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Sparse least-squares reverse time migration using seislets

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ABSTRACT

I propose an approach for sparse least-squares reverse time migration (LSRTM) using seislets as a basis for the reflectivity distribution. This basis is used along with a dip-constrained preconditioner that emphasizes image updates only along prominent dips during the least-squares iterations. These dips can be estimated from the standard migration image or from the gradient using plane-wave destruction filters or structural tensors. Numerical tests on synthetic and field datasets demonstrate the benefits of this method for mitigation of aliasing artifacts and crosstalk noise in multisource least-squares migration.

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1. Introduction

Least-squares migration (LSM) has been shown to produce images with better balanced amplitudes, fewer artifacts and better resolution than standard migration (Dai and Schuster, 2009; Duquet et al., 2000; Lailly, 1984; Nemeth et al., 1999; Plessix and Mulder, 2004; Tang, 2009; Wong et al., 2011). However, the computational cost of LSM makes the application of this algorithm prohibitive for large-scale industrial 3D problems. Morton and Ober (1998) and Romero et al. (2000) proposed blended source migration where they blended several shotgathers into one supergather which is then migrated. This approach, although very effective in reducing the computational cost, suffers from crosstalk noise which severely degrades the quality of the migrated image. Later, Dai and Schuster (2009) and Schuster et al. (2011) extended the blended source migration technique to multisource least-squares migration and showed that the crosstalk noise can be mitigated by an iterative migration of supergathers. Chen et al. (2015) used a structural smoothing operator (Liu et al., 2010) to smooth the image updates along the local dips during simultaneous-source LSRTM and showed that artifact-free images can be obtained by directly migrating the simultaneous-source data without first deblending them. Xue et al. (2016) incorporated shaping regularization (Fomel, 2007) into LSRTM and used structure-enhancing filtering to mitigate the migration artifacts caused by simultaneous-source or incomplete data.

Besides the computational cost, errors in the migration velocity model and inadequate physics taken into account by the modeling and the adjoint equations hinders the potential of LSRTM to produce images of superior quality than any other migration algorithm (Dutta et al., 2014; Dutta and Schuster, 2014). To account for the inaccuracies in the migration velocity model, Luo and Hale (2013, 2014) modified the conventional L2-norm data misfit function used in LSM, i.e., instead of minimizing the difference between the predicted and the observed traces, they minimized their difference after correcting for non-zero traveltime shifts that were computed using dynamic warping (Hale, 2013). Hou and Symes (2015a,b) proposed a modification of the LSRTM algorithm in the subsurface offset domain where they used an asymptotic inverse of the extended Born modeling operator and weighted norms in model- and data-spaces to accelerate the convergence of LSRTM even in the presence of substantial velocity errors. To account for statics and near-surface velocity errors, an interferometric LSM approach was proposed by Sinha and Schuster (2016) who crosscorrelated the reflection events picked from a reference layer with the traces associated with reflections from deeper interfaces. After the crosscorrelation, the deeper reflection data get redatumed to the reference reflector and the effect of statics in the overlaying layers above the reference reflector get eliminated. The crosscorrelated data, also referred to as crosscorrelograms, are then used as the input data for LSM.

Different preconditioning or regularization techniques were also proposed to mitigate some of the above-mentioned problems related to LSRTM. For example, Wang and Sacchi (2007) use a cost function for one way wave-equation based LSM with regularization constraints for smoothness along offset-domain common image gathers (CIGs) and reflectivity sparseness in depth. Cabrales-Vargas and Marfurt (2013) also formulated a regularized least-squares Kirchhoff migration problem where they used a penalty function that controls the

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amount of roughness in common reflection point gathers (CRPGs). They used a three-point mean filter in every CRPG to remove the aliasing artifacts. Total variation regularization based approaches (Anagaw and Sacchi, 2012; Lin and Lianjie, 2015) have also been used with LSM to obtain images with sharp interfaces and discontinuities.

Another approach to mitigate the migration artifacts in LSRTM is to use a change of basis for the reflectivity using Radon and wavelet-like transforms. Wavelet transforms provide a compact basis for data decomposition which in turn is useful for formulating efficient signal processing and depth imaging algorithms. Such transforms usually exploit the directional properties of an image through the use of suitable basis functions. They provide a perfect reconstruction of the parameters after forward and inverse transforms, are efficient to compute, and use minimal redundancy. Thus, different wavelet-like transforms such as the digital wavelet transform (DWT), curvelets, shearlets, etc., are often used in geophysical applications like data compression, interpolation, data regularization and denoising (Candes et al., 2006a,b; Dessing, 1997; Foster et al., 1994; Herrmann et al., 2009b; Wapenaar et al., 2005). In the context of LSM, Herrmann et al. (2009a) and Herrmann and Li (2012) used curvelets and Dutta et al. (2016, 2015) used local-Radon transform as a change of basis for the reflectivity and demonstrated that with sparsity promoting imaging techniques, high-quality images can be obtained from LSRTM using undersampled or noisy data.

Fomel and Liu (2010) introduced the theory of the seislet transform that is more suitable for representing seismic data. They use basis functions that are aligned along dominant seismic events or dips. In 2D or 3D, the basis functions from the seislet transform follow locally linear events obtained from the input data using local plane-wave destruction filters (Claerbout, 1992; Fomel, 2002). Through numerical tests, they demonstrated the superior compression, interpolation and denoising properties of the seislet transform over the digital wavelet transform. Using the projection onto convex sets (POCS) framework (Abma and Kabir, 2006), a sparsity-based approach using the seislet transform has been used by Gan et al. (2015) and Gan et al. (2016b) to interpolate undersampled seismic data. Seislet transform has also been used with different regularization constraints for deblending of simultaneous-source seismic data (Chen, 2015; Chen et al., 2014; Gan et al., 2016a), for random noise attenuation (Chen, 2016; Chen et al., 2016, 2015) and for multiple attenuation (Wu et al., 2016).

The above listed properties of the seislet transform make it an appealing tool for use in seismic imaging problems such as least-squares migration (LSM) or full waveform inversion (FWI). In this paper, I propose using the seislet transform as a change of basis for the reflectivity during LSRTM. In addition, I also use a dip-constrained preconditioner which ensures that the image updates occur only along some pre-estimated dips or slopes. These dips or slopes are estimated from a standard migration image or from the gradient using a plane-wave destruction filter. Numerical tests on synthetic and field data show that this approach can efficiently suppress the crosstalk noise in multisource LSM and mitigate the aliasing artifacts caused by severely undersampled data.

This paper is divided into four sections. After the Introduction, the second section describes the theory of LSRTM using seislets as basis functions for the reflectivity. Numerical results on synthetic and field data are presented in the third section and the conclusions are in the last section.

2. Theory

Under the single scattering Born approximation, the observed data, **d**, can be written as

$$\mathbf{d} = \mathbf{Lm}. \tag{1}$$

Here **L** is a linearized Born modeling operator that predicts the data from the reflectivity image, **m**. In conventional LSM, the reflectivity **m** is estimated by minimizing the misfit function, $\phi(\mathbf{m})$, given by (Nemeth et al., 1999)

$$\phi(\mathbf{m}) = \frac{1}{2}(\mathbf{Lm}-\mathbf{d})^T(\mathbf{Lm}-\mathbf{d}) + f(\mathbf{m}). \tag{2}$$

Here $f(\mathbf{m})$ is a regularization term that imposes constraints on the solution **m**. If the reflectivity is expressed as a weighted sum of seislet basis functions (see Appendix), we have

$$\mathbf{m} = \mathbf{S}\hat{\mathbf{m}}. \tag{3}$$

Here **S** represents the inverse seislet transform and $\hat{\mathbf{m}}$ represents the seislet coefficients. After this transformation, Eq. (1) can be expressed as

$$\mathbf{d} = \mathbf{LS}\hat{\mathbf{m}}, \tag{4}$$

and the objective function in Eq. (2) gets modified as

$$\phi(\hat{\mathbf{m}}) = \frac{1}{2}(\mathbf{LS}\hat{\mathbf{m}}-\mathbf{d})^T(\mathbf{LS}\hat{\mathbf{m}}-\mathbf{d}) + f(\hat{\mathbf{m}}). \tag{5}$$

If the prior model is of zero mean and known variance, then the regularization term $f(\hat{\mathbf{m}})$ can be expressed as

$$f(\hat{\mathbf{m}}) = \frac{1}{2}\hat{\mathbf{m}}^T C_{\hat{\mathbf{m}}}^{-1}\hat{\mathbf{m}}, \tag{6}$$

where $C_{\hat{\mathbf{m}}}$ represents the covariance of $\hat{\mathbf{m}}$. Thus, the objective function for estimating $\hat{\mathbf{m}}$ is given by

$$\phi(\hat{\mathbf{m}}) = \frac{1}{2}(\mathbf{LS}\hat{\mathbf{m}}-\mathbf{d})^T(\mathbf{LS}\hat{\mathbf{m}}-\mathbf{d}) + \frac{1}{2}\hat{\mathbf{m}}^T C_{\hat{\mathbf{m}}}^{-1}\hat{\mathbf{m}}. \tag{7}$$

The gradient of Eq. (7) can be written as

$$\frac{\partial\phi(\hat{\mathbf{m}}_i)}{\partial\hat{\mathbf{m}}_i} = \mathbf{S}^T\mathbf{L}^T(\mathbf{LS}\hat{\mathbf{m}}_i-\mathbf{d}) + C_{\hat{\mathbf{m}}_i}^{-1}\hat{\mathbf{m}}_i, \tag{8}$$

and the corresponding normal equations are given by

$$\left(\mathbf{S}^T\mathbf{L}^T\mathbf{LS} + C_{\hat{\mathbf{m}}_i}^{-1}I\right)\hat{\mathbf{m}} = \mathbf{S}^T\mathbf{L}^T\mathbf{d}. \tag{9}$$

The matrices $\mathbf{S}^T$ and **S** can be implemented using the fast forward- and inverse-seislet transforms, respectively (Fomel and Liu, 2010). Hence, the choice of seislet transform as a suitable basis is appealing for a least-squares migration or full waveform inversion problem where it is not feasible to explicitly compute and store these

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