CANADIAN JOURNAL OF EXPLORATION GEOPHYSICS
VOL 32, NO 1 (JUNE 1996), P 63-72

SUPPRESSION OF SHORT-PERIOD MULTIPLES – DECONVOLUTION OR MODEL-BASED INVERSION?

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ABSTRACT

It is difficult to effectively suppress short-period seismic multiples via predictive deconvolution whenever autocorrelations of the input data are similar to autocorrelations of the desired output data. In such situations, there are no obvious choices for prediction distance and operator length. Alternatively, this paper presents two other methods for suppressing short-period multiples and enhancing primary reflections. One approach uses deconvolution via two sequential Wiener shaping filters. The first Wiener filter shapes the earth's impulse response to a reflectivity function in order to suppress multiples and a second Wiener filter shapes the seismic wavelet to a spike in order to perform wavelet deconvolution. This sequential Wiener shaping deconvolution approach works well if we have a reliable estimate of the reflectivity from well logs. The second proposed approach is a least-squares inversion method which models the primaries and multiples in the seismic trace by adjusting reflection coefficient parameters. The success of this model-based inversion approach depends on the accuracy of reflection coefficient parameterization. The effectiveness of reflectivity estimation by either deconvolution or model-based inversion is dependent on the validity of assumptions used in either method. Both methods require some knowledge about the earth's reflectivity in order to work effectively.

INTRODUCTION

Predictive deconvolution has proven to be a useful tool for suppression of multiples and has been a standard part of seismic processing flows following the pioneering research of Robinson (1954) and Peacock and Treitel (1969). As Peacock and Treitel (1969) point out, predictive deconvolution filters are usually designed by examining the autocorrelations of traces prior to deconvolution. For the purposes of multiple suppression by predictive deconvolution, the key parameters are prediction distance and operator length. The prediction distance is generally set equal to estimates of the multiple period. The operator length is often set approximately equal to the wavelet length. In statistical terms, Robinson and Treitel (1980) point out that the operator length should be set equal to the autoregressive order of the time series. Predictive deconvolution works well for predictable arrivals such as water-bottom reflections – especially in the plane wave domain (Treitel et al., 1982). In fact, other than the zero-offset domain, the plane-wave domain is the only domain where reflected arrivals are truly predictable (Yilmaz, 1987).

It is not the purpose of this paper to criticize a useful process such as predictive deconvolution. However, there are problems with short-period interbed multiples in Alberta Nisku reef seismic sections which are not amenable to multiple suppression by predictive deconvolution. The underlying reason is related to the fact that autocorrelations for "primaries only" reflections can be nearly identical to autocorrelations of "primaries plus multiples" in the input data. Since the design of predictive deconvolution operators is based on differences between the autocorrelations of input traces and desired deconvolutions, it is not surprising that predictive deconvolution has not always been effective for this situation.

Whenever predictive deconvolution is ineffective for suppressing these short-period multiples, we look for other alternatives. The most commonly applied technique is the use of CMP (common-midpoint) stacking. In CMP stacking, we rely on differences in NMO (normal moveout) between primaries and multiples so that stacking will enhance primary energy and attenuate multiples. In the present case of interbed multiples, multiples have slightly more NMO than primaries and can be partially attenuated by stacking. However, procedures such as deconvolution and inversion will hopefully further improve this multiple attenuation.

In this investigation, two other methods were used to attenuate multiples. In one method we essentially compute a Wiener shaping filter that attempts to shape the impulse

Manuscript received by the Editor January 22, 1996; revised manuscript received March 1, 1996.
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The funding for this research was made available by the Natural Sciences and Engineering Research Council of Canada (NSERC), by Petro-Canada and by the sponsors of the Memorial University Seismic Imaging consortium (MUSIC). Their support is gratefully acknowledged. In particular, the author would like to thank Bill Goodway and Lee Hunt for bringing the problem of Nisku reef interbed multiples to the author's attention. I would like to thank Andy Burton and Han-Xing Lu of MUSIC for their work on the real data in this area which allowed for insight into modelling studies. I also thank Sven Treitel for many discussions on the topic of inversion and deconvolution related to multiple attenuation and other problems and Enders Robinson for his review of this paper.

response containing primaries and multiples into the reflectivity function containing primaries only. The impulse response is defined as the response of the layered medium to a delta function source. It contains primaries defined by the reflections and all multiples associated with these primaries. The reflectivity function is the sequence of reflection coefficients for the layered medium, which represents the ideal trace for interpretation.

A second method considered here is the least-squares inversion procedure described by Lines and Treitel (1984) which used reflection coefficient parameters in a convolutional model of the seismic trace. These reflection coefficient parameters are computed so that the model response matches the seismic data in a least-squares sense. The inversion provides a model for the data and ideally provides the correct reflectivity estimate.

We test these multiple suppression methods in a model study using synthetic data derived from the logs of a well drilled into the Nisku Formation. These synthetic data provide a basis for comparing the success of deconvolution versus model-based inversion.

Methodology

The deconvolution methods are based on Wiener filtering, a process which is lucidly described in many publications including the textbook by Robinson and Treitel (1980). Wiener filters are derived from solutions to the normal equations given by:

$$\mathbf{R}\,\mathbf{f} = \mathbf{g}\,, \tag{1}$$

where $\mathbf{R}$ is the autocorrelation matrix for the input data, $\mathbf{g}$ is a vector containing the cross-correlation of the input with the desired output and $\mathbf{f}$ is a vector containing the Wiener filter.

Wiener filters can be used to compute predictive deconvolution filters if the desired output is some future version of an input seismic trace value. Wiener filters can also be designed as wavelet spiking filters whenever the desired output is a delta function for an input wavelet. For multiple suppression we can compute a Wiener filter which attempts to shape the input impulse response of a layered medium into the medium's reflectivity function. If successful, this filter should deconvolve multiples from input traces leaving only primaries in the output. In the deconvolution used here, we sequentially use both a multiple suppression filter and a wavelet spiking filter to provide a reflectivity estimate.

Our second approach, the least-squares inversion method, attempts to model the multiples in the seismic trace rather than deconvolving the multiples with a digital filter. The multiples are modelled by adjusting the reflection coefficients. In mathematical terms one minimizes the sum of squares between data trace and model response values given by:

$$S = \sum_t (y_t - f_t)^2, \tag{2}$$

where y_t = seismic trace sequence and f_t = model response time sequence.

The model response, f_t, is given by the convolution of a source wavelet with the impulse response.

This minimization is accomplished by setting

$$\frac{\partial S}{\partial r_j} = 0$$

for $j = 1,2,...,m$, where r_j are the reflection coefficient values. As shown by Lines and Treitel (1984), this minimization leads to a set of equations given by

$$\mathbf{A}^{\mathbf{T}}\mathbf{A}\mathbf{x} = \mathbf{A}^{\mathbf{T}}\mathbf{b}, \tag{3}$$

where $\mathbf{A}$ is a Jacobian matrix whose elements are partial derivatives of model response values with respect to the model parameters given by:

$$A_{ij} = \frac{\partial f_i}{\partial r_j}.$$

(If multiples are weak compared to primary reflections, these Jacobian values are closely approximated by the seismic wavelet values in a convolutional trace model.) The vector $\mathbf{b}$ contains discrepancies between the trace and model response values, i.e., $b_i = y_i - f_i$. The solution, $\mathbf{x}$ to the normal equations, in (3), produces the adjustment to the reflection coefficients which improve the fit of the model to the data in a least-squares sense. Since the convolutional trace model contains multiples whose amplitudes are proportional to products of reflection coefficients, it is a nonlinear function of reflection coefficients. The nonlinearity of the inverse problem requires that reflection coefficients be estimated from linear least-squares inversion in an iterative fashion. At each iteration, we solve for the reflection coefficient adjustment using (3) and recompute the model response. At each iteration we monitor the size of S and iteratively update the reflection coefficient parameters until S becomes smaller than some specified tolerance. Unfortunately, the use of linearized methods to solve nonlinear problems does not guarantee that convergence will always be obtained.

There are various issues involved in this type of inversion. In our convolutional model, we either have to have a good wavelet estimate or we can include the wavelet values as parameters and estimate these wavelet parameters. In using the latter approach, we inevitably face nonuniqueness problems.

Also, it is important to specify an adequate number of reflection coefficients in our model. Generally, this is a somewhat subjective choice based on some knowledge of the geology section (perhaps with the aid of well logs). We now compare the performance of multiple suppression methods on a model data set from an Alberta Nisku reef play.

Results

This model study uses a wavelet which is easily estimated and deconvolved. The exponentially damped sinusoid of Figure 1 (left) has an exact 3-term inverse (Treitel and Lines,

1982) which makes it ideal for deconvolution experiments. (In this case, the sinusoid's frequency is 50 Hz.) Figure 1 (right) also shows that the wavelet can be reliably estimated from a typical seismic trace (later shown in Figure 3) by use of the Kolmogorov minimum-phase estimation method (ref., Lines and Ulrych, 1977; Claerbout, 1992).

The reflectivity sequence in Figure 2 (left) was derived from a Nisku reef well. The reflectivity function can be used to compute an impulse response for a layered earth by using an acoustic synthetic seismogram program from Robinson (1967, p.137). The impulse response sequence values are also shown in Figure 2 (right).

The convolution of the impulse response with the seismic wavelet of Figure 1 produces a seismic trace containing primaries and multiples. Figure 3 shows a comparison of primaries-only synthetics with traces containing both primaries and multiples. The effect of multiples becomes especially pronounced in the time window between time samples 170-230.

It was originally hoped that the autocorrelations would allow us to design a predictive deconvolution operator to suppress multiples. However, Figure 4 shows that the autocorrelations of the traces with primaries + multiples are very similar to those autocorrelations for primaries only. Hence, it is difficult to design a predictive deconvolution operator.

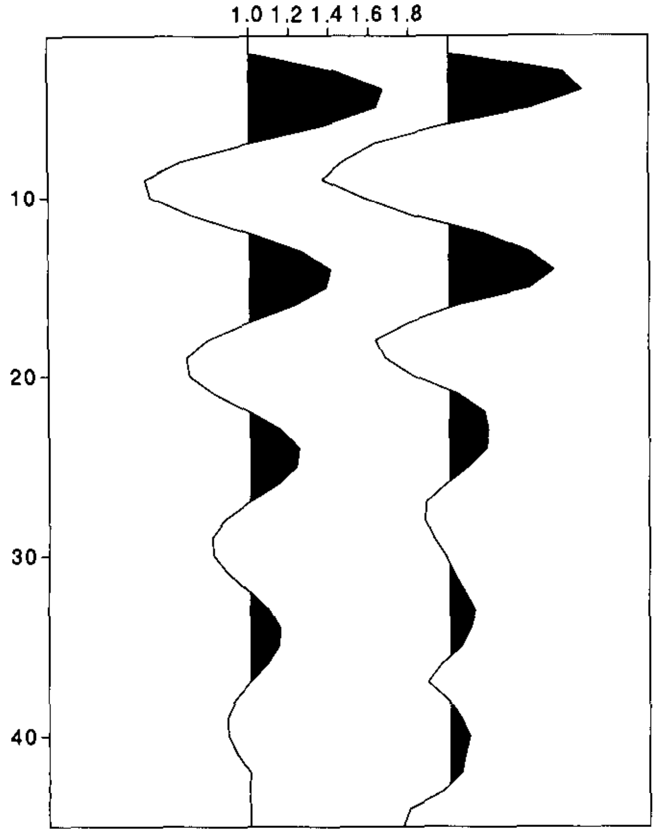

Fig. 1. The wavelet (50 Hz damped sinusoid) used for the study is shown (on the left) along with a wavelet estimate (on the right) obtained using the Kolmogorov method on a typical seismic trace. Sample numbers are on the vertical axis.

Instead of using predictive deconvolution, I use another approach which uses two Wiener filters. As previously mentioned, one Wiener filter is designed to suppress multiples; the second filter deconvolves wavelets. The first Wiener filter is one which shapes the impulse response into the reflectivity function. This type of filter could only be applied to real data if one had accurate knowledge of the reflectivity function from well logs. As shown in Figure 5, the application of this Wiener shaping filter to the impulse response traces of Figure 3 produces traces which more closely resemble the reflectivity traces of Figure 3. The strong multiple energy between samples 200 and 250 has been suppressed. The application of a subsequent Wiener spiking filter is shown in Figure 6. This wavelet deconvolution should ideally represent the reflectivity traces of Figure 2. The major reflections in the wavelet deconvolution correspond with those in the reflectivity; however, phase differences exist between the arrivals in Figure 2 and Figure 6 due to the initial step of imperfect multiple suppression.

This type of two-stage Wiener deconvolution appears effective but does rely on perhaps an unrealistic assumption that the reflectivity for traces near a well is identical to the reflectivity at a well site. Experience shows that this assumption is often not realistic (Lee Hunt, pers. comm.).

An alternative procedure used least-squares inversion to match model responses to seismic data by adjusting reflection coefficient parameters (ref., Lines and Treitel, 1984). The key parameterization problems here involve knowledge of the number of reflection coefficients and their location. The initial estimates of the reflection coefficient amplitudes do not appear to be as crucial as their location – provided we have reliable knowledge of the seismic wavelet. In our trial inversions in this paper, we started with reflection coefficients whose values were ±0.1. A criterion for convergence of the least-squares inversion involves fitting the data with the model response. However, since this is a nonlinear inversion problem, convergence is not always assured.

After five iterations of least-squares inversion, the model reflection coefficient parameters estimates are those shown on the right-hand side in Figure 7. In Figure 7, we compare the actual reflection coefficients (left-hand side) to those estimated by the inversion (right-hand side). In five iterations of adjusting reflection coefficients, the misfit error between data and model traces decreases to about 37% of its original value. This improvement in fit is obtained by the reflection coefficients changing from their initial values of 0.1 to those shown in the figure. The fit of the model response to the data is shown by examination of Figure 8 which compares the input traces (left-hand side) to the model traces (right-hand side).

Conclusions

This model study has addressed the question of: "How do we handle short-period interbed multiples when predictive deconvolution is inappropriate?" This problem arises in some Alberta Nisku reef plays where interbed multiples exist.

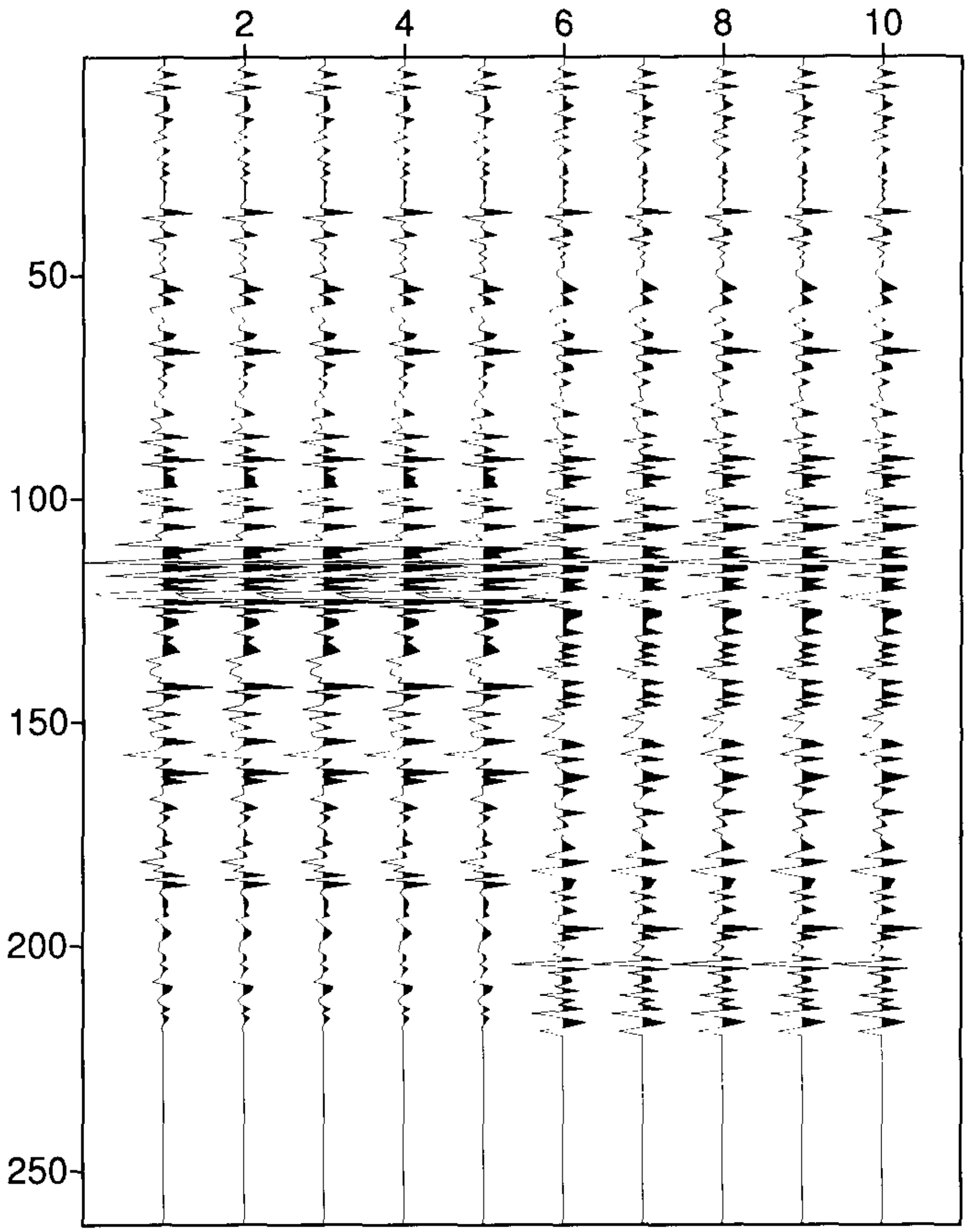

Fig. 2. This reflectivity sequence (repeated 5 times on the left-hand side) is derived from an Alberta Nisku reef well and contains the reflection coefficients. The impulse response (repeated 5 times on the right-hand side) is derived from the reflectivity sequence and contains both reflection coefficients and multiples. The vertical axis gives sample numbers (with sample interval = 2 ms).

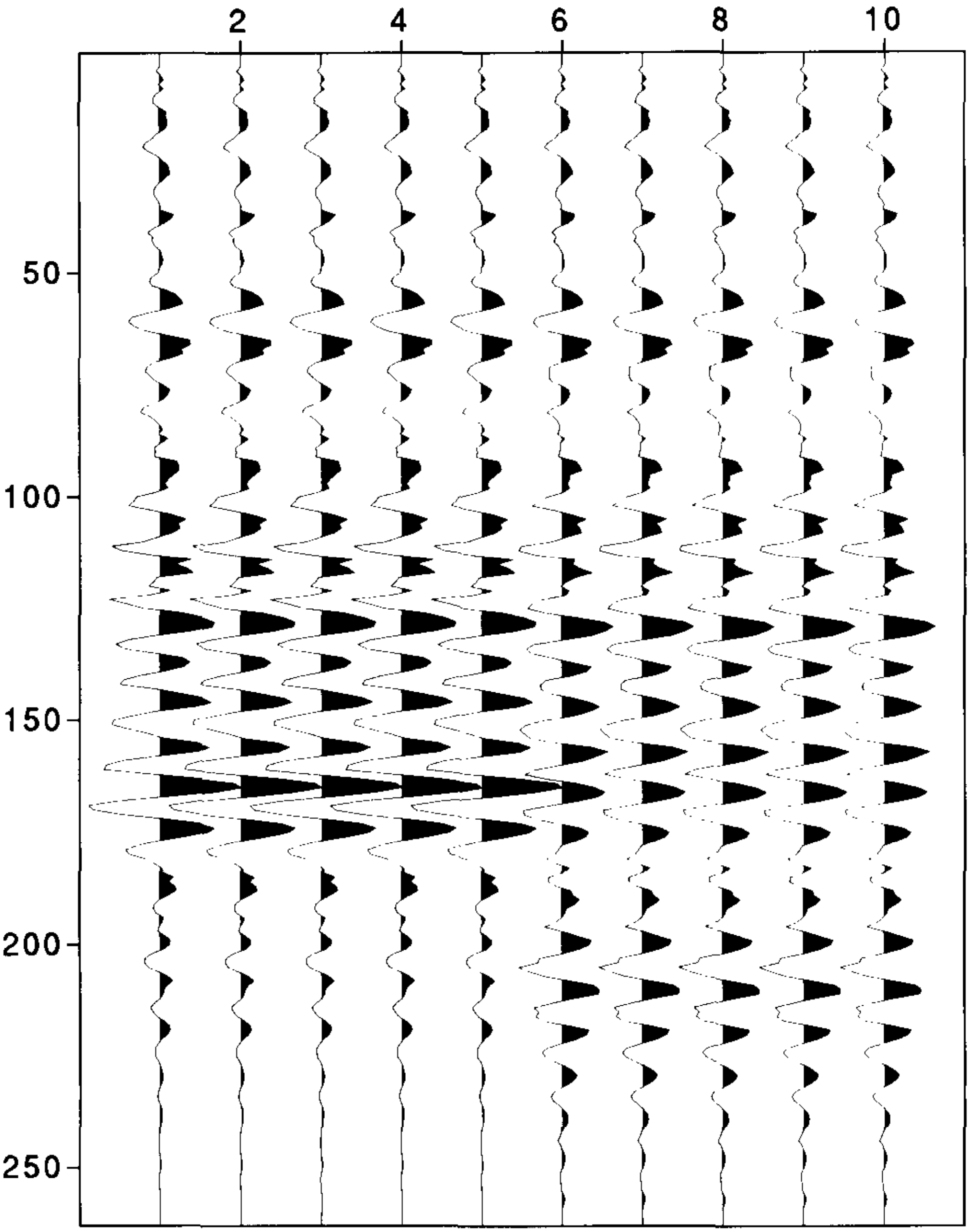

Fig. 3. A comparison of primaries-only synthetic with traces containing primaries + multiples. The "primaries only" traces (5 traces on left) are convolutions of the wavelet with reflectivity. The "primaries + multiples" traces (5 traces on right) are convolutions of the wavelet with the impulse response.

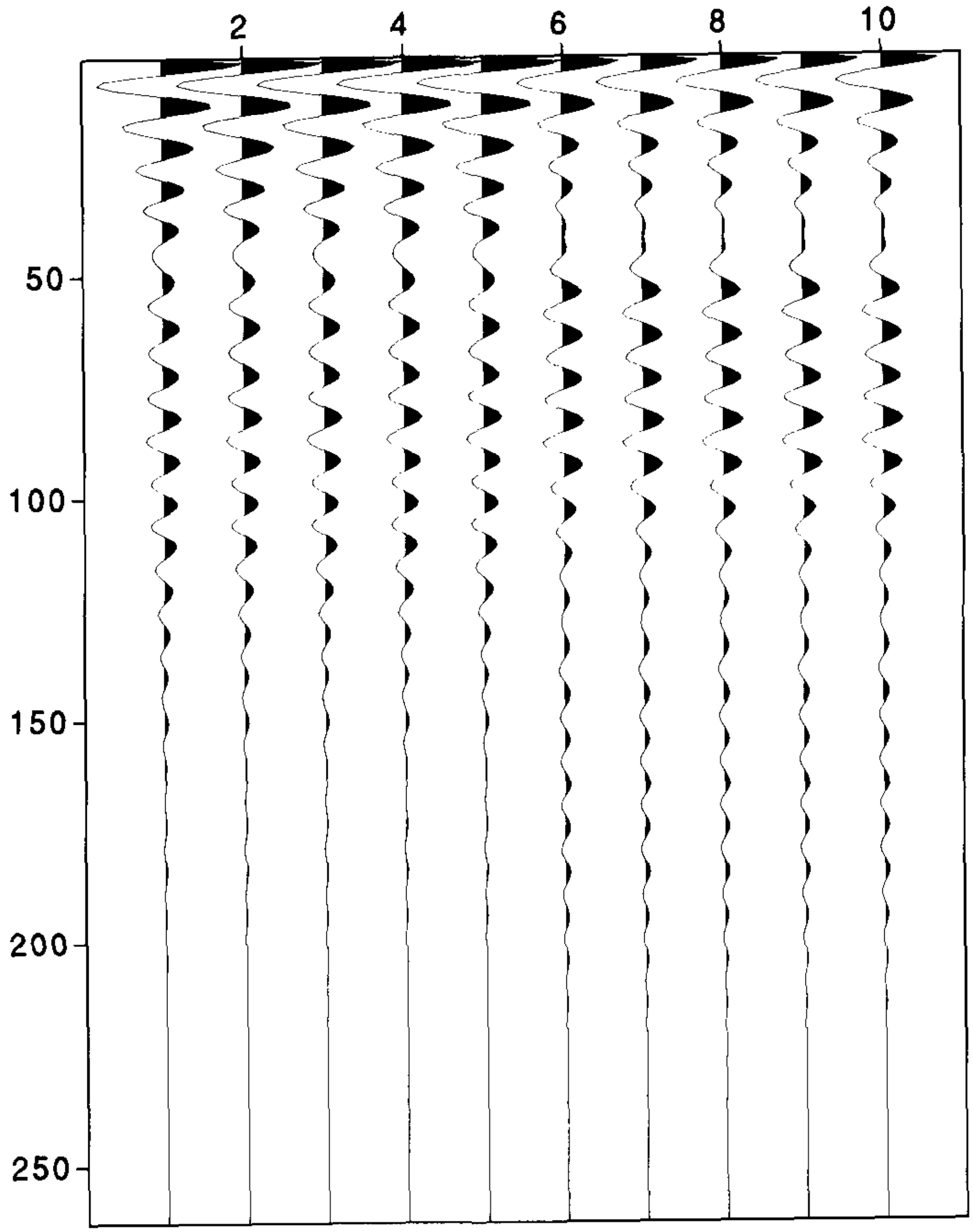

Fig. 4. The autocorrelations for the traces of Figure 3 show little difference between autocorrelations of "primaries only" traces and "primaries plus multiples" traces.

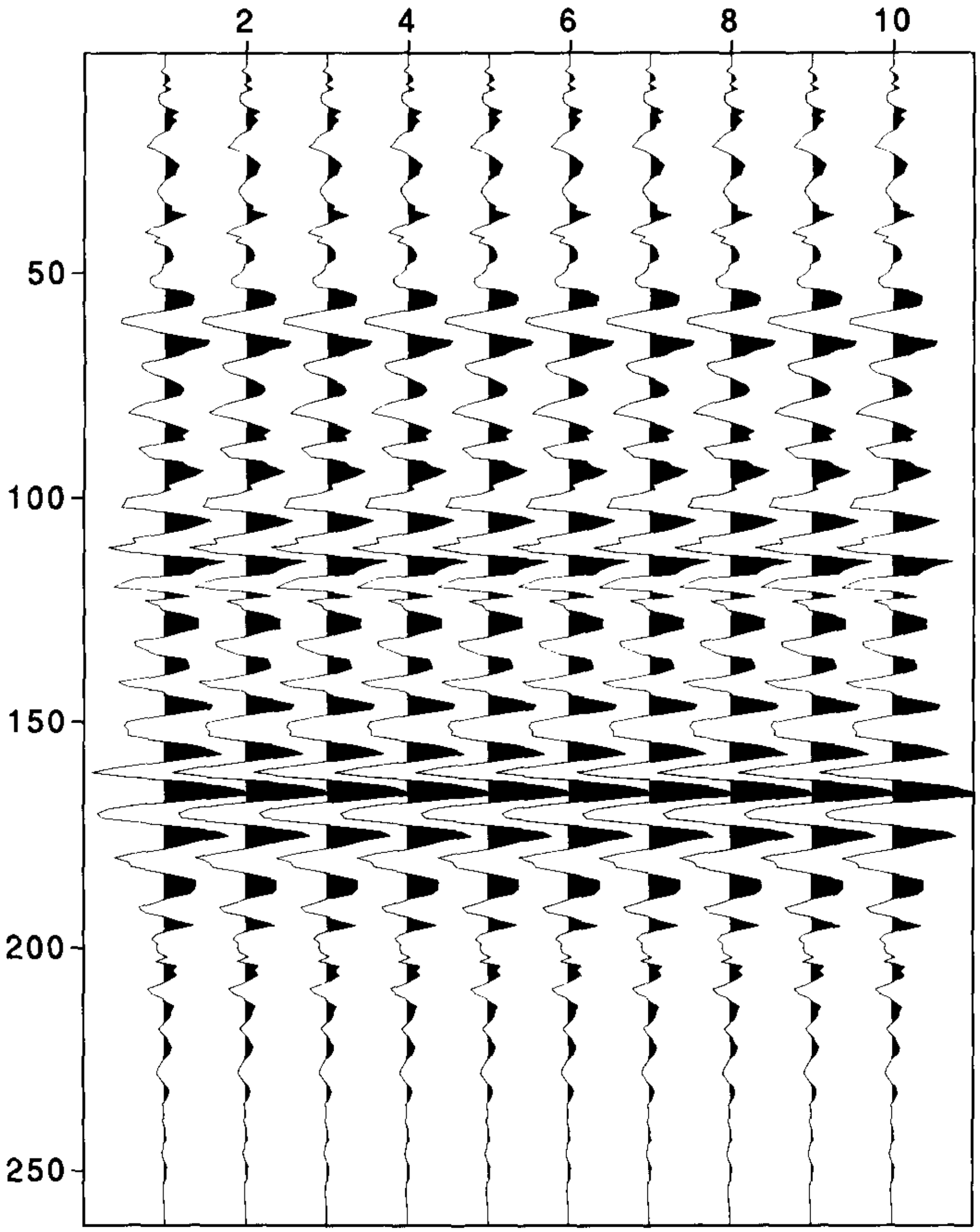

Fig. 5. Deconvolution of the "primaries plus multiples" traces produces traces which resemble the "primaries only" traces of Figure 3.

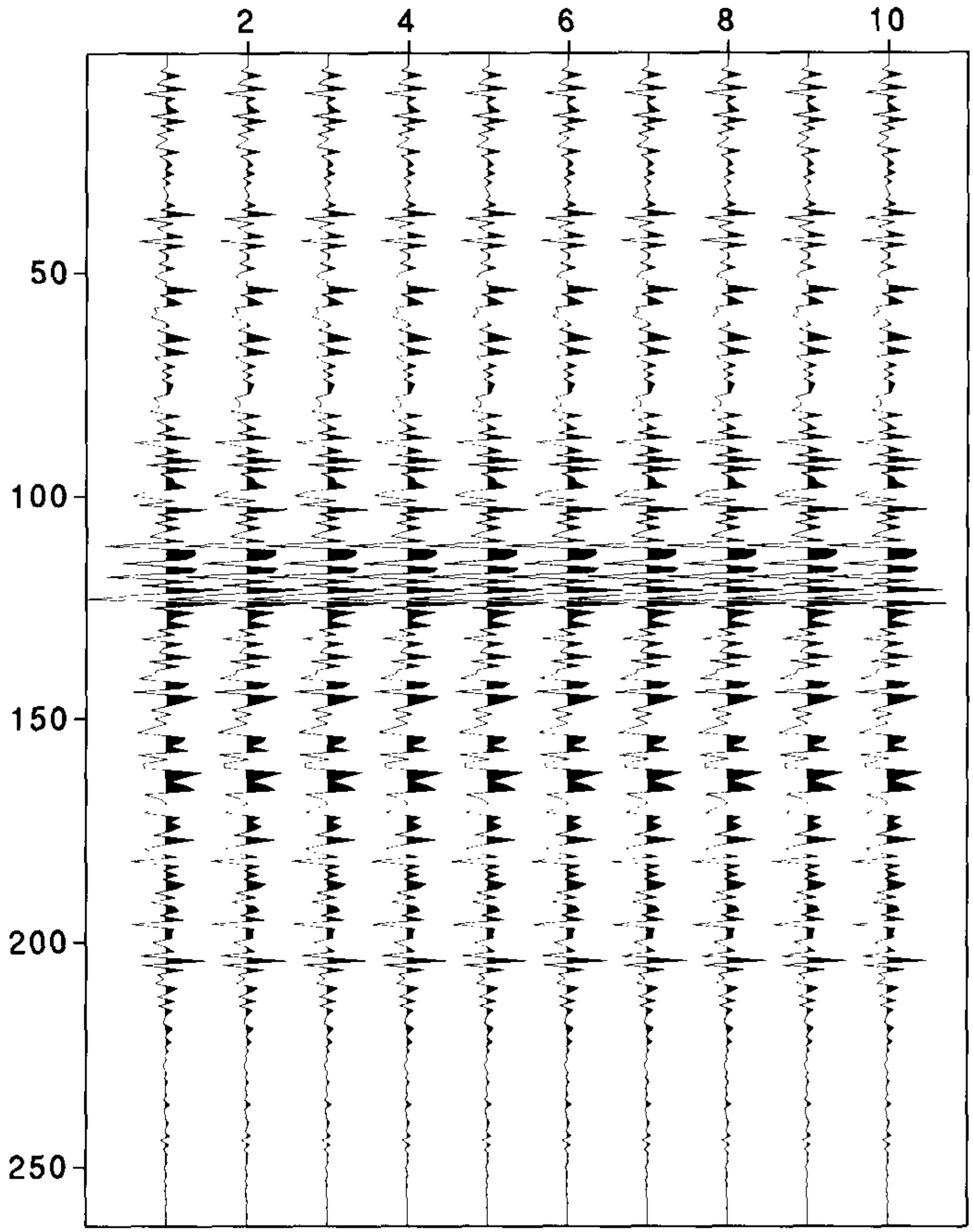

Fig. 6. Wavelet deconvolution of the traces in Figure 5 shows some resemblance to the desired reflectivity of Figure 2.

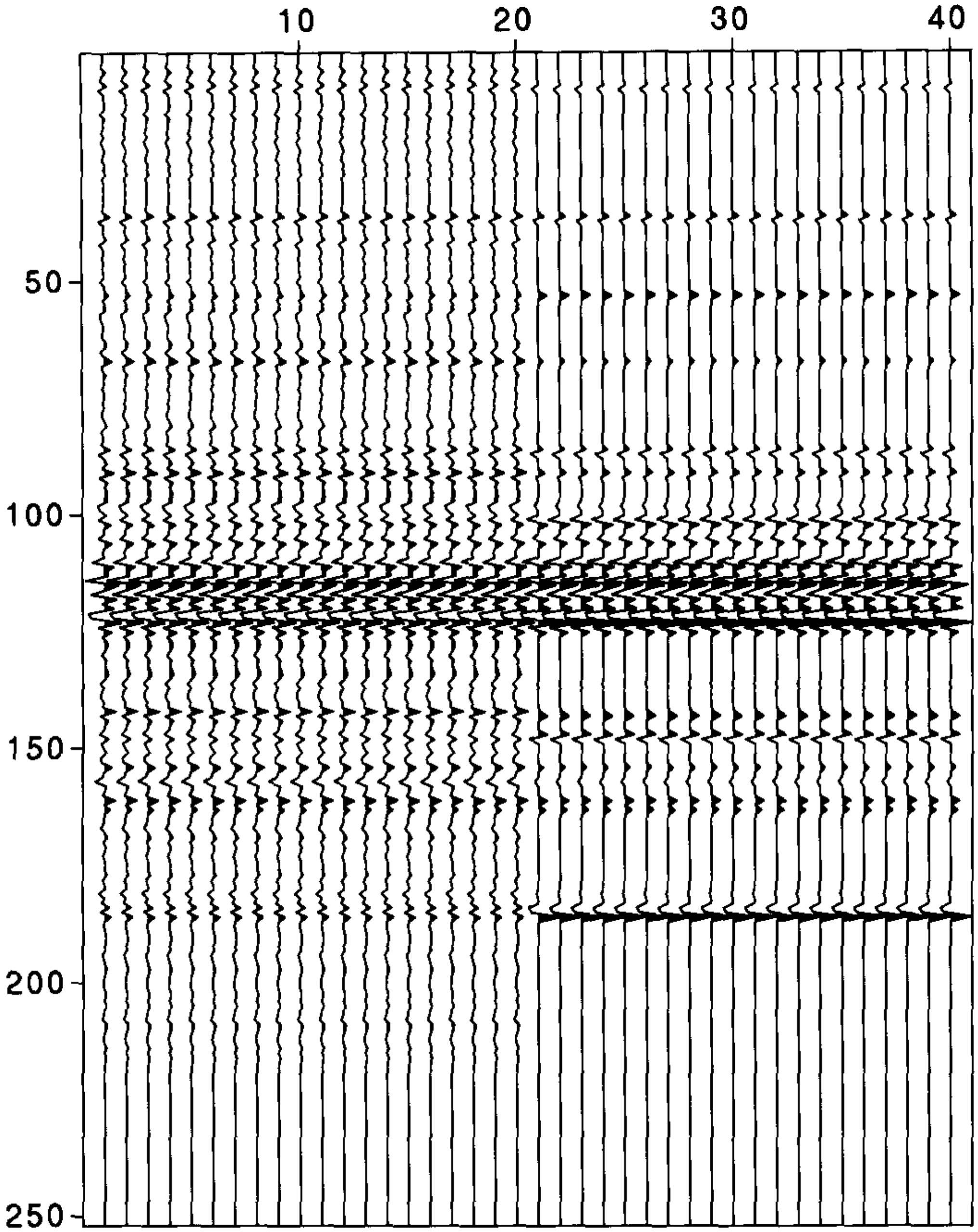

Fig. 7. Parametric least-squares inversion estimates of reflectivity (right-hand side) shows similarity to desired reflectivity (left-hand side) with slight phase distortion.

Two techniques were tried. One technique used two cascaded Wiener shaping filters, similar to those described by Robinson and Treitel (1980). The first Wiener filter shapes the primaries + multiples (impulse response) trace to the primaries-only sequence (reflectivity trace). The second Wiener filter is "a spiking filter" which shapes the wavelet to a spike. This sequence of Wiener filters appears to work well; however, the deconvolved data do have some phase shifts due to imperfect multiple removal. Moreover, the assumptions involved in designing the Wiener shaping filters may be unrealistic for some real-data cases.

The second approach, described by Lines and Treitel (1984) uses least-squares inversion to estimate reflection coefficient parameters by treating both primaries and multiples as signal to be modelled, rather than treating multiples as noise to be deconvolved. This approach can work well if we can reliably parameterize the location of reflection coefficients and their positions. Recently, Simon O'Brien of Memorial University has generalized the model-based approach by using ray tracing to effectively handle marine water-bottom multiples and intends to publish this research in his Ph.D. thesis.

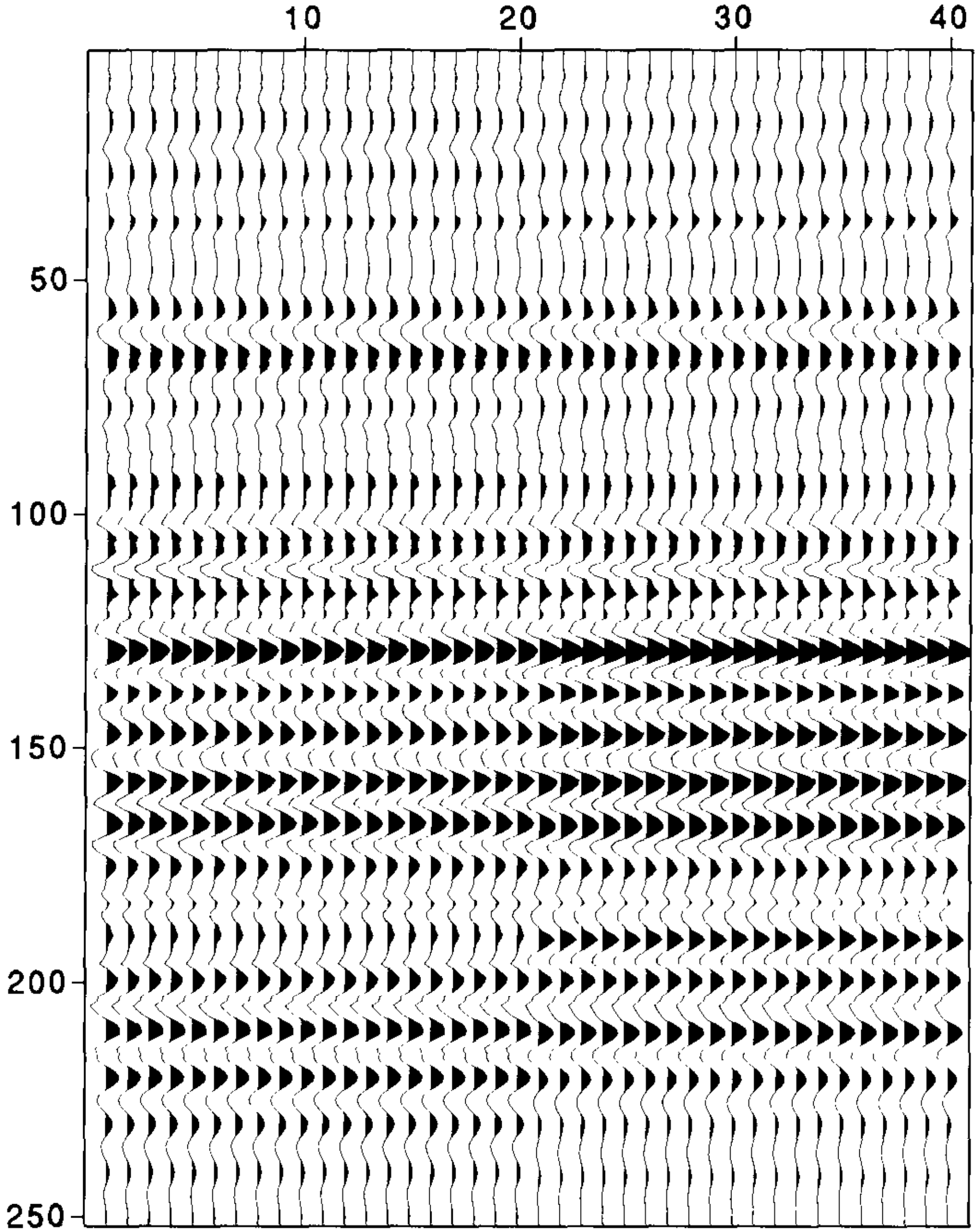

Fig. 8. A comparison of data traces (20 traces on left-hand side) is closely matched by model response from inversion process (20 traces on right-hand side).

REFERENCES

Claerbout, J.F., 1992, Earth soundings analysis: processing versus inversion: Blackwell Scientific Publ.

Lines, L.R. and Treitel, S., 1984, Tutorial: a review of least-squares inversion and its application to geophysical problems: Geophys. Prosp. **32**, 159-186.

______ and Ulrych, T.J., 1977, The old and the new in seismic deconvolution and wavelet estimation: Geophys. Prosp. **25**, 512-540.

Peacock, K. and Treitel, S., 1969, Predictive deconvolution: theory and practice: Geophysics **34**, 155-169.

Robinson, E.A., 1954, Predictive decomposition of time series with application to seismic exploration: Ph.D. thesis, MIT (also, Geophysics **32**, 418-484).

______, 1967, Multichannel time series analysis with digital computer programs: Holden-Day.

______ and Treitel, 1980, Geophysical signal analysis: Prentice-Hall, Inc.

Treitel, S. and Lines, L.R., 1982, Linear inverse theory and deconvolution: Geophysics **47**, 1153-1159.

______, Gutowski, P. and Wagner, D.E., 1982, Plane wave decomposition of seismograms: Geophysics **47**, 1372-1401.

Yilmaz, O., 1987, Seismic data processing: Society of Exploration Geophysicists.