Journal of Applied Geophysics 89 (2013) 125–133

Contents lists available at SciVerse ScienceDirect

Journal of Applied Geophysics

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

Seismic attenuation qualitative characterizing method based on adaptive optimal-kernel time–frequency representation

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ARTICLE INFO

Article history:
Received 19 April 2012
Accepted 14 December 2012
Available online 23 December 2012

Keywords:
Seismic attenuation
Time–frequency analysis
Adaptive optimal-kernel time–frequency representation
Direct hydrocarbon indicator

ABSTRACT

The main issue of seismic attenuation characterizing method based on time–frequency analyzing method is the time–frequency resolution. The adaptive optimal-kernel time–frequency representation, which has high time–frequency resolution comparing with commonly used time–frequency analyzing method, is investigated. The seismic attenuation qualitative characterizing method based on adaptive optimal-kernel time–frequency representation is proposed. The synthetic data example and 3D field-data example reveal that the proposed method can qualitatively characterize seismic attenuation, and the attenuated anomaly of this field-data example coincides with gas reservoir well.

1. Introduction

Almost 30 year ago, Taner et al. (1979) noted the occurrence of lower apparent frequencies for reflectors on seismic sections beneath gas and condensate reservoirs, and these anomalies can be used as direct hydrocarbon indicator especially in thick reservoirs. These anomalies, which can not be apparent on a broad-band stack, can be observed clearly in spectrally decomposed sections. Many time–frequency analyzing methods were used in seismic interpretations, such as short time Fourier transform (STFT; Marfurt and Kirlin, 2001; Partyka et al., 1999), continuous wavelet transform (CWT; Li and Liner, 2008; Matos and Marfurt, 2009; Sinha et al., 2005, 2009; Zhu et al., 2009), S transform (Chen et al., 2009; Jinghuai et al., 2003), Cohen's class time–frequency representation (Li and Zheng, 2008; Steeghs and Drijkoningen 2001; Ralston et al., 2007; Xiaoyang and Liu, 2009; Zhang and Lu, 2009), and matching pursuit related methods (Castagna et al., 2003; Chakraborty and Okaya, 1995; Liu and Marfurt, 2007; Sun et al., 2002; Wang, 2007, 2010).

Chen Wenchao and Gao Jinghuai (2007) used the modified best matching seismic wavelets (MBMSW) to characterize seismic attenuation. Chen et al. (2009) used S transform (Jinghuai et al., 2003; Stockwell et al., 1996) to detect low frequency shadow of gas reservoirs. The CWT and S transform have different time–frequency resolution in low frequency and high frequency, and the time–frequency resolution of CWT and S transform is restricted by Heisenberg uncertainty theorem. Matching pursuit, which was presented by Mallat and Zhang (1993), has high time–frequency resolution. Matching pursuit and its related methods were also used to detect low-frequency shadows associated with hydrocarbon (Castagna et al., 2003; Sun et al., 2002). However, matching pursuit is high computational complexity method and the result depends on the dictionary seriously.

The main job of Cohen's class time–frequency representation (Cohen, 1989) is finding suitable kernel function to eliminate cross-term interference and preserve auto-term. Fixed-kernel time–frequency representations (Choi and Williams, 1989; Zhao et al., 1990) are only suitable for a limited class of signals. Time–frequency representation with signal-dependent optimal kernel can optimize its kernel function to different classes of signals (Baraniuk and Jones, 1993). However, for signal whose characteristics change with time, especially for seismic signal, time–frequency representations with signal-dependent kernel function and fixed kernel function can not track these changes with time. Adaptive optimal-kernel time–frequency representation (AOKTFR) proposed by Jones and Baraniuk employs kernel function which can be adapted with time (Jones and Baraniuk, 1995), and its kernel function is optimized locally in a sliding window. So the AOKTFR is more concentrated and readable than fixed kernel time–frequency representation, and the time–frequency resolution of AOKTFR is not restricted by the Heisenberg uncertainty theorem. AOKTFR also has application in seismic sequence analysis. For its large computation cost, Philippe gave up using AOKTFR to extract attributes, but used signal-dependent optimal kernel time–frequency representation instead (Steeghs and Drijkoningen 2001).

In this work, we do not focus on estimating the Q factor, but focus on characterizing 3D seismic data's attenuation qualitatively by using AOKTFR. This paper is organized as follows: In section II, the principle

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0926-9851/$ – see front matter
http://dx.doi.org/10.1016/j.jappgeo.2012.12.006

of AOKTFR is investigated and is used to synthetic signal to test the time–frequency resolution. Then, the seismic attenuation qualitative characterizing method based on AOKTFR is proposed, and the proposed method is used on a synthetic example. In section III, the seismic attenuation qualitative characterizing method based on AOKTFR is used on real field-data example to illustrate its effectiveness.

2. Method

2.1. Principle of AOK TFR

The instantaneous autocorrelation function of a signal $s(t)$ is defined as

$$R(t,\tau) = s\left(t+\frac{\tau}{2}\right)s^{*}\left(t-\frac{\tau}{2}\right) \tag{1}$$

where τ is the time delay variable. The most important time–frequency distribution, Wigner–Ville distribution, is defined as the Fourier transform of instantaneous autocorrelation function with respect to τ,

$$WVD(t,\omega) = \int_{-\infty}^{+\infty} s\left(t+\frac{\tau}{2}\right)s^{*}\left(t-\frac{\tau}{2}\right)e^{-j\omega\tau}d\tau. \tag{2}$$

Wigner–Ville distribution has the highest time–frequency resolution. However, the bilinear characteristic causes serious cross-term interference. For instance, a signal which contained two time-shifted and frequency-modulated Gaussian signals,

$$s(t) = \pi^{-1/4}\exp\left[-\frac{\alpha}{2}(t-t_1)^2 + j\omega_1 t\right] + \pi^{-1/4}\exp\left[-\frac{\alpha}{2}(t-t_2)^2 + j\omega_2 t\right] \tag{3}$$

one is concentrated at (t_1,ω_1), and the other is centered at (t_2,ω_2). Then the Wigner–Ville distribution of $s(t)$ is

$$\begin{aligned} WVD(t,\omega) &= 2\exp\left[-\alpha(t-t_1)^2 - \frac{1}{\alpha}(\omega-\omega_1)^2\right] + 2\exp\left[-\alpha(t-t_1)^2 - \frac{1}{\alpha}(\omega-\omega_1)^2\right] \\ &+ 4\exp\left[-\alpha(t-t_m)^2 - \frac{1}{\alpha}(\omega-\omega_m)^2\right]\cos[(\omega-\omega_m)t_d + \omega_d(t-t_m) + \omega_d t_m] \end{aligned} \tag{4}$$

where $t_m = (t_1+t_2)/2$ and $\omega_m = (\omega_1+\omega_2)/2$ denote the geometric time and frequency means between the two individual Gaussian signals, $t_d = t_1 - t_2$ and $\omega_d = \omega_1 - \omega_2$ are the distance between two individual Gaussian functions in time and the frequency domains. The first two terms of Eq. (4) are auto-terms, and the last term represents cross-term at (t_m,ω_m), midway between the two auto-terms. The synthetic signal and its Wigner–Ville distribution are shown in Fig. 1. The cross-term is at the midway, and oscillates in both time and frequency directions, which make interpretation of Wigner–Ville distribution difficult. So cross-term is critical in multi-component signal analyzing and should be eliminated in the application.

If the integral variable in Eq. (2) is not time delay τ but t, the signal's ambiguity function can be defined as

$$AF(\theta,\tau) = \int_{-\infty}^{+\infty} s\left(t+\frac{\tau}{2}\right)s^{*}\left(t-\frac{\tau}{2}\right)e^{j\theta t}dt \tag{5}$$

here the variables τ and θ are parameters of ambiguity plane. The bridge between Wigner–Ville distribution and ambiguity function is 2D Fourier transform

$$WVD(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} AF(\theta,\tau)e^{-j\theta t - j\omega\tau}d\theta d\tau \tag{6}$$

$$AF(\theta,\tau) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} WVD(t,\omega)e^{j\theta t + j\omega\tau}dtd\omega. \tag{7}$$

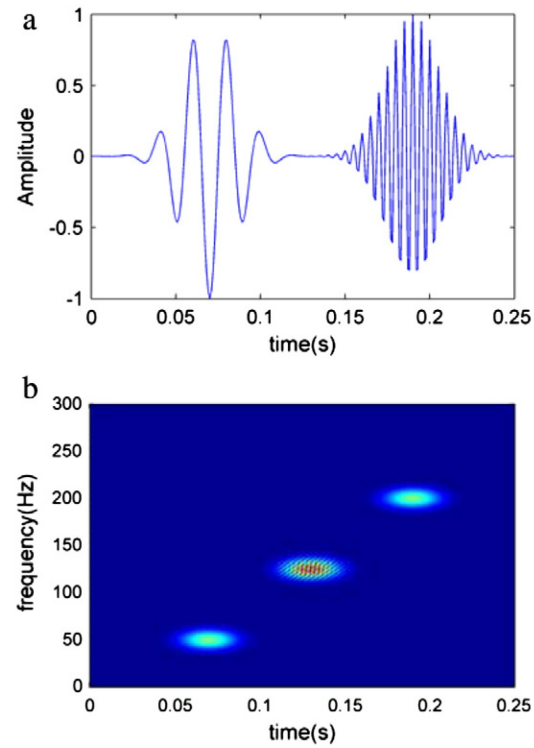

Fig. 1. The Wigner–Ville distribution of a synthetic signal which contain two time-shifted and frequency-modulated Gaussian signals (a) real part of synthetic signal; (b) Wigner–Ville distribution of synthetic signal. The cross-term is at the midway between the two auto-terms. It oscillates in both the time and frequency directions.

Each bilinear time–frequency distribution in Cohen's class can be interpreted as the 2D Fourier transform of a weighted version of the ambiguity function (Cohen, 1989)

$$P(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} AF(\theta,\tau)\Phi(\theta,\tau)e^{-j\theta t - j\omega\tau}d\theta d\tau \tag{8}$$

where kernel function $\Phi(\theta,\tau)$ can be treated as the weighted function. Different choices for kernel function $\Phi(\theta,\tau)$ yield widely different time–frequency representation. Referring to multi-component signals, auto-terms are centered at the origin of ambiguity domain, while cross-terms are centered at a distance away from the origin (the auto-terms in Eq. (4) are Gaussian functions, and cross-term is oscillation term. Since the relation between Wigner–Ville distribution and ambiguity function is Fourier transform, the oscillated cross-term in Eq. (4) must be away from origin at ambiguity plane). The distance is proportional to the distance between the two components being analyzed in time–frequency plane (Qian, 2001). This property indicates that kernel function should be designed as a 2D low-pass filter. Choi–Williams representation (Choi and Williams, 1989) and Cone-shape representation (Zhao et al., 1990) are some well-known members in Cohen's class.

Signal-dependent optimal kernel time–frequency representation based on radially Gaussian kernel (Baraniuk and Jones, 1993) can optimize its kernel function according to the ambiguity function. This algorithm computes the ambiguity function of the entire signal, determines the optimal kernel $\Phi_{opt}(\theta,\tau)$ based on ambiguity function $AF(\theta,\tau)$, and obtains the optimal time–frequency representation via 2D Fourier transform according to Eq. (8). However, for signals whose characteristics change with time or online implementation, especially for reflected seismic trace, adaptation of the kernel function over time is beneficial because it permits the kernel to match the local signal characteristics. AOKTFR alters the kernel function at