Should we have labels for deep learning ground roll attenuation?

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SUMMARY

Ground roll attenuation of land seismic data is still an outstanding and challenging problem. Deep learning is a powerful tool for separating signal from noise. Recently, supervised deep-learning-based methods have been applied to ground roll attenuation. However, they require a large set of corresponding clean seismic datasets as labels. Constructing realistic training samples for network training is an unsolved problem. To circumvent it, we proposed an unsupervised deep learning method for attenuating ground roll where no training labels are utilized. The generator network first learns self-similar features before any learning. Therefore, if the reflections are self-similar in the time-space domain, but the ground roll is not, the network can extract the reflections before the ground roll. To make reflections look more self-similar than the ground roll, we apply the normal moveout (NMO) correction to flatten the reflections. Access to NMO correction makes the method also model-driven. The combinations of data-driven deep learning and a model-driven procedure are critical to the success of the proposed method. We use both synthetic and field shot data to illustrate the fidelity and validity of the proposed methods. The field data example shows that our proposed method can attenuate strong scattered ground roll.

INTRODUCTION

Ground roll is composed of surface wave modes that we usually interpret it as coherent noise. The main characteristics of the ground roll are dispersion, high amplitude, low frequency, and low speed. Ground roll masks the desired reflections, and we must attenuate it without compromising reflections before subsequent processing tasks.

In the past, researchers proposed many methods for ground roll attenuation. Among them, filtering methods are most frequently used, including *f-k* filtering (Embree et al., 1963; Treitel et al., 1967), wavelet domain filtering (Deighan and Watts, 1997; Chen et al., 2017) and curvelet transform filtering (Yarham et al., 2006; Naghizadeh and Sacchi, 2018). These methods can effectively attenuate ground roll. We point out that their attenuating ability may be impaired when reflections and ground roll severely overlapped in specific time-frequency zones or in the $f-k$ domain.

Techniques also exist that attenuated ground roll after NMO correction. The fact that primary reflections after NMO are approximately horizontal is important for designing coherent filters to isolate coherent noise or reflections (Liner, 1999). Porsani et al. (2010) proposed a ground-roll attenuation method based on singular value decomposition (SVD). The SVD computation was performed on the flattened reflections after NMO, and this method yields better results than *f-k* filtering methods. Chiu (2013) introduced a randomizing operator into a Multichannel Singular Spectrum Analysis (Oropeza and Sacchi, 2011) for a better attenuation of ground roll. The randomizing operator reorganized coherent ground roll into incoherent noise, but primary reflections after NMO are still nearly horizontal.

Deep learning is a popular topic and develops rapidly in recent years. Especially in the field of image processing, deep-learning-based methods have made breakthroughs. At the same time, deep learning has also been applied to various applications of seismic data processing, including random noise denoising (Liu et al., 2020), ground roll attenuation (Li et al., 2018) and strong background-noise separation (Liu et al., 2019). Constructing training samples and then feeding them to the network for training seems to be a standard workflow for denoising methods based on deep learning. However, the latter requires a large set of clean seismic data, an imposition that may be hard to satisfy in practice. Although the processing speed of deep learning can be significantly improved, estimating a large number of genuinely realistic-looking synthetics for training is a challenge. Therefore, it is necessary to develop unsupervised deep learning methods for denoising seismic data. Zhang et al. (2019) proposed an unsupervised random noise attenuation method based on autoencoder. Similarly, Liu et al. (2020) proposed a method for pre-stack random noise attenuation based on deep convolutional networks without labels.

In this abstract, we propose a new ground-roll attenuation method based on unsupervised deep learning. Our proposed method combines the merits of deep learning and the knowledge of approximate moveout velocities. Firstly, we apply the NMO correction to the raw seismic data for flattening the reflections. After the NMO correction, the reflections are nearly horizontal and self-similar, while the ground roll is not. Then, we utilize deep convolutional networks to extract self-similar features. Inspired by Ulyanov et al. (2018), we realize that the process of extracting self-similarities by learning noisy seismic data using a generator network with randomly initialized inputs. In the training process, the generator network can model the self-similarly horizontal reflections leaving the ground noise in the noise space. After the specified number of iterations in the optimization process, the generator network can easily extract all the horizontal reflections. The subtraction of the extracted reflections from the raw seismic data yields the attenuated ground roll. NMO flattening in shot gather is not fully correct as reflections in the shot domain can have apexes that are asymmetric with offset. Nevertheless, the assumption is valid for sedimentary environments with non-significant structural dips. We mention that the hyperbolic moveout assumption in the shot domain is also used by industry-proven methods such as those proposed by Perkins and Zwaan (2000) and Le Meur et al. (2008).

METHOD

In this section, we present our unsupervised method for ground-roll attenuation. Firstly, we introduce the model formulation. Then, we show the architecture of the deep generator network. Finally, we provide some information about the strategy for model training.

Model formulation

We model the seismic data, denoted by a vector $\mathbf{r}_0$, as a superposition of reflections and ground roll

$$\mathbf{r}_0 = \mathbf{r} + \mathbf{g} + \mathbf{n}, \tag{1}$$

where $\mathbf{r}$ represents reflections, $\mathbf{g}$ is the ground roll noise, and $\mathbf{n}$ is the random nosie. We parameterize the seismic data $\mathbf{r}$ via a generator network as follows

$$\mathbf{r} = f_\theta(\mathbf{z}), \tag{2}$$

where f represents the nonlinear generator network, θ denotes the network parameters comprising the weights and bias of the network filters, and $\mathbf{z}$ is a random vector. Inserting equation (2) into equation (1) gives leads to

$$\mathbf{r}_0 = f_\theta(\mathbf{z}) + \mathbf{g} + \mathbf{n}, \tag{3}$$

where the only unknown parameters are θ. Then, the task of ground roll attenuation from the seismic data is equivalent to finding the optimal network parameters θ^* to minimize the energy function:

$$\theta^* = \arg\min_\theta E\left(f_\theta(\mathbf{z}); \mathbf{r}_0\right). \tag{4}$$

The energy function $E\left(f_\theta(\mathbf{z}); \mathbf{r}_0\right)$ used in this abstract is the following formulation:

$$E\left(f_\theta(\mathbf{z}); \mathbf{r}_0\right) = \|f_\theta(\mathbf{z}) - \mathbf{r}_0\|^2. \tag{5}$$

Once θ^* is determined, we can obtain the recovered reflections quickly from the output of the generator network $\mathbf{r}^* = f_{\theta^*}(\mathbf{z})$.

Network architecture

The network architecture adopted in our work is a U-Net type fully convolutional network comprising downsample blocks, skip blocks, and upsample blocks. Convolutional layers, batch normalization, downsampling layers, upsampling layers, and activation function layers are the basic units, as shown in Figure 1. We use 5 downsample blocks, and 5 upsample blocks to code and decode the input, which provides feature extraction capability at multiple scales. Furthermore, the convolutional filters enable the network to extract self-similar features at multiple scales. The number of feature channels increases with downsampling, from 8 to 128, which is a trade-off between feature extraction ability and computing efficiency. Also, we make several modifications compared to the original U-Net. First, to reduce checkerboard artifacts caused by the upsample blocks, we replace bi-linear interpolation with transposed convolution. Secondly, substituting leaky RELU for RELU to prevent neuron annihilation. Thirdly, we adopt a skipping block strategy to avoid the gradient vanishing problem.

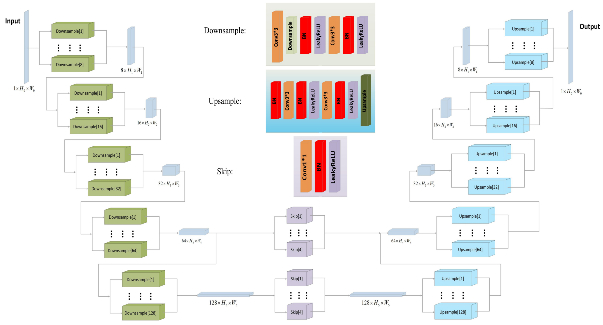

Figure 1: The network architecture used in this abstract

Model training

As it can be seen from Equation (4), our proposed method is an optimization problem under l_2 norm. The code vector $\mathbf{z}$ is sampled from $[-1, 1]$ uniform distribution and has the same spatial dimensions as $\mathbf{r}_0$. Optimization of Equation (4) is an unsupervised network training problem that only relies on the determined code vector $\mathbf{z}$ and the raw seismic data $\mathbf{r}_0$. The ADAM optimizer is applied to train the network and iteratively solve the optimization problem. When training starts, the network parameters are randomly initialized to θ_0. Then, the energy function in Equation (5) decreases gradually as the training continues. At each iteration, the parameters θ are mapped to a network output $\mathbf{r} = f_\theta(\mathbf{z})$. We can regard the optimization process as the reconstruction process of $\mathbf{r}_0$ by the generator network. In other words, the network gradually extracts features along with the training process.

The features extracted by the network in different training periods are different. Due to the specific network structure in Figure 1, the network can extract self-similar features at multiple scales. Therefore, the network can reconstruct reflections because they have self-similar features. However, the network cannot extract self-similar features from random noise. Hence, it cannot restore random noise. In other words, in the early iterations of training, the network mainly reconstructs the reflections. After a long time of iterative training, the network starts to rebuild the noise. Therefore, we can use the generator network to suppress random noise by adopting an early stopping strategy.

Before training, we apply NMO correction to the raw seismic data $\mathbf{r}_0$ to flatten the reflections. The horizontal reflections have more self-similarities than ground roll, so the generator network can reconstruct them before the ground roll, as shown in Figure 2. By selecting a specific number of iterations, we can separate the ground roll from the reflections. Although the best results can be achieved by tuning the number of iterations carefully, we found that a wide range of iteration numbers give us acceptable results.

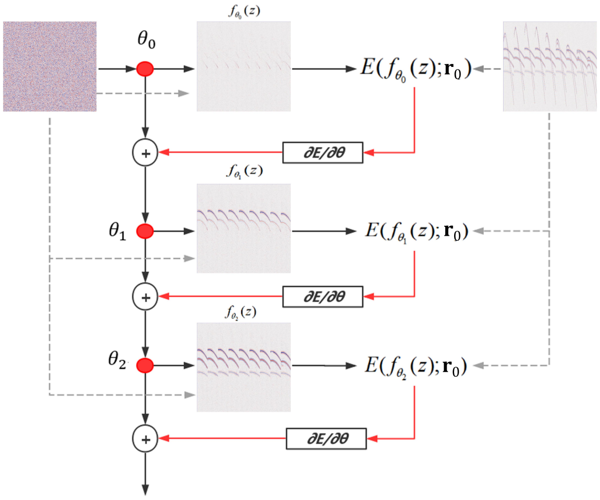

Figure 2: The training process of the network.

EXAMPLES

Synthetic example

Figure 3 shows the synthetic data modeled in the frequency domain. The synthetic data is composed of three reflections modeled by hyperbolic events and ground roll modeled by linear events. This shot model contains 9 gathers, and each of them has 40 traces with a 40m spatial sampling interval. The time sampling interval is 4 ms, and the interval between receiver lines is 120m. The velocity of reflections and zero offset travel time are known. Therefore, we can apply the NMO correction to the reflections and flatten them. Figure 3 shows the estimated ground roll obtained by subtracting Figure 3b from Figure 3a. We see that the ground roll is almost completely removed, and no significant reflection energy is lost.

Field data example

The field data is a land data acquired in Western China. We use a common-shot gather containing 16 receiver lines to examine the effectiveness of the proposed method. To get better attenuation results, we recommend a three-step process procedure. First, we remove industrial noise following Chen et al. (2019). Then, we remove part of the ground roll under the premise of not damaging the reflections following Chen et al. (2017). Finally, we use NMO correction to flatten reflections. As shown in Figure 4, we notice that the energy of the ground roll is significantly weakened, and the target layer becomes clear. Figure 5 is an enlarged result of the part shown in the red block of Figure 4. It can be seen that some clean and continuous reflections are recovered, especially in the regions indicated by the yellow box and the red arrow. Most energy of the strong scattered ground roll is attenuated without significant loss of reflections energy.

CONCLUSION

We propose an unsupervised method based on deep learning for ground roll attenuation without requiring high-quality training labels. We use a generator network to reconstruct the raw seismic data. The network has a strong multi-scale self-similarities feature extraction capability to recover the reflections. NMO correction is applied to flatten the reflections before network training. Both synthetic and field data are utilized to demonstrate the effectiveness of the presented method.

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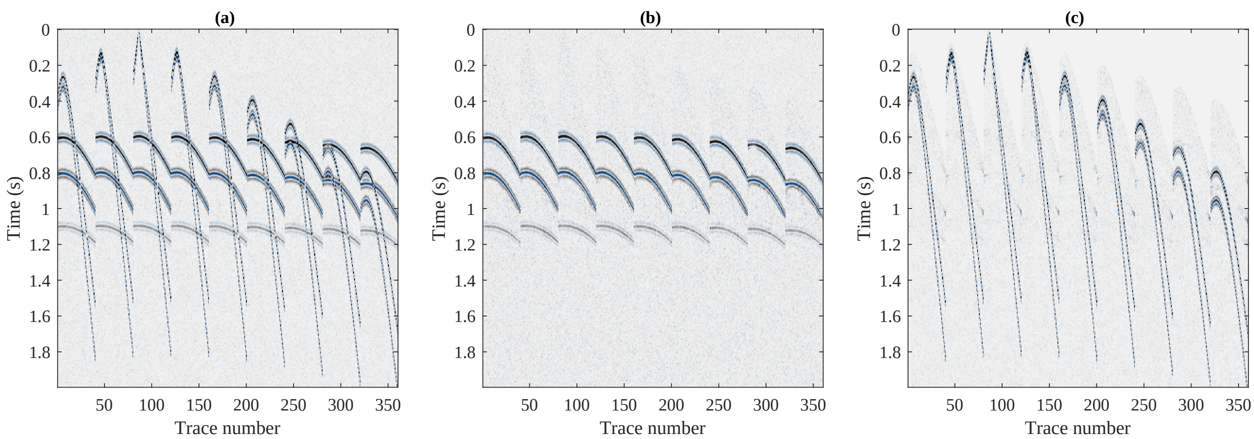

Figure 3: Synthetic example. (a) Synthetic data composed of reflections modeled by hyperbolic events and gound roll modeled by linear events. (b) Reflections obtained by the proposed method. (c) Ground roll obtained by the proposed method.

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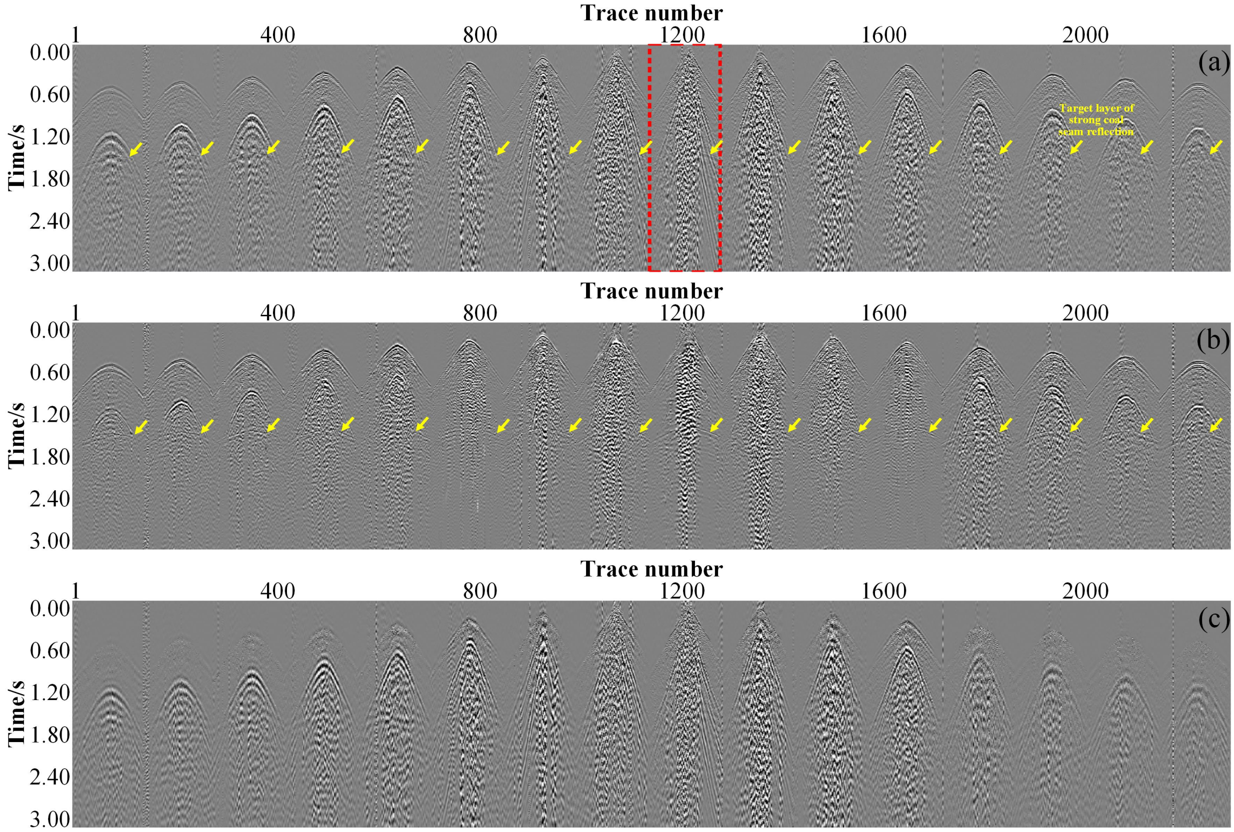

Figure 4: Field data result. (a) Original data. (b) Separated reflections. (c) Separated ground roll.

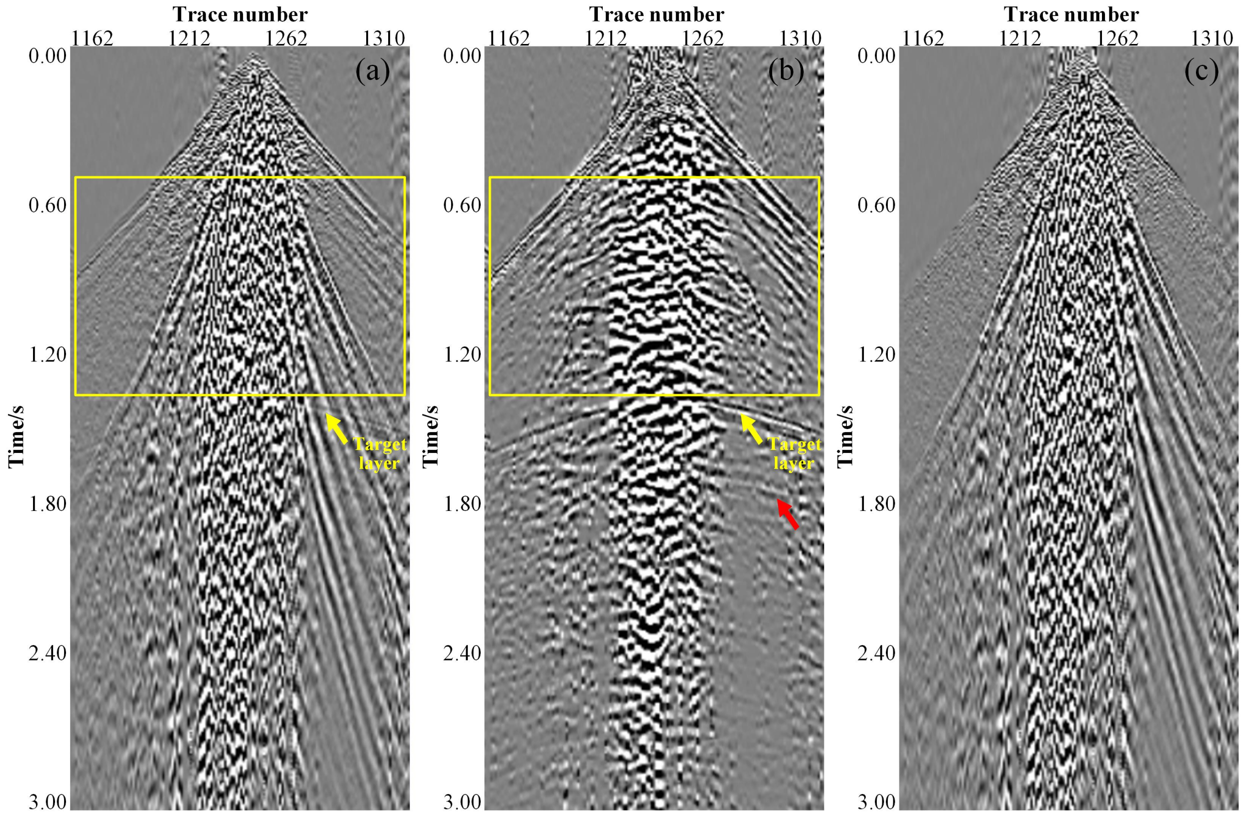

Figure 5: Zoom results of field seismic data. (a) Original data. (b) Separated reflections. (c) Separated ground roll. Most energy of the strong scattered ground roll is attenuated and many reflections indicated by the yellow box and the red arrow are recovered.

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