Adaptive ground roll attenuation with localized eigenimage filtering

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Summary

Effective attenuation of strong ground roll while preserving the signal is still a challenging task for land seismic data processing. Eigenimage filtering, either in time domain or frequency domain, has been proposed to attenuate ground roll. The key concept is to construct a noise model from eigenimages and remove it from input data. The main task is therefore to optimize the selection of eigenimages that best construct the noise model. The amplitudes and apparent velocities of ground roll often vary with frequency, time and spatial locations. To closely model ground roll and therefore attenuate more noise without signal leakage, the selection of eigenimages needs to adapt to frequency, temporal and spatial variations. We adopt an approach that can be localized in frequency, time and space domains. The input data is first divided into several overlapping frequency bands. For each frequency band, a signal level is estimated based on reflection data outside of the ground roll cone. The eigenimage decomposition and the signal-to-noise ratio (SNR) based selection of eigenimages are conducted on localized overlapping time-space windows. In addition, to address erratic noise that is widely present in land data, amplitude outliers are excluded from the SNR estimation. Testing results show that the adaptive approach presented in this paper is robust and is able to remove most of ground roll energy while preserving the underlying signal.
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Introduction

Ground roll is one of the most dominant coherent noise types in land seismic data. It has distinctive characteristics of low frequency, low velocity and high amplitude. The strong ground roll noise masks the signal energy at near offsets and deep reflections at farther offsets. It can have severe adverse effects on subsequent processing. Effective attenuation of ground roll is a crucial step in land data processing. Various methods have been proposed for ground roll attenuation based on the distinctive characteristics of this noise, including f-k filtering (Yilmaz, 1987), Radon methods (Trad et al., 2003), wavelet transform filtering (Deighan and Watt, 1997), and curvelet transform filtering (Yarham et al., 2008, Yang, et al., 2019). Some of the methods, especially those based on the velocity difference between ground roll and reflection signal, could suffer from irregular trace spacing and data aliasing. In addition, the ground roll energy and apparent velocity often significantly vary with frequency, travel-time and space, which makes it more difficult to get clean denoise result while preserving the signal.

Eigenimage filtering with singular value decomposition (SVD) has been used for ground roll attenuation. Examples have shown that it is robust to irregular trace spacing and data aliasing (Chiu and Howell, 2008, Cary and Zhang, 2009, Chiu, 2019). The basic idea of eigenimage filtering is to decompose the input data into eigenimages with SVD, where a few eigenimages that correspond to the largest eigenvalues are selected to construct a noise model. Such noise models are then subtracted from the input data. Chiu (2019) performs eigenimage filtering in frequency domain over local time-space windows and chooses the first two or three eigenimages to represent the noise model. The method to optimally select the number of eigenimages is not clearly stated in the method. Cary and Zhang (2009) applies eigenimage filtering in time domain over spatial windows. This method selects the number of eigenimages to construct the noise model based on an estimation of SNR of the data. We found that the lack of consideration of time-variance of the ground roll in this method limited the ability to accurately construct the noise.

Intuitively, there will be residual ground roll noise left in the data if too few eigenimages are selected to represent the noise model, while choosing too many eigenimages will lead to obvious signal leakage. One main challenge therefore is to optimize the selection of eigenimages. We follow Cary and Zhang's approach to determine the number of eigenimages based on SNR estimation. We extended the method to be fully adaptive in all three dimensions; frequency, time and space. The number of eigenimages needed to construct the noise models can change with different frequency bands, different spatial locations and different times.

Decomposed eigenimages could consist of both signal and noise, especially when the amplitude level of noise is not significantly higher than the background signal. In most cases, there is no exact number of eigenimages that can be used to remove noise perfectly without damaging the signal. There is a trade-off between attenuating noise and preserving signal. When SNR is relatively high, even the first eigenimage could comprise a significant amount of signal. In such cases, a threshold is used, based on the estimated SNR, to stop the noise model construction, so that noise attenuation is only conducted for local areas with low SNR.

Method

Our method performs eigenimage filtering over local time-space windows in band-limited time domain, and the noise attenuation is constrained to a ground roll cone defined by a t-x curve. This curve is used to align the ground roll and to

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increase the chances of the ground roll energy being focused in the first few eigenimages. This realignment of the ground roll energy reduces aliasing of the noise and enables better separation of the ground roll and underlying signal. The input data is then divided into several overlapping frequency bands. In each frequency band, a signal energy level is estimated from reflection data outside the ground roll cone. The data inside the ground roll cone is partitioned into overlapping time-space windows. A SNR is estimated in each of the local windows. SVD is performed in each window and, using the estimated SNR, the eigenimages for noise construction are determined for each window. The noise model is then subtracted from original input data. Assuming that the working frequency band for ground roll attenuation is divided into three bands, Figure 1 shows the flow chart of our proposed approach.

For the method proposed in this paper, the key is to obtain an appropriate SNR estimation of data that is localized in frequency, time and space. The SNR estimation can be distorted by erratic noise that is abundant in land data. Amplitude outliers should be excluded from SNR estimation. To avoid signal leakage, ground roll attenuation can be disabled for local data areas with relatively high SNR, which makes the noise attenuation more adaptive.

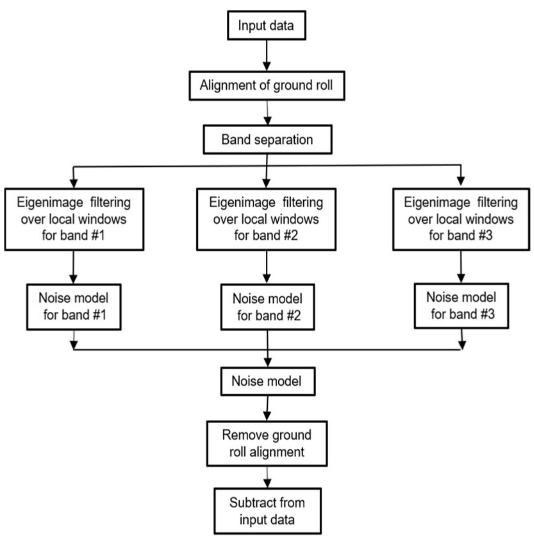

Figure 1. Flow chart of eigenimage filtering for ground roll attenuation, assuming that the working frequency band is divided into three bands.

Examples

A 3D land dataset is used to evaluate our ground roll attenuation approach. In this dataset, the ground roll pattern and energy level vary significantly across the survey area. A consistent set of parameters was able to be applied to the entire dataset. The ground roll attenuation results, shown in Figure 2 (prestack shot records) and Figure 3 (a stack line), demonstrate the successful adaption of our algorithm to the variation of the ground roll noise, and SNR across the survey.

Figure 2 shows the denoise results of two shot gathers. In the relatively clean shot gather shown in Figure 2a, most of the ground roll energy is attenuated, as shown in figure 2b. No obvious reflection events can be seen in the data difference shown in figure 2c, which indicates that the signal is well preserved. Figures 2d to 2f show the results for a shot gather with strong ground roll. For this case, ground roll masks the deep reflection events. After noise attenuation, those deep events are revealed. The reflection signal amplitudes appear consistent and balanced inside and outside the ground roll cone. While there is some ground roll residue at near offsets, most of the ground roll energy is effectively attenuated. No signal leakage is observed from the difference.

To further evaluate possible signal leakage, stacks are generated for the input data and ground roll attenuation results. Figure 3a shows the stack from the input data, where extensive noise is present. The coherent reflection events are not continuous, and we can barely see any deeper events. As shown in Figure 3b, a much cleaner stack is obtained after ground roll attenuation. In this area, reflections are flat and continuous on the stack sections. In the difference stack shown in Figure 3c, we do not see any flat and spatially continuous events.

Conclusion

In this paper, we present an approach that employs localized engenimage filtering for ground roll attenuation. To effectively attenuate noise without signal leakage, the eigenimages that represent the noise model are selected based on a SNR estimation, which is adaptive to the frequency, temporal and spatial variations of the ground roll energy. To make our method robust to erratic noise, the amplitude outliers are excluded from SNR estimation. In addition, thresholding of estimated SNR makes noise attenuation more adaptive for better signal preservation. Results on field data show that our method is able to attenuate most of ground roll energy while preserving the signal.

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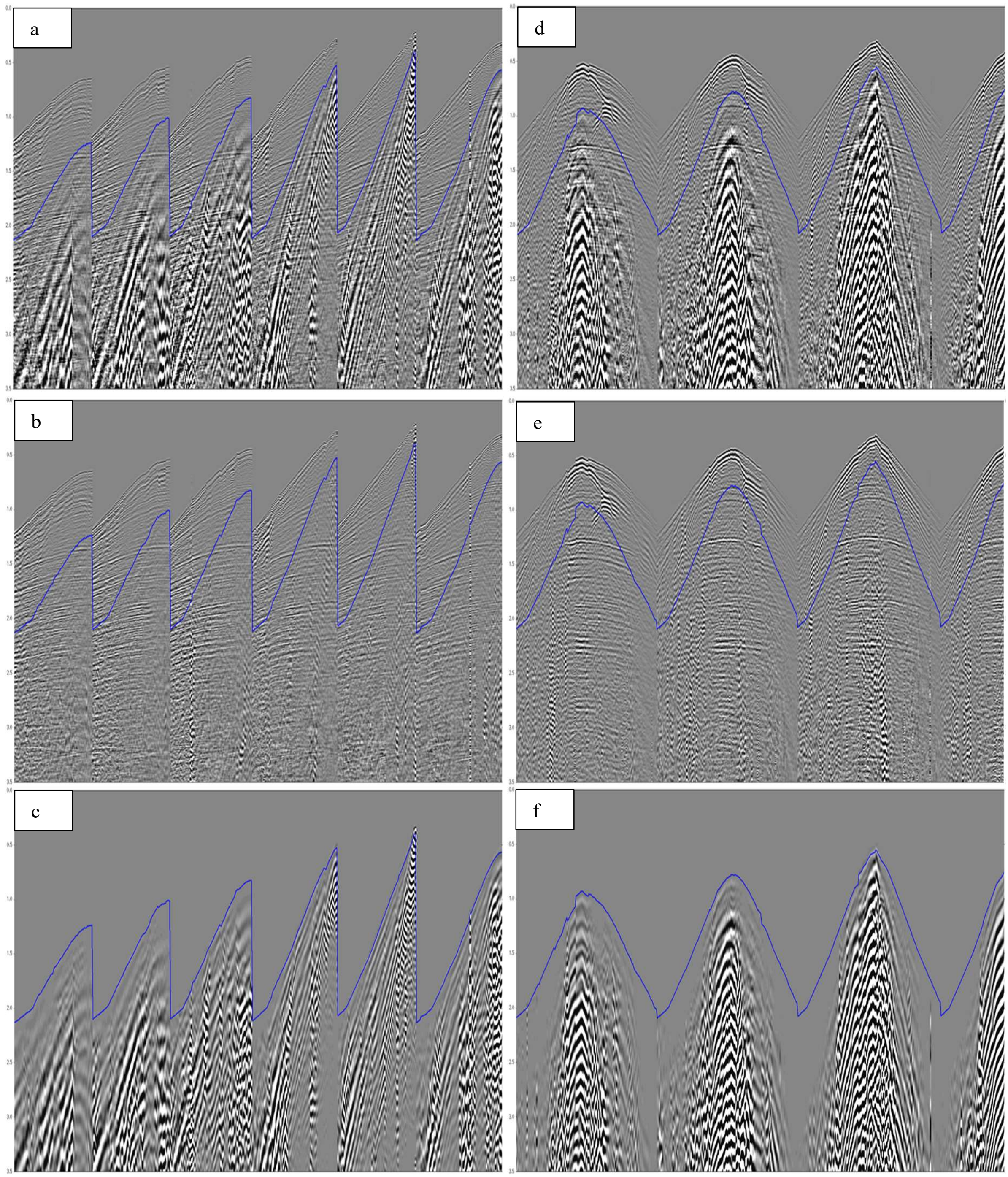

Figure 2. Ground roll attenuation for 3D shot gathers: (a) a shot gather from a 3D survey, (b) after ground roll attenuation, (c) the difference. (d) another shot gather from the same 3D survey, (e) after ground roll attenuation, (f) the difference (the blue curve defines the ground roll cone).

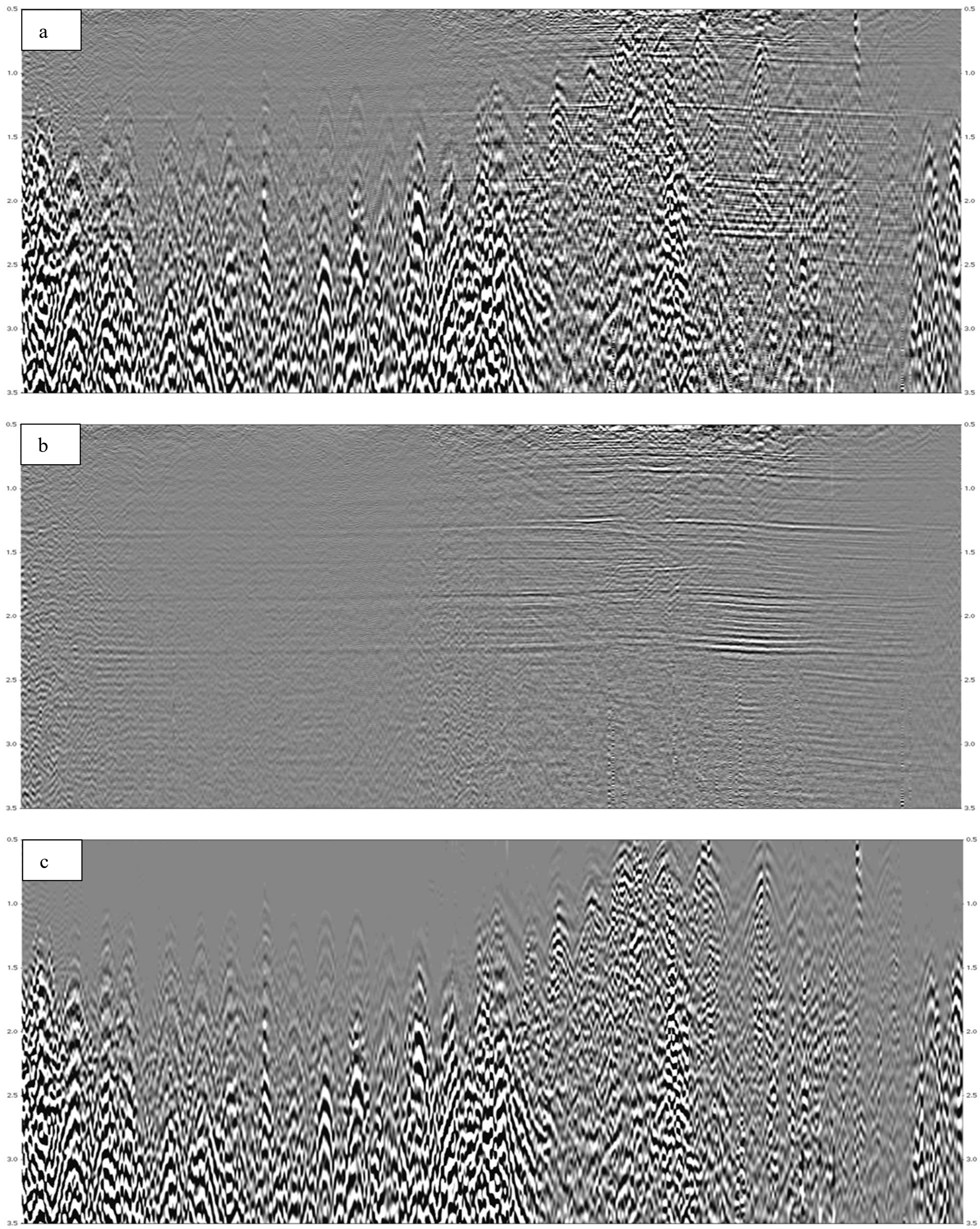

Figure 3. QC stacks for ground roll attenuation. (a) one inline of CDP stack of a 3D survey, (b) stack after ground roll attenuation, and (c) is the difference between (a) and (b).

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