

An adaptive scheme for processing multitrace marine seismic data

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A deconvolution method based on the adaptive linear filtering technique has been developed for processing multitrace time-varying seismic data. In this adaptive algorithm the combined filter coefficients are being continuously updated as the seismic trace is being processed. The convergence factor of the adaptive algorithm obtained from the combined trace information is a major controlling parameter that regulates both speed and stability of the adaptive process. This constant convergence factor has been used to process the multitrace information. The developed method has been tested on a field sample of marine seismic data from the western continental margin of India. Results reveal that the methodology is effective in comparison to the conventional method of predictive deconvolution in removing the water bottom multiples.

Various types of multichannel filters have been designed for suppression of coherent noise, stacking problems and velocity analysis¹⁻³. The fast method which recursively calculates the required prediction filter is called the LWR (Levinson-Wiener-Robinson) algorithm. The LWR algorithm is valid typically for a time-invariant input sequence but finds applications in other cases like non-stationary and complex valued data^{4,5}. For the time-varying input sequence, various authors have proposed alternative methods to the LWR algorithm. One such approach of treating the time-varying seismic sequence is to divide the input into sections and performing a combined deconvolution^{6,9}. The other approach of treating the time-varying sequence is known as adaptive filtering and is based on the method of steepest descent in which the coefficients are updated as each data point is deconvolved¹⁰. However, their treatment is for single-channel systems whereas present day seismic reflection data. In this study, the adaptive procedure¹⁰ has been extended to process multitrace seismic data. One of the main controlling parameters in the adaptive deconvolution is the convergence factor. The rate of convergence has been suitably accounted for from the combined trace information. The method has been tested on marine seismic data that contain time-varying water bottom reverberations, which account for the majority of the recorded signal energy. Short period multiples are discriminated on the basis of approximate periodicity. For suppression of the multiples, a sample of six marine seismic data traces from

the western continental margin of India have been used and shown the advantage of the proposed scheme in comparison with the conventional predictive deconvolution which is routinely applied in seismic data processing.

Materials and Methods

Given an input signal $X_p(t)$ $p = 1, 2, \dots, m$, where m is the number of traces and a desired signal which is a time advanced version of the input signal i.e. $X_p(t + \gamma)$ with γ as the prediction distance, one can predict $\hat{X}_p(t + \gamma)$ based on the input $X_p(t)$. If the predicted filtered output is not equal to the desired signal then there is some prediction error and this is given by¹¹

$$e(t) = [X_p(t + \gamma) - \hat{X}_p(t + \gamma)] \quad \dots (1)$$

The estimated trace can be represented as

$$\hat{X}_p(t + \gamma) = X_p^T(t) F_p(t) \quad \dots (2)$$

where eq. $F_p(t)$ are the filter coefficients.

Substituting Eq. (2) in Eq. (1) we get

$$e(t) = [X_p(t + \gamma) - X_p^T(t) F_p(t)] \quad \dots (3)$$

The mean square error (MSE) is given by

$$\begin{aligned} \varepsilon(t) &= E[e^2(t)] = E[[X_p(t + \gamma) - X_p^T(t) F_p(t)]^2] \\ &= E[X_p^2(t + \gamma) - 2X_p(t + \gamma) X_p^T(t) F_p(t) \\ &\quad + F_p^T(t) X_p(t) X_p^T(t) F_p(t)] \quad \dots (4) \end{aligned}$$

If the initial filter of MSE surface were $[F_p(0), \varepsilon(0)]$ then the next filter coefficients are updated by

$$F_p(1) = F_p(0) - \nabla_F[\varepsilon(0)] \quad \dots (5)$$

where $\nabla_F[\varepsilon(0)]$ is the gradient which is given by

$$\nabla_F[\varepsilon(0)] = \frac{\partial \varepsilon}{\partial F_p} \quad \dots (6)$$

Using Eq. (4) the gradient in (6) becomes

$$\begin{aligned} \nabla_F[\varepsilon(0)] = & E[-2X_p(t+\gamma)X_p^T(t) \\ & + 2F_p(t)X_p(t)X_p^T(t)] \end{aligned} \quad \dots (7)$$

Substituting Eq. (7) in Eq. (5) we get

$$\begin{aligned} F_p(1) = & F_p(0) + 2\mu [X_p(t+\gamma)X_p^T(t) \\ & - F_p(t)X_p(t)X_p^T(t)] \end{aligned} \quad \dots (8)$$

where μ is a constant and $2\mu = \mu$ is the convergence factor of the algorithm. Thus the above equation can be generalized as

$$\begin{aligned} F_p(t+1) = & F_p(t) + \mu [X_p(t+\gamma) \\ & - F_p(t)X_p(t)X_p^T(t)] \end{aligned} \quad \dots (9)$$

For simplicity let us consider a case of processing two traces simultaneously. Then the equations reduce to

$$F_1(t+1) = F_1(t) + \mu [X_1(t+\gamma) - F_1(t)X_1(t)]X_1^T(t) \quad \dots (10)$$

and

$$F_2(t+1) = F_2(t) + \mu [X_2(t+\gamma) - F_2(t)X_2(t)]X_2^T(t) \quad \dots (11)$$

Eqs (10) and (11) can be combined and can be written in matrix form. In compact form this equation can be generalized and written as

$$F_p(t+1) = F_p(t) + \mu \Lambda [X_p(t+\gamma) - \Lambda F_p(t)] \quad \dots (12)$$

where $F_p(t+1)$ and $X_p(t+\gamma)$ are column vectors where $p=1,2,\dots,m$ and

$$\Lambda = \begin{bmatrix} X_1(t)00\dots0 \\ 0X_2(t)0\dots0 \\ \dots\dots\dots\dots\dots \\ 00\dots0X_m(t) \end{bmatrix}$$

is the diagonal matrix.

The convergence of Eq (12) is guaranteed provided $0 < \mu < 2/\lambda_{\max}$ where $\lambda_{\max}$ is the maximum eigen

value. The convergence factor or the proportionality constant is of great importance in the adaptive algorithm. To obtain the best convergence factor for the multi trace data we first begin with the computation of the auto and cross-correlation of the trace information i.e the block Toeplitz matrix⁸. This matrix is stabilized by a process of normalization and adding pre-whitening parameter. Once a stable matrix is obtained the maximum eigen value of the system is obtained which is used in obtaining the combined convergence factor of the adaptive algorithm. The combined convergence factor has been taken as $\mu = 2/\lambda_{\max}$ where $\lambda_{\max}$ is the maximum eigen value of the auto and cross-correlation matrix obtained from the multi trace information.

The concept of forward-time adaptation and reverse-time adaptation¹⁰⁻¹², has been used in this study to obtain the filter coefficients for the multi trace information. The corresponding equations for the filter coefficients are obtained as

$$F_p(t+1) = F_p(t) + \mu \Lambda [X_p(t+\gamma) - \Lambda F_p(t)] \quad \dots (13)$$

for the forward-time adaptation, and

$$F_p(t-1) = F_p(t) + \mu \Lambda [X_p(t+\gamma) - \Lambda F_p(t)] \quad \dots (14)$$

for the reverse-time adaptation, where γ is the prediction distance.

The final deconvolved traces are obtained by stacking the forward and reverse-time adaptation, which is given by

$$Y(t) = 1/2[Y_{pf}(t) + Y_{pr}(t)] \quad \dots (15)$$

The term in the square brackets of Eq. (13) and Eq. (14) gives the forward-time adaptive deconvolved trace $Y_{pf}(t)$ reverse-time adaptive deconvolved trace $Y_{pr}(t)$ respectively and Eq. (15) yields $Y_p(t)$ the final adaptive deconvolved trace.

Application to Field Data and Results

The adaptive deconvolution method developed to process the multitrace seismic data has been applied to a field marine reflection seismic profile from the western continental margin of India¹³. The marine seismic data contains a lot of noises of which the water bottom multiples is a major concern as they

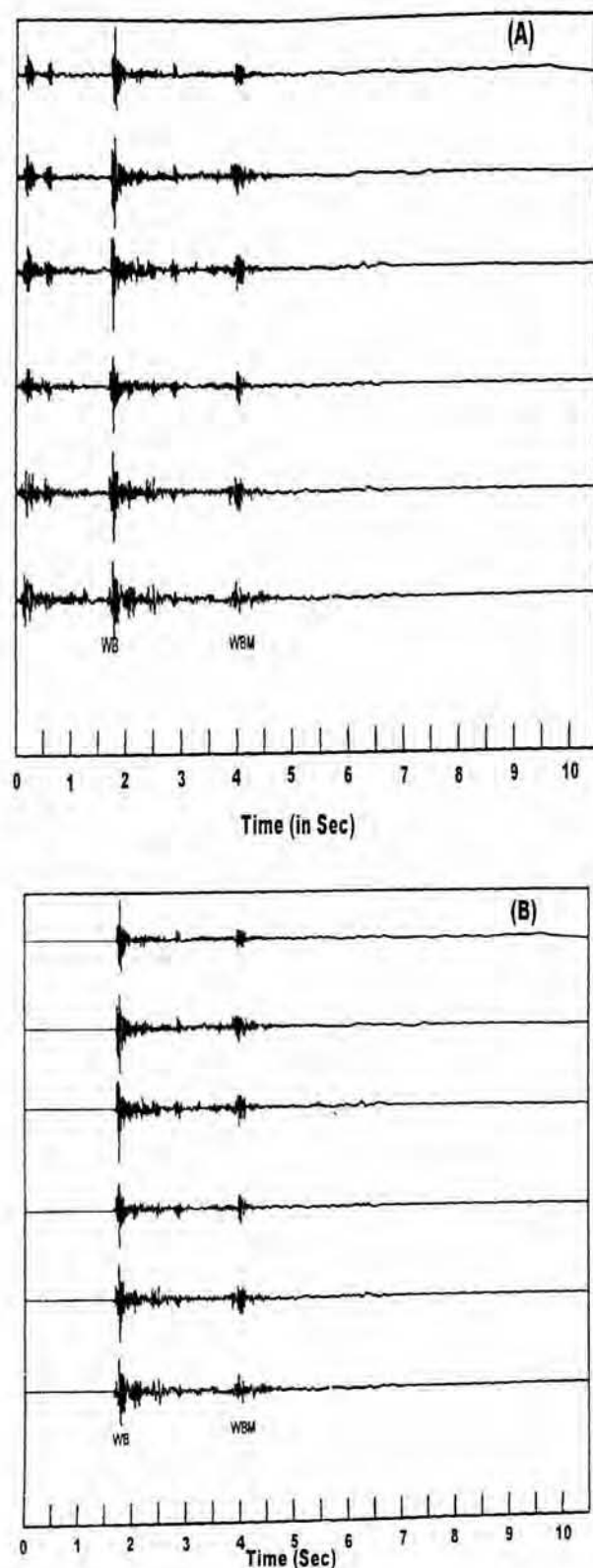


Fig. 1—Plot showing traces of six channel marine seismic data (A) unprocessed (B) data without the direct arrivals and water reverberations (WB = water bottom, WBM = water bottom multiple)

usually mask the valuable signals. In this study, a sample of 6 unprocessed marine seismic traces of 10 sec record length each (Fig. 1A) has been taken. The direct arrivals and water bottom reverberations on the first part of the traces have been removed by muting (Fig. 1B). The correlation statistics of a seismic trace is known to vary with time along the trace, hence any kind of periodicities observed in the data are reflected in the autocorrelogram. In marine environment the water bottom gives rise to strong multiples and in order to know the prediction length the autocorrelation function is computed. The autocorrelation function has been computed for a seismic trace and the results are plotted in Fig. 2 which shows that the periodicities of the multiples is around 2 sec. This helps us to choose the prediction distance in order to suppress the water bottom multiples. The operator length has been taken as 6 sec (or 1500 samples) with the proportionality constant (the convergence factor) of 3.9740608×10^{-3} . This convergence factor is obtained from the auto and cross correlation matrix of the input trace information.

Using Eqs (13) and (14) for the time-forward and time-reverse adaptation respectively, the final deconvolved traces, (which is a stack of both time-forward and time-reverse deconvolved traces) have been obtained (Fig. 3A). From the figure, it is clear that the water bottom multiples have been successfully removed by the proposed scheme. To appreciate the advantage of the proposed scheme, the results have been compared with the conventional predictive deconvolution scheme¹⁴. The conventional predictive deconvolution forms a routine step in the processing of marine seismic data. The predictive deconvolution has been applied on the sample data and the results are plotted in Fig. 3B, which shows that the conventional method fails to suppress the coherent noise observed in the field seismic data in comparison to the proposed methodology.

Discussion

Standard data processing techniques often fail to attenuate the long period multiples. However, this problem has been overcome by adaptive deconvolution technique¹⁰ for a single channel data. Since most of the data are multidimensional in nature the processing of such data requires multichannel deconvolution. Hence this adaptive deconvolution technique has been extended to incorporate multitrace data for sup-

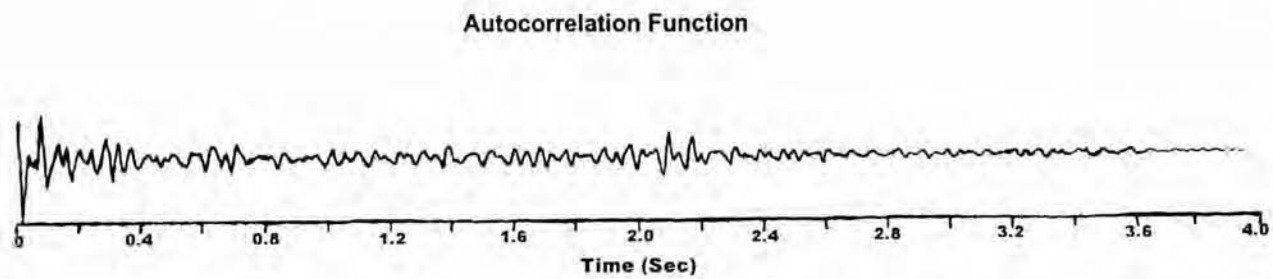


Fig. 2—Autocorrelation function of the input seismic trace.

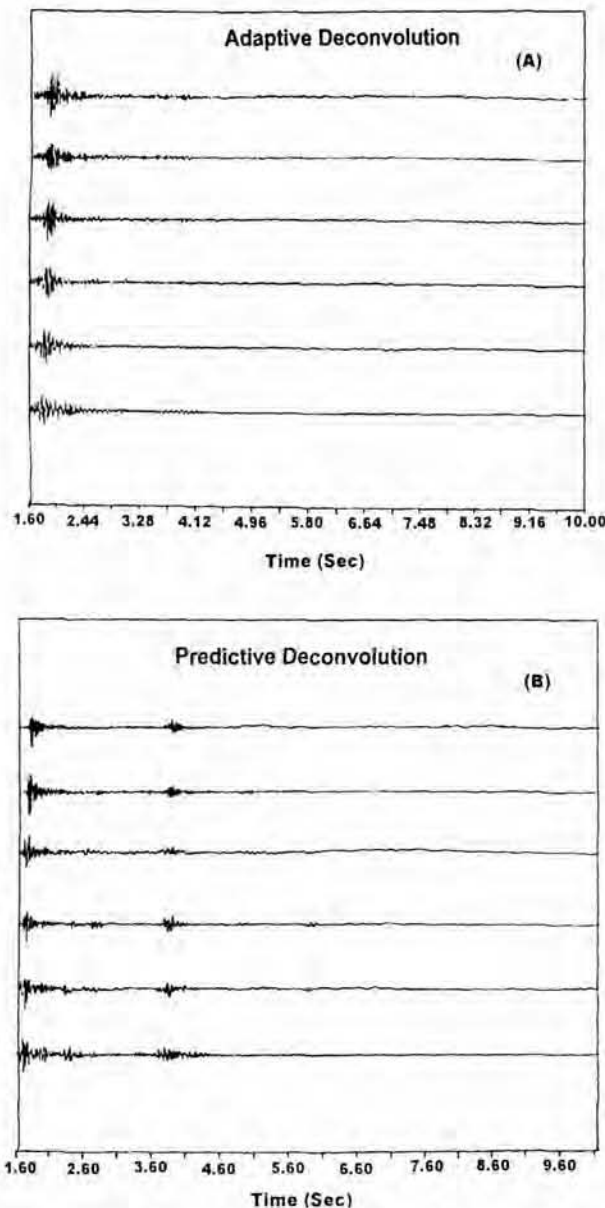


Fig. 3—Deconvolution applied on the sample data (A) showing the effect of adaptive deconvolution (B) showing the effect of the conventional predictive deconvolution.

pressing the water bottom multiples. Using a sample of field recorded marine seismic traces from the western continental margin of India the above proposed methodology has been tested for removing the water bottom multiples. Results obtained show that the water bottom multiples from the seismic traces have been removed which otherwise could not have been removed by the conventional method of predictive deconvolution. Most deconvolution techniques are used to remove the effect of noise in case of little or no dip, whereas in the case of dipping reflectors the removal of noise by this method becomes ineffective as the noise statistics in such cases is very different.

In developing any deconvolution approach the stability analysis is a major concern. In this study, a fixed convergence factor from the multi trace information has been used. This is one of the important parameters, which regulates the speed as well as the stability of the algorithm. However, for time-varying inputs a time-varying convergence factor that is fast and minimizes misadjustments can be used¹⁵. Analysis on the stability of the solution can be carried out by adding pre-whitening parameter and see how the solution develops. Keeping in mind the trade off between stability and accuracy suitable deconvolution techniques need to be developed. Thus use of a time-varying convergence factor has a great future application.

The proposed adaptive deconvolution as well as the predictive deconvolution has been built on the assumption of a white noise reflection sequence. On the contrary the present day data are associated with coloured or scaling noises. For this the concept of scaling noises has been introduced in geophysics particularly to seismics^{16,17} and potential fields¹⁸⁻²⁰. Removal of noises from the time-varying marine seismic

data is now being looked from the fractals point of view and there is immense scope for future research. Thus, scaling deconvolution techniques need to be developed for handling complex marine seismic data.

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