Two-stage Blind Deconvolution

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Summary

In seismic data processing, deconvolution plays a very important role because it permits to increase the temporal resolution of seismic sections and to equalize sources. The deconvolution problem when the wavelet is known is an ill-posed problem that can be tackled via regularization methods. However, the seismic source wavelet is unknown and therefore, it must be estimated from the data prior to deconvolution. In this paper, we examine an algorithm to simultaneously estimate the reflectivity and the wavelet. The method assumes that the underlying seismic reflectivity is a sparse series and that a common seismic wavelet exists for a large number of seismograms with different reflectivity sequences. The method reduces to the alternating minimization of a cost function to promote sparsity in the reflectivity and smoothness in the wavelet.

Introduction

In seismic data exploration, deconvolution is used to estimate, from the observed data, the reflectivity series of the subsurface. In general, deconvolution methods assume that the wavelet is known or that it can be estimated from data via the minimum phase assumption (Robinson, 1967; Peacock and Treitel, 1969; Robinson and Treitel, 1980). It can be shown that for a Gaussian white reflectivity series one cannot estimate the phase of the wavelet. In fact, one can only estimate the amplitude spectrum and utilize the minimum phase assumption to estimate the wavelet. However, it can be shown that phase and amplitude of the wavelet can be estimated using higher-order statistical methods when the reflectivity sequence is white and non-Gaussian. Methods in this category are Minimum Entropy Methods (Wiggins, 1978; Donoho, 1991)) and Cumulant Matching techniques (Tugnait, 1997).

We explore an extension of the method proposed by Canadas (2002) for the simultaneous estimation of the wavelet and the reflectivity series that characterize the subsurface. However, there is an important distinction in our method with respect to the method proposed by Canadas (2002), we estimate a wavelet perturbation and not the wavelet in each iteration. We examine the performance of the algorithm versus SNR and the degree of sparsity of the reflectivity. We also provide a marine real data example where we compare the estimated wavelet with the first break wavelet estimator computed by averaging traces of a constant offset section.

The article is organized as follows. First we review the principles of deconvolution method. Next, we introduce the proposed two-stage blind deconvolution algorithm. Eventually, we examine the synthetic and real data examples to manifest the effectiveness of the proposed blind deconvolution technique.

Theory

The seismic trace $d[n]$ can be expressed as the convolution of the reflectivity sequence $r[n]$ and a wavelet $w[n]$ plus a noise contamination term $e[n]$. This system can be represented in matrix-vector
We now differentiate the cost function (reflectivity. It can be shown that the last assumption (sparsity) is vital to operate with this algorithm. We differentiate the cost function stops changing with iterations. The method will work efficiently with highly uncorrelated spatial reflectivity series. In cases with smooth spatial variations of the reflectivity, one can use the Block Bootstrap (Paparoditis and Politis, 2001) method to generate windows of data with spatially incoherent reflectivity sequences.

The iterative process continues until the wavelet perturbation becomes small enough and the cost function stops changing with iterations.

We start with an initial wavelet and use FISTA to estimate a sparse group of reflectivity sequences (equation 4). With the current estimate of the reflectivity we estimate a wavelet perturbation common to all traces via equation (5). The updated wavelet is filtered with a bandpass filter to guarantee that the wavelet does not have frequency components outside an a priori defined spectral band. The latter is required to stabilize the algorithm and avoid rough estimators of the wavelet. The updated wavelet is then used to re-estimate sparse reflectivity series and so on. The iterative process continues until the wavelet perturbation becomes small enough and the cost function stops changing with iterations. The method will work efficiently with highly uncorrelated spatial reflectivity series. In cases with smooth spatial variations of the reflectivity, one can use the Block Bootstrap (Paparoditis and Politis, 2001) method to generate windows of data with spatially incoherent reflectivity sequences.
Examples

To investigate the performance of the proposed nonlinear optimization algorithm, the correlation of the estimated wavelet with the original one is set as the metric for synthetic seismic data examples. To begin with, a synthetic seismic data is constructed by convolving a sparse reflectivity series with a Ricker wavelet of $60^\circ$ phase rotation. Subsequently, Gaussian and incoherent noise ($SNR = 6$) is added to data. The reflectivity series is portrayed in Figure (1(a)) and the seismic data in Figure (1(b)). The estimated reflectivity calculated by the proposed method is shown in Figure (1(c)). Finally, Figure 2 shows the starting wavelet adopted by our algorithm, the true wavelet and the final estimator of the wavelet.

In order to examine the behaviour of the algorithm under different SNRs and density of reflectors, we have executed 100 realizations of reflectivity sequences and additive noise. The correlation between the true and estimated wavelet is computed for the 100 realizations of synthetic data for each SNR while the density of reflector is kept constant at $40\%$ (meaning $40\%$ samples of the reflectivity are non-zero). The results are shown in Figure (3(a)) which shows the algorithm is quite vulnerable to additive noise. Finally, Figure (3(b)) shows the correlation between the true and estimated wavelet for fixed phase rotation ($60^\circ$) and $SNR = 6$ for the case where we varied the density of the reflectivity. The figure manifests that the method works well when the reflector is sparse and starts to break for reflectivity sequences that are non-sparse.

A windowed section from the Mississippi Canyon marine data set was used for testing the algorithm in a real data scenario (Figure (4(a))). The proposed algorithm was applied to calculate the estimated mixed-phase wavelet and reflectivity series. Subsequently, the seismic data was recovered by convolving the estimated wavelet and reflectivity series. Figure (4(b)) depicts the estimated reflectivity series and Figure (4(c)) represents the recovered seismic data. Eventually, Figure 5 shows the comparison among the estimated, average first-break and initial wavelet for real data.

Conclusion

In this article we have formulated a nonlinear optimization algorithm for estimating sparse reflectivity series and a wavelet perturbation. We have initiated the algorithm with a zero phase wavelet and assuming that the reflectivity series is non-gaussian. The proposed algorithm estimates the wavelet perturbation required to update the wavelet and to estimate the sparse reflectivity. Synthetic and real data examples showed that the method was successful to estimate the wavelet and the reflectivity in situations where one can assume high SNR and sparse reflection sequences. The method also requires that the window of analysis contains sufficient spatial variability of the reflectivity sequence.

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References

Figure 1 Synthetic data example. (a) Original reflectivity series utilized to test the proposed blind deconvolution algorithm. (b) Seismic data modelled by convolution of the reflectivity with a Ricker wavelet with phase rotation $60^0$. The data were also contaminated with noise (SNR = 6.0). (c) Sparse reflectivity series obtained by the proposed blind deconvolution method.

Figure 2 Initial, original, and estimated wavelet for synthetic data with phase rotation $60^0$ and SNR=6.
Figure 3 The normalized correlation between the estimated and true wavelet for different (a) SNRs and (b) density of reflectors (the density measures the percentage of non-zero coefficients of the reflectivity series).

Figure 4 Real data example. (a) A window of the Mississippi Canyon marine seismic data. (b) Reflectivity series estimated via the proposed algorithm. (c) Seismic data after convolution of the estimated reflectivity with the estimated wavelet.
Figure 5 Initial, recovered, and first-break wavelet for real data.