Case Example Showing the Effect of Prior 2D Interpolation on 5D ALFT Prestack Regularization

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Summary

Multichannel interpolation in the last decade has become a standard processing routine to regularize seismic data by filling in missing traces due to acquisition and cost contraints so as to improve the quality of the migration product by reducing aliasing and other artifacts. As with other conventional 5D interpolation methods, the anit-leakage Fourier transform (ALFT) technique also suffers from aliasing effects when directly applied to sparse datasets or simply when upsampling to smaller bin sizes. This paper shows with the aid of a 3D dataset from South Texas, that by applying a prior 2D interpolation based on Spitz (1991) and Porsani (1999) for the case of upsampling, the 5D ALFT interpolation does a better job before and after prestack time migration (PSTM) with the uplift more drastic in the shallow parts of the section. The deeper part of the section where the data is structurally complex also shows improvement by cascading the 2D and 5D interpolations but the uplift is less conspicuous than that seen in the shallow part of the data with flat geology.

Introduction

5D prestack trace interpolation is now widely accepted in the industry as a necessary step in seismic data processing. The processing algorithms for example migration, expects input data that are regularized in different dimensions such as inline, crossline, offset, azimuth and time for optimal performance, effective noise or artifact cancellation and solving aliasing problems.

The other benefits of multichannel prestack trace interpolation are:

- Reduction of acquisition footprints
- Better reflection continuity especially the shallow events and overall increased signal to noise ratio
- Improved multiple attenuation (Hunt et al., 2010b) and marine deghosting (Rickett, 2014)
- Improved AVO analysis (Hunt et al., 2010a)
- Improved AVAZ analysis (Downton et al., 2010)
- Improved reservoir attribute analysis (Chopra and Marfurt, 2013)

Chiu et al. (2013) and Chiu (2014) have beautifully summarized the different 5D conventional interpolation methods currently used in the industry. These methods are:

- The anti-leakage Fourier transform (ALFT) method (Xu et al., 2005, 2010)
- The projection onto convex sets (POCS) method (Abmar and Kabir, 2006)
- The minimum weighted norm interpolation (MWNI) method (Liu and Sacchi, 2004)
- The prediction filter method (Naghizadeh and Sacchi, 2007)
- The rank-reduction-based method (Trickett et al., 2010 and Chen et al., 2016)

- The tensor-based method (Kreimer and Sacchi, 2012) and recently
- The least-squares migration-driven method (Verma et al., 2016)

Although these different interpolation methods are very effective in regularizing unaliased data, they all struggle in interpolating regular missing data that are spatially aliased as in the case of upsampling to smaller bin sizes or when interpolating sparse datasets. Different documented attempts have been made to solve or at least minimize the spatial aliasing problems in 5D interpolation. Hermann et al. (2000) have suggested using a low-frequency unaliased solution in MWNI to constrain the high-frequency solution but Cary (2011) has suggested that such approach did not provide enough basis to solve the aliasing problems. As opined by Chiu (2014), the solution provided by Naghizadeh and Sacchi (2007) using a multistep autoregressive approach to solve the aliasing problem is not flexible enough in computing prediction filters when the data has large and irregular gaps.

Chiu (2014) on the other hand has proposed a method to address the aliasing problem in MWNI by using a prior model as constraints. The prior model was constructed by a linear interpolation along dominant dips to produce a regular initial model for the interpolation. Ng et al. (2015) have also proposed a method of 6D interpolation using MWNI where the 6^{th} dimension is the computed angular weights to connect data across all frequency-wavenumbers as a priori model to solve the aliasing problem. Negut et al. (2011), Wang et al. (2011) and Mott et al. (2015) have utilized the method of cascading two algorithms, firstly, a time-domain dip-scan 2D interpolation as a priori model for upsampling and secondarily, the 5D MWNI to fill in random gaps.

This paper shows a similar cascading procedure using two different algorithms from the earlier authors. Firstly, a combination of 2D F-X prediction and half X interpolation algorithm based on Spitz (1991) and Porsani (1999) as a priori model followed by 5D ALFT interpolation based on Xu et al. (2010). This proposed cascading method has the obvious advantage of not requiring a prior knowledge of the true dips and lateral coherence of the seismic events as well as their estimation. In addition, the 5D ALFT interpolation is able to regularize data without snapping the input traces into bin centers thereby minimizing spatial smearing.

Theory and/or Method

The cascading interpolation procedure used in this paper consists firstly of a 2D interpolator based on Spitz (1991) and Porsani (1999). The 2D method relies on the fact that irrespective of the original spatial interval of the input data and without any attempt to determine the true dip, the linear events present in a section made of equally spaced traces can be interpolated. Through prediction in the F-X domain, the missing traces are expressed as the output of a linear equation. By solving the linear equation (using the half-step prediction filter) whose coefficients depend only on the spectrum of the spatial prediction filter of the input traces, the interpolation operator is estimated.

The second part of the interpolation involves the 5D ALFT regularization. The 5D algorithm maps the input 3D data into the Fourier domain using irregular discreet Fourier transform (Xu et al., 2010), estimates the Fourier coefficients with the anti-leakage Fourier transfer with reduced wavenumber leakage and then outputs the regularized data.

Example

The 3D data example used for the tests was acquired in South Texas in USA. The north-south receiver lines are spaced 1320 feet apart and the east-west shot lines are spaced 880 feet apart. Distance between receivers was 110 feet while the distance between shots was 220 feet. The natural bin size therefore is 55 by 110 feet. In order to maintain a square bin size of 55 by 55 feet and minimize aliasing effects, a reasonable approach as described above is to upsample the crossline by adding extra shots between the existing shot grid using the 2D interpolator and then follow it up with a 5D interpolator to fill random gaps in the data. A second test was also run using only the 5D interpolator to both upsample and fill random gaps in the data and the results compared. Figures 1 to 4 show the stack and timeslice comparisons before PSTM. The improved stack sections and timeslices are obviously the one with the 2D and 5D cascaded interpolation as the issue of aliasing and sparseness of the data are better handled.

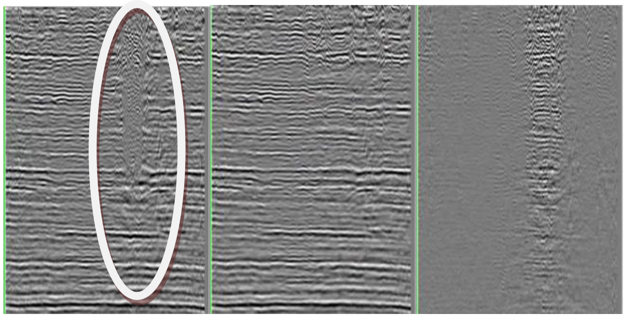

Figure 1: Left is the 5D only interpolated stack in the shallow, middle is the cascaded 2D and 5D interpolated stack section and far right is the difference. The cascaded interpolation shows obvious improvement as it better handles the aliasing and sparseness as highlighted.

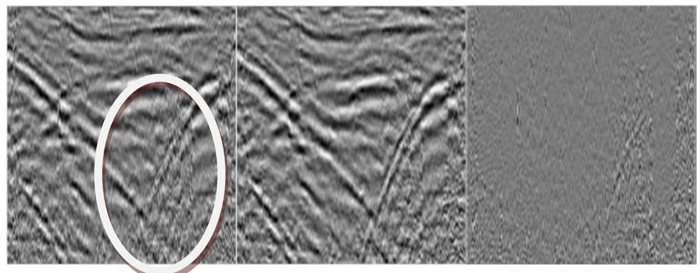

Figure 2: Left is the 5D only interpolated stack in the deep, middle is the cascaded 2D and 5D interpolated stack section and far right is the difference. The cascaded interpolation better handles the aliasing effects as highlighted. The difference is less dramatic when compared to the difference plot of Figure 1 for the shallow events.

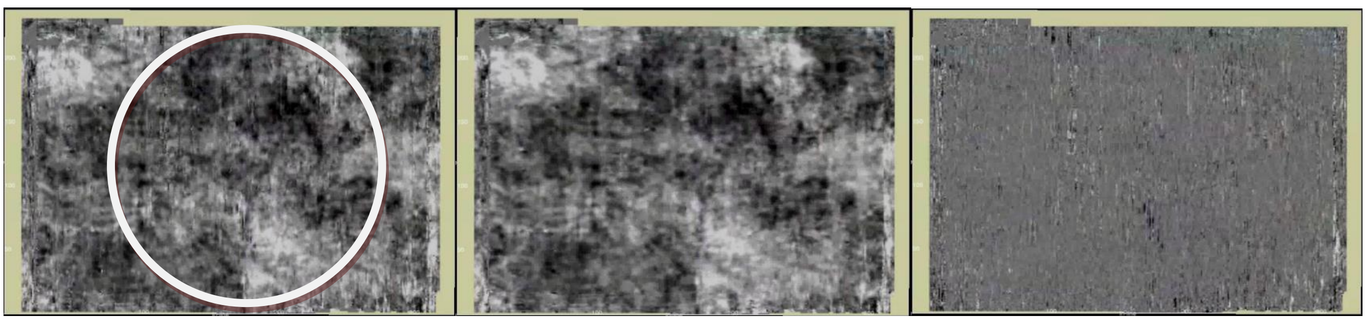

Figure 3: Left is the 5D only interpolated stack timeslice in the shallow, middle is the cascaded 2D and 5D interpolated stack timeslice and far right is the difference. The cascaded interpolation shows a clearer image as it better handles the vertical aliasing/acquisition footprint noise as shown.

We see similar improvement by cascading the two interpolations after PSTM (Figures 5 to 8). As with the stacks and timeslices before PSTM, we also see a marginal improvement of the deeper events after PSTM when compared to the shallow events.

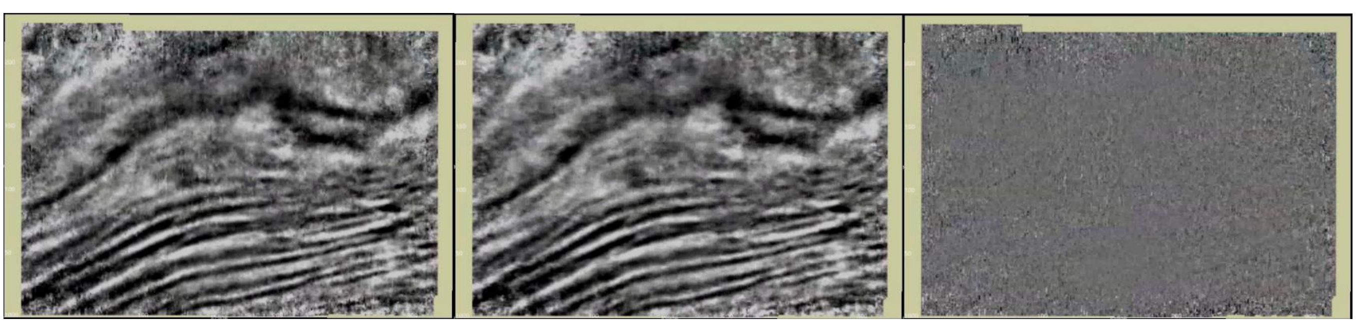

Figure 4: Left is the 5D only interpolated stack timeslice in the deep, middle is the cascaded 2D and 5D interpolated stack timeslice and far right is the difference. The cascaded interpolation shows a clearer/cleaner image as it better handles the aliasing. Compared to the shallow in Figure 3, the improvement of the cascaded interpolation in the deep is less dramatic.

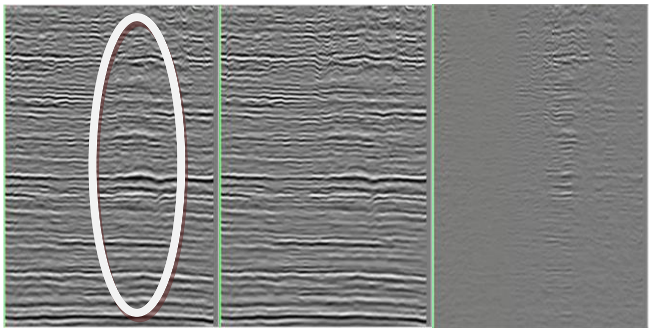

Figure 5: Left is the 5D only interpolated PSTM stack section in the shallow, middle is the cascaded 2D and 5D interpolated PSTM stack section and far right is the difference.
The difference on the far right shows the uplift of the cascaded Interpolation.

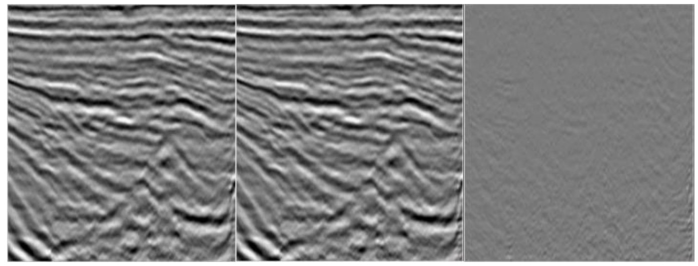

Figure 6: Left is the 5D only interpolated PSTM stack section in the deep, middle is the cascaded 2D and 5D interpolated PSTM stack section and far right is the difference. The difference is marginal when compared to the difference plot of Figure 5.

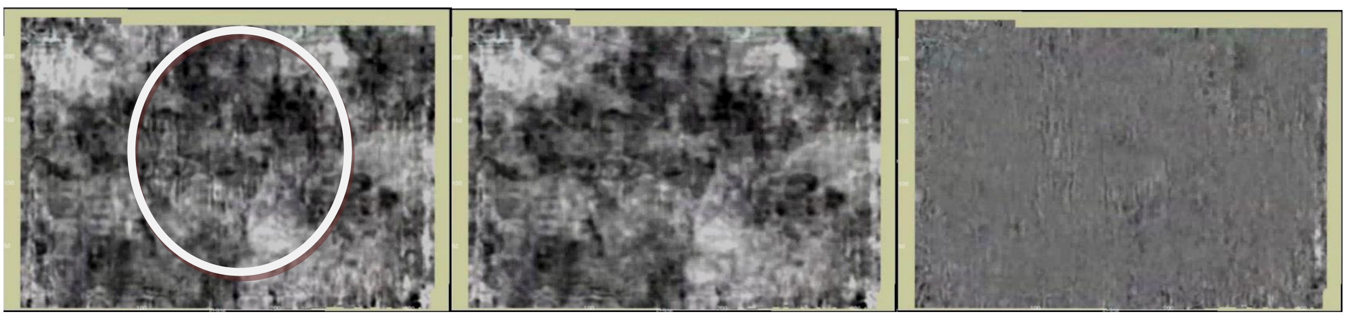

Figure 7: Left is the 5D only interpolated PSTM stack timeslice in the shallow, middle is the cascaded 2D and 5D interpolated PSTM stack timeslice and far right is the difference. The cascaded interpolated timeslice shows a clearer image with less vertical footprint/aliased noise as highlighted.

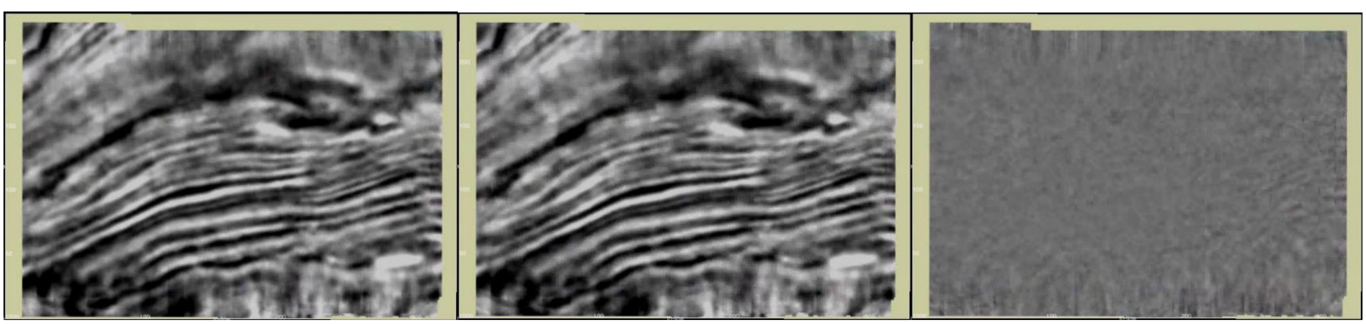

Figure 8: Left is the 5D only interpolated PSTM stack timeslice in the deep, middle is the cascaded 2D and 5D interpolated PSTM stack timeslice and far right is the difference. The cascaded interpolated timeslice shows a cleaner image with less vertical footprint/aliased noise. The vertical footprint/aliased noise shown in the difference plot is less than that seen in Figure 7 for the shallow events.

Conclusions

On this South Texas 3D, the cascaded 2D F-X and 5D ALFT interpolation showed improvement over the 5D ALFT only interpolation. The cascaded interpolation shows an overall clearer and cleaner image with the improvement more pronounced in the shallow parts of the data.

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