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Random noise attenuation of non-uniformly sampled 3D seismic data along two spatial coordinates using non-equispaced curvelet transform

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ABSTRACT

The attenuation of random noise is important for improving the signal to noise ratio (SNR). However, the precondition for most conventional denoising methods is that the noisy data must be sampled on a uniform grid, making the conventional methods unsuitable for non-uniformly sampled data. In this paper, a denoising method capable of regularizing the noisy data from a non-uniform grid to a specified uniform grid is proposed. Firstly, the denoising method is performed for every time slice extracted from the 3D noisy data along the source and receiver directions, then the 2D non-equispaced fast Fourier transform (NFFT) is introduced in the conventional fast discrete curvelet transform (FDCT). The non-equispaced fast discrete curvelet transform (NFDCT) can be achieved based on the regularized inversion of an operator that links the uniformly sampled curvelet coefficients to the non-uniformly sampled noisy data. The uniform curvelet coefficients can be calculated by using the inversion algorithm of the spectral projected-gradient for ℓ_1-norm problems. Then local threshold factors are chosen for the uniform curvelet coefficients for each decomposition scale, and effective curvelet coefficients are obtained respectively for each scale. Finally, the conventional inverse FDCT is applied to the effective curvelet coefficients. This completes the proposed 3D denoising method using the non-equispaced curvelet transform in the source-receiver domain. The examples for synthetic data and real data reveal the effectiveness of the proposed approach in applications to noise attenuation for non-uniformly sampled data compared with the conventional FDCT method and wavelet transformation.

1. Introduction

At present, with increasing seismic exploration in complex areas, such as mountains, desert, loess, and sandy soil, the subsurface structure of the exploration targets also become more and more complex. Meanwhile, seismic data often contain a lot of random noise, such as microseismic, background interference, environmental interference, etc. The random noises contaminate the effective signal in seismic data processing, and random distortions make it difficult to perform the subsequent data processing steps. Eventually it will reduce the signal-to-noise ratio (SNR). As a consequence, noise attenuation is a fundamental problem in seismic exploration (Liu et al., 2015; Wang et al., 2016; Amani et al., 2017). Moreover, the complex geographical conditions make it impossible to completely suppress the random noise at the acquisition stage, even with some effective denoising measures taken to improve the SNR in the field. Therefore, effective digital denoising methods are highly desirable to improve the SNR of the prestack data to meet the requirements of subsequent data processing tasks (Li et al., 2015; Zhao et al., 2016).

Recently, many effective methods have been proposed to eliminate random noise (Liu et al., 2012; Gan et al., 2016; Chen et al., 2016; Trickett and Burroughs, 2009). One of the most widely used methods is sparsity-promoting transform with fixed-basis functions, for example, the discrete cosine transform (Lu and Liu, 2007), the Fourier transform (Trickett, 2003), the wavelets transform (Mallat, 2009), the curvelet transform (Ma and Plonka, 2010), the seislet transform (Fomel and Liu, 2010), contourlets (Do and Vetterli, 2005), shearlets (Labate et al., 2005), and bandelets (Pennec and Mallat, 2005), as well as the classic Radon transform (Ibrahim and Sacchi, 2014). The principle of all these denoising approaches is to separate signal from noise in a sparse transformation domain. By choosing some appropriate threshold value for the sparse coefficients, the random noise can be effectively suppressed. In order to achieve the desired denoising effect, the basis function of the sparse representation is required to capture the seismic wavefronts as accurately as possible. A small number of large coefficients should be able to represent the main features of the original data, while a large number of small coefficients corresponding to the random noise should be filtered out by the threshold operator. However, most of these effective denoising methods assume uniform sampling along all axes, and have a poor denoising effect when the sampling is non-uniform. Due to physical limitations in land surveys and feathering of cable in marine surveys, real seismic data are usually acquired on non-uniform grids. If treated as from uniform sampling, the data do not yield continuous wavefronts in shot

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gathers, and the resulting error will further affect the subsequent subsurface image.

To address this issue, geophysicists commonly use binning to bring non-uniformly sampled data to the uniform grid. However, this method discards the actual recording locations and is only a low-dip and low-frequency approximation, so it will reduce the resolution of the seismic profile. At the same time, many researchers also proposed the Fourier transform-based non-uniform method to solve this problem (Duijndam et al., 1999; Hindriks and Duijndam, 2000; Xu et al., 2005; Zwartjes, 2005). However, when the subsurface structure becomes complex or in high-dip-angle events, Fourier transform-based methods suffer from an error of high prediction because of the large number of dip components to be predicted (Chen and Ma, 2013). Furthermore, they are not successful in processing seismic data that include nonlinear events. It is commonly believed that the fewer components required to represent the signal, the more successful the transformation in signal denoising will be. Many researchers therefore prefer the fast discrete curvelet transform (FDCT). By virtue of its anisotropic shape, the FDCT method can provide a nearly optimal representation of signals and it is well adapted to detect wavefronts because aligned curvelets correlate well with them locally. The application results also show that FDCT-based denoising method has been proved as a method that increases the SNR of the seismic images more than the other introduced methods and has minimum undesired influence on such images (Neelamani et al., 2008, 2010; Herrmann, 2010; Lari and Gholami, 2014; Górszczyk et al., 2015; Mortezanejad and Gholami, 2016). However, the initial implementation premise of the FDCT still assumes a uniformly sampled grid along all axes (Zhang et al., 2015). If we ignore the actual non-uniformity of spatial sampling, FDCT can no longer detect them correctly. Hennenfent and Herrmann (2006) and Hennenfent et al. (2010) proposed a non-equispaced fast discrete curvelet transform (NFDCT), with similar effectiveness and robustness as the FDCT. However, Hennenfent and Hermann only consider 2D random noise attenuation of non-uniformly sampled data by introducing the 1D NFFT.

In this paper, we extend the NFDCT-based 2D denoising method to 3D along two spatial dimensions. In order to save memory space and improve the computation speed, denoising directly aims at every time slice extracted from the 3D noisy data in the source-receiver domain. The 2D NFFT is introduced to replace the 2D FFT during the process of the conventional FDCT-based denoising method, and the regularized inversion of the operator that links the curvelet coefficients to non-uniformly sampled noisy data is constructed. Then the uniform curvelet coefficients can be calculated by using the inversion algorithm of the spectral projected-gradient for ℓ_1-norm problems. To avoid the over-thresholding effect that may occur by using a global threshold factor, suitable local threshold factors proportional for each scale are chosen for the uniform curvelet coefficients, and effective curvelet coefficients can be obtained respectively for each scale. At the last stage, we can get the 3D denoised data by using the conventional inverse FDCT (IFDCT) for the effective curvelet coefficients. We provide numerical tests demonstrating that our method is effective and robust in attenuating the non-uniformly random noise, superior to the conventional FDCT method.

2. Curvelet transform

The curvelet transform tries to find the contribution from each point of data in the *t-x* domain to isolated directional windows in the *f-k* domain (Candès and Donoho, 2004). If we let $\mathbf{y}(t,x)$ represent seismic data in the *t-x* domain, we can define a set of curvelet functions $\boldsymbol{\psi}_{j,\,l,\,k}$ where the index parameters j, l, k indicate the scale (from coarsest to finest), the angle or dip, and the location of the curvelet coefficients, respectively. Curvelets can be thought of as wavelets with the additional important property of directionality (dip). The continuous curvelet transform can be represented as the inner product of the data $\mathbf{y}(t,x)$ and the curvelet function

$$\mathbf{c}(j,l,k) = \langle \mathbf{y}, \boldsymbol{\psi}_{j,l,k} \rangle = \int_{R^2} \mathbf{y}(t,x)\overline{\boldsymbol{\psi}_{j,l,k}(t,x)}\mathrm{d}x, \tag{1}$$

The curvelet transform is multiscale, multidirectional, and localized. It corresponds to a specific tiling of the *f-k* domain into scales that are dyadic bands—i.e., bands whose radial width doubles every scale—centered around the zero-frequency zero-wavenumber, or so-called DC point. These scales are subsequently broken up into parabolic angular wedges. The term "parabolic" refers to the relation between the length and width of a wedge, i.e., length ∝ width^2. Fig. 1 sketches the resulting curvelet tiling of the f-k domain. Because of the parabolic scaling, the number of wedges doubles with every other scale and the curvelets, which live in wedges, become more and more anisotropically shaped.

In our study, we adopt the FDCT. Candès et al. (2006) proposed two new 2D discrete procedures to implement the curvelet transform: the FDCT via unequally spaced fast Fourier transform (FDCT via USFFT) and the FDCT via wrapping specially selected Fourier samples (FDCT via wrapping). In this paper, we focus on the FDCT via wrapping. Our algorithm was developed using the curvelet transform provided by the package CurveLab. In the rest of this paper, we refer to the FDCT via wrapping as the curvelet transform.

3. Nonequispaced curvelet transform

The FDCT via wrapping expands by a factor of approximately eight in two dimensions. Its forward and inverse transforms are superior because of its simpler implementation and therefore faster execution especially when dealing with large numbers of data. The main steps of its analysis operator are as follows: (1) apply the analysis 2D FFT to get the Fourier coefficients; (2) form the angular wedges and wrap

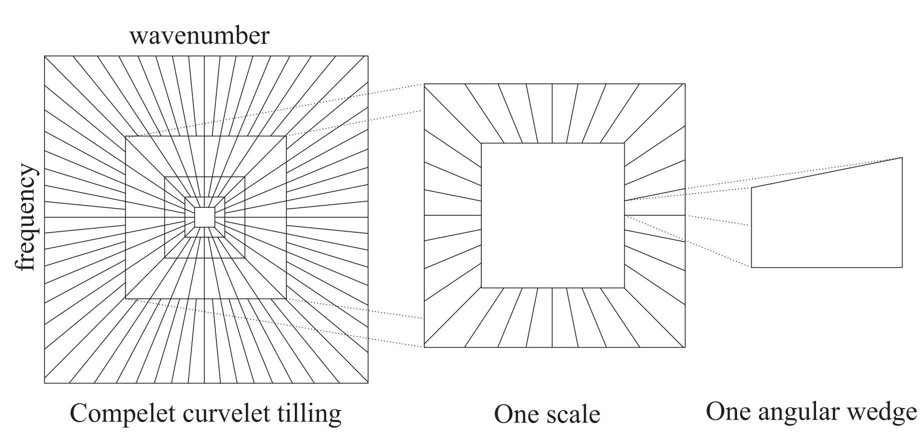

Fig. 1. Schematic curvelet tiling of the f-k plane. From left to right: complete DC-centered tiling, jth dyadic scale, and one angular "parabolic" wedge.