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Blind surface consistent wavelet estimation

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Summary

In land seismic data, the source and receiver responses are often equalized using surface consistent deconvolution (SCD) techniques. This deconvolution method generally decomposes the seismic trace into a source function, a receiver response, a reflectivity term and an offset-dependent component. In most cases the focus is on the removal of the source and receiver effects. SCD uses second order statistics, and therefore phase can not be estimated. Consequently, the minimum phase assumption is adopted for the source and receiver components. Recent developments in blind wavelet estimation methods from seismic data offer much promise for addressing the SCD problem with no prior assumptions on the phase. In this paper, we propose a blind surface consistent wavelet estimation method based on an extension of the Euclid deconvoluton method.

Introduction

Seismic reflection data can be viewed as a filtered representation of the Earth's response. Hence, deconvolution is often used as a standard seismic processing technique to estimate and remove these filters. Several flavors of deconvolution algorithms exist with each using different decompositions of the seismic trace and assumptions in order to estimate the deconvolution operators. Unlike spiking deconvolution, which is single-trace based, SCD is a multichannel deconvolution approach. SCD takes advantage of the data redundancy to equalize receiver and source signatures (Levin, 1989; Cambois and Stoffa, 1992). SCD can be performed in the log/fourier domain (Taner and Koehler, 1981; Morley and Claerbout, 1983; Cambois and Stoffa, 1992; Cary and Lorentz, 1993; van Vossen and Trampert, 2006) or in the time domain (Levin, 1989).

In this study, we expand Euclid deconvolution (Rietsch, 1997) to the case of SCD. In other words, the homogenous system of equations arising in Euclid deconvolution is reformulated in terms of SCD and an alternating optimization algorithm is proposed to estimate source and receiver wavelets that permit to estimate their associated inverse filter to equalize the pre-stack volume.

Theory

To explain the surface consistent extension of the Euclid deconvolution, let us consider the following model:

$$D_{ij}(z) = S_i(z)G_j(z)R_{ij}(z) \tag{1}$$

where $D_{ij}(z)$, $S_i(z)$, $G_j(z)$, $R_{ij}(z)$ represent the z-transform of the noise-free seismic trace, the source function, the receiver response, and the medium response respectively. The index i represents source number and the index j represents the receiver number. From (1) one can also write the equation describing another trace within same shot gather as

$$D_{im}(z) = S_i(z)G_m(z)R_{im}(z). \tag{2}$$

Dividing (1) by (2) leads to

$$D_{im}(z)G_j(z)R_{ij}(z) - D_{ij}(z)G_m(z)R_{im}(z) = 0. \tag{3}$$

Similar steps can be used for a pair of traces with common receivers to obtain

$$D_{nj}(z)S_i(z)R_{ij}(z) - D_{ij}(z)S_n(z)R_{nj}(z) = 0. \tag{4}$$

Equations (3) and (4) form a homogeneous system of equations. This system of equations can be written in matrix notation

$$\begin{pmatrix} \widetilde{\mathbf{D}_{im}\mathbf{G}_j} & -\widetilde{\mathbf{D}_{ij}\mathbf{G}_m} & 0 \\ \widetilde{\mathbf{D}_{nj}\mathbf{S}_i} & 0 & -\widetilde{\mathbf{D}_{ij}\mathbf{S}_n} \end{pmatrix} \begin{pmatrix} \mathbf{r}_{ij} \\ \mathbf{r}_{im} \\ \mathbf{r}_{nj} \end{pmatrix} = \mathbf{A}\mathbf{r} = 0 \tag{5}$$

where $\mathbf{r}$ is a column vector representing the multichannel reflectivity in the time domain; $\widetilde{\mathbf{D}_{im}\mathbf{G}_j}$, and $\widetilde{\mathbf{D}_{nj}\mathbf{S}_i}$ correspond to convolution matrices derived from $D_{im}(z)G_j(z)$, and $D_{nj}(z)S_i(z)$ respectively. In this case, we are interested in a non-trivial solution $\mathbf{r} \neq 0$. Since the seismic data used for SCD deconvolution is often contaminated by noise, the optimal solution should be required to minimize (5) in a least square sense:

$$\underset{\mathbf{s},\mathbf{g},\mathbf{r}}{\text{argmin}} \quad E^2 \quad = \quad \underset{\mathbf{s},\mathbf{g},\mathbf{r}}{\text{argmin}}\{\mathscr{F}(\mathbf{d},\mathbf{s},\mathbf{g},\mathbf{r})\} \tag{6}$$

where

$$E^2 = (\mathbf{A}\mathbf{r})^T(\mathbf{A}\mathbf{r}).$$

Consequently, for (5) to have a non-trivial solution, $\mathbf{A}^T\mathbf{A}$ must have one vector with a zero eigenvalue (Rietsch, 1997). Since there exist a large combination of trace pairs that can be used to derive the homogeneous system of equations for large data sets, $\mathbf{A}$ becomes a large sparse block matrix. To further constrain the solution space we decide to use a regularization term, $\mathscr{H}(\mathbf{r})$, to enforce sparsity in the reflectivity. Thus, the cost function J to be minimized is defined as:

$$\underset{\mathbf{s},\mathbf{g},\mathbf{r}}{\text{argmin}} \quad J \quad = \quad \underset{\mathbf{s},\mathbf{g},\mathbf{r}}{\text{argmin}}\{\mathscr{F}(\mathbf{d},\mathbf{s},\mathbf{g},\mathbf{r}) + \mu\mathscr{H}(\mathbf{r}) \quad \text{subject to} \quad \mathbf{r}^T\mathbf{r} = 1\}. \tag{7}$$

The cost function in (7) can be minimized by iteratively solving the following subproblems:

$$\text{"}\mathbf{r}\text{−step"}: \quad \mathbf{r} = \underset{\mathbf{r}}{\text{argmin}}\{\mathscr{F}(\mathbf{d},\mathbf{s},\mathbf{g},\mathbf{r}) + \mu\mathscr{H}(\mathbf{r}) \quad \text{subject to} \quad \mathbf{r}^T\mathbf{r} = 1\} \tag{8}$$

$$\text{"}\mathbf{s}\text{−step"}: \quad \mathbf{s} = \underset{\mathbf{s}}{\text{argmin}}\{\mathscr{F}(\mathbf{d},\mathbf{s},\mathbf{g},\mathbf{r})\} \tag{9}$$

$$\text{"}\mathbf{g}\text{−step"}: \quad \mathbf{g} = \underset{\mathbf{g}}{\text{argmin}}\{\mathscr{F}(\mathbf{d},\mathbf{s},\mathbf{g},\mathbf{r})\}. \tag{10}$$

Note that equation (8) is identical to the method described by Kazemi and Sacchi (2013) where $\mathscr{H}(\mathbf{r})$ is the Huber norm. The iterative algorithm is primarily centered around (8) whereby estimates

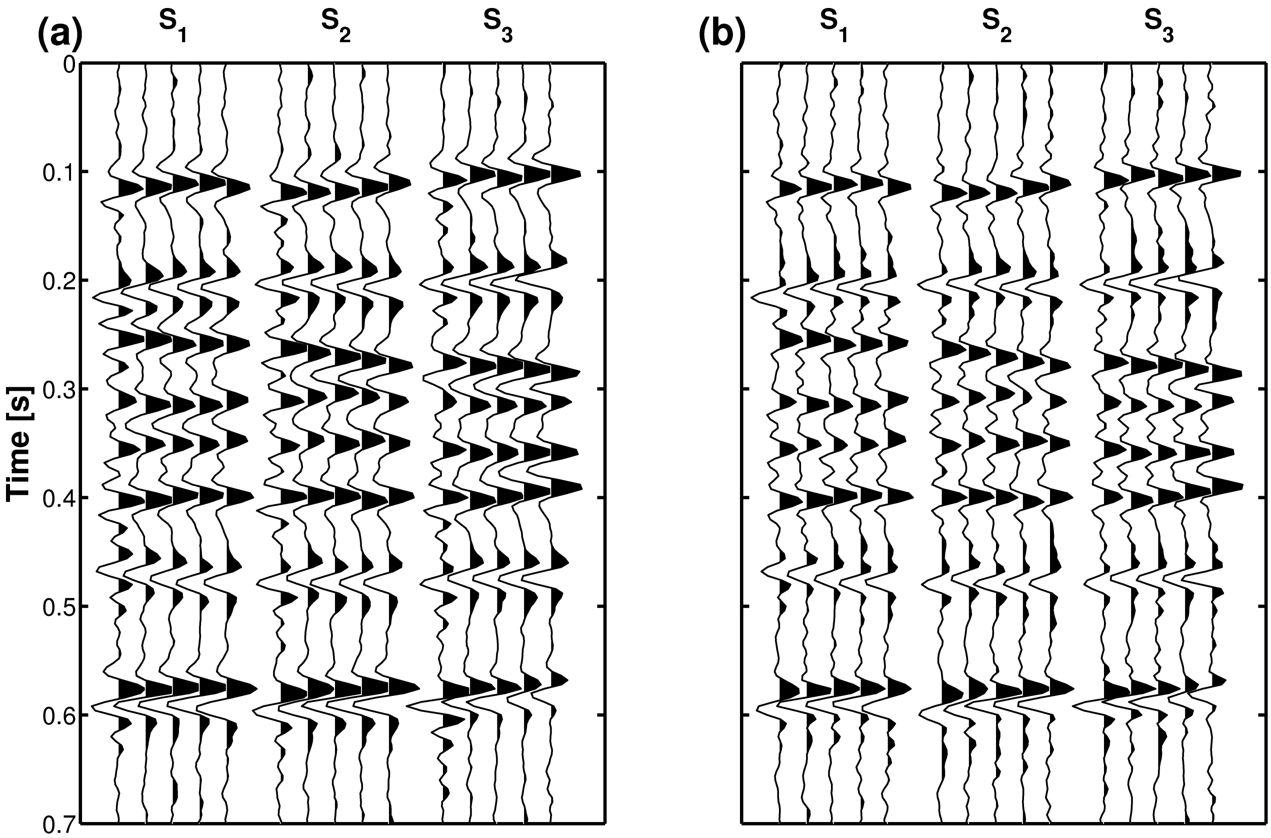

***Figure 1** : a) Synthetic data of three shot gathers (SNR = 20; Acquisition geometry: $\mathbf{S}_1 = \mathbf{S}_2 = \mathbf{S}_3$; $\mathbf{G}_1 \neq \mathbf{G}_2 = \mathbf{G}_3 = \mathbf{G}_4 = \mathbf{G}_5$); b) The effect of source and receiver equalization on data in Figure 1a using wavelet estimates in Figure 2.*

for the source and receiver function are being updated accordingly (equations 9 and 10) at each iterative step. In this study, we contend that (9) and (10) are equivalent to a surface consistent least squares problem for estimating the source and receiver operators respectively. Hence, we use the least squares approach to further simplify and speed up the iterative algorithm.

Example

In the example, we use three synthetic shot gathers (Figure 1a) obtained by convolving the source functions, with the receiver functions and sparse reflectivities. All shot gathers are generated with identical sets of receiver functions. The signal to noise ratio is defined as $\sigma_{data}/\sigma_{noise}$. Figure 1b shows the data after the source and receiver effects have been deconvolved. The quality of the blind surface consistent wavelet estimates used for the deconvolution is shown in Figure 2. In the inversion process, the wavelets are assumed to be stationary throughout the time domain of the input data. The algorithm does a reasonable job in estimating the source and receiver wavelets for each trace in the data.

Conclusion

Surface consistent deconvolution is an important step for processing land seismic data especially when such data are to be used for applications that are sensitive to amplitude variations. Thus it is important to remove source and receiver effects that contribute significantly to such amplitude variations. In this paper, we have discussed a surface consistent method that blindly estimates the source and receiver functions, which can then be used to deconvolve the data. The fundamental difference with existing SCD methods is that no assumptions for phase are made. The proposed

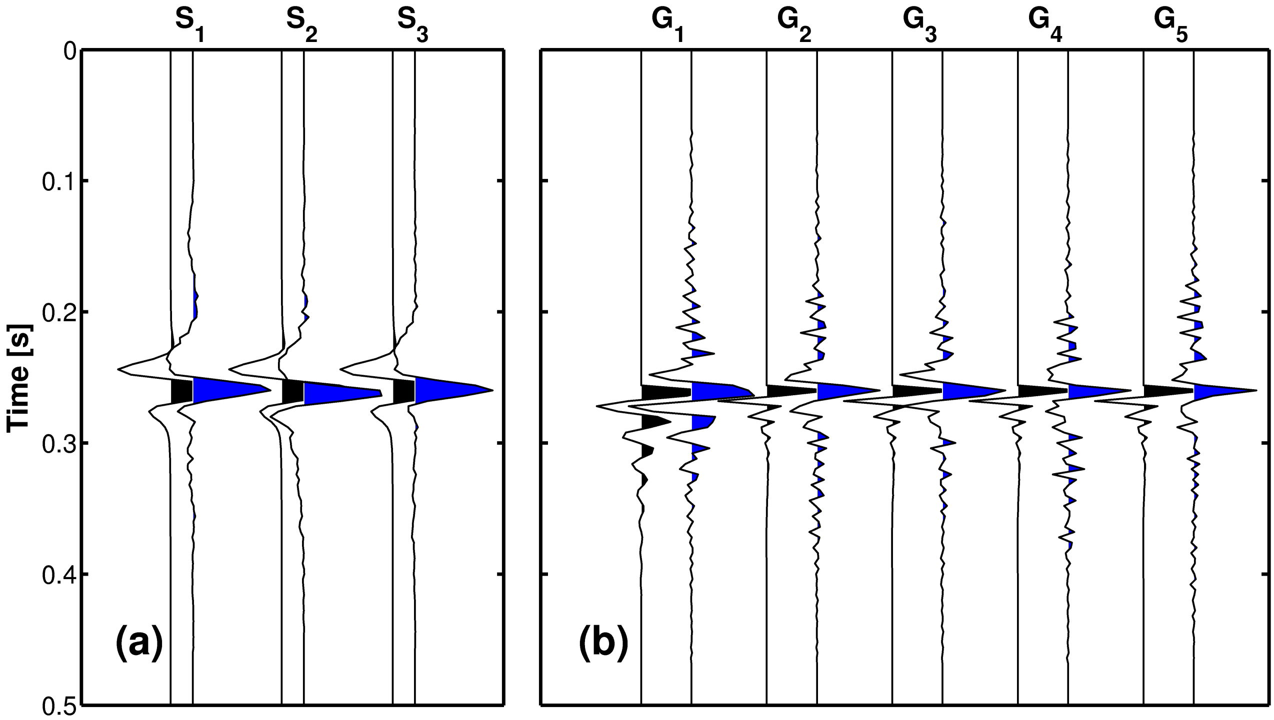

Figure 2 *: a) Wiggle plot of true (black) and recovered (blue) source functions; b) Wiggle plot of true (black) and recovered (blue) receiver functions.*

method looks promising and requires further research and tests using field data.

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