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Seismic random noise attenuation and signal-preserving by multiple directional time-frequency peak filtering

Chao Zhang [a], Yue Li [a], Hong-bo Lin [a,*], Bao-jun Yang [b]

[a] Department of Information, College of Communication Engineering, Jilin University, Changchun 130012, China
[b] Department of Geophysics, Jilin University, Changchun 130026, China

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ABSTRACT

Time-frequency peak filtering (TFPF) is an effective method for seismic random noise attenuation. The linearity of the signal has a significant influence on the accuracy of the TFPF method. The higher the linearity of the signal to be filtered is, the better the denoising result is. With this in mind, and taking the lateral coherence of reflected events into account, we do TFPF along the reflected events to improve the degree of linearity and enhance the continuity of these events. The key factor to realize this idea is to find the traces of the reflected events. However, the traces of the events are too hard to obtain in the complicated field seismic data. In this paper, we propose a Multiple Directional TFPF (MD–TFPF), in which the filtering is performed in certain direction components of the seismic data. These components are obtained by a directional filter bank. In each direction component, we do TFPF along these decomposed reflected events (the local direction of the events) instead of the channel direction. The final result is achieved by adding up the filtering results of all decomposition directions of seismic data. In this way, filtering along the reflected events is implemented without accurately finding the directions. The effectiveness of the proposed method is tested on synthetic and field seismic data. The experimental results demonstrate that MD–TFPF can more effectively eliminate random noise and enhance the continuity of the reflected events with better preservation than the conventional TFPF, curvelet denoising method and F–X deconvolution method.

1. Introduction

The reflected events contained in the seismic data play an important role in the study of geological structures. However, the noise contamination corrupts the quality of the reflected events and disturbs the identification of geological information. Therefore, the noise attenuation is crucial to seismic data analysis (Klemperer and Brown, 1985; Zhang and Klemperer, 2005; Zhang and Ulrych, 2003). Usually, random noise can be generated during data acquisition by various sources and this noise is unpredictable in space and time. So, it is difficult to remove random noise from the seismic data. In recent years, many efforts have been made for seismic random noise attenuation (e.g., Abma and Claerbout, 1995; Cao and Chen, 2005; Jones and Levy, 2006; Wang, 1999, 2002). However, most of the existing denoising methods do not work well in the case of low signal-to-noise ratios (SNRs). It performs poorly in signal preservation, which leads to a decline of the fidelity in seismic data processing. Thus, one of the tasks is to design a denoising method to balance the noise attenuation and signal preservation, especially when the SNR is low.

* Corresponding author.
E-mail address: hblin@jlu.edu.cn (H.-b. Lin).

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TFPF is a one-dimensional (1-D) time-frequency filtering algorithm. It can give an unbiased estimation where the signal is linear in time and embedded in white Gaussian noise (Barkat and Boashash, 1999; Boashash and Mesbah, 2004; Zahir and Hussain, 2002). It has been successfully applied to the seismic data processing field (Li et al., 2009; Lin et al., 2007, 2013; Zhang et al., 2013). This method enhances non-stationary signals from random noise through frequency modulation and instantaneous frequency estimation by taking the peak in the time-frequency distribution. In general, we use pseudo Wigner–Ville distribution (PWVD) to realize local linearity. The unbiased estimation condition of the TFPF can be better satisfied if the signal has a high degree of linearity. The nonlinearity of signals will result in amplitude loss in the TFPF. So how to increase the linearity is crucial to the TFPF. One of the effective solutions is to filter along the reflected events. It also takes the coherence between the adjacent channels into consideration, which has a positive effect on the continuity of reflected events. With this in mind, an improved TFPF algorithm has been developed and filtering along a radial trace with an angle to the channel direction (Wu et al., 2011). However, a fixed radial filtering trace cannot fit with the curve reflected events effectively, which leads to some limitations in actual application. A similar trace to the reflected events for filtering is important (Tian and Li, 2014), but the field seismic data is too complicated to find a suitable trace for all the reflected events.

This paper introduces a Multiple Directional Time-Frequency Peak Filtering technique. To do the TFPF along the reflected events, we decompose the 2-D matrix of seismic data into multiple direction components. The direction decomposition is equivalent to the use of some linear segments to approximate the curve reflected events. The distributions of the events in each direction component show as the straight line and have the same slope; the slope direction is the direction of decomposition. So, TFPF could be done along a group of parallel radial filtering traces with the same slope as the decomposed reflected events in each direction component. The sum of the filtering results from all the given directions as the final processed result. The direction decomposition is realized using the directional filter bank. Our method makes the filtering along the reflected events possible by a novel idea without finding the accurate traces of all the reflected events.

2. Time-frequency peak filtering

Let the noisy signal $s(t)$ be modeled by the equation:

$$s(t) = x(t) + n(t), \tag{1}$$

where $x(t)$ is the band-limited non-stationary deterministic signal and $n(t)$ is the random noise. The goal of this algorithm is to recover the signal $x(t)$ from the observed signal $s(t)$. TFPF extracts the valid signal in the following steps (Boashash and Mesbah, 2004).

First, we encode the noisy signal $s(t)$ as the instantaneous frequency of the analytic signal $z_s(t)$ via frequency modulation; $z_s(t)$ can be expressed as:

$$z_s(t) = e^{j2\pi\mu \int_0^t s(\lambda)d\lambda}, \tag{2}$$

where μ is a scaling parameter analogous to the frequency modulation index.

Then we calculate the Wigner–Ville distribution (WVD) of the analytic signal $z_s(t)$ through

$$WVD_{z_s}(t, f) = \int_{-\infty}^{\infty} z_s(t + \tau/2) z_s^*(t - \tau/2) e^{-j2\pi f\tau} d\tau, \tag{3}$$

where t and f are the time and frequency variables, respectively.

Finally, we estimate the peak of $WVD_{z_s}(t, f)$ to obtain the instantaneous frequency of $z_s(t)$. Since we encode the noisy signal $s(t)$ as the instantaneous frequency of $z_s(t)$ by Eq. (2), the estimated instantaneous frequency is the estimation of the signal $x(t)$, which is expressed as:

$$\hat{x}(t) = \arg \max_f [WVD_{z_s}(t, f)]/\mu. \tag{4}$$

where $\hat{x}(t)$ denotes the estimation of the signal $x(t)$, $\hat{f}_{z_s}(t)$ is the estimated instantaneous frequency of $z_s(t)$.

The TFPF method is unbiased for a linear signal $x(t) = \alpha t + C$ (α and C are constants) from white Gaussian noise. The bias $B(t)$ is defined as $B(t) = E[\hat{x}(t) - x(t)]$, E denotes the mathematical expectation. If a signal is embedded in a stationary white Gaussian noise background, the final derivation result of the bias $B(t)$ of the TFPF algorithm is written as (Boashash and Mesbah, 2004):

$$B(t) = \arg \max_f (WVD_{z_x}(t, f) \underset{f}{*} (4\pi^2 k_{n_2} \mu^2 / ((2\pi^2 k_{n_2} \mu^2)^2 + (2\pi f)^2))) - x(t), \tag{5}$$

where $WVD_{z_s}(t, f)$ denotes the WVD of $z_x(t)$ as Eq. (3) and k_{n_2} is the second cumulant of the noise $n(t)$. For the case where the signal $x(t)$ is linear in time, $B(t)$ become:

$$\begin{aligned} B(t) &= \arg \max_f (\delta(f - x(t)) \underset{f}{*} (4\pi^2 k_{n_2} \mu^2 / ((2\pi^2 k_{n_2} \mu^2)^2 + (2\pi f)^2))) - x(t) \\ &= \arg \max_f (4\pi^2 k_{n_2} \mu^2 / ((2\pi^2 k_{n_2} \mu^2)^2 + (2\pi (f - x(t)))^2)) - x(t) = 0. \end{aligned} \tag{6}$$

Equations (6) are derived in the case of stationary white Gaussian noise. However, the analysis can also be applied to other types of noise as long as the signal $x(t)$ is linear in time because the $B(t)$ in Eq. (5) is independent of the k_{n_2} of the noise. Hence, if the signal is linear in time, TFPF can give an unbiased estimation.

However, the reflected seismic signals are nonlinear. So, there must be a bias in the filtering processing by the TFPF. To reduce the bias, TFPF adopts the PWVD, which is the windowed version of the WVD to make the signal approximately linear within the window. The PWVD is defined as (Barbarossa, 1997):

$$PWVD_z(t, f) = \int_{-\infty}^{\infty} h(\tau) z(t + \tau/2) z^*(t - \tau/2) e^{-j2\pi f\tau} d\tau, \tag{7}$$

where $h(\tau)$ is a window function sliding with time.

The PWVDs of an analytic Ricker wavelet contaminated by an additive white Gaussian noise (SNR = 0 dB) are