

# We N112 01

## Data Reconstruction Using a Six-dimensional Model Space

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# SUMMARY

While 5D data reconstruction has become widespread in recent years, we show that the use of 5D model spaces in some settings may result in sub-optimal handling of structures exhibiting HTI traveltime behaviour. To overcome these problems we propose the use of a 6D model space based on an extension of equations previously used for 3D Radon demultiple. The model is obtained using a sparse solver based on the anti-leakage Fourier transform. Synthetic and real datasets exhibiting HTI anisotropy are used to illustrate the signal preserving benefits of the approach.



#### Introduction

Multi-dimensional data reconstruction has become commonplace in many regions as an effective strategy to increase the signal-to-noise ratio of low fold wide azimuth data and modify spatial sampling prior to imaging. A similar approach may also be used to improve the signal-to-noise ratio of high fold point-source point-receiver data which pre-stack may have high noise levels (Poole, 2011). Algorithms using all four spatial dimensions simultaneously are more consistent than working with lower dimensional subsets of an input dataset.

Many 5D data reconstruction algorithms have been developed which may be based on one of several spatial definitions (e.g. (shot-x, shot-y, receiver-x, receiver-y), (midpoint-x, midpoint-y, offset-x, offset-y), (midpoint-x, midpoint-y, offset, azimuth)). Note that although the input data is five-dimensional, it is only irregularly sampled in four spatial dimensions (the time direction is regularly sampled). Some algorithms assume that input data consists of an irregular coverage on a fixed grid, e.g. minimum weighted norm interpolation (Trad, 2009), projection onto convex sets (Abma and Kabir, 2006), rank reduction (Trickett et al., 2010). Other methods which respect the input sampling more precisely include the non-uniform Fourier transform, and the anti-leakage Fourier transform (Xu et al., 2005, Poole, 2010).

One theme linking several of the algorithms is the use of model domain weights which reduce the impact of irregular input sampling and allow the interpolation of data beyond the point of aliasing. The success of sparseness constraints relies on the model space specification being representative of the behaviour of the input data. Within small space-time windows this is often generally the case where complex structures may be simplified to linear events.

In this paper we introduce the use of a six-dimensional model space to improve the spatial reconstruction of five-dimensional data. We demonstrate the effectiveness of this approach by denoising a dataset exhibiting horizontal transverse anisotropy.

#### Theory

The forward Fourier transform of the recorded data at a single temporal frequency in four irregularly sampled spatial dimensions may be defined as:

$$m(K_x, K_y, K_h, K_\theta) = \sum_{n=1}^{N} w_n d_n e^{2\pi i x_n K_x} e^{2\pi i y_n K_y} e^{2\pi i h_n K_h} e^{2\pi i \theta_n K_\theta}$$
(1)

where *m* is the Fourier transform,  $d_n$  are the input data for one frequency slice,  $x_n$ ,  $y_n$ ,  $h_n$ , and  $\theta_n$  are the recording coordinates of each trace in the midpoint-x, midpoint-y, offset, and azimuth directions respectively, and  $K_x$ ,  $K_y$ ,  $K_h$ , and  $K_\theta$  are wavenumbers in each spatial dimension. The coordinates in the above notation are assumed to be normalized to the range 0 to 1. The integration weights,  $w_n$ , may be derived using Voronoi tessellation and are normalized to sum to unity.

Often the model is derived using spatio-temporal windows within which we consider the data to consist of a number of linear events. While this assumption is generally reasonable in the midpoint-x, midpoint-y, and offset directions, events are not generally linear in the azimuth direction. Although the use of small azimuthal windows may overcome this problem, often this is not possible due to the high variation of sampling in azimuth. One way to overcome this problem is to alleviate the necessity for azimuthal windowing by changing the model parameters to make them more appropriate for the kinematic behavior of the data.

Hugonnet et al. (2008) propose the use of a 4D Radon domain using elliptical parameters and demonstrate its benefits for 3D Radon demultiple in regions exhibiting azimuthal timing variations. We extend equation 1 based on the parameterization of Hugonnet et al. (2008) resulting in a spatially five-dimensional model space as given by equation 2:

$$m(K_x, K_y, Q, R, S) = \sum_{n=1}^{N} w_n d_n e^{2\pi i x_n K_x} e^{2\pi i y_n K_y} e^{2\pi i q_n Q} e^{2\pi i r_n R} e^{2\pi i s_n S}$$
(2)



where  $q_n = h_n^2$ ,  $r_n = h_{xn}^2 - h_{yn}^2$ ,  $s_n = 2h_{xn}h_{yn}$ .  $h_{xn}$  and  $h_{yn}$  relate to the offset of each trace in the x- and y-directions respectively. Q, R, and S relate to parabolic model parameters with dimension time/length<sup>2</sup>.

To reduce spectral leakage and encourage orthogonality of the model parameters, m is derived using an iterative application of equation 2 following the method of Xu et al. (2005). Model parameters are derived one at a time starting with the strongest and working to the weakest. After a model parameter is derived it is inverse transformed to the input positions and subtracted before further parameters are computed.

While the use of a high dimensional model space can increase computational runtimes, it should be noted that the model space is also very sparsely populated. Once the significant regions of the model domain have been identified the transform is not significantly slower than the standard 5D approach.

The model may then be used to reconstruct data at any surface source/receiver location. Denoising may be optionally applied by attenuating energy in the model domain. This may involve attenuating regions of the model space relating to coherent noise or by attenuating the weaker model parameters which relate to background random noise.

#### Synthetic example

We generated a synthetic dataset based on a horizontal layer exhibiting HTI anisotropic travel-time behaviour. The input source and receiver positions were taken from a real dataset. A comparison was made between the data regularisation results using a 5D model space and the proposed 6D model space. A perfect result was generated for comparison by modelling the synthetics on the output positions. The results, shown in Figure 1, illustrate the shortfall of a 5D model space in regions exhibiting strong azimuthal anisotropy. The regularised data at high offsets using a 6D model space are significantly more accurate than the use of a 5D model space, leading to a better match with the perfect synthetic.



*Figure 1*) *CMP* gather comparing data regularisation using 5D and 6D model spaces for an event with strong azimuthal anisotropy.

### Real data example

The following real data example comes from a 3D land dataset acquired in Uganda. The acquisition utilised 100 m shot line spacing and 100 m receiver line spacing. The shot and receiver spacings were 25 m and 12.5 m respectively. This resulted in a stacked dataset with a nominal fold of 84.

Figure 2 compares pre-migration denoising of these data using a 5D model space versus the proposed 6D model space. While we observe a similar level of denoising between the results, it is evident that the 6D algorithm has achieved a small improvement in overall signal preservation. Figure 3 makes the same comparison after stack where the 5D model space is seen to exhibit some cross-hatching noise at the timing of an event with HTI azimuthal anisotropy. The difference using the 6D model shows similar noise attenuation without the cross-hatching.

Common offset vector (COV) data were time migrated following which 6D denoising was employed as pre-processing prior to HTI azimuthal velocity analysis using the method of Davison et al. (2011). The resulting moveout parameters were used to gather flatten the pre-denoise data which is displayed in Figure 4. We observe an overall improvement in gather flatness and improved spatial consistency using the proposed method.



#### Conclusions

We have introduced a 5D data regularisation algorithm using a 6D model space solved iteratively in a similar way to the anti-leakage Fourier transform. Following Hugonnet et al. (2008) the proposed model space is designed to accurately preserve detailed (e.g., HTI) traveltime behaviour which conventional regularisation is ill-equipped to handle. Synthetic and real datasets highlight the beneficial properties of the 6D model definition for preservation of HTI azimuthal anisotropy though improved signal preservation.

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Figure 2) CMP comparison of denoising results using 5D and 6D model spaces.



Figure 3) Stack comparison of denoising results using 5D and 6D model spaces.





b) HTI correction derived from input



c) HTI correction derived from 6D denoise



CIP gather

Outer stack

Figure 4) Post migration HTI velocity analysis before and after denoise using 6D model space.

### References

Abma, R., and Kabir, N. [2006] 3d interpolation of irregular data with a POCS algorithm. *Geophysics*, 71, E91–E97.

Davison, C., Ratcliffe, A., Grion, S., Johnston, R., Duque, C., Neep, J. and Maharramov, M. [2011] Azimuthal velocity uncertainty: estimation and application. 81<sup>st</sup> Annual International Meeting, SEG, Expanded Abstracts.

Hugonnet, P., Boelle, J-L., Mihoub, M. and Herrmann, P. [2009] High resolution 3D parabolic Radon filtering. *71<sup>st</sup> EAGE Conference & Exhibition*, Expanded Abstracts.

Poole, G. [2010] 5D data reconstruction using the anti-leakage Fourier transform. 72nd EAGE Conference & Exhibition, Expanded Abstracts.

Poole, G. [2011] Multi-dimensional coherency driven denoising of irregular data. 73rd EAGE Conference & Exhibition, Expanded Abstracts.

Trad, D. [2009] Five-dimensional interpolation: Recovering from acquisition constraints. *Geophysics*, 74, V123.

Trickett, S.R., Burroughs, L., Milton, A., Walton, L. and Dack, R. [2010] Rank-reduction-based trace interpolation. 80<sup>th</sup> Annual International Meeting, SEG, Expanded Abstracts.

Xu, S., Zhang, Y., Pham, D. and Lambare, G. [2005] Anti-leakage Fourier transform for seismic data Regularization, *Geophysics*, 70, 87-95.