Seismic data denoising by combining self-supervised and supervised learning

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Summary

Noise removal is a standard part of seismic data processing; however, deterministic workflows may require specific adaptations and parameter tuning for each dataset. Conventional ground-roll noise attenuation methods involving domain transform or decomposition can be time-consuming. Recent studies have demonstrated that machine learning (including supervised, self-supervised and unsupervised approaches) can be an effective tool for seismic noise removal. However, in most applications, the proposed method targets one or other of coherent or incoherent noise. In this study, we propose a workflow for a field dataset containing both coherent (ground-roll) and incoherent noise components. The workflow is built by sequentially combining supervised and self-supervised methods. For the incoherent noise, we train a neural network directly with field data in a self-supervised approach; however, by careful design and selection of the training data, we can also target noise that is coherent over a short range. For the coherent noise, we train a second neural network with supervised learning using synthetic data; we found that this can be directly applied to field data without any additional training which makes this approach very computationally efficient. The synthetic training data need to be thoughtfully augmented to include the key features of the target field test sets. We demonstrate that the proposed workflow can effectively and efficiently remove multiple types of noise from seismic data.

Introduction

Seismic data are always contaminated by noise from different sources in both land and marine acquisition. The signal to noise ratio (SNR) directly affects the quality of the outputs from imaging and inversion and therefore, in fine, the accuracy and confidence of interpretation for both exploration and characterization. Hence, methods to attenuate the noise and improve the SNR are commonly applied in seismic data pre-processing workflows. Denoising methods have continued to evolve over the years, with recent approaches including wavelet transform (Alali et al., 2018), curvelet transform (Naghizadeh and Sacchi, 2018), f-x deconvolution (Gulnay, 2017), singular value decomposition (Gan et al., 2015) and variational mode decomposition (Yu and Ma, 2018). In parallel, the rapid development of machine learning (ML) technology has resulted in a variety of data-driven denoising approaches being proposed and tested (Zhao et al., 2019; Saad and Chen, 2020; Li and Ma, 2021; Yao et al., 2022). Self-supervised approaches, which do not require labels, such as the so-called blind-spot or noise-to-void methods used in image processing (Krull et al., 2019) have been shown to be effective for attenuating certain kinds of noise from seismic data, e.g., DAS (van den Ende et al., 2021) and DAS-N2N (Lapins et al., 2023) for the case of Distributed Acoustic Sensing (DAS) data. However, many denoising tools fail either to remove all the complex noise or to preserve the energy of the seismic signal. Moreover, these denoising methods are often designed to address one or two specific types of noise. When noise with different characteristics is presented, the denoising results are usually not satisfactory.

In this study, we address a land dataset contaminated by various types of noise, which is either incoherent from trace to trace or coherent only over a few traces; it also contains strong, ground roll, which is considered as coherent noise for the subsequent acoustic imaging workflow (figure 3). We propose a ML-based workflow to remove both coherent and incoherent noise components from the seismic data. The first step, which targets the incoherent noise, uses a neural network (NN) trained in a self-supervised way on the field data: no clean data are required as labels. For the second step, the NN is trained in a supervised way using synthetic data from the SEAM Land data project (Regone et al., 2017) to remove ground-roll noise in field data. We first quantitatively test the performance with synthetic data where the ground truth is available. Then, we apply the ML workflow on field data and compare against the results obtained from a deterministic denoising workflow.

Method

We first train our two NNs and then apply a workflow composed of the following steps: 1) preprocessing, 2) incoherent/short-range coherent noise attenuation with the self-supervised NN, 3) ground roll attenuation with the supervised NN and 4) post-processing (Fig 1b). In the first step, the trace amplitudes of the input seismic data are balanced; this is also done for the training, where data augmentation is used to increase the diversity of the training set for the supervised learning. More specifically we stretch and shift both signal and noise traces so that they more closely resemble the real data. The post-processing reverses the scaling applied in first step to recover the original amplitudes.

A. Self-supervised learning for incoherent/short-range coherent noise attenuation

In this step, small patches of size 12 traces by 1024 time samples are generated with sliding windows. In each patch, three adjacent traces, selected randomly, are blanked out. Then the original patches are used as labels and the patches with missing traces are used as inputs. The NN is trained
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Figure 1: a) an example of the different kinds of noise we aim to remove, b) proposed noise-attenuation workflow.

Figure 2: one line from a Barrett synthetic shot gather used as unseen test data in the training of the ground-roll removal network: A) ground-roll noise B) signal C) full response (signal + noise). SSIM for signal is 0.9095, for noise is 0.9246.

with 1,500 small patches extracted from 10 shot gathers. The biggest advantage of self-supervised learning approach is that the labels are directly generated from the field data rather than requiring some processing effort to create the labels from noise-free seismic data. The training set is carefully designed to exclude traces with short-range coherent noise with the idea that the NN will not be able to predict the kinds of events it has not seen in the training data. To improve performance, we replace the classic Unet, proposed in the jDAS algorithm, with the Inception Unet. The inception modules contain parallel paths with convolution blocks of different kernel sizes to capture features at multiple scales. Previous results (Sun et al., 2022) suggest that this can provide more accurate predictions across multiple traces. Different versions of the inception blocks are tested during hyperparameter tuning.

B. Supervised learning for ground-roll removal

In the supervised learning step, we train the NN with the synthetic dataset from the SEAM Phase II Barrett model (Regone et al., 2017). For this, the near-surface and deep seismic responses are modelled separately by judicious choice of boundary conditions and categorized as noise and signal respectively. They are added together to make the input dataset, while being preserved independently to act as labels for the training. The NN architecture is again an Inception Unet but it is modified to have two output paths: one to predict the seismic signal, the other the noise. The model is trained with 108 synthetic shot gathers. The training time is about one hour on 1 NVIDIA A100 GPU, which is very similar to that for the unsupervised training. After training the ground-roll removal NN, we tested its performance quantitatively on 10 other, unseen shot gathers.
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from the Barrett dataset: the trained NN does a reasonable job of separating the signal from the noise for these data, as illustrated in figure 2. The predicted signal and noise components are visually very close to the true ones and we see that the differences between the ground truth labels and the predicted components are minimal (figure 2A & 2B). The full response (signal + noise) is well maintained during the signal-noise separation process (figure 2C), that is, the seismic energy is well-conserved and the predicted signal errors are mainly from the leakage of noise into signal channel and vice versa. The average Structural Similarity Index Measure (SSIM)/NMAE (mean absolute error / input mean absolute value) is 0.9348/0.04656 for the signal and 0.9512/0.04981 for the noise (Table 1). [SSIM values range between 0 to 1, with larger values meaning greater similarity between the compared panels.] The fact that the SSIM is close to 1 and NMAE is smaller than 5% confirm that the prediction accuracy is quite high and that the signal can be well separated from the noise.

### Table 1: mean SSIM, MAE and MSE for Barrett synthetic data.

<table>
<thead>
<tr>
<th></th>
<th>signal channel</th>
<th>noise channel</th>
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<tbody>
<tr>
<td>SSIM</td>
<td>0.9348 ± 0.0247</td>
<td>0.9539 ± 0.0297</td>
</tr>
<tr>
<td>NMAE</td>
<td>0.04656 ± 0.00205</td>
<td>0.04981 ± 0.00327</td>
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Field Data Application

The field data exhibit three distinct types of the noise: 1) ground-roll, 2) second-source noise and 3) noise bursts (figure 1a). Ground-roll and second-source are coherent noise while the noise bursts are incoherent. We first test the performance of the ground-roll removal NN on these field data. Despite the fact that the synthetic “noise” used in the training includes energy other than ground roll, the NN does a good job of removing the ground-roll noise from these data (figure 3). The reflection events that were previously masked by the ground roll appear to be well-recovered, showing good continuity where the ground roll is removed. For comparison, we show results obtained from a more conventional (non-ML) approach applied by a processing contractor. We note that, overall, the two results look broadly similar. However, the ML approach seems to preserve more effectively the later-arriving seismic events (figure 3, green arrows); both methods leave some residual ground-roll noise (figure 3, yellow box) and both seem to affect the character of the underlying events. We believe that the computational cost of the ML denoising is very competitive with the conventional approach, once the NN is trained: The prediction time for each shot gather is only around 1s. on a single NVIDIA A100 GPU, and the process is embarrassingly parallel if multiple GPUs are available. The success of our NN on real data after training only on synthetics suggests that it may work well on other datasets.

Figure 3: results of two shot gathers (A & B) from supervised denoising step as example. (Left) input data, (middle) results after ML denoising to remove ground-roll noise and (right) results after conventional denoising process from contractor.
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with little or no further training. But cases with significant near-surface heterogeneity or topography and associated backscattering will probably remain challenging. To remove all three types of noise, we ran the full workflow proposed in the Method section (figure 1b). The self-supervised denoising removes most of the noise burst energy in the unseen test gathers (figure 4, a2&b2): furthermore, the choice of architecture and selection of training data enables the self-supervised approach to attenuate strongly the second-source noise despite its short-range coherence. The output from this first denoising stage is then passed as input to the second, supervised denoising step, which removes most of the ground-roll noise (figure 4, a3&b3). The underlying seismic reflection events are generally well-reconstructed after the ML denoising process. However, we notice that the overall amplitudes of these events are slightly reduced although they seem to be smooth and continuous at the places where the ground-roll noise has been removed (figure 2, green arrows). Some artefacts from the ground roll remain in the later part of the section but these correspond to depths below our targets. Overall, our workflow successfully attenuates the various types of noise present in the field data while preserving the underlying signal that will be used in subsequent imaging studies.

Conclusions

We propose a new workflow which combines two ML-based tools, trained with self-supervised and supervised learning respectively, for seismic data denoising in a case where several types of noise are identified with very different characteristics. We show that the proposed workflow can effectively and efficiently remove both incoherent and coherent ground-roll noise with a successful application to field data. Preprocessing to balance the intensity of the seismic events significantly improves prediction accuracy. Careful selection of training data and the introduction of Inception blocks into the Unet architecture enabled self-supervised learning to produce a NN which can remove not only incoherent noise, such as the bursts seen on this dataset, but also second-source noise (coherent over short ranges) while preserving the signal. Supervised training of a second NN using only synthetic data from the SEAM Barrett model produced a tool which successfully removed ground-roll noise from our field data without any further training. Application of the NN is computationally efficient so this ML approach is likely to be competitive with conventional ground-roll removal methods. Overall, our workflow gave satisfactory results on the real dataset we show here; it remains to be seen whether adaptations may be needed for application to other datasets. We note that the two ML-based tools can in principle be applied as stand-alone tools.

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