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ATTENUATION OF SHORT-PERIOD MULTIPLES IN SEISMIC DATA PROCESSING OF THE JEQUITINHONHA BASIN, BRAZIL

Silmara L.R. Oliveira[1], Rosângela Corrêa Maciel[2], Michelângelo G. da Silva[1] and Milton José Porsani[1]

ABSTRACT. Short-period multiples attenuation is a difficult problem for shallow water marine seismic data processing. In the past few decades many filtering methods have been developed to solve this problem and to improve the quality of seismic imaging. The Wiener-Levinson predictive deconvolution method is one of the most useful and well known filter methods used in the seismic data processing flow. It is a statistical approach to reduce redundancy along the time variable seismic trace, allowing us to both improve the time resolution and also attenuate multiple reflections of the seismic traces. One of the assumptions of the Wiener-Levinson method is that the seismic wavelet is stationary along the entire seismic trace. However, this is not true for real seismic data and to bypass this limitation the method is normally applied using fixed time windows, distributed along the seismic trace. The present study tested a new adaptive predictive deconvolution approach for the attenuation of short-period multiples. The new approach is based on a sliding window of fixed length that is shifted sample by sample along the entire seismic trace. At each position, a new filter is computed and applied. The implied systems of equations are solved by using a recursive Levinson-type algorithm. The main difference with respect to the conventional Wiener-Levinson approach is that the filter is updated for each data sample along the trace and no assumption is imposed on the data outside the considered window. The new adaptive predictive deconvolution approach was tested using a seismic line of the Jequitinhonha Basin acquired by Petrobras. The results demonstrated that the new approach is very precise for the attenuation of short-period multiples, producing better results than the ones obtained from the conventional Wiener-Levinson predictive deconvolution approach. The results were obtained with filters of 25 coefficients, predictive distance of 5 samples and window length equal to 55 samples.

Keywords: seismic processing, Jequitinhonha Basin, adaptive predictive deconvolution, multiple of attenuation, Wiener-Levinson deconvolution.

RESUMO. A atenuação de reflexões múltiplas de curto período, presentes nos dados sísmicos adquiridos sobre lâmina d'água rasa, representa um grande problema do processamento de dados sísmicos marítimos. Nas últimas décadas, vários métodos de filtragem de dados sísmicos têm sido desenvolvidos com o propósito de atenuar reflexões múltiplas e melhorar a qualidade das seções sísmicas. O método de filtragem conhecido como deconvolução preditiva de Wiener-Levinson é bastante utilizado na indústria do petróleo. Ele permite melhorar a resolução temporal dos dados sísmicos e atenuar reflexões múltiplas, podendo ser visto como um método estatístico que remove a coerência temporal dos traços sísmicos. O método de Wiener-Levinson pressupõe que o pulso sísmico é estacionário, fato este que não ocorre nos dados sísmicos reais. Para contornar este problema, o método de Wiener-Levinson é normalmente aplicado utilizando-se janelas de tempo fixas, distribuídas ao longo do tempo de registro. No presente trabalho, empregamos um método de deconvolução preditiva adaptativa no qual as janelas de tempo deslizantes são deslocadas amostra a amostra ao longo de todo o traço sísmico. Os sistemas de equações são resolvidos com o algoritmo recursivo tipo-Levinson. Na deconvolução de Wiener-Levinson, com janelas de tempo fixa, os filtros são gerados e aplicados dentro de cada janela. Já na deconvolução preditiva adaptativa o algoritmo calcula um novo filtro a cada posição da janela deslizante. Para teste da nova abordagem utilizamos os dados sísmicos da Bacia de Jequitinhonha, cedidos pela Petrobras. Os melhores resultados foram obtidos com filtros de 25 coeficientes, distância de predição igual a 5 amostras e janela móvel de 55 amostras. Os resultados obtidos com a nova abordagem demonstram que a deconvolução preditiva adaptativa atua com eficácia na atenuação de múltiplas de curto período, apresentando resultados melhores que os gerados pelo método de deconvolução preditiva de Wiener-Levinson.

Palavras-chave: processamento sísmico, Bacia do Jequitinhonha, deconvolução adaptativa, atenuação de múltiplas, deconvolução de Wiener-Levinson.

[1]Universidade Federal da Bahia, INCT-GP/CNPq, Centro de Pesquisa em Geofísica e Geologia, Instituto de Geociências, Campus Universitário da Federação, Salvador, BA, Brazil – E-mails: silmaralorena@yahoo.com.br; mgs@cpgg.ufba.br; porsani@cpgg.ufba.br

[2]Universidade Federal do Rio Grande do Norte, INCT-GP/CNPq, Centro de Ciências Exatas e da Terra, Departamento de Geofísica. Campus Universitário, Natal, RN, Brazil – E-mail: rosangela@geofisica.ufrn.br

INTRODUCTION

The objective of seismic reflection is to obtain seismic images that best represent the geological structures in the subsurface. The presence of multiples in the seismic image hinders the interpretation, because they can be misinterpreted as primary events (Maciel, 2007). In addition to this problem, the data migration step can be impaired due to the fact that multiples are treated as primary.

The short-period multiples are coherent noises that originate from the reverberation of the seismic energy in a not very thick layer with strong impedance contrasts.

The attenuation techniques for multiples explore the differences in the Normal Moveout (NMO) and the periodic features of such events. The prediction and suppression of short-period multiples are great challenges to seismic processing since periodicity is not well defined.

The deconvolution method is often employed in seismic processing data to compress the pulse and, therefore, improve the definition of reflections of the recorded data. This technique also allows removing reverberations and multiple events, thus restoring reflectivity the best way possible. The predictive deconvolution is a statistical method based on the periodicity of multiples. However, this method's success is limited to short offsets and horizontally stratified media, situations where periodicity it is better observed.

Another limitation of this method is the stationarity of the process. To solve this problem, some authors (Clarke, 1968; Griffiths et al., 1977) developed the adaptive predictive deconvolution approach, where in conditions of non-stationarity of the seismic pulse, the recorded trace is split in windows to make it more stationary. A specific filter is determined and applied to each window.

This work used the adaptive predictive deconvolution approach for the attenuation of short-period multiples. Two methods were tested: (I) Wiener-Levinson Adaptive Predictive Deconvolution (WLAPD) with fixed windows; and (ii) Morf-Porsani Adaptive Predictive Deconvolution (MPAPD) with sliding windows.

Morf et al. (1977) developed an efficient Levinson type algorithm to solve the Normal Equations (NEs) associated to the problem of linear prediction (unit prediction distance $L = 1$), in which no hypothesis is formulated about the data outside the considered window. Porsani (1991) extended the Morf algorithm to arbitrary prediction ($L > 1$). In these cases, the NEs matrix does not have the Toeplitz structure any longer and the reverse filter obtained with the Morf-Porsani algorithm will contribute only to the data inside the window, unlike the Wiener-Levinson (WL) filter that considers null amplitudes of trace samples outside the window.

GEOLOGY OF THE BASIN

The sedimentary Jequitinhonha Basin is located on the South Central coast of Bahia, between the 15th and 18th parallels south. It borders Alto de Olivença in the Almada Basin to the north, and the Volcanic Bank of Royal Charlotte and its projection toward the coast to the south, thus separating it from the Cumuruxatiba Basin. The Jequitinhonha Basin is located on the south border of the Sao Francisco Craton. The Basin has an area of approximately 10,000 km^2, of which 9,500 km^2 are submerged (7,000 km^2 up to 1,000 m water depth and 2,500 km^2 between 1,000 and 2,000 m water depth). The basement consists of granitic and gneissic rocks (Santos et al., 1995).

The stratigraphic framework of the basin is characterized by the following formations:

1. Native Group – consists of the Mariricu formation with two distinct members: the Mucuri Member formed by thick clastic and fluvial-lacustrine fines of Alagoas age, and the Itaúnas Member characterized by neoalagoas evaporites representing a marine environment of restricted circulation;
2. Barra Nova Group – consists of two formations. The São Mateus formation represented by thick clastic deposited on the deltaic fans and the Regência Formation consisting of high and low energy carbonates from the neritic environment. This group age has been dated as Albian and Cenomanian;
3. Espírito Santo Group – consists of three formations. The Rio Doce Formation characterized by coarse sandstones of the tertiary coastal fans. The Caravelas Formation consists of tertiary neritic carbonates of high and low energy. The Urucutuca Formation is formed by thick pelites and, neo-Cretaceous and tertiary sandstones, deposited on the slope and basins;
4. Barreiras Formation – is the neo-Cenozoic clastic coverage of the terrestrial portion.

The Sequences Stratigraphy

Rift Sequences – the K40 sequence corresponds to the lower part of the Mariricu Formation, of Eoalagoas age. The K50 sequence is the transition that closes the Eocretaceous taphrogeny, represented by evaporites of the Itaúnas Member.

Passive Margin Sequences – the beginning of the marine sedimentation is characterized by the neritic clastics and carbonates of the Barra Nova Group, of albo-Cenomanian age, persisting up to the Coniacian, forming the K60 and K80 sequences.

The oceanic conditions deepened starting from the Senonian, and the sequences K90-T30 (Santonian-Oligocene), T40-T50 (Oligocene-Miocene) and T60 (Pliocene-Holocene) were recognized. These sedimentary packages deposited initially under transgressive conditions, and from the beginning of Eocene, a regressive system consisting of alluvial fans, carbonate shelf, slope and basin, settled.

According to Chagas (2003), the stratigraphic architecture of the wider and younger Aptian/Eoalbian Rift is similar to that of an extended basin. This pattern may reflect an unusual heat contribution, that begun during the Barremian, caused by the dome formed, whose volcanic rocks extruded only in the south neighborhood of the basin during the Paleocene and Eocene.

ADAPTIVE PREDICTIVE DECONVOLUTION (APD)

Conventional deconvolution assumes a stationary process; therefore, limiting the nature of the variation of the seismic pulse that occurs during the propagation in the subsurface. The adaptive deconvolution is a tool that overcomes this limitation, since the seismic trace can be split in time windows. Each window is approximately stationary, to which a specific filter is determined and applied.

The filter coefficients are determined using an adaptive algorithm that updates the filter for each point of the seismic trace as to minimize the error associated to deconvolution result.

It is required to estimate the initial window size for the filter to work. Thus, a sliding window with samples is defined and the filter with the coefficients is updated at each window position.

Wiener-Levinson Adaptive Predictive Deconvolution (WLAPD)

The predictive filtering is described by the discreet convolution formula and is represented as a linear prediction (Robinson, 1980) as follows,

$$\tilde{x}_{t+L} = \sum_{k=1}^{n} x_{t-k+1}\tilde{h}_k \tag{1}$$

where

- $\tilde{x}_{t+L}$ is the signal predicted over time, from the linear combination of the values $x_t, \ldots, x_{t-n+1}$;
- L is the prediction distance;
- $\tilde{h}_k$ is the prediction filter.

The term e_{t+L} is the prediction error in the $t+L$ sample, representing the difference between the reading and the calculated sample, given by

$$e_{t+L} = x_{t+L} - \tilde{x}_{t+L} \tag{2}$$

The error operator with L prediction distance is represented as follows,

$$1, \underbrace{0, 0, \ldots, 0,}_{(L-1\,zeros)} -\tilde{a}_1, -\tilde{a}_2, \ldots, -\tilde{a}_n\,.$$

where the $[n]$ non-null coefficients of the filter act on the seismic trace, x_t, at past times, preserving the L samples related to primary reflections.

For $L = 3$ and $n = 3$, the matrix becomes

$$\begin{bmatrix} e_0 \\ e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ \vdots \\ e_{t+3} \\ \vdots \\ e_m \\ e_{m+1} \\ e_{m+2} \\ e_{m+3} \\ e_{m+4} \\ e_{m+5} \end{bmatrix} \begin{bmatrix} x_0 & 0 & 0 & 0 & 0 & 0 \\ x_1 & x_0 & 0 & 0 & 0 & 0 \\ x_2 & x_1 & x_0 & 0 & 0 & 0 \\ x_3 & x_2 & x_1 & x_0 & 0 & 0 \\ x_4 & x_3 & x_2 & x_1 & x_0 & 0 \\ x_5 & x_4 & x_3 & x_2 & x_1 & x_0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{t+3} & x_{t+2} & x_{t+1} & x_t & x_{t-1} & x_{t-2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_m & x_{m-1} & x_{m-2} & x_{m-3} & x_{m-4} & x_{m-5} \\ 0 & x_m & x_{m-1} & x_{m-2} & x_{m-3} & x_{m-4} \\ 0 & 0 & x_m & x_{m-1} & x_{m-2} & x_{m-3} \\ 0 & 0 & 0 & x_m & x_{m-1} & x_{m-2} \\ 0 & 0 & 0 & 0 & x_m & x_{m-1} \\ 0 & 0 & 0 & 0 & 0 & x_m \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ -\tilde{a}_1 \\ -\tilde{a}_2 \\ -\tilde{a}_3 \end{bmatrix} \tag{3}$$

Observe in matrix (3) that

$$e_j = x_j, \quad \text{for } j = 0, 1, 2,$$

thus, the L samples of the trace that referring to the primaries are preserved.

The quadratic form corresponding to the prediction error vector is

$$Q = \sum_t e_t^2 \tag{4}$$

The coefficients of the prediction error operator should be calculated so as the quadratic error is minimized. Minimizing the quadratic error and expanding the Normal Equations (NEs), we obtain,

$$\begin{bmatrix} r_0 & r_1 & \dots & r_{n-1} \\ r_1 & r_0 & \ddots & \vdots \\ \vdots & \ddots & \ddots & r_1 \\ r_{n-1} & \dots & r_1 & r_0 \end{bmatrix} \times \begin{bmatrix} -\tilde{a}_1 \\ -\tilde{a}_2 \\ \vdots \\ -\tilde{a}_n \end{bmatrix} = \begin{bmatrix} r_L \\ r_{L+1} \\ \vdots \\ r_{L+n-1} \end{bmatrix} \tag{5}$$

Matrix (5) has banding in relation to the main diagonal and is known as band-structure autocorrelation Toeplitz matrix whose coefficients represent an estimate of the autocorrelation $\left(r_j = \sum_j x_k x_{k-j}\right)$ of the seismic pulse.

The conventional WL deconvolution method estimates the inverse filter based on the Least Square Method (LSM), which results in the system of NEs shown in (5). For a filter with $[n]$ coefficients, this system can be resolved through the Levinson Recursion (LR). This method assumes that the seismic pulse is of minimum phase; since the inverse filter obtained as a solution of NEs is always of minimum phase. Therefore, its use with real data does not always meet the assumptions implied on the method.

Vector $\tilde{a}$ minimizes the error in Equation (5). And as a function of the elements of this vector, it is possible to get the expression of the total sum of the minimized errors: $E_{a,n}$

$$\min\{Q\} = E_{a,n} = r_0 - \sum_{k=1}^{n} r_{L+k}\tilde{a}_k \tag{6}$$

The expanded NEs are obtained by combining the expressions (5) and (6). To simplify the vector $\tilde{a}$, we adopt:

$$-\tilde{a}_j = \tilde{a}_j, j = 1, 2, \dots, n$$

$$\begin{bmatrix} r_0 & r_L & r_{L+1} & \dots & r_{L+n-1} \\ r_L & r_0 & r_1 & \ddots & r_{n-1} \\ r_{L+1} & r_1 & r_0 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & r_1 \\ r_{L+n-1} & r_{n-1} & \dots & r_1 & r_0 \end{bmatrix} \times \begin{bmatrix} 1 \\ a_1 \\ \vdots \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} E_{a,n} \\ 0 \\ \vdots \\ \vdots \\ 0 \end{bmatrix} \tag{7}$$

The WL sliding windows refer to windows of fixed time length set on the interval $x_t, \dots, x_{t+L}$, imposing that the data are equal to zero outside the considered interval, that is, $x_k = 0$ for $t > k > t + L$. In this case, for each window position, the NEs system associated with the prediction filter is a Toeplitz matrix that can be resolved with the LR.

For a window defined in the interval $x_k, \dots, x_{k+L}$, the autocorrelation is estimated and the WL inverse filter of n coefficients is calculated through the LR, and, thus, the filter for the $K + L$ position is obtained.

Morf-Porsani Adaptive Predictive Deconvolution (MPAPD)

Morf et al. (1977) developed an efficient Levinson-type algorithm to solve the NEs associated to the linear prediction problem, in which no hypothesis is made concerning the data outside the considered window. In this case, the NEs matrix is not a Toeplitz matrix any longer, and the inverse filter with the Morf algorithm takes into account only the data inside the window.

The direct prediction operator obtained, through the linear combination of past values, predicts the next point with the lowest error (Montenegro, 1996) and, in terms of Least Square Method (LSM), the prediction error is,

$$e_{a,n} = x_{n+1} \begin{bmatrix} 1 \\ a_n \end{bmatrix} \tag{8}$$

where, $[1\ a_n^t]$ is the direct prediction error operator (PEO) and,

$$\begin{bmatrix} x_n & \dots & x_0 \\ x_{n-1} & \dots & x_1 \\ \vdots & \vdots & \vdots \\ x_{m-1} & \dots & x_{m-n-1} \end{bmatrix} \tag{9}$$

is the matrix corresponding to the entry signal, x_t, with length m.

The expanded NEs are,

$$\begin{bmatrix} x_{n+1}^t & x_{n+1} \end{bmatrix} \begin{bmatrix} 1 \\ a_n \end{bmatrix} = C_{a,n} \begin{bmatrix} 1 \\ a_n \end{bmatrix} = \begin{bmatrix} E_{a,n} \\ 0_n \end{bmatrix} \quad (10)$$

It is known that $e_{b,n}$ is the error vector associated with reverse PEO, then

$$e_{b,n} = x_{n+1} \begin{bmatrix} b_n \\ 1 \end{bmatrix} \quad (11)$$

Similarly,

$$\begin{bmatrix} x_{n+1}^t & x_{n+1} \end{bmatrix} \begin{bmatrix} b_n \\ 1 \end{bmatrix} = C_{b,n} \begin{bmatrix} b_n \\ 1 \end{bmatrix} = \begin{bmatrix} 0_n \\ E_{b,n} \end{bmatrix} \quad (12)$$

From (10) and (12), it is observed that $C_{a,n} = C_{b,n}$ and that their elements are a function of the number of coefficients (n) of the prediction error operator. Thus, making $C_n = C_{a,n} = C_{b,n}$, it is possible to represent equations (10) and (12) in a single matrix,

$$C_n \begin{bmatrix} 1 & b_n \\ a_n & 1 \end{bmatrix} = \begin{bmatrix} E_{a,n} & 0_n \\ 0_n & E_{b,n} \end{bmatrix} \quad (13)$$

The Morf algorithm solves the two equations shown in (13).

The predictive adaptive Morf deconvolution uses sliding windows that preserve data amplitude for the given time interval, similar to the adaptive WL windows. However, the data outside the window are not assumed to be null.

Using the principles of the Morph algorithm, Porsani (1991) developed an adaptive algorithm that updates the window prediction filter to be solution of the next window using arbitrary prediction ($L > 1$). This algorithm associates the algebraic relations of the NEs matrix with the subsequent windows, allowing the attenuation of short-period multiple reflection events.

The adaptive algorithm solves efficiently and exactly the NEs for each position of the sliding window over time, contrary to the NEs with Toeplitz structure that are resolved through the LR, where the prediction error operator is not the exact solution of the NEs.

APPLICATION AND RESULTS

The deconvolution methods were tested in the 214-0266 seismic line acquired in the Jequitinhonha Basin, available at the CPGG-UFBA database. The parameters, number of coefficients (N) and distance of prediction (L) used in the deconvolution methods were $N = 25$ and $L = 5$ samples, respectively.

The following steps were used to process the data:

- Preprocessing
- Bandpass Filtering
- Organization in Common Offset Families
- Adaptive Deconvolution
- Organization in Common Mid Point Families
- Velocity analysis
- NMO Correction + mute
- Stacking

Application of the WLAPD

The data were organized in Common Mid Point (CMP) families to apply the WL adaptive deconvolution. Figure 1 shows the division of the traces of CMP in four windows fixed in time.

Figure 5(b) shows the good results that were obtained using the parameters described above. This figure shows that the reverberations seen throughout the CMP, especially in the shorter offsets, were attenuated. The events are better defined and compressed in (b) than in (a).

Figure 2 shows the preliminary stacked seismic section without the filtering of multiples. In the shallow water region, the figure shows that the reflections are masked by short-period multiples, making it difficult to distinguish accurately the reflections of interest.

The velocity analysis is performed again after applying the WL filter, and the end result is shown in Figure 3. The comparison of the stacked section with the preliminary section shows a great attenuation of short-period multiples, and consequent enhancement of the reflections of interest.

Application of the MPAPD

The Morf-Porsani adaptive predictive deconvolution was applied to the data organized in common offset families and the deconvolution was performed in different size windows as shown in Figure 4. There are two windows of deconvolution to each trace, $J_{(i)}, i = 1, \ldots, 11$ and J_m. The window $J_{(i)}$ is the initial deconvolution window; the value of the number of samples of this window varies for each trace along. Due to this variation, eleven coordinates corresponding to the trace and number of samples were chosen to interpolate these values for all traces of the panel allowing the initial window to vary. The value of J_m window does not vary, however, for the system to be stable, the window has to be greater than $(2 \times N) + 2$, where N is the number of coefficients of the filter. The window J_m is mobile and it will be displaced sample by sample along the trace to obtain a filter for each window position.

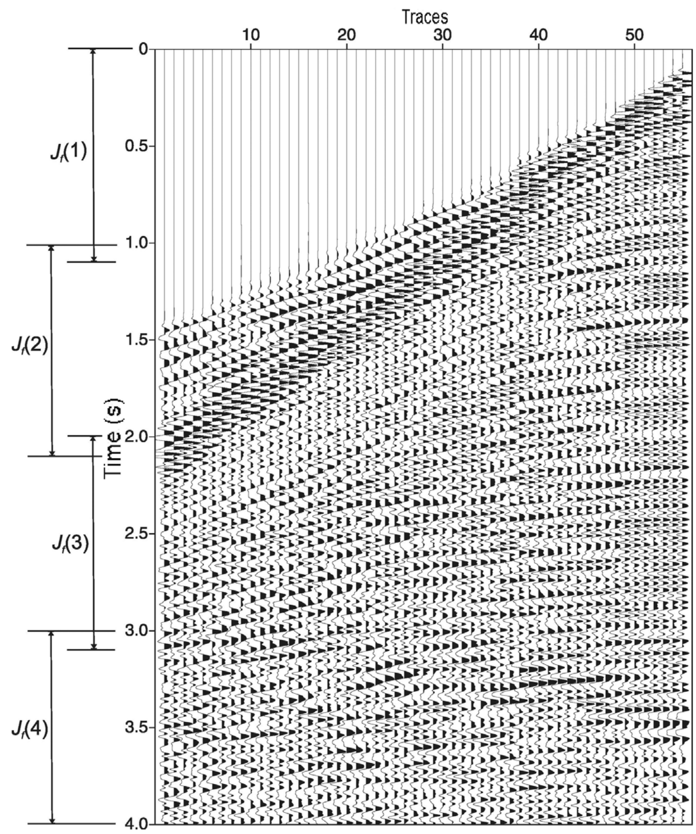

Figure 1 – Windows in time $J_{(i)}, i = 1, 2, 3, 4$, used in WLAPD application.

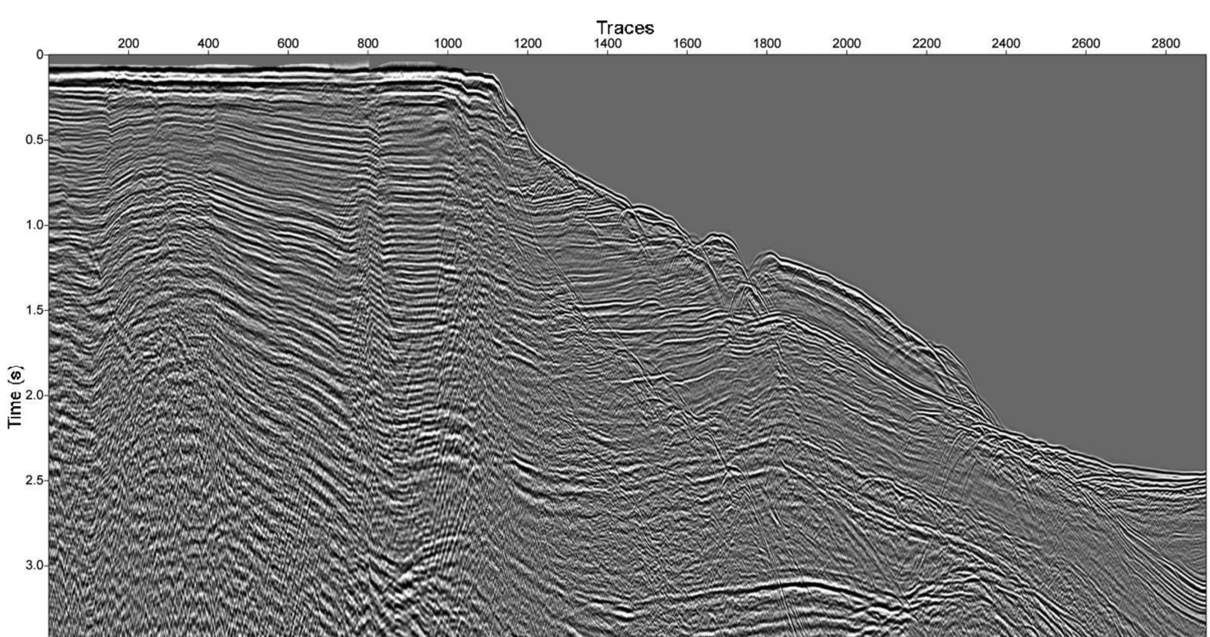

Figure 2 – Preliminary stacked seismic section.

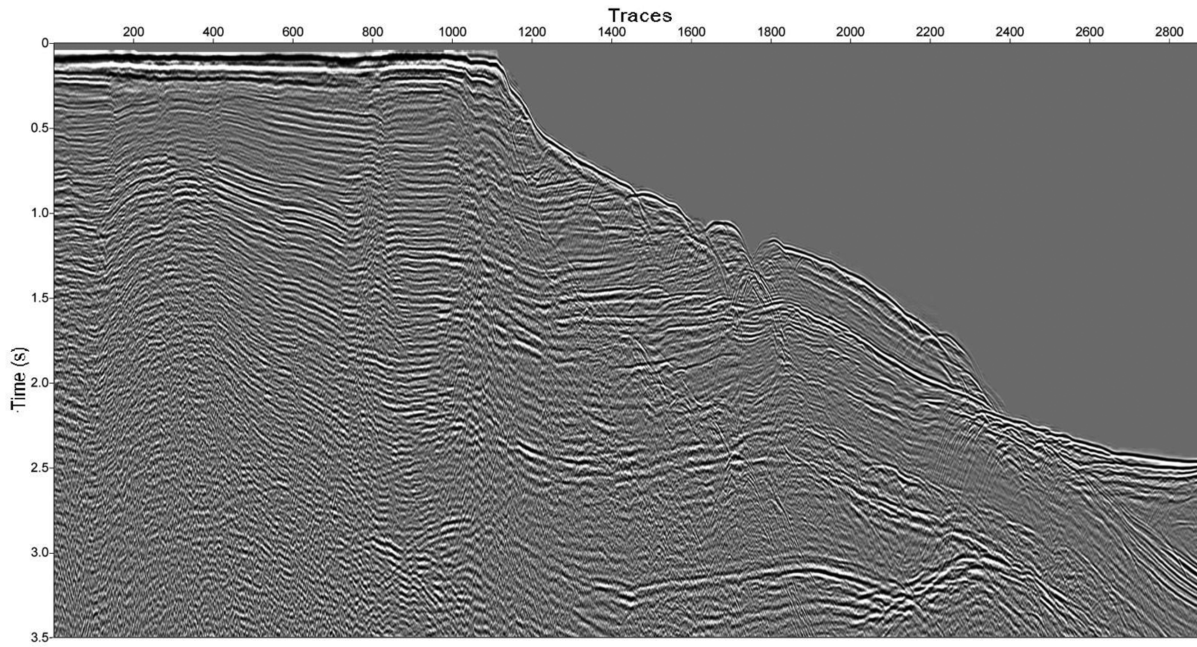

Figure 3 – Stacked section after applying the WLAPD.

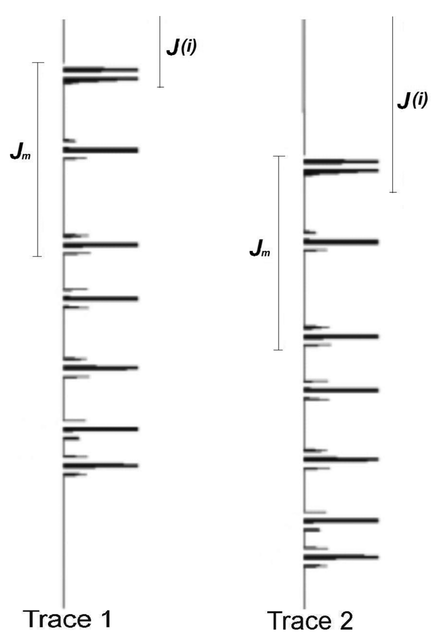

Figure 4 – Schematics showing the relationship between the initial deconvolution window $J_{(i)}, i = 1, \ldots, 11$ and the mobile window J_m.

The filtering of multiples was effective enough with the method of Morf-Porsani adaptive deconvolution. The short-period multiples related with the reverberation of the seismic wave in the shallow water region were attenuated satisfactorily, despite some assumptions of the deconvolution method regarding the suppression of multiples.

Figure 5(c) illustrates the application of the MPAPD in CMP. The good attenuation of the reverberations present in the data can be seen when compared to the original CMP (Fig. 5(a)).

Figure 6 illustrates the stacked seismic section obtained by applying the Morf-Porsani adaptive predictive deconvolution. The result is better than that obtained by the WL method. Some events are better defined than previously, while the multiples were better suppressed. Reflectors of interest are observed approximately after 1.0 s, which could not be seen before the filtering. The reflector at 0.5 s became clearer and it is possible to observe better its continuity. There was also a visible improvement of the image in the region of faults.

The parameters used were defined to improve the image in the shallow water region, which has short-period multiples with features distinct than the multiples present in the break of slope. Therefore, in the deeper water region, the section lost some quality.

CONCLUSIONS

The predictive adaptive deconvolution methods are a good tool to attenuate short-period multiples.

The WL deconvolution method with 4 fixed windows yielded good results. The window size should be carefully defined due to the method's premise that the pulse is stationary, and the size chosen attended the method requirements.

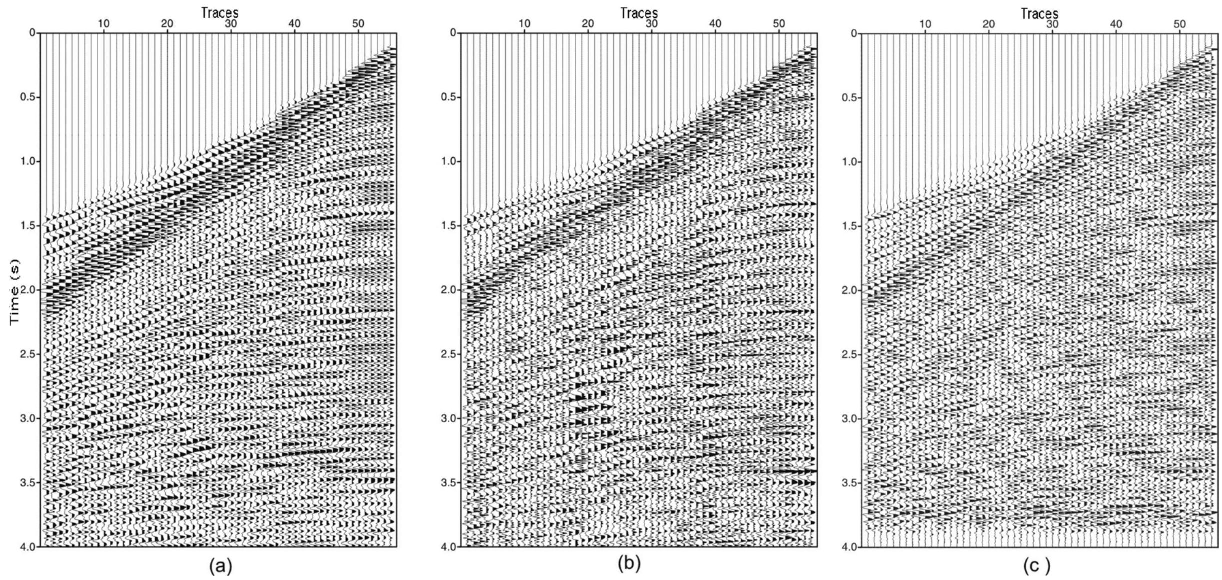

Figure 5 – CMP 298 section (a) original, (b) after applying the WLAPD, and (c) after applying the MPAPD.

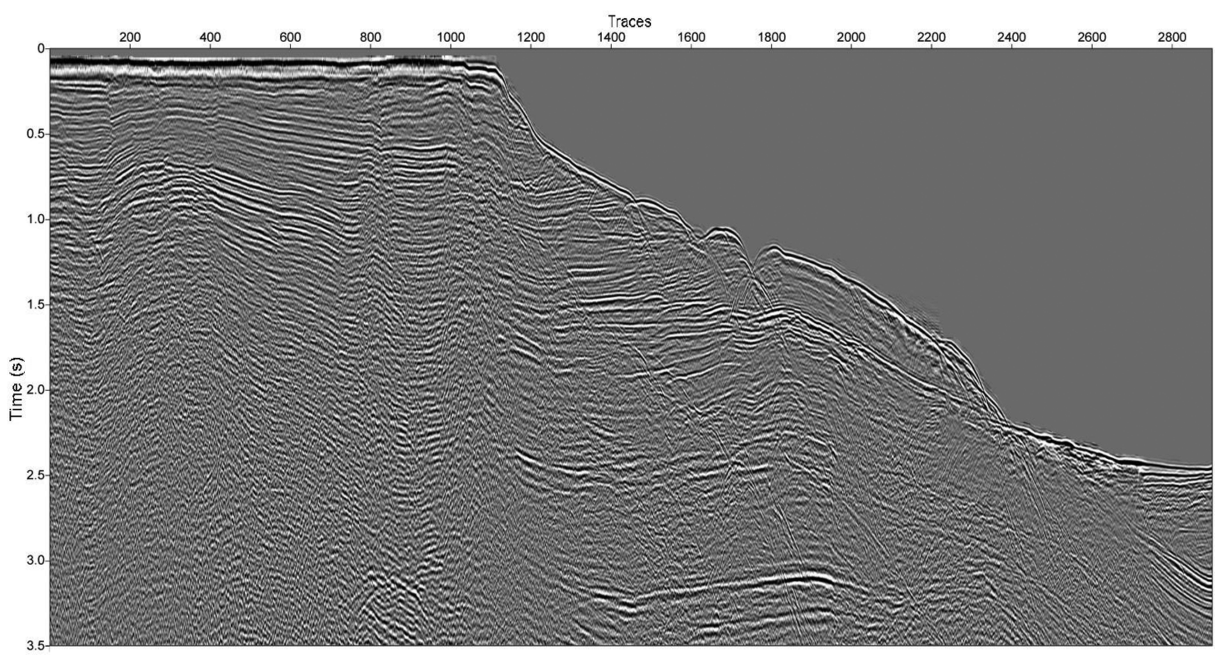

Figure 6 – Stacked section after applying the MPAPD.

The choice of number of filter coefficients and the mobile window length used in the Morf-Porsani adaptive deconvolution influences the quality of the results obtained. The smaller the filter and the window, the less effective is the algorithm. The best results were obtained for 25 and 5 samples, respectively. These values used in the method of Morf-Porsani adaptive deconvolution were able to suppress and attenuate the short-period multiples efficiently, enhancing the primary reflections, and enabling an even better interpretation of the obtained seismic-stratigraphic section.

The deconvolution method is already used in the industry of seismic data processing. Therefore, the technique of adaptive predictive deconvolution can be further explored to improve the existing methods, and become of great value to improve the subsurface images.

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NOTES ABOUT THE AUTHORS

Silmara Lorena dos Reis Oliveira. Bachelor degree in Geophysics from UFBA, 2009. Areas of interest: seismic data processing.

Rosangela Corrêa Maciel. Bachelor degree in Civil Engineering from UFPA, 1997. Master's degree in Geophysics from UFPA, 2002. Ph.D. in Geophysics from UFBA, 2007. Currently, works as a professor in the Geophysics Department of the Universidade Federal do Rio Grande do Norte. Since 2009, works as a Researcher/Partner of the Petroleum Geophysics INCT/CNPq Project. Has experience in Geosciences, focusing on Applied Geophysics, acting on the following topics: seismic processing, multiples suppression, multi-channel deconvolution, CRS stacking and filtering methods.

Michelângelo Gomes da Silva. Bachelor degree in Surveying Engineering from the EEA, 2001. Master in Petroleum Exploration Geophysics from UFBA, 2004. From 2004 to 2006, worked as a researcher at CNPq-UFBA. Professional experience as a geophysicist of seismic processing in the ANP-UFBA Projects from 2006 to date. Since 2009, works as a Researcher/Partner of the Petroleum Geophysics INCT/CNPq Project. The main areas of interest are filtering methods, seismic reflection data processing and seismic interpretation.

Milton José Porsani. Bachelor degree in Geology from USP, 1976. Master's degree in Geophysics from UFPA, 1981. Ph.D. in Geophysics from UFBA, 1986. From 1986 to the present, works as Researcher at CPGG-UFBA. Post-doctorate in Geophysics, Institute for Geophysics at University of Texas at Austin, USA, September/1992 to October/1993. Professor of the Geophysics Department, GEO-UFBA (1990). Professor of Petroleum Exploration (2000). Researcher 1A CNPq. Coordinator of Oil Exploration Program at CPGG-UFBA. Since 2009, is the coordinator of the INCT Project Petroleum Geophysics/CNPq. Areas of interest: development of mono and multi-channel filtering methods and algorithms, seismic data processing, inversion of geophysical data. Member of SEG, AGU, EAGE and SBGf.