



Preconditioning and denoising prestack onshore seismic data via 5D reconstruction: application to 3D data from the Parnaíba basin

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Abstract

Seismic data reconstruction has gained popularity as a tool to precondition seismic gathers prior to migration and prior to Amplitude-versus-Offset or Amplitude-versus-Azimuth inversion schemes that require preservation of amplitudes with high-fidelity. We center our study on the application of Minimum Weighted Norm Interpolation to the problem of reconstructing data from the Parnaíba Basin, Brazil. Data from this region are particularly problematic because near surface conditions in the area lead to gathers that are severely contaminated by coherent and incoherent noise. Processing these gathers is a challenge. This is particularly true when one needs to estimate subtle structural information to assist the discovery and management of reservoirs of hydrocarbons. In this type of environment, interpolation should be planned as an essential part of preconditioning processing flows.

We compare stacks and partial stacks before and after 5D reconstruction and conclude that 5D reconstruction should to be considered as an integral part of seismic processing flows for onshore surveys in the region.

Introduction

Seismic data 5D reconstruction by means of Fourier synthesis techniques has become a standard tool for preconditioning seismic gathers. The main goal of 5D reconstruction (sometimes called 5D interpolation) is to homogenize fold and to reconstruct weak coherent signals of significance to interpreters.

In essence, one poses seismic data reconstruction as an inverse problem. The Fourier coefficients that synthesize seismic observations are the unknown of the inverse problem. First we must retrieve the Fourier coefficients from the available observations. Then, the estimated Fourier coefficients are used to synthesize data at unobserved spatial positions. The retrieval of the Fourier coefficients from incomplete seismic data is a problem that has been addressed by different methods. For instance, Duijndam et al. (1999) solved the reconstruction problem by means of a band-limited Fourier inversion. Likewise, Sacchi et al. (1988) introduced sparsity in the formulation of the inversion of the Fourier coefficients that

synthesize the data in terms of plane waves in the f - x domain. Li (2004) and Liu and Sacchi (2004) introduced 5D seismic data reconstruction via Minimum Weighted Norm Interpolation (MWNI). The latter is a method that incorporates simplicity constraints in the Fourier coefficients that are used to model the seismic data. Similarly, Xu et al. (2005) proposed a Fourier reconstruction method named Anti-leakage Fourier transform (ALFT) that is based on a greedy algorithm that imposes simplicity (or sparsity) in the distributing of the Fourier coefficients that synthesize the seismic data. Under this category of methods, we can also mention Matching Pursuit (MP) interpolation (Schonewille et al., 2009; Ozemir et al., 2008), Projection onto Convex set reconstruction (POCS) (Abma and Kabir, 2006) and Fourier reconstruction via sparse inversion (Zwartjes and Gisolf, 2007)

The aforementioned techniques are utilized to reconstruct seismic data that depends on one or more spatial dimensions. In general, these methods are used to cope with the problem of seismic data regularization in mid-point offset-domain. Several authors have investigated the applicability of MWNI to real data (Trad, 2009; Jin 2010, Chiu 2014) and have also discussed the limitations of the method (Cary, 2011). Finally, it should be mentioned that Hunt et al. (2010) investigated the impact of MWNI on AVO studies.

Fourier reconstruction methods such as MWNI, ALFT, MP, POCS etc. have been predominantly envisioned to regularize fold. In general, these methods assume data that are irregularly distributed on an input grid and reconstruction algorithms are adopted to populate data into grid points with missing observations. On the other hand, interpolation of regularly sampled data, as a mean to increase trace density on one or more spatial dimensions, is often tackled by techniques such as FX prediction filtering interpolation (Spitz, 1991; Porsani, 1999) and FK interpolation (Gulunay, 2003).

In this paper we consider the application of MWNI to reconstruct a seismic volume acquired via an orthogonal acquisition in the Parnaíba Basin. Imaging in the area is quite important because interpreters must make an effort to delineate the top and the base of intrusive rocks in order to define crucial areas of accumulation of hydrocarbons. The horizontal variation of the velocities is observed mainly in upper levels where the Cretaceous sediments are deposited. In the upper portion of the data a low velocity zone (LVZ) usually occurs in the area. The LVZ is made up of weathering layers and/or unconsolidated sediments deposited over an erosive unconformity. The LVZ generates several kinds of surface and random noises (ground roll, air blast, spikes, bursts,

reverberations, etc.), which must be attenuated during the seismic processing.

Theory

Consider a 5D seismic data volume $D(f,x,y,h,a)$ where the variable f indicates temporal frequency. The spatial variables could indicate, for instance, inline-midpoint (x), cross-line midpoint (y), offset (h) and azimuth (a). The spatial data can be projected onto a regular grid via a simple binning process. In this case, the seismic volume can be identified via $D(f,i_1,i_2,i_3,i_4)$ where $i_k=1..N_k$ indicates the index for the spatial variable k and N_k is the total number of bins for the k -th spatial coordinate. Clearly, not all grid points will contain an observation. In other words, a given midpoint position (i_1,i_2) will not contain all azimuths and offsets. The ideal data is the volume $D(f,i_1,i_2,i_3,i_4)$ where all spatial positions $i_k=1..N_k$ are observed. In general, not all offset and azimuths exist in the observed volume. The latter can be written in mathematical form as follows

$$D^{\text{obs}}(f,i_1,i_2,i_3,i_4)=T(i_1,i_2,i_3,i_4) D(f,i_1,i_2,i_3,i_4), \quad (1)$$

where $T(i_1,i_2,i_3,i_4)$ is the so called sampling operator that takes the following values $T(i_1,i_2,i_3,i_4)=0$ if bin i_1,i_2,i_3,i_4 is empty and $T(i_1,i_2,i_3,i_4)=1$ if bin i_1,i_2,i_3,i_4 contains an observation. Clearly equation (1) is an inverse problem where one attempts to estimate the complete data $D(f,i_1,i_2,i_3,i_4)$ from a set of incomplete observations given by $D^{\text{obs}}(f,i_1,i_2,i_3,i_4)$. The problem is underdetermined and therefore, an infinity number of solutions exist (Liu and Sacchi, 2004). In the MWNI algorithm rather than attempting to estimate the reconstructed data $D(f,i_1,i_2,i_3,i_4)$ directly from observations, one estimates the Fourier coefficients, $c(f, k_1,k_2,k_3,k_4)$, that model the data

$$D(f,i_1,i_2,i_3,i_4) = \text{IFT}\{c(f, k_1,k_2,k_3,k_4)\} \quad (2)$$

where IFT indicates the inverse Fourier Transform. Putting it all together, MWNI estimates $c(f,k_1,k_2,k_3,k_4)$ directly from $D^{\text{obs}}(f,i_1,i_2,i_3,i_4)$ and then uses the estimated Fourier coefficients to synthesize the ideal data $D(f,i_1,i_2,i_3,i_4)$. The mathematical procedure to estimate the final solution uses the Iterative Reweighted Least-Squares method. Details of the algorithm can be found in Liu (2004).

Synthetic example

The MWNI algorithm is controlled by one trade-off parameter that permits us to define the degree of fitting of the reconstructed traces to the original data. Contrary to popular belief, a good interpolation method should never fit the data exactly. Recorded data contains noise and one must tune the reconstruction method to simultaneously reconstruct and denoise the data. In other words, overfitting noisy observations must be avoided.

Figure 1 shows a slice of a 3D cube containing three dips that was decimated and then reconstructed. The cube size is 60 X 60 in space with 200 time samples. A Ricker wavelet of central frequency of 60Hz was used to model the dipping events.

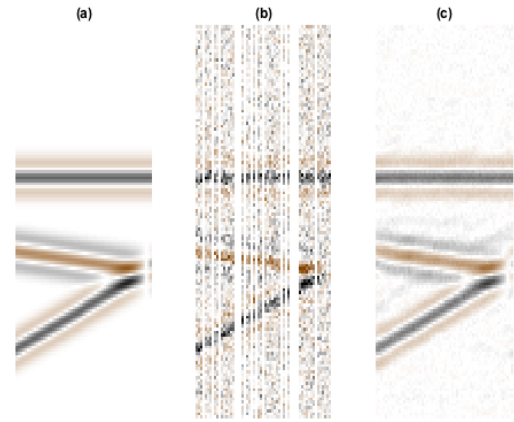


Figure 1. a) Slice of 3D cube. b) Data after decimation and contamination by noise (SNR=2). c) Reconstructed data.

Figure 1a is the original uncorrupted slice of the 3D cube. Figure 1b was extracted after decimating the 3D cube and adding noise. For the decimation, we remove 40% of the traces randomly. The data was contaminated with white Gaussian to simulate a signal with SNR=2. Figure 3c demonstrates the ability of MWNI to reconstruct and denoise the data simultaneously. Figure 2 displays the average amplitude spectra of the data in Figure 1. Clearly, the amplitude spectra of the uncorrupted and reconstructed data are almost indistinguishable. From Figure 2, one can confirm that the reconstruction process preserved the frequency content of the original signal.

The MWNI algorithm was applied to a 3D cube. It is important to stress that the method can handle cubes of any dimensions.

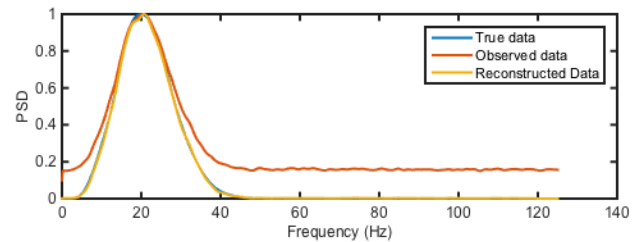


Figure 2. Amplitude of spectra of data displayed in Figure 1.

Field data example

We have applied 5D reconstruction to a data set acquired via explosives in the Parnaiba Basin, northern Brazil. These data correspond to a typical orthogonal survey in the area. Targets in the area are often difficult to image due to severe noise contamination. The latter makes processing this type of data a challenge. Our seismic data processing flow includes

1. Apply field static corrections

2. Geometrical spreading correction
3. Coherent noise attenuation
4. Surface consistent deconvolution
5. Spectral balancing
6. Estimation of stacking velocities
7. NMO correction
8. Residual statics corrections
9. Re-estimation of stacking velocities
10. NMO correction
11. Regularization

The regularization process consisted on

1. Binning into desired 4D spatial grid (inline and crossline midpoints, offset and azimuth)
2. 5D reconstruction via MWNI
3. Generation of partial and full stacks

For comparison purposes, we have also computed the non-regularized 5D volume to form partial and full stacks. In essence, we are interested in comparing stacks and partial stacks before and after 5D reconstruction. Clearly, the reconstructed pre-stack volume should become the input to prestack time or depth migration methods. However, for this particular study and for the time being, we have restricted our analysis to stacks and partial stacks after and before reconstruction.

In this example, we apply MWNI to a 5D cube of data (5D reconstruction). We first binned our survey via the parameters provided in Table 1. Size of the inline and cross-line bins are set by the original geometry. On the other hand, number of offset and azimuths per CMP bin require some careful analysis. In general, a very small bin size in offset and azimuth will produce extremely sparse grids and we might end up not having enough data to run high-quality reconstructions. Our offset and azimuth bin sizes were tuned to yield a 4D spatial grid with about 10-15% of its grid points occupy by traces.

Table 1. 4D spatial grid utilized by MWNI.

	<i>In-line midpoint</i>	<i>Cross-line midpoint</i>	<i>Offset</i>	<i>Azimuth</i>
Number of bins	211	31	32	8
Min	0m	0m	150m	-180°
Max	10500m	750m	3250m	135°

The field data patch of analysis consists of an inline and crossline midpoint swath of 221 x 32 CMPs. Each CMP

contains 32 offsets and 8 azimuths bins, respectively. The swath contains a total of 1674496 grid points ($1674496 = 211 \times 31 \times 32 \times 8$) of which only about 25000 grid points are occupied by traces. In other words, 85% of the 4D spatial grid is empty. This can be observed in Figure 3 where we provide the fold map for the swath. The intensity of color highlights the number of traces per CMP bin irrespectively of offset and azimuth. Each CMP should contain about $256 = 32 \times 8$ traces. However, the fold map shows a maximum fold of 78 traces and a minimum fold of 12 traces.

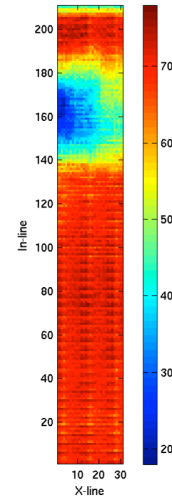


Figure 3. Fold map of the swath used for this study.

Figure 4a shows the data for one CMP gather prior to reconstruction. Figure 4b shows the CMP gather after reconstruction via MWNI. For illustrative purposes, we show one CMP gather but we stress that all the swath is simultaneously reconstructed by MWNI. Continuing with our analysis, Figures 5a and 5b show near offset partial stacks for cross-line 16. The near offset stack was computed by averaging the first 8 offsets and all azimuths. Similarly, Figures 6a and 6b show partial stacks obtained by averaging mid-range offsets before and after reconstruction via MWNI, respectively. The mid-range offset stack was computed by averaging offsets 14-18 and all azimuths. To finalize, we also show partial far-offset stacks in Figures 7a and 7b. The far offset stack was computed by averaging the last 5 offsets (28-32) and all azimuths. Clearly, one could have also stack over a group of azimuths.

The full stacks for cross-line 16 before and after reconstruction via MWNI are portrayed in Figures 8a and 8, respectively.

Conclusions

In many areas of the world, onshore data sets often offer several processing challenges. This particular work

centered on a feasibility study of 5D reconstruction to precondition data from the North Region of Brazil.

We have adopted a Fourier reconstruction method to simultaneously reconstruct and denoise data acquired via an orthogonal survey. We have demonstrated that 5D reconstruction can be adopted to improve the SNR of partial stacks. High-quality partial stacks are essential for processes that require high-fidelity amplitudes such as AVO or AVAz.

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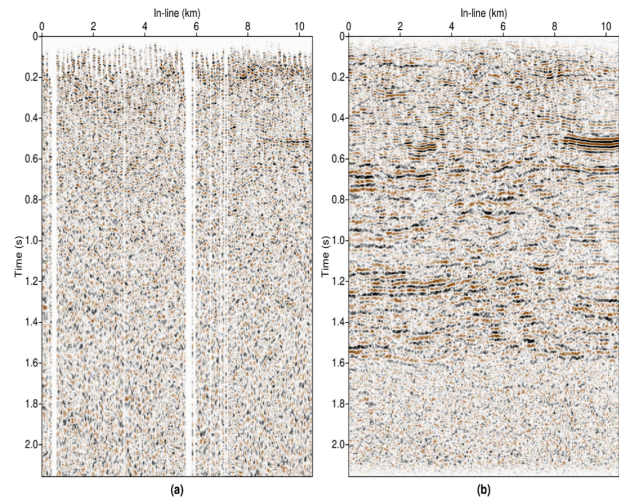


Figure 5. Near-offset stacks. Stack of offset sectors 1 to 8 and all azimuths for cross-line 16. a) Before reconstruction. b) After reconstruction via MWNI.

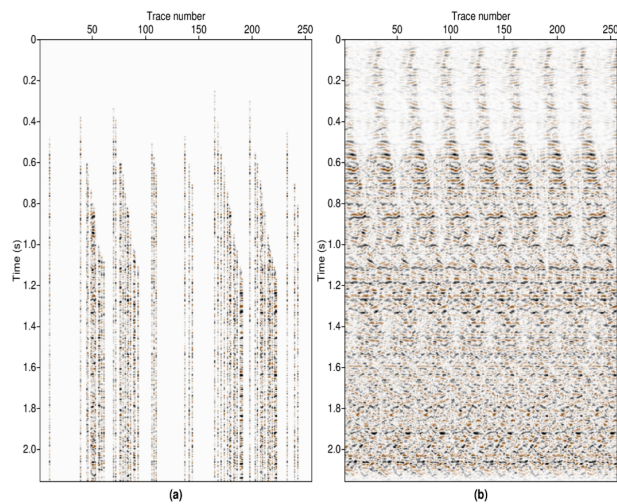


Figure 4. CMP corresponding to x-line 16 and in-line 120 in Figure 1. a) Data prior to regularization. b) Data after 5D reconstruction via MWNI. Horizontal axis is consecutive trace number indexed first by azimuth and then by offset. The data has been binned in 32 offset and 8 azimuth sectors.

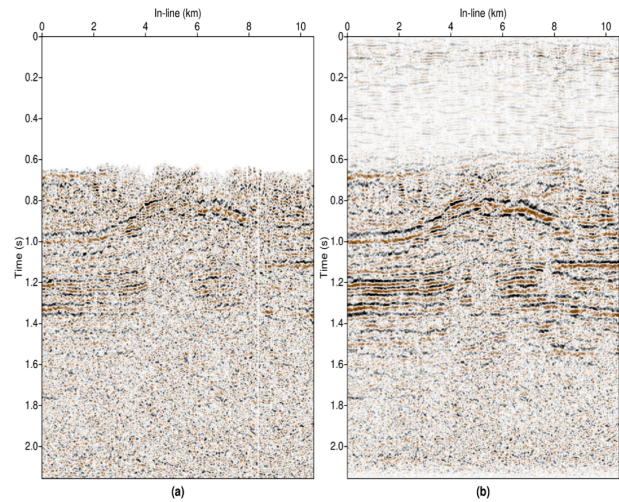


Figure 6. Mid-range offset stack. Stack of offset sectors 14 to 18 and all azimuths for cross-line 16. a) Before reconstruction. b) After reconstruction via MWNI.

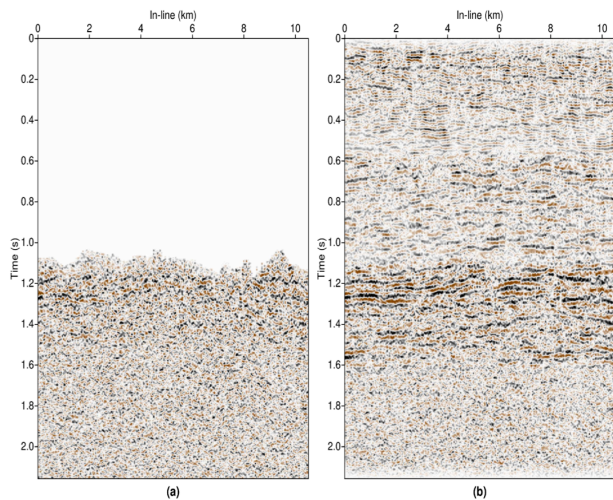


Figure 7. Far offset stack. Stack of offset sectors 28 to 32 and all azimuths for cross-line 16. a) Before reconstruction. b) After reconstruction via MWNI.

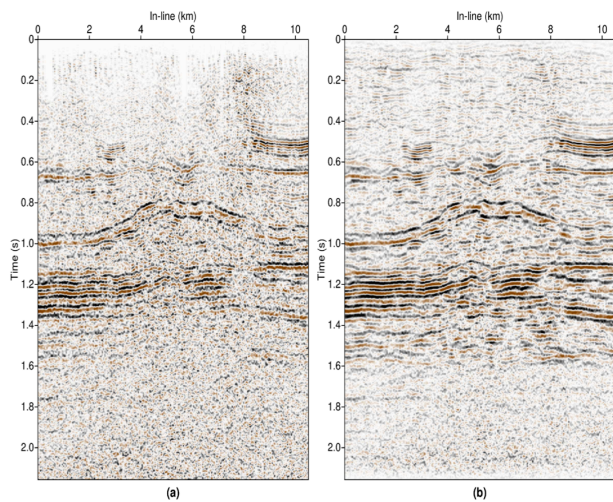


Figure 8. Stack of all offset and azimuths for cross-line 16. a) Before reconstruction. b) After reconstruction.

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