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Application of Convolutional Neural Network in Automated Swell Noise Attenuation

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Summary

Noise attenuation is a crucial and recurrent step in the seismic processing sequence. After noise attenuation, quality control (QC) is a mandatory process to ensure that the level of noise left in the data is acceptable and no signal leakage has occurred. This process is usually done by geophysicist and is time consuming and subjective. We train a U-Net convolutional neural network model to automatically perform the QC after swell noise attenuation and label the seismic samples as signal, noise or signal leakage. We show that the classification of the acquired seismic data after the swell noise attenuation with the trained model is very reliable and robust and model is able to detect both residual noise and signal leakage. We also propose a framework to use the classification result to steer the denoise process in an automated fashion. If the model detects residual noise or signal leakage during the denoise process, the selected parameters are automatically tuned to produce the best possible result for each seismic record. We demonstrate that the automated denoise process outperforms the fixed parameters denoise process.

Introduction

Noise attenuation is a crucial and recurrent step in the seismic processing sequence. Different types of noise can be addressed by different noise attenuation algorithms. For example, one typical noise type found in marine seismic data is swell noise. Swell noise is usually high amplitude noise with a low frequency character, caused by waves and turbulence. During seismic processing, swell noise is usually attenuated by statistical detection and reconstruction, the specifics can vary between different algorithms. The goal is to remove as much noise as possible without distorting the signal (signal leakage).

After noise attenuation, quality control (QC) is a mandatory process to ensure that the level of noise left in the data is acceptable and no signal leakage has occurred. Geophysicists often perform QC by visual inspection in different seismic domains. However, this process is time consuming, and hence only a fraction of the actual seismic data is usually inspected. This can introduce the risk of missing localized residual noise or signal leakage. If an area with residual noise or signal leakage is found during QC, current practice is to manually update and re-run the noise attenuation procedure, after which QC is performed once more by the geophysicist. As the size of exploration surveys is continually increasing, it is often found that the parameters for the noise attenuation algorithm tuned for the test line(s) may not be optimal for the whole survey.

Martin et al. (2015) and Bekara (2019) both present methods that try to automate the QC process. Both derive attributes that quantify the similarity between signal remaining, and noise removed, for each shot record and apply machine learning based classifications of the multidimensional attribute space. We propose a method which uses deep learning to facilitate the denoise QC process. In common with the aforementioned papers, the engine for noise attenuation does not change but the actual seismic records are used as input to the classification algorithm and classification is performed sample by sample. We also aim to use the classification to steer optimal denoising within each shot record.

Methodology

In this study, we focus on hydrophone swell noise attenuation. First, we create an image segmentation classification model to automatically label the seismic samples after noise attenuation as signal, noise or signal leakage. This model can be used to classify the result of the denoise process, and this classification can be used as a QC tool on its own. However, we also propose to use the classification result to steer the denoise process in an automated fashion. If the model detects residual noise or signal leakage during the denoise process, the selected parameters are automatically tuned to produce the best possible result for each seismic record.

Classification model

The network model used is the U-Net convolutional network (Ronneberger et. al. 2015). U-Net was originally developed for classification of medical images, but has gained popularity in the seismic community. The input to the model is a seismic tile with 336x336 samples. The model has 21x21 samples in the lowest resolution layer and there are 16 filters for the first encoder. The model has three output classes: signal, noise and mask. Supervised training was used to train the model. Training data were seismic shot gathers after noise attenuation and the corresponding noise removed. To create the training data it was important to ensure that the signal estimate contains as little noise as possible and that the noise estimate contains no residual signal. This can be achieved either by manual or conditional selection. We chose conditional selection through the available real seismic library. Around 10,000 seismic tiles were used to train the model with 20% held for verification and 10% for the test. The accuracy of the model on the verification data was 98.7%. We anticipate that the accuracy could be further improved in the future by adding more data to the training dataset.

The model can be used to classify the noise attenuation process. If the input to the classification is the shot gather after the noise attenuation, any sample classified as noise is a sample with considerable residual noise. On the other hand, if the input to the classification is the noise removed after the noise attenuation, any sample classified as signal is a sample with considerable signal leakage. For classification of signal leakage we have found it useful to compare the difference in noise removed between two subsequent noise removal steps. This approach can be applied both when incremental noise suppression is applied, and when the noise attenuation is repeated with a set of parameters that leads to harsher denoise. In either case, the signal leakage will tend to stand out when evaluating the incremental change.

Automated noise attenuation

When residual noise or signal leakage is detected in seismic data, it can often be addressed by applying the same processing flow with alternative noise attenuation parameters. A reliable classification model can make the decision on-the-fly to re-tune the parameters. Even though there are often a number of parameters that can be changed in the noise attenuation algorithm, it is often the case that only a few need to be adjusted to have maximum impact on noise attenuation performance.

Our framework currently assumes that a geophysicist will build the noise attenuation process on the test line(s) as they do today. When the process is run at production scale, the classification model will tune the selected parameters to produce a better result than could be achieved by the original parameters. This is schematically presented in Figure 1.

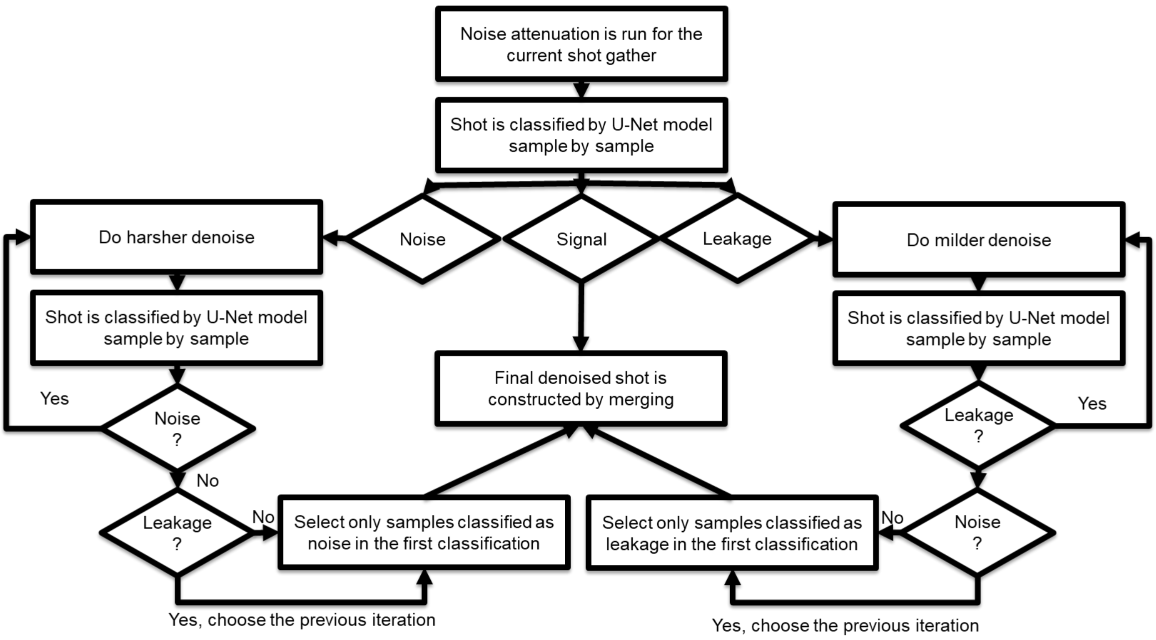

Figure 1: Schematic flowchart of the automated denoise process.

Example

We first show the performance of the classification model to classify the output of the noise attenuation process. Figure 2 shows an example of a classified shot gather with three different levels of noise attenuation. The model is able to identify residual noise left in the data with high accuracy.

Figure 3 summarizes the classification results for the full line containing the record in Figure 2 after different levels of noise attenuation. As the noise attenuation becomes harsher, the percentage of clean samples increases for all the shots as demonstrated in Figure 2. Let us assume that noise attenuation level 2 was selected during testing for full-scale production. This level of the noise attenuation leaves some residual noise in some of the shot gathers (green marks in Figure 3c). If we increase the harshness of the noise attenuation to level 3, almost all the residual noise is attenuated to the level our model was trained for (green marks in Figure 3d). However, the model also detects a considerable level of signal leakage (red marks in Figure 3d).

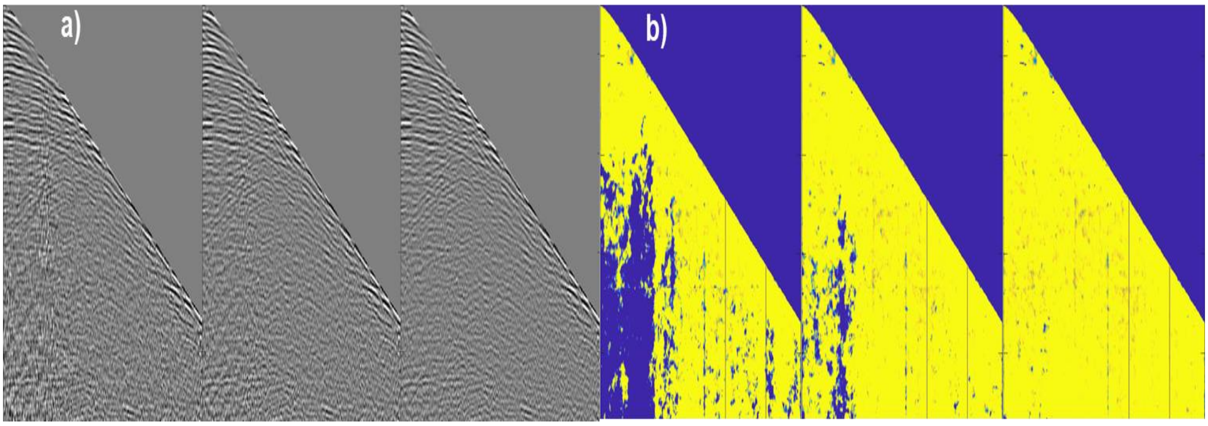

Figure 2: a) A shot gather with three different levels of noise attenuation. Noise attenuation is harsher from left to right. A high-cut filter is applied to the shot gather to display only the frequency range that is affected by the noise attenuation. b) Corresponding classification for detecting noise free signal for every sample. Blue and yellow colours represent probability of zero and one, respectively.

A better noise attenuation process would replace the noisy samples after noise attenuation level 2 with harsher noise attenuation provided that harsher noise attenuation does not generate any signal leakage. In addition, if we observe signal leakage after noise attenuation level 2 for any samples, we would like to apply a milder noise attenuation to those samples. This is possible using the information determined by the classification and can be done automatically on-the-fly. Figure 3e shows the overall result of the automated noise attenuation. It is clear that the automated noise attenuation not only improves the noise attenuation, but also suppresses signal leakage (compare the red marks in Figures 3c and 3e). Figure 4 shows a comparison between the automated noise attenuation and noise attenuation level 2 for the selected traces in different domains. All domains present superior noise suppression with the automated noise attenuation. Note the improvement in the coherency of reflected energy in the stack image (Figure 4h).

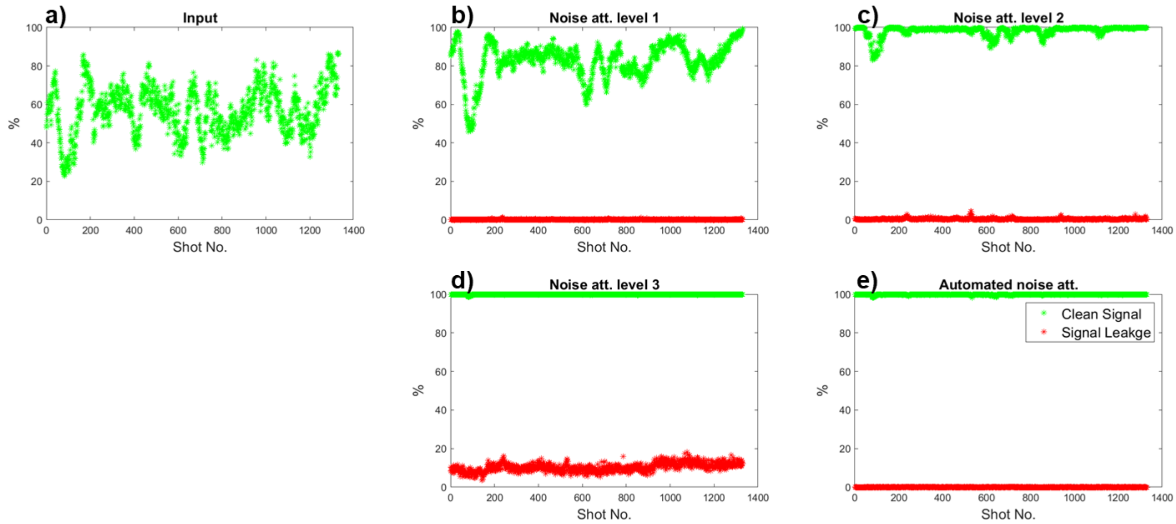

Figure 3. Percentage of samples classified by the model as clean samples (green marks) and signal leakage (red marks) for a) input and after b) level 1 noise attenuation, c) level 2 noise attenuation, d) level 3 noise attenuation, and e) automated noise attenuation.

Conclusions

The U-Net network is able to classify seismic samples after noise attenuation as clean or noisy samples. This network is also able to detect samples with signal leakage when the attenuated energy is classified. By incorporating the U-Net network in the noise attenuation algorithm in an automated fashion, it is possible to improve noise attenuation and minimize signal leakage.

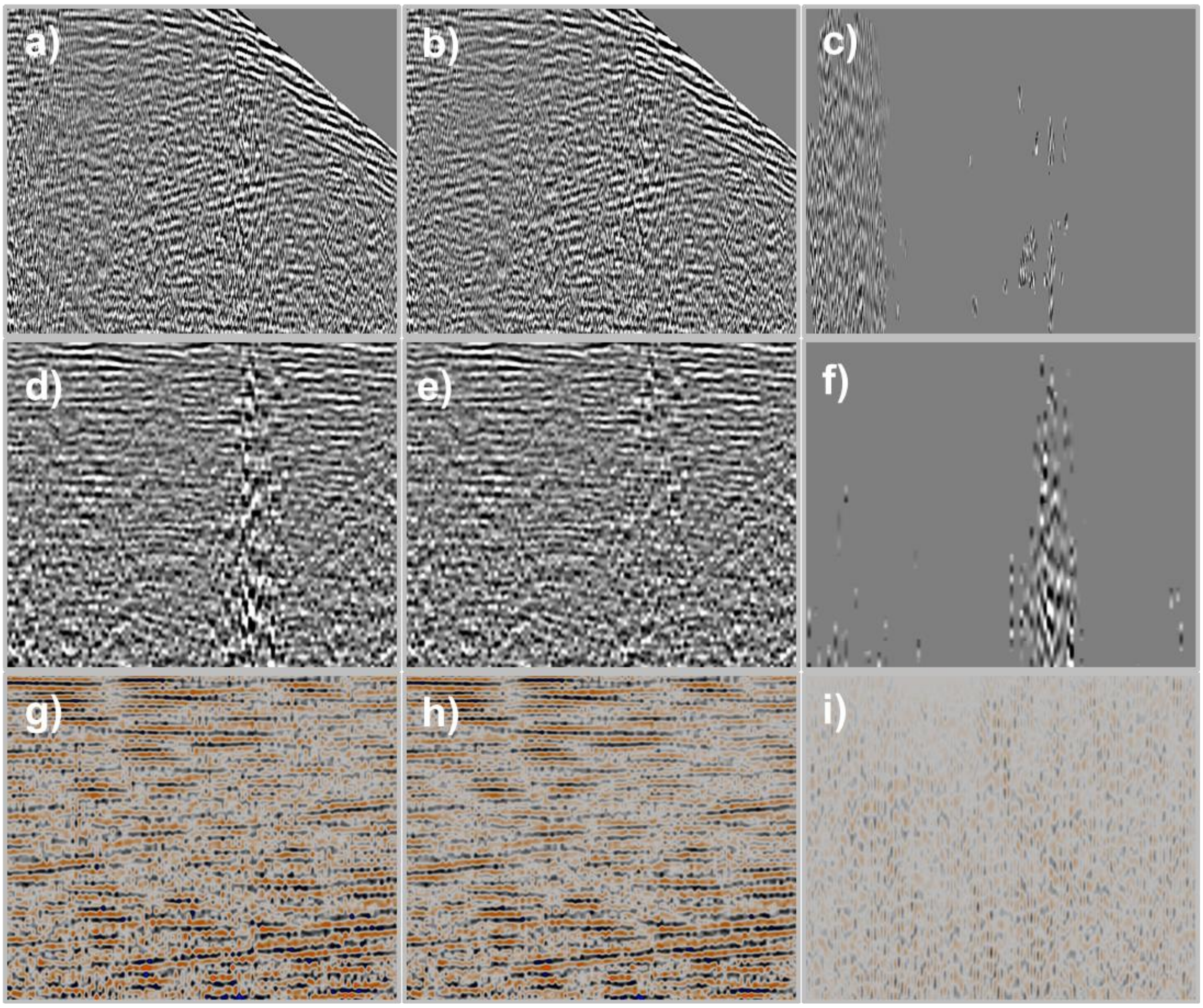

Figure 4. a), d) and g) output of noise attenuation level 2 displayed for a selected shot gather, common channel gather and stack, respectively. b), e) and h) output of automated noise attenuation for the same traces displayed in a), d) and g), respectively. c), f) and i) difference between noise attenuation level 2 and automated noise attenuation.

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