Radon modelling with time-frequency sparseness weights

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Summary

A flexible Radon modelling algorithm using time-frequency sparseness weights is introduced. The method may be used for a number of applications and combines the dealiasing and time resolution benefits of existing methods. Compared with a frequency domain sparseness approach, the proposed method results in improved attenuation of low moveout multiples and better primary preservation. Demultiple results using a North Sea dataset are shown.

Introduction

Multiples generate a high level of contamination in seismic data, masking the true Earth response we aim to record. The contamination may consist of internal multiples within the Earth as well as multiples relating to the free surface. An ever increasing number of demultiple algorithms have been developed to work in various geological settings (see Verschuur, 2006 for a detailed summary). While these techniques provide various levels of success, many datasets still exhibit residual multiples which are often targeted by Radon demultiple.

Radon demultiple (Hampson, 1986) is applied pre-stack either before migration in the common midpoint (CMP) domain or after migration within a common image point gather (CIG). Whichever domain is used, the method targets multiples that have a difference in moveout compared to corrected primary reflections of interest. The method makes a model of the data (generally either parabolic or hyperbolic model domains are used) following which multiples are isolated by muting the primary reflections. The multiples are reverse transformed back to the *x-t* domain following which they are subtracted from the input data.

Radon transforms in deep water settings can be particularly challenging because the multiples are often aliased. Herrmann et al. (2000) introduced a high resolution Radon demultiple strategy based on weighted least squares. Working in the frequency domain, the algorithm began by deriving a low frequency Radon model using least squares inversion. The result for the low frequencies was then used to derive model domain sparseness weights which constrained the Radon model for the higher frequencies, thus resulting in a de-aliasing effect.

Although used less frequently, sparse time domain Radon demultiple allows the benefit of changing sparseness weights in time (Schonewille and Aaron, 2007). While this avoids the necessity for working within temporal windows, the same sparseness weights are used for all frequencies.

We introduce a flexible Radon algorithm utilizing a time-frequency domain model. The strategy allows the use of time-frequency sparseness weights which combine the benefits offered by frequency domain and time domain Radon methods. In addition the method derives Radon domains for a multitude of spatial windows simultaneously to avoid window edge effects.

While described in the context of demultiple the method may be used for other applications. Examples include data regularization and deghosting.

Theory

Based on a parabolic model, the Radon equations may be defined as a summation of model parameters in the frequency domain as follows:

$$d_w(\omega, n) = \sum_{m=1}^{M} a_w(\omega, m) e^{-i\omega q\,(m) h^2(n)} \qquad (1)$$

where ω is the angular frequency, d_w is a spatial window of input data with trace index n, a is the parabolic Radon model with trace index m, q is the parabolic moveout parameter in s.m^{-2}, and h is the offset of a given input trace. The subscript w indicates we are working within a spatial window of data where the events may be approximated by parabolas. Although expressed in the frequency domain, the concept may also be applied in the time domain as described by Trad et al. (2003). In the time domain case the problem becomes much larger because instead of solving a small least squares problem for each frequency slice separately we solve for the full τ-q model in one go.

Instead of working either in the time domain or frequency domain, we propose deriving the Radon model for different octaves in the time-frequency domain simultaneously. Working in this way increases the dimensionality of the model domain. Instead of the model existing in the τ-parabola domain (in the case of time domain Radon), it now exists in the τ-parabola-octave domain. Solved using conjugate gradient inversion, the reverse parabolic stack operators are applied in the frequency domain for efficiency based on the following expression:

$$d_w(\omega, n) = \sum_{m=1}^{M} \left[e^{-i\omega q\,(m) h^2(n)} \sum_{v=1}^{V} a_w(\omega, m, v) \right] \qquad (2)$$

where index v represents the octave number (for example, v = 1 is 2.5 to 5 Hz, v = 2 is 5 to 10 Hz, etc.). For the adjoint

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operation, the right hand summation relates to model duplication and bandpass filtering. Bandpass filter tapers provide some overlap between adjacent octaves.

Once the time-frequency Radon model has been found using least squares inversion, model domain sparseness is implemented using the iteratively reweighted least squares inversion scheme as described by Trad et al. (2003). Sparseness weights are allowed to vary as a function of tau and parabola for all octaves. As in Herrmann et al. (2000), sparseness weights derived on low frequencies are used to prevent aliasing at higher frequencies.

Figure 1 illustrates a model from the inversion for a synthetic dataset based on peg leg multiples associated with water depth 100 m and primary reflection at 3200 m in a North Sea setting. The offset range is 100 m to 6000 m with increment 100 m. The left hand panel shows the input CMP. The right hand displays show time-frequency parabolic Radon displays for L2-norm and the proposed algorithm for parabola range -50 ms to 200 ms moveout. The least squares solution shows a spread of both multiple and primary energy across all parabolas. The proposed method shows much better separation of primary and multiple energy.

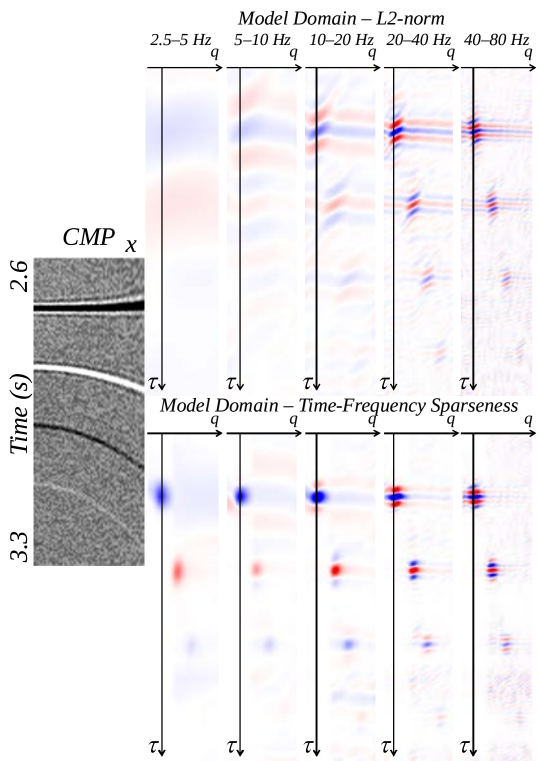

Figure 1: Synthetic CMP gather and associated model domain using L2-norm and the proposed time-frequency sparseness method.

Figure 2 compares Radon demultiple results with a 36 ms cut using L2-norm inversion, inversion using frequency domain sparseness, and inversion using the time-frequency sparseness as proposed. The figure illustrates how the time-frequency method does a better job of attenuating the multiples while preserving primary energy.

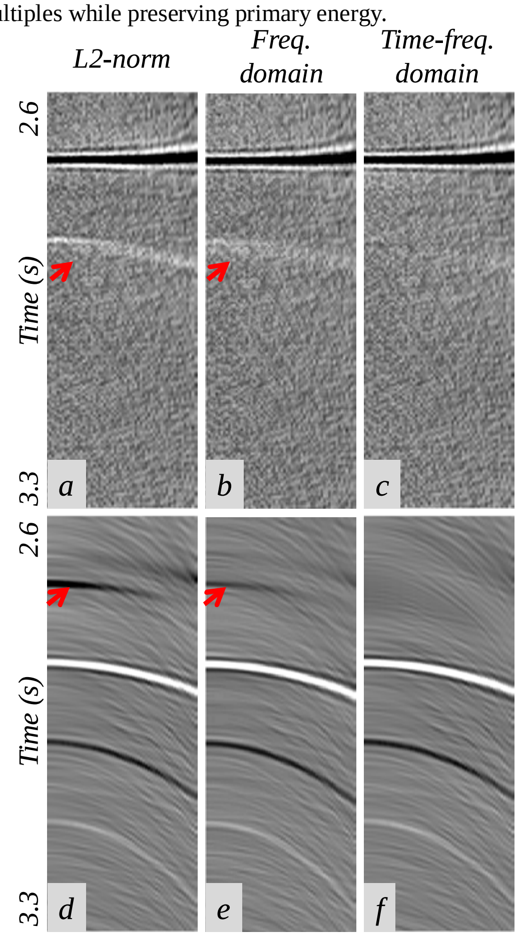

Figure 2: Synthetic CMP gather demultiple results for a) L2-norm solver, b) frequency domain sparseness, and c) time-frequency domain sparseness. Multiple energy removed is given in figures d), e) and f) respectively.

An additional implementation step provides the derivation of time-frequency Radon models for all spatial windows simultaneously. Working on all spatial windows at the same time is one way to limit any imprint relating to spatial windowing. The approach works on the full gather, whilst deriving model domains for each spatial window by including tapering and summation of data relating to each spatial window within the inversion, as shown in the following equation:

$$d(\omega,n) = \sum_{w=1}^{W} s(n,w)\left[\sum_{m=1}^{M}\left[e^{-i\omega q(m)h^2(n)}\sum_{v=1}^{V} a(\omega,m,v,w)\right]\right] \quad (3)$$

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where w is the spatial window index, and the scalar function s relates to the tapering together of the reverse parabolic stack of each spatial window to form the full gather. The scalars may be based on linear, cosine or other methods and should sum to unity for each output trace, n.

While the method is presented in the context of multiple attenuation, it should be recognized that the same principles may also be used for other processing algorithms. Examples include linear noise attenuation, deblending, receiver ghost attenuation and source designature.

Real data example

The real data example comes from a variable depth streamer acquisition (Soubaras, 2010) in the North Sea. The acquisition deployed twin dual-level airgun source arrays (Siliqi et al., 2013) and towed 10 streamers with 100 m separation. Radon demultiple was applied on common image gathers (CIGs) using a parabolic cut of 200 ms. Figure 3 displays CIGs before demultiple, after demultiple using frequency domain sparseness, and after the proposed time-frequency Radon algorithm. While both methods were broadly effective at removing the multiples, the red arrows on the difference sections reveal how the frequency domain approach attenuated some primary energy, the time-frequency less so. Stack sections before demultiple, after frequency domain Radon, and after time-frequency domain Radon are shown in Figure 4. The red arrows highlight some evidence of primary damage in the frequency domain result. The green arrow shows stronger multiple attenuation using the time-frequency Radon method.

Conclusions

We have proposed a time-frequency domain Radon modeling algorithm. The algorithm may be used for a number of applications and the flexibility of sparseness weights in the time-frequency domain allows the benefits of frequency domain and time domain Radon algorithms. The results of the algorithm for demultiple on synthetic and real data illustrate the effectiveness of the approach for improved separation of primary and multiple energy.

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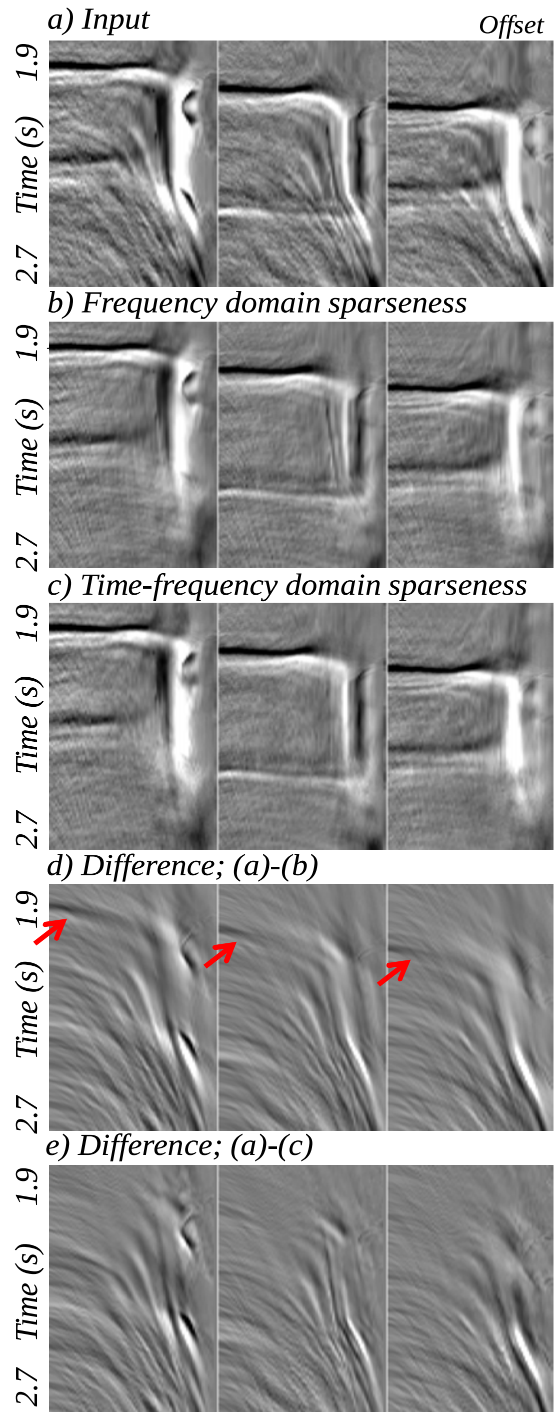

Figure 3: Common image gather Radon demultiple comparison of a) input data, b) Radon demultiple using frequency domain sparseness, c) Radon demultiple with the proposed time-frequency sparseness method, d) frequency domain multiple model (a)-(b), e) time-frequency domain multiple model (a)-(c).

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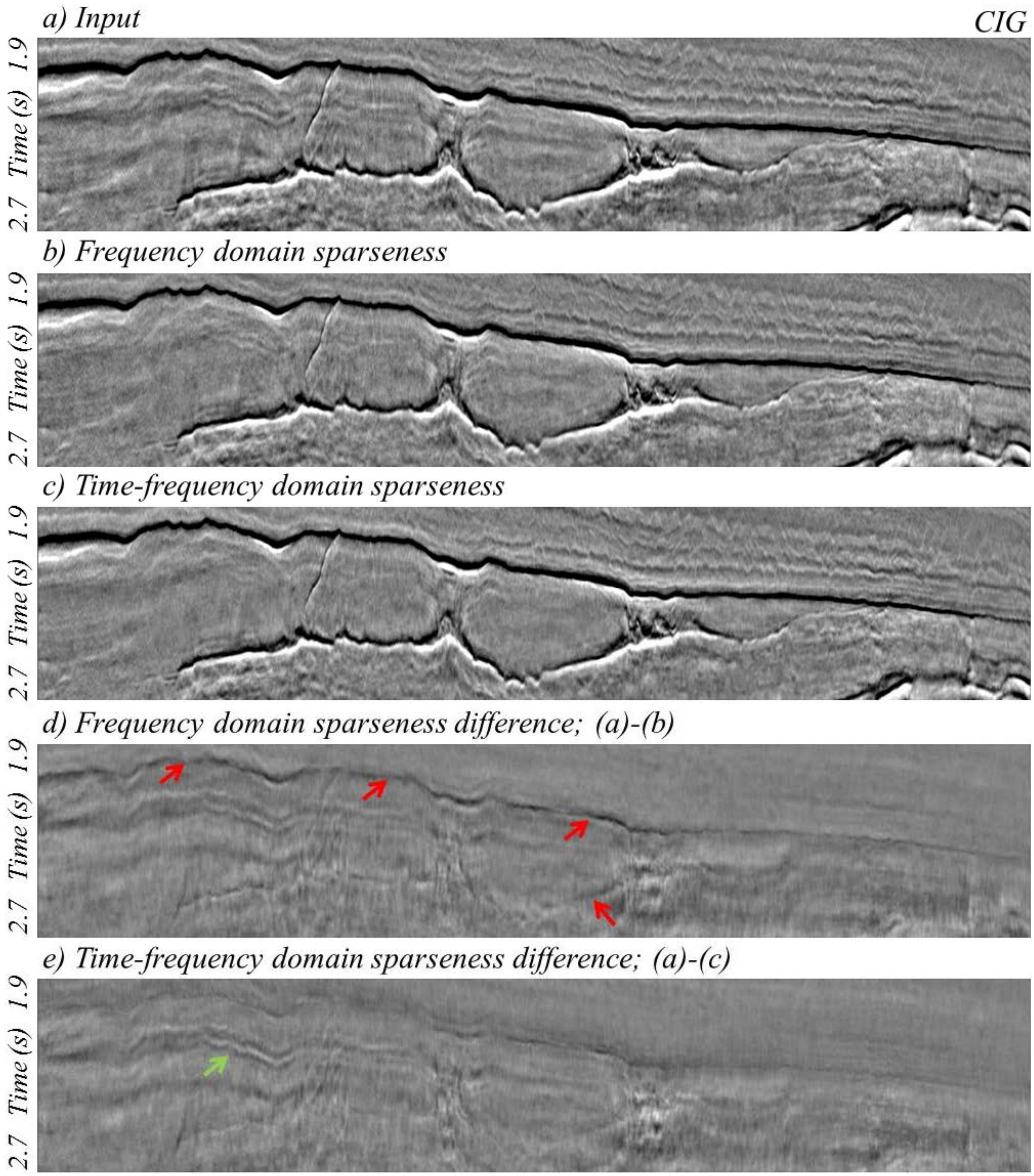

Figure 4: Post-migration stack Radon demultiple comparison of a) input data, b) Radon demultiple using frequency domain sparseness, c) Radon demultiple with the proposed time-frequency sparseness method, d) frequency domain multiple model (a)-(b), e) time-frequency domain multiple model (a)-(c).

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EDITED REFERENCES

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