Recent progress regarding logarithmic Fourier-domain bidirectional deconvolution

Qiang Fu

ABSTRACT

Bidirectional deconvolution in the Fourier domain is a new method of removing the mixed phase wavelet from seismic data. I demonstrate that this is self-preconditioned, therefore a scheme that has a preconditioner in the logarithmic Fourier-domain deconvolution is not necessary. I show a simple synthetic test case which incorporates a gain function into the deconvolution method.

INTRODUCTION

Usually, a seismic data trace d can be defined as a convolution of a wavelet w with a reflectivity series r. This can be written as $d = r * w$, where $*$ denotes convolution. Blind deconvolution seeks to estimate the wavelet and reflectivity series using only information contained in the data. Previously, seismic blind deconvolution has used two assumptions, namely whiteness and minimum phase. The whiteness assumption supposes that the reflectivity series r has a flat spectrum, while the minimum-phase assumption supposes that the wavelet w is causal and has a stable inverse. Recently, some new methods have been proposed to limit the effect of these two assumptions in seismic blind deconvolution.

In Zhang and Claerbout (2010a), the authors proposed to use a hyperbolic penalty function introduced in Claerbout (2009) instead of the conventional L2 norm penalty function to solve the blind deconvolution problem. With this method, a sparseness assumption replaces the traditional whiteness assumption. Furthermore, Zhang and Claerbout (2010b) proposed a new method called "bidirectional deconvolution" in order to overcome the minimum-phase assumption. Bidirectional deconvolution assumes that any mixed-phase wavelet can be decomposed into a convolution of two parts, $w = w_a * w_b$, where w_a is a minimum-phase wavelet and w_b is a maximum-phase wavelet. To solve this problem, they estimated two deconvolution filters, a and b, which are the inverses of wavelets w_a and w_b, respectively. Since Zhang and Claerbout (2010b) solved the two deconvolution filters a and b alternately, we call this method the slalom method. Shen et al. (2011a) proposed another method to solve the same problem. They used a linearized approximation to solve the two deconvolution filters simultaneously. We call this method the symmetric method. Fu et al. (2011a) proposed a way to choose an initial solution to overcome the local-minima problem caused by the high nonlinearity of blind deconvolution. Shen et al. (2011b) discussed an important aspect of any inversion problem: preconditioning and how it improves bidirectional deconvolution. All of the aforementioned methods solved the problem in the time domain. Claerbout et al. (2011) proposed a new logarithmic, Fourier-domain, bidirectional deconvolution to solve the same problem. Fu et al. (2011b) showed that this new method converges faster than the above-mentioned time-domain methods

In this paper, I will attempt to answer an important question: Should we use a preconditioner with the logarithmic Fourier-domain bidirectional deconvolution? I will then show an example of including a gain function in this method.

NO NEED FOR PRECONDITIONING

Previous time-domain implementations of bidirectional deconvolution (Shen et al. (2011a) and Fu et al. (2011a)) have required preconditioning for both stabilizing the deconvolution result and accelerating the convergence speed. For those methods, we used a prediction error filter (PEF) as our preconditioner. However, using the PEF introduced a polarity change and a time shift problem, because it caused a spike in the first lobe of the Ricker wavelet. However, in the new Fourier-domain method,

$$\begin{aligned} r_{new} &= FT^{-1}(De^{U_{new}}) \\ &= FT^{-1}(De^{U+\alpha\Delta U}) \\ &= r * FT^{-1}(e^{\alpha\Delta U}), \end{aligned} \tag{1}$$

where r is the residual, D is the data (the uppercase letter indicates a Fourier-domain variable), and U is the logarithmic parameterization of the deconvolution filter.

I find that within the iterations, the problem is self-preconditioned. The new update of the u parameter is convolved with the previous residual, so we do not need the PEF preconditioner. Figures 1 through 3 show the comparison between the deconvolution results on a common-offset gather of marine data with and without the PEF preconditioner. In this comparison, I use the 99.5 percentile of all residuals as the threshold for the hyperbolic penalty function. Figure 1 shows the common-offset data gather. Figure 2 shows the deconvolution results with and without the PEF preconditioner. Figure 3 shows the estimated wavelets with and without preconditioning. From this comparison, we can see clearly that the quality of the result without the PEF preconditioner is not inferior to the result with the PEF preconditioner. In addition, the result without the preconditioning avoids the polarity change and time shift. This is caused when the PEF preconditioning introduces an unwelcome initial solution into the deconvolution scheme. This is most obvious in the comparison of the estimated wavelets in Figure 3.

We found that with slightly different initial solutions or parameters of the deconvolution scheme, we could get quite significantly different results. This could be caused either by the nonlinearity or by the null space of the inversion problem; can

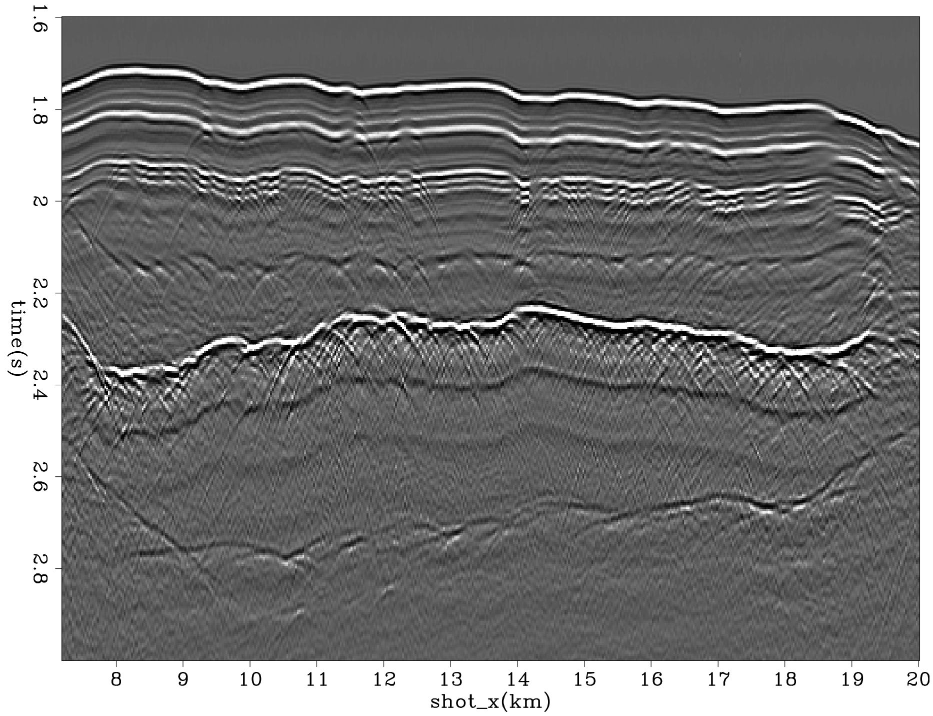


Figure 1: A common-offset section of a Gulf of Mexico data set. [**ER**]

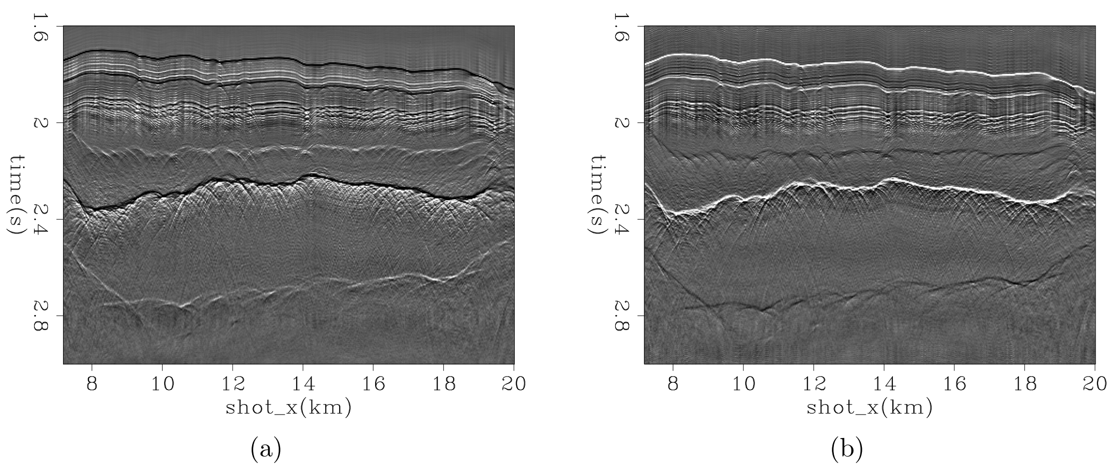


Figure 2: Deconvolution results (a) with and (b) without PEF preconditioning. [**ER**]

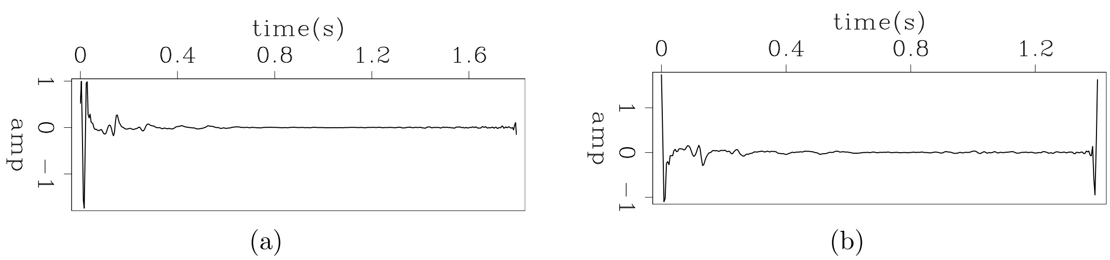


Figure 3: Estimated wavelets (a) with and (b) without PEF preconditioning. [**ER**]

not comfirm which is the reason for this phenomenon. Claerbout et al. (2012) claim that the null space may be the major reason, and that therefore a regularization is helpful and may be necessary to solve this problem. However it is still early to draw this conclusion, and more tests are still needed to answer this question.

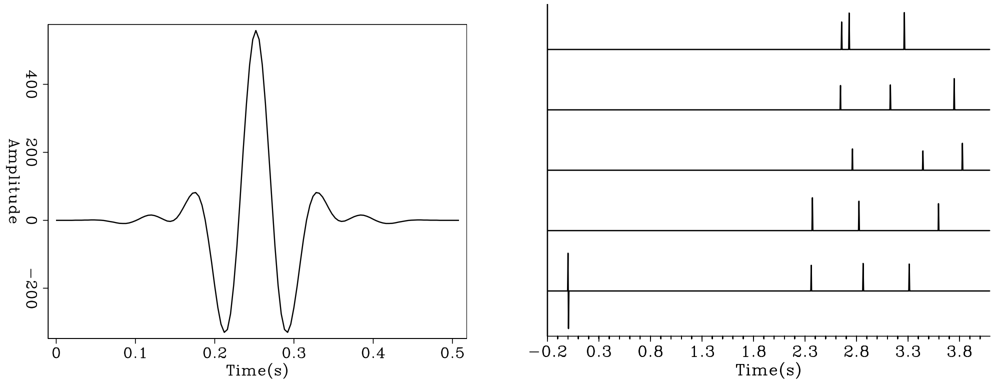
SYNTHETIC DATA EXAMPLE FOR GAIN FUNCTION

In real field data, there usually is an amplitude decay with time. This can be caused by geometric divergence and other factors. The larger the amplitude in the data, the larger the residual. Therefore, the deconvolution will honor early data more than later data. Hence we need a gain function in the deconvolution to boost the contribution of later data.

Claerbout et al. (2012) provide the complete, step-by-step derivation of the gain function in the Fourier-domain bidirectional deconvolution approach. I test the this gain method on a simple synthetic data example. I use a five-trace simple spiky reflectivity model convolved with a zero-phase synthetic wavelet to make the synthetic data. In particular, I put a dipole at the beginning of the fifth trace of the model. If the deconvolution honors the beginning more than the end of the traces, it will tend to make one spike rather then a dipole at that location in the output. On the other hand, if the deconvolution does not incorrectly emphasize the beginning of the traces, we will get a dipole back. Figure 4 shows the synthetic model and wavelet, and Figure 5 shows the synthetic data without and with decay. Figure 6 shows the recovered wavelet and model by deconvolution without gain. Because there is no decay in the data, the result is nearly perfect. Then I add a decay to the model, proportional to the time squared. Figure 7 shows the recovered wavelet and model by deconvolution of this decaying data without gain. So that the decayed end of the traces would be evident, I applied a time-squared scale on the time axis in Figure 7(b). The results are poor; there is only a spike rather than a dipole at the beginning of the fifth trace in the output. However, when I include the gain function in the deconvolution following the implementation discussed above, I get the results shown in figure 8. I also applied a time-squared scale on the time axis in Figure 7(b). By including the gain function in the deconvolution to correctly balance the amplitudes, I can get nearly perfect results again.

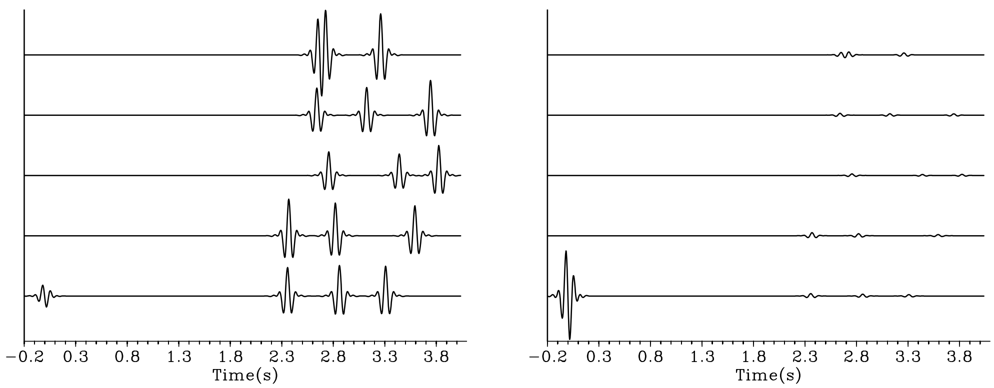
CONCLUSIONS

I showed that the logarithmic Fourier-domain bidirectional deconvolution is self-preconditioned, so that no extra perconditioner is needed. Also I showed a synthetic example of including gain function in this deconvolution scheme. These work improve our understanding and implementation of Fourier-domain bidirectional deconvolution.



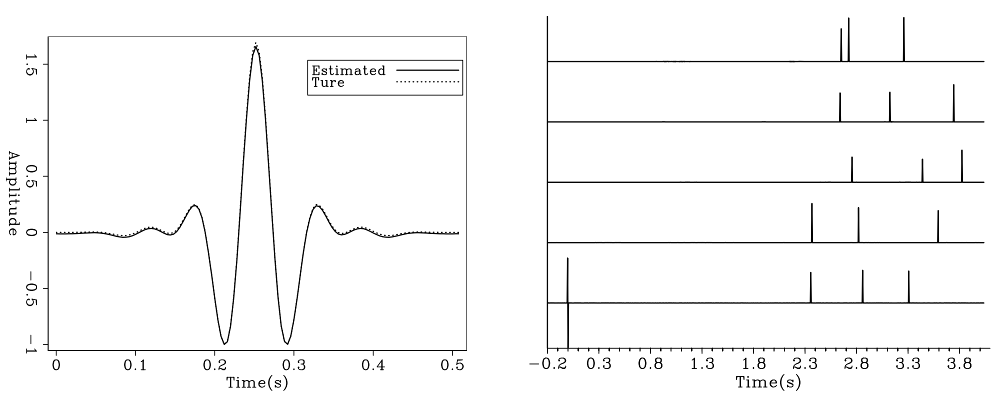
(a) (b)

Figure 4: Wavelet (a) and five-trace model (b) used for synthetic example. [**ER**]



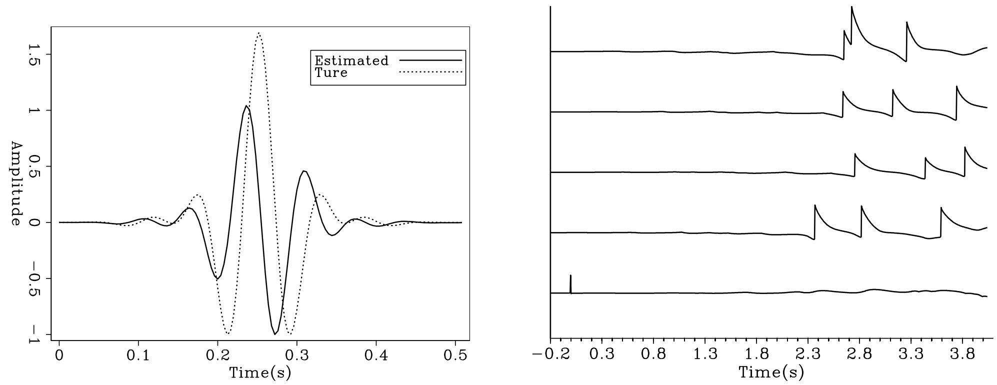
(a) (b)

Figure 5: Five-trace synthetic data set without (a) and with decay proportional to the time squared (b). [**ER**]



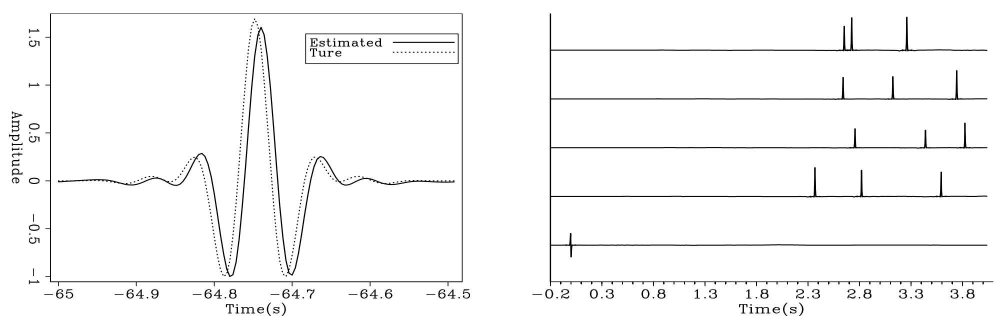
(a) (b)

Figure 6: Estimated wavelet (a) and recovered result (b). [**ER**]



(a) (b)

Figure 7: Estimated wavelet (a) and recovered result (b) of decay data without gain. For easily see the decayed end of the traces, a time squared scale are applied on the time axis in the result (b). [**ER**]



(a) (b)

Figure 8: Estimated wavelet (a) and recovered result (b) of decay data with gain. For easily see the decayed end of the traces, a time squared scale are applied on the time axis in the result (b). [**ER**]

ACKNOWLEDGMENTS

I would like to thank Jon Claerbout, Yang Zhang, Shuki Ronen, Antoine Guitton, Robert Clapp and Dave Nichols for helpful discussions of our research. I also thank the sponsors of the Stanford Exploration Project for their financial support.

REFERENCES

Claerbout, J., 2009, Blocky models via the L1/L2 hybrid norm: SEP-Report, **139**, 1–10.

Claerbout, J., Q. Fu, and Y. Shen, 2011, A log spectral approach to bidirectional deconvolution: SEP-Report, **143**, 297–300.

Claerbout, J., A. Guitton, and Q. Fu, 2012, Decon in the log domain with variable gain: SEP-Report, **147**, 313–322.

Fu, Q., Y. Shen, and J. Claerbout, 2011a, An approximation of the inverse Ricker wavelet as an initial guess for bidirectional deconvolution: SEP-Report, **143**, 283–296.

———, 2011b, Data examples of logarithm Fourier-domain bidirectional deconvolution: SEP-Report, **145**, 101–116.

Shen, Y., Q. Fu, and J. Claerbout, 2011a, A new algorithm for bidirectional deconvolution: SEP-Report, **143**, 271–282.

———, 2011b, Preconditioning a non-linear problem and its application to bidirectional deconvolution: SEP-Report, **145**, 117–130.

Zhang, Y. and J. Claerbout, 2010a, Least-squares imaging and deconvolution using the hybrid norm conjugate-direction solver: SEP-Report, **140**, 129–142.

———, 2010b, A new bidirectional deconvolution method that overcomes the minimum phase assumption: SEP-Report, **142**, 93–104.