Seismic Deconvolution Revisited With Curvelet Frames

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Summary

We propose an efficient iterative curvelet-regularized deconvolution algorithm that exploits continuously varying reflections in seismic images. Curvelets are a new multiscale transform that provide sparse representations for images (such as seismic images) that comprise smooth objects separated by piece-wise smooth discontinuities. Our algorithm combines curvelet-based convolutional deconvolution operator inversion with noise regularization that is performed using non-linear curvelet coefficients shrunken by a threshold.

Context

Two different types of deconvolution:
- **wavelet** (deconvolution operator estimated)
- **homomorphic** (deconvolution operator known)

Dispersion (curvelet frames)
- minimum structure/large coefficients
- high-pass
- non-linear curvelet coefficients
- piece-wise smooth discontinuities
- smooth curves with faults and pinch outs
- robust under noise
- optimal for images with a wide range of applications (e.g. migration, primary-multiple separation) as long as:
- the model has intermittent regularity, e.g. reflection on smooth curves with faults and pinch outs.
- the covariance matrix of the noise is near diagonal in curvelet frames.

Curvelet Frames (Guadix & Donoho, 06)

- What are they?
- High-pass filter
- Piece-wise smooth discontinuities in the 2-D O-3-D Fourier domain into anisotropic wavelets of second dyadic order
- Parabolic scaling law (length = width)

Figure 1: Positioning of the 2-D O-3-D Fourier domain

- Curvelet properties:
  - Multi-scale
  - Multi-directional
  - High-anisotropic
  - Localized both in space & frequency

Figure 2: Curvelets & spatial data

In words, we want to deconvolve the data and stabilize the process by imposing a sparseness constraint on the curvelet representation of the model.

2-D Synthetic Examples

- Example 2
  - The true Mermozouse reflectivity is convolved with a Ricker wavelet. White Gaussian noise is added (SNR = 8dB).

Figure 3: Curvelets whose essential support does not overlap but are close in the data do not affect the deconvolution since their frame coefficients correpspond to the structure and are strongly regular in the sense that they maximize large frame coefficients.

Figure 4: Soft thresholding is an element-by-element operation whose result only depends upon the magnitude of the data and the corresponding threshold.

Curvelets & spatial data

Figure 5: Spatial (left) and frequency (right) view of six nested curvelets at different scales and angles for a dataset that comprises curvelets, real curvelets live in two angular wedges symmetric about the zero frequency point.

Figure 6: Wiener-based deconvolution improves the frequency content of the section but suffers from noise and gives rise to ringing effects.

Figure 7: Curvelet-based deconvolution outperforms Wiener-based deconvolution by providing an estimate with a lower ringing effect and highly enhanced continuity along wavetrains.

Figure 8: noisy data

Figure 9: Wiener-based deconvolution improves the frequency content of the section but suffers from noise and gives rise to ringing effects.

Figure 10: Curvelet-based deconvolution outperforms Wiener-based deconvolution by providing an estimate with a lower ringing effect and highly enhanced continuity along wavetrains.

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