Journal of Applied Geophysics 135 (2016) 155–162

Contents lists available at ScienceDirect

Journal of Applied Geophysics

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

Discontinuity enhancement based on time-variant seismic image deblurring

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ARTICLE INFO

Article history:
Received 3 March 2016
Received in revised form 12 September 2016
Accepted 7 October 2016
Available online 12 October 2016

Keywords:
Discontinuity enhancement
Seismic image deblurring
Point spread function
Deconvolution
Fault detection

ABSTRACT

Post-stack 3D seismic data is spatially blurred by the effects of migration operators with limited aperture widths, which is not conducive to discontinuity (such as fault, channel, etc.) detection. By approximating the migration blur with a time-invariant point spread function (TIPSF), seismic image deblurring methods have been used to obtain data with enhanced discontinuity. Better discontinuity detection results can be achieved on the deblurred data than on the original data. Since the migration blurs are always time-dependent, a time-variant PSF (TVPSF) estimation method is proposed in this paper to approximate these blurs. In our method, initial PSFs corresponding to each horizontal time slice (HTS) from a 3D seismic data are first obtained. Then, PSFs corresponding to adjacent time slices are divided into the same categories based on their similarities. With average PSFs calculated in each category, linear interpolation is performed to estimate PSFs for the whole data set. Finally, we perform seismic image deblurring HTS by HTS with these estimated PSFs. To suit different signal-to-noise ratios (SNR) in these HTSs of the 3D seismic data, the whitening factor of the Wiener filter for each HTS is adjusted adaptively. Using field dataset examples, we demonstrate that the performance of our proposed TVPSF method outperforms the TIPSF method.

1. Introduction

Identification and detection of faults and stratigraphic features are crucial in seismic data interpretation. The 3D seismic coherency cube, proposed by Bahorich and Farmer (1995), is a common tool for delineating seismic faults. The first generation coherence algorithm (C1) is based on second order statistics and deals with only three traces. Though being computationally efficient, this method may lack robustness, especially when dealing with noisy data (Marfurt et al., 1998). The second generation coherence algorithm (C2) is based on multitrace semblance (Marfurt et al., 1998). Compared with the C1 algorithm, the C2 algorithm shows higher vertical resolution and better immunity to noise. The third generation coherence algorithm (C3) based on an eigenstructure approach is developed by Gersztenkorn and Marfurt (1999). The C3 algorithm has a higher resolution and is more robust than the C1 and C2 algorithms (Marfurt et al., 1999). Cohen and Coifman (2002) estimate coherence through calculating the seismic local structural entropy (LSE), which is more efficient than the C3 algorithm. Lu et al. (2005) present a higher-order statistics-based supertrace coherence-estimation algorithm (ST-HOSC) and a supertrace coherence algorithm (ST-C1). The ST-C1 and ST-HOSC algorithms preserve the computational efficiency of the C1 algorithm and provide more capability to restrain noises. Li et al. (2006) propose a dip-scanning coherence algorithm (STC3) by combining the eigenstructure analysis with the supertrace technique. The STC3 algorithm further improves the quality of the coherence image and is robust to noise.

There exist a number of other techniques to enhance and detect the seismic discontinuity, such as the horizon-based curvature attributes (Roberts, 2001), the curvature volume analysis (Chopra and Marfurt, 2010), the supertrace-based algorithm with robust slope estimation (Zhang et al., 2013) and an improved coherence estimation combined with complex seismic trace analysis (Wang et al., 2015). On the other hand, image processing techniques are often used to enhance seismic attributes, such as edge detection (Al-Dossary and Marfurt, 2003), image enhancement (Narhari et al., 2007), the coherence cube enhancement (Wang and Lu, 2010), and etc. Post-stack 3D seismic data is blurred spatially by the effect of migration operators with limited aperture widths (Hu et al., 2001). The goal of image deblurring is to reconstruct the original scene from a degraded observation. Classical image deblurring seeks an estimate of the true image assuming the blur is known (e.g., Oliveira et al., 2009; Zhao et al., 2013; Liu et al., 2014; Huang et al., 2014; Shi et al., 2016). In contrast, blind image restoration tackles the much more difficult problem where the degradation is unknown (Campisi and Egiazarian, 2016). Some representative algorithms for blind image restoration are the iterative methods (Nagy et al., 2004,), total least squares (Mastronardi et al., 2004), the algorithm

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http://dx.doi.org/10.1016/j.jappgeo.2016.10.008
0926-9851/

based on higher-order statistics (Lu, 2006), learning-based algorithms (Nakagaki and Katsaggelos, 2003) and the Bayesian restoration algorithm (Chantas et al., 2006). For seismic image deblurring, only the degraded images of 3D seismic data are known. It is a Blind Deconvolution (BD) problem which is the process of estimating the true image and the blur (PSF) from the degraded image. Since the size of Post-stack 3D seismic data is much larger than 2D image, and the enormous computation amount limits the application of BD related algorithms. In this paper, we mainly concentrate on estimating the time-variant PSFs, and utilizing self-adaptive 2D Wiener filters with stable and high computation efficiency to eliminate the effects of blur.

Lu et al. (2004) first introduce image deblurring to enhance 3D seismic data volume, which is denoted as TIPSF (Fig. 1(a)). The deblurred seismic data volume can be obtained by utilizing a self-adaptive 2D Wiener filter to remove the effects of the PSF. Then, a discontinuity detection method (say, the coherence algorithm) on the deblurred seismic data instead of on the original seismic data is used to obtain a better result. However, the influences of the migration operators vary from shallow to deep regions, and the signal-to-noise ratio (SNR) of the deblurred HTS is rather sensitive to the whitening factor of the Wiener filter. The time-invariant PSF and constant whitening factor for all HTSs in TIPSF method may result in poor deblurring results and amplified noise.

In this paper, we propose a time-variant PSF estimation algorithm for seismic image deblurring, which is denoted as TVPSF (Fig. 1(b)). We first obtain a series of initial PSFs' estimates from each HTS. Time windows with adaptive length are constructed according to the similarities of these initial PSFs' estimates. Then, we use the average of these initial PSFs' estimates as the final PSF estimate of the center point in this time window. For non-center sample points, linear interpolation is implemented to calculate their final PSFs. At last, a 2D Wiener filter is used to eliminate the effects of the PSFs. The whitening factors are also selected adaptively according to the energy curve of the 3D seismic data. With an onshore field dataset of China, we validate the effectiveness of the proposed method.

2. Method

The key step of the seismic image deblurring is to estimate the PSF. The degraded seismic HTS $g(x,y,t_i)$ can be represented as the two-dimensional convolution of the true seismic HTS $f(x,y,t_i)$ with a PSF $h(x,y,t_i)$ (Gonzalez and Woods, 2002):

$$g(x,y,t_i) = f(x,y,t_i) \circledast h(x,y,t_i) + n(x,y,t_i), \quad x,y \in \mathbb{Z}, \quad i \in (1,N) \tag{1}$$

where N is the number of time samples, $n(x,y,t_i)$ denotes the additive Gaussian noise with standard deviation σ, $\circledast$ denotes the spatial convolution operator, and $\mathbb{Z}$ is a set of integer numbers. Since convolution in spatial domain is equal to multiplication in wave-number domain, we can rewrite the Eq. (1) in wave-number domain as

$$G(u,v,t_i) = F(u,v,t_i)H(u,v,t_i) + N(u,v,t_i) \tag{2}$$

where the terms in capital letters are the Fourier transforms of corresponding terms in Eq. (1).

The auto-correlation of the PSF can be estimated by windowing the auto-correlation $M_g(m,n,t_i)$ of degraded seismic HTS $G(u,v,t_i)$ (Lu, 2005):

$$M_h(m,n,t_i) = \left(\sum_{j=i-L_p/2}^{j=i+L_p/2} M_g(m,n,t_j) \right) W_2(m,n) \tag{3}$$

where L_p is the length of the pth adaptive window, $W_2(m,n)$ is a 2D Hanning window which can be generated by two 1-D Hanning windows:

$$W_2(m,n) = W_1(m)W_1(n). \tag{4}$$

The auto-correlation of the degraded seismic HTS $M_g(m,n,t_i)$ can be calculated by

$$M_g(m,n,t_i) = \mathrm{IFFT}_2(G(u,v,t_i)G^*(u,v,t_i)) \tag{5}$$

where IFFT_2 represents the 2D inverse Fourier transform, $G^*(u,v,t_i)$ is the complex conjugate of $G(u,v,t_i)$.

By setting the phase spectrum of the PSF as zero, the power spectrum can be estimated as

$$P_H(u,v,t_i) = \mathrm{FFT}_2(M_h(m,n,t_i)), \tag{6}$$

where FFT_2 represents the 2D forward Fourier transform, $P_H(u,v,t_i)$ is the power spectrum of the PSF.

Then, the estimation of the PSF with zero-phase spectrum in wave-number domain can be given by:

$$H(u,v,t_i) = (P_H(u,v,t_i))^{1/2}. \tag{7}$$

We assume that the Gaussian noise $n(x,y,t_i)$ and the true seismic HTS $F(u,v,t_i)$ are uncorrelated, the Wiener filter (Kundur and Hatzinakos, 1996) based on minimum mean square error criterion can be expressed in the wave-number domain

$$B(u,v,t_i) = \frac{H^*(u,v,t_i)P_F(u,v,t_i)}{P_F(u,v,t_i)P_H(u,v,t_i) + P_N(u,v,t_i)}, \tag{8}$$

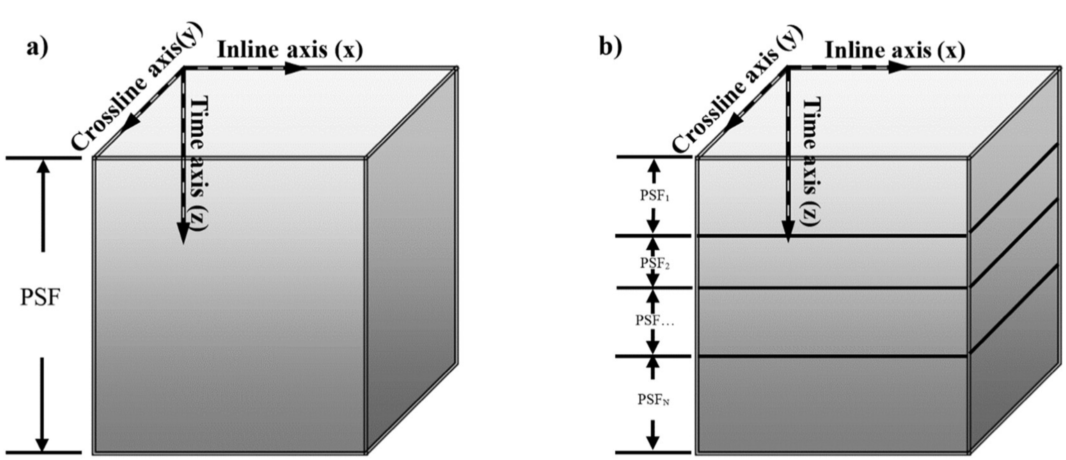

Fig. 1. Illustration of the seismic image deblurring using (a) the TIPSF and (b) TVPSF algorithm.