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Ground roll attenuation via NMO-Stack deconvolution and transform-domain noise synthesis

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Summary

Ground roll is a coherent noise in land seismic data that contaminates useful signals such as reflections. Therefore, it is important to find efficient ways that remove this noise and still preserve the signal. We present a signal and noise separation framework that utilize hyperbolic moveout assumption on reflections, coupled with synthesis of noise such as ground roll. This framework yields a least-squares problem which we solve using a sparsity-promoting program that gives coefficients modeling both signal and noise. Thereafter, subtraction of the predicted noise from the observed data produces only reflections whose amplitudes are well preserved. We demonstrate this technique on both synthetic and field data contaminated with different modes of ground roll.

Introduction

Coherent noise removal, such as ground roll attenuation, is one of the first steps in seismic data processing. Characterized by its low-frequency content and high amplitudes, ground roll can conceal crucial information present in weak amplitude reflections. Furthermore, the dispersive nature of ground roll makes it difficult to model and challenging to remove in land seismic data processing.

Various methods have been proposed to attenuate ground roll while simultaneously preserving the seismic signal of interest such as reflections. This noise separation process becomes more challenging when the frequency contents of reflections and ground roll overlap. For seismic data with non-overlapping frequency between ground roll and the reflections, $f-k$ domain filtering usually suffices to attenuate the ground roll (Yilmaz, 1987). Although the processing methods vary in their assumptions and theory, we can categorize them as filtering-based or model-based using adaptive subtraction. Indeed, there are methods that may not fit into any of these categories such as those using matching filters (Saatcilar and Canitez, 1988; Jiao et al., 2015) or eigenimage filtering (Cary and Zhang, 2009).

Filtering based techniques utilizes the properties of ground roll and signal in some transform domains for separation. For instance, $f-k$ domain filtering relies on separating noise from signal using frequency information. Similarly, other transforms have been exploited to separate signal from noise. For example, Askari and Siahkoohi (2008) uses the S and x-f-k transforms, while the curvelet transform (Candes et al., 2006) was used by Yarham and Herrmann (2008) and recently by Naghizadeh and Sacchi (2018). On the other hand, model-based methods exploit the physics of seismic wave propagation for separation. This category includes interferometric ground-roll removal (Halliday et al., 2010), $f-x$ domain modeling and inversion (Perkins and Zwaan, 2000).

Regardless of the approach to ground roll attenuation, the main drawback in many of these methods is determining a trade-off between energy of preserved signal and magnitude of suppressed noise. Notably, the filtering methods usually suffers from amplitude loss in the signal especially where the signal and noise partially overlap.

In this paper, we leverage the benefits of model-based and transform-based processing of signals to separate ground roll from seismic data. Our technique relies on access to the normal moveout

(NMO) velocity extracted during seismic reflection data analysis. First, we propose modeling seismic reflections using the hyperbolic NMO and stacking operators (Thorson and Claerbout, 1985). In addition, we synthesize ground roll using Fourier or curvelet coefficients, so that our noisy data is a combination of modeled reflections, synthesized ground roll and additive noise. This combination allows us to cast ground roll attenuation as a regularized least-squares inverse problem. Through sparsity-promoting optimization techniques, we find coefficents that model both signal and noise while fitting the data to our model. The final stage is the subtraction of the predicted ground roll from the observed data. We demonstrate this procedure on both synthetic and field data examples.

Theory

To arrive at a formulation for coherent noise removal, we model seismic data, denoted by a vector $\mathbf{d}$, as a superposition of signal and different types of noise, i.e.

$$\mathbf{d} = \mathbf{d}_s + \mathbf{d}_c + \mathbf{d}_i + \mathbf{n} \tag{1}$$

where $\mathbf{d}_s$ is the noise-free signal, $\mathbf{d}_c$ is the coherent noise (e.g. ground roll), $\mathbf{d}_i$ is any kind of impulsive noise, and $\mathbf{n}$ is additive noise (we assume Gaussian band-limited noise). To simplify the problem of separating signal from noise, we ignore the contribution by the impulsive noise term.

For a laterally invariant earth medium with reflectivity $\mathbf{r}$, we can model vectorized prestack seismic data as

$$\mathbf{d}_s = \mathbf{L}_s \mathbf{u} \tag{2}$$

where $\mathbf{u} = \mathbf{C}\mathbf{r}$; $\mathbf{C}$ is a convolution operator that depends on the wavelet $\mathbf{w}$. The linear operator $\mathbf{L}_s = \mathbf{N}^T \mathbf{S}^T$ is composed of stacking $\mathbf{S}$ and NMO $\mathbf{N}$ operators. The superscript T denotes the transpose of the operator. By assuming a laterally invariant media, $\mathbf{N}$ is parameterized by the NMO velocity V_{NMO}. For a given velocity and zero-offset travel times τ, this model produces data using the hyperbolic NMO assumption. Solving for $\mathbf{u}$ in equation (2) becomes an NMO-Stack-Deconvolution problem, if the wavelet is unknown. Because $\mathbf{L}_s$ does not have a unique inverse, the inversion process becomes unstable and may require an approximation of the inverse as discussed by Thorson and Claerbout (1985). We use this $convolution + stacking$ model to describe the reflections in our data.

To model the noise (ground roll), we note that seismic data exhibit a sparse (or compressible) representation in certain transform such as Fourier (Xu et al., 2005) or curvelets (Candes et al., 2006), demonstrated by (Herrmann and Hennenfent, 2008; Naghizadeh and Sacchi, 2010). Therefore, we define the $synthesis$ model which describes seismic data (coherent noise such as ground roll) as

$$\mathbf{d}_c = \mathbf{L}_c \mathbf{v} \tag{3}$$

where $\mathbf{v}$ is a sparse (or compressible) representation of $\mathbf{d}_c$, and $\mathbf{L}_c$ is any transform that maps (curvelet) coefficients to vectorized seismic data. To meet our objective of effectively separating the noise from signal, we simply adapt the $convolution + stacking$ and $synthesis$ models to fit the observed data in a least-squares sense as we discuss in the next section.

Modeling and Inversion

By modeling $\mathbf{d}_s$ and $\mathbf{d}_c$ using equations (2) and (3), respectively, equation (1) can be written as

$$\mathbf{d} = \mathbf{A}\mathbf{x} + \mathbf{n} \tag{4}$$

where $\mathbf{A} = \begin{bmatrix}\mathbf{L}_s & \mathbf{L}_c\end{bmatrix}$, $\mathbf{x} = \begin{bmatrix}\mathbf{u} \\ \mathbf{v}\end{bmatrix}$. In practice, we can find a solution to equation (4) using ℓ_1-regularized least-squares inversion by minimizing the following cost function

$$J = \quad \|\mathbf{d} - \mathbf{A}\mathbf{x}\|_2^2 + \mu\|\mathbf{x}\|_1 \tag{5}$$

where μ is a user-defined regularization parameter. To solve equation (5), we use the software package SPGℓ_1 (Van Den Berg and Friedlander, 2008). The solution $\tilde{\mathbf{x}}$ is split into two parts, i.e. $\tilde{\mathbf{x}} = \begin{bmatrix}\tilde{\mathbf{u}} \\ \tilde{\mathbf{v}}\end{bmatrix}$. From these parts, we can synthesize signal $\tilde{\mathbf{d}}_s$, and coherent noise $\tilde{\mathbf{d}}_c$ via equations (2) and (3), respectively. Finally, we subtract $\tilde{\mathbf{d}}_c$ from observed data $\mathbf{d}$ to obtain the noise-free data.

Synthetic Example

We model synthetic data shown in Figure 1 in the frequency domain, as the superposition of a series of hyperbolic events modeling reflections, and linear events modeling ground roll. The non-dispersive linear events are distinguished by their slowness $(p = 1/v)$, where v is the velocity. The reflections are characterized by their RMS or stacking velocities v_j and zero offset travel time t_j for the j-th event. In practice, we could incorporate elements of dispersion in modeling ground roll. However, we do not consider this step since our methodology is independent of a realistic model for ground roll. In designing the modeling operator for the signal, $\mathbf{L}_s$, we use the offset (shot to receiver distance) to contruct the normal-moveout operator $\mathbf{N}$. To synthesize ground roll, we choose $\mathbf{L}_c$ as the 2-D curvelet transform, although other transforms may be applied here. Figure 1(c) shows the predicted ground roll and the final separation result is shown in Figure 1(d). Clearly, no significant reflection energy is lost in the separation process when one compares Figures 1(a) and 1(d). Finally, we could also generate noisy data by adding some random Gaussian noise to the data in Figure 1(b). Instead, we discuss this scenario using real data in the next section.

Field data Example

The field data used here is from a fixed spread 3-D land data acquisition. Receivers are finely sampled along several inlines with two shots in the middle of the receiver spread. We extract a common shot gather, comprising four receiver lines, from this data set for our analysis. As shown in Figure 2(a), the recorded data is contaminated by ground roll characterized by different dispersive modes. In addition, we assume the incoherent noise in the data is gaussian in order to apply our method here. To synthesize the noise in this data, we choose $\mathbf{C}$ as the 2-D Fast Fourier transform. Figure 2(b) shows the predicted ground roll using our proposed method. After subtracting this prediction from the observed data, we recover the reflections shown in Figure 2(c). We notice that the ground roll energy has been significantly attenuated. Further analysis would involve looking at the $f-k$ spectra of the data before and after our method is applied. We can then compare the result with a simple $f-k$ dip filtering method or any other conventional technique.

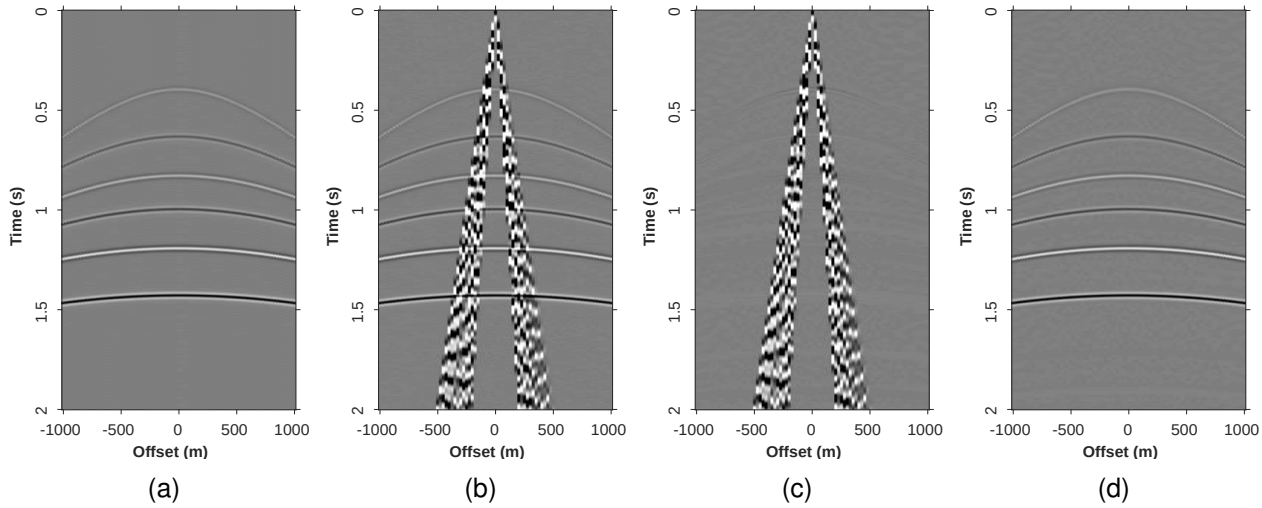

Figure 1: Synthetic Example. (a) Hyperbolic events modeling reflections (b) Data comprised of hyperbolic events, and linear events modeling ground roll. (c) Predicted ground roll (d) Estimated signal obtained by subtracting (c) from (b).

Conclusion

By constraining seismic reflections to lie along hyperbolic paths using normal moveout and stacking operator, and synthesizing ground roll with Fourier or curvelet coefficients, we use a regularized least squares approach to adapt our model to observed data. To obtain data without ground roll, we extract the part of our model that corresponds to the noise and subtract it from the noisy input data. In the synthetic examples, we observe an accurate prediction of the ground roll, which allows us to effectively extract the signal. Finally, the field data results show that we can successfully remove ground roll from land seismic data sets with significant ground roll energy that varies across several inlines.

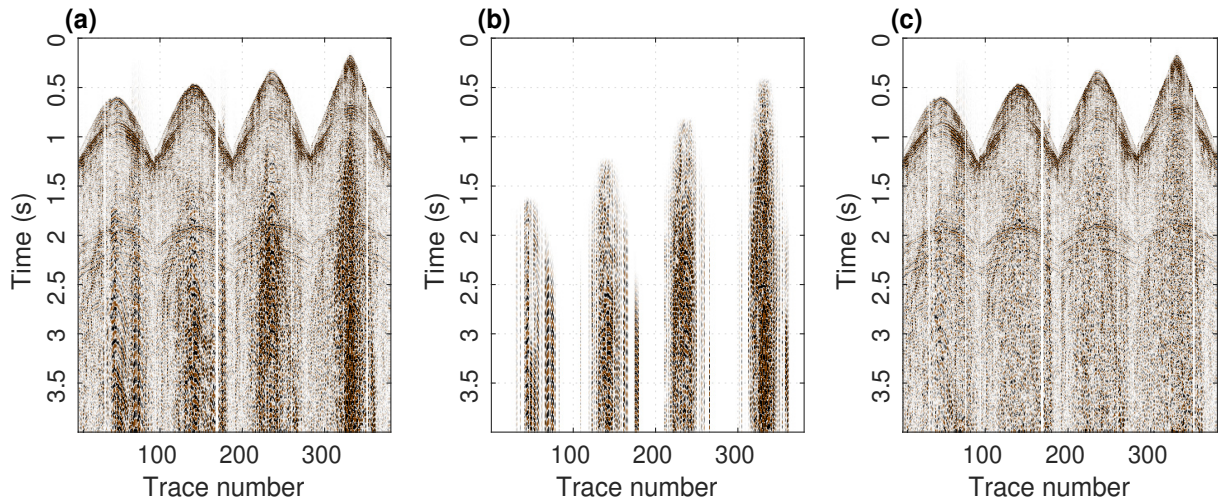

Figure 2: Field data result. (a) Original data contaminated with ground roll (b) Predicted noise (ground roll) via the proposed method. (c) Difference between (a) and (b) revealing the signals (reflections).

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