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Using a time-frequency distribution to identify buried channels in reflection seismic data

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ABSTRACT

Geological events such as thin beds and channels cannot be easily revealed on seismic sections due to the interference of reflections from the top and bottom of the layer. Buried channel is one of the hydrocarbon traps, which is important in oil and gas exploration. Spectral decomposition can be used to indicate subtle changes in channel thickness. In using the Fourier transform only the frequency content of the changes is displayed; hence, the exact onset of the changes is missed. Time-frequency distributions are suitable approaches to display and interpret information embedded in non-stationary signals such as seismic signals. Spectral decomposition can be used for seismic attributes calculation, which is used for imaging of thin beds. The conventional spectral decompositions such as Short Time Fourier Transform (STFT) and Wigner–Ville Distribution (WVD) have limitations in terms of Heisenberg uncertainty principle and cross-terms artefacts, respectively. In this paper, we used the Reduced Interference Distribution (RID) for buried channel identification to overcome the mentioned limitations. We compared the obtained results of RID with those of Smoothed Pseudo WVD. The real seismic data is selected from one of the western oil fields of Iran. Our results indicate that a better resolution is achieved by RID in both vertical and lateral stratigraphic features.

1. Introduction

Seismic waves are mechanical waves that travel through the Earth's layers or along its surface. Seismic signals propagate into the Earth and reflect from boundary separating rocks with different properties [1]. Indeed, seismic reflection records carry important information, such as amplitude and frequency, associated with the Earth and its subsurface structure. Seismic waves are non-stationary because the Earth acts as a low-pass filter and changes the frequency content of seismic signals during the propagation [2]. Ordinary 3-D seismic data contains energy reflected from the subsurface at a wide range of frequencies, all of which are compounded in a typical seismic volume. Different frequencies of seismic reflection data can image geological features with frequency-dependent nature. Geological interpretations from seismic reflection data are mostly drawn from the time-amplitude domain. It is used to improve and increase the application of seismic data sets for geological interpretations [3]. Spectral decomposition can be helpful to see the amplitude or phase of reflections at particular frequencies. Besides, the spectral decomposition analysis allows the geophysicist to quantify amplitude variation with frequency and extract geological information from seismic data associated with frequency that normally cannot be viewed in conventional seismic data [4].

Fourier transform is not a suitable tool to analyze non-stationary signals. It cannot show the frequency variations of seismic signals over time. Time-frequency analysis is more appropriate for seismic data due to their non-stationary nature. Spectral decomposition has been widely used in seismic data processing and interpretation. We can explore stratigraphic settings, thin beds and buried channels using spectral decomposition of seismic sections [4–7]. The spectral decomposition can be employed to detect low-frequency shadows associated with hydrocarbons [8–10]. Sinha et al. in [11] employed the continuous wavelet transform to computing a time-frequency map for seismic signal. Time-frequency map is used for seismic attributes computation. Askari and Siahkoohi in [12] attenuated the ground roll noise (a common type of coherent noise in seismic data) from seismic data using the S and x-f-k transforms. Roshandel Kahoo and Siahkoohi in [13] performed amplitude versus offset (AVO) analysis in the time-frequency domain

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for detection of the gas reservoir. They used modified high resolution time-frequency transforms to suppress random noise from seismic data using peak filtering method [14]. The spectral decomposition can be used for time varying deconvolution [15,16].

There are several methods in literature for spectral decomposition, such as short time Fourier transform (STFT) [17,18], Wigner–Ville distribution (WVD) [19,20], wavelet transform [21] and S-transform [22,23]. Conventional spectral decomposition methods have some limitations, such as the Heisenberg uncertainty principle and cross-terms existence, which limit their applications in analyzing non-stationary signals. The conventional method of making a time-frequency map using the STFT limits time-frequency resolution by a predefined window length [11]. Therefore, the valuable information is lost or blurred in the time-frequency representations due to a trade-off between the time and frequency resolution. No window function is used to calculate the WVD of a signal. Therefore, WVD has high resolution both in time and frequency domain. However, the applications of this distribution are limited by cross-terms existence. Several methods such as Pseudo WVD (PWVD) and Smoothed Pseudo WVD (SPWVD) have been introduced to eliminate the cross-terms [24–27]. Smoothed versions of WVD use a time and frequency dependent function as a kernel to reduce cross terms. However, these methods reduce the energy distribution concentration in time-frequency plane [14, 28–30]. Cone shaped distribution (CSD) and adaptive spectrogram (ADS) are used for reducing cross-terms in biological signal [31]. In this paper, we used Reduced Interference Distribution (RID) [32] to calculate the time-frequency distribution which is found to be more appropriate for this application. Seismic signals are broadband (8–80 Hz) FM signals and RID is a suitable choice here. This method of distribution with slight impact on the time-frequency resolution increasingly reduces the cross terms.

Analysis of thin-bed tuning on seismic reflectivity has been studied extensively [33–37]. During the last decade, spectral decomposition technique has proven to be an excellent tool to describe thin beds associated with channel sands, alluvial fans, and other similar structures [38]. In this paper, we focused on extracting seismic attributes based on the RID such as instantaneous center frequency, instantaneous bandwidth frequency, root mean square (RMS) frequency, peak frequency and peak amplitude. These attributes are directly related to the thickness of the thin-bed. Since a buried channel is like a thin-bed, we used the extracted attributes for detection of buried channels.

2. Methodology

In this section first we explained one of the effective time-frequency distributions and also a way in which to improve them. We then illustrated the nature of seismic data and the characteristics of thin layer on seismic sections, and proposed some useful seismic attributes to reveal buried channels.

2.1. Time-frequency distribution

Resolution of time and frequency in STFT is limited by the Heisenberg uncertainty principle. One of the advantages of WVD over the STFT is to distribute energy density in time-frequency plane without losing time or frequency resolution. The WVD of signal $x(t)$ is defined as [39]:

$$WVD(t,f)=\int_{-\infty}^{+\infty} X\left(t+\frac{\tau}{2}\right)X^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \quad (1)$$

where $X(t)$ is the analytic signal of signal $x(t)$, $X^*(t)$ denotes the complex conjugate of $X(t)$, f is frequency, t is time and τ is the time delay. The analytic signal is a complex signal [40] and can be computed as:

$$X(t)=x(t)+jH\big[x(t)\big] \quad (2)$$

where $H[x(t)]$ is the Hilbert transform of $x(t)$ and $j=\sqrt{-1}$. $K_X(t,\tau)$ is defined as the instantaneous autocorrelation function of $X(t)$:

$$K_X(t,\tau)=X\left(t+\frac{\tau}{2}\right)X^*\left(t-\frac{\tau}{2}\right) \quad (3)$$

By substitution of Eq. (3) into Eq. (1), we can rewrite Eq. (1) as:

$$WVD(t,f)=\int_{-\infty}^{+\infty} K_X(t,\tau)e^{-j2\pi f\tau}d\tau \quad (4)$$

Eq. (4) shows that WVD is equal to the Fourier transform of the instantaneous autocorrelation function of $X(t)$ with respect to τ.

Because of bilinear characteristic, cross-terms interference is emerged for multi-component signals. For a signal composed of two components $x(t)=x_1(t)+x_2(t)$, based on the quadratic superposition principle [20,41], the WVD is defined as:

$$WVD_x(t,f)=\underbrace{WVD_{x_1}(t,f)+WVD_{x_2}(t,f)}_{auto\text{-}terms} + \underbrace{WVD_{x_1,x_2}(t,f)+WVD_{x_2,x_1}(t,f)}_{cross\text{-}terms} \quad (5)$$

The two last terms in right hand of Eq. (5) are cross-terms with the following characteristics [20,41]:

1- They are found midway between the interacting components;
2- They oscillate proportionally to the inter-components' time-frequency distance;
3- They have a direction of oscillation orthogonal to the straight line connecting the components.

PWVD and SPWVD are two well-known distributions with less cross-term compared with WVD. In these distributions, the cross-terms are reduced by smoothing the time-frequency representation due to their oscillation property. The smoothing reduces the cross-terms, but with the cost of reduction of resolution in time-frequency representation.

Here we exploit the RID method for reducing cross-terms which has the least impact on the resolution of the time-frequency representation. This distribution belongs to the general Cohen class of distributions. Cohen's distribution of a signal $x(t)$ is defined as [42]:

$$TFR_x(t,f)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} e^{j2\pi v(t-u)}g(v,\tau)X\left(t+\frac{\tau}{2}\right)X^* \times\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}dv\,du\,d\tau \quad (6)$$

where $g(v,\tau)$ is a 2D kernel and specifies the distribution. The kernel of RID emphasizes the auto-terms and deemphasizes the cross-terms. The RID keeps almost all the desirable properties of the WVD, but with considerably reduced interference. In this paper, we used Binomial kernel, which is a particularly attractive discrete form which can be computed very efficiently [32].

To study the efficiency of the WVD, PWVD, SPWVD and RID, we tested them on a synthetic signal. The synthetic signal is composed of the sum of two sweep signals that have been repeated twice with total time of 4 s and sampling interval of 0.004 s. Two sweep