Journal of Applied Geophysics 136 (2017) 353–363

Contents lists available at ScienceDirect

Journal of Applied Geophysics

journal homepage: www.elsevier.com/locate/jappgeo

Seismic random noise attenuation via 3D block matching

Sajjad Amani[a,b,*], Ali Gholami[b], Alireza Javaheri Niestanak[c]

[a] Geophysics Laboratory, Graduate School of Engineering, Kyoto University, Japan
[b] Institute of Geophysics, University of Tehran, Tehran, Iran
[c] Exploration Directorate, National Iranian Oil Company, Tehran, Iran

ARTICLE INFO

Article history:
Received 16 August 2015
Received in revised form 7 November 2016
Accepted 11 November 2016
Available online 16 November 2016

Keywords:
Block matching
Random noise attenuation
Transform domain methods
Combination methods
Signal to noise ratio

ABSTRACT

The lack of signal to noise ratio increases the final errors of seismic interpretation. In the present study, we apply a new non-local transform domain method called "3 Dimensional Block Matching (3*DBM*)" for seismic random noise attenuation. Basically, 3*DBM* uses the similarities through the data for retrieving the amplitude of signal in a specific point in the f–x domain, and because of this, it is able to preserve discontinuities in the data such as fractures and faults. 3*DBM* considers each seismic profile as an image and thus it can be applied to both pre-stack and post-stack seismic data. It uses the block matching clustering method to gather similar blocks contained in 2*D* data into 3*D* groups in order to enhance the level of correlation in each 3*D* array. By applying a 2*D* transform and 1*D* transform (instead of a 3*D* transform) on each array, we can effectively attenuate the noise by shrinkage of the transform coefficients. The subsequent inverse 2*D* transform and inverse 1*D* transform yield estimates of all matched blocks. Finally, the random noise attenuated data is computed using the weighted average of all block estimates. We applied 3*DBM* on both synthetic and real pre-stack and post-stack seismic data and compared it with a Curvelet transform based denoising method which is one of the most powerful methods in this area. The results show that 3*DBM* method eventuates in higher signal to noise ratio, lower execution time and higher visual quality.

1. Introduction

Accurate images of subsurface structures are necessary in seismic exploration of hydrocarbon reservoirs. These images are usually corrupted/contaminated with both random and coherent noises. In order to attenuate these noises, many denoising methods have been proposed so far. In this study, we further propose a seismic random noise attenuation method. Many methods in the frequency–space (f–x) domain have been proposed for attenuation of random noises, via employing the Fourier transform to extract a few dominant harmonics by preserving a finite number of frequency or wavenumber components in the frequency domain (Naghizadeh and Sacchi, 2012). Canales (1984) introduced the f–x prediction technique. After that, many f–x domain methods appeared for random noise attenuation (Bekara and VanderBaan, 2009; Chase, 1992; Chen and Ma, 2013; Gulunay, 2000; Hao et al., 2011a; Liu et al., 2011, 2012; Naghizadeh and Sacchi, 2011, 2012; Oropeza and Sacchi, 2009; Sacchi and Kuehl, 2011; Soubaras, 1994; Trickett, 2003, 2008; Trickett and Burroughs, 2009). The fundamental of all f–x denoising methods is that the spatial signals at each single frequency are composed of a superposition of a limited number of complex harmonics (Naghizadeh and Sacchi, 2012). The main advantages of these filter domain approaches are their speed and easier implementation. However, when the structure of subsurface becomes complex or in the high-dip-angle events, the f–x methods suffer from an error of high prediction because of large amount of dip components to be predicted (Chen and Ma, 2013). Furthermore, the f–x algorithms are not successful in processing of seismic data including nonlinear events (Deng et al., 2010).

To compensate the limitations of the Fourier transform in dealing with the time–frequency analysis in the non-stationary time series, the concept of Short Time Fourier Transform (STFT) was developed which has a fixed width of time window. In all of the STFT methods, undesirable computational complexities arose when either narrowing of the window is required for better localization or widening of the window is required to obtain a more global picture (Miao and Moon, 1994).

After that the Wavelet transform was introduced (Daubechies, 1988, 1990; Mallat, 1989; Rioul, 1991) which has the capability of combining the features of both time and frequency information. A further advantage of the Wavelet transform which distinguishes itself from any STFT is its zoom-in and zoom-out capabilities. Unlike the STFT in which the width of the window is fixed, the Wavelet transform localizes signals in a variable window (Miao and Moon, 1994).

* Corresponding author.
E-mail addresses: sajjad.amani@alumni.ut.ac.ir (S. Amani), a.gholami@ut.ac.ir (A. Gholami), a.javaheri@niocexp.ir (A. Niestanak).

http://dx.doi.org/10.1016/j.jappgeo.2016.11.014
0009-2541/

Since the 1990s, Wavelet transform has been used often in speech recognition, image processing and seismic data denoising because of its nice localization characteristics (Zhenwu et al., 2009). For suppression of random noises, many Wavelet transform approaches have been proposed (Chen et al., 2012; Wu et al., 2006; Zegadi and Zegadi, 2010; Zhang and Ulrych, 2003; Zhang et al., 2004). The Wavelet transform is a multi-scale geometric analysis tool (Hao et al., 2011b) and primarily suitable for isotropic singularities. Although it can be applied to the time–frequency analysis of the signals, it has only limited directions (Hao et al., 2011b) and fails to represent approximately those anisotropic singularities such as the boundary and linear characteristics of seismic data, which are very common in practice. It is the reason that some degree of fuzzy phenomenon inevitably emerges when applying Wavelet transforms to fusion, compression, or denoising of seismic signals (Wang et al., 2010). Also, the filters used to implement the Wavelet transform overlap in the frequency domain, which leads to internal aliasing (Foster et al., 1997).

For compensation of the Wavelet transform limitations, the Curvelet transform was proposed by Candes and Donoho (1999). It originated from the Ridgelet transform. After that the second generation of Curvelet transform was introduced by Candes et al. (2006) which decreased the computation time. Finally, Candes et al. (2006) proposed fast discrete Curvelet transform based on the second generation which is easier and faster than the former discrete method and greatly decreases the redundancy of the traditional algorithm (Hao et al., 2011b). Basically, the Curvelet transform makes a Wavelet transform of the signal and decomposes it into a series of sub-band signals with different scales; and then, performs a local Ridgelet transform on every sub-band in which their sizes can differ from the scale (Wang et al., 2010). Many researchers e.g. Dong et al. (2013), Hao et al. (2011b), Kumar and Herrmann (2009), Neelamani et al. (2008), Starck et al. (2002), Wang et al. (2010, 2013) , and Zhenwu et al. (2009) used the Curvelet transform for seismic denoising. Neelamani et al. (2008) showed that for random noise attenuation of seismic data, Curvelet transform is better than Wavelet transform. However, the harmonic nature of the Curvelet elements makes it difficult to recover the sharp discontinuities like faults and results in fine scale artifacts around them (Lari and Gholami, 2014).

There are also other methods for suppression of random noises in seismic data, such as using band-pass, f–k, and kx–ky filtering (Yilmaz, 2001) which mute undesired portion of the data in the Fourier domain cost-effectively but lead to signal distortion and spatial correlation of background noise, least squares (Deng et al., 2010; Tyapkin et al., 2009) which are very effective tools for smoothing and interpolation of data in three dimensions (Milanfar, 2013), however, they have high cost and highly dependent to the accuracy of background model information, inversion methods like total variations (Lari and Gholami, 2012) which have higher edge-preserving characteristics, lower ability in retrieving smooth regions and output results with lower signal to noise ratio with respect to the Curvelet methods (Lari and Gholami, 2014), and non-local means (Bonar and M. Sacchi, 2012; Maraschini and Turton, 2013) which their basic idea is to denoise each sample or pixel within an image by utilizing weighted average of other similar samples or pixels. The computational time and sensitivity to accurate filter parameters of the non-local means methods need to be reduced which restrict their applications.

In this paper, we introduce a non-local transform-domain image denoising strategy called "3D Block Matching (3DBM)" based on an enhanced sparse representation in transform domain. The original algorithm was proposed in 2007 by Dabov et al. as a noise attenuation tool for digital images (Dabov et al., 2007). We use the 3DBM algorithm for attenuating of seismic random noises. It is important to note that there is no difference between our algorithm and that of Dabov et al. (2007) except the application in seismic field and comparison with Curvelet transform based denoising method.

The basic idea behind this algorithm is the presence of some degree of redundancy within the data due to the repetition of geological structures such as the curvature of an anticline and the lineation of a fault. Here in this method, we consider a noisy seismic cross section like an image. Then the image is divided into many blocks with the same sizes (i.e. square blocks with specific number of samples). The enhancement of the sparsity is achieved by grouping similar blocks into 3D data arrays which we call "groups". After 3D transforming of each group to another domain, the random noises will be significantly separated from the main signal due to the similarity between the signals contained in grouped blocks. Then, after the shrinkage of the transform spectrum, a 3D estimate of the group which consists of an array of jointly filtered 2D blocks will be obtained. The filtered data is transferred to the time domain using an inverse 3D transform. Then each block returns to its main position. Although the basic idea is similar to non-local means methods, here in this method we enhance the random noise attenuation proficiency using grouping similar data and transferring data to a sparse domain. This procedure reveals even the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each individual block. We show that the proposed method outperforms the state-of-the-art Curvelet transform based denoising method (CTD) both visually and in the sense of signal to noise ratio (SNR).

In the next parts, we will first explain thoroughly about the 3DBM method, then compare it with conventional CTD method in several synthetic and real examples.

2. Theory of 3D block matching

The 3D block matching (3DBM) algorithm consists of two main steps that have similar general structures with different processing details. In the first step, a basic estimation of the seismic profile is obtained by removing a part of random noises' energy using hard-thresholding. In the second step, using the basic estimation gained in the previous step and a Wiener filter, a significant part of random noises will be removed while preserving the features of signal. Each of these two steps consists of five successive subsections: 1. 3D grouping of similar parts in the data, 2. 3D transformation of that group, 3. Shrinkage of the transform spectrum, 4. Inverse 3D transformation, and 5. Return the obtained estimates of similar parts to their original locations. The three successive subsections, i.e. 3D transformation of a group, Shrinkage of the transform spectrum, and Inverse 3D transformation are called "Collaborative filtering". After processing of all parts, the obtained estimates can overlap and thus there are multiple estimates for each part of seismic image. We aggregate these estimates using adoptive weights to form an estimation of seismic profile. In the next parts, we will introduce all steps in details.

2.1. Step1

In this step, a basic estimate of the noisy data is calculated as follows:

2.1.1. 3D grouping of similar blocks

Let us consider the following model for seismic data $\mathbf{z}:\mathbf{X}\rightarrow\mathbf{R}$:

$$z(x) = y(x) + e(x), \qquad x \in X \tag{1}$$

where z is the noisy measured seismic data, y is the noise free seismic data of interest, e is zero-mean, white noise with variance σ^2 and x is the 2D spatial coordinate of the top left of data point that belongs to the domain $X \subset Z$. 3*DBM* considers each seismic section as an image and then divides it into many blocks Z_x with the same size $N \times N$ (i.e. with the same number of samples). Various block sizes have different impacts on the final results (see the "Discussion 4" section). For