geoconvention
Virtual Event
September 13 - 15
2021

Seismic Swell Noise Processing with Machine Learning Methods

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Summary

Removal of coherent noise (e.g., swell, SI) is an early step in the seismic processing workflow. If noise is not appropriately handled, it can contaminate the final seismic image, interfere with the processing algorithms' performance, and affect the quality of amplitude-based attributes. Traditional seismic attenuation methods need parameter tuning and quality control (QC) to obtain clean gathers with minimal effect on the signal. Their results often require laborious QC to check for residual noise or areas with attenuated signal in need of special attention and parameter fine-tuning. Machine Learning (ML) can potentially solve some of the drawbacks of traditional methods. Here we share two different ML strategies to approach the denoising problem. The first is a classification algorithm that predicts if seismic gathers were processed optimally. The second approach avoids using conventional denoising methods as it employs a deep learning architecture to remove the swell noise from seismic shot gathers. We address the need for labelled training data by combining clean shot gathers (with swell noise removed) with swell noise gathers recorded in the field for a convenient signal vs. noise separation.

Methods

Our classification workflow work builds upon Bekara and Day (2019), contrasting the efficacy of different classifiers. To demonstrate the performance of the first method, we used data acquired in South America. Figure 1 shows an example of the denoising of a shot gather with three different sets of parameters (optimal Figure 1a, mild Figure 1c, and harsh Figure 1e). The noise models are shown in Figures 1b, 1d, and 1f, respectively.

We evaluated several classifiers, including support vector machines (SVM), random forest (RF), artificial neural network (ANN), and convolutional neural network (CNN). The CNN approach provided the best results. It also required no additional work on feature generation because raw shot gathers are an input. Table 1 summarizes our findings using the validation dataset of 6846 shot gathers with one-third of each label group (2282 optimal, 2282 mild, and 2282 harsh).

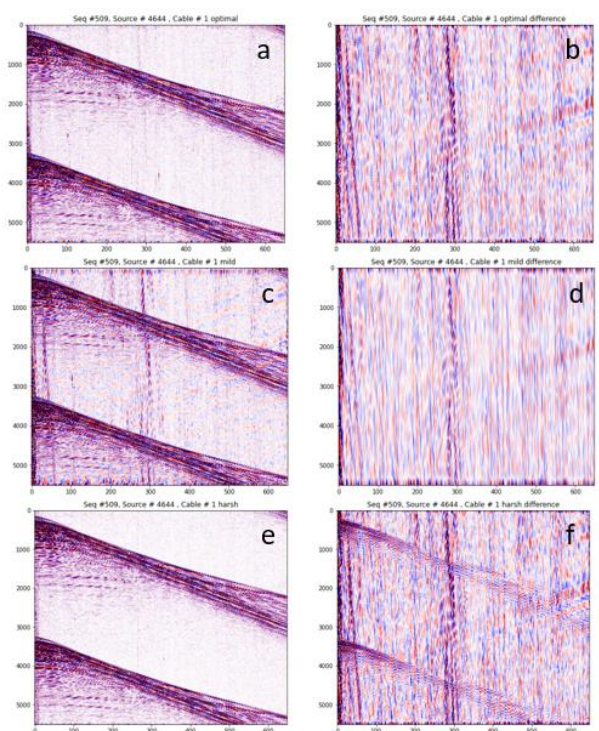

Figure 1. Examples of shot gathers with optimal (a), mild (c), and harsh (e) processing and their corresponding noise models (b, d, f).

Classifier	Precision	Recall	F1-Score	Accuracy
SVM	0.87	0.87	0.87	87.48%
RF	0.91	0.89	0.89	89.35%
ANN	0.96	0.96	0.96	95.80%
CNN	1.00	1.00	1.00	99.53%

Table 1. Summary of different ML algorithms' performance to classify shot gathers according to the swell noise attenuation outcome into optimal, mild, and harsh.

The second denoising strategy comprised training a deep learning architecture to remove swell noise from seismic shot gathers. Alwon (2018), Richardson and Feller (2019) used a similar approach to solve this problem. We employ a U-net with Residual blocks using AdamW optimizer and leaky Relu activation function. A vital consideration is whether to use synthetically generated or real field data for model training and validation. It is easy to separate signal from noise when using synthetic data, but the model may not generalize well especially when applied to real world data. On the other hand, field data with a clean separation of noise vs. signal may take significant effort to generate. We propose a novel approach to build a training dataset. Our workflow combines clean shot gathers (with harsh swell noise removed) with swell noise gathers recorded in the field for an easy signal vs. noise separation.

Figure 2 summarizes our results. The shot gather in the first row was processed by a conventional method. Figures 2a and 2d show the same raw navmerge image. The noise removed with traditional processing is shown in Figure 2b. The cleaned image result is on Figure 2c. The deep learning noise results are shown in Figure 2e. The two noise models (2b and 2e) look practically identical. Figure 2f presents a noise-free image after deep learning denoising. There is minimal residual noise left in the shot gather after denoising with the deep learning model. We conclude that the quality of the results of our workflow are comparable with the traditional approach.

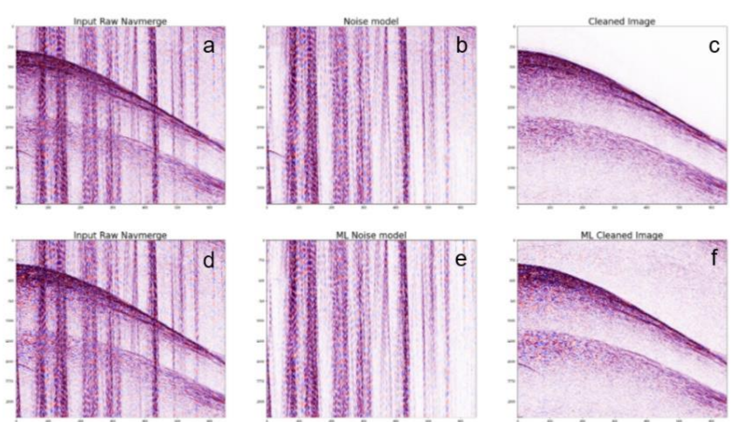

Figure 2. Navmerge input shot gathers (a) is used in the conventional denoising workflow to remove swell noise (b) from the signal (c). The same gather (d) was denoised with a trained deep learning model. After swell noise (e) subtraction from the input cleaned shot gather (f) was obtained.

References

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