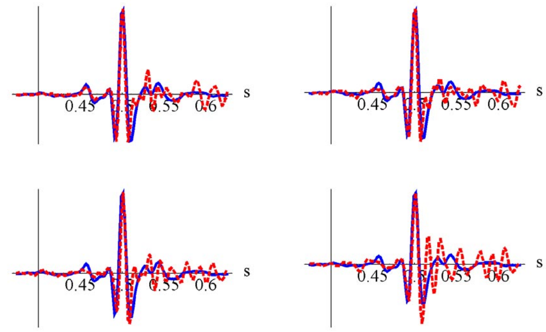

Figure 3: MBWP models of the seismic wavelet for Vibroseis acquisition, shown as the solid blue line, overlain on the first arrival from a Vibroseis source in a VSP experiment, the dashed red line.

Modeling predictive deconvolution of noisy data

Conventional predictive deconvolution assumes that the reflectivity of the earth is statistically white and that the data contain no noise. It also assumes that the seismic wavelet is minimum phase. Using the MBWP technique it is possible to examine the consequences of violating these assumptions.

The predictive deconvolution operator directly depends on the autocorrelation of the seismic data trace. The MBWP model of the seismic data trace in Equation 3 contains two terms: a signal term and a noise term. Assuming that the reflectivity and the noise are uncorrelated and white, the autocorrelation of the MBWP model, $\mathbf{R}_x(\tau)$, is

$$\mathbf{R}_x(\tau) = \sigma_s^2 \mathbf{R}_s(\tau) + \sigma_n^2 \mathbf{R}_n(\tau) \qquad (4)$$

The autocorrelation of the MBWP model contains two terms, an autocorrelation of the model seismic wavelet and an autocorrelation of the filtered noise. A result of assuming that the reflectivity and noise are white is that these two autocorrelations can be thought of as the autocorrelation of the signal and the autocorrelation of the noise in the seismic data. These autocorrelation functions are scaled by the strength of the signal and noise, or signal-to-noise ratio, in the data.

As an example, Figure 4 shows an autocorrelation function for a seismic wavelet and its spectrum. Similarly, Figure 5 shows an autocorrelation function for the filtered noise and its spectrum.

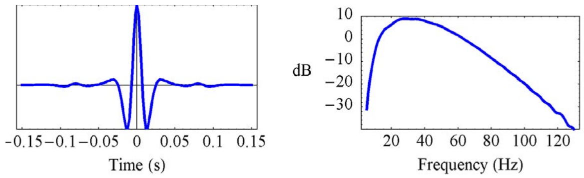

Figure 4: The autocorrelation and spectrum of the MBWP model of the signal.

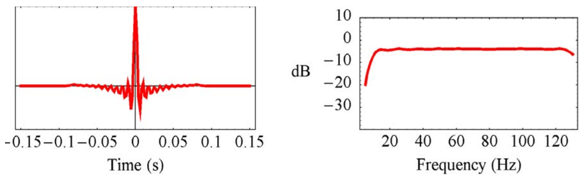

Figure 5: The autocorrelation and spectrum of the MBWP model of the noise.

The signal and noise autocorrelation functions are then scaled to match the signal-to-noise ratio in the data prior to adding them together to form a model of the autocorrelation of the seismic data trace. Figure 6 shows how the normalization is done. For this case, the level of the signal and noise is chosen so that signal is 12 dB higher than the noise at 40 Hz.

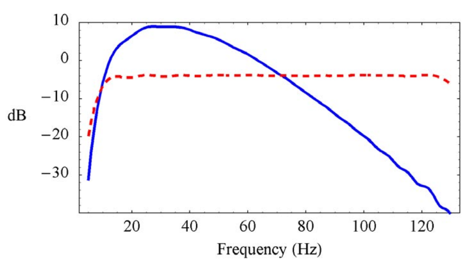

Figure 6: The spectra of the signal autocorrelation (solid blue) and the noise autocorrelation (dashed red.) normalized so that there is a 12 dB signal-to-noise ratio at 40 Hz.

Figure 7 shows the autocorrelation function that results from adding the signal and noise autocorrelation functions and its spectrum.

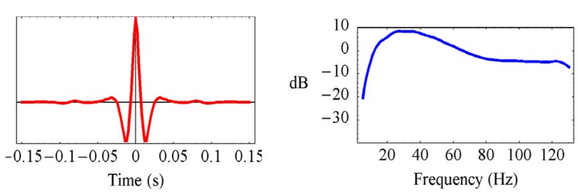

Figure 7: The autocorrelation and spectrum of the MBWP model of the seismic trace, the sum of the signal and noise.

This is the MBWP model of the autocorrelation function and spectrum that predictive deconvolution sees when deconvolving the seismic data. It contains both the properties of the signal and noise. One can use this autocorrelation function to compute a deconvolution operator. This deconvolution operator can then be applied to the MBWP estimate of the seismic wavelet yielding a model of the wavelet after application of predictive deconvolution.

Verifying the model of the deconvolved seismic wavelet

Figure 8 shows the deconvolved VSP data from the dynamite source shown in Figure 2. It also contains the MBWP model of the deconvolved seismic wavelet.

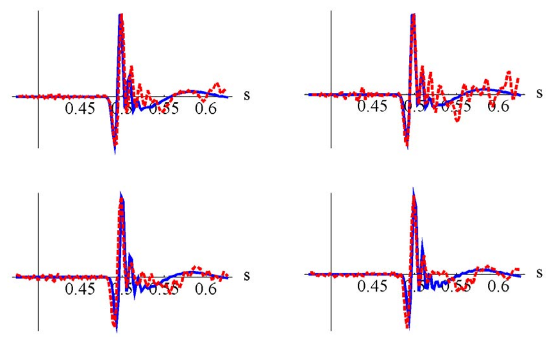

Figure 8. MBWP models of the deconvolved seismic wavelet for dynamite acquisition, shown as the solid blue line, overlain on the deconvolved first arrival from a dynamite source in a VSP experiment. (See Figure 2.)

Figure 9 shows the same comparison except, in this case, the seismic source is a Vibroseis sweep.

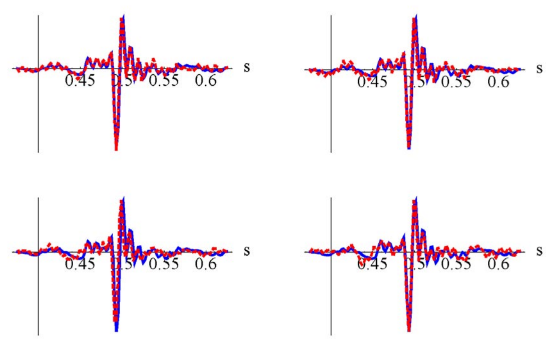

Figure 9. MBWP models of the deconvolved seismic wavelet for Vibroseis acquisition, shown as the solid blue line, overlain on the deconvolved first arrival from a Vibroseis source in a VSP experiment. (See Figure 3.)

There is good agreement for both the dynamite and Vibroseis source deconvolved VSP data and the deconvolved model. This is indicative of the ability of the MBWP model to account for the effects of random noise on predictive deconvolution.

The distorted model wavelet accounts for the effects of deconvolving a mixed-phase wavelet with additive noise. The wavelet model can used to design a residual filter that shapes the distorted wavelet to zero phase. Application of the residual filter to the data after deconvolution drives the wavelet in the data to zero phase. It is important to note that this procedure is done independently for each source of data. No attempt is made to statistically match data using crosscorrelation functions.

Estimating parameters for the MBWP model from the data

The MBWP model of the seismic wavelet contains terms that are defined by the acquisition in the field and a term involving the amount of absorption in the data. Typically, absorption is modeled as an exponential loss of frequency. The amount of loss is then determined by a parameter, *q*.

To model predictive deconvolution using MBWP, one needs to know the signal-to-noise ratio of the seismic data. Both the signal-to-noise ratio and the amount of absorption are parameters in the MBWP procedure that must be determined before one can compute a model of the deconvolved seismic wavelet. The Fourier transform of the MBWP model for the autocorrelation of the seismic trace, Equation 4, can be written as

$$X(\omega) = 10\log_{10}[10^{k_s/10} w_s(\omega)\exp(-\omega/q) + 10^{k_n/10} w_n(\omega)]$$

w_s contains the terms in the seismic wavelet with the exception of absorption. Absorption is explicitly modeled as an exponential loss of amplitude with frequency and depends on the parameter, *q*. (The "time" of the *q* estimate is assumed to be at 1 s.) w_n contains the terms in the filtered noise. The terms k_s and k_n are used to specify the amount of signal and noise, or indirectly the signal-to-noise ratio, in the data. The form of these two expressions enables them to be interpreted as dB.

Using this form for the MBWP model, it is possible to determine a *q* value and the signal-to-noise ratio by fitting the model to the spectrum of the autocorrelation of the seismic data trace. Figure 10 shows the result of fitting the model spectrum to the data spectrum.

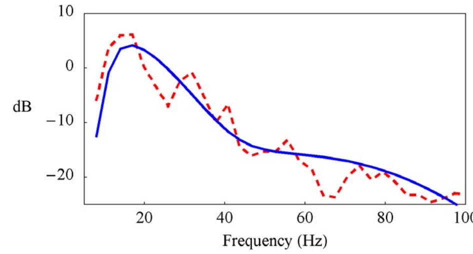

Figure 10. MBWP model spectrum in solid blue compared to trace spectrum in dashed red. The result of this model fitting procedure is a *q* value and a signal-to-noise ratio that produces a model spectrum that matches the spectrum of the seismic data.

Although certainly valuable for producing MBWP estimates of the seismic wavelet, these parameter estimates may be useful in themselves. Since the MBWP parameter estimation procedure is run on a trace-by-trace basis, it is possible to produce map views showing the amount of absorption and signal-to-noise ratio in a seismic survey. Running the parameter estimation procedure over different time windows in the data even allows for determination of interval *q* values.

Conclusions

Model-based wavelet processing is a technique for modeling the seismic wavelet. Since the MBWP model accounts for the effects of additive noise, it can model the degrading effect of noise on predictive deconvolution. One technique to verify the MBWP model of the seismic wavelet is to use it to derive filters to match the wavelets in mixed-source seismic surveys. Another means to verify the model wavelet is by comparing phase corrected data to synthetic seismograms. Here we verified the MBWP models of the seismic wavelet by comparing them to the first arrival in a VSP experiment. Furthermore we have shown that how to account for the effects of mixed-phase wavelets and noise on predictive deconvolution and compared these models to the deconvolved first arrivals in the VSP experiment.

References

Connelly, D., and Hart, D., 1985, Model-based wavelet processing of deconvolved seismic data: 55th Ann. Internat. Mtg., Soc. Expl. Geophys., Expanded Abstracts, 491-495.

Hootman, B. W. and Hart, D. I., 1998, The realities of processing mixed-source seismic surveys: 68th Ann. Internat. Mtg., Soc. Expl. Geophys., Expanded Abstracts, 1436-1439.