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Compressive sensing for seismic data reconstruction via fast projection onto convex sets based on seislet transform

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ABSTRACT

According to the compressive sensing (CS) theory in the signal-processing field, we proposed a new CS approach based on a fast projection onto convex sets (POCS) algorithm with sparsity constraint in the seislet transform domain. The seislet transform appears to be the sparest among the state-of-the-art sparse transforms. The FPOCS can obtain much faster convergence than conventional POCS (about two thirds of conventional iterations can be saved), while maintaining the same recovery performance. The FPOCS can obtain faster and better performance than FISTA for relatively cleaner data but will get slower and worse performance than FISTA, which becomes a reference to decide which algorithm to use in practice according the noise level in the seismic data. The seislet transform based CS approach can achieve obviously better data recovery results than $f-k$ transform based scenarios, considering both signal-to-noise ratio (SNR), local similarity comparison, and visual observation, because of a much sparser structure in the seislet transform domain. We have used both synthetic and field data examples to demonstrate the superior performance of the proposed seislet-based FPOCS approach.

1. Introduction

Most of the time, seismic data processing needs a regular and dense dataset input, which is of extreme importance for obtaining a high-resolution result. However, during the data acquisition process, many different reasons may result in the missing traces, including economic reasons, ground surface limitations, and regulatory reasons. Seismic data reconstruction is such a pre-condition procedure that can be used to remove sampling artifacts, filling the gaps, and to improve amplitude analysis, which is indispensable for the subsequent processing steps including high-resolution processing, wave-equation migration, multiple suppression, amplitude-versus-offset (AVO) or amplitude-versus-azimuth (AVAZ) analysis, and time-lapse studies (Trad et al., 2002; Liu and Sacchi, 2004; Abma and Kabir, 2005, 2006; Wang et al., 2010; Naghizadeh and Sacchi, 2010; Chen et al., 2014a; Zhong et al., 2015).

In recent years, because of the popularity of compressive sensing (CS) based applications (Candès et al., 2006b), there exists a new paradigm for seismic data acquisition that can potentially reduce the survey time and increase the data resolution (Herrmann, 2010). Compressive sensing (CS) is a relatively new paradigm in signal processing that has recently received a lot of attention. The theory indicates that the signal which is sparse under some basis may still be recovered even though the number of measurements is deemed insufficient by Shannon's criterion. The principle of CS involves solving a least-square minimization problem with a L_1 norm penalty term of the reconstructed model, which requires compromising a least-square data-misfit constraint and a sparsity constraint over the reconstructed model. The iterative shrinkage thresholding (IST) and the projection onto convex sets (POCS) are two common approaches used to solve the minimization problem in the exploration geophysics field.

Inspired from the fast iterative shrinkage-thresholding algorithm (FISTA) introduced in Beck and Teboulle (2009), we propose a similar faster version of POCS (FPOCS). Sparsity of seismic data has been explored utilizing different transforms, such as Fourier transform, curvelet (Candès et al., 2006a; Liu et al., 2016), synchrosqueezed wavelet transform (Chen et al., 2014c), double sparsity dictionary (Chen et al., 2016). We compare the sparseness of different well-known sparse transforms by displaying the transform domain and drawing the transform domain coefficients decaying curves. The comparison shows that the seislet transform is obviously sparser than other alternative sparse transforms. Thus, we use the seislet transform (Fomel and Liu, 2010; Chen et al.,

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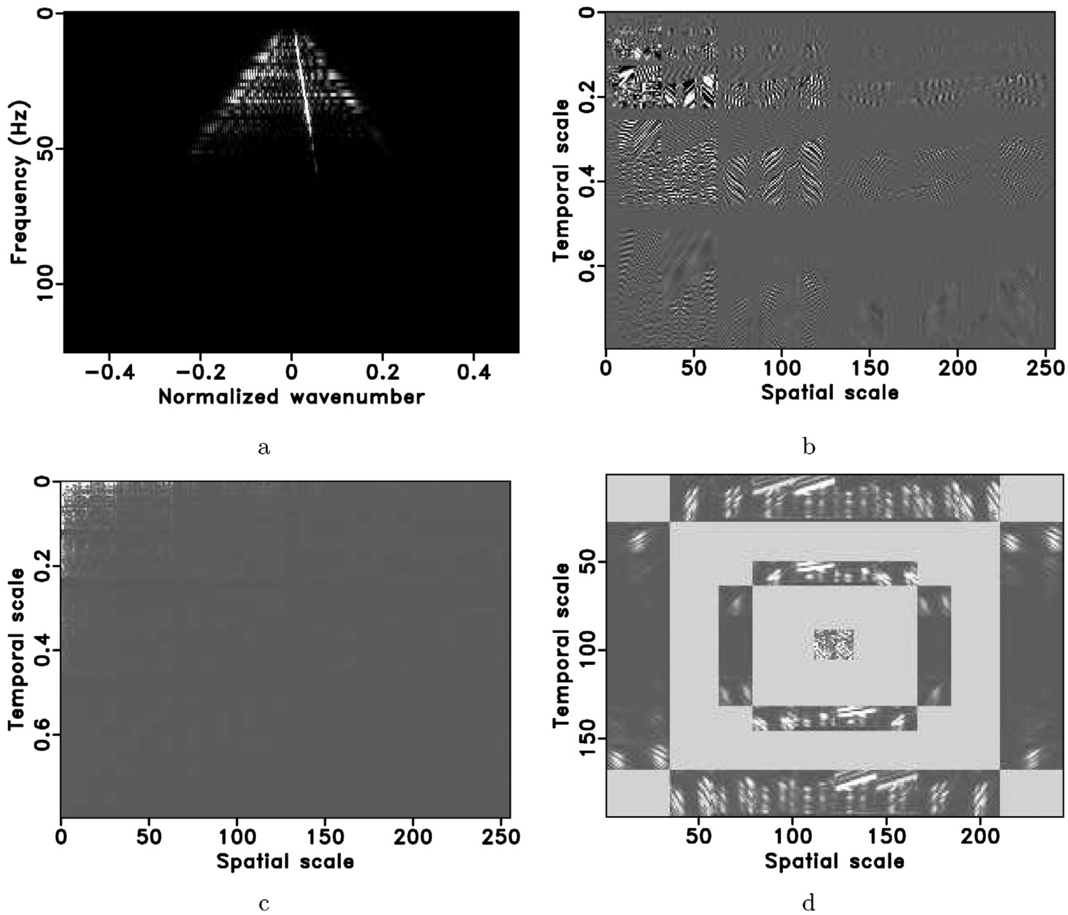

Fig. 1. Comparison among different sparsity-promoting transforms based on the synthetic example shown in Fig. 3a. (a) 2-D Fourier transform domain. (b) 2-D wavelet transform domain. (c) 2-D seislet transform domain. (d) 2-D curvelet transform domain.

2014b; Gan et al., 2015) as the sparsity promoting transform in the compressive sensing data recovery framework in order to explore its related behaviors. Both synthetic and field data examples show that the proposed seislet based FPOCS can obtain better and faster data recovery than the $f-k$ transform based POCS method.

The contributions of the paper can be divided into three aspects. (1) We extend the acceleration strategy used previously in the IST approach to POCS approach, and compare the performance difference of IST and POCS (and related FISTA and FPOCS) in seismic data with different noise level and pointed out that the selection of IST or POCS depends on the noise level of seismic data. (2) We compare the transform domain sparsity of different well-known sparse transforms in terms of the plotted sparse coefficients and coefficients decaying diagrams, and find out that the seislet transform has a much sparser transform domain structure than Fourier transform, wavelet transform, and the curvelet transform. (3) The seislet-based CS approach for seismic data reconstruction is initially investigated and the performance of seislet-based approach and $f-k$ based approach are compared in terms of the reconstruction signal-to-noise ratio (SNR), local similarity comparison, and visual observation.

2. Methods

2.1. Problem statement

The interpolation problem in a CS framework can be summarized in the following model:

$$\mathbf{d}_{obs} = \mathbf{S}\mathbf{d}, \mathbf{m} = \mathbf{A}\mathbf{d} \tag{1}$$

where $\mathbf{d}_{obs}$ is the observed data, $\mathbf{S}$ is the sampling operator, $\mathbf{d}$ is the unknown data we would like to estimate, $\mathbf{A}$ is the sparsity-promoting transform, and $\mathbf{m}$ is the transform domain coefficients.

The synthesis based approach solves the following problem:

$$\min_{\mathbf{m}} \left\|\mathbf{d}_{obs}-\mathbf{S}\mathbf{A}^{-1}\mathbf{m}\right\|_2^2 + \lambda\|\mathbf{m}\|_1, \tag{2}$$

where $\mathbf{A}^{-1}$ denotes the inverse sparsity-promoting transform.

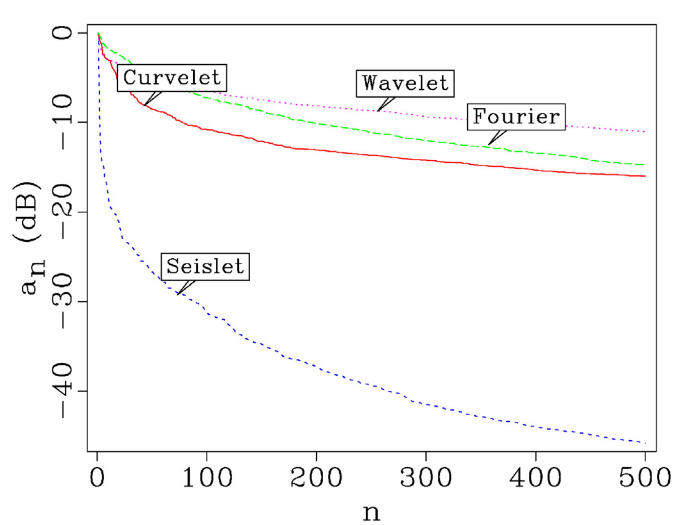

Fig. 2. Coefficients decreasing diagram of different sparsity-promoting transforms.