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Seismic random noise attenuation based on adaptive time–frequency peak filtering

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ABSTRACT

Time–frequency peak filtering (TFPF) method uses a specific window with fixed length to recover band-limited signal in stationary random noise. However, the derivatives of signal such as seismic wavelets may change rapidly in some short time intervals. In this case, TFPF equipped with fixed window length will not provide an optimal solution. In this letter, we present an adaptive version of TFPF for seismic random noise attenuation. In our version, the improved intersection of confidence intervals combined with short-time energy criterion is used to preprocess the noisy signal. And then, we choose an appropriate threshold to divide the noisy signal into signal, buffer and noise. Different optimal window lengths are used in each type of segments. We test the proposed method on both synthetic and field seismic data. The experimental results illustrate that the proposed method makes the degree of amplitude preservation raise more than 10% and signal-to-noise (SNR) improve 2–4 dB compared with the original algorithm.

1. Introduction

Seismic data is usually corrupted by strong random noise, thus improving SNR of seismic data is the key to explore oil and gas resources. Facing the problem of strong random noise and weak valid signal in the seismic data, many methods have been developed for random noise attenuation and reflected event recovery, such as Wiener filter (Gao et al., 2011), empirical mode decomposition (Bekara and Baan, 2009), adaptive filtering (Ristau and Moon, 2001), and polynomial fitting technique (Li et al., 2013). These methods are often useful to suppress the random noise, and some of them have been applied to practical seismic exploration. However, these methods poorly perform with non-stationary signals, particularly when the SNR is below a given threshold (Boashash, 1992a,b). So how to effectively attenuate random noise and improve the SNR of noisy seismic records, particularly for the records with weak reflection events, are goals that many geologists want to reach.

TFPF has been successfully applied to seismic random noise suppression (Jin et al., 2005; Lin et al., 2007, 2008a,b), and it can also recover the band-limited deterministic signal without prior knowledge (Boashash and Mesbah, 2004). The TFPF method is unbiased for the class of signal which is linear in time and embedded in stationary white Gaussian noise (WGN) (Boashash and Mesbah, 2004). However, most of the actual signals are nonlinear and non-stationary such as seismic signal. The common solution is to adopt the windowed version of Wigner–Ville distribution, namely pseudo Wigner–Ville distribution to realize the local linearity of noisy signal. Existing researches show that effective suppression of random noise and preservation of signal amplitude are contradictory to the requirement of window length (Tian and Li, 2014). As a result, TFPF equipped with fixed window length would cause the valid signal loss and noise suppression inadequate. Therefore, in 2014, the fuzzy C-means clustering piecewise TFPF has been proposed (Lin et al., 2014). Fuzzy clustering method uses the feature space to distinguish signal and noise in seismic data. Short window length is set for signal segment, and long window length is set for noise segment. However, while dealing with seismic data which contains high frequency reflected events, it is hard to segment accurately and causes serious distortions between signal and noise.

In order to solve the problems above, adaptive TFPF is proposed in this paper. Its basic principle is that it applies the improved intersection of confidence intervals to get the filtering window length of each point. The filtering window length is short in the position of reflected events and long in the other positions. According to this characteristic, adaptive segmenting is finished by filtering window lengths' short-time energy. The noise segment is the position whose short-time energy is greater than the threshold, and the signal segment is the position whose short-time energy is less than the threshold. Besides, we also distinguish the buffer segments in the noise segments. And then the optimal window lengths are calculated by empirical equation (Wu et al., 2011).

The outline of this paper is as follows. In Section 2, we present the basic principle of conventional TFPF. In Section 3, we describe the derivations of the adaptive TFPF including the improved intersection of confidence intervals, adaptive segmenting method and selection of optimal

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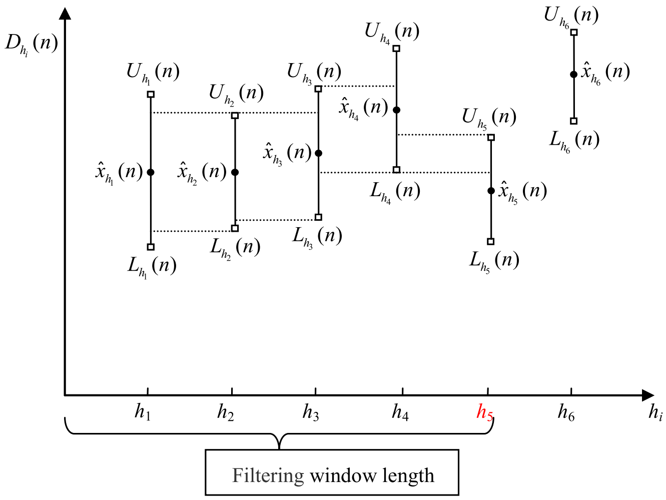

Fig. 1. Schematic of improved intersection of confidence intervals.

filtering window length. In Section 4, we show the performance of adaptive TFPF on both synthetic models and field data. Finally, we draw conclusions in Section 5.

2. Basic principle of conventional TFPF

Seismic waves could be considered as band-limited non-stationary deterministic signals. These signals can be modeled by the following equation:

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

where $x(n)$ denotes the pure seismic components, $v(n)$ denotes the additive random noise, and n is the sampling point. To implement TFPF, the noisy signal $s(n)$ is encoded by frequency modulation as instantaneous frequency of unit amplitude analytic signal, which can be written as

$$z_s(n) = e^{j2\pi\mu \sum_{m=0}^{n} s(m)} \tag{2}$$

where μ is a scaling parameter analogous to the frequency modulation index. After frequency modulation and encoding, the noisy signal $s(n)$ transforms into the instantaneous frequency of the analytic signal $z_s(n)$.

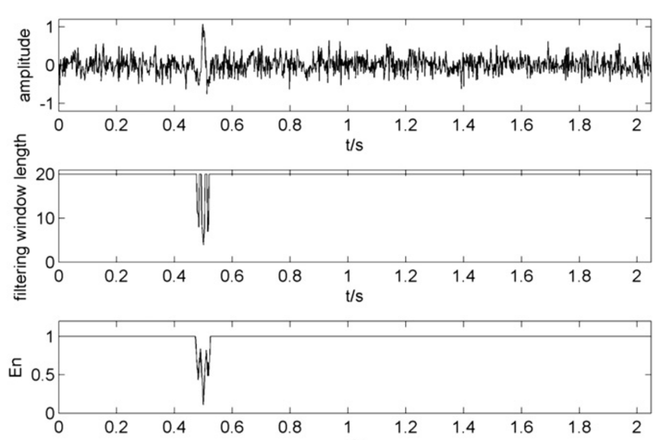

Fig. 2. The noisy synthetic seismic data, filtering window lengths and normalized short-time energy.

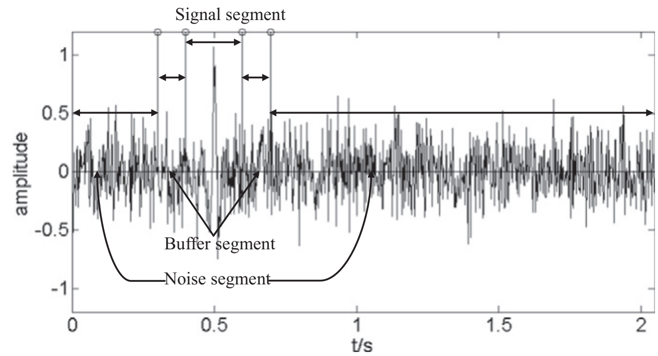

Fig. 3. Schematic of adaptive segmenting.

And then, through estimating the peak in the frequency of pseudo Wigner–Ville distribution of $z_s(n)$, we can get the recovered signal as

$$\hat{x}_h(n) = f_z(n) = \frac{\arg\max_f [PW_z(n,f)]}{\mu} \tag{3}$$

where $PW_z(n,f)$ represents the pseudo Wigner–Ville distribution of $z_s(n)$. The pseudo Wigner–Ville distribution with time-varying window $h(m)$ is defined as follows,

$$PW_z(n,f) = \sum_{m=-\infty}^{\infty} h(m) z_s^{*}(n-m) z_s(n+m) e^{-j4\pi fm} \tag{4}$$

where "*" denotes the conjugate operator. The length of window function $h(m)$ is a trade-off parameter for random noise attenuation and signal preservation.

The optimal filtering window length can be expressed as a function of the dominant frequency f_d and the sampling frequency f_s for the worst bias case (Wu et al., 2011),

$$WL = \frac{0.384 f_s}{f_d}. \tag{5}$$

For a given seismic record, f_s is fixed so that the window length is only related to f_d. In other words, different frequency signals correspond to different optimal window lengths. A fixed window length is not suitable for all signal frequencies in conventional TFPF. So it is very meaningful to make accurate segmenting for the seismic signal.

3. Derivations of the adaptive TFPF

3.1. Improved intersection of confidence intervals

Seismic data contains deterministic signal and random noise, so it is difficult to be segmented because of the direct influence of noise. Aiming at getting the filtering window length of each point, we apply the improved intersection of confidence intervals which is based on Chebyshev inequality to preprocess seismic data.

For a seismic record of $s(n)$ denotes a seismic record, where $n = 1, 2, \ldots, N$ (N denotes the sampling point in the seismic trace), and its valid component is $x(n)$. After TFPF which is equipped with a window length of h, we could get the estimated value $\hat{x}_h(n)$. We take those into the Chebyshev inequality,

$$P\{|x(n) - \hat{x}_h(n)| < \varepsilon\} \geq 1 - \frac{\mathrm{var}[\Delta \hat{x}_h(n)]}{\varepsilon^2} \tag{6}$$

where ε denotes an arbitrary positive number.